FROM TOUGH-ON-CRIME TO SMART-ON-CRIME: THE RACIAL IMPACT OF POLICING FELONY DRUG OFFENSES IN THE 21ST CENTURY

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ABSTRACT OF THE DISSERTATION

From Tough-on-Crime to Smart-on-Crime: Policing Felony Drug Offenses in the 21st Century

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From the 1970s through the early 2000s, the policing of drug crime in America was marked by a "tough on crime" approach. This ethos influenced the ways in which police managed public safety, resulting in the adoption of police paramilitary units (PPUs) and the overuse and misuse of order-maintenance stops and warrants for drug offenses. Yet these units and practices are known to be associated with racialized patterns of policing. Over the past decade, a number of police agencies have transitioned towards a "smart on crime" ethos that rejects the "tough" approach in favor of evidence-based strategies often touted as race-neutral. This ideological shift in policing was especially pronounced in Atlanta, where a PPU was disbanded and replaced with data-driven units after several high-profile incidents of police abuse came to light. One of the consequences of the move to "smart" drug policing, then, should be a conspicuous decline in racial disparities. In this dissertation, I examine whether and how the move from "tough" to "smart" policing styles influences the role of race in the enforcement of felony drug crimes. Using data from the Context of Drug Enforcement project, I explore racialized patterns of policing in both the "tough" (2005) and "smart" (2012) eras; use multilevel models to understand the relationship between specialized units (PPUs and data-driven units) and certain tactics (warrants and order maintenance stops) with race in each era; and estimate fixed effects models to assess how the change in ethos, in specialized units, and in tactics affected racial disparities in drug policing across eras. The findings reveal a complicated story, with Atlanta Police Department's shift in ethos contributing to changes in some but not all aspects of racialized drug arrest patterns and, even then, only marginally. This is partially a consequence of the minor and nuanced role played by these units and tactics in generating racial disparities in arrests in the first place. While the shift to a "smart on crime" ethos can generate a substantial redirection away from the policing of drug crime more broadly, it may do little to alleviate significant racial disparities in drug arrests.

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Introduction

The last few decades have witnessed a monumental rise in incarceration rates in the United States, a phenomenon often referred to as mass incarceration (National Research Council, 2014). This rise in incarceration has disproportionately impacted people of color. Indeed, racial disparities in rising incarceration rates is one key feature of this generational change (Clear, 2007). Both overall increases and racial disparities in incarceration have been largely driven by the War on Drugs (Mauer, 2006).

One major contributor to the racial disparity in incarceration via drug offenses has been changes in policing, specifically the introduction of "tough on crime" practices. A great deal of research has described the role of charging and sentencing decisions in the creation of racial disparities in incarceration (Walker, Spohn, & DeLone, 2011), yet arrests represent the first stage in a cycle that can lead to incarceration. As Goldstein (1960) noted, arrests are the primary from of discretion in the criminal justice system, determining what decisions are even open to other criminal justice actors, and "tough on crime" practices often emphasize the use of arrests for drug offenses (Beckett, 2016).

The tough on crime movement emerged roughly around the mid-1970s and lasted through the early years of the 21st century, focusing on an approach to offending that emphasized severity and harshness. The "tough on crime" movement, its relationship to drug offenses and the resultant racial disparities are tied to the recent militarization of policing, especially the expansion of what researchers have called police paramilitary units (PPUs), or specialized units that embody a variety of militaristic traits (Kraska & Kappeler, 1997). The "tough on crime" movement has also led to an emphasis on certain tactics: order-maintenance stops and search and arrest warrants (Balko, 2015; Beckett, 2016).

But policing has undergone a significant transformation since the mid-2000s. Nationally, there has been a shift from "tough on crime" tactics towards "smart on crime" tactics (Drakulich & Kirk, 2016; Sherman, 2013; Telep, 2016). This shift has been especially pronounced in Atlanta, Georgia. After a number of crises involving order-maintenance stops and raids to serve warrants by their drug-focused PPU, Red Dog, the city disbanded the PPU; announced they were shifting towards community policing and data-driven initiatives; and moved away from targeting drug crime toward targeting violent crime (Blau, 2016; Geraghty & Velez, 2011). Thus, Atlanta provides the ideal case study of the shift in ethos from "tough on crime" to "smart on crime" in policing. Research suggests that police departments are often reluctant to change (Dabney, 2010), and yet while other police departments were slowly moving towards the "smart on crime" approach, few experienced a series of crises like those in Atlanta. These experiences sparked a marked shift in policy during a time when these issues had not yet reached national significance. Thus, changes in the association between race and arrests for drug offenses during this time are likely tied to local changes in police tactics. While research has evaluated the crime-reduction benefits of this shift (Mazerolle, Soole, & Rombouts, 2007), it has yet to address the impact on racial disparities. Further, few studies have investigated the units and tactics that lead to racialized patterns of policing within each era, to better understand the processes that produce these patterns.

To examine this shift in policing, I employ multiple statistical models to test a series of hypotheses investigating the role of race within each era and to compare across eras. First, I investigate the role of race in drug arrests within the "tough on crime" era, examining its relationship to certain units (PPUs) and tactics (order-maintenance stops and serving warrants). Next, I investigate the same issues within the "smart on crime" era, focusing on the use of certain units (data-driven units) and the same tactics. Finally, I aggregate arrests up to the census tract level to examine change in the non-white arrest rate and racial disparities across eras, specifically examining how much of that change is due to reductions in the use of specialized units, order maintenance stops, and warrants.

In this dissertation, I will begin by describing the rise in incarceration, focusing specifically on racial disparities and the role that drug crimes have played. I then will discuss how "tough on crime" policing has contributed to the racial disparity in incarceration. In Chapter 2, I discuss what we currently know about PPUs and the use of order-maintenance stops and the serving of warrants. Next, in Chapter 3, I contextualize the shift in policing at a national level and the data-driven approaches that replaced PPUs. I then focus directly on the shift that occurred within Atlanta. In Chapter 4, I describe my data and methods, including an examination of racialized patterns of policing in each era. In Chapter 5, I examine the sources of racialized patterns of policing within the "tough on crime" era, exploring the role of Red Dog, order maintenance stops, and warrants. In Chapter 6, I examine the sources of racialized patterns of policing in the "smart on crime" era, exploring the role of data-driven policing, order maintenance stops, and warrants. In Chapter 7, I investigate whether the non-white arrest rate and racial disparities have decreased across eras, and whether changes in the use of specialized units and tactics are partially responsible for any observed decline in racial disparities. Finally, in Chapter 8, I summarize my findings and provide context for what these findings say about race and approaches to policing within a large, diverse American city.

Chapter 1. Drugs, Race, and the Era of "Tough on Crime" Policing

In this chapter, I begin by discussing mass incarceration, its impact on racial disparities in justice, and the role that the War on Drugs played. I then describe the rise in the "tough on crime" ethos that accompanied the War on Drugs. Finally, I examine how this ethos has changed policing in America, and how that change was linked to racialized patterns of drug arrests.

Mass Incarceration, the War on Drugs, and Race

For most the 1900s, the rate of incarceration remained relatively stable, yet since the 1970s, it has risen markedly. From 1973 to 2009, the incarceration rate quadrupled, and the sheer number of people in prison rose from 200,000 to 1.5 million (National Research Council, 2014). This increase is in addition to the hundreds of thousands of individuals held in local jails. Not only is growth in incarceration historically unique, but it is also considerably out of step with other western developed democracies. While the United States accounts for only 5% of the world's population, as of 2012 it accounted for 25% of the world's prison population (National Research Council, 2014).

Racial disparities in the prison population have also increased over the last few decades. According to the National Research Council (2014), in 2010, the rate of incarceration for African Americans was six times that for whites, and the rate of incarceration for Hispanics was three times that for non-Hispanic whites. Despite surveys that suggest the rate of use and involvement in sales of drugs is lower for African Americans than for whites, arrest and incarceration rates for drug offenses among people of color have grown dramatically since the 1970s, a time when there was already a disparity for drug arrests of 2-to-1 (National Research Council, 2014). Considering this, it is not surprising that Pettit and Western (2004) view prison as the modal life event, above college or the military, for black men in America. Wacquant (2002) believes prison is the fourth peculiar institution used to reinforce a racial hierarchy in the United States, alongside slavery, Jim Crow Laws, and Northern and Midwestern ghettos. And Beckett (1997) finds that, among Americans, attitudes towards crime control align quite well with attitudes towards race, such that those who express more prejudiced views tend to also favor a tougher criminal justice system.

While mass incarceration is somewhat reflective of changing crime rates, some of the largest increases in the prison population came during times when the crime rate was either holding steady or declining (National Research Council, 2014). Clear (2007) provides a broad history that points to some other key contributors, positing new foci in each decade that built upon policies that were already expanding incarceration. He cites rising crime rates and the switch to determinate sentencing as the culprit in the 1970s, an increased focus on drug crimes in the 1980s, tougher policies for violent offenders in the 1990s, and a targeting of recidivists in the early 2000s.

Among the causes cited by Clear (2007), the growing attention to drug offenses, often dubbed the "War on Drugs," has garnered substantial attention among researchers attempting to explain mass incarceration. In his book, *Race to Incarcerate*, Mauer (2006) posits that it was not a shift in crime that led to this change in incarceration, but a shift in crime policy. While some have argued that changes in attitudes towards all crime were led to the increase in incarceration (Pfaff, 2017), reflecting broad shift towards a "tough on crime" approach, it was the "tough on crime" approach towards drugs that has led to the greatest racial disparities, mostly because of the large degree of discretion provided to criminal justice actors when addressing drug offenses (Mauer, 2006).

There is a long history tying drug offenses to race and ethnicity within the United States, and it is rooted in racialized moral panics about the presumed effects of drugs (Provine, 2007). These panics center on an assumed causal relationship between drugs and more serious crime yet, while a correlation certainly exists, empirical evidence and theoretical arguments for a causal relationship are fairly tenuous (Bennett, Holloway, & Farrington, 2008). Goode (2012) identified three possible explanations: enslavement, predisposition, and intensification. The enslavement explanation is the one that most closely aligns with the moral panics over drugs, stating that drugs capture their users through their effects and by fostering dependence. This, then causes users to commit crime that they otherwise would not. The predisposition explanation argues that the connection between drugs and more serious crime is a result of the same sorts of people having a tendency towards engagement in both. In short, drugs are related to crime because drug users are more likely to commit crime irrespective of use; some other factor of their life "predisposes" them towards both behaviors. Finally, the intensification model is a combination of the two, positing that there is some level of predisposition, but also some level of enslavement, such that drugs intensify preexisting tendencies towards property and violent crime. Goode argues that the intensification model is the only one that is consistent with current research findings. This explanation does not posit a direct causal relationship between drugs and serious crime, but instead a much more complicated one in which a substantial portion of the relationship is due to previous life circumstances, not drugs.

Even if one were to assume the enslavement explanation is correct, it is unlikely that most of the resulting crime would be due to the effects of the drugs themselves. Goldstein (1985) suggested three models for the connection between drugs and violent crime. The first model, the psychopharmacological explanation, assumes that the physiological effects of drugs themselves lead to criminal behavior. While some evidence of this exists, especially for stimulants, much of this relationship may be driven by social and environmental factors associated with drug use (Chermack & Blow, 2002). The second model, the economic-compulsive model suggests that the desires of addiction result in the use of crime to obtain money for drugs. Some evidence of such crime exists, but a recent review found that it only explained a small portion of drug-related violent crimes such as robbery (White, Jackson, & Loeber, 2009). Finally, the systemic model posits that violence related to drugs is not due to the drugs themselves (either their immediate effects or their withdrawal symptoms), but instead to their status as an illegal substance. This status cuts off drug users and dealers from legal forms of recourse for conflict and encourages conflict with criminal justice authorities. Goldstein (1985) believes that the bulk of evidence supports this final model as an explanation for the relationship between drugs and violent crime. Thus to the extent that drugs do cause serious crime, it is unlikely that the drugs themselves are responsible for the bulk of it.

Regardless of the reason for the link between drug use and sales and serious crime, policies have acted on this correlation by intensifying enforcement of drug laws, and have done so in a racialized manner. The 1909 Report of the International Opium Commission stated that cocaine is a “creator of criminal and unusual forms of violence” and posited that it is has caused “abnormal crimes” among “humbler Negroes” (International Opium Commission, 1909, p. 51). In a 1914 *New York Times* article written by a doctor, the abilities of “Negro cocaine fiends” to withstand bullets was discussed (E. H. Williams, 1914), which mirrored accounts of a “Negro” who had been made crazy by cocaine attacking a North Carolina officer with a knife (Spillane, 1994). Very similar language was used to describe the effects of marijuana on “Mexicans, Spaniards, and Latin Americans” and of opium on the Chinese (Bonnie & Whitebread, 1974; Lusane, 1997). Indeed, these sorts of descriptions about marijuana, positing the drug caused a “lust for blood” and “superhuman strength,” led to the law that criminalized it, The Marihuana Tax Act of 1937 (Provine, 2007).

The racialized notion of a connection between drugs and violence is not just a product of the early 1900s. Sensationalistic coverage of crack cocaine often cited gang violence to justify laws that led to substantial racial disparities in sentencing, such as the Anti-Drug Abuse Act of 1986. These laws punished the sale of crack cocaine (a drug more often sold and used by black men and women) 100 times more harshly than powder cocaine (a drug more often sold and used by white men and women) (Provine, 2007). Behaviors and objects can become subtly racialized which, in turn, influences both the beliefs of the public and the policies that are enacted. Beckett, et al. (2005) posit that policies that may appear race neutral—such as the disparity in sentencing between crack and powder cocaine or, to preview a topic discussed in more detail later, the use of PPUs to serve narcotics warrants—reflect racialized notions of drug use and sales, and they find support of this association for crack cocaine sentencing in Seattle, WA. As Powell and Hershenov noted, "The war on drugs could more aptly be called a war on minority populations" (1991, p. 559).

"Tough on Crime" Policing

Beyond racialized notions of drug offenses, the War on Drugs led to realized racial disparities in criminal justice processing through the development of "tough on crime" tactics. These tactics became the primary mechanisms through which the War on Drugs operated. The primary reason that the War on Drugs and "tough on crime" tactics coexisted so well was because of attitudes towards drug offenses. Popular beliefs and theories of drug use fall under two broad theoretical frameworks (Belenko, 2000). Under one, drug use and abuse is viewed as a disease or public health issue and, under the other, drug use and abuse is viewed as a moral issue for which drug users possess some level of control and responsibility. These views influence public policy towards drugs, with the first suggesting a treatment-based approach and the second a punishment-based approach. Since the rise in incarceration, a time that marked the beginning of the "tough on crime" movement, policies and legislation have clearly reflected the latter (Spohn & Belenko, 2013). As Balko (2015) notes, it was "Nixon's dehumanization and demonization" of drug users, his ability to frame drug use as a moral issue and thus drug users and sellers as immoral that drove the "tough on crime" mindset.

Police have not always practiced "tough on crime" policing. The institution of policing as something recognizable by a modern understanding of police is a relatively recent occurrence with roots dating back to only the early 1800s (Monkkonen, 1992), but for much of their brief history prior to the 1970s, policing operated quite differently. While there are no hard and fast historical lines delineating policing techniques, Kelling and Moore (1988) write of three eras of policing. Robert Peel founded the first modern uniformed and organized police force in London in 1829, using his military experience to create an organization that could effectively bring about formal social controls (Monkkonen, 1992). American cities copied this model and, while founded on military principles, early policing was far less connected to military tactics and attitudes than current policing (Balko, 2015). In this first of three eras, the *political era*, police functioned as local watchmen and social service providers. With a mostly decentralized structure, police in the political era became fixtures within the communities they patrolled and, in addition to discouraging crime, they often filled roles that are now assumed by various social service agencies, such as providing shelter for the homeless (Kelling & Moore, 1988; Monkkonen, 1992). From the introduction of policing to America in the 1840s up to the early 1900s, this era reigned.

The next era, the *reform era*, began in the 1930s and continued for a few decades (Kelling & Moore, 1988). This era was led by August Vollmer, a Berkley, CA police chief, and his protégé, O. W. Wilson who professionalized policing in an attempt to rid it of corruption. In order to accomplish this, they created distance between police and other local public agencies; restricted the goals of policing to crime control, eliminating the social work mandate of the previous era; standardized police work, leaving police with few tools for enforcement other than arrests; promoted distance and neutrality in relation to the communities police patrolled; practiced preventive patrol and rapid response to calls for service; and borrowed hierarchical structure, dress standards, and language from the military (Kelling & Moore, 1988). The mode of policing that developed during this era is often referred to as the "standard model" or the "professional model."

While Kelling and Moore argue that a third era of policing began forming in the 1970s, the *community problem-solving era*, both the authors and others have also argued that the standard model has remained the norm through the late 1990s and early 2000s (Kelling & Moore, 1988; National Research Council, 2004). The ideas emphasized in community policing and problem-oriented policing influenced the form policing took in the 1970s, 80s, 90s and early 2000s. Many agencies heard the call for more proactive policing echoed in both strategies, but proactive enforcement rarely took the shape described in early writings on community and problem-oriented policing. Instead of involving innovative problem solving and community collaboration, it involved the arrests common to the standard model of policing and the frequent stop and searches that become popularized later by broken windows theory (Kelling & Bratton, 1998; National Research Council, 2004). As discussed in further detail below, Kraska and Kappeler (1997) argue that the early community policing movement was morphed to fit the needs of the "tough on crime" era.

The “tough on crime” movement traces back to Richard Nixon’s 1968 “law and order” platform, which was the Republican response to rising crime rates, yet it eventually became the de-facto response for both parties when Bill Clinton adopted it in the mid-1990s (Chernoff, Kelly, & Kroger, 1996; Holian, 2004). As the fear of crime became a salient national issue, tougher approaches to crime rose in popularity (Holian, 2004). The focus of the “tough on crime” movement was clear: drug offenses. Balko (2015) details how the Nixon administration strategically chose to go after drug offenses because the more serious property and violent offenses that concerned many Americans were not crimes over which the federal government had influence. Violent and property crimes were local and state issues, and thus local and state politicians would be the ones to benefit from reductions to such crimes. But drug sales often crossed not just state but also national borders, making them a clear candidate for federal enforcement.

The federal government used funding through Law Enforcement Assistance Administration and its successor agencies—the Office of Justice Assistance, Research, and Statistics, and the Office of Justice Programs—to spread the drug war to the state and local level by offering financial support to state and local law enforcement agencies for programs that attacked the sales and use of drugs (Balko, 2015; Beckett, 2016). They also spread the War on Drugs to local and state agencies through assistance with training and the provision of equipment (Beckett, 2016). While this targeting of drug offenses at a federal level and support for targeting at state and local levels began with Nixon, it continued with the administrations to follow, ramping up with even greater velocity during the Reagan administration (Balko, 2015; Beckett, 2016).

Coinciding with this focus on drugs, the “tough on crime” mentality was motivated by a view of offenders as morally culpable. The “tough on crime” ethos argued against “liberal social policies” as “a means of supporting criminals” and “coddling” them (Ramirez, 2013, p. 333), and it argued for enhanced punishment of criminals, a view of criminality as a moral issue, and a view of criminals as rational decision makers (Chernoff, Kelley, & Kroger, 1996). It relied heavily on deterrence and rational choice theories of crime, and eschewed economic or situational explanations of crime (Chernoff, Kelley, & Kroger, 1996). This led to policing strategies that built upon the standard model of policing and its “one size fits all” approach to law enforcement. Among the approaches were routine patrols; intensive enforcement, especially in the form of stop and searches; raids and crackdowns; and arrests as the primary outcome of stops (Kraska & Kappeler, 1997; Mazerolle et al., 2007). Generally, the “tough on crime” era asked police to take a proactive and aggressive approach to crime, seeking out offenders and dealing with them harshly (National Research Council, 2004). This mentality can even be seen in the recruiting materials that police used, which emphasized aggressive and physical tactics, such as “tackling suspects, rappelling out of helicopters, shooting guns, kicking down doors, and siccing dogs on people” (Balko, 2014, p. 306).

The “tough on crime” approach to policing represents a clear departure from the past. This is most easily apparent by examining the wide range of policing styles and techniques that that characterize American law enforcement. Wilson (1977) posited three general styles: the first is the service style, in which police respond to all requests, but are relatively unlikely to make an arrest; the second is the watchman style, in which police do whatever is needed to maintain order; and the third is the legalistic style, in which police are extremely likely to make an arrest. Policing in the political era often took the form of either the watchman style or the service style; in the early reform era, it took the form of the service model mixed with the legalistic model; and since the “tough on crime” ethos has been influencing policing, much of police activity combines the legalistic and watchman styles, with police using arrests to maintain order.

Not only is the overall style historically unique, but the techniques, particularly the heavy-handed use of arrests, are also unique. Black (1976) identified four styles of police response: the conciliatory response, which might take the form of a mediation between conflicting parties; the compensatory response, such as a fine; the therapeutic response, which can take the form of counseling or referral; and the penal response, which takes the form of an arrest. The political era relied more heavily on compensatory and therapeutic responses, and while the reform era initiated greater reliance on penal responses, the “tough on crime” era has led to a near total reliance on the penal response. As arrests are the first step towards the potential for incarceration (Goldstein, 1960), it is not surprising that the emphasis on arrests in the “tough on crime” era contributed to the growth in incarceration, especially for drug offenses.

In addition to growth in incarceration, mass incarceration is also marked by racial and ethnic disparities in incarceration. Racial and ethnic disparities are not new to policing. Police manuals discussing problems with policing racial and ethnic minorities appeared as early as 1944 (Monkkonen, 1992), and the Kerner Commission investigated issues of race and policing in the U.S in 1968. Whereas aggressive policing tactics were certainly a problem in these earlier eras, Goffman (2014) argues that for much of history under-policing, or a lack of a police presence, was the main source of distance between African American and Hispanic communities and the police. With the War on Drugs and the "tough on crime" movement, under-policing was replaced by over-policing, or an increased and more aggressive police presence (Goffman, 2014). It may also be the case under-policing remains a common problem in African American and Hispanic communities when it comes to serious violent crimes, with over-policing becoming a problem for more minor offenses, especially drug offenses, over the last few decades (Leovy, 2015). Whichever best explains the role that under-policing has played in the troubled relationship between police and communities of color, it is clear that over-policing has played an increasingly large role in policing drugs (Dunn, 2015).

The last few decades have evidenced a clear and rising racial and ethnic disparity in arrest rates for drug offenses, with African Americans and Hispanics being arrested at much higher rates than whites (Golub, Johnson, & Dunlap, 2007; Mosher, 2001), yet survey research suggests that African Americans and Hispanics do not use or sell drugs at a higher rate, and may even use or sell them at a lower rate (Beckett, Nyrop, Pfingst, & Bowen, 2005; Johnston, O'Malley, Bachman, & Schulenberg, 2005; Snyder & Sickmund, 2008). Rather than reflect differences in drug offending, racial disparities in drug arrests were a result of "tough on crime" tactics (Alexander, 2012).

Of late, uses of force against black men have sparked a great deal of media coverage, yet as Lowery (2016) notes these dramatic events are symbolic and hide the more mundane racial disparities prevalent in aggressive policing. In the wake of the

Rodney King beating by multiple LAPD officers, an incident that sparked riots and widened the rift between black communities and the police, the Christopher Commission Report (1991)—an independent report the evaluated the use of force in the LAPD—found that the emphasis placed on arrests and on tough tactics had harmed trust for officers in certain communities. In conducting ethnographic work among young black men in Philadelphia, Goffman (2014) found that both those who were actively involved in crime and those who were not were subject to frequent police stops and experienced aggressive tactics. She concluded that the race of the individual, the racial composition of the neighborhood, and the levels of education and poverty determined the level of aggressive policing that individuals experienced.

A great deal of additional evidence supports the notion that African Americans are disproportionately targeted by the sorts of aggressive policing tactics common to the "tough on crime" model (Gelman, Fagan, & Kiss, 2007; Weitzer & Tuch, 2005). In a qualitative study of young black men in St. Louis, Brunson and Miller (2006) found that black men reported numerous contacts with police, and that the contact was more aggressive in nature than that experienced by white men. Further, many of incidents described by their subjects involved a search for drugs or officers assuming those stopped has used or sold drugs.

The relationship between "tough on crime" tactics for drug offenses and racialized patterns of enforcement can be also be observed at the neighborhood level. Many studies have found that the racial composition and socioeconomic status of a neighborhood are connected to more aggressive policing tactics (Brunson & Weitzer, 2009; Gau & Brunson, 2009; Weitzer, 2000). Weitzer (2000) examined the experiences of black and white residents in three neighborhoods: a predominately white middle-class neighborhood, a predominately black middle-class neighborhood, and a predominately black lower-class neighborhood. He found that perceptions and experiences tended to be worse for black residents, but were less pronounced in middle-class neighborhoods. In fact, black residents of the middle-class black neighborhood only reported poor treatment by the police when they were in a lower-class black neighborhood.

Residents interviewed by Weitzer provided two explanations for this pattern of findings. First, the difference in treatment by neighborhood could be a result of the higher crime rates in lower-class neighborhoods, and thus higher levels of fear and perceptions of danger among the police in that neighborhood. This, in turn, could alter police behavior. Klinger (1997) would agree with this notion. He suggested that police activity in a neighborhood is partially determined by an assessment of the level of crime and disorder in that neighborhood, but noted that police may not always make such assessments based on actual measures of crime and disorder. Instead, they may rely on characteristics they believe are related to crime and disorder, such as economic conditions and racial composition.

The second explanation is that better economic conditions create local political access, and thus residents of middle-class neighborhoods, regardless of race, are better able to hold police accountable for their behavior. As Weitzer puts it in describing the middle-class black neighborhood, “The neighborhood is home to politically connected people, doctors, lawyers, and a strong civic association that would not hesitate it complain to the authorities about police abuse" (p. 147). Whatever the explanation, aggressive, proactive tactics seemed to occur primarily in the lower-class neighborhood, with more reactive tactics in the middle-class neighborhoods.

Brunson and Weitzer (2009) furthered the investigation of neighborhood race and class by examining three economically disadvantaged neighborhoods with different racial compositions: one predominately black, one predominately white, and one racially mixed. Not only did these neighborhoods have similar economic conditions, but they also had similar crime rates, yet Brunson and Weitzer found stark differences between the experiences of young men in each neighborhood. They found a lack of police presence within the white neighborhood, so much so that some residents expressed a desire to see police more often. By contrast, in both the black and mixed neighborhood, residents reported an excessive police presence and expressed a desire to see police less often. All respondents believed that white residents and white neighborhoods received better service from police, and while white residents were subjected to "tough" tactics, they were subjected to them far less often than were black residents. They also observed an interaction of individual and neighborhood race, with the experiences of white residents varying by neighborhood. Specifically, whites received better treatment in white neighborhoods and poorer treatment in mixed or black neighborhoods. Yet for black residents, the racial composition of the neighborhood did not matter. They received poor treatment and increased police attention regardless of location.

While it is clear that "tough on crime" tactics result in disparate effects by individual race and neighborhood racial composition, theory to explain these findings is scant. Kraska (2006) notes that there is a general deficit of theory in criminal justice research: “Criminal justice/criminology does not have a recognized and readily accessible theoretical infrastructure about the criminal justice system and crime control…within our leading scholarly journals, theory development and testing is targeted primarily at explaining crime” (p. 169-170). A great deal of theory assesses why, when, how, and by and to whom crime occurs, but there is very little theory that assesses why, when, how, and by and to whom the criminal justice system acts. This is especially true within policing, where research is “largely descriptive and atheoretical” (Manning, 2001). Further, work on racial disparities in policing is notably lacking in testable theory (Engel & Calnon, 2004).

Warren et al. (2006) note this lack of theory and discuss some potential mechanisms of racialized patterns of policing. They describe four possible sources of racial and ethnic disparities in policing: prejudice and racial animus, cognitive bias and stereotyping, racial profiling, and deployment patterns. Prejudice and racial animus occur when racial disparities are a result of an individual officer’s racist beliefs. Because police agencies proscribe such behavior, and because feelings of racial animus have been decreasing over the decades, Warren and colleagues (2006) believe that this is only a minor contributor to racial disparities in policing. Nonetheless, Balko (2014) notes that aggressive advertising may have encouraged more aggressive individuals to apply to police forces, and similarly it is possible that the coded racial language that accompanied the War on Drugs and “tough on crime” tactics have encouraged more racist individuals to apply to police forces.

The second mechanism, cognitive bias and stereotyping, is a subconscious version of the first. Cognitive bias and stereotyping are a result of the well-studied phenomenon of using obvious characteristics, such as race, to make assessments when one lacks more detailed information. These assessments are based on subconscious stereotypes, and the use of such stereotypes is common among all people, not just police officers. Research has found that black men are often viewed as “symbolic assailants” by the criminal justice system (Anderson, 1990). The view of young black men as “symbolic assailants” may even extend to neighborhoods, through what has been called “ecological contamination” (Terrill & Reisig, 2003). Just as black individuals are viewed as symbolic assailants, black neighborhoods are painted with the same subconscious biases. Finally, this stereotype may be exacerbated by a biased reporting of crime by crime victims. The notion of a symbolic assailant is a broad societal construct, and victims of crime may perpetuate biases in policing if their descriptions of offenders reflect these stereotypes.

“Tough on crime” policing may have led to increased racial disparities via this mechanism. By asking police to engage in more proactive, aggressive policing and relying on the number of arrests to measure their success, departments have ensured police are much busier than in previous eras (National Research Council, 2004). This high level of activity means that officers have less time to gather details about any particular person or neighborhood, and thus may instead rely on stereotypes. In addition, the language of the War on Drugs, and way in which certain drug types and behaviors have become racialized may have changed stereotypes, further increasing the association between black individuals and neighborhoods with “symbolic assailants.”

The third mechanism is racial profiling, which is when police act on race as one among many characteristics of a typical offender. This can take the form of drug interdiction profiles of out-of-place profiling. Drug interdiction profiles are a list of characteristics that were designed to help law enforcement spot potential drug dealers or smugglers, and may either implicitly or explicitly encourage the targeting individuals of certain races or ethnicities (American Civil Liberties Union, 1999). Originally developed by the Drug Enforcement Agency (DEA), these profiles also appear to identify such a wide range of (often contradictory) behaviors that they provide justification for nearly any stop (Cole, 1999). In addition, if certain racial or ethnic groups fit other common characteristics of offenders such as having a greater rate of young males within their population, this may lead may further lead to disparities in policing. Out-of-place profiling occurs when African Americans and Hispanics are stopped because they are in predominately white neighborhoods, with the underlying assumption being that because their race does not match the predominate race of that neighborhood, they are unlikely to be residents of the neighborhood (Fagan, Dumanovsky, & Gelman, 1999).

An example of such profiling made it to the Arizona Supreme Court in *State v. Dean* (1975). Johnny Soto Dean was sitting in a parked car in an apartment complex when he was stopped and searched by police officers. In addition to appearing nervous, the officers said they stopped him for being out of place as a Hispanic male in a predominately white neighborhood. Dean argued that because the stop was based on his race/ethnicity, it was invalid, but the Arizona Supreme Court came down in favor of the officers, stating that race could be used as justification for a stop so long as race or ethnicity were not the sole reason for the stop, a ruling with which the United States Supreme Court agreed ("United States v. Martinez-Fuerte," 1976). Drugs played pivotal roles in both types of racial profiling, and both also served the goals of “tough on crime” policing by increasing the range of situations in which police officers can make stops and arrests without directly witnessing illegal activity.

The final mechanism is deployment patterns. Since random preventive patrols were found to be ineffective (Kelling, Pate, Dieckman, & Brown, 1974), it has been rare for police departments to deploy themselves equally across all neighborhoods. Instead, police are often deployed in greater force to neighborhoods with higher crimes rates. As these tend to be neighborhoods with more African American and Hispanic residents (Krivo & Peterson, 1996), deployment patterns may unintentionally lead to racial disparities in stop and arrest rates. Further, if members of certain racial groups are more likely to spend time in public spaces, the effect of deployment of officers along public street segments will more substantially impact those individuals. The racialized notion of drugs combined with the emphasis on drug enforcement during the “tough on crime” era may have led to even greater deployment in African American and Hispanic neighborhoods (Beckett, 2016). Due to the emphasis on arrest during the “tough on crime” era, police are more likely to engage in frequent arrests in those neighborhoods, which in turn provides evidence to support continuing patrol of those communities.

Walker, Spohn, and DeLone (2012) conceptualize discrimination as a continuum. At one end is systemic discrimination which, in the case of policing, would imply discrimination among all police and at all levels and stages of policing. The mechanisms discussed above do not support this the level of racial discrimination during the "tough on crime" era. At the other end of the continuum is individual discrimination, which is discrimination that results from the actions of specific police officers. Both stereotyping and racial animus suggest this discrimination may have been present in the "tough on crime era." In the middle of the continuum are contextual and institutional discrimination. Contextual discrimination occurs when racial discrimination is present within only certain contexts, such as certain geographic regions or for certain crimes. With its emphasis on drug offenses, the "tough on crime" era has likely increased contextual discrimination via drug cases and, through deployment patterns, it may have increased those patterns within certain neighborhoods. Institutional discrimination occurs when policies or procedures that are not inherently discriminatory have discriminatory outcomes. The discrimination that results from deployment patterns is an example of this.

This chapter highlighted the racial disparities in the rise in incarceration, and the ways in which the War on Drugs enhanced these disparities. The War on Drugs was accompanied by a "tough on crime" ethos, and this ethos affected the way in which police practice their craft, which led increased racial disparities. In the next chapter, I discuss a type of specialized policing unit (police paramilitary units) and some specific tactics (order maintenance stops and warrants) that resulted in discriminatory outcomes.

Chapter 2. PPUs, Tactics, and Racial Disparities

In the previous chapter, I defined "tough on crime" policing and discussed the ways in which it has led to increased racial disparities in arrests, especially for drug offenses. Police paramilitary units (PPUs) developed during the "tough on crime" era, are particularly emblematic of the "tough on crime" ethos and have played a large and expanding role in the War on Drugs. Following a description of PPUs and their connection to the War on Drugs, I describe two strategies commonly associated with racialized patterns of policing: order-maintenance policing and serving warrants.

Police Paramilitary Units (PPUs)

Police paramilitary units (PPUs) are a type of specialized unit. Specialized units are new to policing, first emerging as part of a key feature of the reform movement: centralization of control (National Research Council, 2004). Specialized units do not answer to specific precinct commanders, but instead to the centralized police leadership, thus giving high-ranking police officials greater control over the particular issues addressed by each specialized unit (Kelling & Moore, 1988). Those issues might include traffic enforcement, juvenile delinquency, vice, domestic violence, gangs, bombs, arson, hate crimes, or drugs, among many other subjects (National Research Council, 2004). Specialization benefits police departments by allowing them to better focus on key issues and by sending a message to the public that police are attuned to these issues. Yet it is their very specialization as well as the lack of precinct/district/zone control that often makes specialized units difficult to manage, increasing the potential for abuses of power and instances of corruption (National Research Council, 2004).

As their name implies, police paramilitary units borrow a great deal from the military. But borrowing from the military is not new to policing, and thus it is not surprising that many local police departments were quick to adopt PPUs. Modern policing was founded on military principles (Monkkonen, 1992), and much of its current organizational structure and language resembles the structure and language of the military (National Research Council, 2004). Police and military also share a thematic bond: they represent the two major sources of governmental coercive power (Kraska & Kappeler, 1997). As Bittner (1970) noted, the ability of police to use force is omnipresent in all police-citizen interactions. Whether force is present or not, the potential for force changes citizen behavior (both in contact with police and in anticipation of contact with police) and police behavior. Thus, any police behavior involves some level of coercive power. This same potential for force shapes all military behavior as well. Police discretion allows for force to be employed by any individual officer in any particular situation (Sykes, 1985). Yet, unlike the military, Sykes argues that police are difficult to control: "Street policing as a community-based institution, with its idiosyncratic nature, resists attempts at administrative rationalization" (p. 59). In theory, militarization reduces discretion by providing a rigid structure, but in practice it provides only the perception of a solution, and "the military symbols nurture the public view of strict organizational supervision" (Sykes, 1985, p. 59). The community-based aspects of policing make it difficult for even a rigid structure to reign in discretion. Nonetheless, many police agencies have eagerly embraced the structure provided by the military (Kraska, 2007).

Special Weapons and Tactics (SWAT) teams (also called Special Response Teams, Emergency Response Units, and Tactical Action Groups) were one of the earliest examples of PPUs, and in even their origins, the racial tensions that would plague current PPUs are foreshadowed. In the Summer of 1965, a California Highway Patrol officer, Lee Minkus, was driving through Watts, a predominately black neighborhood in Los Angeles, when he pulled over a young black man, Marquette Frye, because another driver said that Frye's car was weaving. What started as a fairly amicable stop soon turned contentious and, by the time another officer hit Frye in the head with a baton, a large crowd had gathered. This crowd initiated what grew into the Watts Riots, a violent six-day period in Los Angeles (Balko, 2014). These riots were the result of accumulated poor treatment of black Angelinos at the hands of Los Angeles Police Department (LAPD) Chief William Parker, who during the riots called the rioters "monkeys" (Davis, 1992).

In response to the violence, LAPD inspector Daryl Gates founded the first SWAT team, a tactical unit designed to address excessively violent situations. To create this unit, Gates sought the help of the military, believing the violence he was seeing in Los Angeles was analogous to the violence the military was dealing with in Vietnam (Gates, 1992). The spread of SWAT teams throughout the 1960s was not only a response to urban riots, but also to high-profile mass murders like Charles Whitman's shooting at the University of Texas at Austin (Balko, 2014; Klinger & Rojek, 2008). On August 11, 1966, Charles Whitman, after killing his mother and wife, climbed to the top of the clock tower at the University of Texas at Austin and shot more than thirty people, killing thirteen of them. Austin police were unprepared for such an event, with guns that could not reach Whitman from the ground. After over an hour, three officers and a civilian finally made it into a position that allowed them to shoot and kill Whitman (Balko, 2014). Riots and shootings like this led to the widespread adoption of SWAT teams and other PPUs, because, as Balko (2014) argues, "the riots in Watts and other urban areas may have instilled in Middle America fears of a rising black criminal class, but there was still some safety in the suburbs. Whitman's rampage on a college campus popped that bubble" (p. 58). Up until that point, many white Americans saw violence as an issue restricted to black neighborhoods; after Whitman, that assumption no longer appeared true.

Following this, police agencies have increasingly become militarized, as "police agencies and police officers take on more and more characteristics of an army" (Balko, 2014, p. 35). Kraska (2007) conceptualized militarization of police departments as a continuum, with all police departments somewhere on the scale, and the existence and normalized use of PPUs is one dimension that contributes to the overall militarization of a department, as these units borrow a great deal from the military. Kraska and Kappeler (1997) outlined the ways in which PPUs can be distinguished from other police units and beat officers. First, they distinguish themselves via their equipment, specifically their weapons. Borrowing military language, they often refer to themselves as "heavy weapons units," and they commonly use the Heckler and Koch MP5 submachine gun, a gun used by elite military units such as the Navy Seals. They might also use semi-automatic and automatic shotguns, sniper rifles, and M16s. PPUs also differentiate themselves in their access to nonlethal weapons, which aid in conducting “dynamic entries” (entering a location through force). These include tear gas, percussion grenades, stinger grenades, beanbags launched by shotguns, battering rams, hydraulic doorjamb spreaders, and explosives that help breach doorways. They may even use armored personnel carriers. Second, they differentiate themselves by their structure. As Kraska and Kappeler (1997) note, they model their structure after the military, operating and training “collectively under military command structure and discipline” (4). Third, they differentiate themselves via their status. They view themselves as “elite,” and are viewed by other police in their department as “elite.” Finally, they differentiate themselves through their appearance. Unlike other officers, they wear “black or urban camouflage ‘battle dress uniforms (BDUs),’ lace-up combat boots, full body armor, Kevlar helmets, and sometimes goggles with ‘ninja’ style hoods” (4).

Kraska (1996) argues that the “drug war fury of the 1980s and 1990s” (p. 417) escalated the use of PPUs thorough the U.S The crack epidemic and associated gang issues were used as justification for militarization, and many small and large agencies cited the drug war as the rationale for forming a PPU, with such units answering the call during 1980s and 1990s for more proactive work and a tougher stance on drugs (Kraska & Cubellis, 1997). Chambliss (1994) described how a PPU in Washington, DC, the Rapid Deployment Unit (RDU), that was originally designed to respond to riots, began to focus on the policing of drug offenses because riots were so infrequent. In assessing the various changes that could reduce the use of PPUs, Balko (2014) argues the most effective change would be to end the War on Drugs.

The connection between the War on Drugs and the expanding use of PPUs is also partially a result of the power of language. Metaphors frame an issue. The metaphor of "war" inherently invites the use of military-like tactics as a solution (Kraska, 1996). As Kraska and Kapeller (1997) put it: "The ideological filter encased in the war metaphor is 'militarism,' defined as a set of beliefs and values that stress the use of force and domination as appropriate means to solve problems and gain political power, while glorifying the tools that accomplish this" (p. 1). It takes advantage of notions of masculinity that emphasize a "soldier" or "warrior" identity in young men to encourage male police officers to use force (Kraska, 1996). Further, this language and the eager adoption of these units has the potential to influence the culture and behavior of all officers in a department, regardless of their specific role (Balko, 2014; Kraska & Cubellis, 1997; Kraska & Kappeler, 1997).

While Kraska and Kappeler (1997) detailed many ways in which PPUs can be differentiated from other police units and officers, one notable absence from this list is their role. It is odd that a specialized unit like PPUs cannot be differentiated by their role, as the very purpose of specialized units is to focus on a problem that differs from ordinary police work (National Research Council, 2004). When founded in the 1960s, most PPUs were designed to respond to the infrequent but often dangerous occurrences of riots, terrorism, barricaded suspects, and hostage situations. As Balko (2014) notes, there is a legitimate role for PPUs, and that role is restricted to this small set of situations. But the War on Drugs has led—to borrow a military term—to 'mission creep' for many PPUs (Kraska & Kappeler, 1997). Two areas of normal police operations in which PPUs have encroached are order-maintenance stops and the serving of search and arrest warrants (Balko, 2014; Chamliss, 1994; Kraska & Kappeler, 1997). In the following sections, I discuss how order-maintenance stops and warrants have grown as a result of the War on Drugs, and how each is associated with racial disparities in policing.

Order-Maintenance Stops

While frequent stops and searches have been a part of policing since the 1960s when then New York governor Nelson Rockefeller introduced his stop-and-frisk bill (Balko 2014), police did not focus inordinately on order-maintenance and associated minor offenses until years after the 1982 article written by academics James Q. Wilson and George Kelling introduced broken windows theory in the *Atlantic Monthly* (Wilson & Kelling, 1982). While the article was not a clear articulation of a theory in the scientific sense, it promoted a set of ideas about why crime rates varied by neighborhood and how police could be address neighborhoods with higher crime rates. According to Wilson and Kelling, serious crime was a product of minor disorder. Such disorder could be physical disorder, like a broken window or graffiti, or social disorder, like panhandling or loitering. Neighborhoods with high levels of disorder send signals that residents of the neighborhood are unable to exert sufficient informal social controls or unable to marshal sufficient formal social controls, and thus the neighborhood is likely to be one in which serious crime will be ignored. While research suggests that disorder plays at most a minor role in the offending calculus, and is more likely linked to crime via some third variable which better explains both, such as neighborhood poverty or collective efficacy, this theory caught on within policing (Harcourt & Ludwig, 2006; Herbert, 2006; Sampson, Raudenbush, & Earls, 1997).

One reason for its success was timing. The 1980s were at the heart of the War on Drugs and the “tough on crime” era, and police were being asked to crack down on drug offenses and be more proactive in their efforts (Beckett, 2016). Broken windows theory provided a solution to both. It allowed police to focus on offenses that were easily visible, such as graffiti or loitering, making proactive policing easy, and provided a justification for a stop, which allowed police to search for drugs. While the theory left a lot of room for interpretation on how disorder offenses should best be policed, it has been read by police as encouraging frequent stops and arrests for minor offenses, or the heavy enforcement of disorderly offenses in what is often called order-maintenance policing (Beckett, 2016; Gau & Brunson, 2009). Even though evidence suggests that this style of policing is ineffective, it has become a staple within many police departments alongside many other police tactics for which there is little evidence, such as random preventive patrol and rapid response to calls for service (National Research Council, 2004).

Order-maintenance stops have also been appealing to PPUs, and thus what was originally a strategy used primarily by beat cops or officers working in specialized narcotics or gang units has begun to be used by PPUs (Kraska & Kappeler, 1997). Kraska and Cubellis (1997) note the general expansion of PPUs into the realm of “mainstream policing” (p. 626), and Kraska (1996) briefly discusses their use in patrolling high-crime neighborhoods. The War on Drugs has not only transformed policing in general from reactive to proactive in nature, but it has transformed PPUs, which were originally exclusively reactive (e.g., responding to hostage situations or barricaded suspects) (Kraska, 2007). Chambliss (1994) found that the RDU was practicing a form of broken windows policing in its vehicular stops, looking for minor traffic violations in order to justify a stop. And as Dunn (2015) notes, such stops are likely to occur as vehicle stops rather than pedestrian stops in cities outside of New York or other large northeastern centers with robust public transportation systems, as vehicles, not public transportation and walking, are the predominant mode of transportation.

Ironically, the adoption of community policing and the use of PPUs in order-maintenance stops coincided. Community policing asked officers to involve the community in the decision making process, use measures other than arrests to solve problems, and make sure they were addressing problems that the community valued (Skogan, 2006). Yet, oddly, PPUs conducting order-maintenance stops were incorporated into police forces as a *form* of community policing. For example, a substantial portion of departments interviewed in Kraska and Kapeller's study said they used PPUs for order-maintenance style patrols, and one commander said:

> We conduct a lot of saturation patrols. We do 'terry stops' and 'aggressive' field interviews. These tactics are successful as long as the pressure stays on relentlessly. The key to our success is that we're an elite crime fighting team that's not bogged down in regular bureaucracy. We focus on 'quality of life' issues like illegal parking, loud music, bums, and neighbor troubles. We have the freedom to stay in a hot area and clean it up – particularly gangs. Our tactical enforcement team works nicely with out department's emphasis on community policing (p. 13).

To understand this seemingly illogical approach to community policing, it is helpful to examine the ways that community policing grew. Over time, two strands of community policing developed. The first strand matched the original description, and was focused on empowering communities and building bonds between police and community members. The second strand invoked broken windows policing (Kraska, 2007). Broken windows theory is aimed at enhancing informal social controls, and thus rebuilding community strength. It uses the symbol of police as watchmen, trading on an old model of policing to advocate police as managers of a community, helping regulate minor issues to prevent major ones. While police could easily have taken this idea and used it to justify a version of community policing more consistent with the original ethos, instead it was taken to justify enhanced enforcement of minor offenses with aggressive stop and search procedures and the goal of high arrest numbers (Kraska, 2007).

Order-maintenance policing, whether undertaken by PPUs or beat officers, is linked to racialized patterns of policing (Dunn, 2015; Fagan et al., 1999; Gelman et al., 2007). Dunn (2015) notes that there are hundreds of court cases alleging racial profiling in vehicle stops for minor violations as of 2007. A report by the RAND Corporation found small but noticeable racial disparities as a result of order-maintenance policing tactics (Ridgeway, 2007). Further, these policing tactics are concentrated in disadvantaged, often predominately minority neighborhoods (Fagan et al., 1999; Terrill & Reisig, 2003). Brunson and Weitzer (2008) found that what they referred to as "unwarranted" stops— stops in which the young man stopped did not believe there was either any reason or any good reason for his stop—were more common among young black men than white men and more common in predominately black or integrated neighborhoods than in predominately white neighborhoods. In their interviews of young black men in St. Louis, Brunson and Miller (2006) found that much of the dissatisfaction with and lack of trust in police stemmed from what their respondents perceived as stops that appeared to have no or little justification. And Weitzer (2000) found that subjects reported aggressive, order-maintenance style tactics as most common in a poor black neighborhood in Washington, DC. Both individual and neighborhood-based racial disparities are likely to result from order-maintenance policing.

Key reasons that order-maintenance policing tactics are likely to result in racialized patterns of policing is the difficulty in defining disorder, the way in which this practice enhances police discretion, and the ability of proactive officers to steer enhanced discretion towards the goal of greater arrests. Order-maintenance policing focuses on disorder, and disorderly behavior "eludes precise articulation of the specific behaviors that should be considered unacceptable…the idea of "public (dis)order" is far more defintionally fluid than are criminal codes delineating particular prohibited behaviors" (Gau & Brunson, 2009, p. 4). Further, there is often a lack of congruity between one's perception of disorder and the actual level of disorder (Hinkle & Yang, 2014; Hipp, 2007). Because the focus on disorder opens up such a large and indefinable range of behaviors, there is potential for anyone to be stopped. This provides officers with a great deal of discretion in deciding who to stop and what to do after a stop. Indeed, "the fact that order-maintenance deals with relatively low-level, non-serious offenses means that there is a lot of room for police discretion and this discretion, in turn, means there is considerable latitude for order-maintenance tactics to be applied in a discriminatory fashion" (Gau & Brusnon, 2006, p. 6).

When it comes to discretion after the stop, “tough on crime” tactics have a clear prescription: make an arrest whenever possible (Beckett, 2016). As to discretion before the stop, where police make stops and who they stop is likely determined by their notion of who a criminal is and where criminals live (Klinger, 1997). According to Klinger, police behavior varies by neighborhood and varies, in part, according to an officer’s perception of the crime in a neighborhood. Perceptions of crime, though, are not always based on actual crime rates, but instead on perceived economic conditions or racial composition (Klinger, 1997, 2004). As mentioned earlier, police often see black residents as symbolic assailants and black neighborhoods suffer from the same stereotype (Anderson, 1990; Brunson & Miller, 2006). Indeed, research suggests that neighborhood racial composition and signs of poverty may be more strongly linked to the perception of crime and disorder than are actual measures of crime or disorder (Sampson & Raudenbush, 2004). Even residents of poor, predominately African American neighborhoods associate race and poverty with higher crime and, in turn, higher crime with over-policing (Brunson & Weitzer, 2009; Weitzer, 2000). As Benner (2002) writes, “the locations the police choose to patrol and what drugs they choose to target are largely a function of where they perceive ‘the work is.’ Those decisions are not made in isolation from the totality of our cultural beliefs, stereotypes, and perceptions” (p. 223). And court rulings have allowed for race and neighborhood racial composition to be considered when police are deciding on how to act (e.g., *State v. Dean*, 1975). When police work under a “tough on crime” ethos that encourages proactive tactics, the use of order-maintenance policing is likely to result in racially patterned policing. Yet order-maintenance policing is not the only tactic which has enhanced racialized patterns of policing as a result of the War on Drugs; the serving of search and arrest warrants has also had detrimental effects.

Serving Warrants

Serving warrants is a fairly standard policing procedure, but as Balko (2014) notes, entering an individual's place of residence to serve warrants runs contrary to a principle that has long held power within the American psyche: the notion that one's home is "a place of refuge, peace, and sanctuary" (p. 5). This belief is encapsulated in the Castle Doctrine, an aspect of British common law that took hold in America. Indeed, it was one of the reasons for America's break from Britain, as early Americans viewed the quartering of British soldiers in private American homes as a violation of the Castle Doctrine (Balko, 2014; Benner, 2002). The basic idea behind the Castle Doctrine is that, because the home is a place of refuge, the government should only be able to enter one's home when a failure to do so might result in violent or terrible outcomes, when no other option to prevent such outcomes exists, and after giving the residents a chance to let authorities in peacefully (Balko, 2014). It is debatable whether the apprehension of drug users and sellers meets this threshold, yet the War on Drugs on has led to a substantial increase in the use of search and arrest warrants.

In data from the San Diego, CA area in 1998, Benner (2002) found that 50% of all search warrants were for narcotics offenses, whereas only 23% were used in cases of violent crime, 24% for property crime, and 3% for some other reason. To put this in perspective, with a sample of 214 total search warrants, if not for the War on Drugs, the greater San Diego area would have served 107 fewer search warrants in 1998. During the War on Drugs, the United States Supreme Court increased police power to serve warrants. One decision reduced the standard to obtain a search warrant (*Illinois v. Gates*, 1983), and another held that illegal searches which would otherwise be subject to the exclusionary rule were permissible so long as officers believed they were acting legally (*United States v. Leon*, 1984). Benner (2002) argues that these changes have increased police power to serve warrants in situations in which they might not have enough evidence to be sure they have correctly identified an individual worthy of a warrant, especially since police often rely on questionable sources such as confidential informants. Financial motivations created during the War on Drugs have also led to an increased use of warrants (Kraska & Kappeler, 1997). Asset forfeiture laws passed in the 1980s allowed for direct financial benefit to police departments for any property obtained during any search that results in an arrest, regardless of whether it eventually results in a conviction (Williams, Holcomb, Kovandzic, & Bullock, 2010).

Serving warrants also increasingly become a common activity for PPUs during the “tough on crime” era (Balko, 2014; Klinger & Rojek, 2008; Kraska & Kappeler, 1997). In addition to qualitative evidence suggesting that a PPU in Washington, D.C. engaged in a high-level drug warrant work (Chambliss, 1994), a few studies have quantified the massive increase in PPU involvement in warrants. Kraska and Kappeler (1997) sent a 40-item survey to a sample of U.S. law enforcement agencies serving at least 50,000 citizens, resulting in a 79% response rate among 690 agencies. They found that nearly 90% of responding agencies had PPUs; many had formed their agencies in the 1970s; their PPUs were becoming more and more active over the course of the 1980s and 1990s; and in addition to increasing the use of order-maintenance policing, they were engaging in a high frequency of warrant work. Serving warrants accounted for 75.9% of all call-out activity (non-patrol work), with terrorist incidents, hostage situations, and barricaded suspects—the incidents many of these units were founded to address—constituting only 0.09%, 3.6%, and 13.4% of their activity, respectively.

Kraska and Cubellis (1997) conducted a similar study with smaller agencies (those serving between 25,000 and 50,000 citizens), resulting in a response rate of 72% among 770 agencies. They found that 65% of small law enforcement agencies had a PPU; of those without one, 28% planned to create one within a few years; many were formed in the 1980s; they became more active over the 1980s, and increased their activity dramatically in the 1990s; and as with larger agencies, warrant work represented the largest portion of call-out activity. In total, 66% of call-outs were for serving warrants, with only 0.1% for terrorist incidents, 5% for hostage situations, and 24% for barricaded suspects. Rojek and Klinger (2008) found that a vast majority of PPU operations between 1986 and 1998 consisted of warrant service (87.5%), with far fewer operations involving barricaded suspects (3.0%) or hostage situations (18.8%). Further, while the average number of barricaded suspect and hostage situation operations per agency did not vary substantially between 1986 and 1998, the number of warrant operations per agency rose dramatically over this time period, increasing from 4.7 per agency in 1986 to 14.6 in 1998, and peaking at 18.9 in 1991.

Not only were PPUs engaging in more warrant work, but they were also training for it more. While agencies were most likely to train for barricaded suspects (95%), building searches (94%), and hostage incidents (92%), training for narcotics warrants was quite common (91%). More agencies trained for narcotic warrants than they did for hostage rescues (87%), downed person rescues (86%), other warrants (80%), automobile or van assaults (80%), suicidal subjects (71%), bus assaults (64%), area searches (60%), civil unrest (49%), aircraft assaults (12%), train assaults (11%), or water-borne assaults (7%) (Rojek & Klinger, 2008).

The increasing use of warrants was driven by both the proactive policing styles advocated by the "tough on crime" ethos and by the War on Drugs. Kraska and Kappeler (1997) argue that the War on Drugs led to a large increase in search warrants and a lesser increase in arrest warrants because police were encouraged to proactively go after offenders. Drugs provided an easy target for proactive initiatives, as it was far easier to build evidence that would support a search or arrest warrant for drug crime than for property crime or violent crime (Barnett, 1987). Police believe that there is inherent danger in serving warrants at the homes of potential drug dealers, and while dangerous, the level of fear is not matched by statistical evidence wherein police death or injury are fairly rare (Balko, 2014). Regardless of actual danger, though, perceived danger led police to react by placing "violence specialists" (Kraska & Cubellis, 1997, p. 625) like PPUs in charge of warrant work. While there are numerous anecdotes to suggest that having heavily armed units conduct warrant work may actually increase the risk of injury to both police and civilians, this has nonetheless been the action taken by many police departments (Balko, 2014; Kraska & Kappeler, 1997).

Equally critical to the use of PPUs for narcotics warrants is the belief that that the subject of a warrant can easily and quickly dispose of evidence, as drugs are far easier to dispose of than the evidence of violent or property crimes (Balko, 2014; Kraska & Cubellis, 1997; Kraska & Kappeler, 1997). In *Ker v. California* (1963), the Supreme Court found that police did not need to knock when entering a residence if they believed they were in danger or that a knock would give the suspect time to destroy evidence. A year later, then New York State Governor Nelson Rockefeller passed a bill that allowed officers to enter residences without first knocking, leading to the very first appearance of the phrase "no-knock raid" (Balko, 2014). No-knock raids allow officers serving search or arrest warrants to enter a premise without notifying the occupant and using force to enter, often called a "dynamic entry" (Kraska & Kappeler, 1997). Dynamically serving warrants is exactly the sort of strategy one would expect PPUs to take on during the War on Drugs: it is proactive, and thus satisfies the call for reform of the standard model of policing; it is aggressive, and thus satisfies the call for being "tough on crime"; it is easy to build cases against drug offenders; and serving warrants dynamically prevents drugs and drug paraphernalia from being disposed of, satisfying the call for a focus on drug crimes. Indeed, in phone interviews with police agencies, Kraska and Cubellis (1997) found that nearly all of the agencies either created their PPU or increased the activity of their PPU to conduct no-knock warrants in search of drugs, guns, or money related to the sales of drugs.

Warrants are used more often to arrest people of color and people in predominately minority or economically disadvantaged neighborhoods. Chambliss (1994) found that warrant work carried out by the RDU varied with the racial composition of the neighborhood, and Kraska (1996) suggested that no-knock warrants are more common in economically disadvantaged areas. One of the most comprehensive studies of search warrants was Benner's (2002) work in San Diego, which assessed the racial patterns of search warrants served throughout the greater San Diego area. Benner found that the three zip codes with the most search warrants were predominately African American or Hispanic. These three zip codes were 88% non-white, 95% non-white, and 78% non-white, respectively, and collectively, they accounted for 44% of all narcotics warrants served in the San Diego area. By contrast, only 3% of search warrants occurred in predominately white neighborhoods. In the three predominately minority zip codes, 96% of all individuals served a search warrant were non-white, and within the whole of the San Diego area 81% of all individuals served a warrant were non-white, despite the fact that the city was 55% white. These findings were particularly pronounced for certain drugs, with blacks overrepresented in searches for cocaine and Hispanics in searches for methamphetamine.

Benner notes that many search warrant cases are built on information from confidential informants, and many confidential informants are users or sellers who are caught and incentivized to provide information that will bolster a search warrant. Because of this, disparities in the serving of warrants may result from disparities in who is stopped and arrested. Thus, racially patterned order-maintenance policing may, in turn, produce racially patterned warrants. Essentially, if the police intelligence supporting search and arrest warrants involves bias, this will result in warrants that display racial bias. The racial disparities caused by one proactive, aggressive policing strategy exacerbate racial disparities produced by another proactive, aggressive policing strategy.

PPUs are a strategy particularly emblematic of the “tough on crime” era, and since their creation, their role has quickly expanded to serve the War on Drugs. Order-maintenance policing and serving warrants are also heavily linked to the War on Drugs and appear to be responsible for some of the racially patterned policing of this era.

Clearly, the “tough on crime” era in policing has led to an increase in racial disparities in justice partially as a product of increasing militarization and two specific policing tactics. Yet, as detailed in the next chapter, this approach appears to be fading, replaced by “smart on crime” practices, changes that could lead to reductions in the racial disparities linked to “tough on crime” policing.

Chapter 3. A Change in Policing

In this chapter, I discuss the nascent shift from a "tough on crime" ethos to a "smart on crime" ethos, and the accompanying changes to police tactics. This shift took place in a dramatic fashion in Atlanta, GA over the last decade, a process that I detail in the second section of this chapter. Finally, I discuss the reasons that this shift in policing might result in reductions in racial disparities as well as the reasons why it might not, which includes a closer examinations of the tactics and ethos that replace "tough on crime" policing.

The "Smart on Crime" Shift in Policing

Over the past decade, there has been a noticeable shift in policing tactics. Driven by the ineffectiveness, inefficiency, and harms to citizens of many "tough on crime" tactics, there has been a movement away from "tough" approaches and towards "smart" approaches (Drakulich & Kirk, 2016). For years, politicians of both parties invoked "tough-on-crime" rhetoric, but as public opinion shifted, so has the rhetoric of politicians: "Rather than touting their 'tough-on-crime' credentials, many politicians are now proclaiming that they are being 'smart-on-crime' by supporting evidence-based, cost-efficient alternatives to incarceration" (Wozniak, 2016, p. 180). These sentiments have been echoed by the former U.S. Attorney General Eric Holder in his announcement of the "Smart on Crime Initiative" and by former President Barack Obama (Office of National Drug Control Policy, 2013; United States Department of Justice, 2013). Evidence of the change can also be witnessed in the overhauling or repeal of drug laws at the state level and in federal initiatives for evidence-based policing practices (Desilver, 2014).

The ethos of the “smart on crime” movement, as stated by the DOJ, suggests this movement should direct limited resources to the highest priorities; promote fair law enforcement that reduces disparities in justice; ensure fair responses to low-level offenses; focus on prevention and reducing recidivism; and protect vulnerable populations (United States Department of Justice, 2013). The “smart on crime” regime aims to accomplish these goals through policing strategies such as community policing, problem-oriented policing, hot spots policing, and intelligence-led policing (Bueermann, 2012; Mazerolle et al., 2007; Ratcliffe & Guidetti, 2008).

It is worth unpacking the “smart on crime” strategies to understand how they differ from the “tough on crime” strategies. First, the form of community policing promoted under the “smart” era is one more closely aligned with the original ideals of community policing, not one that borrows from broken windows theory. Second, problem-oriented policing (POP) is a strategy that promotes the use of creative solutions to common crime problems. This strategy works in conjunction with community policing, relying on both official police data and community input to identify problems. Police then analyze these problems, develop a response based on their analysis, and assess the success of their response. Unlike “tough on crime” strategies, officers use arrest as only a last resort, and instead find solutions in practices like situational crime prevention, which involves manipulating aspects of the environment to decrease crime (Braga, 2010, 2014; Clarke, 1997).

Another “smart” strategy, hot spots policing is based on a simple idea: crime is not equally distributed across a city’s geography, but instead certain crime clusters in very specific areas, such as near particular buildings or at particular intersections (Braga, 2001). Thus, for police to best address crime, they should focus their resources where it occurs. While this basic idea could lead to many different police activities within those locations, Braga and Weisburd (2010) strongly recommend that officers avoid using arrests, and Braga and Bond (2008) find that greater crime control benefits are realized when police do not use arrests or stops, but instead rely on situational crime prevention strategies.

Intelligence-led policing (ILP) can be viewed as POP with enhanced analytic capabilities and multijurisdictional information sharing (Carter & Carter, 2009). It was used in England for decades, but ILP was only recently widely adopted in America as a response to the terrorist attacks on September 11, 2001 (Carter & Carter, 2009). ILP asks agencies to look for and solve problems in the fashion of POP, and also to use data analysis to anticipate problems, take preventative measures, and share their analysis with other agencies. As such, intelligence-led policing is often accompanied by data-driven units for agencies large enough to support in-house analysis (Ratcliffe & Guidetti, 2008), and smaller agencies rely on outside analytic resources, such as fusion centers (Lewandowski, Carter, & Campbell, 2017). A key difference between ILP and “tough on crime” tactics is that ILP does not rely on stops or arrests to solve crime problems. As with all other “smart” strategies discussed thus far, ILP encourages creative, non-traditional solutions to crime problems, suggesting that the work of analysts should inform the solution, not some larger ethos about being "tough" or an overreliance on specific tactics simply because they have been used in the past (Carter & Carter, 2009).

While many of these tactics were in existence in the "tough on crime" era, with problem-oriented policing (POP) dating back to Goldstein's work in 1979, "tough on crime" tactics dominated policing throughout the late 20th century and early 21st century (National Research Council, 2004). "Smart on crime" as a national movement is a new phenomenon, with the Smart Policing Initiative first providing federal funding as recently 2009. Considering this, it is helpful to take a closer look at some of the motivations that prompted many local police departments to transition. The motivations behind the "smart on crime" strategy are many, varied, and differ by department, but generally respond to four related but distinct problems with "tough on crime" tactics: finances; efficacy; legitimacy; and racial/ethnic disparities (National Research Council, 2004; Telep, 2016).

First, the financial crisis of 2008 and the cost of funding militarized units steered many departments away from "tough" tactics and towards "smart" tactics, which are often touted as a far more cost-efficient way to reduce crime (Bueermann, 2012; United States Department of Justice, 2013). Second, substantial evidence suggests that "tough" policing tactics are ineffective in addressing drug crimes (Caulkins & Reuter, 2010; Mazerolle et al., 2007), whereas "smart" tactics are effective in addressing drug crimes (Braga & Bond, 2008; Braga et al., 2006; Ratcliffe, 2002). In a systematic review of drug law enforcement policing strategies, Mazerolle, et al. (2007) found that strategies emblematic of a "tough on crime" ethos such as crackdowns, raids, intensive policing, and multijurisdictional taskforces either lacked evidence or had mixed evidence of effectiveness, while strategies emblematic of a “smart on crime” ethos such as community policing and POP proved much more effective.

Third, police shootings and botched raids during the “tough on crime” era led many to question whether police were trustworthy and legitimate sources of authority (Balko, 2014; Lowery, 2016). As procedural justice, or actions that lead individuals to believe they have been treated fairly, are strongly linked to feelings of legitimacy, it is not surprising that the more aggressive tactics of the “tough on crime” ethos jeopardize legitimacy (Tyler, 2003). Finally, while racial/ethnic disparities have a long history in policing, specifically the policing of drug offenses, they have become forefront issues of late (Lowery, 2016; Telep, 2016). Efficiency, effectiveness, and legitimacy are well studied in policing literature, but the ability of new strategies to minimize harms such as racial disparities is severely understudied (Telep, 2016).

With the racial patterns in arrests leading to racial disparities in incarceration; with the strong association between “tough on crime” policing and racialized drug arrest patterns; and with the clear shift in policing that has occurred quite recently, an examination of whether and how “smart” tactics influenced the racialized patterns of drug arrests is necessary. Yet studying this on a national level presents problems. There are nearly 20,000 law enforcement agencies in the U.S., and U.S. police agencies have no centralized, national control (National Research Council, 2004). Local agencies are not bound to each other formally, and changes in one need not occur in any others. And because law enforcement agencies are jurisdictionally focused, they are attentive to local concerns, not national concerns, so they often differ (National Research Council, 2004).

The degree to which any individual department changes will be based on what has occurred within their own jurisdiction and neighboring jurisdictions. National events have broad impact, but unless these events occur within their own district, police can always claim these events do not apply to them (Lowery, 2016).

Thus, assessing the shift in policing requires a jurisdiction in which change has clearly occurred, and one such area is the focus of this study: Atlanta, GA. The problems that occurred in Atlanta and responses to those problems are discussed in the next section, making clear this is an area that has felt the full effect of the shift from “tough on crime” tactics to “smart on crime” tactics.

Policing in Atlanta

Atlanta, Georgia was hit especially hard by the rise in property and violent crime that occurred over the 1970s and continued through the 1980s, as well as the crack cocaine epidemic (Hornsby, 1992). In the 1980s, Atlanta responded to these crime issues, with then Public Safety Commissioner George Napper publicly promising to be “aggressive and visible,” echoing the “tough on crime” ethos of the time. More specifically, in April of 1988, Napper announced the creation of the Red Dog Unit, a PPU designed to deal with drug offenders (Hornsby, 1992).

Originally named after a football play that involves blitzing a quarterback, the unit was designed to put pressure on drug dealers in much the same way the play puts pressure on quarterbacks, again making clear its aggressive tactics. The units’ name was later described as an acronym for “Running Every Drug Dealer Out of Georgia,” a clear reference to both its aggressive tactics and focus on drugs (Bagby, 2007). Red Dog, as one article described it, was "known for its fatigues and in-your-face tactics" (Visser & Garner, 2011). As another article notes, Red Dog had the "image in the eyes of some as a rough-riding band of tough guys to whom the rules, seemingly, just don't apply ("Atlanta police disband Red Dog," 2011). The goal of Red Dog was to increase police presence in areas with a high level of drug activity, and they were designed to "attack" such problems, "disrupting the activity and running down the dealer" (Atlanta Police Department, 2001, p. 11). With equipment and dress common to the military, they used aggressive tactics to enforce drug laws in the city (Geraghty & Velez, 2011). Red Dog epitomized the "tough on crime" era in Atlanta with a focus on drug offenses and the aggressive use of arrests as the primary crime-fighting tool. Even a decade later, in 1999 and 2000, this focus was still clear, with APD annual reports from the time highlighting their high drug arrest statistics (Atlanta Police Department, 2000; Atlanta Police Department, 2001). Indeed, former officers have reported that during this period, the APD had arrest quotas, and officers were promised rewards such as pizza or shorter workdays if they exceeded the minimum targeted number of arrests (Cook, 2013).

But in the mid-2000s, the APD discovered that "tough on crime" tactics could lead to tragic events, which would generate a backlash that would eventually catalyze a shift in the department's ethos and practice. As a *CNN* article begins, "Before #BlackLivesMatter became a trending hashtag, before names like Michael Brown, Laquan McDonald and Walter Scott filled national headlines, before protestors took to the streets of Charlotte and Baltimore, Atlanta Police had a moment of reckoning" (Blau, 2016). That reckoning began on a November night in 2006 when 92-year-old Kathryn Johnston was killed by Red Dog officers serving a no-knock search warrant at her home. Johnston was a long-time resident of what was once a black middle-class neighborhood, but had become an area with a great deal of crime, including drug activity. Commonly referred to as “The Bluff,” the neighborhood was home to the largest open-air heroin market in the South (Blau, 2016). Knowing the danger her neighborhood posed, Johnston owned a .38 revolver. So, when Red Dog officers conducted a no-knock dynamic entry on her home in which they removed burglar bars and rammed the door down, unaware the intruders were police, she fired. The officers returned fire, shooting 39 bullets, five of which hit and killed Johnston.

The warrant occurred because one of the officers involved felt under pressure to meet his quota of nine arrests and two search warrants per month (Blau, 2016). After planting evidence on a suspected drug dealer, the officers pressured him for information, and he gave them Johnston’s address, claiming they’d find a kilo of cocaine there. The officers filed paperwork for a no-knock warrant in which they claimed an undercover informant had bought drugs there; this had not occurred. When the officers discovered that Johnston’s home had no drugs, they planted marijuana on her, and tried to bribe the undercover informant they named in the warrant paperwork to lie. In 2009, the officers involved were sentenced to prison for 5-10 years, with 3 years of parole, and a fine of $8,180 to cover the cost of Johnston’s funeral. In 2010, the city of Atlanta was ordered to pay $4.9 million to Johnston’s family as the result of a lawsuit. Johnston’s death reminded the city of the problems with the APD. Civil rights attorney Mawuli Davis said of the incident, “people in communities of color believed officers in certain APD departments operated as a band of thugs. The exposure was too much to turn a blind eye.” This, though, was only the first tragic incident involving Red Dog officers.

Two years later, Red Dog officers were patrolling Atlanta’s West End area when they stopped Ricky Sampson. During the stop, the officers pulled down Sampson’s pants and boxers, inspecting his buttocks and genitals for drugs in front of his girlfriend and other bystanders. They found nothing. Sampson filed suit against the officers, some of whom were plaintiffs in other lawsuits for similar strip searches (Cook, 2013). In the course of the suit, two of the officers involved released affidavits saying that their actions were due to the arrest quotas. As former officer Cayenne Mayes said, “My supervisors and commanding officers encouraged these searches in more than one way. They told us to ‘always check the underwear’…making very clear that Red Dog teams had to meet arrest quotas” (Cook, 2013). The other officer, Stalone Davis, said, “I was not a rogue officer. I was following orders to make a strong presence, make arrests, help get drugs off the street” (Cook, 2013). Finally, in 2009, the Red Dog Unit raided the Atlanta Eagle, a gay bar in Midtown Atlanta, using a dynamic entry. They believed they would find public sex, illegal drugs, and illegal weapons. Instead, they found nothing illegal, and in the course of the search, they forced patrons of the Atlanta Eagle to lie face down in spilled beer and broken glass, shoved and kicked them, and yelled slurs. The city eventually settled the lawsuit against them for $1.2 million as a result of this incident, and promised to reform the department (Geraghty & Velez, 2011).

The APD did reform. As Georgia State University Professor Dean Dabney said following the events described above, the APD leadership "did not take it lightly. They blew it up, started over, and put their best people in charge—ethical leaders who cleaned up messes" (Blau, 2016). According to Weisburd and Braga (2006), even when an innovation is clearly better than the existing strategy, a crisis must occur in order to motivate an industry to adopt the innovation, and the crisis should shape the form that the innovation takes. While community policing, intelligence-led policing, and other "smart on crime" strategies had been around for decades, it took a crisis for the APD to embrace such innovations. The crisis was created by a "tough on crime" mentality and the PPUs that embodied this mentality; a focus on drug offenses; and the targeting of disadvantaged, minority communities. Thus, the changes in the APD reflected a steering away from "tough" tactics and toward "smart" tactics, a lessened focus on drug offenses, and a growing sensitivity towards policing disadvantaged, minority communities.

First, Atlanta became less "tough" by eliminating their PPU. Soon after the Atlanta Eagle raid, and just two weeks after another controversy over a strip search pursuant to a traffic stop, the APD announced that it would disband Red Dog in early 2011 ("Atlanta police disband Red Dogs", 2011). They also became less "tough" by reducing their use of no-knock warrants substantially (Blau, 2016). This reduction came as a result of new requirements that must be met for no-knock warrants to be issued, requirements which were so strict that in 2014 only one no-knock warrant was served, and in 2015, none were (City of Atlanta, 2016).

Second, Atlanta became "smarter" by utilizing the principles of intelligence-led policing. In the APD's 2010 annual report, the Crime Analysis Unit is highlighted. This unit focuses on trends in violent and property crime to inform police activity, and borrows some principles from intelligence-led policing (Atlanta Police Department, 2011). In addition, the unit that replaced the Red Dog not only focused on violent crimes instead of drug crimes, but also incorporated "trend analysis" and was designed to be data-driven (Atlanta Police Department, 2011, p. 21). In a response to activists from AtlIsReady, the mayor of Atlanta claimed that the APD is one of only fifteen law enforcement agencies across the country that was designated as a model city under former President Obama's Task Force on 21st Century Policing, which issued recommendations consistent with a "smart on crime" approach (City of Atlanta, 2016).

Third, Atlanta became less focused on drugs by redirecting its attention to violence. To take the place of Red Dog, they created the Atlanta Proactive Enforcement and Interdiction (APEX) Unit, which focused on violent crime. This shift in focus is also apparent in the APD's annual reports. While reports from earlier years made a point of reporting drug arrest statistics, from 2010 on, the reports only published numbers for serious violent and property crimes (Atlanta Police Department, 2000; Atlanta Police Department, 2001; Atlanta Police Department, 2011; Atlanta Police Department, 2012; Atlanta Police Department, 2013; Atlanta Police Department, 2014). As even clearer evidence of the change, between 2010 and 2016, the department decreased the number of narcotics arrests by 40% as part of an active effort to focus on repeat and violent offenders instead of drug offenders (Blau, 2016).

Fourth, Atlanta became more attuned to the needs of disadvantaged, minority communities. In 2010, the department created the Community Oriented Policing Section, a change that both Mayor Kasim Reed and Chief Turner highlighted in the Atlanta Police Department's annual report for that year (Atlanta Police Department, 2011). The Community Oriented Policing Section handles many disorderly issues through community partnerships, issues that were previously handled through stops and arrests via order-maintenance policing (Atlanta Police Department, 2012). As Chief Turner writes in the 2012 annual report, the department is now "working collaboratively with our citizens, our law enforcement, and public and private-sector partners on long-term and holistic solutions to crime" (Atlanta Police Department, 2012). Chief Turner cited the shift towards community policing and away from stop and arrest metrics as one of the largest changes that occurred during this transition (Blau, 2016). "Instead of policing a community, we're talking about being part of a community," Turner said, in reference to the shift in tactics and efforts to encourage officers to live in the areas they police (Blau, 2016). Further, there are a number of smaller programs that promote community outreach, especially to younger community members (City of Atlanta, 2016).

The APD also created an independent citizens review board that reviews allegations of police misconduct and the department also began to hold training on "Fourth Amendment issues," according to a statement issued following the Sampson case (Blau, 2016; Cook, 2013). Consequently, the APD now requires fourteen hours of cultural awareness training for all officers (City of Atlanta, 2016). Civil rights attorney Mawuli Davis noted that the events following the Kathryn Johnston case helped make the

APD more accountable to the community, made the APD "more transparent," and allowed it better relate to the communities it polices (Blau, 2016). Mayor Reed said of these efforts, "I don't think trust has been fully restored. It's far better than during the period when we lost Kathryn Johnston. It is improving," (Blau, 2016).

The APD has changed substantially over less than a decade. They are a department that fully captures the shift from "tough on crime" policing to "smart on crime" policing. But just because they have changed their tone, rhetoric, units, and training does not mean that they have produced real reductions in the racialized patterns of drug arrests prevalent under "tough," drug-focused tactics. There are good reasons to suspect drug arrests may still contribute to racial disparities in justice in Atlanta.

Will the Change Result in Change?

Local law enforcement agencies are complex entities. Logistically, they are hierarchical, formal, agencies tasked with jobs that provide them a great deal of power over citizens, and yet they are unable to consistently monitor their employees due to the mobile nature of the work (National Research Council, 2004; Sykes, 1985). Conceptually, they are simultaneously tasked with serving the very same communities they regulate, working for people they may in the future stop and arrest, or the friends and family of those people (National Research Council, 2004). The bureaucratic challenges and contradictory mission statements inherent to the profession make it difficult to determine whether and how change will take root in police departments. The problem of assessing change is further complicated when assessing racial patterns of policing as a result of a shift towards “smart on crime” tactics, as recent research suggests such tactics may also lead to problems with race and police. To better understand whether change may have resulted from this shift within the APD, I begin by reviewing historical examples for and against change, then discuss the theories about police organizational change, and finally examine some of the issues scholars have begun to notice with the “smart on crime” approach.

Innovation is not new to policing. New techniques and strategies are frequently developed, adopted, and in some cases discarded (Weisburd & Braga, 2006). This provides a rich history of attempted changes, allowing for examples of both successful and unsuccessful innovations. Unsuccessful change takes a number of forms. First, unsuccessful change may occur because an innovation is not fully implemented, but is instead only partially or seemingly adopted, as is the case of community oriented policing and POP within some police departments (Braga, 2014; Kelling & Moore, 1988). Second, unsuccessful change may occur because the change is limited in its influence to certain departments or certain individuals. For example, an evaluation of Compstat found that many beat officers, unlike their higher-ranking peers, did not understand the mission of Compstat, which led to a lack of implementation among those officers (Dabney, 2010). As another example, surveys of analysts found that many analysts believe police officers do not appreciate analysis, failing to practice policing according to the data-driven model (Taylor, Kowalyk, & Boba, 2007).

Third, unsuccessful implementation can occur because even though a new strategy is adopted, an older or different strategy is still practiced. As noted previously, the implementation of order-maintenance policing under the heading of community policing was commonplace throughout the 1980s and 1990s (Kraska & Kappeler, 1997). Another study observed the standard policing model being utilized even though the police department under study claimed to be practicing a Compstat model (Willis, Mastrofski, Weisburd, & Greenspan, 2003). Finally, unsuccessful change can occur when police engage in a full, faithful implementation, but the underlying problem is not affected. According to Sykes (1985), the adoption of a more militaristic style during the move from the political to the professional era created a great deal of structural change, but failed to truly reign in discretion. And Desmond and Valdez (2012) found that a full implementation of a third-party policing style – similar to problem-oriented policing but with greater reliance on public-private partnerships—still led to racial disparities.

Unsuccessful changes may also occur because police cling to tradition. According to Johnson (1981),

> They [police administrators] refuse to reconsider basic assumptions and tactics of their work…[instead they] cling to [old ones]. Reform from within police departments thus remains rooted in traditional assumptions.

For example, Braga and Weisburd (2010) discussed how police departments avoided rejecting preventive patrol even after research had suggested it did not work. In addition, even when they embrace change, police are often slow to change. Johnson (1981) believes that police are slower to change than any other local government agency. Likewise, Braga (2014) notes that, "progress in policing is incremental and slow" (p. 11), a sentiment echoed by Dabney (2010): "Numerous scholars have observed that change comes slowly and painfully to police organizations" (p. 46).

There are, though, a few noteworthy successes in changes to policing. First, Ratcliffe (2008) described the last fifteen years as the homeland security era of policing due to the widespread adoption of ILP. Motivated by the events of 9/11, and strongly aided by the federal government through financial incentives and local assistance via Department of Homeland Security guided programs, ILP has been adopted by departments both large and small (Carter & Carter, 2009). This is not only a success story for ILP but, as ILP relies on POP and community policing in order to function effectively, it also suggests that the last fifteen years have led to a fuller, more faithful adoption of those strategies as well (Carter & Carter, 2009). Second, Weisburd and Braga (2006) argue that over the past three decades, police have undergone monumental changes in their mission, relationship with the community, and strategies, noting this period evidenced a historically dramatic shift in policing. Third, Blau (2016) posits that the changes the APD instituted in Atlanta were substantial enough to effectively avoid the dissatisfaction with police expressed in many other cities throughout the U.S. over the past few years (Lowery, 2016). Finally, only a few of the examples of unsuccessful changes are entirely unsuccessful. Many are at least partially successful, and thus it is possible the APD and the greater Atlanta area did not completely solve their problems by changing to a "smart on crime" regime, but changed enough to demonstrate some reduction in the racialized patterns of policing produced by the "tough on crime" era.

Weisburd and Braga (2006) suggest that "systematic observation of police practices is a relatively modern phenomenon" (p. 1), and thus historical examples of either successful or unsuccessful implementation are of limited assistance in predicting whether the shift from "tough" to "smart" tactics will result in real change. General theories about changes in policing help further anticipate and contextualize the potential findings. In an article assessing the implementation of Compstat, Willis, Mastrofski, and Weisburd (2007) discuss two theories of why Compstat has been so widely adopted and how it operates once adopted. The first is the technical or rational theory, and the latter is known as the institutional theory. Both assume that police departments are self-interested, and will respond to external pressures in ways that most benefit their department. However, from there, they differ. The technical/rational theory assumes that police departments have clear goals and metrics for those goals, and aim to fulfill them as productively and efficiently as possible. Departments will create procedures and processes that best help them meet this challenge. The form of Compstat originally instituted by Chief William Bratton in New York City is an example of this (Willis et al. 2007). It borrowed principles from the business sector in order to increase efficiency and effectiveness.

Institutional theory, on the other hand, does not assume that police departments act rationally or institute rational processes (Willis et al. 2007). In this model, the actions of a police department are largely influenced by cultural forces. The institutional model explains change best when organizations have unclear goals and metrics and lack of direct competition, which is true of many police departments. Under this theory of change, police departments are not necessarily responding rationally to a need to improve their metrics when they alter behavior, but instead by a need to match their peer agencies. Essentially, they seek to resemble other police departments. Through this resemblance, they achieve legitimacy. Their notion of what it means to resemble other police departments may come from various sources, including other departments, government officials, or the media. Departments may resemble other departments by directly copying them, by seeking the help of experts, or as a result of an outside organization putting pressure on them to change. In short, in a technical/rational model, a department changes to improve their mission and metrics, and in an institutional model, a department changes to be sure they are behaving in the way a police department is “supposed” to behave.

These two theories are not incompatible, and can simultaneously explain changes in policing. Likely, some of the changes that occurred in Atlanta could be explained by a technical/rational perspective and others by an institutional perspective. Yet to some degree, the technical/rational and institutional theory are at odds, for the technical/rational predicts real and substantial change at all levels, while the institutional predicts a decoupling, with changes occurring at the structural level so as to align with the desired principles, but with routine work remaining largely the same (Willis, Mastrofski, & Weisburd, 2007). Considering the racial tensions created by Red Dog during the 1980s, 1990s, and early 2000s, if the change was a result of technical/rational concerns, it should result in a more noticeable reduction in racial disparities in drug arrests than if it was a result of the by the institutional model of change.

Sherman (2013) proposed an alternative theory of changes in policing. His theory posits that police are a particularly open system. Police are far more responsive to the demands of their “constituency” (p. 393) than many other agencies. This belief is a result of the local structure of policing in the U.S., which requires they respond to local concerns, and the ability of scandals to motivate change (National Research Council, 2004). He posits a fairly complex model in which these scandals and local calls to action do not influence police practice directly, but do influence government policies that in turn shape the policing human capital (i.e., police leaders, police scholars, police funders), and this shapes police practices. If Sherman's theory about how police absorb and respond to external demands is accurate, it suggests real change should be realized in Atlanta. As his theory suggests that police are responsive to external demands, the APD should demonstrate noticeable change. Indeed, Warren and Tomaskovic-Devey (2009) found that racial disparities in searches conducted by highway patrol officers in North Carolina reduced as a result of media coverage of racial profiling. In addition, he suggests government policies are one route towards change. As Atlanta experienced pressure from the FBI and from local leaders following the highly visible and tragic events that occurred, it is likely that noticeable change should result. Finally, his theory models change as a slow process, and the APD did not change instantly, but instead over a number of year.

In general, evidence and theories of change paint a mixed picture. On the one hand, police should be resistant to change and may only make changes in order to mirror an idealized police department but not to truly change the experiences of the communities they serve. Thus despite the clear evidence of an overhaul in policing styles in the late 2000s and early 2010s, it is reasonable to expect these broad changes in rhetoric and organization my not be reflected in the daily activities of officers and their immediate superiors. Yet the work of Sherman (2013), implies that when police are responding to local crises (as Atlanta was), they will act as open systems, responsive to change because of the pressure from the community they serve, and the history of policing exhibits clear examples of dramatic shifts in tactics. Theories of change in policing do not offer clear predictions for whether or not to expect a reduction in racialized patterns of policing as a result of the shift from “tough on crime” tactics to “smart on crime” tactics, but they do provide a clearer understanding of how such a shift might occur. A change requires direct, local pressure, and will likely be met with resistance even if embraced by police leadership. Further, even if change occurs, it may not have the intended effect or may not be faithfully practiced. While this does not allow for clear predictions about what to expect when examining drug arrests within and across eras, it provides proper context for the results of such an examination, placing them within the complex system that is a large, urban police department.

The nature of the strategies the APD adopted provide another lens through which to understand the potential for real change. One of the core components of “smart on crime” policing is the use of data to drive decision making about where and who to police. POP, ILP, and hot spots policing are data-driven strategies. This means they rely upon data collected by the APD, and the work of analysts to synthesize that data, in order to determine where they will focus their attention (D. L. Carter & Carter, 2008). Ferguson (2017) discusses the unintended consequences of this approach. Data-driven policing is designed to use prior police data to predict where future crime will occur, and thus targets high crime areas, but this often means targeting predominately minority neighborhoods and individuals. Data-driven policing has experienced popularity because it offers a superficially race-neutral approach to crime. The massive datasets and sophisticated models employed to conduct such analyses create the appearance of objectivity, yet these tactics are only as good as the data upon which they are built. As Ferguson notes, the data used in these analyses is "fraught with all-too-human bias, fear, distrust, and racial tension" (location no. 113). Stated differently, "disproportionate minority contact with the criminal justice system seeds the algorithms" that generate these analyses (Ferguson, 2017, location no. 1075). The analyses are built upon the data gathered by police officers with all of their inherent biases. In the case of Atlanta, much of this data used in the "smart on crime" era was collected by Red Dog and beat officers during the "tough on crime" era (Ferguson, 2017). These issues are also perpetuated at the neighborhood level; biased patrol patterns, with officers spending more time and thus making more stops and arrests in predominately minority neighborhoods, are the data input into analytic models that inform where officers will spend more time in the future (Ferguson, 2017).

Ferguson also argues that analyses of crime are not being used to alter approaches to crime, but instead to simply reinforce existing strategies. These analyses do not offer causal explanations of crime, but instead merely highlight correlation, offering "insight without explanation" (Ferguson, 2017, location no. 216). If, for example, a data-driven unit notices cocaine sales appear to be quite high near Northside Drive NW and Martin Luther King, Jr. Dr. SW—the location of the former Georgia Dome and current Mercedes-Benz Stadium—officers will not necessarily know why this is occurring or what the best form of intervention is unless certain information is collected and analyzed (what activities individuals are engaged in before arrests, why they met at this particular location, have they bought or sold cocaine at other locations, etc.). If all that the analyses produce are correlations between a location and crime, as current literature suggests they often do (Braga, 2001; Ferguson, 2017), then these tactics do not necessarily result in different approaches to policing. These analyses may simply use data to redirect arrests in a manner informed by past arrests, rather than being used as an alternative to arrest, despite alternatives to arrest being the recommendation of most “smart on crime” tactics (Braga, Kennedy, Waring, & Piehl, 2001; Braga et al., 2006; D. L. Carter & Carter, 2008; J. G. Carter & Phillips, 2015).

An adoption of data-driven tactics was not the only change that the APD made. The APD also created a community policing unit and enhanced their community outreach efforts through various other programs (Atlanta Police Department, 2012, 2013, 2014). Community policing involves alternatives to arrests as a way to address crime, and thus a faithful adoption of this strategy is likely to result in real changes to drug arrests patterns (Skogan, 2006). In addition, the department steered away from an aggressive approach to drug crime, and moved towards greater enforcement of violent crime (Blau, 2016). Finally, the APD increased their training requirements around constitutional rights and racial and ethnic issues in policing (City of Atlanta, 2016). These changes to the APD should result in the agency making fewer overall arrests and, especially, fewer drug arrests. It is unclear, though, whether these changes should also result in changes to the racialized patterns of arrests.

The mechanisms for racialized patterns of policing discussed by Warren et al. (2006) provide some insight. Cognitive bias and stereotyping occur when detailed information is absent, and thus officers make assessments based on obvious characteristics instead, such as gender, age, or race. Thus, this process will be common among police officers forced to make quick decisions about stops or arrests. “Tough on crime” policing may have enhanced the use of stereotypes by asking officers to meet unreasonable arrest metrics, and thus not allowing time for more informed judgments about who to arrest, forcing a reliance on such heuristics (Cook, 2013). Because “smart on crime” tactics reduce arrest numbers, there is time for more thoughtful judgements, and thus a lessened need to rely on stereotypes. In addition, the decreased pressure to make drug arrests may also have resulted in a reduced reliance on racial profiling tactics such as drug interdiction profiles and out-of-place stops. These tactics provide additional rationales for stops, but in an era in which drug arrests are not incentivized, there may be little need to rely on these rationales (Warren & Tomaskovic-Devey, 2009).

The trainings offered may have an impact on officers’ racialized notions of drug use that are the basis for stereotyping, and the move away from drugs as the focus of policing may have also reduced stereotypes related to drug offenders (Desilver, 2014), which should lead to reductions in racialized patterns of policing. The effect of deployment patterns on racialized patterns of policing, though, is more complicated. During the “tough on crime” era, the racialized notion of drug use may have led to increased deployment in communities of color due to the belief that such neighborhoods have higher rates of drug use and sales. Data-driven policing may result in improvements, if the data demonstrates these assumptions to be false, but if the data simply builds upon old patterns of policing it is likely to result in continued racialized patterns of policing

(Ferguson, 2017). Whether deployment results in disparities in arrest will depend on the sources of data used by the APD and the actions officers are directed to take when they address drug issues (i.e., arrests or alternatives to arrest).

In recent history, policing has shifted from "tough on crime" tactics to "smart on crime" tactics. This shift has occurred quite noticeably within Atlanta, GA, where a few high-profile incidents led to the disbandment of a PPU, the creation of a community policing unit, and the adoption of intelligence-led, data-driven strategies. Yet historical examples, theories, the nature of the change, and the mechanisms of racialized patterns of policing tell an ambiguous story about whether to expect this change to result in concrete reductions in racial disparities in arrests

Summary

Racial disparities in incarceration rates have been rising over the past few decades, and this is in part due to "tough on crime" policing and the War on Drugs (Mauer, 2006; National Research Council, 2014). The use of PPUs, order maintenance stops, and warrants have exacerbated racialized patterns of policing (Beckett, 2016; Benner, 2002; Kraska & Kapeler, 1997; Ridgeway, 2007). But police rhetoric has changed, shifting away from "tough" tactics and the War on Drugs and toward "smart" tactics and violent offenses (Darkulich & Kirk, 2016; Telep, 2016) – a shift that was marked within Atlanta, GA (Blau, 2016).

The impact of this change on racial disparities has yet to be assessed. Moreover, whether this change in ethos will result in reduced racial disparities in drug arrests is difficult to predict. Criminological theory and evidence related to this issue provides a mixed story, with some theories and findings suggesting a noticeable shift in the racialized patterns of policing should occur and other suggesting that this is unlikely. With such little evidence and theory to draw upon, investigation into this issue is particularly important. In the next chapter, I describe the data and methods I will use to investigate the impact of shift from the "tough on crime" to the "smart on crime" policing on racialized patterns of policing within the APD.

Chapter 4. Methodology

This dissertation investigates the role of race in felony drug arrests within the "tough on crime" era, within the "smart on crime" era, and across eras. A thorough investigation of the significant shift in policing methods that occurred across these two eras requires a detailed examination of specialized units (PPUs, data-driven units) and specific tactics (order-maintenance policing, search and arrest warrants) within each era. The literature shows that "tough on crime" policing operates differently from "smart on crime" policing in its focus on drug crime, use of PPUs, use of order-maintenance stops, and use of warrants. Prior research has also highlighted how these differences can result in changes to the policing of minority individuals and within predominately minority neighborhoods. Thus, this dissertation examines how race and neighborhood racial composition are associated with practices within the "tough on crime" era; specifically, the differential deployment of PPUs, (over)reliance on order-maintenance stops, and the (mis)use of search and arrest warrants characterizing the "tough on crime" era.

Similar units and practices are then examined within the "smart on crime" era to understand how the role of specialized units in policing drug crime changed as the nature and type of specialized units were transformed, and how the use of order maintenance stops and search and arrest warrants changed as the underlying ethos of the police department shifted. Finally, I use data aggregated to the census-tract level to compare the role of race in drug arrests across the two eras, examining changes in racial disparities and how changes to the use of specialized units and certain tactics are connected to racial disparities. Addressing these issues provides insight into the impact of two starkly different policing ethoi on racial disparities in drug arrests; the ability of police departments to change in response to local crises; and the tactics and units that affect racialized patterns of policing in both eras.

In this section, I outline the research design for this dissertation. The aim of this section is to explain how the approach detailed below serves as a robust initial evaluation of the impact that the movement from "tough on crime" policing to "smart on crime" policing—and associated changes in the use of tactics and units—had on racial disparities in drug offense enforcement by exploring the role of race both within and across eras. This section begins by addressing five data and measurement topics important to all analyses presented in this paper: the overall analytic strategy; the geography covered by the data; missing data; the nature of the sample; and how race is measured and racial disparities are assessed. I then describe the racial patterns of arrest in each era, comparing them to residential patterns to better understand how race is implicated in drug arrests. This provides a greater understanding of the data, and establishes that clear racial patterns of arrests existed within both eras and warrant further exploration. Next, I outline my hypotheses and analytic strategy for examining the "tough on crime" era. I then outline my hypotheses and analytic strategy for examining the "smart on crime" era. Finally, I outline my hypotheses and analytic strategy for examining changes across eras.

General Data and Measurement Topics

Overall Analytic Strategy

To analyze the racialized patterns of policing, analyses are broken into three sections. Chapter 5 examines patterns of policing in the “tough on crime” era and their association with race and racial composition; Chapter 6 both examines patterns of policing in the “smart on crime” era and their association with race and racial composition; and Chapter 7 compares racialized patterns of policing across eras. Later in this chapter, I describe the racialized patterns of policing that exist in both eras. In the following three chapters, I attempt to explain those racialized patterns within each era, and to understand changes in racialized patterns of policing across eras.

Specifically, in Chapter 5, focused on the “tough on crime” era, two multivariate models are employed to examine the association between arrestee race and neighborhood racial composition with a) specialized policing units and b) policing tactics. Current literature suggests PPUs can produce racialized patterns of policing (Balko, 2015), and I explore this with my first set of models. Multivariate models will also be used to answer a similar question about policing tactics. The tactics of interest include order maintenance stops and the serving of search and arrest warrants, activities associated with racialized inequalities in policing (Benner, 2002; Brunson & Miller, 2006; Brunson & Weitzer, 2008). Both tactics were widespread in the “tough on crime” era, and were employed during some of the negative incidents that sparked change in Atlanta (Blau, 2016). These will be compared to the reference category, which is comprised of any other tactic employed in a drug arrest. All models will be built iteratively to provide a more nuanced understanding of the source of racial disparities in policing drug offenses.

The analyses in Chapter 5 parallel those in Chapter 6. Data-driven units that employ hot spots and intelligence-led policing tactics replaced PPUs generally in Atlanta and are as emblematic of the "smart on crime" ethos as PPUs were of the "tough on crime" ethos (Blau, 2016; City of Atlanta, 2016; Ferguson, 2017). Thus, in the "smart on crime" section I investigate whether race and neighborhood racial composition are associated with the use of data-driven activities. To date, only a few studies have investigated the racial impact of "smart on crime" tactics (Desmond & Valdez, 2012). This section will also investigate whether warrants and order maintenance stops are linked to race and racial composition within this era. While these tactics should be used less often in a "smart on crime" era, when used, they may still disproportionately focus on non-white citizens and neighborhoods.

The analyses described so far will allow for a comparison for within-era findings, but they do not provide a rigorous quantitative assessment of change. To formally examine this, in Chapter 7, I investigate changes in the race of arrestees across eras; whether changes in the use of specialized units, warrants, and order maintenance stops are associated with changes in the race of arrestees. To do so, I aggregate all data to the census tract level, create measures of the non-white arrest rate and racial disparities in arrests as well as measures of the changing use of specialized units and tactics, and employ fixed effects models that allow for a comparison within census tracts over time.

Data Sources

While the exact sample used to answer each research question varies, all analyses rely on data from the Contexts of Drug Enforcement (CODE) project, which includes quantitative arrest data and various census tract-level measures. The CODE dataset was developed by Dr. Elizabeth Griffiths as part of a larger National Science Foundation grant entitled "Race, Place, and Discretion in the Handling of Drug-Free Zone Charges" (NSF 1252125). The CODE dataset provides arrestee and case characteristics for all closed felony drug cases involving adult offenders in Fulton County, Georgia in 2005 and 2012.[1] The CODE dataset contains information on each arrest, including the top charge on arrest and the type of drugs involved in the arrest. It also contains demographic data on the arrestee, including race, gender, and age at the time of arrest.

The CODE dataset is an arrestee-case dataset, meaning that each observation represents a particular person arrested within each case. To illustrate, were an individual arrested twice for different felony drug charges in 2005, that person would appear twice within the data. If, during one of those arrests, that individual were arrested alongside a friend who was also charged with a felony drug offense, then two observations would appear in the dataset – one for each arrestee within the same case.

[1] The larger dataset includes adult arrestees in all closed felony drug cases in 2003, 2005, 2008, 2009, and 2012 across Fulton County. These data were collected as part of a major project on drug free zones, community context, and court processing of felony drug cases in the non-complex trial division of the Superior Court in Fulton County, Georgia. The project was supported by a grant to E. Griffiths, K. Levine, V. Topalli, and J. Hinkle from the National Science Foundation (NSF Grant Number SES-1252125) and to E. Griffiths and K. Levine from Emory University's Race and Difference Initiative (2010-11).

The PIs on the CODE project have granted the author access to arrest location information and all available arrest reports for cases in 2005 and 2012, neither of which will be included in the publicly available data. Arrest locations were geocoded to X-Y coordinates, which was accomplished through a multi-stage process in ArcGIS that involved manual re-checks of all addresses to ensure valid geocoding results. Geocoded incidents were then linked to census tract measures. Census tract data for 2000 and 2010 are derived from the Neighborhood Change Database (NCDB), normalized to 2010 census tract boundaries. Communities and crime scholars often employ census tracts as proxies for neighborhoods (Lyons, Vélez, & Santoro, 2013; Peterson & Krivo, 2010); this dissertation will follow this approach. As the most proximate years for in which the decennial census occurred, 2010 census data is used for 2012 arrests, and 2000 census data is used for 2005 arrest reports.

The arrest reports provide a unique source of insight into the circumstances surrounding police stops and arrests. They typically contain short narrative descriptions of the context of the stop according to the arresting officer, and provide information on some of the decision features of the arrest. These arrest report narratives were used to construct codes that capture the context of a police stop, in particular distinguishing two types of arrests from all others: those arising from order-maintenance stops and those arising from the serving of warrants. These narratives also indicate when a specialized unit was involved in an arrest.

Arrest report narratives from 2005 and 2012 were used to create a single categorical variable with three categories that, collectively, encompass the tactics of a police stop. Due to the wide range of tactics on which police rely and the large amount of discretion afforded to law enforcement, the circumstances of a police stop can vary substantially (National Research Council, 2004). That variability is captured through a coding process that assesses the rationale for a police stop as described by the arresting officer in the arrest report narrative. Codes incorporate two layers of information. First, the codes identify the officer's activity at the time of a stop, such as routine patrol or being dispatched to a location. Second, the codes identify the activity of the arrestee that motivated the stop, such a drug deal or driving over the speed limit. The second layer does not represent the reason for the arrest, but instead the reason for the stop. As the data are composed of felony drug arrestees, the charges on arrest always involve at least one felony drug-related offense, and occasionally additional non-drug offenses. But in many cases, the rationale for a stop is not drug-related. For example, in 2012 among all stops that resulted in a felony drug arrest when an officer was on routine patrol, only 32.6% were motivated by an officer suspecting or witnessing a drug offense. Others were, for example, motivated by some sort of disorderly activity, such as panhandling, but resulted in a drug arrest when the officer found drugs on the panhandler.

These codes for tactics were developed in collaboration with dissertation chair, Dr. Elizabeth Griffiths and dissertation committee member, Dr. Josh Hinkle; the arrest reports for 2012 were coded in collaboration with both Drs. Griffiths and Hinkle and I coded 2005 arrest reports using the methods developed when coding 2012 (see Appendix A for a full list of possible codes and Appendix B for a description of the coding protocol). These codes are translated into three tactic types: stops that result from order-maintenance policing; stops that result from serving a warrant (search or arrest); and stops that result from any other activity or rationale.

Order-maintenance policing involves officers stopping, and when possible, arresting individuals engaged in socially or physically disorderly behaviors, such as panhandling, loitering, or littering, as well as generally suspicious activity (Wilson & Kelling, 1982). These stops are conducted when officers are engaged in some form of patrol and thus the operationalization of order-maintenance stops began with the first layer of arrest report codes. All patrol activities were identified, which included "routine patrol" and "directed patrol." Within these two categories of patrol, four second-layer activities were identified and combined to capture order-maintenance policing. The first is "disorder" which refers to any stop motivated by an arrestee engaging in some minor disorderly activity, such as drinking in public or panhandling (see Appendix A for a full list of the types of disorder). The second is suspicious behavior by an individual or a vehicle. This occurs when an officer does not clearly identify an offense, but instead relies upon some generalized sense that the person or vehicle is "suspicious" in order to justify the stop. In their description of officers maintaining order, Wilson and Kelling (1982) paint a picture of officers who not only rely on physical signs of crime or disorder but also upon a general sense of who belongs in a neighborhood and why. Determinations about who does and doesn't belong may be made using intuitions about the "suspiciousness" of a person or vehicle.

The third activity is what officers refer to as "pedestrian checks," which occur when an officer stops an individual without the pretense of suspicion or having witnessed an offense. These have been included as they may be used when suspicion cannot be articulated, and because they match the sort of unjustified stops that Brunson and Weitzer (2009) found were common to order-maintenance policing. These categories fully encompass the initial operationalization of order maintenance stops, which includes all pedestrian order maintenance stops. All analyses were also run using a second operationalization that includes traffic stops (unless they were conducted at a safety checkpoint). According to Dunn (2015), in cities outside of New York, driving is common, and thus order-maintenance policing is as likely to occur for minor vehicle violations as it is for minor pedestrian violations. Minor vehicle violations include most traffic stops, except for stops for speeding that result from a speed trap. This second operationalization includes both pedestrian and traffic order maintenance stops.

Operationalizing warrants was simpler. Two activities in the first layer of codes, “search warrants” and “arrest warrants,” were combined. Research has found that no-knock warrants are particularly problematic (Kraska, 1996, 2007; Kraska & Cubellis, 1997; Kraska & Kappeler, 1997), but unfortunately, arrest report narratives did not always indicate whether a warrant was a no-knock warrant, and thus no-knock warrants could not be distinguished from warrants in which police presence was announced.

Arrest reports were also used to code the involvement of specialized units within each era. In 2005, I coded for Red Dog involvement in an arrest. If the officer writing the report was a part of the Red Dog unit, he/she usually noted this in the report. To code for Red Dog arrests, I incorporated all cases in which Red Dog was mentioned as well as all cases in which a Red Dog officer was mentioned. Arrest reports often mention that an officer is associated with Red Dog, and this information was used to ensure that arrest reports which may have failed to mentioned Red Dog but which involved an officer clearly identified as a Red Dog officer were flagged as Red Dog arrests. These adjustments were made only for officers explicitly mentioned as being Red Dog officers; 77.86% (n=809) of Red Dog codes were added via this process. I took a conservative approach to coding for Red Dog arrests, only coding an arrest as such when I was sure the arrest involved at least one Red Dog officer. Thus, while it is unlikely that any non-Red Dog arrests were incorrectly coded as Red Dog arrests, it is possible that some Red Dog arrests were incorrectly coded as non-Red Dog arrests. This sort of measurement error is more likely to lead to Type 2 Errors than Type 1 Errors; in essence, all estimates would be conservative estimates of relationship between Red Dog and race.

In 2012, the arrest reports were used to code for the presence of data-driven tactics. Specifically, this incorporated the presence of directed patrols and use of data-driven units. Directed patrols are an indication of a data-driven approaches to crime in which data on past crime patterns is used to guide where officers will focus their patrol efforts in the future. Such strategies align with the principles of intelligence-led and hot spots policing (Braga, 2001; Braga & Bond, 2008; D. L. Carter & Carter, 2008; J. G. Carter & Phillips, 2015). In addition, certain APD units were involved in data-driven policing efforts in 2012, including the Atlanta Proactive Enforcement and Interdiction Unit (APEX) unit, Field Investigation Team (FIT), and the Crime Suppression Unit (Atlanta Police Department, 2012).

The CODE dataset was also supplemented with violent and property crime data and police zone boundaries obtained from the APD for 2005 and 2012. The 2005 data were obtained via request to the APD[2], and the 2012 data were obtained from the APD website. The 2012 arrest data were already geocoded; to obtain X-Y coordinates for the 2005 violent and property crime data, I geocoded the addresses using the Google Geocoding Application Programming Interface (API) through a Python script. Police zone shapefiles were linked to census tracts through a spatial join in ArcGIS 10.5.1.

I selected 2005 as the year to represent "tough on crime" policing because the death of Kathryn Johnston occurred in 2006 and the strip search of Ricky Sampson in 2008. Arrests in 2005 occurred as near to these incidents as possible without overlapping them. Proximity is important because these incidents served as catalysts for a policing crisis in Atlanta. They also represent the worst extremes of "tough on crime" policing. I chose 2012 as my operationalization for the "smart on crime" era because this is the first year after the crises and the first year after Red Dog was disbanded and replaced. Further, by 2012 Atlanta had also implemented a community policing section and begun to focus on a data-driven approach to crime (Atlanta Police Department, 2012; Blau, 2016).

One common threat to internal validity when analyzing data that spans multiple time periods is history, or the occurrence of an event that confounds the results. Any other events that influence racial differences in drug arrests during the period of study may confound the findings of this dissertation. While some of these can be measured and

[2] Drs. Josh Hinkle and Dean Dabney at Georgia State University assisted me in the acquisition of these data.

thus statistically controlled (e.g., economic conditions), many cannot because the data needed to account for them does not exist (e.g., popularity of certain types of drugs). The longer the time between measurement of each era, the greater the probability that such an event will occur. This threat is minimized, to the greatest extent possible, by defining the “tough on crime” era as 2005 and the “smart on crime” era as 2012, and thus focusing on changes within a seven-year period (Frankfort-Nachmias & Nachmias, 2007). These are years that directly precede and directly follow the crisis in the policing in the Atlanta area, representing the narrowest possible historical window for analyzing this issue. These operationalizations were carefully selected with these issues in mind.

Geography

Atlanta is the largest city in Georgia (420,003 residents in 2010, 5.2 million in the greater Atlanta area), the state capital, and the seat of Fulton County (Ambrose, 2004). While Fulton County contains most of Atlanta, a small portion (approximately 5% of the total square miles) of the city lies in DeKalb County (Carpenter, 2004). CODE project data encompass all felony drug arrests of adult arrestees in Fulton County. The three events that propelled a policing crisis were specific to the Atlanta Police Department (APD). For this reason, this dissertation focuses exclusively on arrests in Atlanta for which the APD was involved.

As noted above, a small section of Atlanta will be missing from this analysis as it lies in DeKalb County. There is good reason to expect that results found in the Fulton County section of the city would be similar to those found in the DeKalb County section.

Police zones cross county lines, and thus this region is not distinct in terms of police leadership (Atlanta Police Department, 2001, 2011). Specifically, Zone 6 is split across Fulton and DeKalb counties. Frontline leadership, like sergeants and lieutenants responsible for particular beats and zones, is one of the strongest determinants of police practices, potentially more so than individual officer preferences (Engel & Worden, 2006; Klinger, 2004; Mastrofski & Willis, 2010; Nowacki, 2011). Thus police behavior observed in the Fulton County section of Zone 6 is likely similar to that observed in the DeKalb County section of Zone 6. Nonetheless, while DeKalb only represents a small section of the city and findings in DeKalb are unlikely to vary from those within Fulton County, the lack of data from DeKalb County is a weakness of these analyses, and the findings should be understood to reflect only the Fulton County section of Atlanta.

Missing Data

In total, the CODE dataset contains 5,760 observations in 2005 and 1,692 observations in 2012. Many of these, though, are not relevant as they were arrests conducted by an agency other than the APD or they were conducted outside of Atlanta. In 2005, 20.4% (n=1,172) of cases were conducted by other agencies, and of those cases conducted by the APD, 34.2% (n=1,571) were outside of Atlanta. Eliminating these observations left a sample of 3,017 observations in 2005. In 2012, 28.0% (n=474) of cases were conducted by other agencies, and of those cases conducted by the APD, 1.7% (n=20) were outside of Atlanta.[3] In 2012, the final sample is thus 1,198.

During both years, data were missing on key dependent and independent variables, which reduced the sample size from 3,017 in 2005 and 1,197 in 2012 (4,214 in total) to 2,758 (8.6% reduction) in 2005 and 987 in 2012 (17.5% reduction), resulting in a total sample size of 3,744 (11.2% reduction). Cases that did not have accompanying arrest narratives or had arrest narratives that were insufficient for coding purposes resulted in missing data. In addition, cases that did not have associated address data or had address information that could not be geocoded due to the poor quality of the address data (e.g., a missing street direction, a missing or inaccurate zip code) were treated as missing. Because my study necessitates the use of both arrest data and narrative arrest reports, the potential for missing data is greater than if I relied on only a single source.

Missing data comes in three forms: missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR). MCAR data is missing in a way that does not depend on observed or missing data values. The process determining missing data is essentially random, and little if any adjustment needs to be made. MAR data is missing in a fashion that depends on observed data, but not upon missing data. Here, the missingness is not random, but it is dependent on the data

[3] There is a stark reduction in rate of felony drug arrests conducted by the APD outside of Atlanta between these two years. While arrests outside of Atlanta are not the focus of this dissertation, and thus the underlying reasons for this change were not investigated in depth, based on arrest report narratives, this shift appears to be largely driven by changes in the use of multi-agency task forces in 2005. Regardless of the reason, the magnitude of the change certainly suggests that, in line with their public rhetoric, between 2005 and 2012, the APD reevaluated the ways in which they police felony drug arrests.

available to an analyst and thus appropriate adjustments can be made. Finally, MNAR data is missing in a way that depends on both the observed and missing data, and in no way resembles a random process. In the final case, few adjustments can be made (Newman, 2014). Essentially, MAR and MNAR represent systematic missingness, and MCAR represents random missingness. Nothing about the raw data from Fulton County suggested that missing or poor quality narrative and address data was in any way systematic or connected to the cases themselves; instead, these missing data appear to be simply a product of errors and inefficiencies in record keeping. There is little reason to suspect that this process is systematic, unless those police officers with poor record keeping habits also to have a different approach to policing drug offenses or consistently arrest individuals of only certain races or ethnicities, and unfortunately, without clear officer identifiers in the data, both possibilities are difficult to test.

Missing data has the potential to create two issues: bias and inferential error. In the first, a model parameter is either over or under-estimated because the sample of non-missing cases does not accurately represent the true sample, or the sample that would have resulted had no cases been missing. This is only a concern when data are missing in a systematic fashion (MAR or MNAR), as these are cases in which it is possible that the non-missing data does not accurately represent the whole sample (Newman, 2014). The second issue, inferential error, occurs when a hypothesis test results in either a Type I (false positive) or Type II (false negative) error, incorrectly inferring that either statistically significant relationships exist when they in fact do not or that they do not exist when in fact they do. In the case of missing data, a Type II error is far more likely due the reduced sample sizes that result from missing data (Cheema, 2014; Jakobsen, Gluud, Wetterslev, & Winkel, 2017; Newman, 2014).

There are a variety of ways to handle the issues created by missing data, but some of the more common are listwise deletion, alternatively known as complete case analysis; single imputation; and multiple imputation (Newman, 2014). In listwise deletion, only those cases with complete data are analyzed. In single imputation, missing values are replaced with a single value, often the mean for that variable. In multiple imputation, numerous partially-imputed datasets are created, and final estimates are combined to get final parameter and standard error estimates. While it is widely agreed upon that single imputation is an inappropriate solution to missing data of any type as it may introduce substantial measurement error, recommendations diverge on whether listwise deletion or some form of multiple imputation is the preferred solution in any particular case (Allison, 2001; Cheema, 2014; Jakobsen et al., 2017; Newman, 2014; Sterne et al., 2009).

In this case, I use listwise deletion accompanied by a careful examination of the consequences of missing data. As the one of the primary concerns with missing data is possessing a sufficient sample size, when one has a large sample size even after dropping cases with missing data (as is the case here), it has been argued that listwise deletion is a less risky approach as it avoids the possibility of introducing additional measurement error to the data through imputation, despite the robustness of some of these techniques (Cheema, 2014). The gain in efficiency offered by imputation may be offset by the potential introduction of additional measurement error (Cheema, 2014). Indeed, Cheema (2014) recommends that when the sample size is approximately 1,000 or greater (as is the case here), that the decision to use imputation should be based solely on whether the observed sample accurately represents the full sample, and as noted earlier, it is unlikely that there is some systematic process governing when addresses are of poor quality or arrest reports are too short to be coded. Others have echoed this recommendation (Jakobsen et al., 2017). In addition, when the overall level of missingness is low (around 5%) and the source of missingness is not clearly systematic, listwise deletion is recommended as the impact of missingness is likely to be negligible (Jakobsen et al., 2017). Finally, when data are missing in this study, they are either missing for all outcome variables (i.e. type of arrest) or half of the independent variables (i.e., any tract-level variable), and on occasion, for both. When missingness occurs for all or most of the variables included in an analysis, it is recommended that listwise deletion be used with a careful examination of the consequences of missing data. This is because multiple imputation relies on the values of non-missing variables to impute values for missing variables, and thus when missingness occurs for most or all variables, this method cannot be used or its strengths are attenuated (Jakobsen et al., 2017; Newman, 2014).

To fully address missing data issues, I more closely examined the missing data. Table C.1 and C.2 in Appendix C describe the source of missing data within each year and examine whether missing data differ from observed data on any demographic and case characteristics. In each year, a similar number of cases are missing, but these represent a greater proportion of all cases in 2012 as there are fewer total observations. Of those missing, very few are missing both address and arrest report narrative information, and across the two years, about equal proportions are missing only address information or only narrative information. Yet within each year, the main source of missingness differs. In 2005, most missing data is the result of missing address data, and in 2012, most missing data is the result of missing narrative data. Address reporting in arrest report narratives was less formalized in 2005, and the quality of addresses varied from report to report; thus, it is not surprising that this is the main source of missing data in 2005. In 2012, address data are significantly improved, yet more narratives were either missing or incomplete. In 2005, to the extent that the complete cases do not represent the total cases, it is likely to have the greatest effect on inferences drawn about tract-level variables, including racial composition. In 2012, if the complete cases do not represent the total cases, measurement error is likely to occur for the outcome variables. Nonetheless, it seems unlikely that particular tracts in 2005 or particular arrest tactics or units in 2012 would disproportionately contribute to the missing data in each year, and instead both seem to be more likely a product of inconsistent record keeping.

In 2005, there is no relationship between whether an observation is missing and the race, gender, or age of the arrestee (see Table C2 in Appendix C). There is also no relationship between whether an observation is missing and the most serious charge on arrest and types of drugs involved in an arrest. In short, in 2005, missing and non-missing cases do not differ on any of variables which can be measured on both types of observations. There is not clear pattern to missingness in 2005, and thus it is likely that the complete observations are generally reflective of the total sample of observations.

In 2012, there is no relationship between whether an observation is missing and the race or gender of an arrestee. But missing observations, on average, involve younger arrestees and are more likely to involve marijuana and to be for a more serious drug charge. It is possible that inferences for race will be affected by these differences if age, severity of drug charge, and use or sales of marijuana are linked to race, but it is impossible to predict the effect of these differences on the relationship between race and data-driven policing, order maintenance stops, and warrants. This is especially the case as these differences are likely to have varied effects on different outcomes. For example, warrants are likely to involve serious charges and older arrestees and order maintenance offenses are likely to involve less serious charges and younger arrestees (Balko, 2015; Brunson & Miller, 2006; Brunson & Weitzer, 2008). What they do clearly suggest is that using listwise deletion means the results for 2012 pertain to a sample of felony drug arrestees that are slightly older, less involved with marijuana, and less involved with sales or intent to sell offenses than the total population of arrestees in that year. The focus of this study is on race. Chi-square tests and t-tests reveal black and non-white arrestees are more likely to be charged with serious drug crimes ($p<.001$), with charges involving marijuana ($p<0.001$), and to be older ($p<0.001$), and thus estimates using the non-missing observations are likely to be conservative estimates, understating the relationship between black or non-white variables and any outcomes. This is because cases more likely to involve black or non-white arrestees are also more likely to be missing. Findings in Chapter 5 and 6 are interpreted with these limitations in mind.

Sample Selection

When a sample is selected in a process that is not independent of the outcome, selection bias is a concern. This is not an uncommon problem in criminological research (S. Bushway, Johnson, & Slocum, 2007). Within this field of study, reliable data often comes from administrative records that are only available because an individual has reached a certain stage within the criminal justice process, and thus selection bias pervades much of criminological and criminal justice research. For example, Lundman & Kaufman (2003) analyzed bias in traffic stops. To enter their study, an individual had to have at least one traffic stop, and thus outcomes are only observed for individuals involved in a traffic stop. Yet the researchers wanted to investigate bias among all individuals at risk for a traffic stop. The estimate for this larger population is known as the unconditional estimate. When one has a sample that is not randomly selected, the estimate of the outcome of interest conditioned on membership in a subgroup will be biased (S. Bushway et al., 2007). Using a sample of individuals stopped at least once to investigate overall risk of a traffic stop thus leads to the potential for biased estimates.

Research on racialized patterns of policing often aim to speak for patterns of bias for individuals and within neighborhoods not only for those individuals actually arrested, but for all potential arrestees. Yet the sample used in this dissertation consists of all individuals arrested for a drug arrest within two years—2005 and 2012—in the Fulton County section of Atlanta.

One of the most common methods for addressing the problem of selection bias is Heckman's two-step estimator (Heckman, 1976), whereby selection into the sample is estimated using a probit model, which is used to calculate the inverse Mills ratio. The inverse Mills ratio is then inserted into the ordinary least squares model for the outcome of interest. This correction, though, does not apply to this study for two reasons. First, this correction requires that the outcome of interest be a variable that can be estimated using ordinary least squares (OLS). Many of the analyses in this dissertation involve outcomes that are dichotomous and multinomial. Second, the Heckman correction requires some indication of the unconditional population. If one has full information on the unconditional population, the Heckman correction would not be necessary, yet it assumes that researchers have some data on the unconditional population in order to estimate the selection model. In this case, this means that I would need to have some sense of the entire population of individuals at risk of an arrest.

This, though, is not a problem. First, in the absence of exclusion restrictions, an uncorrected model is preferable. Exclusion restrictions are variables used to estimate selection into the model that are not also used within the substantive model. It is difficult to imagine variables that would determine arrest for a drug offense (selection), but not also be connected to the tactic or unit involved in that arrest or to broader patterns of racial disparities. In cases such as this, it is recommended that the model be estimated without a correction because, while estimates with a Heckman correction are unbiased, in the absence of exclusion restrictions they are inefficient (Puhani, 2002; Stolzenberg & Relles, 1990). This is a common rationale within criminological research for not using the Heckman correction, even when the data allows for it (which these data do not) (S. Bushway et al., 2007).

Second, common methods for estimating the full population of potential arrestees, such as the capture-recapture technique, often assume the arrested population bears some similarity to the population eligible for arrest but not arrested. As Bouchard and Tremblay (2005) note, “For all practical purposes, arrested offenders are not viewed as a biased sample of a larger population of potential offenders who just happen to commit fewer and less serious crimes, but as a representative sample of a population of active offenders on the street who are likely to be arrested at the same rate as those who have already been arrested” (p. 736). This common estimation method proceeds with the assumption that offenders arrested only once and twice do not vary dramatically from those at risk of arrest but not arrested. Within the CODE data, most defendants are arrested either once or twice. Of the 7,528 defendants in 2005 and 2012, 6,413 appear once and 436 appear twice, with only 85 appearing more than twice. Thus, the CODE sample may, in fact, represent the population at risk of arrest fairly well.

Finally, there are two good reasons to prefer a sample of drug offenders which include only arrestees. First, because all individuals within the sample, by design, have been arrested on at least a single drug charge within either 2005 or 2012, sub-groups within this population are more similar on a number of unobservable characteristics because they have been “selected” for arrest. As van Schellen, Poortman, & Nieuwbeerta (2012) noted when comparing the effect of marriage on offending within a sample of offenders, married and unmarried individuals in a sample of offenders are likely to be far more similar “with regard to unmeasured characteristics that influence both the likelihood of offending and marriage” (p. 554) precisely because they are all offenders. The similarity between these two groups helps account for unobservable differences between those who are married and those who are not.

Similarly, arrestees of different races are likely to be far more similar on a number of unobservable characteristics than “potential arrestees” of different races, and arrests conducted with different tactics and by different units are likely to be more similar than “potential arrests” conducted using different tactics and units. While a sample of all police stops would compare a group of wide-ranging individuals, this sample compares a group of similarly situated individuals precisely because they share in common the experience of arrest.

Second, examining differences among a sample of arrestees allows for a direct assessment of the causes of differential arrest rates. Most studies on race and policing focus on the differential rates of stops by race or neighborhood racial composition, implying that the nature and type of policing being investigated produces those inequities (Beckett et al., 2005; Gelman et al., 2007). I focus, instead, how the nature and types of arrests that are made may be racialized, more directly investigating the assumed mechanism producing differential arrest rates. For example, Gelman et al. (2007) found in that in New York City, order maintenance tactics were associated with higher rates of stops of black and Hispanic men. Implicit in such a study is the assumption that not only are higher rates of stops disruptive to the lives of these men in the immediate, but that they lead to higher rates of arrests and are thus more disruptive in the long term, and begin a cycle of justice involvement that may permanently effect the lives of those young men (Brunson & Miller, 2006). Examining patterns racial patterns of arrest by the units of tactics involved in those arrests allows for a direct assessment of this assumption.

Assessing Race and Racial Disparities

In this dissertation, I examine the relationship between race and policing in two different eras. To do so, I measure race in two ways: individual arrestee race and neighborhood racial composition. Individual arrestee race refers to the race of individuals arrested by the APD, and any observed relationships between individual race and certain tactics and units could imply that those tactics and units are used differently across racial groups. Yet a vast body of research suggests that, because police departments are geographically organized agencies (Klinger, 2004), racial disparities also express themselves as neighborhood differences (Brunson & Miller, 2006), with police making proportionately more arrests in neighborhoods with more minority residents. When I explore the effect of certain tactics and units within each era, I employ both measures as independent variables. When I explore changes across eras, I use racial composition to construct race-specific arrest rates and measures of racial disparity in arrests (Ousey & Lee, 2008).

Measuring race and racial disparities is a complex endeavor with no gold standard upon which to rely (Alpert, Dunham, & Smith, 2007). Indeed, Alpert, Dunham, and Smith (2007) list numerous strategies that have been attempted and, within their own study, employ multiple methods to assess racial disparities in stops and post-stop activities in the Miami area. The difficulties associated with measuring race and racial disparities can categorized into two primary issues: finding an appropriate benchmark and accounting for police action.

Benchmarks are used to account for the fact that in any particular location not all races are equally at risk for police interaction (e.g., stop, search, arrest). According to the 2010 Decennial Census, Atlanta is 54.0% black, 38.4% white, 3.1% Asian, and 5.2% Hispanic. Thus, simply in terms of the demographics, equal representation by drug arrest data should not be expected. In fact, were all races and ethnicities arrested in exactly equal proportions to their presence in the population, racial disparities (in absolute, but not relative terms) might be identified merely due to the unequal representation by race in the city (e.g., more than half of all drug arrests in the city would be of blacks).

The incorporation of police action and information about the case is employed because different police and suspect behaviors may result in racial disparities in stops for reasons not related to suspect race or ethnicity. The incorporation of case-related data helps account for legal covariates likely associated with police action, and allows race-related coefficients to be interpreted as attributable to a racial effect (Fryer, 2016, 2018).

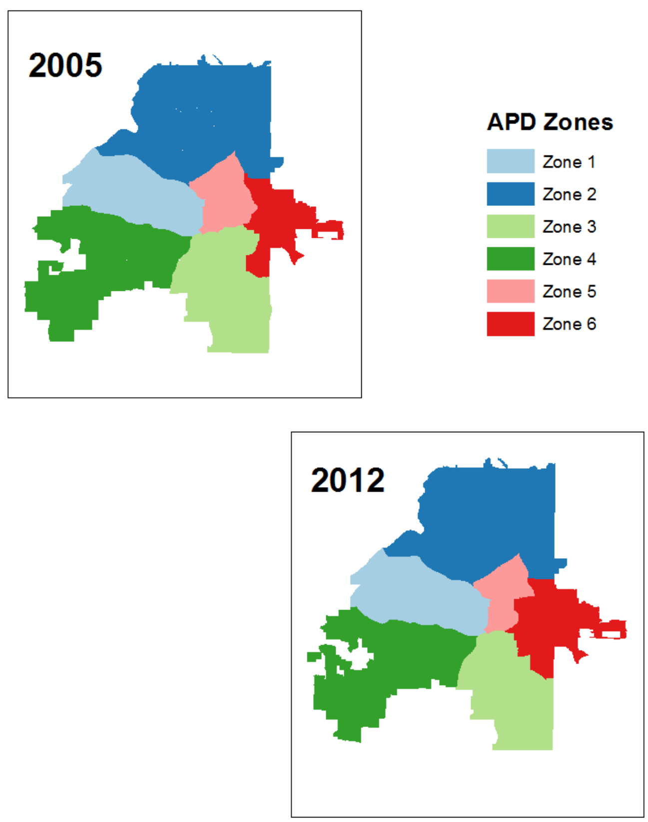
Bearing this in mind, I build models iteratively to better understand how relevant characteristics modify the relationship between race and police activity. The first two analytic chapters (Chapters 5 and 6) of this dissertation examine the effect of arrestee race on the use of police tactics or units within each era. Here the question is not whether there are racial disparities across Atlanta, but whether race is associated with certain units and tactics within each era. For example, research suggests that PPUs like Red Dog should be more likely to arrest non-white individuals (Chambliss, 1994). The regression models in these sections are a test of that question, and similar questions about police tactics.

In Chapters 5, 6, and 7, I discuss the importance of all my control variables to the questions being addressed in detail, but below I summarize their general purpose. I include measures of individual race, gender, and age, as well as the drug types involved in an arrest and the most serious drug charge upon arrest. In my multivariate models, controlling for arrestee characteristics allows for an assessment of whether race is the salient demographic measure connected to arrest type, or whether arrest type is better explained by other demographic features commonly associated with offending and police decision making. Case characteristics control for arrest attributes, and thus control for potential legal and temporal factors that could lead to racially biased outcomes. In more fully specified models, I include neighborhood-level measures. The primary measure of interest is racial composition. This variable permits an understanding of whether certain tactics or units are more prevalent among arrests that occur in neighborhoods with higher rates of minority residents. I also include measures of social disorganization and Index violent and property crime rates. Measures of social disorganization help assess whether the effect of individual race on tactics or units is better explained by neighborhood economic conditions that others have theorized may guide officer decision making (Klinger, 2004). Neighborhood crime rates ensure that the effects of race are not due to police focusing on areas with the highest index crime rates.

Finally, indicators of police zones are added to the model. APD zones are akin to what are called precincts or districts in other large police departments. Zones divide up the city so that in places as large and diverse as Atlanta, centralized leadership is not directly responsible for overseeing the activities of all officers (National Research Council, 2004). Instead, they oversee the actions of specialized units and the actions of zone leadership (Atlanta Police Department, 2011, 2012). In turn, zone leadership, known as zone commanders, oversee the activities of the officers working within their zones. Police tactics do and should vary across locations and much of this variation is governed by the workgroups that develop in police zones (Engel & Worden, 2006; R. R. Johnson, 2012; Klinger, 2004). Because behavior is likely to vary so substantially by police zones within a large department, in addition to controlling for zone membership, I also explore variation across zones. It is possible that racial disparities in types of arrests may not occur across the whole of Atlanta and yet at the same time, be quite pronounced within certain zones.

Because zones divide up police activities geographically, they focus on distinct areas of the city with potentially distinct crime problems and resident populations. Figure 1 shows the zone border in 2005 and 2012 respectively (the border changed slightly during this time period). Zone 1 is responsible for what the 2011-2012 APD annual report calls West Atlanta (Atlanta Police Department, 2012). Acknowledging that crime rates will vary year-to-year, arrest statistics from annual reports suggest that Zone 1 has a fairly high level of violent and property crime, while Zone 2, in North Atlanta, has low levels of almost all crimes with the exception of larceny. Zones 3 and 4, in Southeast and Southwest Atlanta, respectively, have some of the highest levels of violent crime in the city, while Zone 5 in Midtown-Downtown has low levels of violent crime, but incredibly high levels of larceny. Finally, Zone 6 is located in East Atlanta, and tends to have moderate levels of violent crime, and fairly low levels of property crime (Atlanta Police Department, 2000, 2001, 2011, 2012, 2013, 2014). Atlanta is also a geographic hub of travel

Figure 1. APD Zone Boundaries in 2005 and 2012



throughout the region and different zones intersect with different major highways. In addition to the varied leadership styles for the zone commanders in each zone, these geographic and crime differences are likely to lead to variation by zone in the impact of race on felony drug arrests.

In the final chapter, I assess the change in racial disparities across eras and the effect of aggregate arrest characteristics (units and tactics) on racial disparities in arrests using a fixed effects model at the neighborhood level. Here, many of the previously discussed variables are included in a form suitable for census-tract level data. Aggregated policing tactics and units are added as righthand side variables as is the era of the arrest (i.e. year). As dependent variables, I first examine the race-specific arrest rates and then examine a measure of racial disparity. Following prior research, I measure the arrest rate for as the number of arrests that involve individuals of that race within a census tract over the number of residents of that race in the census tract. I measure racial disparities as the ratio of the arrest rate for any particular race and the total arrest rate within a census tract (Ousey & Lee, 2008).

Racial Patterns of Arrest in Each Era

In this section I provide a detailed description and comparison of the racial patterns of arrest within each era. This functions not only as a description of the data and key variables within the data, but also provides clear, strong evidence of racialized patterns of policing in each era that warrant further exploration. The analyses in this section focus on both the 2005 and 2012 CODE data.

Measuring Race in the CODE Data

I will begin with a definition of race that includes the full range of categories available within the CODE dataset: non-Hispanic white, non-Hispanic black, Hispanic, non-Hispanic Asian, non-Hispanic Native American, and other, which provides a rich understanding of race in Atlanta. Due to the small number of arrestees who are Hispanic, non-Hispanic Asian, non-Hispanic Native American, and other, I analyze race using two dichotomous operationalizations. As most research on the racial disparities in criminal justice points to differences between black arrestees and all others (Brunson & Miller, 2006), race is first operationalized as a dichotomous variable in which 1 signifies black, and 0 signifies white, Hispanic, Asian, Native American, or other.

Yet some research also finds racial disparities for other non-white arrestees. For example, Benner (2002) found that Hispanics were more likely than whites to be targeted for cocaine and for methamphetamine search warrants in San Diego. The history of drugs in America suggests that there may be specific racialized notions of drug use and sales for Hispanic and Asian Americans (Provine, 2007). For these reasons, the second operationalization of race is as a dichotomous variable comparing non-white to white arrestees. A 1 signifies black, Hispanic, Asian, Native American, or other, and 0 signifies white. Hereafter, for simplicity and to conserve space, I often use the term “race” to refer to both operationalizations of this variable and “non-white” to refer to the categories coded as 1 in both operationalizations. For example, when running a model that regresses policing unit on race in Chapters 5 and 6, I am actually speaking of running two models, each with a unique operationalization of race.

As with arrestee race, I use two operationalizations for neighborhood racial composition that match the arrestee race variables. First, to match the arrestee-level variable in which a 1 signifies an arrestee is black, the percent non-Hispanic black within a census tract is measured. Next, to match the arrestee-level variable in which a 1 signifies an arrestee is non-white, the percent non-Hispanic black, non-Hispanic Asian, non-Hispanic Native American, Hispanic, and other race are combined into a single percentage. Similar operationalizations of neighborhood racial composition have been used in other work investigating racial disparities in policing tactics (Desmond & Valdez, 2012). As with arrestee race, I will hereafter refer to "racial composition" of a neighborhood as short hand for all of the above-mentioned operationalizations, and "percent non-white" as shorthand for both percent non-white and percent black, dependent on the model under consideration.

Racial Patterns of Drug Arrests across Atlanta

I begin the examination of racialized patterns of policing in both eras by exploring the overall distribution of arrests by race. First, I compare the race of arrestees by APD officers to the overall racial composition of Atlanta. Table 2 provides this comparison. The first and second columns feature the percentage of arrestees distinguished by race and ethnicity in 2005 and 2012, respectively, and the third and fourth columns report the citywide racial composition for the 2000 Decennial Census and 2010 Decennial Census, respectively. A few important conclusions can be drawn from this table. First, most felony drug arrests within Atlanta in both eras involve black individuals, followed by white individuals, and very few arrests involve Hispanic, Asian, or individuals or another race or ethnicity. Despite a non-negligible and growing Hispanic and Asian population in Atlanta, arrests mostly involve either black or white individuals.

Second, the race of felony drug arrestees clearly changes across eras. In 2012, the percent of arrestees who are black has reduced by 4.7% of its 2005 level (3.9 percentage points), and percent of arrestees who are white has increased by 44.8% of its 2012 level (3.9 percentage points). While these changes are substantively small, they nonetheless represent some movement away from policing practices focused almost entirely on black individuals.

Finally, in both eras and among all racial and ethnic groups, the percentage of arrestees was significantly different from the percentage of residents. The two sample test of the equality of proportions (performed using the prtesti command in Stata 14.1) confirmed that for each racial or ethnic group the proportion of arrestees was significantly different from their proportion in the residential population ($p<0.001$). As this table makes clear, the racial composition of the city and that of those arrested in the city are widely disparate. The proportion of arrestees who are black is much higher than their proportion in the residential population, while the proportion of arrestees of any other race or ethnicity is much lower than their proportion in the residential population. Atlanta is a majority black city, but the arrestee population is even more predominately black than the residential population. For example, in 2005, black Atlantans have an arrest rate that is 148% their residential rate, whereas white Atlantans have an arrest rate that is 27.8% their residential rate.

Table 1. Race of Arrestees and Race of Atlanta Residents

	Arrestee Race, 2005 (n=2,758)	Arrestee Race, 2012 (n=987)	Residential Race, 2000 (n=416,474)	Residential Race, 2010 (n=420,003)
White, Non-Hispanic	8.7%	12.6%	31.3%	36.3%
Black, Non-Hispanic	90.4%	86.5%	61.0%	53.4%
Hispanic	0.7%	0.6%	4.5%	5.2%
Asian, Non-Hispanic	0.1%	0.2%	1.9%	3.1%
Other (Native American, Hawaiian Pacific Islander, and other race)	0.0%	0.1%	1.3%	2.0%

Examining the distribution of arrests in space allows for a clearer understanding of whether arrests are spatially clustered. Any observed clustering may help explain disparities in citywide arrest rates as a product of the neighborhoods in which police focus their efforts. Figure 2 below presents these patterns by mapping arrests in which the arrestee is black and arrests in which the arrestee is white in each era across Atlanta. Global Moran's I tests for spatial clustering show statistically significant evidence of clustering by race in both eras, rejecting the null hypothesis that arrestee race is distributed in a spatially random fashion ($p<0.001$). This suggests that differences in arrest rates by race may be a function of differences in where police focus their efforts.

Figure 2. APD Arrests by Race and Year

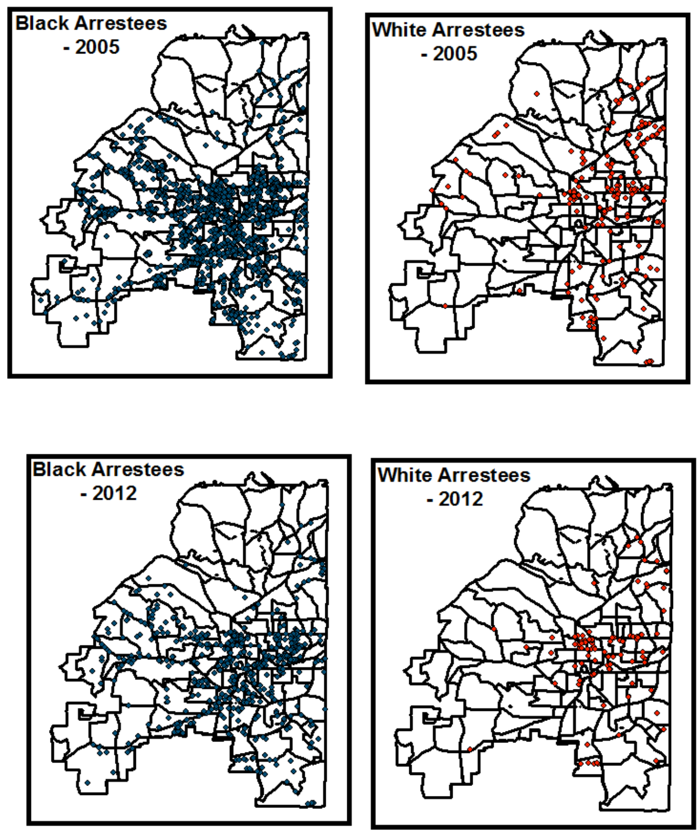
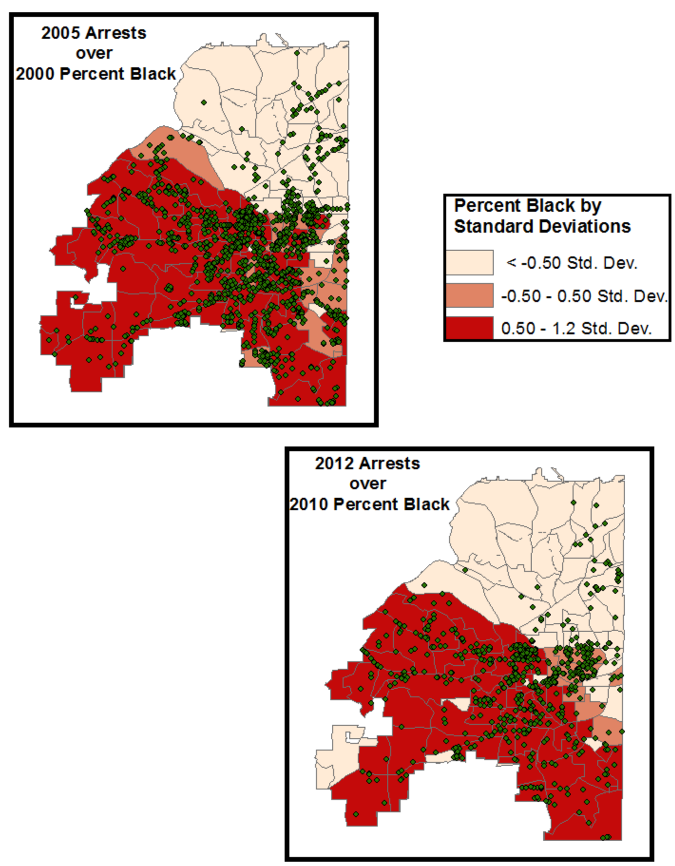


Figure 3 illustrates all arrests in Atlanta by the APD over two choropleth maps of racial composition by census tract within each era. Both choropleth maps use standard deviational units to map the percentage of the tract that is black, with darker shades of blue representing higher proportions of black residents. While arrests are dispersed across the whole of Atlanta, in both eras, neighborhoods with high and moderate levels of black residents have higher numbers of arrests. Indeed, the mean number of arrests is 10.5 in 2005 and 9.28 in 2012 in neighborhoods with the lowest level (<0.5 standard deviations) of black residents; 35.4 in 2005 and 18.4 in 2012 in neighborhoods with the moderate level (between -0.5 and 0.5 standard deviations) of black residents; 31.9 in 2005 and 8.6 in 2012 in neighborhoods with the highest level (> 0.5 standard deviations) of black residents. One-way analysis-of-variance models reveal that these differences are statistically significant ($p<0.001$). There is a clear relationship between neighborhood racial composition and the number of arrests in a neighborhood, with the lowest numbers of arrests occurring in neighborhoods with the fewest

Figure 3. Arrests by Census Tract Racial Composition



non-white residents. This lends further evidence to the notion that discrepancies between the race of arrestees and the race of residents in Atlanta may be due to the location of arrests, providing support for the importance of investigating the racial composition of the neighborhoods in which arrests occur.

Racial Patterns of Drug Arrests within Atlanta Neighborhoods

Even if police make more arrests in predominately non-white neighborhoods, within those neighborhoods they may be still arresting more non-white individuals than would be expected based on the resident population of each neighborhood. Table 2 and Figures 4 and 5 examine this possibility further. The first column of Table 2 presents the average percentage of arrestees for three racial groups (white, black, and non-white) within census tracts in 2005 and the second column presents the same values for census tracts in 2012. Using the sample of neighborhoods with arrestees in 2005 and 2012, respectively, the third and fourth column present the average percentage of residents of each racial group within census tracts for 2000 and 2010. As is clear when comparing columns one to three and columns two to four, the average black and non-white census tract arrest rates are greater than their equivalent residence rate, and white arrest rates are considerably less than their equivalent residence rates. Paired sample t-tests confirm that all of these mean differences are statistically significant at a $p<0.001$ level.

Table 2. Census Tract Arrestee and Residential Racial Composition

	Mean (SD) Arrestee Racial Composition, 2005 (n=113)	Mean (SD) Arrestee Racial Composition, 2012 (n=97)	Mean (SD) Residential Racial Composition, 2000 (n=`113)	Mean (SD) Residential Racial Composition, 2010 (n=97)
White, Non-Hispanic	17.13 (27.89)	12.61 (21.58)	29.29 (35.06)	25.38 (30.09)
Black, Non-Hispanic	82.06 (28.33)	85.68 (23.51)	63.84 (37.93)	64.96 (34.52)
Non-White or Hispanic	82.87 (27.89)	87.39 (21.58)	70.70 (35.06)	74.62 (30.09)

Figures 4 and 5 illustrate these patterns for 2005 and 2012. The difference between the percentage of arrestees in each neighborhood who are of a particular race and the percentage of residents in each neighborhood who are of the same race are calculated. Higher values indicate that, for example, the percentage of non-white arrestees is higher than the percentage of non-white residents in that particular neighborhood; a value of zero indicates that the percentage of non-white arrestees is exactly equal to the percentage of non-white residents; and negative values indicate that the percentage of non-white residents is greater than the percentage of non-white arrestees. Figure 4 graphs the histograms for these differences for whites and non-whites in 2005 and the Figure 5 graphs the histogram for the same differences in 2012.

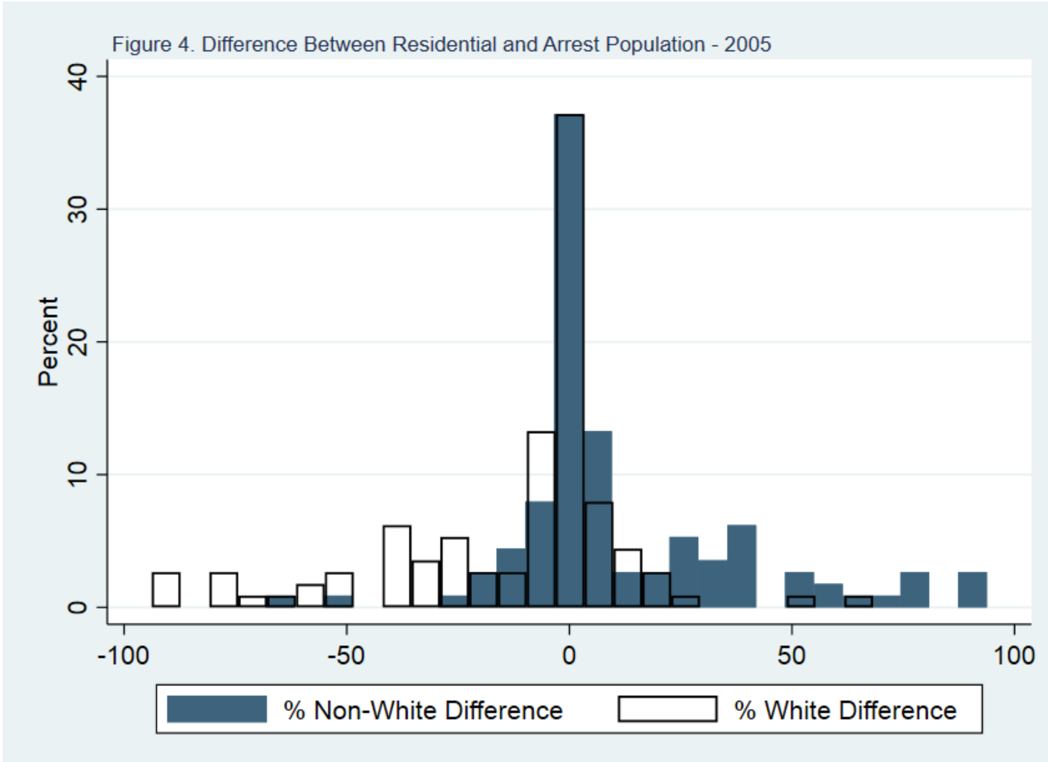


Figure 4. Difference Between Residential and Arrest Population - 2005
Percent
0
10
20
30
40
-100
-50
0
50
100
% Non-White Difference
% White Difference

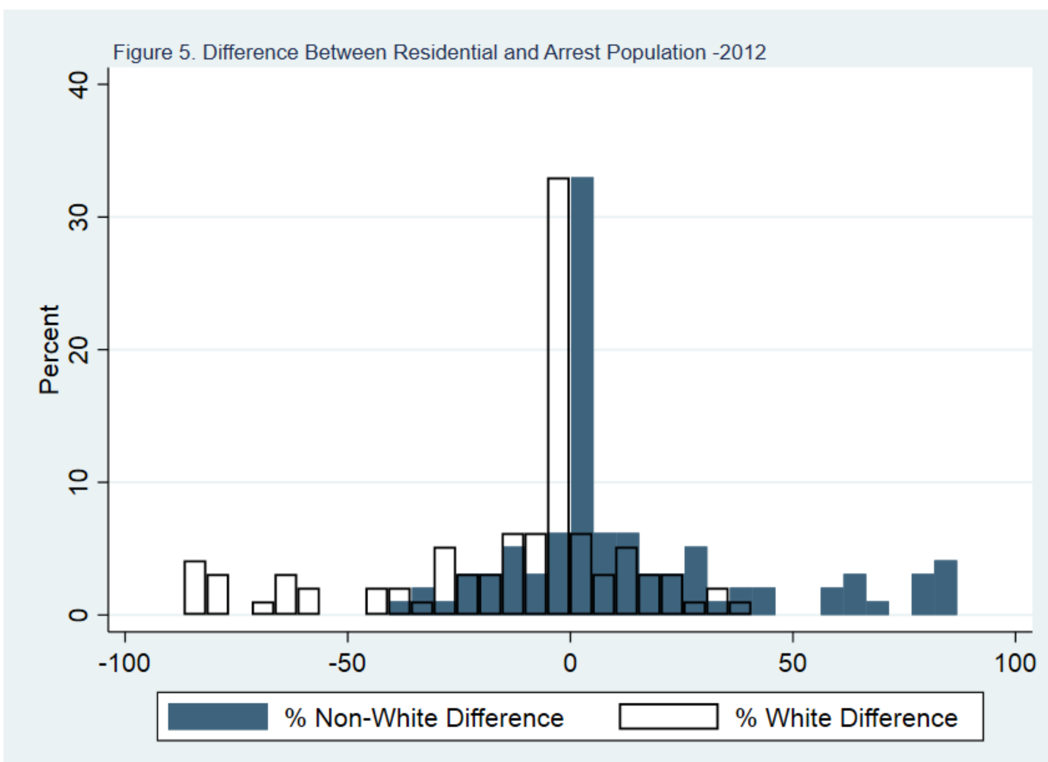


Figure 5. Difference Between Residential and Arrest Population -2012
Percent
0
10
20
30
40
-100
-50
0
50
100
% Non-White Difference
% White Difference

A few patterns are worth noting. First, in both eras, for white and non-white individuals, most differences cluster around zero, suggesting that in most neighborhoods the composition of arrestees and residents approximately match. This lends support to the notion that one major factor in determining the racialized patterns of policing is the locations in which police make arrests. If police make more arrests in predominately non-white neighborhoods, they are likely to arrest a higher proportion of non-white residents.

Second, for those neighborhoods in which the difference is not near zero, the non-white differences are nearly always positive, with only a few census tracts demonstrating negative differences. Put more simply, when the difference between the percentage of arrestees who are non-white and the percentage of residents who are non-white is not zero, it is far more likely to be that the non-white percentage of arrestees is higher than the non-white percentage of residents. The converse is true for differences between white arrests and residential rates.

Finally, these patterns hold for both eras. In each era, the percentage of non-white arrestees in a neighborhood is, on average, greater than their share of the population in a neighborhood. Specifically, in 2005, the mean non-white difference in percentages is positive (11.84) as is the mean black difference (20.96), while the mean white difference is negative (-11.84). The patterns are similar in 2012; the mean non-white difference in percentages is positive (12.78) as is the mean black difference (20.72), while the mean white difference is negative (-12.78).

Collectively, these descriptive statistics demonstrate that the race and ethnicity of arrestees is not equally distributed across Atlanta neighborhoods and does not match the overall composition of the city, with non-white individuals being arrested more frequently than would be expected based purely on their share of the population. At both the citywide level and neighborhood level, these differences are statistically significant and notable in their magnitude. The citywide discrepancy between the black proportion of the residential population and their proportion of the arrestee population is approximately 30% in each era (Table 1) and the mean discrepancy between black residential and arrestee proportions within neighborhoods is approximately 20% (Table 2). In short, there are clear racialized patterns of felony drug arrests in Atlanta within both eras that warrant further exploration and explanation.

"Tough on Crime" Analyses

There are clear racialized patterns of policing in 2005, yet some aspects of policing may contribute more heavily to these patterns. In the "tough on crime" chapter, I will attempt to explain the racialized patterns of policing as a product of a particular type of policing unit and types of policing tactics. I first explore whether arrestee race and neighborhood racial composition are positively correlated with the involvement of an APD PPU, Red Dog, in a felony drug arrest. After this, I examine whether arrestee race and neighborhood racial composition are positively correlated with either the use of order maintenance policing tactics or the use of search and arrest warrants as the primary tactic involved in a felony drug arrest. In both sets of analyses, I examine these issues across the city as a whole and within each police zone. The analytic plan for each analysis is described in greater detail below.

Research Question 1

My first research question involves the use of police paramilitary units (PPUs) to enforce drug crime. Specifically, I ask whether APD's PPU, Red Dog, is associated with the race of an arrestee and racial composition of a neighborhood. I hypothesize that non-white arrestees will be more likely to be arrested for a drug offense by officers in the Red Dog unit and that Red Dog will be more likely to make arrests in a neighborhood as the percentage of non-white residents increases.[4] PPUs have been linked with racialized police practices nationally and within Atlanta (Blau, 2016; Kraska & Kappeler, 1997). In the "tough on crime" era, it is likely that the behavior of PPU officers contributed to the racialized patterns of policing described in the previous section.

To test this, I use logistic regression models, with the involvement of the Red Dog unit treated as a dichotomous dependent variable. With a dependent variable that has a Bernoulli distribution, estimating a regression using a linear regression model can lead to issues with heteroscedasticity, normality, and linearity (Long, 1997). Binary response models, such as the logistic regression model (often called logit models), provide a solution to these issues by using maximum likelihood estimation to predict the latent probability of an event occurring, in this case, an arrest being made by a Red Dog officer.

[4] See Appendix D for a list of hypotheses.

I use multilevel modeling to examine Red Dog's relationship with the racial composition of a neighborhood. Specifically, I use a multilevel logistic random intercept regression model. While hierarchical data can be treated using disaggregation or aggregation, neither technique provides an ideal solution. Disaggregation involves treating level-2 variables (here, neighborhoods) as though they are level-1 variables, and in so doing violates the assumption of independence of observations (Beaubien, Hamman, & Boehm-Davis, 2001; Osborne, 2000). Aggregation involves raising level-1 variables to a higher level (here, averaging all arrestees within a neighborhood), and in so doing not only changes the nature of the research question by eliminating the potential to examine level-1 variables, but also potentially results in a loss of between 80-90% of variability due to level-1 differences (Raudenbush & Bryk, 2002). Multilevel modeling avoids both of these issues, allowing for the simultaneous examination of level-1 (arrestee) and level-2 (neighborhood) variables without violating the assumption of independence of observations. Even in models that only include level-1 regressors, this allows for a proper treatment of the clustering of arrests within neighborhoods (Raudenbush & Bryk, 2002).

I begin by describing my analytic method, and the variables used in each of my models, and after this, I define the operationalization for each of these variables. The substantive importance of each of these variables is described in greater detail in Chapters 5 and 6. As mentioned earlier, I will build this model iteratively, beginning with the following model:

$$logit\big(pr(RedDog = 1)\big) = \alpha + \beta_1 Race_{ij} + \beta_2[Arrestee\ Characteristics]_{ij} + \mu_j + \varepsilon_{ij} \qquad (1)$$

In which i = 1,…,N indexes arrestees; j = 1,…,K indexes neighborhoods; α is the intercept; β_1 is the slope for arrestee race; β_2 are the slopes for two arrestee characteristics; μ_j is the random effect of the intercept; and ε_{ij} is the residual. In this model, a positive coefficient of X on the race variable indicates that non-white arrestees have an X greater log odds of being arrested by an officer in the Red Dog unit than do white arrestees when controlling for other relevant characteristics of the arrestee.

Following this, I add a vector of case characteristics to the equation 1:

$$\begin{aligned} &logit\big(pr(RedDog = 1)\big) \\ &\qquad = \alpha + \beta_1 Race_{ij} + \beta_2[Arrestee\ Characteristics]_{ij} \\ &\qquad + \beta_3[Case\ Characteristics]_{ij} + \mu_j + \varepsilon_{ij} \end{aligned} \tag{2}$$

Here, a positive coefficient of X on the race variable indicates that non-white arrestees have an X greater log odds of being arrested by the Red Dog unit than do white arrestees when controlling for other relevant characteristics of the arrestee and of the arrest.

Next, I add census-tract racial composition and three measures of social disorganization to equation 2:

$$\begin{aligned} &logit\big(pr(RedDog = 1)\big) \\ &\qquad = \alpha + \beta_1 Race_{ij} + \beta_2[Arrestee\ Characteristics]_{ij} \\ &\qquad + \beta_3[Case\ Characteristics]_{ij} + \gamma_1 RacialComposition_j \\ &\qquad + \gamma_2[Social\ Disorganization]_j + \mu_j + \varepsilon_{ij} \end{aligned} \tag{3}$$

In which γ are the slopes for neighborhood-level regressors. This allows not only for an examination of racial disparities when accounting for surrounding racial composition, but also an examination of the role played by racial composition. Here, a positive coefficient of X on the race variable indicates that non-white arrestees have an X greater log odds of being arrested by the Red Dog unit than do white arrestees when controlling for other relevant characteristics of the arrestee and the arrest, as well as the racial composition and social disorganization of the neighborhood in which the individual was arrested. A positive coefficient of X on the racial composition variable, indicates that a 1 percent increase of non-white residents in a neighborhood, when controlling for a number of arrestee and case specific characteristics including arrestee race and neighborhood social disorganization, increases the log odds of being arrested by the Red Dog unit by X.

Finally, I add a measure of index violent, property crime, and zone membership to equation 3. Zone membership is captured using six census-tract level variables that indicate which APD zone(s) a census tract lies within. Specifically, I test:

$$\begin{aligned} logit\big(pr(RedDog = 1)\big) \\ &= \alpha + \beta_1 Race_{ij} + \beta_2[Arrestee\ Characteristics]_{ij} \\ &+ \beta_3[Case\ Characteristics]_{ij} + \gamma_1 RacialComposition_j \\ &+ \gamma_2[Social\ Disorganization]_j + \gamma_3[Index\ Crime]_j \\ &+ \gamma_4[Zone\ Membership]_j + \mu_j + \varepsilon_{ij} \end{aligned} \tag{4}$$

A positive coefficient on individual race or racial composition in this model can be interpreted as in the previous model with the addition that these relationships persist when controlling for violent and property crimes and localized patterns of policing.

Finally, citywide patterns of policing may mask within-zone patterns of policing. Because of the importance of zone membership to police behavior, it is possible that the patterns observed across the city will differ from those found within individual zones. For example, perhaps Red Dog's arrests are not connected to race or racial composition across the city, but within Zones 1 and 5, arrestee race is strongly linked to the use of Red

Dog. In this case, non-white Atlantans are, on average, no more likely to be arrested by Red Dog, but non-white Atlantans who live, work, or spend significant amounts of time in the areas covered by Zones 1 and 5 are more likely to be arrested by Red Dog. To measure this, I remove zone membership from equation 4 and run these new models in each zone, using a sample that is restricted to only arrests occurring in tracts that overlap with that zone. I discuss the significance of the zone-specific findings for each research question in detail within Chapters 5 and 6.

These models involve a number of covariates. Below, I briefly define the operationalization of these covariates. In Chapters 5, 6, and 7, I discuss the rationale for including each variable, and any modifications that were made. The models begin by including two arrestee characteristics, gender and age. Gender is measured a dichotomous indicator of whether the arrestee is male, with female or other as the reference category. Age is the age of the arrestee at the time of arrest. While age is not normally distributed, logging age did not improve the distribution, so I left this variable in its original metric in all models.

The vector of covariates capturing case characteristics includes the severity of the offense and the type of drugs involved in an offense. Severity is defined as a categorical variable with the categories of *possession*, *intent-to-sell*, and *sales or greater (trafficking and manufacturing)*. Arrestees coded 1 for the possession category have no drug charge more serious than possession. Arrestees with a 1 on the intent to sell category have at least a single intent to sell charge and may also have possession charges. Arrestees with a

1 on sales, trafficking, or manufacturing charge must have at least one sales, trafficking, or manufacturing charge, and may also have intent to sell and possession charges.

Drug type is represented by a series of dichotomous variables which are not mutually exclusive. For example, an arrest may involve both cocaine and marijuana, in which case it would have a value of "1" for both of those drug type variables, and "0" for all other drug type variables. As amphetamine arrests are rare, I combined methamphetamine and amphetamine arrests into a single category. Arrests involving various hallucinogens commonly referred to as party drugs were also rare, and thus they were combined into a single category including ketamine, LSD, MDMA, or GHB. The other drug types are heroin, cocaine, marijuana, and unspecified controlled substances.

I also include three measures that cumulatively capture neighborhood levels of social disorganization (Sampson et al., 1997). The first is concentrated disadvantage, which is measured as the averaged, summed z-scores for the following variables: percent on public assistance, percent female-headed households, percent unemployed, percent less than 18-years-old, and percent in poverty. This operationalization is based on that used by Sampson, Raudenbush, and Earls (1997), excluding one variable, percent black. Percent black is excluded because neighborhood racial/ethnic composition is one of the primary independent variables in my analyses. The second measure is residential instability. This is operationalized as the averaged, summed z-scores for the percent of the houses that are renter-occupied and the percent of people who lived in a different house five years ago (Peterson & Krivo, 2010; Sampson et al., 1997). Finally, I control for immigrant concentration within a census tract. While Sampson, Raudenbush, and

Earls' (1997) measure of immigrant concentration was a combination the percent foreign-born and percent Latino, I use only percent foreign-born in this study. Percent Latino is not included for the same reason as percent black: neighborhood racial/ethnic composition is one of my primary independent variables.

Index crime rates are captured as the rate of violent crime and the rate of property crime. Violent crime is measured as the sum of all homicides, rapes, robberies, and aggravated assault incidents within a census tract over that census tract's population. Property crime is measured as the sum of all burglaries and thefts within a census tract over that census tract's population. In 2005, these are separate measures. In 2012, they are combined into a single measure due to collinearity.

Finally, police zones are defined by the zone boundaries designated by the APD for the year 2005 and 2012, respectively. Census tracts are not perfectly nested within police zones, and thus while some census tracts lie wholly within a single zone, many cross zones. I code zone membership as all zone with at least some overlap with a census tract, in order to best capture all the groups of officers responsible for policing that neighborhood. Because of the small number of zones, and because I am interested only in zone membership for the purposes of this dissertation (and not any particular characteristics of the zone), I capture zones as a tract-level variable instead of using a cross-classified multilevel model.

Research Question 2

Order-maintenance stops are a common tactic of "tough on crime" policing (Beckett, 2016), especially among PPUs tasked with enforcing drug offenses (Kraska & Kappeler, 1997), are linked to racially disparate law enforcement outcomes (Beckett, 2016; Brunson & Miller, 2006; Brunson & Weitzer, 2008), and may enhance racial disparities within police departments (Beckett, 2016; Chambliss, 1994). Likewise, issuing search and arrest warrants for drug offenses was common in the "tough on crime" era, especially among PPUs. The serving of these warrants often involves aggressive tactics emblematic of the "tough on crime" ethos (Balko, 2015; Kraska & Kappeler, 1997), and the use of search and arrest warrants for drug enforcement has been linked to racialized patterns of policing (Balko, 2015; Benner, 2002). Thus, my second research question examines whether the use of search and arrest warrants and/or the use of order maintenance stops are associated with either the race of an arrestee and/or the racial composition of the neighborhood in which an arrest occurs? I hypothesize that arrests of non-whites and those arrested in neighborhoods with higher proportions of non-white residents will be more likely to involve order maintenance stops and/or search or arrest warrants than to involve any other policing tactics.

These analyses will mirror the analyses discussed in the previous section, investigating whether race and racial composition are related to the use of order maintenance tactics and search and arrest warrants, building the models iteratively to better explore the full impact of arrestee race and racial composition. The independent variables used in these analyses are identical to those described earlier. Because of this, instead of reiterating the specifics of the analyses or measurement of independent variables, I focus on the primary distinction: the different estimation technique.

The dependent variable in this analysis is an indication of the tactics used in an arrest across three categories: arrests that involved an order maintenance stop, arrests that involved a search or arrest warrant, and all other arrests. Nominal variables are best assessed using multinomial response models, which are designed for cases in which the dependent variable is polytomous and not ordered. Multinomial response models can be viewed as an extension of the binary response model, producing a number of pairwise comparisons that are essentially binary response models. Yet using multinomial response models is preferable to using numerous binary response models due to the increased efficiency of simultaneously estimating comparisons as opposed to assessing one at a time (Long, 1997). Further, comparison of multiple binary response models assumes that they are derived from the same sample, which by definition cannot be true; this problem is avoided by using a multinomial response model (Long, 1997). Thus, for this set of analyses, I use multilevel multinomial logistic regression models. These models produce a set of coefficients comparing the log odds of an arrest being of two of the three types (order maintenance or search and arrest warrants) in comparison to the reference category (all other stops). Findings in these models allow for an understanding of how race and racial composition are related to the use of order maintenance stops or search and arrest warrants when accounting for demographic, case, and neighborhood characteristics.

"Smart on Crime" Analyses

In the “smart on crime” chapter, I investigate the factors that help to explain racialized patterns of policing in the “smart on crime” era. To do so, I ask two research questions. First, I ask whether race and racial composition are related to the use of the data-driven policing that replaced Red Dog as the APD transitioned to a “smart on crime” model. Second, I ask whether race is related to the use of order maintenance policing tactics or the serving warrants in the “smart on crime” era. The analyses for these research questions mirror those discussed in the “tough on crime” section. For this reason, I focus on where they differ from the measures and analyses described in the previous section instead of reiterating identical measurement and analytic details. As with the “tough on crime” analyses, greater attention is devoted to the substantive significance of each model and variable construction in Chapters 5 and 6.

Research Question 1

Analyses in this section mirror those in the “tough on crime” section. In the “tough on crime” section, my first research question was whether Red Dog was associated with the race in the “tough on crime” era, and I hypothesized that non-white arrestees and individuals arrested in neighborhoods with higher proportions of non-whites would be more likely to be arrested for a drug offense by officers in the Red Dog unit than by other APD officers. While many changes occurred between 2005 and 2012, one of the most significant changes was the disbandment of Red Dog. This unit was replaced by a data-driven style of policing that is emblematic of the “smart on crime” approach.

"Smart on crime" strategies were a response to racialized policing and are presumed to be based on race-neutral criteria; thus, they should not be associated with the race of the arrestee. But according to Walker, Spohn, and DeLone (2011), types of discrimination fall along a continuum in terms of pervasiveness, with systemic discrimination at one end and individual discrimination at the other. Systemic discrimination describes discrimination present in all settings and contexts, and individual discrimination describes discrimination that results from an individual's beliefs and actions; between these two extremes lays institutional discrimination. Institutional discrimination occurs when policies or procedures that are not inherently discriminatory have discriminatory outcomes. While data-driven policing is not inherently discriminatory, it may result in discriminatory outcomes because it relies on information gathered by officers, many of whom were trained in the "tough on crime" era; even though the intelligence is assumed neutral, it is built upon information gathered by subjective, biased sources (Ferguson, 2017). As such, I ask whether data-driven policing is associated with individual race and neighborhood racial composition, and I hypothesize that non-white arrestees will be more likely to be arrested using data-driven tactics within the "smart on crime" era than by police not explicitly using these tactics.

I employ a set of models similar to those used to assess the effect of race and racial composition on Red Dog policing in the "tough on crime" era. The data-driven dependent variable captures all "directed patrol" activity as well as all arrests involving three specific data-driven units that have been identified using APD annual reports: the crime suppression unit, the Field Investigation Team (FIT), or APEX (Atlanta Police

Department, 2011, 2012, 2013, 2014). These models are built in the same iterative fashion as those used in the “tough on crime” chapter, and all neighborhood variables are measured using census data from 2010.

Research Question 2

For my second research question in the “smart on crime” chapter, I ask whether the use of order maintenance stops and/or warrants are associated with the race and racial composition in the “smart on crime” era. I hypothesize that non-white arrestees and individuals arrested in neighborhoods with higher proportions of non-whites will be more likely to be arrested for a drug offense via order maintenance stops and warrants than via any other policing tactic. The shift away from “tough on crime” tactics and the disbandment of a PPU should reduce the use of order-maintenance stops and warrants for drug crime. Yet these tactics have been strongly linked to racialized patterns of policing in the past (Benner, 2002; Brunson & Miller, 2006; Gelman et al., 2007), and may still be associated with race within the “smart on crime” era. Further, recent research has found that these tactics continue to lead to racial disparities in the “smart on crime” era (Baumgartner, Christiani, Epp, Roach, & Shoub, 2017; Chanin, Welsh, & Nurge, 2018; Torres, 2015) and that even agencies that have made a shift to “smart on crime” policing may still be policing in a racially disproportionate manner (Desmond & Valdez, 2012). Thus while these are tactics that were (over)used in the “tough on crime” era, it worth understanding whether they have a similar effect on race in the “smart on crime” era. To assess this, I use the same set of iterative models described in the “tough on crime” section. The dependent variable is operationalized in the same manner as it was for the "tough on crime" section.

Era Comparison Analyses

In the final analytic chapter, I assess whether significant changes to the racialized patterns of policing have occurred as a result of the shift from "tough on crime" to "smart on crime" policing. The previous analyses will have examined the impact of arrestee race on drug arresting units and tactics within each era separately. This enables a clear, nuanced understanding of how race and racial composition impact the policing of drug arrests within two very distinct eras of policing, but it does not allow for an understanding of change across eras. Descriptive data presented earlier clearly demonstrates a racialized pattern of policing in both eras, yet there is also good reason to expect that disparities will have attenuated as a result of the transition from "tough on crime" to "smart on crime" tactics. The "smart on crime" era de-emphasized the focus on drug arrests, was a response to a number of racialized incidents within Atlanta, and espoused a set of race neutral tactics (Blau, 2016; Bueermann, 2012). While findings for the past four research questions can be qualitatively compared to determine if such a reduction was realized, I use the analyses in Chapter 7 to formally test this proposition. I ask two questions. First, I ask whether the era in which an arrest occurs is related to the arrest rates and racial disparities for non-whites. Second, I ask whether changes in the use of specialized units, order maintenance stops, or warrants are related to reductions in non-white arrest rates or racial disparities.

Research Question 1

To investigate whether the era in which an arrest occurs is related to the race of arrestees within a census tract, I examine the relationship between era and the rate of non-white arrestees and the racial disparities in a census tract. I hypothesize that the “smart on crime” era will be negatively correlated with the non-white arrest rate and negatively correlated with racial disparities. Despite the presence of racialized patterns of policing in the “smart on crime” era, I predict that the “smart on crime” era will evidence an attenuation of the racialized patterns of policing characterizing the “tough on crime” era.

I use a fixed effects regression model, with units of census-tracts by era. This means that each observation is a census tract within a particular era, and thus for every census tract, there will be two observations: a 2005 observation and a 2012 observation. This allows me to investigate neighborhood-level racial arrest patterns, holding census tract membership (as measured by the 2010 boundaries) constant so that I can investigate census-tract level effects with all time-invariant differences between census tracts removed. This can be viewed as alternative estimation of a multilevel model, but while the models in previous sections allow for variation across level-two units, here level-two units are fixed. The level-one units are time periods (specifically, 2005 and 2012, or the “tough on crime” era and the “smart on crime” era) which are nested with census tracts. Tract-level variables which vary by time can be assessed and, because all constant measures of census tracts are fixed (which effectively controls for census-tract differences I cannot measure), these models eliminate one source of omitted variable bias (Bartels, 2009; McCaffrey, Lockwood, Mihaly, & Sass, 2012).

To estimate these models, variables within the CODE dataset measured at the arrestee–level must be aggregated to the census tract level for each era. I will run two models with identical independent variables but different dependent variables. The first model predicts the rate of non-white arrestees within a census tract (calculated as the number of black arrestees over the number of black residents, and non-white arrestees over non-white residents respectively). I will include a dichotomous independent variable that captures era, with a value of 1 indicating that observation is from the "smart on crime." Thus, a negative coefficient of X on the era variable would indicate that, net all time invariant unobserved variables, the "smart on crime" era is associated with X fewer arrests per 100 non-white residents in a census tract.

I also control for census tract measures that vary across time. This includes variables capturing neighborhood demographics that mirror the individual demographics used in prior models. Using 2000 and 2010 census data, I include change in the percent of males between the ages of 15 and 34. This is a common neighborhood measure that accounts for the greater involvement of young males in crime (Peterson & Krivo, 2010), and mirrors the individual level control variables for gender and age of arrestees. I also control for changes to the three social disorganization variables defined previously: concentrated disadvantage, immigrant concentration, and residential instability. The model accounts for changes to overall crime trends by incorporating measures of change in the violent and property crime rates. In addition to controlling for changes to violent and property crime, I also control for changes to drug crime. To do so, I include measures of the ratio of possession with intent to sell arrests and the ratio of sales, manufacturing, and trafficking arrests for each census tract in each era. I do the same for drug type, including the percentage of arrests involving each type of drug. While it may be useful to account for the overall reductions in the level of arrests—and figures presented earlier in this chapter make clear that there was a substantial reduction—I do not directly control for changes in the overall rate of drug arrests. I leave this out of my model because the racial disparity measure discussed in more detail below includes the overall arrest rate in its calculation, and thus including this variable as an independent variable would result in endogeneity issues. A reorganization of zones in 2011 slightly realigned the zone boundaries, and thus census tract membership varies by era. This variation is also included in the final model in order to control for the impact of changes in the police leadership overseeing a particular neighborhood. In this model, I test the following:

$$\begin{aligned} \gamma_{it} = \alpha_i + \beta_1 Era_{it} + \beta_2[Percent\ Young\ Males]_{it} + \beta_3[Social\ Disorganization]_{it} \\ + \beta_4[Index\ Crimes]_{it} + \beta_5[Drug\ Crime]_{it} + \beta_6[Zone\ Membership]_{it} \\ + \mu_{jt} \end{aligned} \tag{6}$$

Where t = 1,…,N indexes era; j = 1,…,K indexes neighborhoods; γ_{it} is the number of black arrestees in neighborhood *i* and era *t*; α_i is the unknown intercept for each census tract; β_1 is the coefficient for era; β_{2-6} are the coefficients for the control variables, and μ_{it} is the residual.

Next, I conduct the same set of analyses on the measure racial disparity in arrests. Following the example of Ousey and Lee (2008), I calculate racial disparity as the natural logarithm of the non-white arrest rate over the total arrest rate. Higher scores on this variable indicate a greater disparity. For example, a value of 2.00 indicates that that in that census tract, non-whites are arrested at twice the rate of all residents. This allows for an examination of the impact of changes in policing on racial disparities in arrests, when controlling for changing and time invariant neighborhood measures linked to drug arrests. It provides a more nuanced understanding of the impact of the changes. Changes to the non-white arrest rate suggest that non-whites are being arrested differentially by era relative to their share of population, while changes to the racial disparity suggest the non-white arrest rate *relative* to that of whites changed across eras. Essentially, it accounts for whether a proportionally similar change was experienced by whites.

Research Question 2

Finally, I analyze whether changes in the use of specialized units and tactics across eras affected racialized patterns of arrests. Generally, these analyses attempt to explain any changes observed in the prior sections. Specifically, I ask whether changes to the use of specialized units, order maintenance stops, and search and arrest warrants result in changes to the racial disparities associated with drug arrests. The use of these units and tactics is likely to be linked to racialized patterns of policing, and thus reductions in their use should be linked to reductions in the non-white arrest rate and arrest rate racial disparities in arrest rate (Benner, 2002; Chambliss, 1994; Ferguson, 2017; Gelman et al., 2007). Therefore, I hypothesize that decreases in the use of specialized units, order maintenance stops, and search and arrest warrants will be associated with reductions in the non-white arrest rate and racial disparities.

The analysis in this section mirrors that in the previous section, and thus I devote this section to the primary difference: the independent variables of interest. I create a three new variables that I examine in place of the “smart on crime” era dummy variable. The first indicates the rate of arrests by a specialized unit in each tract and era. In 2005, this is the rate of Red Dog arrests in each census tract, and in 2012, this is the rate of all data-driven arrests in each census tract. Coefficients on this term measure how changes in the use of specialized units to address drug crimes are connected with racial disparities in policing. As the specific specialized units are quite distinct in each era, I am unable to analyze the impact of the type of specialization. For example, if I could measure PPUs in the “smart on crime” era, I could assess the impact of reductions in their usage. But the nature of the change in Atlanta was not proportional but absolute. They did not reduce the use of PPUs, they wholly ceased use in favor of an entirely new data-driven strategy. Nevertheless, I am able to examine whether the overall use of specialized units impacts racial disparities.

I also measure the change in use of order maintenance stops and warrants across eras. I capture this as the rate of order maintenance stops in a census tract within each era and the rate of arrest and search warrants in a census tract within each era, with the total number of arrests in the census tract as the denominator. Here, coefficients represent the relationship between changes to these tactics and racial disparities in drug arrests across eras. For example, a negative coefficient in the model regressing the non-white arrest rate on use of order maintenance tactics would suggest that decreases in the use of order maintenance tactics are associated with a reduction in the non-white arrest rate. Within each model, I also incorporate all covariates found in equation 6 in order to control for their relationship with race and racial disparities.

Conclusion

To examine the role of specialized units, order maintenance stops, and the use of warrants in producing racialized patterns of policing, and whether the shift in policing tactics and ethos has tempered those inequities, this dissertation examines a number of related research questions. First, this dissertation explores the relationship between both race and neighborhood racial composition with arresting unit and tactics in the "tough on crime" era. This provides a clear, nuanced understanding of the role that certain units and tactics played in producing the racialized patterns of policing within this era. Second, this dissertation explores the same relationships within the "smart on crime" era, which helps better unpack the role of certain units and tactics common to a new era of policing. Finally, this dissertation uses census-tract level data to assess arrests across eras, arresting units across eras, and arrest tactics across eras. While both eras are associated with racialized patterns of policing, these final questions test whether disparities are attenuated by the transition from "tough on crime" to "smart on crime" policing. Collectively, these findings should allow for a better understanding of types of units and tactics that contribute to racialized patterns of policing, and whether substantial departmental change can result in noticeable changes in the racial pattern of policing within a major U.S. city.

Chapter 5. "Tough on Crime" Policing in Atlanta

During the "tough on crime" era, the prison population rose dramatically, and this rise in incarceration was not equally felt across race or ethnicity, with black and Hispanic Americans experiencing far greater criminal justice attention than their white, non-Hispanic counterparts (Mauer, 2006; National Research Council, 2014). The "tough on crime" approach was common across the criminal justice field, including among local police, with many police departments taking on explicitly aggressive approaches to crime in response to the rising crime rates of 1980s and 1990s. This was especially the case for drug offenses, as drug offenses allowed for greater discretion on the part of law enforcement actors, greater involvement of the federal government, and were believed to be responsible for rises in violent and property crime (Balko, 2015; Beckett, 2016; Lynch, Omori, Roussell, & Valasik, 2013). For many police agencies during this era, “tough on crime” policing resulted in the adoption of police paramilitary units (PPUs) and a greater reliance on order maintenance stops and the use of search and arrest warrants (Beckett, 2016; Kraska & Kappeler, 1997). Research suggests that PPUs, the use of order maintenance stops, and the use of search and arrest warrants may have exacerbated racialized patterns of policing (Benner, 2002; Brunson & Miller, 2006; Chambliss, 1994; Weitzer, 1999).

In the early to mid-2000s, Atlanta was among one of the many large U.S. cities employing a “tough on crime” approach to policing (Blau, 2016). To address drug crimes, the city relied upon a PPU known as Red Dog, which actively pursued drug arrests throughout the city (Geraghty & Velez, 2011). Within that unit, and department-wide, the use of order maintenance stops and serving warrants were common tactics employed to combat drug offenses (Blau, 2016). As was demonstrated in Chapter 4, clear patterns of racialized policing existed in the Atlanta in at the heart of the “tough on crime” era, in 2005, yet it is unclear how or whether Red Dog, order maintenance stops, and warrants contributed to these patterns.

Only a few years ago, scholars and journalists were predicting the end of “tough on crime” tactics, with the field’s move towards being “smart on crime” (see Chapter 6) (Badger, 2014; Drakulich & Kirk, 2016), yet within the past year, there has been a resurgence of the “tough on crime” approach as a result of a change in federal leadership within the executive branch generally, and specifically within the Department of Justice

(Dicamillo, 2017). As the federal government acts as a major source of funding for state and local agencies, this change in ethos has the potential to influence police across the nation. Thus a better understanding of the "tough on crime" era is of current concern.

Research suggests PPUs within the "tough on crime" era may police in a manner that intensifies existing racial disparities in policing, especially for drug crimes, yet this research is limited to descriptive accounts of the actions of such units (Balko, 2015; Chambliss, 1994). Similarly, research on the link between warrants and racialized patterns of policing in the "tough on crime" era is limited to only a single descriptive quantitative study (Benner, 2002), and work on the relationship between order maintenance policing and race in the "tough on crime" era has either been qualitative and with small samples or focused on northeastern cities, especially New York, where stop and frisk tactics have garnered ample news coverage (Brunson & Weitzer, 2008; Gelman et al., 2007). In short, these findings are limited either methodologically or geographically. In addition, they do not account for intra-jurisdictional variation in police practices, which past research connects to racial disparities in policing (Beckett et al., 2005; Lynch et al., 2013)

In this chapter, I address the above limitations. By using Atlanta, Georgia as a case study, I extend research on the impact of policing on race within the "tough on crime" era. Specifically, I use hierarchical logistic regression models to explore the relationship between both individual race and neighborhood racial composition and the deployment of Red Dog; and hierarchical multinomial regression models to explore the relationship between both individual race and neighborhood racial composition and the use of order maintenance stops and the serving of warrants. I account for a range of individual, case, and neighborhood level covariates likely to affect the relationship between race and the use of these units and tactics, and explore the impact of policing zones on these relationships, as a vast body of policing research suggests that in large police departments, intra-jurisdictional variations in police practices may be substantial.

Race and Red Dog

One of the factors that is particularly likely to contribute to the racialized patterns of policing within a "tough on crime" regime is the widespread use of PPUs to address drug offending (Chambliss, 1994). This potential link has been established through qualitative research in Washington, D.C. and historical analysis of their impact across the past few decades (Balko, 2015; Chambliss, 1994; Klinger & Rojek, 2008; Kraska & Cubellis, 1997; Kraska & Kappeler, 1997). Yet to date, no research has investigated whether there is a quantitative link between PPUs and racialized policing. This section addresses this gap in the literature by exploring the relationship between race and the use of Atlanta's narcotics-based PPU, Red Dog.

In total, 24.91% (n=687) of all felony drug arrests in 2005 involved Red Dog officers and, among the 113 Atlanta census tracts with any drug arrest in 2005, the rate of Red Dog arrests ranged from 0% to 100% of all arrests, with a mean of 21.67% and median of 18.92%. Table 1 displays the bivariate relationships between use of Red Dog and all arrestee-case level covariates included in the models discussed below; Table 2 displays the relationship between all neighborhood level covariates and the rate of Red

Dog arrests within a neighborhood. Chi-square, t-test, and Pearson correlation coefficients reveal that Red Dog arrestees were on average a few years younger than those arrested by other officers; were more likely to involve intent or sales, trafficking, and manufacturing charges; were more likely to involve cocaine, methamphetamine/amphetamines, hallucinogens or other party drugs, and marijuana; were more likely to be arrested in neighborhoods (census tracts) in Zones 1 and less likely to be arrested in Zone 4. At a bivariate level, race and racial composition are not correlated with the use of Red Dog, yet there are a variety of factors which may lead Red Dog (and non-Red Dog) officers to make arrests that are not accounted for by bivariate statistics. Understanding the relationships between Red Dog and race when accounting for these other factors provides a clearer understanding of how Red Dog arrests may be linked to race (Fryer, 2016, 2018). Further, it allows for explorations of how the relationship between Red Dog and race may vary across the multitude of drug arrests in Atlanta in 2005. As Lynch, et al. (2013) note, case studies of a single city at a single point in time allow for a fuller, richer exploration of race and policing, one that considers the historical and political context of the that place in that moment.

Table 1. Arrestee-Case Level Variables by Red Dog, 2005

(n=2,758)	Non-Red Dog Arrests (n=2,071)	Red Dog Arrests (n=687)
	Mean (SD)/Proportion	Mean (SD)/Proportion
Black[1]	90.15%	91.70%
Non-White[2]	91.07%	92.43%
Male[3]	87.93%	89.37%
Age at Arrest***	33.24 (0.25)	31.08 (0.40)
Top Charge on Arrest[4]***		
Possession	58.09%	36.54%
Intent to Sell	36.75%	49.24%
Sales, Trafficking, Manufacturing	5.17%	14.12%
Drug Involved in Arrest[5]		
Meth/Amphetamines**	3.19%	5.39%
Cocaine**	72.96%	66.67%
Heroin	3.43%	3.20%
Marijuana***	22.21%	33.04%
Hallucinogens/Party Drugs**	3.19%	5.53%
Unspecified	5.50%	4.08%

+p<.10, * p<.05, ** p<.01, *** p<.001

[1]Reference category: non-black.

[2]Reference category: white, non-Hispanic.

[3]Reference category: female or other gender.

[4]Reference category: possession.

[5]Categories not mutually exclusive.

Table 2. Neighborhood Level Variables by Red Dog, 2005

(n=113)	Pearson Correlation Coefficient/ Proportion Red Dog Arrests
Percent Black	0.01
Percent Non-White	0.01
Concentrated Disadvantage	0.05
Residential Instability	-0.03
Percent Foreign Born	-0.03
Property Crime Rate[1]	-0.08
Violent Crime Rate[1]	0.03
Zone Membership[2,3]	
Zone 1*	28.16%
Zone 2	25.24%
Zone 3	18.95%
Zone 4*	15.48%
Zone 5	18.88%
Zone 6	17.77%

+p<.10, * p<.05, ** p<.01, *** p<.001

[1]Per 100 people.

[2]Categories not mutually exclusive.

[3]T-test of proportion Red Dog arrests in neighborhoods within and outside of each zone.

To fully explore the relationship between race and Red Dog, I build a model iteratively, exploring interaction effects as indicated by existing research. Building models iteratively allows for a careful exploration of how various factors are linked to racialized patterns of policing among Red Dog officers. It is important to bear in mind the reference category for the dependent variable in these models, which is arrests by all other officers. Thus these models do not explore Red Dog arrest behavior in general, but instead how Red Dog arrest behavior differs from their counterparts in other units in the APD. The models incorporate, in order, demographic variables, case characteristics, measures of social disorganization, and neighborhood crime rates and police zones. The final model accounts for all relevant arrestee, case, and neighborhood characteristics that are likely to explain when Red Dog is involved in an arrest, and in so doing, accounts for the reasons other than race itself that Red Dog may exhibit racialized patterns of policing.

To understand the relevant factors which may affect Red Dog's involvement in an arrest, and how they may be connected to race, it is useful to consider the situations to which Red Dog was designed to respond. Red Dog is focused on drug arrests, and particularly on drug arrests that involve a high volume or drugs, active drug dealers, or drug-involved individuals who are also involved in more serious criminal activity (Atlanta Police Department, 2000, 2001). Unlike other APD officers, Red Dog officers were more heavily focused on drug offenses as opposed to property, violent, or public order offenses. Further, to the extent that other officers were focused on drug offenses, they were less likely to target drug cases involving a large volume of drugs or active drug dealers than were Red Dog officers. Red Dog officers were able to patrol the city freely and were not located within any particular zone. Yet they were required to make a large number of arrests and serve a large number of warrants (Cook, 2013), and thus they may have focused on areas with particularly high crime rates in order to meet those needs. The need to make a high volume of drug arrests may have concentrated their activity in certain areas of Atlanta despite their lack of formal affiliation with any particular zone.

While Red Dog and arrestee race are not linked at a bivariate level, it is possible that other demographic characteristics or aspects of the case explain some of variability of race, and thus when they are accounted for, the values on race variables more closely align with their unique effect on determining Red Dog involvement. Thus it is worth further exploring this relationship to both better understand the factors that do predict Red Dog involvement and determine more confidently whether race is among them.

Table 3 presents the findings for two models. Model 1 incorporates three arrestee characteristics—race, gender and age. Research has found that among drug abuse treatment patients, drug arrests are more likely to peak later in life, and thus those more heavily involved with drugs are likely to be older (Prendergast, Huang, Evans, & Hser, 2010). The same study found that men are more likely to be heavily involved with drugs than are women, and an investigation of heroin users found that men are more likely to be arrested for dealing drugs than are women (Curry & Latkin, 2003). It follows that Red Dog officers would be more likely than are their counterparts in other APD units to arrest older male drug offenders.

Table 3. Random Intercept Logit Models for the Effect of Individual Race on the Involvement of Red Dog, 2005

(n=2,758)	**Model 1 Odds Ratio (SE)**		**Model 2 Odds Ratio (SE)**	
	Black[1]	**Non-White[2]**	**Black[1]**	**Non-White[2]**
Race	1.14 (0.27)	1.12 (0.27)	1.49 (0.38)	1.47 (0.38)
Male[3]	1.07 (0.16)	1.07 (0.16)	1.05 (0.16)	1.05 (0.16)
Age at Arrest	0.98 (0.00)***	0.98 (0.00)***	0.99 (0.01)	0.99 (0.01)
Top Charge on Arrest[4]				
Intent to Sell			1.83 (0.22)***	1.83 (0.22)***
Sales, Trafficking, Manufacturing			4.40 (0.95)***	4.40 (0.95)***
Drug Involved in Arrest[5]				
Meth/Amphetamines			3.43 (1.15)***	3.36 (1.11)***
Cocaine			1.30 (0.25)	1.30 (0.25)
Heroin			1.36 (0.52)	1.35 (0.51)
Marijuana			1.55 (0.25)**	1.55 (0.25)**
Hallucinogens/Party Drugs			2.20 (0.66)**	2.21 (0.66)**
Unspecified			1.02 (0.33)	1.02 (0.33)

+p<.10, * p<.05, ** p<.01, *** p<.001
[1] Reference category: white, Asian, American Indian, Hispanic, or other race.

[2] Reference category: white.

[3]Reference category: female or other gender.

[4]Reference category: possession.

[5]Categories not mutually exclusive.

Model 2 then incorporates case characteristics, specifically, top charge on arrest and drugs involved in an arrest. As Red Dog is charged with focusing on individuals heavily involved in drug offending, Red Dog should make more arrests that involve drug offenses more serious than possession (i.e., intent to sell, sales, trafficking, or manufacturing) (Atlanta Police Department, 2000, 2001). In addition, because this unit is charged with addressing the most serious drug problems, it should conduct a high rate of arrests for those drugs drawing greater public concern. In 2005, national and local panic was building about the use of party drugs such as MDMA and GHB and the use of methamphetamine. While cocaine use was declining, the use of MDMA was increasing dramatically during the 1990s (Cuomo, Dyment, & Gammino, 1994), and it continued to increase into the 2000s. MDMA was associated with an increase in arrests and emergency department visits, sparking fears of a drug epidemic (Landry, 2002). Use of MDMA use was not only increasing nationwide, but specifically within Atlanta (Theall, Sterk, & McDonald, 2001), as was GHB (Nicholson & Balster, 2001).

Not only are these drugs likely to draw Red Dog attention because of their increased prevalence, but also because they are linked to greater drug use and greater involvement in other crime. Methamphetamine use is common among drug abuse treatment participants with moderate and high drug arrest trajectories, but markedly lower among those with consistently low rates of drug arrests (Prendergast et al., 2010). Users of club drugs are likely to use many other drugs as well (Fendrich, Wislar, Johnson, & Hubbell, 2003), and this is especially true of GHB (Degenhardt, Darke, & Dillon, 2002). In addition, GHB use is often involved in cases of rape (Nicholson & Balster, 2001), and those who use other club drugs (LSD, MDMA, and ketamine), according to the National Survey on Drug Use and Health (NSDUH), are also more likely to be involved in other criminal behavior (Wu, Schlenger, & Galvin, 2006).

Further, use and sales of drug types is often racialized (Beckett et al., 2005). During the early 2000s, the primary sources of methamphetamine in Atlanta were smuggling operations from Mexico and local labs which were operated predominately by white males (Theall et al., 2001), and the primary source of MDMA was smuggling operations from various European countries (Theall et al., 2001). Among arrestees in

2000 who tested positive for methamphetamine in the Atlanta area, all were white (Theall et al., 2001), and other studies have found that, when compared with Hispanics, Asians, and whites, African Americans are the racial/ethnic group least likely to use methamphetamine (Oetting et al., 2000). By adjusting those features of a drug arrest, the measure of arrestee race in Model 2 presents the correlation between Red Dog and race when controlling for demographic factors (gender and age) and case characteristics (most drug serious charge and drugs involved in an arrest).

There a few noteworthy findings in the models reported in Table 3. First, Model 1 makes clear that the only demographic characteristic connected to Red Dog's involvement in an arrest is age, with younger arrestees more likely to have been arrested by Red Dog. Individuals who are one year older have 2% lower odds of their arrest involving a Red Dog officer. While research suggested that Red Dog would make arrests of older individuals as they are more likely to have serious drug involvement, these counterintuitive findings may be a result of the age distribution in this sample. Felony drug arrestees in Atlanta are an older sample of offenders, with an average age of almost 33. Past research into drug and crime involvement and age employed significantly younger samples (Prendergast et al., 2010), and thus ages that are "old" within previous studies, such as the late twenties and early thirties, would be "young" within this sample. This relationship, though, is explained by case characteristics. As is clear in Model 2, when controlling for case severity and drug type, age is no longer significantly related to Red Dog involvement.

Second, Model 2 demonstrates that the most serious drug charge and the drug type are both strongly linked to Red Dog's involvement in an arrest. Intent, sales, trafficking, manufacturing, marijuana, methamphetamine/amphetamine, and hallucinogen charges are all associated with increased odds of the involvement of Red Dog. As expected, Red Dog's activities center on an entirely different set of drug felonies than do their counterparts throughout the rest of the APD. Red Dog's arrest patterns instead seem to be largely governed by the severity of drug cases and the types of drugs involved, a finding that aligns with their objective (Atlanta Police Department, 2000, 2001).

Finally, race does not emerge as significant in any of the four models. Yet it is worth further exploring the role of race. Because their objective is to address the most serious drug offenses, Red Dog officers may have less discretion when handling cases that involve more serious charges and drugs like methamphetamine and party drugs, and thus the effect of race may vary by charge and drug type. A cross tabulation with Chi Square tests for significance reveal that black and non-white arrestees are more likely to be arrested for intent charges, and less likely to be arrested for possession charges or sales, trafficking, or manufacturing charges ($p<0.001$); they are also less likely to be arrested for charges involving methamphetamine or amphetamines ($p<0.001$) and hallucinogens or other party drugs ($p<0.001$). I employ interactions between both race and drug type and charge type to test whether, in less severe cases and in those cases not involving drug types that law enforcement was especially concerned with in 2005, arrests by Red Dog are linked to the race of the arrestee. The findings are displayed in Table 4, which presents the odds ratio for an arrest involving Red Dog by drug type/charge type, race, and the interaction of the two. For simplicity, only the interaction and main effects are displayed, yet all models control for the series of covariates found in Model 2.

Table 4. Random Intercept Logit Models for the Effect of Individual Race on the Involvement of Red Dog with Charge Type Interactions, 2005

(n=2,758)	Top Charge Odds Ratio (SE)		Methamphetamine Odds Ratio (SE)		Hallucinogens Odds Ratio (SE)	
	Black[1]	Non-White[2]	Black[1]	Non-White[2]	Black1	Non-White[2]
Race	1.87 (0.54)*	1.82 (0.50)*	1.62 (0.42)+	1.72 (0.46)*	1.78 (0.48)*	1.74 (0.49)*
Top Charge on Arrest[3]						
Intent to Sell	3.39 (1.56)**	3.17 (1.56)*				
Sales, Trafficking, Manufacturing	8.72 (5.02)***	9.35 (5.40)***				
Drug Involved in Arrest[4]						
Meth/Amphetamines			4.13 (1.48)***	4.57 (1.86)***		
Hallucinogens/Party Drugs					6.01 (2.54)***	5.70 (0.24)***
Race*Intent to Sell	0.51 (0.24)	0.55 (0.28)				
Race*Sales, Trafficking, Manufacturing	0.46 (0.29)	0.43 (0.27)				
Race*Methamphetamine/Amphetamines			0.42 (0.26)	0.33 (0.21)+		
Race*Hallucinogens/Party Drugs					0.23 (0.12)**	0.26 (0.14)*

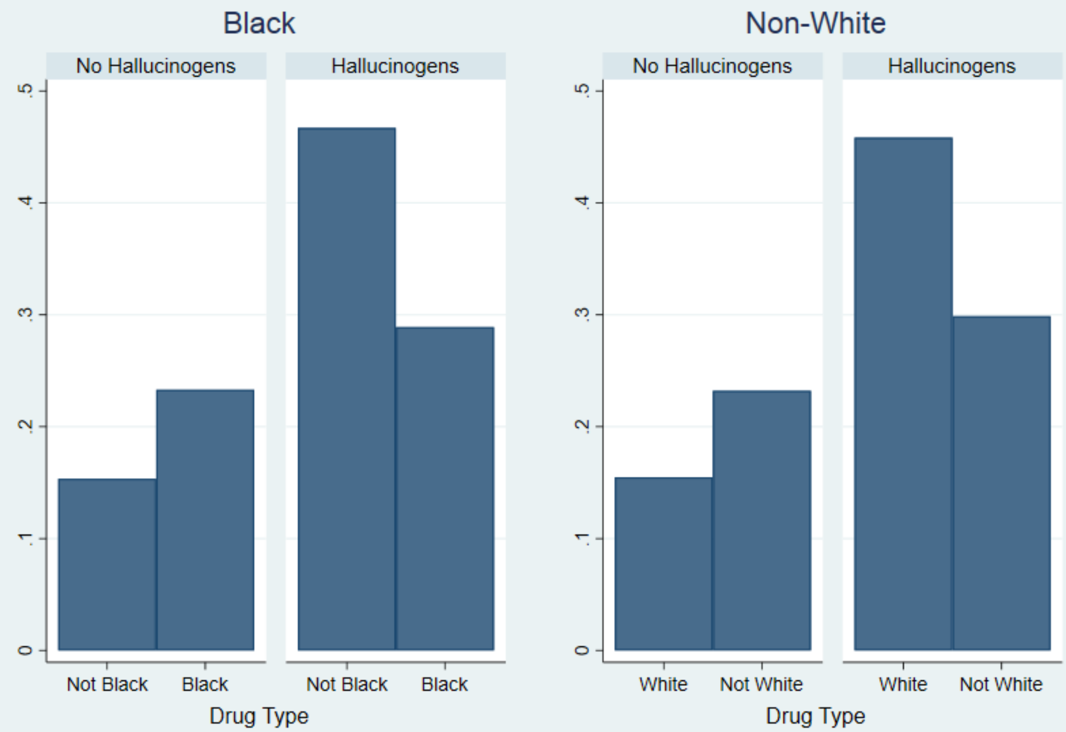
+p<.10, * p<.05, ** p<.01, *** p<.001
[1]Reference category: white, Asian, American Indian, Hispanic, or other race.

[2]Reference category: white.

[3]Reference category: possession.

[4]Categories not mutually exclusive.

Figure 1. Probability of a Red Dog Arrest by Race and Drug Type, Level-1 Model



A clear pattern is evident in Table 4. Hallucinogen arrests of black or non-white individuals have 78% and 75%, respectively, lower odds of involving Red Dog, while hallucinogen arrests that of non-black or white individuals are far more likely to involve Red Dog. Equally striking is the effect of race when an arrest does not involve hallucinogens. For arrests of all other drug types, black and non-white individuals have 84% and 82% higher odds of the arrest involving Red Dog. As Figure 1 makes clear, drug type is key to understanding the relationship between Red Dog and race; the impact of race is inverted depending on the drugs involved. While the interaction effect is non-significant, the main effects for methamphetamines/amphetamines and the most serious drug charge on arrest tell a similar story. Specifically, when an arrest does not involve methamphetamines/amphetamines, non-white arrestees have 72% higher odds of the arrest involving Red Dog than do white arrestees. When the most serious charge on an arrest is possession, non-white arrestees have 82% greater odds of the arrest involving Red Dog.

A study of Seattle, WA revealed that crack cocaine was driving the racialized patterns of policing within that city (Beckett et al., 2005). It seems that a similar phenomenon is occurring for Red Dog in Atlanta in 2005. At the time, methamphetamines and hallucinogens were increasing in popularity, associated with overall greater drug use and criminal involvement, and with health issues that could put one in a situation necessitating a law enforcement response (Cuomo et al., 1994; Degenhardt et al., 2002; Fendrich et al., 2003; Landry, 2002; Nicholson & Balster, 2001; Oetting et al., 2000; Theall et al., 2001; Wu et al., 2006). While rates of arrest for these drugs were low overall (3.73% for methamphetamine and 3.77% for hallucinogens), Red Dog officers were significantly more likely to make arrests for these drugs than were other APD officers; Red Dog's rate of methamphetamine arrests was 69% higher than that among other APD officers, and their rate of hallucinogen arrests was 73% higher. The only other drug type for which Red Dog was more likely to make an arrest was marijuana. Because drug usage and sales for particular drugs often varies by race, and because methamphetamine and hallucinogens are particularly likely to be used and sold by whites (Copes, Kerley, Angulski, & Zaleski, 2014; Floyd et al., 2010; Fox & Rodriguez, 2010; Yacoubian, 2002), Red Dog's focus on these two drug types masks the racial patterns of policing associated with Red Dog's arrests of all other drug types. While, broadly, arrestee race is not a significant predictor of the involvement of Red Dog, for arrests that do not involve methamphetamine or party drugs, black or non-white drug arrestees are at greater risk of Red Dog involvement.

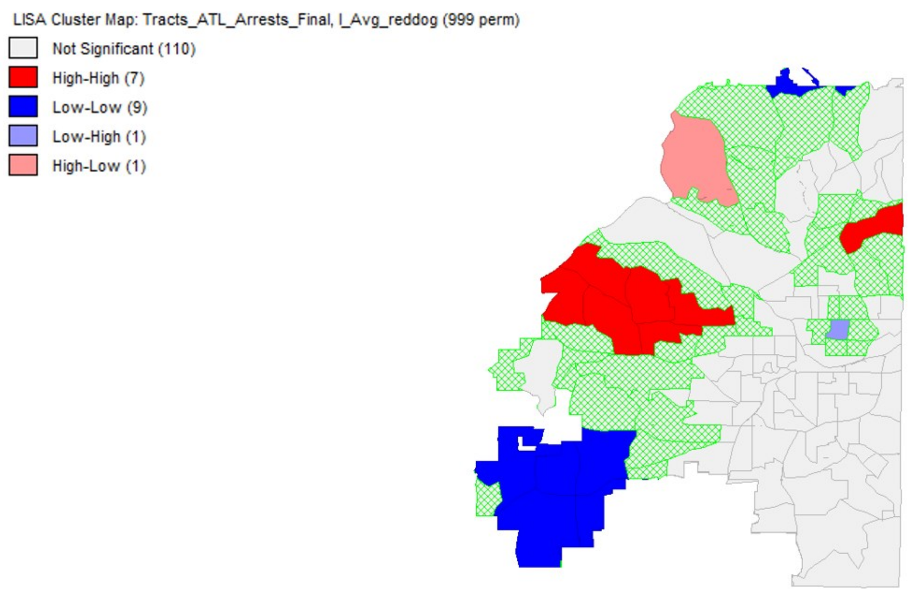
Further, Red Dog focuses on more serious drug involvement. There do not appear to be any clear racial patterns for serious drug offenses. Yet this masks patterns of behavior that occur when drug charges are less serious. Compared with arrests by other APD officers, arrests by Red Dog for less serious drug involvement are more likely to involve non-white arrestees. Again, broadly, arrestee race does not predict Red Dog involvement, but for less serious drug offenses, it is a significant predictor of Red Dog involvement.

Racialized patterns of policing may also be visible at a more macro level. Research has found that police behavior varies according to the racial composition of a neighborhood (Brunson & Weitzer, 2008; Weitzer, 1999). Police do not patrol evenly across all neighborhoods within their jurisdiction (National Research Council, 2004). Research to date suggests the importance of measuring intra-jurisdictional variation in the deployment of drug law policing, and suggests that police deployment and activities depend on a local, social understanding of a neighborhood by the police patrolling it (Lynch et al., 2013). Indeed, four decades of research indicate that environmental factors play a key role in determining police behavior, with police responding to community conditions as much or more than they do to departmental policies and practices (Klinger, 2004). Police can conceptualize neighborhoods as problem places for a variety of reasons, and these conceptualizations result in differential police activity. Yet unlike many other units within the APD, Red Dog is not assigned to a particular zone or beat.

Instead, they are a distinct unit with the ability to work across zones (Atlanta Police Department, 2000, 2001). Because of this, if there is any noticeable geographic pattern to their arrests, it should be because the serious, persistent drug behavior they are charged with addressing is geographically patterned.

To determine whether this is the case, I use multi-level models that control for factors which are likely correlated with the presence of Red Dog. Before explicitly modeling these relationships, though, it is useful to determine if Red Dog arrests exhibit any sort of geographic patterning. Using GeoDa 1.8.14, clustering across the city of the rate of Red Dog arrests in a census tract was examined with the global Moran's I statistic. The Red Dog arrest rate is defined as the number of Red Dog arrests over the number of total felony drug arrests in a census tract. The global Moran's I compares the actual distribution of the rate of Red Dog arrests to 999 random permutations to determine whether the pattern of arrests differs significantly from spatial randomness. The results indicate that the citywide clustering of Red Dog arrests is statistically distinct from spatial randomness ($I = 0.10$; $p<0.05$). This global statistic, though, indicates clustering across the entire city; spatial clustering of Red Dog arrests is more easily understood through an exploration of local clustering. To examine this, the local Moran's I was used. This test allows for an examination of specific census tracts in Atlanta where either high or low rates of Red Dog-involved arrests cluster. Figure 2, below, illustrates these clusters using a significance level of $p<0.05$. The color within the tract designates the type of cluster or lack thereof core. The green crosshatch pattern identifies the non-significant neighbors of clusters, to provide a sense of the group of neighborhoods that contribute to these localized patterns. This figure demonstrates a clear pattern of clustering, with much lower rates of Red Dog involvement in the southwestern area of the city, and two clusters of high rates of Red Dog involvement further north. In short, these finding suggest that Red Dog arrests are geographically patterned, and that they operate most frequently in distinct parts of the city.

Figure 2. Local Moran's I Clusters of Rate of Red Dog Arrests



To determine if these geographic patterns follow racial patterns, I build upon Model 2 (shown in Table 3) by adding a measure of racial composition and a series of neighborhood measures (see Model 3 reported in Table 4). The measure of racial composition aligns with the arrestee-level race variable in each model, and thus when arrestee race is operationalized as black the racial composition variable is the percent black, and when the arrestee variable is operationalized as non-white, the racial composition variable is the percent non-white. Models are built iteratively to better understand which, if any, neighborhood covariates are linked to Red Dog arrests. Recall that Red Dog is charged with addressing the most serious drug issues and drug issues that are linked to more serious crime (Atlanta Police Department, 2000, 2001). As such, they are likely to spend more time patrolling neighborhoods in which more serious drug crime occurs or, at least, in which they believe more serious drug crime occurs.

One of the core predictors of higher levels of crime is social disorganization (Peterson & Krivo, 2010; Sampson et al., 1997). Social disorganization has been linked in particular to the sort of serious property and violent crime that, when associated with drug offenses, is likely to draw the attention of Red Dog officers (Osgood & Chambers, 2006; Peterson & Krivo, 2010). Further, even if these measures were not associated with actual levels of crime, police may believe they are, using signs of social disorganization such as poverty as an indication of where to focus their efforts (Klinger, 1997; Weitzer, 1999). Police are responsive to community conditions, with socioeconomic conditions playing a large rule in an officer's perception of a neighborhood (Klinger, 2004). Neighborhoods with high levels of social disorganization also often have a higher rate of non-white residents (Peterson & Krivo, 2010). Thus, it is important to account for the effect of social disorganization on where Red Dog officers make arrests in order to better understand the relationship between Red Dog and race.

Red Dog may also rely on more direct indicators of serious crime, such as where violent crime and property crime occur. There is often overlap between the where drug crime occurs and where violent and property crime occur (Baumer, Lauritsen, Rosenfeld, & Wright, 1998; Gorman et al., 2005; James, Johnson, & Raghavan, 2004; Martínez, Rosenfeld, & Mares, 2008). Further, while the nature of causality between drug use and property or violent crime is unclear, those more heavily involved in drug offending are also more likely to be heavily involved in other criminal activity (Bennett et al., 2008), especially intimate partner violence (Cunradi, Caetano, & Schafer, 2006; James et al., 2004) and gang activity (Bellair & McNulty, 2009). Thus violent and property crime rates may provide a good indicator to Red Dog officers of where they are likely to find individuals engaging in more serious drug behavior.

A vast body of research suggests that the factors which most directly influence geographic patterns of behavior are localized leadership and workgroups, or in the case of the APD, police zones (Engel & Worden, 2006; R. R. Johnson, 2012; Klinger, 2004; Knight, 2015; Mastrofski & Willis, 2010). Zones/beats/precincts matter when examining racial differences in police activity because they play such a large role in determining police behavior (Fryer, 2016). Crime statistics reported in the Atlanta Police Department annual reports are organized and reported by zone, and thus APD is no exception to the norm of thinking about crime within this particular geographic/organizational lens (Atlanta Police Department, 2000, 2001, 2011, 2012, 2013, 2014).

In Model 3 of Table 4, I add a measure of neighborhood racial composition and neighborhood-level indices that collectively capture social disorganization: concentrated disadvantage, residential instability, and percent foreign born. In Model 4 of Table 4, I add the violent and property crime rates and zone membership of all census tracts. A few noteworthy results stand out.

Table 4. Random Intercept Logit Models for the Effect of Individual Race and Racial Composition on the Involvement of Red Dog, 2005

(n=2,758)	Model 3 Odds Ratio (SE)		Model 4 Odds Ratio (SE)	
	Black[1]	Non-White[2]	Black[1]	Non-White[2]
Race	1.45 (0.39)	1.42 (0.39)	1.51 (0.40)	1.49 (0.40)
Male[3]	1.05 (0.16)	1.05 (0.16)	1.05 (0.16)	1.05 (0.16)
Age at Arrest	0.99 (0.01)	0.99 (0.01)	0.99 (0.00)	0.99 (0.00)
Top Charge on Arrest[4]				
Intent to Sell	1.82 (0.22)***	1.83 (0.22)***	1.82 (0.22)***	1.83 (0.22)***
Sales, Trafficking, Manufacturing	4.44 (0.95)***	4.45 (0.95)***	4.41 (0.94)***	4.41 (0.94)***
Drug Involved in Arrest[5]				
Methamphetamine/Amphetamines	3.50 (1.18)***	3.44 (1.14)***	3.50 (1.18)***	3.44 (1.15)***
Cocaine	1.30 (0.25)	1.31 (0.25)	1.29 (0.24)	1.29 (0.25)
Heroin	1.36 (0.51)	1.35 (051)	1.26 (0.45)	1.26 (0.45)
Marijuana	1.53 (0.25)**	1.54 (0.25)**	1.54 (0.25)**	1.53 (0.25)**
Hallucinogens/Party Drugs	2.24 (0.69)**	2.25 (0.68)**	2.15 (0.65)*	2.16 (0.66)*
Unspecified Controlled Substance	1.02 (0.34)	1.02 (0.34)	1.04 (0.35)	1.04 (0.35)
Racial Composition	1.00 (0.01)	1.00 (0.01)	1.00 (0.01)	1.00 (0.01)
Concentrated Disadvantage	1.15 (0.20)	1.15 (0.20)	0.94 (0.13)	0.93 (0.13)
Residential Instability	1.00 (0.11)	1.00 (0.11)	1.02 (0.11)	1.01 (0.11)
Percent Foreign Born	0.99 (0.01)	0.99 (0.01)	1.00 (0.01)	0.99 (0.01)
Property Crime Rate[6]			0.98 (0.02)	0.98 (0.02)
Violent Crime Rate[6]			1.13 (0.19)	1.13 (0.18)
Zone Membership[5]				
Zone 1			1.42 (0.30)+	1.41 (0.29)
Zone 2			0.99 (0.39)	0.99 (0.39)
Zone 3			0.73 (0.13)+	0.73 (0.13)+
Zone 4			0.47 (0.10)***	0.47 (0.10)***
Zone 5			0.82 (0.20)	0.83 (0.20)
Zone 6			1.32 (0.40)	1.33 (0.40)

+p<.10, * p<.05, ** p<.01, *** p<.001

[1]Reference category: white, Asian, American Indian, Hispanic, or other race.

[2]Reference category: white.

[3]Reference category: female or other gender.

[4]Reference category: possession.

[5]Categories not mutually exclusive.

[6]Per 100 people.

First, contrary to expectations, in both models, neither arrestee race nor neighborhood racial composition are significant. Second, neighborhood levels of disorganization do not determine where Red Dog officers make arrests relative to their APD counterparts. While existing literature establishes that these factors are correlated with levels of crime and that officers often rely on them as signs of an area with high crime rates, they are not related to where Red Dog makes drug arrests in 2005 anymore than they are related to where other APD officers make drug arrests. This does not mean that Red Dog is not focused on socially disorganized communities, but that they are no more likely to be involved in arrests in socially disorganized communities than other APD officers. In effect, both Red Dog officers and other APD officers are equally influenced by the social disorganization and racial composition of a neighborhood when securing drug arrests. Third, the rates of property or violent crime also do not increase the odds of an arrest involving Red Dog compared to other officers. While the unit's focus is not on violent or property crimes, but on drug crimes, it is surprising that neighborhoods with more serious crime do not appear to be emphasized by Red Dog officers relative to their counterparts, as the unit is charged with enforcing the most serious drug issues and, in turn, these issues are often connected to other criminal activity. Finally, zone membership, unlike the other neighborhood-level variables, is related to the involvement of Red Dog, with Red Dog arrests being more common in Zone 1 and less common in Zones 3 and 4 relative to non-Red Dog drug arrests. These patterns mirror the high and low clusters found in in Figure 2.

The headquarters for Red Dog, in the Special Operations Section, is approximately the same distance from the headquarters of all six zones, thus it is unlikely they are simply patrolling closer to their headquarters (Atlanta Police Department, 2000, 2001). Yet even for a unit like Red Dog, which is not assigned to any particular zone, it appears that zones matter more than social disorganization and rates of violent and property crime for explaining where arrests are made. It is expected that Red Dog officers obtain information about where drug crimes are occurring from officers who are assigned to specific zones and, thus, they think and practice within these geographic parameters, focusing on certain zones over others.

To further explore the role that zones play in Red Dog felony drug arrest patterns, I re-run models within each zone, controlling for all factors in Model 4 except for zone membership. For example, such a model was replicated for Zone 1 by using only tracts that are within or overlap the Zone 1 police district. The results of these analyses are displayed in Table 5, wherein the coefficients for only race and racial composition are shown. These analyses allow for a more complete understanding of whether, within each zone, when accounting for relevant arrestee, case, and neighborhood level covariates, Red Dog arrests are influenced by the race of arrestee or the racial composition of a neighborhood.

Two takeaways are noteworthy from these results. First, within zones, the racial composition of the census tract does not have any significant effect on whether an arrest involves Red Dog officers compared to other APD officers. Second, for some zones, there is a significant relationship between an arrestee's race and whether he or she is arrested by Red Dog officers, controlling for the racial composition of the neighborhood. Across the city, Red Dog felony drug arrests are not racially patterned, but within certain zones, their arrests are racially patterned. Police are loosely coupled organizations (Nowacki, 2011), and in large departments like the APD, police practices are rarely department-wide, but instead specific to a smaller organizational units like zones, driven by the mid-level managers in those units and the workgroups that form among officers who spend large amounts of time together (R. R. Johnson, 2012; Klinger, 1997, 2004). While Red Dog is not assigned to any particular zone, arrest reports reveal that Red Dog officers often work with or receive tips on the location of drug activity from other APD officers who are tied to particular zones. Thus, they too may be influenced by these localized workgroups. In essence, Red Dog officers behave differently in different zones. Specifically, in Zones 5 and 6, nonwhite arrestees have greater odds of being arrested by a Red Dog officer.

Table 5. Zone-Specific Random Intercept Logit Models for the Effect of Individual Race and Racial Composition on the Use of Red Dog, 2005

	Black[1] Odds Ratio (SE)					
	Zone 1 (n=1,047)	**Zone 2 (n=200)**	**Zone 3 (n=881)**	**Zone 4 (n=586)**	**Zone 5 (n=997)**	**Zone 6 (n=285)**
Race	1.36 (0.72)	0.93 (0.31)	1.57 (0.97)	1.35 (1.29)	2.69 (1.14)*	2.88 (1.64)+
Racial Composition	0.99 (0.01)	1.00 (0.01)	0.99 (0.01)	0.99 (0.08)	1.01 (0.01)	0.97 (0.02)
	Non-White[2] Odds Ratio (SE)					
	Zone 1 (n=1,047)	**Zone 2 (n=200)**	**Zone 3 (n=881)**	**Zone 4 (n=579)**	**Zone 5 (n=997)**	**Zone 6 (n=285)**
Race	1.53 (0.90)	1.20 (0.36)	1.39 (0.88)	Omitted[3]	2.83 (1.22)*	2.78 (1.53)+
Racial Composition	0.99 (0.01)	0.99 (0.01)	0.99 (0.29)	0.99 (0.89)	1.01 (0.01)	0.97 (0.02)

+p<.10, * p<.05, ** p<.01, *** p<.001

[1]Reference category: white, Asian, American Indian, Hispanic, or other race.

[2]Reference category: white.
[3]No white arrestees in this zone were
arrested by Red Dog, thus those observations were dropped
Note: full controls included but not shown (see Table 4)

Race and Arrest Types

While PPUs do not explain the racial inequalities in arrests within Atlanta in 2005, two types of tactics may explain them. Specifically, research suggests that warrants and order maintenance stops, respectively, may contribute disproportionally to racialized patterns of drug arrests. Table 6 presents the proportions of arrests involving each set of tactics. Warrants constitute slightly more than 16% of arrest tactics, and order maintenance stops occur in either 18.64% (without traffic stops) or 29.88% (with traffic stops) of arrests, depending on how they are defined.

Table 6. Tactics that Lead to Arrest, 2005

(n=2,758)	N (%)
Pedestrian Stop Operationalization	
Serving Warrants	447 (16.21%)
Order Maintenance Stops	509 (18.64%)
Other Tactics	1,802 (65.40%)
Pedestrian and Traffic Stop Operationalization	
Serving Warrants	447 (16.21%)
Order Maintenance Stops	824 (29.88%)
Other Tactics	1,487 (53.92%)

To explore the relationship between race and arrest tactics, I use multilevel multinomial models. I again build models iteratively, controlling for aspects of arrestee and case characteristics that may predict the types of tactics involved in an arrest, and later adding social disorganization, crime rates, and zone membership to the model. Building models iteratively allows for a clearer understanding of the factors that explain when particular tactics are used, and how they are linked to race and racial composition. The results are displayed in Tables 7 and 8. Table 7 provides the results when order maintenance stops include both pedestrian and traffic stops, and Table 8 displays the results when order maintenance stops include only pedestrian stops.

I begin with a model that incorporates arrestee race, gender, and age. Age has been found to be correlated with the level of drug and criminal involvement (Loeber & Farrington, 2014; Prendergast et al., 2010). Warrants are often issued in cases involving greater drug or other criminal activity, and thus the use of warrants is likely to be correlated with age. Gender is linked to order maintenance stops, such that these stops are particularly common for young, non-white men (Brunson & Miller, 2006). Controlling for both allows for an understanding of the connection between race and arrest tactic net the effect of age and gender. Model 1 in Tables 7 and 8, though, do not account for the types of charges or drugs involved in a case. To better isolate the impact of race on arrest tactics, the second model in each table adds these case characteristics. Arrest warrants in Atlanta are often built upon an investigation of more serious drug charges. Specifically, officers act on warrants after buy-bust operations, surveillance activities, or citizen reports that help to establish a clear pattern of drug sales. On the contrary, order maintenance stops, by definition, are not motivated by any serious drug activity. If they were, officers would have highlighted those rationales as the reason for the stop. Thus, they are unlikely to yield anything more serious than a possession or intent to sell arrest. To the extent that non-white Atlantans are more heavily involved in certain types of drug activity, it is crucial to control for the top charge on arrest to obtain a clear picture of the relationship between race and arrest tactics.

Methamphetamine and hallucinogen usage and sales was peaking in 2005, and there were both national and local panics about these drug issues (Cuomo et al., 1994; Fendrich et al., 2003; Oetting et al., 2000; Theall et al., 2001; Wu et al., 2006). As is apparent in the arrest reports from Atlanta, obtaining a search or arrest warrant takes time and effort on the part of police, and thus they are likely to employ these measures only for those drugs about which they are most worried. In addition, order maintenance stops, which are motivated by non-drug related behaviors, should involve only those drugs that Atlantans commonly carry. To the extent that the types of drugs carried varies by race, then so should the relationship between order maintenance stops and arrestee race.

Model 1 (in Tables 7 and 8) displays the results for when only arrestee characteristics are included, and Model 2 (in Tables 7 and 8) display the results when case characteristics are added. The results do not vary substantially across operationalizations of order maintenance tactics, and thus I discuss the overall findings. Model 1 reveals that, compared to all other arrest tactics, race is unrelated to the use of order maintenance stops, but it is related to the use of warrants, such that non-white arrestees are significantly more likely to be arrested via a warrant than are white arrestees.

Table 7. Random Intercept Logit Models for the Effect of Individual Race on Police Stop Tactics - Traffic and Pedestrian Stops, 2005

(n=2,758)	Model 1 Odds Ratio (SE)				Model 2 Odds Ratio (SE)			
	Order Maintenance Stops		Warrants		Order Maintenance Stops		Warrants	
	Black[1]	Non-White[2]	Black[1]	Non-White[2]	Black[1]	Non-White[2]	Black[1]	Non-White[2]
Race	1.03 (0.22)	1.04 (0.23)	1.71 (0.48)+	2.17 (0.61)**	1.23 (0.27)	1.25 (0.29)	0.97 (0.31)	1.34 (0.40)
Male[3]	1.40 (0.21)*	1.40 (0.21)*	0.59 (0.11)**	0.57 (0.10)**	1.40 (0.21)*	1.40 (0.21)*	0.55 (0.09)***	0.54 (0.09)***
Age at Arrest	1.00 (0.00)	1.00 (0.00)	1.00 (0.01)	1.00 (0.01)	1.00 (0.01)	1.00 (0.01)	1.02 (0.01)**	1.02 (0.01)**
Top Charge on Arrest[4]								
Intent to Sell					0.76 (0.08)**	0.76 (0.08)*	3.92 (0.75)***	3.85 (0.73)***
Sales, Trafficking, Manufacturing					0.26 (0.07)***	0.26 (0.07)***	4.71 (1.10)***	4.65 (1.09)***
Drug Involved in Arrest[5]								
Meth/Amphetamines					0.95 (0.35)	0.95 (0.34)	1.20 (0.67)	1.49 (0.78)
Cocaine					0.81 (0.15)	0.81 (0.15)	2.41 (0.63)**	2.38 (0.61)**
Heroin					0.89 (0.28)	0.89 (0.29)	1.56 (0.46)	1.61 (0.46)+
Marijuana					0.90 (0.16)	0.90 (0.16)	2.47 (0.51)***	2.44 (0.50)***
Hallucinogens/Party Drugs					1.56 (0.41)+	1.56 (0.41)+	2.00 (0.87)	2.05 (0.89)
Unspecified					1.61 (0.38)*	1.60 (0.38)*	0.94 (0.44)	0.94 (0.44)

+p<.10, * p<.05, ** p<.01, *** p<.001

[1]Reference category: white, Asian, American Indian, Hispanic, or other race.

[2]Reference category: white.

[3]Reference category: female or other gender.

[4]Reference category: possession.

[5]Categories not mutually exclusive.

Table 8. Random Intercept Logit Models for the Effect of Individual Race on Police Stop Tactics - Pedestrian Stops Only, 2005

(n=2,758)	**Model 1 Odds Ratio (SE)**				**Model 2 Odds Ratio (SE)**			
	Order Maintenance Stops		**Warrants**		**Order Maintenance Stops**		**Warrants**	
	Black[1]	**Non-White[2]**	**Black[1]**	**Non-White[2]**	**Black[1]**	**Non-White[2]**	**Black[1]**	**Non-White[2]**
Race	1.26 (0.25)	1.30 (0.25)	1.78 (0.51)*	2.27 (0.63)**	1.45 (0.33)	1.49 (0.35)+	0.97 (0.31)	1.34 (0.40)
Male[3]	1.19 (0.21)	1.18 (0.21)	0.54 (0.09)***	0.53 (0.09)***	1.20 (0.21)	1.19 (0.21)	0.55 (0.09)***	0.54 (0.09)***
Age at Arrest	1.02 (0.01)**	1.02 (0.01)**	1.00 (0.01)	1.00 (0.01)	1.01 (0.01)	1.01 (0.01)	1.02 (0.01)**	1.02 (0.01)**
Top Charge on Arrest[4]								
Intent to Sell					0.70 (0.09)**	0.70 (0.09)**	3.92 (0.75)***	3.85 (0.73)***
Sales, Trafficking, Manufacturing					0.16 (0.07)***	0.16 (0.06)***	4.71 (1.10)***	4.65 (1.09)***
Drug Involved in Arrest[5]								
Meth/Amphetamines					0.89 (0.37)	0.89 (0.37)	1.20 (0.67)	1.49 (0.78)
Cocaine					0.80 (0.19)	0.80 (0.19)	2.41 (0.63)**	2.38 (0.61)**
Heroin					0.72 (0.19)	0.72 (0.28)	1.56 (0.46)	1.61 (0.46)+
Marijuana					0.63 (0.16)+	0.63 (0.16)+	2.47 (0.51)***	2.44 (0.50)***
Hallucinogens/Party Drugs					0.60 (0.22)	0.60 (0.22)	2.00 (0.87)	2.05 (0.89)
Unspecified					1.83 (0.46)*	1.83 (0.46)*	0.94 (0.44)	0.94 (0.44)

+p<.10, * p<.05, ** p<.01, *** p<.001

[1]Reference category: white, Asian, American Indian, Hispanic, or other race.

[2]Reference category: white.

[3]Reference category: female or other gender.

[4]Reference category: possession.

[5]Categories not mutually exclusive.

Model 1 also reveals that female arrestees are more likely to be arrested via warrants. While current criminal justice or criminological literature does not offer an explanation for why female arrestees might be more likely to be arrested via warrant, a close reading of felony drug arrest reports from the APD in 2005 does. When arrests involve search or arrest warrants, officers often arrest all individuals in a house even if they are not the target of the arrest. Thus, the female relatives and significant others of men who are involved in drug and other criminal activity are arrested alongside them; this is not the case in pedestrian stops, traffic stops, or calls for service.

Adding case characteristics to the model (Model 2 of Tables 7 and 8) modify the findings. The inclusion of top charge on arrest and drug types fully explain the racial patterns of arrest for warrants. As expected, warrants are more likely to involve charges more serious than possession. They are also more likely to involve certain drug types, yet the specific types vary from those predicted: cocaine and marijuana as opposed to methamphetamine and hallucinogens. This may be because the tactics used to build warrants are better suited to making cases for the sale of cocaine and marijuana arrests. If, for example, cocaine and marijuana were more likely to involve open-air drug sales at a particular location, then it would be easier to build the case for a search or arrest warrant involving them. Regardless, when these case characteristics are accounted for, the effect of race on arrest via warrant is no longer significant. Thus, it appears that any apparent relationship between race and arrest tactics is largely attributable to the greater involvement of non-whites in specific drug offenses, in particular intent to sell, sales, and trafficking of cocaine and marijuana. In the case of order maintenance stops, race was not significant in Model 1, and it remained insignificant in Model 2 compared to all other arrest tactics. As predicted, both operationalizations of order maintenance stop are more likely to involve possession arrests, and the drug types involved in such arrests are more likely to be an unspecified controlled substance.

While the findings reported in Tables 7 and 8 suggest that racial inequities in felony drug arrests at an individual level are explained by differential involvement with drug severity and type, racialized patterns of arrests may also exist across neighborhoods. Previous studies show that both order maintenance stops and warrants are used more frequently within predominately black and Hispanic neighborhoods (Benner, 2002; Brunson & Miller, 2006; Brunson & Weitzer, 2008; Ingram, 2007). In essence, neighborhood conditions are linked to police decision making, including the decision to make an arrest (Smith, 1986; Sun, Payne, & Wu, 2008; Terrill & Reisig, 2003). Police are neighborhood-based institutions, with their actions largely determined by the boundaries of zones they patrol, guidance provided by zone-specific leadership, and patterns of behavior, economic conditions, and crime that they witness across the blocks that they repeatedly patrol (Klinger, 2004; National Research Council, 2004; Wilson & Kelling, 1982). Crime is geographically patterned (Ackerman & Murray, 2004; Barnum, Campbell, Trocchio, Caplan, & Kennedy, 2016; Ratcliffe, 2004), and thus this reliance on geography to determine police behavior is logical. Yet because neighborhoods within U.S. cities are often racially segregated, this strategy can result in high rates of stops or arrests in predominately minority neighborhoods (Lynch et al., 2013; Peterson & Krivo, 2010).

As with Red Dog arrests, understanding the link between tactics and neighborhood racial composition begins by determining whether the use of warrants and order maintenance stops are geographically patterned. The rate of warrant-based arrests is calculated for each census tract, indicating the percentage of all felony drug arrests in a census tract that are conducted using a search or arrest warrant. Rates of order maintenance arrests are calculated in the same way. The global Moran's I statistic is used to determine whether the rates of warrant and order maintenance stop arrests, respectively, show patterns of clustering across the city that is distinct from spatial randomness. These tests reveal that for warrants ($I = 0.18$; $p < 0.01$) order maintenance stops involving only pedestrians ($I = 0.17$; $p < 0.01$), and order maintenance stops involving both pedestrians and traffic stops ($I = 0.16$; $p < 0.01$), arrests patterns vary significantly from spatial randomness. Significant clusters of arrest tactics as assessed by the local Moran's I (Figures 3, 4, and 5), highlight the nature of this patterning. Order maintenance stops involving only pedestrians are clustered in the western part of the city and downtown; order maintenance stops that also involve traffic stops are clustered in similar areas, although the exact neighborhoods differ; and warrants are also clustered in similar areas, but again within slightly different neighborhoods. In general, while each tactic type clusters within certain neighborhoods, they cluster within different neighborhoods, and thus the factors driving these patterns may also vary.

Figure 3. Local Moran's I Clusters of Rate of Pedestrian Order Maintenance Stops

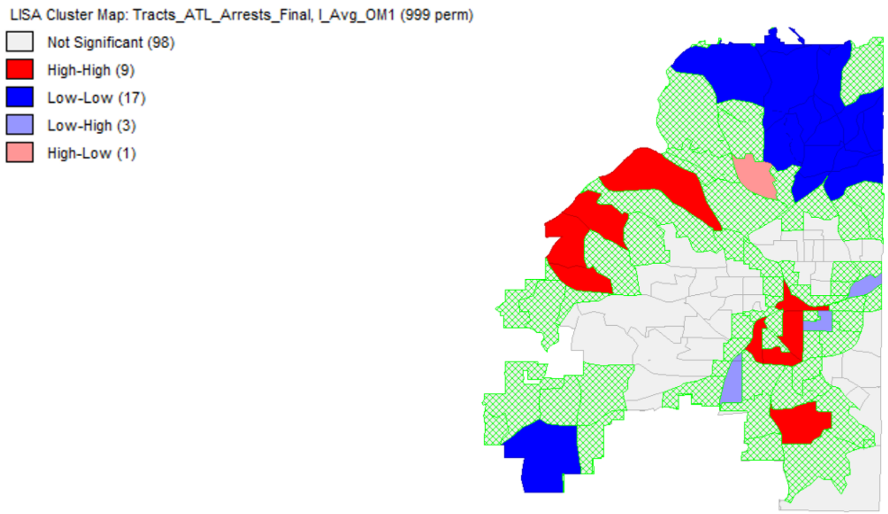


Figure 4. Local Moran's I Clusters of Rate of Pedestrian and Traffic Order Maintenance Stops

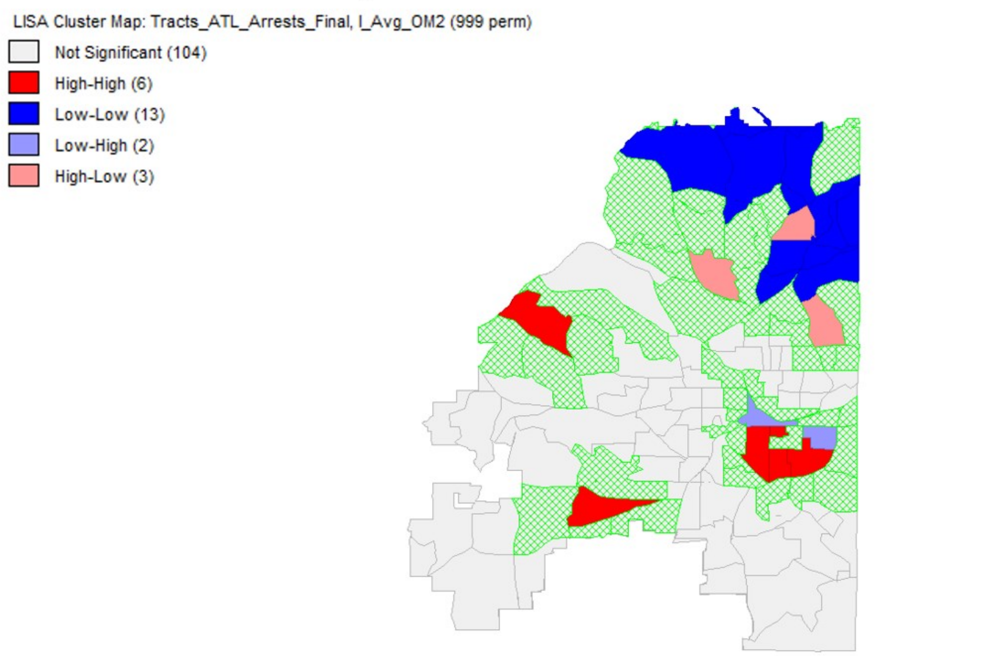
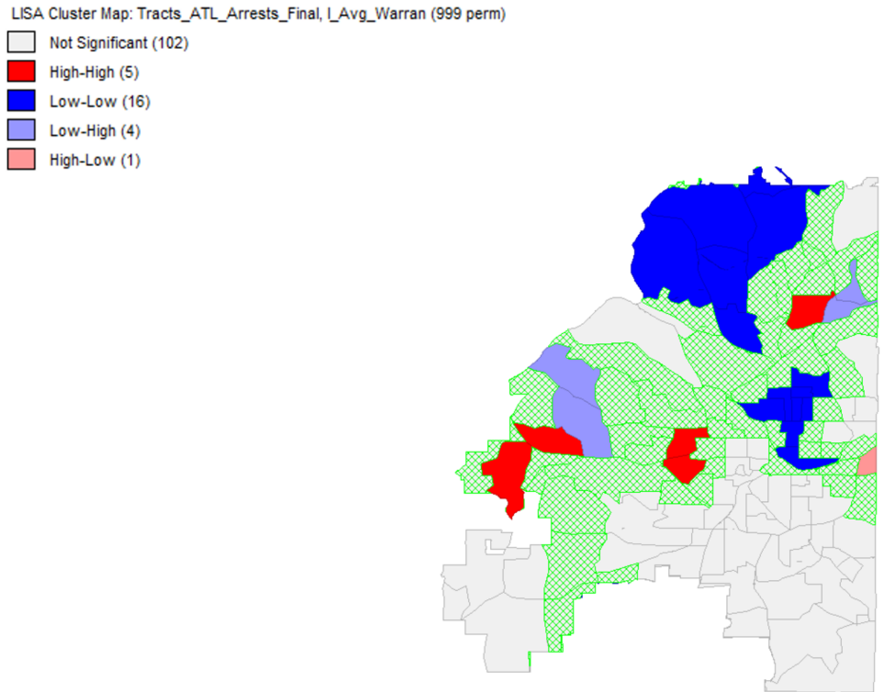


Figure 5. Local Moran's I Clusters of Rate of Warrants



To understand whether these patterns are linked to racial composition, I add neighborhood measures in Model 3 (see Table 9). Levels of social disorganization are often linked to the racial composition of a neighborhood (Peterson & Krivo, 2010), and they are also likely to explain police behavior. Police may rely upon signals of crime in addition to crime itself to determine where they will focus their attention, and social disorganization is one of those signals (Klinger, 1997, 2004). Qualitative research suggests that residents perceive order maintenance stops as more common in neighborhoods with higher levels of economic disadvantage (one measure of social disorganization) regardless of race (Brunson & Weitzer, 2008; Weitzer, 1999), and that the use of warrants are also more often used within disadvantaged neighborhoods (Balko, 2015; Goffman, 2014).

Policing behavior is also directly driven by crime rates. Order maintenance stops occur while officers are on patrol, and thus officers have a great deal of discretion in determining who is stopped and who is arrested (Klinger, 2004). This discretion is greatest for drug offenses (Lynch & Omori, 2014). Officers may rely on violent and property crime as an indication of where they should focus their patrol time, and thus their arrests (Klinger, 1997, 2004). APD arrest reports confirm this; officers often note when a particular area is a "known" high crime area, and occasionally describe the type of crime for which it is known (e.g., prostitution, theft from vehicle).

Warrant activity, too, is likely to be linked to the crime rate. Effort is required in order for officers to obtain approval for a search or arrest warrant (Balko, 2015). This effort is apparent in some of the arrest reports, which describe a great deal of investigatory activity that supports the use of a search or arrest warrant. Considering this effort, officers are unlikely to serve warrants when only minor drug activity is suspected. Instead they may serve them for substantial drug activity (as is confirmed by the link between warrants and more serious drug charges within all models in this section) or for drug activity occurring alongside property or violent crime. While the majority of arrest and search warrants do not discuss the reasons for the warrant, 8.82% of arrest warrants explicitly mentioned a violent crime as the motivation. Rates were lower for search warrants, with 1.21% mentioning either a property or violent crime. Yet in both cases, the modal reason for the warrant was unknown (47.06% for arrest warrants, 49.88% for search warrants), and thus it is likely that more warrants were built around property or violent crimes in addition to drug offenses. Even if a warrant is solely motivated by drugs, the APD may focus on those drug offenses occurring in high crime neighborhoods, assuming that drugs and other crime are linked, which some research supports (Bennett et al., 2008; Cunradi et al., 2006; Gorman et al., 2005). Finally, racial composition and arrest for serious crime are correlated (Parker Karen, Stults Brian, & Rice Stephen, 2005; Peterson & Krivo, 2010). A large body of research suggests that blacks more often reside in areas with high levels of crime (Nowacki, 2011). Thus, if officer behavior is guided by the crime rate of a neighborhood, a model that does not include the crime rate may misidentify a correlation between racial composition and arrest tactics.

Finally, police behavior is largely determined by the zone membership (Klinger, 2004). Police are heavily influenced by the leaders with whom they have direct contact (Lee, Lim, Moore, & Kim, 2013). Formal and informal policies and practices set by leadership within zones will change the decisions officers make when on routine patrol and, in turn, their likelihood of making an order maintenance stop. In influencing field behavior, the tone set by leadership can also affect the gathering of evidence for and use of search and arrest warrants.

As discussed in detail in Chapter 4, zones vary dramatically by the levels of crime and types of crime that they address (Atlanta Police Department, 2000). In addition, in the early 2000s, each zone was also addressing different evolving crime problems, with Zone 1 witnessing a rise in homicide and larceny; Zone 2 in larceny; Zone 3 in assault and homicide; Zone 4 in larceny and auto theft; Zone 5 in burglary; and Zone 6 experiencing a decline in all crime rates in 1999 (Atlanta Police Department, 2000). Not only is each zone unique in its leadership, but it also unique in the crime problems it faces, both of which affect the ways in which police handle drug crime by shaping their understanding of that area and the people living in it (Klinger, 1997, 2004).

Tables 9 and 10 report findings for two models. Model 3 adds racial composition and measures of social disorganization to Model 2 (shown in Tables 7 and 8). Model 4 adds crime rates and zone membership to Model 3. For Model 3, arrests that occur within neighborhoods that have a higher rate of black or non-white residents are more likely to involve order maintenance stops and/or warrants when compared to all other tactic types. In Table 9, a 1% increase in the percent black is associated with a 1-2% increase in the odds that an arrest involved order maintenance tactics or warrants. More meaningfully, the standard deviation for percent black is 37.40, and thus a one standard deviation increase in percent black is associated with a 37.4% increase in the odds that an arrest derives from an order maintenance stop and a 74.8% increase in the odds that it involves a warrant. Patterns are similar for the percent non-white. When compared to all other tactics involved in a felony drug arrest, these two arrest tactics are used more heavily within neighborhoods with a greater percentage of non-white residents even when controlling for characteristics of the arrestee, the case, and a neighborhood's social disorganization. These finding align earlier qualitative research on the topic (Benner, 2002; Brunson & Miller, 2006; Brunson & Weitzer, 2008).

Table 9. Random Intercept Logit Models for the Effect of Individual Race and Racial Composition on Police Stop Tactics - Traffic and Pedestrian Stops, 2005

(n=2,758)	Model 3 Odds Ratio (SE)				Model 4 Odds Ratio (SE)			
	Order Maintenance Stops		Warrants		Order Maintenance Stops		Warrants	
	Black[1]	Non-White[2]	Black[1]	Non-White[2]	Black[1]	Non-White[2]	Black[1]	Non-White2
Race	1.11 (0.25)	1.12 (0.26)	0.72 (0.23)	1.02 (0.31)	1.08 (0.24)	1.10 (0.25)	0.83 (0.28)	1.19 (0.39)
Male[3]	1.41 (0.22)*	1.41 (0.22)*	0.56 (0.10)**	0.55 (0.09)**	1.41 (0.21)*	1.40 (0.21)*	0.55 (0.10)**	0.54 (0.10)**
Age at Arrest	1.00 (0.01)	1.00 (0.01)	1.02 (0.01)**	1.02 (0.01)**	1.00 (0.01)	1.00 (0.01)	1.02 (0.01)**	1.02 (0.01)**
Top Charge on Arrest[4]								
Intent to Sell	0.75 (0.08)**	0.76 (0.08)**	3.94 (0.77)***	3.86 (0.75)***	0.76 (0.08)**	0.76 (0.08)**	3.91 (0.77)***	3.83 (0.75)***
Sales, Trafficking, Manufacturing	0.26 (0.08)***	0.26 (0.08)***	4.99 (1.21)***	4.88 (1.18)***	0.26 (0.08)***	0.26 (0.08)***	5.06 (1.26)***	4.98 (1.23)***
Drug Involved in Arrest[5]								
Meth/Amphetamines	1.06 (0.38)	1.07 (0.38)	1.64 (0.97)	2.01 (1.14)	1.03 (0.37)	1.04 (0.37)	1.64 (0.99)	2.00 (1.14)
Cocaine	0.82 (0.15)	0.82 (0.15)	2.44 (0.62)***	2.41 (0.61)***	0.82 (0.15)	0.82 (0.15)	2.46 (0.62)***	2.44 (0.61)***
Heroin	0.89 (0.28)	0.90 (0.28)	1.55 (0.46)	1.62 (0.47)+	0.99 (0.32)	1.00 (0.32)	1.33 (0.39)	1.37 (0.40)
Marijuana	0.90 (0.16)	0.90 (0.15)	2.40 (0.49)***	2.38 (0.48)***	0.89 (0.15)	0.89 (0.15)	2.42 (0.49)***	2.40 (0.48)***
Hallucinogens/Party Drugs	1.59 (0.41)+	1.59 (0.41)+	1.99 (0.89)	2.03 (0.91)	1.58 (0.40)+	1.59 (0.40)+	1.85 (0.84)	1.88 (0.86)
Unspecified	1.64 (0.38)*	1.64 (0.38)*	0.99 (0.48)	0.99 (0.48)	1.61 (0.37)*	1.61 (0.37)*	1.04 (0.53)	1.04 (0.53)
Racial Composition	1.01 (0.00)*	1.01 (0.00)*	1.02 (0.01)*	1.02 (0.01)+	1.01 (0.01)	1.01 (0.01)	1.01 (0.01)	1.01 (0.01)
Concentrated Disadvantage	1.01 (0.10)	0.99 (0.10)	0.90 (0.17)	0.88 (0.17)	0.94 (0.10)	0.93 (0.10)	0.78 (0.16)	0.77 (0.16)
Residential Instability	0.90 (0.07)	0.90 (0.07)	0.83 (0.11)	0.83 (0.11)	1.00 (0.08)	0.99 (0.08)	1.05 (0.13)	1.05 (0.12)+
Percent Foreign Born	1.01 (0.01)	1.00 (0.01)	0.99 (0.01)	0.98 (0.01)*	1.00 (0.01)	1.00 (0.01)	0.99 (0.01)	0.98 (0.01)
Property Crime Rate[6]					0.99 (0.01)	0.99 (0.01)	0.98 (0.03)	0.98 (0.03)
Violent Crime Rate[6]					0.97 (0.11)	0.98 (0.11)	1.00 (0.12)	1.01 (0.12)
Zone Membership[5]								
Zone 1					1.18 (0.18)	1.17 (0.18)	2.27 (0.45)***	2.26 (0.45)***
Zone 2					0.75 (0.34)	0.75 (0.34)	1.25 (0.49)	1.29 (0.52)
Zone 3					1.42 (0.21)*	1.41 (0.21)*	1.19 (0.29)	1.18 (0.29)
Zone 4					1.05 (0.15)	1.05 (0.15)	0.75 (0.15)	0.75 (0.15)
Zone 5					0.78 (0.14)	0.78 (0.14)	0.52 (0.13)***	0.52 (0.13)**

Zone 6					0.90 (0.23)	0.89 (0.23)	1.17 (0.35)	1.16 (0.35)

+p<.10, * p<.05, ** p<.01, *** p<.001

[1]Reference category: white, Asian, American Indian, Hispanic, or other race.

[2]Reference category: white.

[3]Reference category: female or other gender.

[4]Reference category: possession.

[5]Categories not mutually exclusive.

[6]Per 100 people.

Table 10. Random Intercept Logit Models for the Effect of Individual Race and Racial Composition on Police Stop Tactics - Pedestrian Stops Only, 2005

(n=2,758)	Model 3 Odds Ratio (SE)				Model 4 Odds Ratio (SE)			
	Order Maintenance Stops		Warrants		Order Maintenance Stops		Warrants	
	Black[1]	Non-White[2]	Black[1]	Non-White[2]	Black[1]	Non-White[2]	Black[1]	Non-White[2]
Race	1.29 (0.30)	1.31 (0.31)	0.73 (0.24)	1.02 (0.31)	1.26 (0.28)	1.28 (0.30)	0.84 (0.29)	1.20 (0.41)
Male[3]	1.21 (0.21)	1.21 (0.21)	0.53 (0.08)***	0.52 (0.08)***	1.21 (0.21)	1.21 (0.21)	0.52 (0.08)***	0.51 (0.08)***
Age at Arrest	1.01 (0.01)	1.01 (0.01)	1.02 (0.01)**	1.02 (0.01)**	1.01 (0.01)	1.01 (0.01)	1.02 (0.01)**	1.02 (0.01)**
Top Charge on Arrest[4]								
Intent to Sell	0.69 (0.09)**	0.69 (0.09)**	3.99 (0.79)***	3.90 (0.77)***	0.70 (0.09)**	0.70 (0.09)**	3.96 (0.79)***	3.89 (0.77)***
Sales, Trafficking, Manufacturing	0.16 (0.07)***	0.16 (0.07)***	5.54 (1.36)***	5.42 (1.32)***	0.16 (0.07)***	0.16 (0.07)***	5.66 (1.41)***	5.56 (1.38)***
Drug Involved in Arrest[5]								
Meth/Amphetamines	1.00 (0.41)	1.00 (0.41)	1.66 (0.98)	2.05 (1.15)	0.99 (0.41)	1.00 (0.41)	1.65 (0.99)	2.00 (1.14)
Cocaine	0.80 (0.19)	0.80 (0.19)	2.52 (0.60)***	2.48 (0.59)***	0.82 (0.19)	0.82 (0.18)	2.55 (0.61)***	2.52 (0.60)***
Heroin	0.73 (0.28)	0.73 (0.28)	1.49 (0.47)	1.56 (0.48)	0.84 (0.32)	0.84 (0.33)	1.30 (0.40)	1.35 (0.41)
Marijuana	0.63 (0.15)+	0.63 (0.15)+	2.30 (0.44)***	2.28 (0.43)***	0.64 (0.15)+	0.63 (0.15)+	2.32(0.44)***	2.30 (0.43)***
Hallucinogens/Party Drugs	0.61 (0.23)	0.62 (0.23)	1.48 (0.63)	1.51 (0.64)	0.64 (0.24)	0.64 (0.24)	1.40 (0.60)	1.41 (0.61)
Unspecified	1.85 (0.45)*	1.85 (0.45)*	0.95 (0.45)	0.94 (0.44)	1.83 (0.44)*	1.83 (0.44)*	0.99 (0.50)	0.99 (0.49)
Racial Composition	1.01 (0.00)+	1.01 (0.00)+	1.01 (0.01)+	1.01 (0.01)+	1.00 (0.00)	1.00 (0.01)	1.01 (0.01)	1.01 (0.01)
Concentrated Disadvantage	1.08 (0.17)	1.07 (0.17)	0.91 (0.17)	0.89 (0.17)	0.98 (0.14)	0.97 (0.14)	0.80 (0.17)	0.79 (0.17)
Residential Instability	0.92 (0.07)	0.92 (0.07)	0.83 (0.11)	0.84 (0.11)	0.93 (0.08)	0.93 (0.08)	1.04 (0.12)	1.04 (0.12)
Percent Foreign Born	1.01 (0.01)	1.01 (0.01)	1.00 (0.01)	0.98 (0.01)+	1.00 (0.01)	1.00 (0.01)	1.00 (0.01)	0.99 (0.01)+
Property Crime Rate[6]					0.99 (0.01)	0.99 (0.01)	0.99 (0.03)	0.99 (0.03)
Violent Crime Rate[6]					1.10 (0.11)	1.10 (0.11)	1.01 (0.12)	1.02 (0.12)
Zone Membership[5]								
Zone 1					0.95 (0.14)	0.95 (0.14)	2.16 (0.41)***	2.15 (0.41)***
Zone 2					0.78 (0.31)	0.79 (0.32)	1.36 (0.50)	1.41 (0.53)
Zone 3					1.29 (0.18)+	1.28 (0.18)+	1.11 (0.25)	1.09 (0.25)
Zone 4					1.09 (0.17)	1.09 (0.16)	0.74 (0.14)	0.74 (0.14)
Zone 5					0.94 (0.16)	0.95 (0.16)	0.55 (0.13)*	0.55 (0.13)*

Zone 6					0.73 (0.15)	0.73 (0.15)	1.10 (0.32)	1.09 (0.32)

+p<.10, * p<.05, ** p<.01, *** p<.001
[1]Reference category: white, Asian, American Indian, Hispanic, or other race.
[2]Reference category: white.
[3]Reference category: female or other gender.
[4]Reference category: possession.
[5]Categories not mutually exclusive.
[6]Per 100 people.

This pattern, though, is only significant when order maintenance is operationalized to include traffic stops (Table 9). For non-Northeastern cities, order maintenance policing may take place in cars as often as it does on the street (Dunn, 2015), as the different culture of Sunbelt states like Georgia and the physical layout of cities influences how many pedestrians are on the street at any time (Cooke & Marchant, 2006; Peponis, Ross, & Rashid, 1997; Strom, 2017). The differences across these two operationalizations may be a consequence of the fact that a pedestrian-only operationalization fails to categorize order maintenance traffic stops as such, and thus only captures a particular subset of order maintenance stops.

Model 4 (in Tables 9 and 10) show the results once crime rates and zones are added. When accounting for crime rates and zone membership, racial composition fails to attain significance in any of these models, and while crime rates are not related to the types of tactics used, zones are. Zones both contain parts of the city with a different racial composition and appear to encourage different policing tactics, and thus the former relationship between neighborhood racial composition and arrest tactics may in fact be due to the activities promoted by a particular policing zone.

The above findings, though, should not be taken to mean that arrests involving warrants and order maintenance stops are not racially patterned within the APD. They imply that they are not racially patterned within the APD as a whole, but instead are racially patterned within particular zones. To further investigate this, I rerun zone-specific models, similar to those in the previous section on Red Dog arrests. The results are displayed in Tables 11 and 12, wherein only the race-related variables are shown. Overall, the relationship between race and tactics varies notably by zone. When order maintenance stops include traffic stops, the percent black or nonwhite is positively linked to the use of this tactic in Zone 1, yet individual race is negatively related to the use of order maintenance tactics in this same zone, suggesting that officers in Zone 1 make more order maintenance stops of white individuals in predominately black neighborhoods. This pattern resembles out-of-place racial profiling, in which individuals are stopped and arrested more often because their race does not resemble that of the surrounding neighborhood (Warren et al., 2006). This pattern, though, only occurs in Zone 1.

Table 11. Zone-Specific Random Intercept Multinomial Logit Models for the Effect of Individual Race on Police Stop Tactics - Traffic and Pedestrian Stops

	Black[1] Odds Ratio (SE)					
	Zone 1 (n=1,047)	**Zone 2 (n=200)**	**Zone 3 (n=881)**	**Zone 4 (n=586)**	**Zone 5 (n=997)**	**Zone 6 (n=285)**
Order Maintenance Stops						
Race	0.55 (0.16)*	2.00 (1.14)	1.59 (0.54)	0.51 (0.27)	0.97 (0.30)	1.43 (0.90)
Racial Composition	1.01 (0.01)+	0.97 (0.02)	1.01 (0.01)	0.99 (0.03)	1.00 (0.01)	1.02 (0.02)
Warrants						
Race	0.75 (0.36)	0.91 (0.54)	1.56 (1.06)	0.48 (0.39)	1.12 (0.48)	0.52 (0.56)
Racial Composition	1.00 (0.02)	0.99 (0.83)	1.06 (0.02)**	0.88 (0.05)*	1.02 (0.01)**	1.06 (0.01)***
	Non-White[2] Odds Ratio (SE)					
	Zone 1 (n=1,047)	**Zone 2 (n=200)**	**Zone 3 (n=881)**	**Zone 4 (n=579)**	**Zone 5 (n=997)**	**Zone 6 (n=285)**
Order Maintenance Stops						
Race	0.53 (0.17)*	1.60 (0.80)	1.92 (0.76)+	0.53 (0.52)	0.92 (0.26)	1.33 (0.78)
Racial Composition	1.02 (0.01)+	0.98 (0.02)	1.01 (0.01)	0.99 (0.02)	1.00 (0.01)	1.02 (0.02)
Warrants						
Race	1.82 (1.00)	1.81 (1.59)	1.57 (1.05)	0.91 (0.69)	1.36 (0.69)	0.51 (0.56)
Racial Composition	1.00 (0.02)	0.98 (0.02)	1.06 (0.02)**	0.93 (0.06)	1.02 (0.01)*	1.06 (0.02)***

+p<.10, * p<.05, ** p<.01, *** p<.001
[1]Reference category: white, Asian, American Indian, Hispanic, or other race.
[2]Reference category: white.

Table 12. Zone-Specific Random Intercept Multinomial Logit Models for the Effect of Individual Race on Police Stop Tactics - Pedestrian Stops Only

	Black[1] Odds Ratio (SE)					
	Zone 1 (n=1,047)	**Zone 2 (n=200)**	**Zone 3 (n=881)**	**Zone 4 (n=586)**	**Zone 5 (n=997)**	**Zone 6 (n=285)**
Order Maintenance Stops						
Race	0.73 (0.21)	1.53 (1.24)	1.44 (0.52)	3.92 (4.84)	1.11 (0.32)	2.94 (2.17)
Racial Composition	1.00 (0.01)	1.02 (0.02)	1.01 (0.01)	1.00 (0.06)	1.00 (0.00)	0.99 (0.02)
Warrants						
Race	0.88 (0.41)	0.73 (0.54)	1.42 (1.05)	0.77 (0.54)	1.17 (0.48)	0.50 (0.51)
Racial Composition	1.00 (0.02)	0.98 (0.02)	1.06 (0.02)***	0.88 (0.04)**	1.02 (0.01)*	1.05 (0.02)**
	Non-White[2] Odds Ratio (SE)					
	Zone 1 (n=1,047)	**Zone 2 (n=200)**	**Zone 3 (n=881)**	**Zone 4 (n=579)**	**Zone 5 (n=997)**	**Zone 6 (n=285)**
Order Maintenance Stops						
Race	0.81 (0.24)	1.33 (0.95)	1.50 (0.72)	3.33 (4.82)	1.16 (0.29)	2.77 (1.90)
Racial Composition	1.00 (0.01)	1.03 (0.02)	1.01 (0.01)	1.04 (0.06)	1.00 (0.01)	0.98 (0.02)
Warrants						
Race	2.21 (1.15)	1.50 (1.06)	1.35 (0.98)	1.53 (1.20)	1.45 (0.69)	0.50 (0.51)
Racial Composition	0.99 (0.82)	0.98 (0.03)	1.06 (0.02)**	0.94 (0.05)	1.02 (0.01)*	1.05 (0.02)*

+p<.10, * p<.05, ** p<.01, *** p<.001
[1]Reference category: white, Asian, American Indian, Hispanic, or other race.
[2]Reference category: white.

In terms of warrants, the percent black or nonwhite is positively linked to the use of warrants in Zones 3, 5, and 6, but negatively linked to the percent black in Zone 4. These differences may be attributable to one of three factors. First, increased warrants in Zones 3, 5, and 6 may be linked to higher rates of more serious drug and criminal activity that coincides with higher rates of nonwhite residents within those zones, and the opposite pattern may be occurring in Zone 4. This explanation is unlikely, however, as the model controls for the severity and types of drugs involved in the arrests within those zones and the violent and property crime rates of the neighborhoods within those zones.

A more likely explanation for both findings for warrants and order maintenance stops is that these differences reflect different leadership and culture within each zone. Leadership and culture within Zone 1 may encourage the use of out-of-place racial profiling, whether explicitly or implicitly through deployment patterns and guidance about who to stop that does not directly mention race but alludes to it. Leadership and culture within Zones 3, 5, and 6 may encourage the use of warrants and investigatory activities that provide evidence supporting warrants (e.g., surveillance, repeated buys and busts) in the neighborhoods within these zones that have higher rates of nonwhite residents, and they may encourage the opposite within Zone 4.

Finally, these patterns, especially those observed for warrants, may be attributable to varied racial composition of neighborhoods within each zone. Zones 3, 5, and 6 have average rates of black residents of 79%, 51%, and 40%, respectively. Zones 1, 2, and 4, though, are far more homogenous, with the average neighborhood rates of black residents at 85%, 17%, and 95%, respectively. It seems that the zones in which racial composition has a strong, positive relationship with the use of warrants are those neighborhoods with greater racial diversity, and thus a greater potential for zone leadership and officers to make distinctions based on racial composition.

Discussion

Chapter 4 highlighted the racialized patterns of felony drug arrests in 2005. These patterns did not wholly reflect residential patterns within Atlanta, with black and other non-white Atlantans at a far greater risk of arrest than would be expected based on U.S. Census figures. The aim of this chapter was to better understand the factors that contributed to those racial arrest patterns. Specifically, this chapter examined whether the use of a police paramilitary unit (Red Dog), the use of search and arrest warrants, and the use of order maintenance stops were related to the race of an arrestee or the racial composition of the neighborhood in which they were arrested. Past research informed hypotheses that predicted race would be related to all three, suggesting that Red Dog, serving warrants, and conducting order maintenance stops disproportionately contributed to the racialized patterns of policing in Atlanta in 2005. Yet contrary to these expectations and past research, I found that in fully-specified regression models, race was not linked to the use of Red Dog, the use of warrants, or the use of order maintenance stops across the city as a whole.

Within certain zones and among certain drug types, however, there are distinct racialized patterns of arrests associated with Red Dog, warrants, and order maintenance stops. Specifically, it appears that when arrests are for possession, do not involve methamphetamines or party drugs, or are in Zones 5 and 6, non-white arrestees are proportionately more likely to be arrested by officers in the Red Dog unit than officers in other units. The use of warrants is positively linked to the percent non-white or black in Zones 3, 5, and 6, and the use of order maintenance stops are linked to the percent non-white or black in Zone 1.

Understanding these findings requires an understanding of Atlanta and the APD at the time. In 2005, there were both national and local moral panics about the use and sales of methamphetamine and party drugs like MDMA and GHB (Oetting et al., 2000; Theall et al., 2001; Wu et al., 2006). Red Dog's mission was to focus on the most serious drug offenses and, through the aggressive pursuit of arrests, minimize their impact. Since there was a good deal of panic surrounding these drug types, it is unlikely that Red Dog officers would have as much discretion about the pursuit of methamphetamine, MDMA, or GHB arrests. Yet for drugs that were still being used heavily by Atlantans, but for which the national moral panic had subsided, such as heroin or cocaine, Red Dog officers would have much greater discretion in choosing who to arrest. When such discretion exists, it contributes to the racialized patterns of a policing in this era in disproportionate fashion. A similar explanation can be applied to the distinction between possession arrests and anything greater than possession. Again, Red Dog was charged with addressing the most serious drug crime and thus, for arrests that involved intent-to-sell, sales, trafficking, or manufacturing charges, Red Dog officers likely did not exercise as much discretion about making an arrest. On the other hand, they would have had far greater discretion in choosing when to make an arrest for drug possession, and they used this discretion, too, in a racially disparate manner.

In addition to charge type, zones play a pivotal role in understanding the racialized patterns of policing in this era. Large police agencies are soft bureaucracies, projecting a rigid exterior that appears to the public to represent strong internal controls. In reality, they are loosely coupled organizations in which top tier management exercises little control over individual officer behavior. Management in a police department is unable to control the culture and behavior department-wide, and while some officers will align with departmental guidance, many will adhere to differing subcultures (Jermier, Slocum, Fry, & Gaines, 1991). A great deal of power is held by frontline supervisors, like sergeants and lieutenants, as they serve as the bridge between management and officers on the street. In fact, officers' choices about how to spend their patrol time is determined more by the priorities of their immediate supervisors than by their own personal priorities (Engel & Worden, 2006; Mastrofski & Willis, 2010), and an officer's overall commitment to their job is largely determined by the feedback they receive from these frontline supervisors (R. R. Johnson, 2012).

While supervisors can act as bridge between management and officers, research suggests a disconnect between frontline supervisors and senior management (Knight, 2015). Instead, officers and frontline supervisors work together to construct their perceptions of good performance rather than base their understanding of good policing on what senior management says (Knight, 2015). This occurs because, in a large department, senior management cannot oversee activity across the city and must instead rely on localized management to oversee these activities. Localized management in the APD exists at the zone level, and within zones, officers work with a similar set of individuals, in similar neighborhoods day-after-day. In doing so they develop a distinct workgroup composed of frontline leadership and other officers in that zone (Klinger, 2004). Within these workgroups, officers construct informal norms for policing based on both zone conditions and organizational properties (Klinger, 2004). The policing profession is especially susceptible to this sort of localized norm building because peer group cohesion is quite strong in policing. Officers in a zone rely on each other for physical safety and this creates quick, tight bonds within a workgroup (R. R. Johnson, 2012).

To understand racialized patterns of arrests in a department as large as the APD, it is necessary to examine differences across zones. APD officer norms for policing are not citywide, but zone-wide. This appears to be true even for Red Dog, which is disconnected from any particular zone. Yet because Red Dog officers often work in collaboration with other APD officers or rely on information gathered from other APD officers, their behaviors are also patterned by zones. Finding that Red Dog, warrants, and order maintenance stops are related to the racial composition of neighborhoods within certain zones suggests that these factors do contribute to racialized patterns of policing in Atlanta in 2005, but only in discrete sections of the city. The link between race and Red Dog is not citywide but, within certain zones, it is evident. The same is true of warrants and order maintenance stops. For example, while non-white Atlantans writ large are not more likely have a warrant served at their residence when controlling for neighborhood and case characteristics, Atlantans in Zones 3, 5, and 6 are. As others have found before, the impact of race on the use of certain tactics or units in a large police department is specific to certain parts of a city (Gelman et al., 2007; Goffman, 2014). While Red Dog, warrants, and order maintenance stops were not driven by race at a citywide level, Atlanta is a large, diverse city, and for certain arrestees, the impact of these units and these tactics may be powerful.

In short, the racialized patterns of felony drug arrests in the "tough on crime" era are only partially explained by the use of certain units and tactics. Writ large, Red Dog does not account for these differences, but for select drug offenses and within certain zones, they do contribute to racialized disparities in policing. For order maintenance stops and the use of warrants, there is also no clear, citywide relationship, yet there are clear patterns within zones. In addition, while the relationship between race and the use of warrants is largely explained by drug type and severity, there is nonetheless a strong bivariate relationship between the two. This suggests that warrants contribute to racialized patterns of policing even if that contribution can be explained by the drug offenses associated with warrants. In the next chapter, I conduct a similar exploration of the units and tactics that contributed to racialized patterns of policing after Atlanta transitioned to a "smart on crime" model.

Chapter 6. "Smart on Crime" Policing in Atlanta

Policing has changed substantially over the past decade. In the wake of a backlash against the "tough on crime" tactics common in the 1990s and early 2000s, departments began a slow shift towards a "smart on crime" approach (Telep, 2016). The shift reflected a larger trend towards more evidence-based practice in other areas of the criminal justice system, such as risk-based models for probation and parole (Latessa, Lwemke, Makarios, Smith, & Lowenkamp, 2010; Lovins, Latessa, May, & Lux, 2018).

In the "smart on crime" era, police departments emphasized police-community interactions and creative solutions to crime problems in place of a heavy use of arrests (National Research Council, 2004). In addition, intelligence-led policing (ILP) and other data-driven strategies became increasingly common. Such strategies involve the use of data collected by police departments and other agencies to determine the locations and styles of policing best suited for each city's or area's crime problems (Ferguson, 2017).

This shift was motivated by the failure of the "tough on crime" approach, particularly within four areas. First, the "tough on crime" approach was expensive, and in the midst of the recession, many departments were looking for a cheaper way to police (Bueermann, 2012). Second, the "tough on crime" approach was generally ineffective (National Research Council, 2004). Third, police legitimacy suffered under "tough" tactics, which encouraged behavior that distanced the public from the officers policing their city (Balko, 2015; Lowery, 2016). Finally, racialized patterns of policing and general racial tensions were high during the "tough on crime" era, and so departments turned to tactics like COP and POP to improve police-community relations within black and Hispanic communities, and strategies like ILP to provide a seemingly race-neutral approach to policing (Ferguson, 2017; Lowery, 2016; National Research Council, 2004; Telep, 2016). This shift occurred within Atlanta between 2006 and 2011, and was a response to the behavior of the Red Dog unit. The result was a complete overhaul of the department, with the creation of a community policing unit, the addition of new training, and the replacement of Red Dog with a data-driven unit focused on violent crime, APEX ("Atlanta police disband Red Dogs," 2011; Bagby, 2007; Blau, 2016; Cook, 2013; Visser & Garner, 2011).While the ethos of policing in the "smart on crime" era advocates race neutral tactics, the rising use of data within the criminal justice system over the past few years has been linked to racial disparities (Ferguson, 2017). Yet few investigations have been conducted into the racial implications of this shift (Desmond & Valdez, 2012). As shown in Chapter 4, racialized patterns of policing remained in 2012, and it is unclear what measurable aspects of policing contributed to them.

To better understand race and the policing of drug offenses in the "smart on crime" era, I use (1) hierarchical logistic regression models to explore the relationship between individual race and neighborhood racial composition and the use of data-driven policing strategies and (2) hierarchical multinomial regression models to explore the relationship between individual race and neighborhood racial composition and the use of order maintenance stops and search and arrest warrants. I account for individual, case, and neighborhood covariates likely to affect the relationship between race and the use of these units and tactics, and explore the impact of policing zones on these relationships.

Race and Data-Driven Policing

Data-driven policing was the primary replacement for Red Dog (Blau, 2016), and in agencies across the U.S., data-driven tactics have replaced “tough on crime” tactics and units. These units allow agencies to claim neutrality and objectivity because they are able to attribute their decisions to an analytic source (D. L. Carter & Carter, 2008; J. G. Carter & Phillips, 2015; Ratcliffe, 2002). This logic, though, ignores the fact those analyses are based on data gathered by subjective sources: police officers in both the current and past era of policing (Ferguson, 2017). Data-driven arrests may contribute to racial patterns of policing due to biases involved in the production and collection of the data.

In total, only 4.26% (n=42) of all felony drug arrests in 2012 involved a data-driven unit and, among the 97 Atlanta census tracts with any drug arrest in 2012, the rate of data-driven arrests ranged from 0% to 33.33% of all arrests ($\bar{x}$ = 3.40% and median = 0.00%). Clearly, the use of data-driven units to make felony drug arrests is rare. The rarity of data-driven felony drug arrests, though, is not surprising. While these units were used as a replacement for Red Dog, their adoption occurred simultaneously with a shift in focus towards violent crime (Atlanta Police Department, 2011, 2012, 2013, 2014; Blau, 2016; Cook, 2013). The vast decrease in use of specialized units to address drug crimes is as much a reflection of the change from “tough on crime” to “smart on crime” policing as is the switch from PPUs to data-driven units.

Table 1 provides the bivariate relationships between the use of data-driven units and all arrestee-case level covariates included in the models discussed below; Table 2 reports the relationship between all neighborhood-level covariates and the rate of data-driven arrests within a neighborhood. Chi-squared, t-test, and Pearson correlation coefficients reveal that data-driven arrests are more likely to involve sale, trafficking, or manufacturing charges; more likely to occur in neighborhoods with higher rates of black or non-white residents; more likely to occur in neighborhoods with higher rates of concentrated disadvantage and higher total index crime rates; and more likely to occur in neighborhoods within Zone 3 and less likely occur in neighborhoods within Zones 2 and 6. No data-driven arrests involved methamphetamines/amphetamines or hallucinogens, so these variables were removed from the regression models investigating data driven policing in order to retain the degrees of freedom that would be lost if variables that perfectly predicted the outcome were included in the model. Age is not normally distributed; taking the natural logarithm of age results in a distribution that better approximates a normal distribution, and thus all models include logged age. Violent crime rates and property crime rates were included as two distinct variables in the analyses for 2005, but in 2012, these measures are highly collinear. To correct for this, I combined them into a single measure of the total index crime rate for each neighborhood.

While there is no significant bivariate relationship between arrestee race and the use of data-driven tactics, accounting for other covariates connected to the use of data-driven arrests may reveal noteworthy patterns of arrestee race as a result of suppression effects. While the differences are not significant, data-driven arrests have a higher rate black and non-white arrests than do all other arrests. In addition, neighborhood racial composition exhibits a strong bivariate relationship with the use of data-driven units. As many of these units are used to determine the geographic distribution of officers throughout a city or zone, it is not surprising that data-driven tactics would be strongly linked to geographic patterns of race (Braga, 2001; Ferguson, 2017).

Table 1. Arrestee-Case Level Variables by Data-Driven Policing, 2012

(n=987)	Non-Data-Driven Arrests (n=945)	Data-Driven Arrests (n=42)
	Mean (SD)/Proportion	Mean (SD)/Proportion
Black[1]	86.14%	92.86%
Non-White[2]	87.09%	92.86%
Male[3]	88.57%	95.24%
Age at Arrest	37.52	37.43
Top Charge on Arrest[4]***		
Possession	62.75%	45.24%
Intent to Sell	26.98%	23.81%
Sales, Trafficking, Manufacturing	10.26%	30.95%
Drug Involved in Arrest[5]		
Meth/Amphetamines	4.34%	0.00%
Cocaine	55.87%	54.76%
Heroin	8.47%	11.90%
Marijuana	26.57%	33.33%
Hallucinogens/Party Drugs	2.65%	0.00%
Unspecified	13.12%	4.76%

+p<.10, * p<.05, ** p<.01, *** p<.001
[1]Reference category: non-black.
[2]Reference category: white, non-Hispanic.
[3]Reference category: female or other gender.
[4]Reference category: possession.
[5]Categories not mutually exclusive.

Table 2. Neighborhood Level Variables by Data-Driven Policing, 2012

(n=97)	Pearson Correlation Coefficient/ Proportion Red Arrests
Percent Black***	0.35
Percent Non-White***	0.32
Concentrated Disadvantage**	0.31
Residential Instability	0.11
Percent Foreign Born	-0.16
Total Index Crime Rate[1]**	0.26
Zone Membership[2,3]	
Zone 1	4.07%
Zone 2*	0.00%
Zone 3*	6.52%
Zone 4	3.06%
Zone 5	3.17%
Zone 6*	1.31%

+p<.10, * p<.05, ** p<.01, *** p<.001
[1]Per 100 people.
[2]Categories not mutually exclusive.
[3]T-test of proportion Red Dog arrests in neighborhoods within and outside of each zone.

As with the models in the previous chapter, in order to fully explore the relationship between race and data-driven units, I estimate these models iteratively, mirroring the analytic strategy of the previous chapter: I begin with a model control for demographics; then I add case characteristics; this is followed by a model that adds measures of social disorganization; and finally, at the last stage, I estimate a model that adds the total index crime rate and zones. I also examine zone-specific models. The final models account of all relevant arrestee, case, and neighborhood characteristics that are likely to explain when data-driven units are involved in an arrest and, in so doing, isolate the effect of race and racial composition.

To understand the importance of each control variable, it is useful to consider how data-driven units work. Data-driven policing captures a variety of more specific strategies, including hot spots policing, intelligence-led policing, CompStat, and problem-oriented policing (Braga & Bond, 2008; Braga et al., 2001; Braga et al., 2006; D. L. Carter & Carter, 2008; Dabney, 2010; Weisburd, Telep, Hinkle, & Eck, 2010). While the specifics of each strategy vary, the connective tissue is the use of data (often, administrative data collected by police officers) to inform where police police and how police police (Ferguson, 2017). Essentially, data are employed to direct police to certain locations, towards certain people, and to direct the ways in which police act. In some departments, these strategies are applied universally to all problems, but in many departments—especially in 2012 when these strategies were still novel—they were sequestered within specialized units with limited staff and were often used to target more serious offenses (Ferguson, 2017; Lewandowski, Carter, & Campbell, 2018; Telep, Ready, & Bottema, 2018). This was the case in Atlanta in 2012 (Atlanta Police Department, 2012). Thus the two primary aspects of data-driven policing are the reliance on data and the focus on more serious offenses.

Both of these factors suggest a need to control for gender and age. As Ferguson (2017) notes, one of the inherent issues with the data-driven approach is that while the methods of analysis may not involve explicit bias, the data upon which they are built does as it was collected not by a program, but by police officers, with all of their very human conscious and unconscious biases. A vast body of research establishes that police often focus their attention on young minority men (Brunson & Miller, 2006; Brunson & Weitzer, 2008; Gau & Brunson, 2015), and analyses based on data from the past likely serve to guide officers to focus on the very same people in the "smart on crime" era.

Because data-driven units focus on more serious offenses, I add an indication of the most serious drug offenses in an arrest to this model. Data-driven arrests are rooted in old arrest data, and thus if there is a pattern of heavy enforcement for certain drug types or if certain drug types are associated with violent or property crimes, then drug type should also influence the involvement of data-driven units in arrests. Finally, if there are differences in involvement in certain drug types or charges by race, then failing to control of drug severity and type results in a misspecification of the relationship between race and data-driven units.

A report by the National Drug Early Warning System on drug trends in metropolitan Atlanta reveals that between 2007 and 2012, drug trends were fairly steady across all drug types, although cocaine use was decreasing and heroin was increasing in the years leading up to 2012 (Dew, Golubovic, & Castleberry, 2017). Trends following 2012 reflect current drug issues, with the steep rise in use of methamphetamines and various opioids, including fentanyl, morphine, and heroin, yet these recent drug epidemics had only begun to affect Atlanta as of 2012 (Dew et al., 2017). Reports by the National Drug Intelligence Center in 2010 and 2011 reveal that certain drug types were more commonly trafficked and sold within the city at this time, and that certain drug types are more commonly linked to serious violent or property crime (United States Department of Justice, 2010, 2011). In particular, methamphetamine trafficking and sales were increasing, as were sales of controlled prescription drugs, such as opioids, and sales of both drug types were racialized such that they tended to be more commonly sold by either white or Hispanic individuals (United States Department of Justice, 2010, 2011). Cocaine sales, while not increasing, was quite high, and law enforcement agencies report it as the drug type most commonly associated with violent crimes (United States Department of Justice, 2010).

Based on data from 2012, 2013, 2014, 2015, and 2016, treatment admissions for each drug type in Atlanta during this time period vary substantially by demographics. Prescription opioids and methamphetamine were more common among females, and all other drug types were more common among males; cocaine is far more common among individuals over forty-five, while marijuana and prescription opioids are more common among younger individuals; and marijuana and cocaine are far more common among African Americans, while heroin, prescription opioids, and methamphetamines are far more common among whites (Dew et al., 2017).

Table 3 provides findings from two models. Model 1 incorporates arrestee race, age, and gender. Model 2 adds drug type and severity to Model 1. First, in both models, arrest characteristics are not related to involvement of data-driven units. While there are good reasons to believe that data-driven tactics may focus disproportionately on young, non-white males, this is not the case for felony drug arrests in Atlanta. Second, no single drug type is especially linked to the involvement of a data-driven unit in an arrest. These units focus equally upon all four drug types, which is not particularly surprising because no specific drug type was identified by law enforcement as a particular problem within Atlanta during this time period, and in the years leading up to it. Third, and finally, the odds of a data-driven unit being involved in an arrest increase significantly when the arrest involves a sale, trafficking, or manufacturing offense. Specifically, for the two operationalizations of race, sales, trafficking, and manufacturing offenses are associated with a 316% or 320% increase in the odds of the arrest involving a data-driven unit. Data-driven units often focus on more serious offending. Further, even more so than particular drug types, drug sales are more likely to be associated with other property and violent crime (United States Department of Justice, 2010). This is particularly the case with drug sales that are implicated in gang activity (Bellair & McNulty, 2009; O'Brien, Daffern, Chu, & Thomas, 2013), which is common in Atlanta as the city serves as drug transportation hub to much of the southeastern United States (Dew et al., 2017; Theall et al., 2001; United States Department of Justice, 2010, 2011).

Table 3. Random Intercept Logit Models for the Effect of Individual Race on the Use of Data-Driven Units, 2012

(n=987)	Model 1 Odds Ratio (SE)		Model 2 Odds Ratio (SE)	
	Black[1]	**Non-White[2]**	**Black[1]**	**Non-White[2]**
Race	1.99 (1.03)	1.82 (0.94)	1.98 (0.93)	1.77 (0.83)
Male[3]	2.41 (1.63)	2.42 (1.64)	2.75 (1.96)	2.75 (1.95)
Logged Age at Arrest	0.88 (0.44)	0.89 (0.45)	0.96 (0.50)	0.97 (0.51)
Top Charge on Arrest[4]				
Intent to Sell			1.28 (0.49)	1.28 (0.49)
Sales, Trafficking, Manufacturing			4.16 (1.55)***	4.20 (1.57)***
Drug Involved in Arrest[5]				
Cocaine			0.86 (0.31)	0.88 (0.32)
Heroin			1.69 (0.68)	1.67 (0.66)
Marijuana			0.70 (0.23)	0.72 (0.24)
Unspecified			0.40 (0.26)	0.40 (0.26)

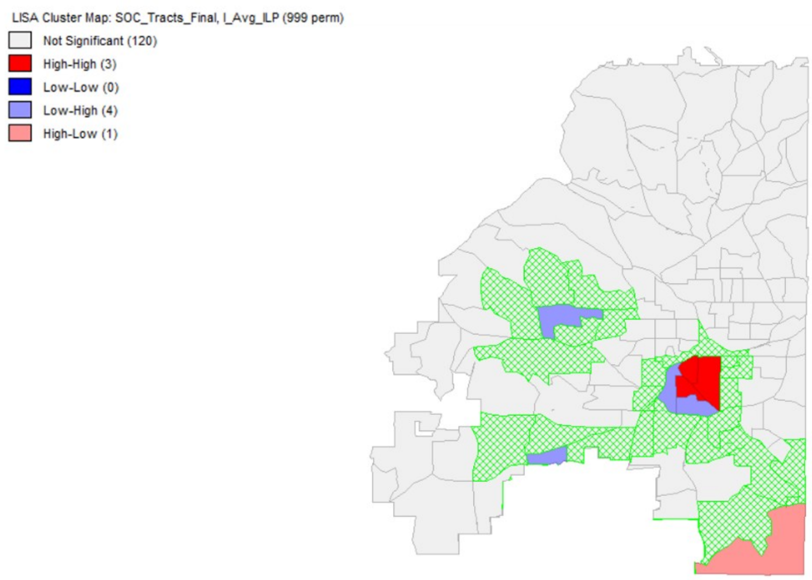
+p<.10, * p<.05, ** p<.01, *** p<.001
[1]Reference category: white, Asian, American Indian, Hispanic, or other race.
[2]Reference category: white.
[3]Reference category: female or other gender.
[4]Reference category: possession.
[5]Categories not mutually exclusive.

While there are no racialized patterns of policing at the arrestee level, racialized patterns of policing may exist across neighborhoods. Data-driven policing focuses on the locations in which crime occurs (Braga, 2001; Ferguson, 2017; National Research Council, 2004), and because police do not patrol across their jurisdictions equally (Klinger, 2004), the geographic patterns already reflected in police activity are likely to be exacerbated in data analysis (Ferguson, 2017). Even though data-driven units do not fall within particular zones, they should reflect the differing patterns of enforcement by zone (Engel & Worden, 2006; R. R. Johnson, 2012; Rowe, 2006). Neighborhoods are often racially homogenous for a variety of reasons, including the settlement patterns of immigrants to America and housing policies that severely limited the options of racial and ethnic minorities (Peterson & Krivo, 2010; Singer, 2004; Wilkerson, 2010). Because of this, different policing patterns by neighborhoods are likely to have racial implications.

To assess this, I add neighborhood level variables to Model 3 (see Table 4), but before explicitly modeling these relationships, I determine if data-driven arrests exhibit geographic patterning. Using GeoDa 1.8.14, the clustering of the data-driven arrest rate was examined with the global Moran's I statistic. The data-driven arrest rate is defined as the number of data-driven arrests over the total number of felony drug arrests in a tract. The results indicate that the citywide clustering of data-driven arrests is statistically distinct from spatial randomness ($I = 0.10$; $p<0.05$). To explore local patterns of spatial clustering, the local Moran's I was used. This test allows for an examination of specific census tracts in Atlanta where either high or low rates of data-driven arrests cluster. Figure 1 illustrates these clusters using a significance level of $p<0.05$. High rates of data-driven arrests cluster around the edges of Zones 5 and 6, near the Downtown and East

Atlanta areas. This area, as well as further west and southwest into Zones 1 and 4, also contains tracts with especially low rates of data-driven arrests surrounded by tracts with high rates. Far south in the city, a tract with high rates of data-driven arrests is surrounded by tracts with low rates. In short, there are clear patterns of spatial clustering by neighborhood, and these patterns appear to be zone-specific.

Figure 1. Local Moran's I Clusters of Rate of Data-Driven Arrests



To determine if these geographic patterns follow racial patterns, I build upon Model 2 in Table 3 by adding a measure of racial composition and a series of neighborhood measures. Social disorganization has been linked to greater drug use (Jang & Johnson, 2001; Winstanley et al., 2008). Further, it is connected to gang activity, which is often associated with more serious drug crime as well as violent and property crime (Mares, 2009), and social disorganization is also directly linked to violent and property crime (Peterson & Krivo, 2010; Sampson et al., 1997). Finally, in choosing where to focus their attention, officers rely On indicators of potential crime, and signs of social disorganization are among those indicators (Klinger, 1997, 2004). Because data-driven units are guided by the actions of past officers and they focus on more serious crime, data-driven units are likely to make more arrests in areas with high levels of social disorganization. Social disorganization and racial composition are often linked in neighborhoods within the U.S., with more disorganized neighborhoods often having higher rates of non-white residents (Peterson & Krivo, 2010).

Data-driven units also focus on direct indications of serious crime, like the violent and property crime rate (Ferguson, 2017). There is an overlap between the where serious drug crime occurs and where violent and property crime occur (Baumer et al., 1998; Gorman et al., 2005; James et al., 2004; Martínez et al., 2008), and those more heavily involved in drug offending are also more likely to be heavily involved in other criminal activity (Bennett et al., 2008), especially intimate partner violence (Cunradi et al., 2006; James et al., 2004) and gang activity (Bellair & McNulty, 2009). Neighborhoods with high rates of violent and property crime likely also have high rates of serious drug crime.

Finally, in departments as large as the APD, and cities as large as Atlanta, police do not function as citywide agencies; they function according to zones (Klinger, 1997, 2004; Mastrofski, Ritti, & Hoffmaster, 1987; Smith, 1986). The data-driven units operating within the APD are not zone-specific, but rather department-wide units (Atlanta Police Department, 2011, 2012, 2013, 2014). Nonetheless, a majority of the agency is organized into zones, and so the geographic boundaries and regions that matter even to officers who are not limited to one particular zone (like Red Dog or data-driven units) are zones. In essence, in large U.S. cities, police think of crime in terms of zones (Klinger, 1997, 2004). In addition, the information data-driven units rely upon often comes from officers who are assigned to a certain zone. Just as Red Dog officers rely on information gathered not only from other Red Dog officers, but from the whole of the APD, so do data-driven units. In fact, the effect of different policing behaviors by zone is likely enhanced for data-driven units because they explicitly rely on this data; using it govern current behavior is the very essence of data-driven policing (Braga, 2001; D. L. Carter & Carter, 2008; J. G. Carter & Phillips, 2015; Ferguson, 2017). If zonal variation is built into that data because police officers behave differently in different zones, then that variation will be directly reflected in the behavior of data-driven officers.

I account for these factors in two models shown in Table 4. Model 3 adds racial composition and social disorganization to Model 2, and Model 4 adds the crime rate and zone membership to Model 3. Because no data-driven arrests occurred in Zone 2, I remove the indicator variable for Zone 2 from the model so as not to lose those observations.[5] There are a couple important takeaways. First, in Model 3, the use of data driven arrests is significantly related to the percent black or non-white in a census tract when controlling for arrestee and case characteristics as well as for measures of social disorganization. In both cases, an increase in the percent black or percent non-white in a census tract is associated with 4% increases in the odds of an arrest involving a data-

[5] While it cannot be examined within the context of the regression model displayed in Table 4, the very absence of any data-driven arrests in Zone 2 suggests racialized patterns of policing among data-driven units by zone. Census tracts in Zone 2 have noticeably lower rates of black or non-white residents, with a mean of 22.01% black residents, compared to 83.96% in Zone 1, 81.90% in Zone 3, 91.95% in Zone 4, 48.46% in Zone 5, and 43.37% in Zone 6.

driven unit. Data-driven units to seem to focus their felony drug arrests in neighborhoods with high rates of non-white residents. Yet when crime and zone membership are added in Model 4, the relationship between neighborhood racial composition and data-driven units loses significance (although it still approaches significance for percent black residents). This suggests that the relationship between racial composition and data-driven units is partially a product of the crime and zone membership. Data-driven units are likely to focus their arrests in neighborhoods with the highest crime rate (Braga, 2001; Ferguson, 2017). In 2012 in neighborhoods across Atlanta, the rate of residents who are non-white is positively correlated with the crime rate ($p<0.01$). If data-driven units focus on areas with high violent and property crime rates, then they may make more arrests in neighborhoods with high rates of non-white residents.

Table 4. Random Intercept Logit Models for the Effect of Individual Race and Racial Composition on the Use of Data-Driven Units, 2012

(n=987)	Model 3 Odds Ratio (SE)		Model 4 Odds Ratio (SE)	
	Black[1]	Non-White[2]	Black[1]	Non-White[2]
Race	1.49 (0.73)	1.43 (0.69)	1.51 (0.75)	1.45 (0.71)
Male[3]	2.68 (1.81)	2.74 (1.89)	2.72 (1.90)	2.75 (1.95)
Age at Arrest	1.01 (0.49)	1.00 (0.5)	0.98 (0.49)	0.97 (0.49)
Top Charge on Arrest[4]				
Intent to Sell	1.28 (0.52)	1.27 (0.51)	1.17 (0.43)	1.17 (0.43)
Sales, Trafficking, Manufacturing	4.43 (1.75)***	4.37 (1.71)***	4.86 (1.93)***	4.93 (1.95)***
Drug Involved in Arrest[5]				
Cocaine	0.87 (0.33)	0.90 (0.34)	0.79 (0.33)	0.81 (0.33)
Heroin	1.51 (0.70)	1.44 (0.67)	1.39 (0.68)	1.29 (0.63)
Marijuana	0.63 (0.23)	0.67 (0.24)	0.62 (0.21)	0.64 (0.22)
Unspecified	0.37 (0.25)	0.38 (0.26)	0.38 (0.26)	0.39 (0.26)
Racial Composition	1.04 (0.02)*	1.04 (0.02)*	1.04 (0.03)+	1.04 (0.03)
Concentrated Disadvantage	1.14 (0.25)	1.12 (0.27)	1.43 (0.43)	1.50 (0.46)
Residential Instability	1.33 (0.27)	1.24 (0.25)	1.06 (0.27)	0.94 (0.23)
Percent Foreign Born	1.08 (0.04)*	1.05 (0.03)+	1.05 (0.03)+	1.03 (0.03)
Total Index Crime Rate[6]			1.03 (0.03)	1.04 (0.03)
Zone Membership[5]				
Zone 1			0.59 (0.36)	0.60 (0.37)
Zone 3			1.09 (0.56)	1.13 (0.61)
Zone 4			0.55 (0.28)	0.57 (0.30)
Zone 5			1.64 (0.88)	1.84 (0.98)
Zone 6			0.72 (0.39)	0.67 (0.37)

+p<.10, * p<.05, ** p<.01, *** p<.001
[1]Reference category: white, Asian, American Indian, Hispanic, or other race.
[2]Reference category: white.
[3]Reference category: female or other gender.
[4]Reference category: possession.
[5]Categories not mutually exclusive.
[6]Per 100 people.

The findings show, however, that crime rates are not related to the use of data-driven models, and neither is zone membership. For zones, this may be because these units are influenced by past data collected by officers working within zones, and so their arrest behavior cannot be distinguished from the current behavior of those officers. That said, since they are likely to focus on more serious offenses, and the presence and enforcement of serious offenses is likely to vary by zone, it is surprising that there is no effect for the zone dummy variables. For crime, it is possible that other variables included in the model (including racial composition) explain some of the relationship between crime and data-driven units.

The change in significance for racial composition from Model 3 to Model 4 implies that zones and crime rates are driving some of the relationship between neighborhood racial composition and data-driven units. To take police departments and the data-driven policing movement at its word, crime rates are the real drivers of police behavior under a data-driven regime and any racialized patterns of policing that result are simply an unintended consequence (Atlanta Police Department, 2011, 2012; Ferguson, 2017). Yet even if that were so, it would still imply (as is demonstrated in Model 3) that data-driven policing is leading to a disproportionate focus on non-white neighborhoods, even if the analysis is rooted in non-racial factors.

While zones are not linked to data-driven policing in Model 4, theory suggests they are relevant to any policing patterns within a large city (Klinger, 1997, 2004), and thus I further explore the relationship between race and data-driven units by zone. I do so by running Model 4 (excepting the zone dummy variables) for census tracts that overlap each zone one zone at a time. The results are displayed in Table 5, and suggest clear patterns by zones for the impact of neighborhood racial composition, but not arrestee race, on the use of data-driven units in felony drug arrests. Specifically, in Zones 1, 3, and 4, data-driven arrests are more likely in census tracts with higher rates of black or non-white residents. Yet in Zone 5, data-driven arrests are less likely in census tracts with higher rates of non-white or black residents. These differences across zones may partially explain why citywide patterns for racial composition do not emerge in Model 4. Critically, though, in many zones, the likelihood of data-driven unit arrests increases as does the non-white population in a neighborhood, and overall, the likelihood of an arrest by a data-driven units varies by zone. As with Red Dog, even though data-driven units are not zone-specific, their actions are guided by zone boundaries.

Table 5. Zone-Specific Random Intercept Logit Models for the Effect of Individual Race and Racial Composition on the Use of Data-Driven Units, 2012

	Black[1] Odds Ratio (SE)				
	Zone 1 (n=341)	**Zone 3 (n=113)**	**Zone 4 (n=75)**	**Zone 5 (n=458)**	**Zone 6 (n=346)**
Race	0.65 (0.42)	Omitted[2]	Omitted[2]	1.80 (0.79)	Omitted[2]
Racial Composition	1.19 (0.05)***	1.17 (0.03)***	1.93 (0.53)*	0.95 (0.02)**	0.99 (0.05)
	Non-White[3] Odds Ratio (SE)				
	Zone 1 (n=341)	**Zone 3 (n=113)**	**Zone 4 (n=75)**	**Zone 5 (n=458)**	**Zone 6 (n=346)**
Race	0.58 (0.36)	Omitted[4]	Omitted[4]	1.67 (0.72)	Omitted[4]
Racial Composition	1.22 (0.10)*	1.41 (0.24)*	3.38 (2.96)	0.96 (0.02)*	1.00 (0.05)

+p<.10, * p<.05, ** p<.01, *** p<.001
[1]Reference category: white, Asian, American Indian, Hispanic, or other race.
[2]No black arrestees in this zone were arrested by data-driven units, thus those observations were dropped
[3]Reference category: white.
[4]No non-white arrestees in this zone were arrested by data-driven units, thus those observations were dropped

Race and Arrest Types

Data-driven units appear to be part of the explanation for the racialized patterns of policing in the "smart on crime" era, but they leave much unexplained. On a citywide level, when accounting for other relevant factors, arrestee race and neighborhood racial composition are not linked to the use of data-driven units. Yet racialized patterns of policing may be attributable to certain tactics, specifically the use of search and arrest warrants and order maintenance stops. Table 6 presents the use of these tactics in the "smart on crime" era. Warrants are the least common arrest tactic, occurring in only 9.73% of all arrests, followed by order maintenance stops, which occur in 34.25% of arrests when traffic stops are included and 18.34% of arrests when only pedestrian stops are included.

Table 6. Tactics that Lead to Arrest, 2012

(n=987)	N (%)
Pedestrian and Traffic Stop Operationalization	
Serving Warrants	96 (9.73%)
Order Maintenance Stops	338 (34.25%)
Other Tactics	553 (56.03%)
Pedestrian Stops Only	
Serving Warrants	96 (9.73%)
Order Maintenance Stops	181 (18.34%)
Other Tactics	710 (71.94%)

To explore the relationship between race and arrest tactics, I again estimate series of multilevel multinomial models built iteratively. The first set of models involve only arrestee-case level variables, and are displayed in Tables 7 and 8. Table 7 displays the results for the operationalization of order maintenance stops that include both traffic and pedestrian stops, and Table 8 displays the results for order maintenance stops that include only pedestrian stops.

Model 1 incorporates arrestee race, gender, and age, because age is correlated with the level of drug and criminal involvement which, itself, is a factor that contributes to the issuing of warrants (Loeber & Farrington, 2014; Prendergast et al., 2010), and gender and age are linked to the use of order maintenance stops with young men being far more likely to be arrested via order maintenance stops (Brunson & Miller, 2006). Controlling for both allows for an understanding of the connection between race and arrest tactic net the effect of age and gender. In Model 2, controls for the most serious charge on arrest and drug types involved in an arrest are incorporated. Warrants are often issued only in cases where there is evidence of serious drug activity or other serious criminal activity, while order maintenance stops are, by definition, motivated by minor disorderly activity and thus are unlikely lead to the discovery of serious criminality (Balko, 2015; Brunson & Miller, 2006). The severity of the drug offense is likely to be connected to the tactics employed to address it.[6] So, too, is drug type, with drugs at the center of epidemics or moral panics being viewed as more serious (Quinones, 2016). While drug trends at this time in Atlanta were steady, cocaine use was quite high and often associated with serious criminality (United States Department of Justice, 2010). Further, drug use and sales during this time was racialized, and thus any racial arrest patterns may be partially attributable to differences in usage or sales (Dew et al., 2017).

A few important conclusions can be drawn from Model 1 in Tables 7 and 8. First, order maintenance stops are not related to arrestee race when compared to other arrest tactics, and this lack of significance does not differ across the two operationalizations of order maintenance or the two measures of race. Second, the use of warrants is related to arrestee race, even when accounting for gender and age, both of which are also related to the likelihood of an arrest involving warrants. In general, non-whites, women, and younger individuals are more likely to be arrested via warrant.

The third conclusion that can be drawn from these analyses, though, comes from the findings of Model 2, which reveal that once the severity and type of drug offense are controlled for, arrestee race is no longer linked to the use of warrants. It appears that, just as in the "tough on crime" era, racial patterns of arrest for warrants are driven by the type

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[6] Because few order maintenance arrests in 2012 involved a charge more serious than intent to sell, intent to sell and sales plus were combined into a single category, and the models were run with a dummy variable indicating that the most serious charge is possession.

and severity of drugs involved in an arrest. This, though, does not necessarily imply that race is not uninvolved in APD warrant arrests, but instead that it may be a product of the APD's focus on different types of drug offenses. In 2012, the APD used warrants in marijuana and cocaine cases and cases with greater severity than possession. In total, 61.46% of warrant arrests involved marijuana, compared to 20.12% of order maintenance stops and 25.14% of all other arrest tactics; only 19.79% of warrant arrests involved possession, compared to 73.67% of order maintenance stops and 62.21% of all other arrest tactics. Marijuana arrests are far more common for non-white arrestees ($p<0.001$; 30.39% as compared to 3.20%), as are arrests for charges more serious than possession ($p<0.001$; 41.76% compared to 12.00%). While interaction effects of these variables and race are not significant, it appears that they explain some of the variation in the use of warrants by arrestee race.

Table 7. Random Intercept Logit Models for the Effect of Individual Race on Police Stop Tactics - Traffic and Pedestrian Stops, 2012

(n=987)	Model 1 Odds Ratio (SE)				Model 2 Odds Ratio (SE)			
	Order Maintenance Stops		Warrants		Order Maintenance Stops		Warrants	
	Black[1]	Non-White[2]	Black[1]	Non-White[2]	Black[1]	Non-White[2]	Black[1]	Non-White[2]
Race	0.69 (0.13)	0.73 (0.15)	3.91 (2.31)*	5.06 (3.45)*	0.91 (0.18)	1.01 (0.21)	1.80 (1.29)	2.36 (1.77)
Male[3]	0.84 (0.24)	0.84 (0.24)	0.45 (0.14)*	0.44 (0.14)*	0.84 (0.24)	0.83 (0.24)	0.41 (0.15)*	0.41 (0.15)*
Logged Age at Arrest	0.89 (0.19)	0.88 (0.19)	0.24 (0.08)***	0.24 (0.08)***	0.62 (0.16)+	0.61 (0.53)+	0.50 (0.22)	0.50 (0.22)
Top Charge on Arrest - Possession[4]					2.33 (0.53)***	2.35 (0.53)***	0.34 (0.13)**	0.34 (0.14)**
Drug Involved in Arrest[5]								
Meth/Amphetamines					1.71 (0.91)	1.81 (0.98)	2.51 (1.96)	2.64 (1.88)
Cocaine					1.12 (0.26)	1.11 (0.26)	2.59 (0.74)**	2.55 (0.72)**
Heroin					1.19 (0.35)	1.23 (0.37)	3.03 (1.48)*	3.21 (1.56)*
Marijuana					1.20 (0.35)	1.18 (0.35)	3.46 (1.08)***	3.44 (1.08)***
Hallucinogens/Party Drugs					2.22 (1.19)	2.19 (1.17)	3.15 (2.28)	3.14 (2.29)
Unspecified					1.04 (0.32)	1.05 (0.33)	1.11 (0.51)	1.12 (0.51)

+p<.10, * p<.05, ** p<.01, *** p<.001

[1]Reference category: white, Asian, American Indian, Hispanic, or other race.

[2]Reference category: white.

[3]Reference category: female or other gender.

[4]Reference category: intent, sales, trafficking, manufacturing.

[5]Categories not mutually exclusive.

Table 8. Random Intercept Logit Models for the Effect of Individual Race on Police Stop Tactics - Pedestrian Stops Only, 2012

(n=987)	Model 1 Odds Ratio (SE)				Model 2 Odds Ratio (SE)			
	Order Maintenance Stops		Warrants		Order Maintenance Stops		Warrants	
	Black[1]	Non-White[2]	Black[1]	Non-White[2]	Black[1]	Non-White[2]	Black[1]	Non-White[2]
Race	1.51 (0.48)	1.49 (0.50)	4.75 (2.92)*	5.94 (4.15)*	1.64 (0.54)	1.60 (0.56)	2.04 (1.50)	2.59 (2.00)
Male[3]	0.78 (0.24)	0.77 (0.24)	0.46 (0.14)*	0.45 (0.14)*	0.79 (0.24)	0.79 (0.25)	0.42 (0.16)*	0.42 (0.16)*
Logged Age at Arrest	2.14 (0.72)*	2.15 (0.72)*	0.28 (0.10)***	0.28 (0.10)***	1.15 (0.39)	1.15 (0.39)	0.63 (0.27)	0.63 (0.27)
Top Charge on Arrest - Possession [4]					2.28 (0.52)***	2.29 (0.53)***	0.28 (0.11)**	0.28 (0.11)**
Drug Involved in Arrest[5]								
Meth/Amphetamines					1.13 (0.69)	1.10 (0.67)	2.11 (1.43)	2.17 (1.36)
Cocaine					0.93 (0.44)	0.94 (0.45)	2.48 (0.70)**	2.46 (0.68)**
Heroin					0.51 (0.28)	0.51 (0.28)	2.67 (1.23)*	2.79 (1.28)*
Marijuana					0.62 (0.27)	0.63 (0.28)	3.21 (0.91)***	3.21 (0.90)***
Hallucinogens/Party Drugs					0.49 (0.30)	0.50 (0.30)	2.13 (1.33)	2.14 (1.35)
Unspecified					0.50 (0.25)	0.50 (0.25)	1.01 (0.45)	1.02 (0.45)

+p<.10, * p<.05, ** p<.01, *** p<.001

[1]Reference category: white, Asian, American Indian, Hispanic, or other race.

[2]Reference category: white.

[3]Reference category: female or other gender.

[4]Reference category: intent, sales, trafficking, manufacturing.

[5]Categories not mutually exclusive.

Racial patterns of policing may also be attributable to differences in the use of tactics by neighborhood racial composition, and this is especially the case for order maintenance stops and warrants, which research suggests are more frequently used within predominately black and Hispanic neighborhoods (Benner, 2002; Brunson & Miller, 2006; Brunson & Weitzer, 2008; Ingram, 2007). Crime is geographically patterned (Ackerman & Murray, 2004; Barnum et al., 2016), police are geographically focused agencies (Klinger, 1997, 2004), and thus different tactics for felony drug arrests may also exhibit geographic patterning. If that patterning falls along racial lines, it may contribute to the racialized patterns of arrests described in Chapter 4.

To formally explore this, I begin examining whether there are clear geographic patterns in the clustering of arrest tactics within neighborhoods. Specifically, I ask whether the rate of arrests that involve order maintenance tactics and the rate of arrests that involve warrants within census tracts cluster in a fashion that is distinct from complete spatial randomness. The Global Moran's I test reveals that order maintenance stops including only pedestrian stops (I = 0.08; $p<0.05$), order maintenance stops including traffic and pedestrian stops (I = 0.15; $p<0.01$), and warrants (I = 0.19; $p<0.01$) exhibit patterns of clustering distinct from complete spatial randomness. Significant clusters of arrest tactics as assessed by the local Moran's I (Figures 2, 3, and 4) show that the nature of clustering varies by tactic. While there are clusters of high rates of order maintenance stops near Zone 6 for both operationalizations of order maintenance stops, the operationalization including traffic stops also has a cluster of high rate neighborhoods near the border of Zones 4 and 1. On the other hand, warrant arrests cluster mostly within Zone 3. Arrest tactics not only cluster within Atlanta, but they cluster in distinct areas, with order maintenance stops common areas where warrants are not and vice versa.

Figure 2. Local Moran's I Clusters of Rate of Pedestrian Order Maintenance Stops

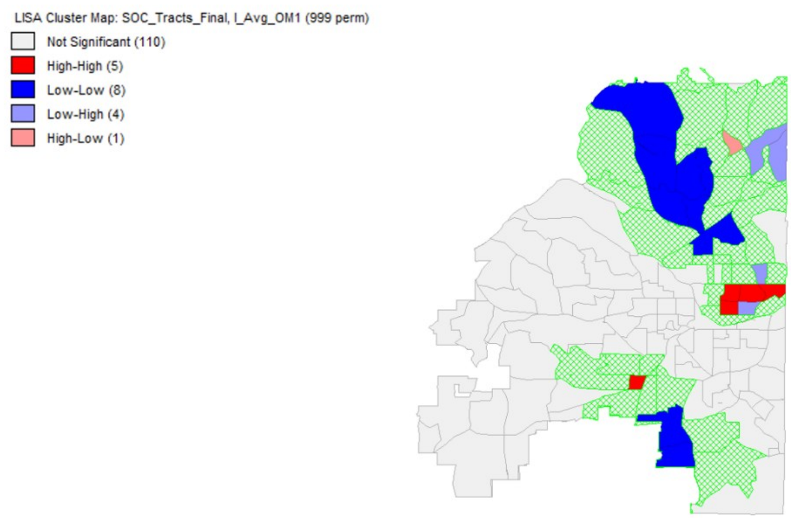


Figure 3. Local Moran's I Clusters of Rate of Pedestrian and Traffic Order Maintenance Stops

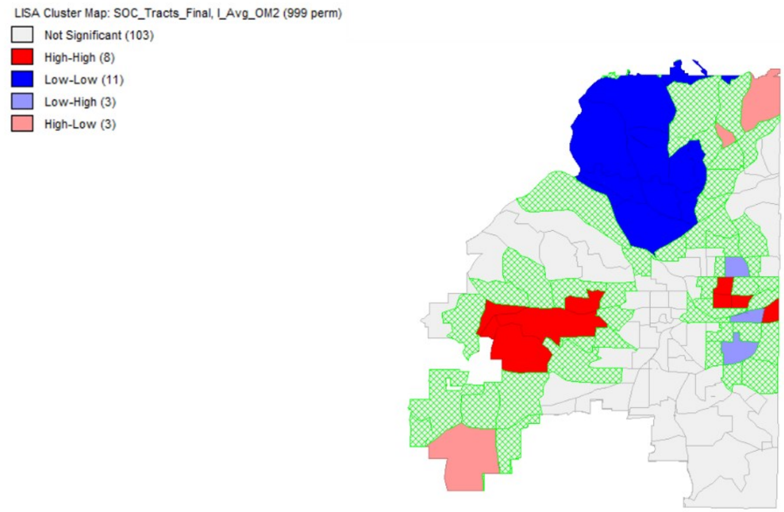
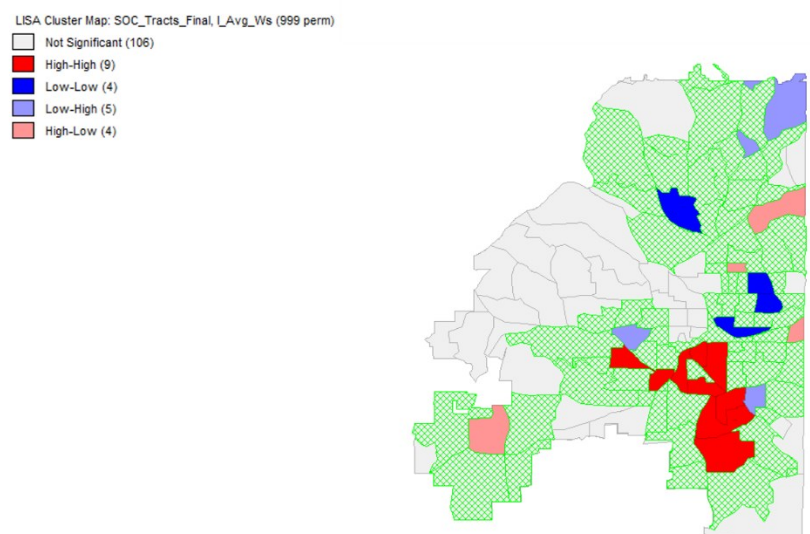


Figure 4. Local Moran's I Clusters of Rate of Warrants



In order to understand whether these patterns are linked to the racial composition of neighborhoods, I begin by adding neighborhood racial composition and three measures that collectively capture social disorganization (Model 3). Following this, I add the total index crime rate and the zone membership of each census tract (Model 4; see Tables 9 and 10). As noted in Chapter 5, social disorganization is linked to police behavior overall, perceptions of disorder, and the use of warrants (Balko, 2015; Brunson & Miller, 2006; Klinger, 1997, 2004). To the degree that social disorganization affects police behavior, it does so by acting as an indirect indication of crime (Klinger, 1997, 2004), but police behavior is also affected by clearer indicators of crime, such as the total violent and property crime rate (Braga, 2001; National Research Council, 2004). Further, it is also directly affected by the local law enforcement leadership, which in the APD is determined by zones (Rowe, 2006). Tables 9 and 10 provide the results of both models, with Table 9 showing results for order maintenance tactics including both pedestrian and traffic stops and Table 10 illustrating the results for order maintenance tactics including only pedestrian stops.

Table 9. Random Intercept Logit Models for the Effect of Individual Race and Racial Composition on Police Stop Tactics - Traffic and Pedestrian Stops, 2012

(n=987)	Model 3 Odds Ratio (SE)				Model 4 Odds Ratio (SE)			
	Order Maintenance Stops		Warrants		Order Maintenance Stops		Warrants	
	Black[1]	Non-White[2]	Black[1]	Non-White[2]	Black[1]	Non-White[2]	Black[1]	Non-White[2]
Race	0.92 (0.17)	1.02 (0.20)	1.61 (1.21)	2.17 (1.73)	0.87 (0.16)	0.97 (0.20)	2.09 (1.58)	2.74 (2.18)
Male[3]	0.83 (0.24)	0.82 (0.24)	0.38 (0.15)*	0.37 (0.15)*	0.82 (0.24)	0.81 (0.23)	0.38 (0.14)*	0.37 (0.14)*
Age at Arrest	0.61 (0.15)*	0.60 (0.15)*	0.49 (0.21)	0.49 (0.21)	0.58 (0.13)*	0.57 (0.13)*	0.53 (0.22)	0.53 (0.23)
Top Charge on Arrest - Possession[4]	2.33 (0.53)***	2.36 (0.54)***	0.37 (0.15)*	0.37 (0.15)*	2.26 (0.52)***	2.27 (0.52)***	0.41 (0.16)*	0.41 (0.16)*
Drug Involved in Arrest[5]								
Meth/Amphetamines	1.70 (0.92)	1.82 (1.00)	3.37 (2.50)	3.66 (2.52)+	2.10 (1.08)	2.18 (1.15)	2.37 (1.92)	2.46 (1.87)
Cocaine	1.12 (0.26)	1.11 (0.26)	2.48 (0.76)**	2.43 (0.73)**	1.16 (0.28)	1.13 (0.27)	2.75 (0.91)**	2.67 (0.86)**
Heroin	1.14 (0.34)	1.18 (0.36)	2.60 (1.50)+	2.77 (1.57)+	1.32 (0.41)	1.35 (0.41)	4.23 (2.73)*	4.35 (2.76)*
Marijuana	1.24 (0.36)	1.22 (0.36)	3.24 (1.13)**	3.21 (1.12)**	1.32 (0.39)	1.29 (0.38)	3.79 (1.33)	3.74 (1.31)
Hallucinogens/Party Drugs	2.28 (1.23)	2.25 (1.22)	3.55 (2.78)	3.52 (2.78)	2.29 (1.28)	2.22 (1.23)	2.68 (2.18)***	2.64 (2.17)***
Unspecified	1.06 (0.32)	1.07 (0.33)	1.14 (0.52)	1.17 (0.53)	1.12 (0.34)	1.13 (0.34)	1.22 (0.57)	1.24 (0.58)
Racial Composition	0.99 (0.01)	0.99 (0.01)	1.00 (0.01)	1.00 (0.01)	1.01 (0.01)	1.01 (0.01)	1.01 (0.01)	1.01 (0.02)
Concentrated Disadvantage	1.38 (0.27)	1.38 (0.28)	1.67 (0.50)+	1.65 (0.50)	1.30 (0.23)	1.29 (0.23)	1.46 (0.43)	1.46 (0.43)
Residential Instability	1.01 (0.1)	1.02 (0.11)	0.76 (0.17)	0.76 (0.17)	1.10 (0.12)	1.07 (0.11)	0.99 (0.19)	0.98 (0.19)
Percent Foreign Born	1.00 (0.02)	1.00 (0.02)	0.96 (0.04)	0.96 (0.04)	1.01 (0.02)	1.00 (0.02)	0.94 (0.03*)	0.93 (0.02)*
Total Index Crime Rate[6]					0.96 (0.01)**	0.96 (0.01)***	0.92 (0.03)**	0.92 (0.03)**
Zone Membership[5]								
Zone 1					0.91 (0.22)	0.90 (0.22)	0.56 (0.21)	0.57 (0.21)
Zone 2					1.59 (0.97)	1.57 (0.92)	7.79 (5.30)**	7.70 (5.19)**
Zone 3					0.72 (0.17)	0.71 (0.17)	2.09 (0.72)*	2.11 (0.73)*
Zone 4					1.21 (0.25)	1.20 (0.25)	0.96 (0.34)	0.97 (0.34)
Zone 5					0.88 (0.19)	0.90 (0.19)	0.74 (0.30)	0.75 (0.31)
Zone 6					2.62 (0.93)**	2.60 (0.91)**	0.79 (0.47)	0.79 (0.47)

+p<.10, * p<.05, ** p<.01, *** p<.001
[1]Reference category: white, Asian, American Indian, Hispanic, or other race.

[2]Reference category: white.
[3]Reference category: female or other gender.
[4]Reference category: intent, sales, trafficking, manufacturing.
[5]Categories not mutually exclusive.
[6]Per 100 people.

Table 10. Random Intercept Logit Models for the Effect of Individual Race and Racial Composition on Police Stop Tactics - Pedestrian Stops Only, 2012

(n=987)	Model 3 Odds Ratio (SE)				Model 4 Odds Ratio (SE)			
	Order Maintenance Stops		Warrants		Order Maintenance Stops		Warrants	
	Black[1]	Non-White[2]	Black[1]	Non-White[2]	Black[1]	Non-White[2]	Black[1]	Non-White[2]
Race	1.80 (0.58)+	1.77 (0.60)+	1.82 (1.39)	2.36 (1.92)	1.67 (0.58)	1.63 (0.62)	2.38 (1.82)	2.99 (2.43)
Male[3]	0.79 (0.25)	0.78 (0.24)	0.39 (0.15)*	0.39 (0.15)*	0.76 (0.24)	0.76 (0.24)	0.40 (0.15)*	0.39 (0.15)*
Age at Arrest	1.11 (0.38)	1.11 (0.37)	0.60 (0.25)	0.60 (0.25)	0.95 (0.31)	0.94 (0.31)	0.64 (0.26)	0.65 (0.26)
Top Charge on Arrest - Possession[4]	2.23 (0.51)***	2.24 (0.51)***	0.31 (0.12)**	0.31 (0.12)**	2.17 (0.51)**	2.16 (0.51)**	0.34 (0.13)**	0.34 (0.13)**
Drug Involved in Arrest[5]								
Meth/Amphetamines	1.05 (0.65)	1.03 (0.64)	2.70 (1.67)	2.85 (1.67)+	1.54 (0.99)	1.43 (0.92)	1.87 (1.29)	1.89 (1.23)
Cocaine	0.91 (0.44)	0.92 (0.45)	2.41 (0.73)**	2.38 (0.70)**	0.92 (0.44)	0.91 (0.44)	2.62 (0.85)**	2.57 (0.81)**
Heroin	0.46 (0.31)	0.46 (0.27)	2.16 (1.17)	2.23 (1.16)	0.60 (0.33)	0.56 (0.30)	3.61 (2.24)*	3.67 (2.25)*
Marijuana	0.65 (0.29)	0.66 (0.29)	2.97 (0.96)**	2.96 (0.95)**	0.69 (0.30)	0.69 (0.30)	3.31 (1.07)***	3.29 (1.05)***
Hallucinogens/Party Drugs	0.51 (0.32)	0.53 (0.31)	2.36 (1.63)	2.36 (1.65)	0.39 (0.25)	0.40 (0.25)	1.78 (1.32)	1.77 (1.32)
Unspecified	0.54 (0.27)	0.54 (0.27)	1.04 (0.45)	1.06 (0.45)	0.56 (0.27)	0.55 (0.27)	1.11 (0.49)	1.13 (0.50)
Racial Composition	0.99 (0.01)	0.99 (0.01)*	1.00 (0.01)	1.00 (0.01)	1.02 (0.01)**	1.02 (0.01)*	1.01 (0.01)	1.01 (0.01)
Concentrated Disadvantage	1.17 (0.35)	1.28 (0.27)	1.54 (0.46)	1.54 (0.44)	1.18 (0.20)	1.22 (0.21)	1.34 (0.39)	1.34 (0.40)
Residential Instability	1.18 (0.19)	1.18 (0.16)	0.77 (0.18)	0.77 (0.16)	1.14 (0.17)	1.07 (0.16)	0.98 (0.19)	0.97 (0.18)
Percent Foreign Born	1.00 (0.02)	1.00 (0.02)	0.95 (0.04)	0.95 (0.04)	1.00 (0.01)	0.99 (0.02)	0.94 (0.03)*	0.93 (0.02)*
Total Index Crime Rate[6]					0.96 (0.01)***	0.96 (0.01)***	0.93 (0.03)**	0.93 (0.03)**
Zone Membership[5]								
Zone 1					0.49 (0.15)*	0.50 (0.16)*	0.54 (0.19)+	0.55 (0.19)+
Zone 2					1.70 (0.79)	1.41 (0.69)	7.04 (3.80)***	6.79 (3.69)***
Zone 3					0.23 (0.07)***	0.24 (0.08)***	2.01 (0.66)*	2.03 (0.66)*
Zone 4					0.66 (0.20)	0.69 (0.22)	0.88 (0.29)	0.89 (0.30)
Zone 5					1.21 (0.30)	1.29 (0.33)	0.79 (0.31)	0.80 (0.32)
Zone 6					2.91 (1.09)**	2.67 (1.02)*	0.64 (0.33)	0.64 (0.33)

+p<.10, * p<.05, ** p<.01, *** p<.001

[1]Reference category: white, Asian, American Indian, Hispanic, or other race.
[2]Reference category: white.
[3]Reference category: female or other gender.
[4]Reference category: intent, sales, trafficking, manufacturing.
[5]Categories not mutually exclusive.
[6]Per 100 people.

There are a few takeaways from these models. First, race and racial composition are not linked to the use of warrants in any model specification. The initial findings that non-white individuals were more likely to be arrested via warrant (Model 1) appears to have been fully explained by the severity of drug activity and types of drugs involved in an arrest.

Second, the only significant finding for race in Model 3 is when order maintenance is defined as only involving pedestrian stops, wherein increases in percent non-white residents are associated with decreases in the odds that arrests involve order maintenance tactics. Yet results from Model 4 suggest that, in the fully specified model, increases in the percent black or non-white in a neighborhood are associated with increased odds that arrests involve order maintenance tactics. In essence, crime and zone membership explain some of the relationship between racial composition and order maintenance stops, and thus when they are accounted for, the value on this variable more closely aligns with its unique effect on determining tactics (MacKinnon, Krull, & Lockwood, 2000). This indicates that in 2012, individuals arrested in neighborhoods with higher rates of non-white residents were more likely to be arrested by pedestrian-based order maintenance tactics than any other tactic when controlling for the social disorganization, crime rate, and zone membership of that neighborhood (Table 10).

By contrast, no effects of either race or racial composition exist for order maintenance tactics when they include traffic stops (Table 9). Whether there is a link between racial composition and order maintenance stops depends on the definition of order maintenance stops. A combined measure of pedestrian and traffic behavior is the definition of order maintenance stops that best aligns with a city like Atlanta where transportation occurs mostly within vehicles (Dunn, 2015). Order maintenance stops for pedestrian behavior represent a subset of those arrests, and align with definitions used in cities with higher rates of pedestrian activity (Gelman et al., 2007). While previous studies have found that traffic stops are more common in neighborhoods with higher rates of non-white residents (Ingram, 2007), the results of Model 4 may be attributable to the nature of this data, which focuses not on stops but on arrests. Past research has focused on less serious forms of enforcement, such as citations, whereas these models focus on felony arrests, distinguishing the tactics that lead to these arrests. When selecting disorderly vehicles to stop, police may be more likely to stop them in non-white neighborhoods, but once stopped, equally likely across all neighborhoods to find anything warranting a felony drug arrest. On the other hand, for pedestrian stops, police may be more likely to both make a stop in a non-white neighborhood and to find evidence of felony drug activity. This may simply be due to the nature of each type of disorder. While some pedestrian disorder provides no indication of involvement with substances (e.g., jaywalking), some provide a better indication than do poor driving behavior (e.g., public drinking, loitering), and thus officers making pedestrian order maintenance stops may simply be better able to assume underlying more serious offenses than their counterparts making vehicular stops.

Results for both tactics and operationalizations make clear the importance of zone membership in determining tactics. Arrests in Zone 6 are associated with an increased odds order maintenance tactics being involved (Model 4, Table 9). Alternatively, warrants are far more likely to occur in Zones 2 and 3 (Model 4, Table 9). Zones matter and they matter in distinct ways for these two types of tactics.

Due to the small sample size within zones and small number of observations within the order maintenance and warrant category in each zone, zone-specific models failed to converge. Thus, rather than relying on multivariate models to display the patterns of race by zone, I use descriptive statistics that give a clear sense of the racially patterned use of certain tactics within zones. Tables 11 and 12 present the rate of black and non-white arrestees for each arrest tactic within each zone, as well as the average rate of black and non-white residents in the neighborhoods experiencing each arrest tactic. For example, in Zone 1 in Table 11, 100% of warrants involve black arrestees, 74.05% of order maintenance stops involve black arrestees, and 86.26% of arrests involving other stops tactics involve black arrestees; these differences are statistically significant. In the same zone, arrests involving warrants occurred in neighborhoods with an average 89.03% percent black residents, order maintenance stops occurred in neighborhoods with an average of 88.13% black residents, and other stop types occurred in neighborhoods with an average of 88.54% percent black residents. Table 11 presents the results when order maintenance stops are defined as including pedestrian and traffic stops, and Table 12 presents the results when they are defined as only including pedestrian stops.

Table 11. Race and Racial Composition by Tactics within Zones - Pedestrian and Traffic Stops, 2012

	Percent Black Arrestees	Percent Non-White Arrestees	Mean Percent Black Residents in Arresting Neighborhoods	Mean Percent Non-White Residents in Arresting Neighborhoods
Zone 1 (n=378)	***	***		
Warrants	100.00%	100.00%	89.03%	94.93%
Order Maintenance - Pedestrian Only	74.05%	74.81%	88.13%	94.48%
Other Stops	86.26%	85.78%	88.54%	94.62%
Zone 2 (n=53)			+	*
Warrants	77.78%	88.89%	46.77%	61.80%
Order Maintenance	64.71%	76.47%	34.18%	55.36%
Other Stops	62.96%	62.96%	19.58%	41.14%
Zone 3 (n=150)			*	+
Warrants	97.30%	97.30%	88.65%	94.71%
Order Maintenance	84.62%	84.62%	83.59%	93.16%
Other Stops	87.84%	89.19%	81.82%	90.16%
Zone 4 (n=152)				
Warrants	100.00%	100.00%	91.79%	97.53%
Order Maintenance	96.36%	96.36%	91.33%	97.00%
Other Stops	97.37%	97.37%	90.63%	96.60%
Zone 5 (n=458)				
Warrants	86.67%	93.33%	60.51%	72.95%
Order Maintenance	78.26%	79.50%	63.02%	74.88%
Other Stops	84.04%	84.40%	60.00%	72.65%
Zone 6 (n=390)			***	*
Warrants	84.62%	84.62%	71.04%	79.63%
Order Maintenance	88.89%	90.28%	54.33%	66.92%
Other Stops	89.27%	89.70%	52.55%	65.89%

+p<.10, * p<.05, ** p<.01, *** p<.001

Table 12. Race and Racial Composition by Tactics within Zones - Pedestrian Stops Only

	Percent Black Arrestees	Percent Non-White Arrestees	Mean Percent Black Residents in Arresting Neighborhoods	Mean Percent Non-White Residents in Arresting Neighborhoods
Zone 1 (n=378)	*	*		
Warrants	100.00%	100.00%	89.03%	94.93%
Order Maintenance - Pedestrian Only	82.69%	82.69%	89.77%	95.22%
Other Stops	81.03%	81.72%	88.14%	94.45%
Zone 2 (n=53)			*	
Warrants	77.78%	88.89%	46.77%	61.80%
Order Maintenance	42.86%	42.86%	35.08%	54.44%
Other Stops	67.57%	72.97%	23.36%	45.15%
Zone 3 (n=150)			*	
Warrants	97.30%	97.30%	88.65%	94.71%
Order Maintenance	90.00%	90.00%	80.34%	92.19%
Other Stops	86.41%	87.38%	82.64%	91.10%
Zone 4 (n=152)				
Warrants	100.00%	100.00%	91.79%	97.53%
Order Maintenance	100.00%	100.00%	92.42%	96.62%
Other Stops	96.33%	96.33%	90.62%	96.80%
Zone 5 (n=458)	*	*		
Warrants	86.67%	93.33%	60.51%	72.95%
Order Maintenance	91.43%	91.43%	61.58%	73.56%
Other Stops	78.99%	79.88%	60.95%	73.43%
Zone 6 (n=390)		+	***	*
Warrants	84.62%	84.62%	71.04%	79.63%
Order Maintenance	94.23%	95.19%	53.76%	66.82%
Other Stops	87.18%	87.91%	53.03%	66.09%

+p<.10, * p<.05, ** p<.01, *** p<.001

These descriptive statistics make clear the racial patterns to the tactics used within each zone. In terms of arrestee race, those arrested via warrants in Zone 1 are far more likely to be non-white ($p<0.001$), and in Zone 5 those arrested by warrants or order maintenance stops are more likely to be non-white ($p<0.05$). In terms of neighborhood racial composition, in Zone 2, arrests involving warrants or order maintenance stops on average occur in neighborhoods with a greater proportion of non-white residents ($p<0.05$), and in Zones 3 and 6, arrest that involve warrants occur in neighborhoods with a greater proportion of non-white residents ($p<0.05$). It is difficult to say more about the aspects of each zone that contribute to these patterns without a more detailed, in-depth investigation into practices promoted by each zones' leaders and the working groups that have developed in each zone. Yet this provides evidence that zones matter when assessing the racialized use of tactics, whether because of the actions promoted by local leaders, practices developed among local working groups, or both (Klinger, 1997, 2004; Rowe, 2006).

Discussion

Chapter 4 highlighted the racial disparities in felony drug arrests in 2012 in Atlanta. Non-white Atlantans were being arrested for felony drug offenses at a rate far greater than their share of the population. The goal of this chapter was to understand whether certain units and tactics could help explain these patterns. To accomplish this, the relationships between race and data-driven units, order maintenance stops, and warrants were examined. In general, findings suggest that at a citywide level, when controlling for other relevant factors, these aspects of policing were not significantly linked to race. Yet examination of iterative models and patterns within zones provides a more nuanced story.

Data-driven units were the primary type of specialized unit used to replace Red Dog in the new, “smart” era of policing (Atlanta Police Department, 2012; "Atlanta police disband Red Dogs," 2011; Visser & Garner, 2011). These units were emblematic of the “smart on crime” era, in which police decision making was informed by an analysis of previous stops, arrests, and calls for service (Braga, 2001; D. L. Carter & Carter, 2008; J. G. Carter & Phillips, 2015; Ferguson, 2017). While on their face, these units seemed to offer a race-neutral approach to policing, scholars have argued that because of their reliance on past data (which is gathered by non-neutral officers), they simply reflect the prejudices of the past (Ferguson, 2017). This may be especially the case at the neighborhood level, as data-driven strategies often focus not on who officers police but on where they police (National Research Council, 2004). In the fully specified models, though, I find no evidence of a link between race and the use of data-driven units.

Yet the story is more complicated than a simple rejection of the assumed problems with data-driven policing. While individual arrestee race played no role in influencing the use of data-driven units, racial composition did. Controlling for arrestee characteristics, case characteristics, and neighborhood levels of social disorganization, the results show that as the percent of non-white residents in a neighborhood increased, so, too, did the odds that an arrest would involve data-driven tactics. This relationship disappeared, however, when neighborhood crime rates and zone membership were added to the model. Crime rates and zone membership are both explicit parts of the analyses data-driven units conduct. Thus, it appears that by following the crime data provided by each zone, data-driven units are directing officers to neighborhoods with more non-white residents. These decisions may be race neutral in so much as they are based predominately on crime rates, but they are nonetheless resulting in a focus on non-white neighborhoods in excess of that shown by other APD units.

In addition, patterns vary in within zones. Even though data-driven units operate citywide (Atlanta Police Department, 2012), because their actions are based on data provided by officers working within zones, the relationship between race and these units varies by zone. Zones govern police behavior, exerting even greater influence than citywide leadership or individual officer preference, so it is no surprise that findings vary by zone (Engel & Worden, 2006; Rowe, 2006). The patterns of stops and arrests for data-driven units reflect the patterns with past data. Non-data-driven officers making stops and arrests within each zone are creating the data that will guide future data-driven arrests, and thus racialized arrest patterns for data-driven units vary by zone because they units are a reflection of data gathered within zones, and as Ferguson (2017) has theorized, exacerbate the patterns within the data. These patterns vary across zones because the behavior of non-data-driven officers vary across zones, and that variation guides data-driven units to certain zones, areas within zones, or people within zones.

While order maintenance stops and warrants were common tactics in the “tough on crime” era, they are still used in the “smart on crime” era. Search and arrest warrants are and have long been a common method for making an arrest (Balko, 2015; Benner, 2002). While policing disorderly behavior dates back equally as long within the profession, the use of arrests to address disorder is relatively new (Harcourt & Ludwig, 2006; Wilson & Kelling, 1982). Despite evidence of the negative consequences of their use (Benner, 2002; Gelman et al., 2007; Natapoff, 2018), the use of order maintenance stops and warrants have remained common even as police departments move into the “smart on crime” era (Balko, 2015; Dunn, 2015). Thus, both tactics may offer partial explanations for racial patterns in policing during the “smart on crime” era. Yet at a citywide level, few significant relationships between race and the type of tactics involved in an arrest were observed. It is only in iterative models and zone-specific descriptive statistics that we see a more nuanced story.

At the individual level, order maintenance tactics and race are not linked, but warrants and race are strongly linked, such that non-white arrestees are far more likely to be arrested via warrants than are white arrestees. Yet this relationship loses significance once the severity of the charge and the type of drugs involved in the arrest are included in the model. The same patterns exist for warrants in 2005. This link between race and warrants may be a product of non-white individuals being more involved in more serious drug offenses and more serious drug types. Alternatively, it may be a result of police investigating more serious drug activity when the individual involved is not white, or focusing on certain drug types more commonly sold and used by non-white residents in Atlanta (e.g., marijuana) and less so upon drug types commonly sold and used by white residents in Atlanta (e.g., methamphetamine) (Theall et al., 2001; United States Department of Justice, 2010). Arrest patterns for warrants by drug type suggest the latter. Regardless, these issues deserve further exploration with alternative data sources the provide greater insight into the rationale of all actors involved in the decision to pursue a warrant, especially considering this pattern occurs within both the “tough on crime” era and the “smart on crime” era. Search and arrest warrants require substantial effort and investment on the part of police (Balko, 2015), and as they are linked to racial patterns of arrests, it is important to understand why to ensure it is not a product of how police use these resource-intensive tactics.

Citywide, the use of warrants is not linked to racial composition, but order maintenance tactics are. The odds of an arrest involving a pedestrian order maintenance stop increases as the percent of non-white residents increases within a neighborhood. The use of order maintenance stops to make felony drug arrests is partially determined by the racial composition of a neighborhood. This, though, does not occur for all order maintenance stops (pedestrian and traffic stops). A variety of factors may be responsible for these varied results, including the possibility that order maintenance pedestrian stops are more likely to be associated with felony drug arrests as pedestrian disorder often provides a better indication of substance use or sales (e.g., public drinking, loitering) than does traffic disorder (e.g., speeding, running a stop sign). It is also possible that, when stopping a pedestrian, the characteristics of a neighborhood are more salient. In arrest report narratives, many pedestrian order maintenance stops occur when the officer him or herself is a pedestrian. Alternatively, most order maintenance traffic stops occur when the officer is also in a car. Something as simple as the speed with which an officer moves from neighborhood to neighborhood may influence the degree to which a neighborhood's racial composition and other characteristics influence decision making.

Finally, once again, patterns vary by zone. While zone-specific models could not be estimated, descriptive statistics provide a sense of the racialized use of tactics by zones. The findings mirror those from the "tough on crime" era, with notable variation by zone in the racialized patterns of using warrants and order maintenance stops. In agencies as large as the APD, local leadership plays a substantial role in understanding racialized patterns of policing. Local leaders and police officer working groups have a dramatic effect on the ways in which policing occurs, such that even within the same city and department, practices vary dramatically by zone (Klinger, 1997, 2004). Part of this variation is how and when different tactics are used, with, for example, the use of warrants in some zones reflecting the race of arrestees across the zone (e.g., Zone 3) and in other zones, differing starkly from the race of arrestees arrested using other tactics (e.g., Zone 1).

At a citywide level, only pedestrian order maintenance stops contribute to racial patterns of policing when controlling for arrestee, case, and neighborhood characteristics, including crime rates and zone membership. Yet this masks links between race and data-driven units and stop tactics that exist within zones, and that are explained by a focus on higher crime areas and on certain types of drug arrests. In short, it does not necessarily imply that these units and tactics are race-neutral, but simply that their connection to race is complicated and deserves further attention. Further, these findings also do not suggest that data-driven units, warrants, or order maintenance stops that include traffic disorder are race neutral, but instead that they are no more racialized than all other APD stops. Since all APD stops in this era reflect racialized policing patterns, this implies that these units and tactics do exhibit racialized patterns of arrest but that those patterns are simply are no greater than those exhibited by other officers. Finally, many of the patterns found in the “tough on crime” era are mirrored in the “smart on crime” era, but this does not mean that changes were absent. In the next chapter, I take a comparative approach to examining changes to the non-white arrest rate and racial disparities in arrest within neighborhoods, asking whether both have decreased as a result of the shift from “tough on crime” to “smart on crime” policing, and whether any observed decreases are related to the decreased use of specialized units, order maintenance tactics, and warrants.

Chapter 7. Policing in Atlanta across Eras

Prior chapters have highlighted era specific racialized patterns of policing. Chapter 4 identified the magnitude of racialized policing within each era, demonstrating that—assuming equal or near-equal involvement in drug use and sales by race/ethnicity—non-white individuals were arrested more often than would be expected based on residential patterns in both the "tough on crime" and "smart on crime" eras. In Chapter 5, the reasons for these patterns in the "tough on crime" era were explored, uncovering the role of Red Dog for certain drug types and within certain zones, and the zone-specific effects of warrants and order maintenance tactics. In Chapter 6, a similar exploration was conducted into the factors that contributed to racialized policing in the "smart on crime" era, highlighting data-driven units' disproportionate focus on neighborhoods with high rates of non-white residents, and, again, on the zone-specific impact of warrants and order maintenance tactics by race and racial composition. Collectively, these chapters described what has occurred within each era and why, but they do not touch upon the degree or kinds of change that have occurred across eras. The current chapter provides an examination of drug policing across the transition from a "tough" to "smart" ethos.

While racialized patterns of policing existed in both eras, it is still possible that the nature and extent of racialized policing varied by era. There is good reason to expect that "smart on crime" policing will reduce but not eliminate racialized patterns of policing (Ferguson, 2017). In that case, a data-driven approach to felony drug crime represents an improvement over the "tough on crime" model. Understanding whether racialized patterns of policing were altered as a result of an ideological shift is vital to the field. A large number of agencies have recently moved toward the "smart on crime" approach (Bueermann, 2012; Telep, 2016; Telep et al., 2018). Yet police departments are often slow to fully implement novel strategies and tactics, with officers often resisting new approaches (Mastrofski & Willis, 2010; Weisburd & Braga, 2006; Willis et al., 2003; Willis et al., 2007). To the extent that a police department is capable of altering the relationship between the ways they police drug felonies and race, the APD is likely to be such an agency. The APD made substantial changes between these two eras, eliminating Red Dog, adopting data-driven strategies, enhancing their community outreach, requiring a slew of new training for all officers, and modifying the ways in which they speak about crime and their overall approach to drug crime (Atlanta Police Department, 2001, 2014; Blau, 2016; City of Atlanta, 2016). Further, the transition was motivated by a series of crises within the city that highlighted the interwoven nature of drugs and the "tough on crime" ethos in producing racially disparate outcomes (Blau, 2016).

The story of Chapters 5 and 6 present a nuanced understanding of the ways in which PPUs, data-driven units, warrants, and order maintenance stops contribute to racialized patterns of arrests within each era. While each played a role, their role was not as direct or clear as past research suggested, and instead tended to be specific to certain drug types, charges, or police zones (Beckett, 2016; Benner, 2002; Ferguson, 2017; Kraska & Kappeler, 1997). Yet an alternative way to examine the effect of these units and tactics is to assess how their use has changed across eras, and whether changes in their use are associated with an attenuation of racialized patterns of policing. While, for example, warrants may not contribute to citywide racialized patterns of policing within either era, a reduction in the use of warrants may reduce racial disparities.

In this chapter, I conduct three analyses that collectively provide a clearer understanding of the transition in ethos within the APD. These analyses focused at the neighborhood level-of-analysis, with all arrest patterns aggregated to census tracts. I first examine bivariate changes across the two eras in independent (e.g., involvement of specialized units in arrests) and dependent (e.g., non-white arrest rate) variables in order to understand how, if at all, the use of specialized units and tactics, and the racialized patterns of felony drug arrests, changed between 2005 and 2012. Second, I employ fixed effects linear regression models to investigate whether the shift in eras is associated with reductions in both the black/non-white arrest rate and racial disparities in felony drug arrests, accounting for numerous neighborhood-level covariates. Finally, I use a fixed effects linear regression model to examine whether changes in the use of specialized units and tactics are associated with reductions in the black/non-white arrest rate or racial disparities in arrests, again controlling for other relevant, time-varying covariates.

Bivariate Changes

To understand the impact of the move from “tough” to “smart” policing of drug offenses, it is first useful to determine whether any change has occurred in racialized patterns of policing and in the use of units and tactics by the APD. Table 1, below, provides this assessment. As noted earlier, all arrests in both eras were aggregated to the census tract-era level, such that each observation in the data represents a particular census tract (n=114) in a particular era (“tough” versus “smart”). This allowed for the creation of the four primary dependent variables: the black arrest rate, the non-white arrest rate, the black arrest disparity, and the non-white arrest disparity. Race-specific arrest rates are defined as the number of black/non-white individuals arrested in a tract divided by the number of black/non-white residents of that tract, multiplied by 100, by era. Thus, for example, a black arrest rate of 1 indicates that, in that census tract, one black person is arrested for every 100 black residents. The measure of disparity is calculated as the black/non-white arrest rate divided by the overall arrest rate. Thus, a black arrest disparity of 3 indicates that, in that census tract, black people are arrested three times as often as are all residents. In regression models, these values are logged to normalize their distribution, but in Table 1, I present the unlogged variables for ease of interpretation. This approach to measuring racial disparities mirrors that used by Ousey and Lee (2008) in their examination of mediators of racial disparities in arrest rates across crime types with varying discretion.

Table 1. Descriptive Statistics by Era

	"Tough on Crime" (2005) (n=114)	"Smart on Crime" (2012) (n=114)	Both Eras (n=228)
	Mean (SD)	**Mean (SD)**	**Mean (SD)**
Dependent Variables			
Black Arrest Rate[1]***	1.21 (1.12)	0.46 (1.00)	0.83 (1.13)
Non-white Arrest Rate[1]***	0.98 (1.00)	0.37 (0.82)	0.68 (0.96)
Black Arrest Disparity*	3.81 (8.65)	2.30 (3.22)	3.06 (6.56)
Non-white Arrest Disparity*	2.00 (2.93)	1.47 (1.24)	1.73 (2.26)
Independent Variables			
Proportion of Arrests Involving Specialized Units***	0.21 (0.21)	0.03 (0.07)	0.12 (0.18)
Proportion of Arrests Involving Warrants	0.15 (0.17)	0.12 (0.20)	0.13 (0.18)
Proportion of Arrests Involving Order Maintenance Stops - Pedestrian Stops Only	0.15 (0.12)	0.13 (0.18)	0.14 (0.15)
Proportion of Arrests Involving Order Maintenance Stops - Traffic and Pedestrian Stops	0.28 (0.20)	0.31 (0.28)	0.29 (0.24)
Control Variables			
Proportion of Arrests Involving Marijuana*	0.26 (0.21)	0.33 (0.32)	0.30 (0.27)
Proportion of Arrests Involving Cocaine***	0.63 (0.25)	0.42 (0.33)	0.52 (0.31)
Proportion of Arrests Involving Heroin*	0.02 (0.07)	0.05 (0.16)	0.03 (0.12)
Proportion of Arrests Involving Unspecified Controlled Substances**	0.06 (0.11)	0.11 (0.18)	0.08 (0.15)
Proportion of Arrests Involving Meth**	0.11 (0.23)	0.04 (0.12)	0.08 (0.19)
Proportion of Arrests Involving Party Drugs**	0.07 (0.17)	0.02 (0.06)	0.05 (0.13)
Proportion of Arrests for Possession*	0.52 (0.24)	0.44 (0.33)	0.48 (0.29)
Proportion of Arrests for Intent to Sell**	0.40 (0.24)	0.29 (0.29)	0.35 (0.27)
Proportion of Arrests for Sales, Trafficking, Manufacturing+	0.15 (0.18)	0.12 (0.17)	0.14 (0.18)
Concentrated Disadvantage	-0.37 (0.94)	-0.28 (0.89)	-0.32 (0.91)
Residential Instability	-0.23 (0.97)	-0.28 (1.1)	-0.26 (1.03)
Percent Foreign Born	6.36 (8.32)	7.59 (8.14)	6.98 (8.23)
Percent Young Males	17.82 (10.96)	16.15 (11.19)	16.98 (11.08)
Violent Crime Rate[1]	1.56 (1.04)	1.40 (1.11)	1.48 (1.08)
Property Crime Rate[1]	8.15 (5.73)	7.4 (4.2)	7.77 (5.03)
Zone Membership[2]			
Zone 1	0.26 (0.44)	0.29 (0.46)	0.28 (0.45)
Zone 2	0.23 (0.42)	0.24 (0.43)	0.23 (0.42)
Zone 3	0.28 (0.45)	0.21 (0.41)	0.25 (0.43)
Zone 4	0.25 (0.43)	0.23 (0.42)	0.24 (0.43)
Zone 5	0.29 (0.46)	0.25 (0.44)	0.27 (0.45)
Zone 6*	0.16 (0.37)	0.26 (0.44)	0.21 (0.41)

+p<.10, * p<.05, ** p<.01, *** p<.001

[1]Per 100 people.
[2]Categories not mutually exclusive.

As Table 1 makes clear, all four outcomes show statistically significant reductions between 2005 and 2012. The black arrest rate dropped from 1.21 per 100 black residents in the "tough on crime" era to 0.46 per 100 black residents in the "smart on crime" era ($p<0.001$), and similarly the non-white arrest rate dropped from 0.98 to 0.37 over the same period ($p<0.001$). These represent substantial reductions, on the order of approximately 62%. The disparity in black and non-white arrests also declined across these two eras. Black residents were arrested at an average of 3.81 times the overall arrest rate in 2005 and only 2.30 times the overall arrest rate in 2012, representing a 40% reduction in the black arrest disparity ($p<0.05$). Non-white residents were arrested at 2.00 times the overall arrest rate in 2005 and 1.47 times the overall arrest rate in 2012, representing a 27% reduction ($p<0.05$).

The total black and non-white arrest rates experienced more pronounced reductions across than did the measures of black and non-white disparity in arrests. To further examine this, Figure 1 graphs the changes in black arrest rate and black arrest disparity for each of the 114 census tracts in Atlanta alongside one another. With a few notable exceptions, most of the lines slope downward for the black arrest rate, indicating a similar pattern of decline across tracts. Yet there is much more variation in the pattern for disparities, with a noticeable proportion sloping upward, indicating increasing racial disparities in some tracts between 2005 and 2012. Clearly, while racialized patterns of policing still exist within the "smart on crime" era, especially in some communities, they are noticeably attenuated as was detailed in Chapter 4. Without accounting for other relevant changes taking place over this period, it appears that the transition in policing ethos resulted in a decline in the relationship between policing drug crime and race.

Figure 1. Black Arrest Rate and Black Arrest Disparity Across Eras

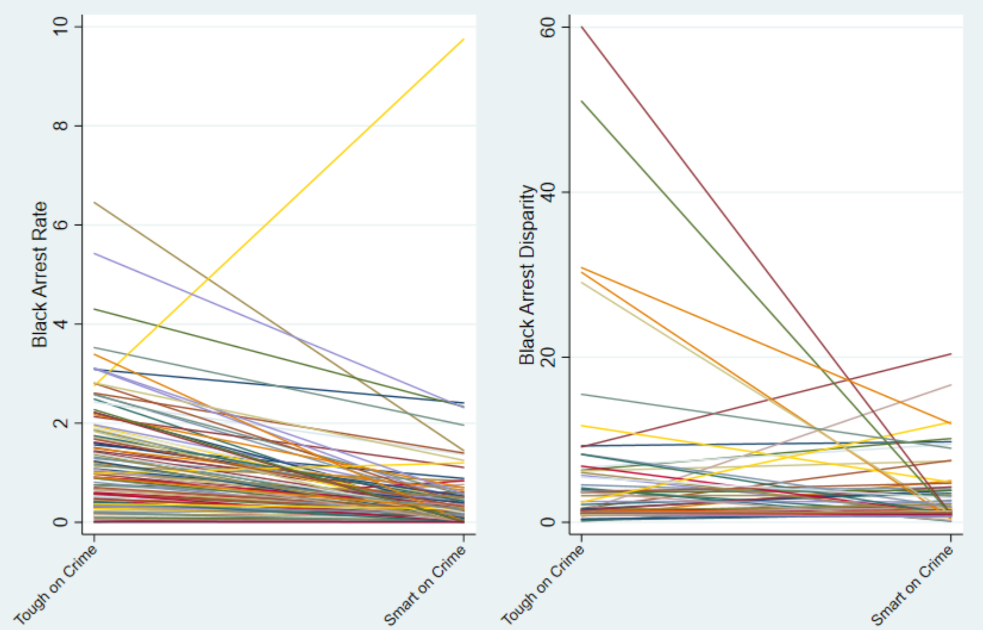


Table 1 also provides summary data on changes in the use of specialized units or tactics. These measures represent the proportion of arrests in a census-tract-era that involve each particular unit or tactic. In the “tough on crime” era, Red Dog constitutes the specialized unit, and in the “smart on crime” era, specialized units refer to all arrests involving a data-driven unit. Interestingly, only the rate of arrests by specialized units changes significantly between 2005 and 2012. In the “tough on crime” era, specialized units were involved in an average of 21% of arrests within tracts, while in the “smart on crime” era, they were only involved in an average of 3% of arrests, representing an 86% reduction. The use of warrants or order maintenance stops, though, did not significantly decline, despite their involvement in the crises that led to the transition in policing ethos

(Blau, 2016). Demonstrable changes in drug policing by the APD focused on the use of certain units rather than tactics. It is possible that once Red Dog was disbanded and replaced with data-driven tactics, the APD paid little attention to other possible modifications to drug crime policing, such as reducing their use of warrants and order maintenance stops. Further, both sets of tactics had, by 2005, become staples of police work, and thus even if the APD aimed to reduce the use of warrants or order maintenance stops, officers may have resisted such a change on the ground (National Research Council, 2004; Willis et al., 2007).

Finally, Table 1 provides an assessment of shifts in demographic and criminal justice variables, all of which are incorporated in the regression models discussed in the following sections. Drug arrest patterns shift dramatically across eras, with arrests for marijuana, heroin, and unspecified controlled substances increasing, and cocaine, methamphetamine, and hallucinogens/party drugs decreasing. These patterns align well with the changing popularity of certain drugs, especially the reduction in methamphetamine and MDMA arrests and the increase in heroin arrests (Quinones, 2016; Reding, 2010; Theall et al., 2001; United States Department of Justice, 2010). In addition, the percentage of arrests in which intent to sell or sales, trafficking, and manufacturing were the most serious charges decreased across eras, suggesting that either the APD focused proportionately more on possession offenses in 2012 or that there was a decrease in drug sales in Atlanta. Finally, between 2005 and 2012, the APD modified the boundaries of their 6 zones, and this resulted in small changes in the proportion of tracts that overlap each zone. Zone 6 experienced the greatest movement, with the zone now overlapping 26% of Atlanta census tracts, compared to only 16% in 2005.

The Effect of Era

Bivariate differences across eras in black/non-white arrest rates and racial disparities demonstrate a reduction in the racialized patterns of drug arrests. Yet the results in Table 1 do not account for other factors which may be simultaneously changing during this time period, and without accounting for such factors, it is unclear whether these reductions can be attributed to the shift from “tough” to “smart” policing within the APD. To account for this, I use a fixed effects regression model, controlling for each of the variables listed in Table 1. Specifically, I control for changes in the types of drugs involved in arrests; the severity of drug arrests; measures of social disorganization; percent young males (percent of males ages of 16-34); violent and property crime rates; and zone membership. A dichotomous indicator of the “smart on crime” era is added to this regression, and when accounting for these control variables, the coefficient on this variable can be read as the effect of a transition from “tough” to “smart” policing.

The types of drugs used and sold vary by race and by era (Copes et al., 2014; Fox & Rodriguez, 2010; Theall et al., 2001; United States Department of Justice, 2010). As the popularity of certain drug types varies over the years, so, too, might the racialized patterns of drug arrests. Table 1 makes clear that drug preferences have varied across eras. The severity of drug arrests may also vary across eras, and as previous chapters have highlighted the relationship between race and arrest severity, this may result in variations in racialized patterns of policing (United States Department of Justice, 2010). Collectively, these measures capture the evolving use and sales of drugs within Atlanta across eras, and including them in the regression models helps reduce the likelihood of incorrectly attributing changes in racialized patterns of arrests to policing changes when they are better attributed to drug popularity or activity.

Levels of social disorganization are often linked to neighborhood crime rates and police use social disorganization as an indication of where to focus their attention (Klinger, 1997, 2004; Mares, 2009; Mosher, 2001). Race and social disorganization are often also often linked (Peterson & Krivo, 2010). Thus, changing social disorganization may lead to a changing drug arrest rate, which in turn may alter racial arrest patterns. Should, for example, the level of social disorganization decrease in a neighborhood, the non-white arrest rate or disparity may decrease there, too, simply because disorganization is declining. Similarly, a vast body of research has linked the proportion of young men within a neighborhood to the crime rate (Akins, Rumbaut, & Stansfield, 2009; Stansfield, Akins, Rumbaut, & Hammer, 2013). Police are also more likely to stop and arrest young men (Brunson & Miller, 2006; Brunson & Weitzer, 2008; Gau & Brunson, 2015). Should the proportion of young men living in a neighborhood change, this will likely shift the drug crime rate and level of attention that police pay to the neighborhood. If this occurs simultaneously with a change in the race of individuals living in or spending time in that neighborhood, then this may result in reductions in the non-white arrest rate or disparity. For example, public housing is often racially segregated and skews toward either older or younger demographics depending on whether the development is designated as elderly or family based. If large public housing developments close, as they did in Atlanta between 2005 and 2012 (Rich, Haspel, Cheong, Kramer, & Waller, 2017), this may result in shifts in the racial composition of census tracts alongside shifts in the age of residents (Garlock, 2014; Goering, Kamely, & Richardson, 2007; Goetz, 2010).

Violent and property crime are linked with drug crime (Bennett et al., 2008; Martínez et al., 2008). Rates of violent and property crime also determine police behavior, motivating deployment patterns (Braga & Weisburd, 2010). Crime rates and race cluster (Peterson & Krivo, 2010), and thus changes in the violent and property crime rate may result in changes in race-specific arrest rates and racial disparities in arrests.

Finally, zone memberships determine police behavior (Klinger, 1997, 2004). Police form working groups within zones and research also suggests that local leadership within a zone is a strong predictor of police actions (Chappell, MacDonald, & Manz, 2006; Klinger, 2004; Rowe, 2006). Thus, when the APD shifted the location of zone boundaries in Atlanta, they altered the ways in which some neighborhoods are policed. For example, in 2012, more neighborhoods are policed by Zone 6 than was the case in 2005, and thus any characteristics of policing within Zone 6 are likely to manifest in changes to the drug arrest rates in the neighborhoods newly under their patrol.

Table 2 provides the results of fixed effects linear regression models. Coefficients in this model can be interpreted as the effect of a change in an independent variable across eras (e.g., change in proportion of arrests involving marijuana). Model 1 presents the results for the black and non-white arrest rate, and Model 2 presents the results for the black and non-white arrest disparity. These analyses make two things clear. First, black ($\beta = -1.09$; $p<0.001$) and other non-white ($\beta = -1.15$; $p<0.001$) residents are being arrested for felony drug offenses less often in 2012 than in 2005, relative to their share of the population. The fact that this finding, which mirrors the bivariate finding in Table 1, persists when controlling for other time-varying factors suggests that the shift in policing ethos is at least partially responsible. As noted in Chapter 4, the APD dramatically reduced the number of drug arrests they conducted across eras. Yet this reduction could have been mostly concentrated among white residents.[7] The findings from Table 1 demonstrate that it was not. Even still, this change could have been explained by evolving drug patterns, social disorganization levels, rates of young male residents, crime rates, or zone membership. Again, the findings from Table 2 suggest that this is not the case.

[7] Due to collinearity with various other measures, models did not include the overall change in number of arrests, but as a sensitivity analysis, models were re-run with this variable included. Its inclusion did not change the sign or significance of the effect of the "smart on crime" era.

Table 2. Fixed Effects Linear Regression Models for the Effect of Era on Black/Non-White Arrest Rates and Black/Non-White Arrest Disparities

(n=228)	**Model 1 Arrest Rate Coefficient (SE)**		**Model 2 Arrest Disparity Coefficient (SE)**	
	Black	**Non-White**	**Black**	**Non-White**
"Smart on Crime" Era	-1.09 (0.19)***	-1.15 (0.16)***	0.19 (0.13)	0.13 (0.10)
Proportion of Arrests Involving Marijuana	1.54 (0.46)***	1.40 (0.38)***	0.88 (0.45)+	0.74 (0.34)*
Proportion of Arrests Involving Cocaine	2.16 (0.35)***	1.79 (0.30)***	1.08 (0.32)**	0.72 (0.22)**
Proportion of Arrests Involving Heroin	-0.21 (1.30)	0.35 (1.18)	-1.55 (0.97)	-0.99 (0.79)
Proportion of Arrests Involving Controlled Substances	2.09 (0.47)***	1.63 (0.39)***	1.25 (0.51)*	0.79 (0.39)*
Proportion of Arrests Involving Meth	0.77 (0.73)	0.40 (0.62)	-0.06 (0.64)	-0.43 (0.51)
Proportion of Arrests Involving Party Drugs	0.64 (0.53)	0.21 (0.46)	1.58 (0.49)**	1.15 (0.43)**
Proportion of Arrests for Intent to Sell	0.41 (0.50)	0.22 (0.43)	0.59 (0.38)	0.41 (0.30)
Proportion of Arrests for Sales, Trafficking, Manufacturing	0.07 (0.45)	-0.01 (0.39)	-0.04 (0.38)	-0.12 (0.29)
Concentrated Disadvantage	-0.33 (0.29)	-0.35 (0.23)	-0.29 (0.20)	-0.31 (0.13)*
Residential Instability	0.24 (0.23)	0.14 (0.20)	0.30 (0.18)+	0.20 (0.13)
Percent Foreign Born	0.01 (0.02)	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)
Percent Young Males	-0.04 (0.02)*	-0.04 (0.01)**	-0.01 (0.01)	-0.01 (0.01)
Violent Crime Rate[1]	0.04 (0.17)	0.05 (0.16)	-0.06 (0.11)	-0.06 (0.09)
Property Crime Rate[1]	0.07 (0.03)+	0.07 (0.03)*	0.02 (0.02)	0.02 (0.02)
Zone Membership[2]				
Zone 1	-0.62 (0.60)	-0.73 (0.58)	-0.24 (0.34)	-0.35 (0.33)
Zone 2	1.55 (0.41)***	1.07 (0.36)**	1.10 (0.38)**	0.63 (0.28)*
Zone 3	0.21 (0.45)	0.25 (0.42)	0.11 (0.26)	0.14 (0.17)
Zone 4	-0.54 (0.38)	-0.56 (0.37)	0.05 (0.17)	0.03 (0.15)
Zone 5	0.34 (0.45)	0.03 (0.42)	0.24 (0.36)	-0.07 (0.22)
Zone 6	0.79 (0.36)*	0.73 (0.35)*	-0.13 (0.21)	-0.19 (0.16)

+p<.10, * p<.05, ** p<.01, *** p<.001
[1]Per 100 people.
[2]Categories not mutually exclusive.

Second, while bivariate findings indicate that the transition from "tough" to "smart" policing resulted in a reduction in the black and non-white arrest disparities, the multivariate findings reported in Table 2 demonstrate that these reductions are better explained by other changes occurring within Atlanta. Era is not linked to either black (β =

0.19; p=0.16) or non-white ($\beta = 0.13$; p=0.19) arrest disparities. The decline in racial disparity across eras may be due to changes in the types of drugs involved in arrests, with cocaine, unspecified controlled substances, and hallucinogens having consistent, strong relationships with racial disparity in arrests. These types of drugs are particularly racialized; cocaine and unspecified controlled substances associated with non-white use and sales, and hallucinogens are associated with white use and sales (Beckett et al., 2005; Brunson & Weitzer, 2008; Cuomo et al., 1994; Landry, 2002; Leukefeld et al., 2002; Nicholson & Balster, 2001). Regardless of the reason, the transition in ethos resulted in a statistically significant reduction in the rate at which black and non-white individuals are arrested, but did not directly reduce the disparity between black and non-black and non-white and white arrests.

The Effect of Units and Tactics

Chapters 5 and 6 investigated three aspects of policing that have been tied to racialized patterns of policing. First, both chapters assessed the role of specialized units. In the “tough on crime” era, the PPU Red Dog was responsible for a large proportion of drug arrests, and research has suggested that such units may disproportionately contribute to racialized patterns of drug arrests (Kraska & Cubellis, 1997; Kraska & Kappeler, 1997). While the findings from Chapter 5 did not support this notion on a citywide scale, Red Dog did play a significant role in racial patterns of drug arrests for certain drug types and within certain zones. As the APD shifted from “tough” to “smart,” they replaced this unit with data-driven units. Such units are explicitly race-neutral, but research demonstrates that they, too, may contribute to the racialized policing (Ferguson, 2017). Findings in Chapter 6 highlight the link between the use of such units and the racial composition of a neighborhood, especially within certain APD zones. The transition to "smart" policing also resulted in the APD shifting focus from drugs to violent and property crime, which brought about a drop in the use of specialized units to police drug crime (see Table 1). If the very use of specialized units to address drug crimes enhances racialized patterns of policing, then tracts experiencing reductions in the use of specialized units should experience reductions in both the black/non-white arrest rate and racial disparities in arrests.

Past research has linked the use of warrants and order maintenance stops to racialized patterns of policing (Benner, 2002; Fagan et al., 1999; Gelman et al., 2007). In general, analyses from Chapters 5 and 6 did not find evidence of this citywide, but within certain zones, there was a relationship between these tactics and both the race of arrestees and the racial composition of the neighborhoods in which they are arrested. Further, in 2012, a citywide relationship between order maintenance stops and race was apparent. While Table 1 did not find evidence of a significant reduction in the use of these tactics across eras, it remains possible that within those tracts experiencing a reduction, the decline in use was associated with a reduction in the black/non-white arrest rate and racial disparities in arrest.

Tables 3 and 4 assess the impact of the use of specialized units and tactics. Findings in Table 3 involve an operationalization for order maintenance stops that includes pedestrian and traffic stops, and findings in Table 4 involve an operationalization that only includes pedestrian stops. All four models include the same set of controls employed in the previous models (see Table 2). A few findings are noteworthy. First, reductions in the use of warrants have no clear or consistent effect on black/non-white arrest rates or disparities. Analyses in Chapters 5 and 6 both found that warrants are associated with racialized patterns of policing, particularly when drug type and severity of charge are not accounted for. Yet warrant use is relatively rare compared to other policing tactics. Thus, it is possible that the absence of a relationship is due to the fact that while warrants may be linked to race, when arrest statistics are aggregated to the tract level, warrants have only a minimal impact on arrest rates and disparities given their rarity.

Table 3. Fixed Effects Linear Regression Models for the Effect of Units and Tactics on Black/Non-White Arrest Rates and Black/Non-White Arrest Disparities - Order Maintenance Traffic and Pedestrian Stops

	Model 1 Arrest Rate Coefficient (SE)		Model 2 Arrest Disparity Coefficient (SE)	
	Black	**Non-White**	**Black**	**Non-White**
Proportion of Arrests Involving Specialized Units	1.53 (0.66)*	1.73 (0.58)**	-0.22 (0.45)	-0.02 (0.32)
Proportion of Arrests Involving Warrants	-1.04 (0.62)+	-0.77 (0.55)	-0.70 (0.48)	-0.44 (0.33)
Proportion of Arrests Involving Order Maintenance Stops	0.37 (0.38)	0.63 (0.34)+	-0.19 (0.37)	0.07 (0.29)
Proportion of Arrests Involving Marijuana	1.02 (0.53)+	0.75 (0.47)	1.06 (0.42)*	0.78 (0.33)*
Proportion of Arrests Involving Cocaine	2.74 (0.39)***	2.31 (0.35)***	1.05 (0.33)**	0.62 (0.24)*
Proportion of Arrests Involving Heroin	-0.96 (1.09)	-0.52 (0.88)	-1.29 (1.07)	-0.85 (0.81)
Proportion of Arrests Involving Controlled Substances	1.35 (0.52)*	0.85 (0.44)+	1.33 (0.50)**	0.83 (0.40)*
Proportion of Arrests Involving Methamphetamine	1.14 (0.79)	0.67 (0.69)	-0.06 (0.67)	-0.52 (0.55)
Proportion of Arrests Involving Hallucinogens/Party Drugs	1.49 (0.56)**	1.25 (0.46)**	1.22 (0.58)*	0.99 (0.45)*
Proportion of Arrests for Intent to Sell	1.10 (0.54)*	0.95 (0.47)*	0.59 (0.41)	0.44 (0.32)
Proportion of Arrests for Sales, Trafficking, Manufacturing	0.49 (0.61)	0.42 (0.55)	0.02 (0.39)	-0.04 (0.3)
Concentrated Disadvantage	-0.55 (0.32)+	-0.57 (0.28)*	-0.25 (0.18)*	-0.26 (0.12)*
Residential Instability	0.23 (0.27)	0.11 (0.25)	0.37 (0.18)	0.25 (0.14)+
Percent Foreign Born	0.00 (0.02)	-0.01 (0.02)	0.01 (0.01)	0.00 (0.01)
Percent Young Males	-0.05 (0.03)+	-0.05 (0.02)*	-0.01 (0.01)	-0.01 (0.01)
Violent Crime Rate[1]	0.21 (0.16)	0.23 (0.16)	-0.13 (0.11)	-0.11 (0.09)
Property Crime Rate[1]	0.06 (0.03)+	0.05 (0.03)+	0.03 (0.02)	0.03 (0.02)
Zone Membership[2]				
Zone 1	-0.79 (0.41)+	-0.90 (0.37)*	-0.22 (0.4)	-0.34 (0.35)
Zone 2	0.51 (0.54)	-0.16 (0.48)	1.05 (0.41)***	0.83 (0.33)*
Zone 3	0.96 (0.47)*	1.05 (0.43)*	-0.04 (0.25)	0.05 (0.17)
Zone 4	-0.34 (0.44)	-0.39 (0.43)	0.11 (0.22)	0.06 (0.19)
Zone 5	0.76 (0.43)+	0.47 (0.41)	0.25 (0.36)	-0.05 (0.23)
Zone 6	0.46 (0.32)	0.37 (0.31)	-0.01 (0.21)	-0.09 (0.16)

+p<.10, * p<.05, ** p<.01, *** p<.001
[1]Per 100 people.
[2]Categories not mutually exclusive.

Table 4. Fixed Effects Linear Regression Models for the Effect of Units and Tactics on Black/Non-White Arrest Rates and Black/Non-White Arrest Disparities - Order Maintenance Pedestrian Stops Only

(n=228)	Model 1 Arrest Rate Coefficient (SE)		Model 2 Arrest Disparity Coefficient (SE)	
	Black	**Non-White**	**Black**	**Non-White**
Proportion of Arrests Involving Specialized Units	1.44 (0.67)*	1.59 (0.58)**	-0.18 (0.45)	-0.03 (0.33)
Proportion of Arrests Involving Warrants	-1.04 (0.61)+	-0.79 (0.54)	-0.70 (0.47)	-0.45 (0.32)
Proportion of Arrests Involving Order Maintenance Stops	1.11 (0.59)+	1.67 (0.53)**	-0.53 (0.53)	0.03 (0.40)
Proportion of Arrests Involving Marijuana	1.09 (0.52)*	0.88 (0.45)+	1.02 (0.40)*	0.80 (0.31)*
Proportion of Arrests Involving Cocaine	2.77 (0.38)***	2.38 (0.34)***	1.03 (0.31)**	0.64 (0.22)**
Proportion of Arrests Involving Heroin	-0.77 (1.10)	-0.23 (0.87)	-1.39 (1.04)	-0.84 (0.79)
Proportion of Arrests Involving Controlled Substances	1.45 (0.53)**	1.01 (0.46)*	1.28 (0.49)*	0.84 (0.40)*
Proportion of Arrests Involving Methamphetamine	1.18 (0.75)	0.76 (0.65)	-0.08 (0.65)	-0.50 (0.53)
Proportion of Arrests Involving Hallucinogens/Party Drugs	1.58 (0.61)*	1.36 (0.52)*	1.18 (0.54)*	0.97 (0.44)*
Proportion of Arrests for Intent to Sell	1.11 (0.55)*	0.95 (0.48)+	0.59 (0.41)	0.43 (0.32)
Proportion of Arrests for Sales, Trafficking, Manufacturing	0.53 (0.57)	0.47 (0.50)	0.01 (0.38)	-0.05 (0.28)
Concentrated Disadvantage	-0.60 (0.31)+	-0.65 (0.26)*	-0.22 (0.19)	-0.27 (0.12)*
Residential Instability	0.19 (0.27)	0.05 (0.24)	0.39 (0.18)*	0.25 (0.13)+
Percent Foreign Born	0.00 (0.02)	-0.01 (0.02)	0.01 (0.01)	0.00 (0.01)
Percent Young Males	-0.04 (0.03)+	-0.04 (0.02)+	-0.01 (0.01)	-0.01 (0.01)
Violent Crime Rate[1]	0.15 (0.16)	0.15 (0.15)	-0.11 (0.11)	-0.11 (0.09)
Property Crime Rate[1]	0.06 (0.03)*	0.07 (0.03)*	0.03 (0.02)	0.03 (0.02)
Zone Membership[2]				
Zone 1	-0.64 (0.43)	-0.69 (0.40)+	-0.29 (0.39)	-0.34 (0.36)
Zone 2	0.77 (0.48)	0.24 (0.42)	1.37 (0.39)**	0.85 (0.31)**
Zone 3	0.78 (0.46)+	0.78 (0.40)+	0.04 (0.25)	0.04 (0.18)
Zone 4	-0.36 (0.54)	-0.42 (0.58)	0.12 (0.19)	0.06 (0.19)
Zone 5	0.76 (0.46)+	0.46 (0.39)	0.25 (0.35)	-0.05 (0.24)
Zone 6	0.38 (0.32)	0.25 (0.32)	0.03 (0.22)	-0.10 (0.17)

+p<.10, * p<.05, ** p<.01, *** p<.001
[1]Per 100 people.
[2]Categories not mutually exclusive.

Second, the effect of reductions in the use of order maintenance policing are dependent on whether order maintenance is conceptualized to involve traffic stops. While there is no statistically significant relationship between changes in order maintenance tactics when defined as including traffic stops, there is when they include only pedestrian stops. Decreased order maintenance stops between periods are associated with decreased non-white arrest rates ($\beta = 1.67$; $p<.01$; Table 4). Order maintenance stops are more common than warrants, and they are the only tactic linked to citywide racialized patterns of policing in a fully specified era-specific model (Chapter 6, Table 10, Model 4). As noted in Chapter 6, this finding might hold for pedestrian order maintenance stops and not for order maintenance stops that include traffic stops for two reasons: (1) the salience of race and racial composition may be greater when officers are on foot, and (2) there is an increased likelihood that pedestrian disorder (e.g., public drinking) may indicate underlying drug crimes compared with vehicular disorder (e.g., running a red light).

Third, among the three key characteristics of arrests, the strongest relationship occurs for the use of specialized units. Increases in the use of specialized units are associated with statistically significant increases in the black ($\beta = 1.44$; $p<.05$; Table 4) and non-white ($\beta = 1.59$; $p<.01$; Table 4) arrest rates, and conversely reductions in their use are associated with reductions in the black and non-white arrest rates. Use of specialized units to address drug crime appears to increase the racialized patterns of policing. These findings align with the current understanding of specialized units as it is believed they are more likely to behave in ways contrary to departmental policy (National Research Council, 2004). Tracts with declining specialized unit use are tracts in which Red Dog involvement in arrests was not simply replaced with data-driven unit arrests. Based on findings from Chapter 5 and Chapter 6, both tactics contributed to racialized patterns of policing in their respective eras in nuanced ways, and thus it is not surprising that reductions in black and non-white arrest rates are realized when Red Dog arrests are replaced with general APD arrests, not data-driven arrests.

Finally, there is no impact of units or tactics on racial disparities. Reductions in the use of specialized units and order maintenance stops involving pedestrians result in reductions in the rate at which non-white residents are arrested, but they have no effect on the discrepancy between non-white arrests and all arrests. In essence, reductions in these practices brought about substantially lowered rates of arrests for non-white Atlantans, but these reductions either mirrored those for white Atlantans or were not substantial enough to alter the racial disparities existing in 2005.

Discussion

This chapter assessed the changes in race-specific arrest rates and racial disparities in arrests that occurred as a result of the overall shift in policing ethos between 2005 and 2012. Particular attention was paid to changes in the use of specialized units, order maintenance stops, and warrants. The findings provide a mixed story for the impact of the movement from "tough" to "smart" policing.

First, I find bivariate reductions in both the black/non-white arrest rate and the black/non-white arrest disparity. Black/non-white Atlantans are arrested for felony drug crimes at a lower rate in the "smart on crime" era (2012) than they were in the "tough on crime" era (2005), and their rate of arrest in the "smart on crime" era better aligns with the overall arrest rate. Yet when these differences are assessed using a model that incorporates changing demographic and crime patterns within Atlanta, only the impact on the black/non-white arrest rate remains statistically significant; the impact on the disparity in arrest rates is no longer significant. Changes to the ways in which the APD police felony drug crime across this period have resulted in reductions in the arrest rate for black/non-white residents, even when controlling for a variety of other factors likely to affect such change, but similar changes are not observed for the arrest disparity by race. Essentially, when controlling for other time-varying factors, black/non-white Atlantans are being arrested for felony drug crimes at a much lower rate in 2012, but they still represent an equally disproportionate share of the felony drug arrests compared to the "tough on crime" era, and are still arrested at a much higher rate than white residents.

Qualitative investigations of the relationships between police and non-white residents of major cities find that participants are not only upset with the disparity in police actions, but also with the sheer volume of police activities (e.g., stops, searches, arrests) that racial and ethnic minorities experience (Brunson & Miller, 2006; Brunson & Weitzer, 2008; Gau & Brunson, 2015; Goffman, 2014; Rios, 2011, 2017; Weitzer, 1999; Weitzer & Tuch, 2005). In interviews with black and white youth in St. Louis, Brunson and Weitzer (2008) found that black youth were both upset with perceived disparate treatment by police officers and with perceived excessive attention from police officers. Rios (2011) uncovered similar findings among black and Latino youth in Oakland, CA, as did Goffman (2014) in Philadelphia and Weitzer (1999) in Washington, D.C. The findings of the current study suggest that, as a result of the shift in the policing in the Atlanta, the former did not change but the latter changed dramatically. If the qualitative results from other settings—St. Louis, Oakland, Philadelphia, and Washington—parallel the lived experiences of Atlantans, then this shift should represent a noticeable, albeit incomplete, improvement in the relationship between police and persons of color in Atlanta.

Next, I assessed the impact of changes in the use of specialized units, warrants, and order maintenance tactics. The use of specialized units declined across this period, and these reductions were associated with decreases in the black/non-white arrest rate, but not with decreases in racial disparities in arrest. In response to various crises in policing, the APD disbanded Red Dog and replaced it with a data-driven approach to policing, but they did not make a 1-to-1 replacement (Blau, 2016). Their new specialized data-driven units may be focused on violent and property crime rather than drug crime, which would align with statements made by APD senior leadership (Atlanta Police Department, 2012; City of Atlanta, 2016), because drug arrests in 2012 are less likely than those in 2005 to involve a specialized unit. Considering the racialized patterns of policing associated with data-driven policing in general and as evidenced in Chapter 6 (Ferguson, 2017), it is not surprising that tracts that experienced dramatic reductions in the rate of involvement of specialized units also experienced dramatic reductions in the non-white arrest rate. This change, though, is not associated with reductions in the arrest disparity. A decrease in the involvement of specialized units in drug policing has resulted in reductions to the likelihood of arrests among black/non-white residents, but it has not changed the fact that black/non-white residents experience a higher likelihood of felony drug arrests than their white counterparts. This could be either because the change in the black/non-white arrest rates brought about by declining involvement of specialized units was not substantial enough to offset this imbalance, or because reductions in the involvement of specialized units affected white arrest rates in a similar fashion.

Finally, despite their association with “tough on crime” policing, warrants and order maintenance stops remained common across eras. Consistency in the rate of warrants is likely due to the long history of this tactic within policing; warrants are a staple of the field, despite evidence that their use is racialized (Benner, 2002; National Research Council, 2004). While order maintenance stops are a relatively newer tactic, adopted primarily within the “tough on crime” era (Beckett, 2016), they have been heavily used since the 1980s and may have become equally engrained in police behavior. Nonetheless, the lack of a reduction in both practices is surprising considering they were associated with the crises that motivated a change in the APD (Blau, 2016). Equally surprising is that fact that in census tracts where their use declined, there was no noticeable impact on non-white arrest rates or racial disparities (excepting order maintenance stops involving pedestrians). By and large, reducing the use of these tactics did not have an effect on racialized patterns of policing drug crime because other tactics are equally likely to produce such patterns.

Collectively, these findings paint a mixed picture of the transition from “tough” to “smart” policing in Atlanta. As evidence of change, bivariate measures indicate reductions in black/non-white arrest rates and racial disparities in arrest; the role of specialized units declined dramatically; when controlling for changing demographic and crime measures, the shift in eras, the reduction in specialized unit usage, and the reduction in pedestrian order maintenance stops resulted in a lower non-white arrest rates. Yet, at the time, the proportionate use of warrants and order maintenance stops remained steady across eras, despite their association with various crises within the APD in the “tough on crime” era; any reductions to the use of warrants and order maintenance stops involving both traffic and pedestrian behavior were not linked to reductions in either the black/non-white arrest rate or racial disparities; and once other changing neighborhood conditions were accounted for, there was no reduction in the arrest disparity across eras or as a product of reduced use of specialized units or tactics. In the final chapter, I discuss the meaning of these findings in the context of those outlined in Chapters 4, 5, and 6, and what, collectively, this research says about race, drugs, and policing in Atlanta in two distinct eras.

<u>Conclusion: Policing Felony Drug Offenses in Atlanta under Two Models</u>

The “tough on crime” ethos pervaded the United States criminal justice system for decades beginning in the 1970s (Campbell, Vogel, & Williams, 2015). This ethos emphasized the aggressiveness of the law enforcement response to crime, promoting harsh punishment within the courts, increased use of revocation in community supervision, and a heavy reliance on arrests within policing – policies that led to a historically and globally unprecedented increase in the rate of, and racial disparities in incarceration (Campbell et al., 2015; Mauer, 2006; National Research Council, 2014). These patterns were driven by a focus on drug offenses, with federal programs and funding explicitly promoting an intensive and aggressive response to drug crimes and drug offenders (Balko, 2015; Mauer, 2006).

Yet over the past decade, a shift occurred broadly within the field of criminal justice, and specifically within policing, advocating a move away from a “tough on crime” ethos and towards a “smart on crime” ethos (Telep, 2016). This was motivated by a variety of factors, including effectiveness, efficiency, and legitimacy (Bueermann, 2012; Lowery, 2016; Mazerolle et al., 2007). But one significant motivation centered on concerns over racialized patterns of policing within large cities across the U.S. (Ferguson, 2017; Lowery, 2016). The shift in ethos promoted a movement away from “tough” units like PPUs and toward “smart” units, under the belief that because data-driven tactics were, on their face, race neutral, they would not lead to the same disparities in the policing of drug crime (Ferguson, 2017). This shift also emphasized the use of alternatives to arrests, like the strategies found in problem-oriented policing and community policing, and placed a greater emphasis on violent and property crime rather than drug crime (Alexander, 2012; Braga et al., 2001; Skogan, 2006).

Long before many other large, urban police departments faced highly publicized problems associated with racial disparities, the Atlanta Police Department experienced such a crisis and addressed it by fully embracing the shift from a “tough” to “smart” ethos (Blau, 2016; Lowery, 2016). In the early and mid-2000s, a number of incidents occurred within the city that sparked this transition, including: the death of an elderly woman at the hands of police; a raid on an Atlanta gay bar that involved abusive, aggressive actions by officers; and a public strip search of young man in the middle of the street (Blau, 2016; Cook, 2013). In response, the APD introduced a series of dramatic changes (Blau, 2016), changes that anticipated those that would occur a few years later in many other cities. They rejected aggressive PPUs by disbanding their drug-focused PPU, Red Dog; embraced data-driven units and community policing; incorporated additional training and outreach; and de-emphasized the importance of making arrests overall, and especially for drug crime (Balko, 2015; Benner, 2002; Blau, 2016; Ferguson, 2017; Gelman et al., 2007; Kraska, 2007).

As early, faithful adopters of the shift from “tough” to “smart,” motivated by widely publicized real and reputational problems within the city, the Atlanta Police Department provides a compelling case study for understanding the effects of this change in ethos on racialized patterns of policing. In this dissertation, I examined how drug policing in Atlanta changed as the police department transitioned from a “tough on crime” to a “smart on crime” ideology, paying close attention to racialized patterns of drug arrests within eras, factors contributing to those patterns, and changes in the policing of drug crime that occurred across eras. I did so by focusing on the race of arrestees and the racial composition of neighborhoods in which drug arrests take place. Drug arrests function as the first step in formal involvement with the criminal justice system, and thus, the use of arrests leads to the racial disparities witnessed at various stages within the system, including incarceration (S. D. Bushway & Piehl, 2001; Cook, 2013; J. A. Goldstein, 1960; National Research Council, 2014).

The findings presented in this dissertation paint a complicated picture, with the APD achieving reductions in overall drug arrests and non-white drug arrest rates across eras, but failing to achieve statistically significant reductions in arrest disparities by race. The stability in racial disparities may be a result of the unexpectedly minor role played by various units and tactics in producing these patterns in the first place. It may also be a product of the resistance to change common in many police agencies (Dabney, 2010; D. R. Johnson, 1981; Mastrofski & Willis, 2010; Sykes, 1985; Weisburd & Braga, 2006; Willis et al., 2003; Willis et al., 2007). Finally, it may reflect the difficulty of addressing racialized patterns of policing, due to the long history of racialized policing and the numerous mechanisms that produce them (Monkkonen, 1992; National Research Council, 2004; Warren et al., 2006).

In the following sections, I summarize racialized patterns of drug arrests examined in this dissertation during the “tough on crime” era (2005) and the “smart on crime” era (2012), as well as the role of specialized units, warrants, and order maintenance stops in shaping these patterns. I then discuss the theory that may explain these findings, policy implications of the findings, and some of the main limitations of this research.

Racial Patterns of Arrests in and across Eras

A series of descriptive statistics presented in Chapter 4 revealed that there were clear racialized patterns in the policing of drug crimes in both eras. In both 2005 and 2012, non-white Atlantans were more likely to be arrested than would be expected based on both their share of the city and their share of the neighborhood population in which arrests occurred. For example, non-white residents in Atlanta were arrested a rate that was 148% larger their residential rate in 2005 and 162% of their residential rate in 2012 at a citywide level. At the same time, findings from Chapter 7 reveal that within Atlanta neighborhoods the non-white arrest rate dropped significantly across eras. Consequently, by 2012, non-white Atlantans were being arrested significantly less often relative to their share of the neighborhood population. These findings may be partially attributable to the dramatic reduction in drug arrests writ large, with the overall number of arrests decreasing by 60% (from 3,017 in 2005 to 1,198 in 2012). Yet such reductions need not have occurred similarly across racial and ethnic groups, and could have been more pronounced for white residents. My findings suggest that they were not; instead, real reductions in the non-white arrest rate occurred. Further, these findings hold in a multivariate model that controls for changing drug, crime, and demographic patterns, as well as changes in zone membership. This highlights one of the clearest signs of change across eras. While racialized patterns of policing existed in both eras, the overall number of drug arrests decreased dramatically and the drug arrest rate for non-white Atlantans also decreased dramatically; both appear to be a result of the transition in policing ethos within the APD.

Yet racial disparities in drug arrests did not exhibit as clear a change across eras. Findings in Chapter 7 revealed a declining racial disparity in drug arrests; that is, while in both eras non-white Atlantans are arrested at a disparate rate, the disparity decreases across eras. However, changing demographic and crime patterns appear to account for all of this decline in arrest disparity across eras. This suggests that while some racial disparities were alleviated between 2005 and 2012, the reduction was not due to changes in APD policing practices, but instead to changes in drug, crime, or demographic patterns. Therefore, while non-white Atlantans were not arrested as often in 2012 as they were in 2005, they were still much more likely to be arrested than their white counterparts, given their share of the residential population. Racialized patterns of policing changed across eras, but the change was primarily in volume not nature.

The lack of change in racial disparities as a result of this shift in policing could be expected, though. While past research has suggested that PPUs, data-driven units, warrants, and order maintenance stops should disproportionately produce racial disparities, they were not operating in that fashion in Atlanta. Relative to other APD officers and tactics, these units and tactics did not disproportionately contribute to racialized drug arrest patterns within the city. While the shift in ethos did not solely revolve around these issues, a large portion of the shift focused on replacing PPUs with data-driven units and was motivated by issues with warrants and order maintenance stops. This focus may be one reason why the shift in ethos failed to generate direct reductions in the racial disparity in drug arrests. In the following three sections, I discuss the meaning of these findings for better understanding the role played by PPUs, data-driven units, warrants, and order maintenance stop in producing racialized drug arrest patterns.

The Role of Specialized Units

Specialized units were the public face of policing drugs in the “tough on crime” era and of the switch to a “smart on crime” mentality. The use of PPUs to address drug crimes grew out of the “tough on crime” movement, with many agencies developing units governed by aggressive tactics and a sole-reliance on arrests as a means of combatting the drug epidemics of the 1980s, 1990s, and early 2000s (Klinger & Rojek, 2008; Kraska & Cubellis, 1997; Kraska & Kappeler, 1997). Atlanta followed this trend, creating a drug-specific PPU, Red Dog, as a response to rising violent and property crime rates and the crack cocaine epidemic in 1980s (Geraghty & Velez, 2011; Hornsby, 1992). Decades later, this unit was responsible for the three main incidents that sparked outrage among Atlantans and forced the city to change the way it approached policing drug offenses. Specifically, Red Dog officers killed an elderly black woman, Kathryn Johnston, during a no-knock search warrant based on inaccurate information; conducted a search of an Atlanta gay bar, and in the process, verbally and physically assaulted bar patrons; and in an order maintenance stop, strip-searched a young black man, Ricky Sampson, in the middle of the street and in front of friends (Bagby, 2007; Blau, 2016; Visser & Garner, 2011). Some of the officers involved in these incidents cited the culture within the unit and APD as a cause, noting that they had arrest and warrant quotas that pushed them to make arrests at all costs (Cook, 2013). These incidents led to cries for reform, and in response, one of the first steps the APD took—a step heavily advertised in local press accounts—was to disband the Red Dog unit ("Atlanta police disband Red Dogs," 2011; Bagby, 2007; Visser & Garner, 2011). Research on a drug-focused PPU in Washington, D.C. found that a similar unit in that city policed in a racially biased manner (Chambliss, 1994). Thus, it is reasonable to assume that Red Dog officers may have disproportionately contributed to the racialized patterns in drug arrests for 2005 observed in Chapter 4, policing in a fashion different than other APD officers.

Yet this is not what the findings presented in Chapter 5 revealed. In a fully-specified regression model accounting for various arrestee, case, and neighborhood characteristics, arrestee race and neighborhood racial composition were not linked to the involvement of Red Dog. This does not imply that Red Dog was making drug arrests in a racially-neutral fashion, but simply that their arrests were no more racially patterned than were those of other APD officers. Indeed, because arrests were racially patterned in this era, the fact that Red Dog does not differ from other APD officers implies they were policing in a racially patterned fashion, but simply one that is no more exaggerated than that of any other APD officer.

Some nuanced links to race do exist. In particular, Red Dog focused heavily on methamphetamine and party drugs, and the use and sale of these drugs predominately involved white Atlantans (Copes et al., 2014; Fendrich et al., 2003; Fox & Rodriguez, 2010). When examining all arrests that do not involve these drug types, black and other non-white arrestees were more likely to be arrested by Red Dog; thus, for cocaine, marijuana, heroin, and unspecified substances, Red Dog was disproportionately contributing to racialized patterns of policing, even if they were not doing so for all drug types. Further, patterns varied by zones, with Red Dog arrests in Zones 5 and 6 showing clear racialized patterns of policing, wherein non-white arrestees were far more likely to be arrested by Red Dog officers, holding other case and neighborhood conditions constant. In these zones Red Dog officers behaved differently than other APD officers policing the same areas, contributing to racial disparities in the policing of drug crime in certain sections of Atlanta.

In place of Red Dog, Atlanta adopted a data-driven approach that involved a number of new units, including APEX, a data-driven unit focused on violent offenders and recidivists (Atlanta Police Department, 2012, 2013, 2014; Blau, 2016; Cook, 2013). This mirrored the shift that had or would occur in numerous large police departments across the country, with agencies adopting intelligence-led policing, hot spots policing, and other strategies that rely on data to make decisions (D. L. Carter & Carter, 2008; Ferguson, 2017; National Research Council, 2004). The attraction of such strategies is that, because they rely largely on past police data to make current policing decisions, they appear to be race neutral. But as Ferguson (2017) has noted, the fact these approaches do not explicitly rely on race to make decisions does not mean they do not have racially patterned and disparate effects, with those patterns rooted in the subjectivity and bias built into the stops and arrests that constitute the data. While the APD assumed such strategies would be an improvement, it is thus possible and even likely that they contributed to racialized patterns of policing in the "smart on crime" era.

Findings from Chapter 6 suggest that, once other relevant arrestee, case, and neighborhood characteristics are accounted for, data-driven drug arrests were no more racially patterned than were drug arrests by other APD officers. This may be a function of their focus on where violent and property crimes occur, as prior to accounting for the total crime rate, data-driven tactics were more likely in neighborhoods with high rates of non-white residents. Yet, while their practices do not focus on race and racial composition more than their APD counterparts, they also do not focus on it any less than their APD counterparts. Data-driven units do not do a better job at ignoring race than the average officer, which suggests that Ferguson (2017) was right. While they give the appearance of making decisions in race neutral fashion, they are no more race neutral than the average APD officer. In addition, while across Atlanta, they are no more racially patterned than other APDS officers, within certain zones they exhibited stronger racial patterns, with data-driven units are more likely to make arrests in predominately non-white neighborhoods even when controlling for the crime rate. Specifically, Zones 1 and 3 exhibit an increased likelihood of a data-driven arrest as the rate of non-white residents increases. In sum, data-driven units citywide are no more race-neutral than average APD officers, and within Zones 1 and 3, they exhibit racialized arrest patterns that are more pronounced than those of the average APD officer.

These findings cannot speak to other ways in which Red Dog or data-driven units may police in a racially disparate fashion. For example, Red Dog and data-driven units may make stops in a racially-patterned fashion that are distinct from the rest of the APD, as research has suggested they do (Chambliss, 1994; Ferguson, 2017). But if they are, these racially-patterned stops are not leading to racially-patterned arrests that are distinct from the rest of the department.

Chapter 7 makes clear that one of the other major changes the APD made was to reduce their overall use of specialized units to address drug crime, a finding in line with the statements made by the department at the time (Atlanta Police Department, 2012;

Bagby, 2007; Visser & Garner, 2011). The APD did not simply replace Red Dog with data-driven units. Instead, much of the drug arrest activity that was formerly conducted by Red Dog, was conducted by various non-specialized APD officers in 2012. And these reductions are linked, when controlling for other time-invariant and time-varying factors with reductions in the non-white arrest rate. They are not, however, linked to changes in in the non-white arrest disparity. Despite the emphasis on PPUs in the "tough on crime" era and the focus on their replacement in the "smart on crime" era both within Atlanta and nationally, these units were only partially responsible for the racialized patterns of drug arrests in their respective eras, and thus the replacement of Red Dog with data-driven units and the overall reduction in use of specialized units had only a minor impact in generating racial disparities. Specific police tactics, especially warrants and order maintenance stops, played just as large a role in the rhetoric around this transition; their impact is discussed in the next two sections.

The Role of Warrants

Serving search and arrest warrants has been a staple of policing for most of the history of the profession, yet their use escalated noticeably during the "tough on crime" era, especially for drug offenses (Balko, 2015; Kraska & Cubellis, 1997; Kraska & Kappeler, 1997; National Research Council, 2004). One outcome of this escalation in the use of warrants was their association with numerous high profile incidents that involved harm to citizens, many of whom were persons of color (Balko, 2015; Chambliss, 1994). This was certainly the case in Atlanta. Two of the high-profile incidents that led to the shift from "tough" to "smart" policing involved the serving of search warrants: the death of Kathryn Johnston and the raid of the Atlanta Eagle (Bagby, 2007; Visser & Garner, 2011). Indeed, one major change the APD made in response to these incidents was to substantially limit their use of no-knock warrants (City of Atlanta, 2016). While racial patterns in warrant use are relatively understudied, one study into their use in San Diego found clear bivariate racial patterns, with drug warrants being served more often in non-white neighborhoods and on non-white San Diegans (Benner, 2002).

Yet while warrants were consistently and strongly linked with arrestee race in Atlanta in both eras—with non-white individuals being far more likely to be arrested by warrant—when accounting for other relevant factors, the use of warrants to make drug arrests was no more linked to racialized patterns of policing than were other tactics. This relationship appears to be mostly explained by the type of drug involved in arrests, with the APD using warrants more often in cases involving marijuana and cocaine. The use of warrants, though, is linked to race within certain zones. In 2005, warrants were more likely in neighborhoods with a higher percentage of non-white residents in Zones 3, 5, and 6, and in 2012, warrants were more likely to involve non-white arrestees in Zone 1 and to occur in predominately non-white neighborhoods in Zone 6. While warrants were not used in a racially patterned fashion across the whole city, once other aspects of an arrest are taken into account, they were used in a racially-patterned fashion with certain zones. This is not unexpected; research suggests that within large police departments, police behavior should vary dramatically within zones/districts/precincts because of the different leadership and work culture, and here it appears that the ways in which warrants are used is one of the many things that vary across zones (Klinger, 1997, 2004; Rowe, 2006).

Despite their salience in the APD crises and the growing concern nationally that using warrants to serve drug arrests could lead to such harmful incidents and racial disparities in policing, the findings of Chapter 7 reveal that the proportionate use of warrants did not decrease across eras. While warrant use declined within some neighborhoods, on average, there was no significant reduction across the city. This consistency in warrant use across eras, though, may not have affected the racialized patterns of policing in Atlanta, as changes to the use of warrants were not linked to changes in the non-white arrest rate or disparity.

Despite their association with high profile incidents and early evidence suggesting their racially biased use, warrants do not appear to be associated with racialized patterns of drug arrests any more than other arrest tactics when accounting for other relevant factors, and they were not linked to any changes in racial disparities or the non-white arrest rate across eras. As with the use of specialized units, this does not necessarily imply that warrants are used in a race neutral fashion. For example, research has highlighted the problem of no-knock warrants (Balko, 2015; Kraska & Kappeler, 1997). It is possible that no-knock warrants are served in a racially-patterned fashion. Other aspects of the ways in which they are served, such as whether harm occurs, may also be racially patterned. But warrants are not the only tactic that proved a problem in the "tough on crime" era nationally and within Atlanta; order maintenance stops did, too.

The Role of Order Maintenance Stops

Order maintenance stops are police-citizen interactions that occur because of minor disorderly behavior, such as jaywalking or loitering. Such stops are not new to policing nor did they originate in the “tough on crime” era, but their use as a means of making arrests under the belief that such arrests will prevent more serious crime is new and is a product of the “tough on crime” ethos (Harcourt & Ludwig, 2006). Such strategies have become staples of the field over the past few decades, adopted by numerous police agencies. Nevertheless, their use has been mired in controversy, with evidence suggesting that they are not only ineffective in reducing crime but that they generate racial disparities (Brunson & Weitzer, 2008; Chambliss, 1994; Fagan et al., 1999; Gau & Brunson, 2015; Gelman et al., 2007). In particular, their association with racial disparities in policing in New York, where they are often referred to as stop-and-frisk or broken windows policing, has garnered national attention (Ridgeway, 2007; Torres, 2015). The use of order maintenance stops was also controversial in Atlanta, with one of the main incidents that led to the shift in policing ethos involving an order maintenance stop. Ricky Sampson was stopped by Red Dog officers without clear evidence of any offense, and in the process this young black man was strip searched in front of his peers, an action which made local news and led to a successful lawsuit against the city of Atlanta (Cook, 2013; Visser & Garner, 2011). In cities like Atlanta, where much of the activity occurs in cars as opposed to on foot, order maintenance stops may also occur in vehicles in the form of minor traffic violations (Dunn, 2015).

This suggests that order maintenance stops should be associated with racialized patterns of drug arrests when compared to other tactics. Their relationship with race, though, varies by era and by the type of order maintenance policing under consideration. When order maintenance policing is defined as involving both pedestrian stops and traffic stops, no citywide relationship between race or racial composition exists in fully specified models, and only a few relationships materialize within zones. For order maintenance stops that include pedestrian stops only, a relationship exists between neighborhood racial composition in the “smart on crime” era, but not in the “tough on crime” era. Pedestrian order maintenance stops are more likely to occur in neighborhoods with higher rates of non-white residents in the “smart on crime” era. The difference in findings across eras may speak to the difference in other tactics across eras. It is possible that no distinction exists in the “tough on crime” era because other arrest tactics were similarly racially patterned in that era. Essentially, it is possible that in the “tough on crime” era all policing tactics were focused on non-white residents and neighborhoods, and thus there was a less of a distinction between order maintenance stops and other tactics. Alternatively, it is possible that order maintenance pedestrian stops are used differently across eras, with a greater focus on non-white residents in the “smart on crime” era. If the latter is true, the reasons are unclear, although it is possible that it is a result of the great deal of discretion in determining who to stop and where to stop afforded by order maintenance (Dunn, 2015). In a reformed Atlanta Police Department, an officer who make arrests that are to some degree motivated by race or neighborhood racial composition may only be able to do so through order maintenance stops.

While the proportion of order maintenance stops leading to drug arrests did not decrease across eras, the importance of pedestrian order maintenance stops in determining racialized patterns of drug arrests is reinforced by findings in Chapter 7. At the neighborhood level, reductions in the use of order maintenance stops involving pedestrians was associated with declines in the non-white arrest rate, but as with Chapters

5 and 6, no relationship was found for order maintenance stops including pedestrian and traffic stops.

The difference in findings based on whether traffic stops are included is likely a function of the unique context of pedestrian stops and ways in which officers use cues from the environment during such stops. While research on the targets of traffic stops has found racial bias (American Civil Liberties Union, 1999; Warren et al., 2006), the findings from Chapter 5 and 6 detail racial patterns only for stops that result in arrests. Pedestrian disorderly behavior often provides clearer clues about underlying substance use or sales. For example, public drinking may be associated with the use of illicit substances, and loitering may be indicative of drug dealers waiting for a sale (St. Jean, 2007). Alternatively, vehicular disorder, such as running a stop light, does not always provide such clues. Consequently, the relationship between pedestrian stops and race (and lack thereof for traffic stops) may be driven by the fact that pedestrian order maintenance stops are more likely to lead to drug arrests than traffic order maintenance stops. In addition, the context for police officers varies by stop type. Most pedestrian order maintenance stops occur while officers are on foot, while most traffic stops occur while they are in their vehicle. Factors like the speed with which one moves through a neighborhood and physical presence on street, with the all sights and sounds associated with the area, may alter the salience of neighborhood characteristics, including racial composition, making them more salient for pedestrian order maintenance stops (Hinkle & Yang, 2014). In essence, pedestrian order maintenance stops may have a greater connection to racial composition because the racial composition of a neighborhood is more apparent to an officer walking through the neighborhood than to an officer driving through. Even in a city like Atlanta, where most activity occurs in vehicles, pedestrian order maintenance stops contribute to racialized arrest patterns. This suggests that findings from previous studies on the racialized patterns of order maintenance police stops, are carried over into racialized arrest rates and thus into formal involvement with the criminal justice system (Gelman et al., 2007).

Collectively, these within and across era patterns provide clues about the reasons for the mixed success of the shift in ethos, and what it implies for change within police departments, especially change in racialized patterns of policing. How these patterns for specialized units, warrants, and order maintenance stops help create a clear narrative around the change from “tough on crime” to “smart on crime” is discussed in the next section.

Explaining Changes in Drug Policing in Atlanta

Police are poorly positioned to change their approach to crime. Police agencies are hierarchical groups that exercise a great deal of power over citizens, but because policing is a mobile profession, leadership is unable to consistently monitor the activities of all officers in their agency (Sykes, 1985). This is particularly the case for large agencies like the APD, wherein behavior is more likely to be monitored by local, zone-specific leadership than by departmental leadership (R. R. Johnson, 2012; Klinger, 2004). Police are further challenged by the dual roles they are required to fill, working for the very same people that they may, in the future, arrest (National Research Council, 2004). In addition, a broad body of literature has discussed the strong cultures that form within police departments, making them resistant to external pressures to alter their tactics, behavior, or outlook (Jermier et al., 1991; National Research Council, 2004).

Change in policing may also be limited by the motivations to change. Two main theories borrowed from organizational literature, and which have previously been used to explain change resulting from the adoption of Compstat (Willis et al., 2007), may provide insight. When applied to policing, while both theories assume that police departments are self-interested and respond to external pressures, they differ in their beliefs about how police will respond to that pressure and why (Willis et al., 2007). According to the technical/rational theory, organizations in general and, in this case, police departments develop clear goals and generate specific measures they can use to judge whether they achieve new goals. As such, they will create a mechanism and framework for accountability that help them to do so. The adoption of Compstat within a variety of agencies, but especially within New York City, is a good example. The New York City Police Department developed clear crime reduction goals, held specific individuals responsible for those reductions, and generated consistent, reliable measures by which to judge success (Dabney, 2010; Willis et al., 2007).

On the other hand, the institutional theory assumes that organizational change is influenced by cultural forces, not by rational processes with clear goals and outcomes. Under this model, police are not responding to external pressures as motivation to make direct changes but instead as motivation to better resemble peer agencies. Essentially, changes are symbolic and designed to ensure that the agency resembles an "ideal" police agency. In general, the technical/rational theory predicts real change at all levels, and the institutional theory predicts a decoupling, with reforms occurring at the structural level to align with the desired principles, but with routine work remaining largely unaffected. These theories are not entirely at odds, and both can explain a single shift in ethos—surely some of the motivation underlying Compstat was promotional in nature, considering the wide publicity the strategy has received (Dabney, 2010; Willis et al., 2007).

The change in the APD illustrates how expectations derived from both theories can operate simultaneously within a single departmental shift, and this may explain why some aspects of racialized policing changed and others did not. As evidence of a technical/rational theory of change, the APD made a number of changes supported by the findings in this dissertation. They did not reduce the relative rate of warrant use or order maintenance stops that include traffic stops, and neither were linked to race or reductions in the non-white arrest rate or disparity. They did reduce the involvement of specialized units in drug arrests, and this was linked to a reduction in the non-white arrest rate. And they made a collective body of changes—including incorporating community policing, new training, and focusing on violent crime over drug crime—that led to an overall reduction in the non-white (and white) arrest rate even when accounting for demographic and criminogenic change in Atlanta over time. Essentially, this set of changes made by the APD resembled technical/rational change, with the actions corresponding to measurable improvement, or in the case of warrant and order maintenance stops that include traffic violations, inaction on components of policing with weak links to race.

Alternatively, as evidence of an institutional theory of change, the APD made a number of changes not based on evidence or failed to make changes based on evidence. While pedestrian order maintenance stops were linked to racial composition and the non-white arrest rate, the APD did not reduce the relative rate of their use, and instead continued to mirror agencies like the NYPD which practiced such stops long after evidence of their racial consequences was widely known. The APD made an effort to draw attention to the disbanding of Red Dog and the replacement of it with data-driven units, despite the fact that Red Dog was no more responsible for racialized policing in the "tough on crime" era than other APD officers, and that data-driven units were no less responsible for racialized policing in the "smart on crime" era. Red Dog and similar PPUs had received substantial negative attention locally and nationally, and so the APD distanced themselves from this approach (Balko, 2015; Blau, 2016); data-driven tactics were becoming increasingly popular with police agencies, and so the APD embraced these strategies despite suspicions that they may not result in race neutral policing (D. L. Carter & Carter, 2008; J. G. Carter & Phillips, 2015; Ferguson, 2017). In addition, had the APD focused on the role that drug type played in racialized policing, they may have drawn different conclusions about how to alter their arrest strategies. Such examination would have provided a clear understanding of how warrants and PPUs function in Atlanta. Finally, the APD does not appear to have attempted to make zone-specific changes. In a large agency like the APD, the solution to the problem of racialized policing of drug offenses is not solely found in agency-wide prescriptions, but in in zone-specific remedies. The wide variation in the relationships between different units, tactics, and race across zones suggests that a policy approach based on the evidence would have focused as much on the nuances across zones as it did on larger departmental adjustments.

The technical/rational approach also emphasizes clear measurement of the outcome of interest, and while police collect a variety of measures, few of them directly speak to racial disparities in policing without further interrogation of the data (National Research Council, 2004). Police are often evaluated on the number of arrests they make, the number of stops they conduct, or the crime rates in the beats/precincts/districts/zones they patrol (Cook, 2013; Dabney, 2010; National Research Council, 2004). Early evaluations of police programs and meta-analyses/systematic reviews often measure success as reductions in the crime rate, with little attention paid to the externalities of new strategies, like increases in racial disparities or reductions in police legitimacy (Harcourt & Ludwig, 2006; Mazerolle et al., 2007; National Research Council, 2004; Weisburd & Eck, 2004). When racialized patterns of policing are not explicitly measured as one of the goals of a change in strategies, then these new strategies are unlikely to fulfill that objective. In a blog post for the National Police Foundation, a retired chief of the Pittsburgh Police Department recommends exactly that: measure community outreach and racial disparities much in the same way that police diligently measure crimes (McLay, 2017). APD reports do not reflect that such measurement occurred between 2005 and 2012 (Atlanta Police Department, 2011, 2012, 2013, 2014; Blau, 2016; City of Atlanta, 2016). An approach that had involved such measurement would have identified the patterns described in this dissertation, and could have made corrections as appropriate. Surely, such an approach would not have been perfect, as the incentives placed on crime reduction have occasionally resulted in perverse outcomes (Cook, 2013; National Research Council, 2004), but it, nonetheless, may have been more likely to bring about real change by simply holding the agency and its staff accountable (Willis et al., 2003; Willis et al., 2007).

An additional explanation for the lack of a reduction in racial disparities, despite the dramatic changes made by the APD and reductions in the non-white arrest rate, is the persistence of racialized policing. Race and policing have long been linked, with racialized police outcomes dating back to the early years of policing in the U.S. (Monkkonen, 1992). The connection between race and drugs in America has just as long a history, with racialized notions of drug use and sales long preceding the movements in the 1970s and 1980s that made such patterns all the more explicit through "tough on crime" tactics (Balko, 2015; Bonnie & Whitebread, 1974; Provine, 2007; E. H. Williams, 1914). What makes these patterns particularly pernicious is the discretion afforded police in addressing drug offenses (Beckett, 2016; J. A. Goldstein, 1960; Lynch et al., 2013), and how this creates an opening for racial disparities in the policing of drug offenses that do not exist for other offenses types. The patterns observed in this dissertation highlight the many ways in which policing and race can be linked. A focus on certain drug types results in a connection between the use of warrants and race; a focus on certain drug types masks a connection between race and Red Dog for other drug types; order maintenance stops and data-driven tactics are linked to the racial composition of neighborhoods in which arrests occur, but not the race of the arrestee; reductions in racial disparities are explained by changing demographic and crime patterns, not by a changing police ethos; reductions in the non-white arrest rate do not coincide with similar reductions in the non-white arrest disparity; and racialized patterns in policing are not identical across the city, but instead their causes and features are zone-specific and thus dependent on all the factors that contribute to differing police behavior across zones.

Policy Implications

Regardless of the exact causes of the patterns observed in this dissertation, these findings provide useful insight into policing policy. First, a reduction in the use of specialized units is associated with reduction in certain aspects of racialized arrest patterns, and thus agencies seeking to reduce the overpolicing of minority communities may benefit from a reducing their dependency on specialized units. Within certain zones and for certain drug types, PPUs and data-driven units make arrests in a racially-patterned fashion, and reducing their use leads to an overall reduction in the non-white arrest rate. Both "tough" and "smart" tactics have rhetorical appeal, allowing police chiefs to demonstrate their proactive efforts to reduce crime (National Research Council, 2004), but police chiefs with a goal of reducing the association between drug arrests and race in their city may be better served by replacing specialized units with regular beat officers.

Second, these findings suggest that agencies aiming to reduce racial disparities in arrest would also benefit from reducing the use of pedestrian order maintenance stops. Previous research has identified racially-patterned police stops (Fagan et al., 1999; Gelman et al., 2007; Ridgeway, 2007), and this dissertation confirms that these patterns carryover into racially-patterned arrests. Officers may find such stops useful as they allow them to proactively engage the public without the necessity of witnessing clear (felonious) criminal activity, but if agencies aim to reduce racialized policing, they may benefit from either limiting the use of such stops or requiring officers to engage in solutions other than arrests when they discover criminal activity, such as the referral to treatment services found in many drug diversion programs (Mazerolle et al., 2007).

Third, policing felony drug arrests is drug-specific. Red Dog's relationship with race varies by drug type, and the relationship between race and the use of warrants is also largely explained by drug type. In order for police departments to understand the racial impact of their drug enforcement policies, they need to examine patterns by drug type, not across drug types. For example, the involvement of marijuana in warrant-based drug arrests may be the result of a number of factors, including marijuana being more likely to be found when serving drug warrants for a serious violent or property offense or police officers focusing on building warrant cases more often for marijuana. The former suggests a process in which warrants serve their intended purpose of addressing serious offending, but the latter suggests (possibly unintentional) police behavior that focuses more directly on non-white Atlantans when building warrant cases. The latter is an issue that police departments can directly address.

Fourth, in large police departments, change needs to occur at the zone-level. While citywide racialized arrest patterns were present in Atlanta in and across both eras, some of the strongest patterns occurred within zones. A vast body of literature highlights the importance of local leadership and working groups in determining individual officer behavior (Klinger, 1997, 2004; Rowe, 2006), and in cities as large Atlanta, individual officer activity can only be practically monitored by these local leaders (Sykes, 1985). Police departments hoping to change the way individual police officers make arrests should focus not only on department-wide efforts, but also on zone/district/precinct-specific efforts that address that activities occurring within those localized workgroups.

Finally, reducing racial disparities in policing is difficult, and departments aiming to do so would benefit from an examination of the specific aspects of their department that contribute to these patterns. The APD made substantial changes in the mid-2000s, and while these changes resulted in real reductions in the overall and non-white drug arrest rates, they did not result in reductions in the racial disparity in drug arrests. Thus, departments aiming for a more robust reduction in racialized policing may benefit from a clearer understanding of factors like those discussed above, albeit specific to their department, to guide their responses.

Limitations

As with all research, the present study has methodological limitations that warrant further discussion. First, this research uses data from a limited set of years, and having a longer continuous time series of pre- and post-change arrests would have strengthened the conclusions drawn within and across eras. Arguably, though, the years available and used within this study (2005 and 2012) are ideal, as they immediately precede and follow the shift in policing ethoi in Atlanta. A longer time series would have required careful consideration of other factors changing in Atlanta during both eras, a consideration that was not necessary when focusing on only a single year within either era. Further, it would have necessitated a more detailed understanding of how changes within a police agency evolve over time, and current research on changes in police tactics and strategies do not provide such an understanding (Weisburd & Braga, 2006). For example, should data have been available from 2012 to 2015, it would have been necessary to have a theory about whether to expect such a change to retain equal strength across all three post-change years, or whether the new style of policing would either decay or grow over time.

Second, for address information, specialized unit codes, and tactic codes, I must rely on the accuracy of police reports. Studies of the accuracy of police reports vary in whether they find them to be reliable reports of incidents (Grant, Gregor, Maio, & Huang, 1998; Shinar, Treat, & McDonald, 1983), yet most of this research was conducted using accident reports, and thus cannot speak directly to the accuracy of drug arrest reports. It is possible that police either (1) inaccurately remembered aspects of an arrest, (2) intentionally or unintentionally left out important aspects of an arrest, or (3) intentionally lied about aspects of an arrest. These may have affected the codes used in this dissertation, and unfortunately, the degree to which this is possible cannot be determined. Yet two possibilities seem likely. Either such errors or omissions are unintentional, in which case it is reasonable to assume they are somewhat random and that, in a large enough sample size, they should have a negligible impact on the outcomes (Frankfort-Nachmias & Nachmias, 2007). Alternatively, errors and omissions may have been intentional, in which case their motivation was likely to present the best case scenario for APD officers. If that is so, then it is likely that the results presented here represent a conservative estimate of any racialized patterns of policing observed within and across eras.

Third, this study finds that zones are a critical element in racialized patterns of policing, but the current study is limited in its ability to understand why. The current data does not provide information on the meaningful differences between zones, such as leadership style, number of senior officers, and the culture of policing within a zone

(Jermier et al., 1991; Klinger, 1997, 2004; Knight, 2015; Mastrofski & Willis, 2010; Rowe, 2006; Terrill & Paoline, 2017). Future research on race and policing would benefit from greater availability of quantitative data about police zones such that it could be incorporated into regression models, or a stronger qualitative investigation into these issues so they could be used to more clearly contextualize cross-zone differences.

Fourth, this study focuses on a single police department within a single city, and thus the external validity of this dissertation's findings is somewhat limited. To analyze an issue like this, it was necessary to focus on a single department, for while other police departments made the shift from "tough" to "smart" policing during the mid-2000s, each department made the change in unique ways and for unique reasons. For example, the motivating crises surrounding Red Dog are rare events, and many departments were not motivated by such dramatic events (Telep, 2016). To accurately understand the effect of this change, it is important to concentrate on a particular department. This, though, means that strictly speaking, the findings in this dissertation relate only to drug arrests in Atlanta. Yet the APD has a similar structure to many large, urban police departments across the nation (Atlanta Police Department, 2011, 2012; National Research Council, 2004), and drug issues in Atlanta do not notably diverge from those in other large cities across the country (Drug Enforcement Administration, 2011, 2018). Thus, it is reasonable to assume that the findings of this dissertation generalize to other large, urban areas and large, urban police departments. Future research should attempt to study similar changes in other police agencies to determine if this dissertation's findings hold across a broader range of settings.

Fifth, while fixed effects models are a robust quasi-experimental approach, they are limited in their ability to accurately identify true causal relationships. Fixed effects models account for time-invariant differences, but time-varying differences need to be directly included in the model. It is possible that the models used in Chapter 7 were missing important time-varying covariates that better explained changes in non-white arrest rates and racial disparities. A similar limitation is true of the random intercept regression models employed in Chapters 5 and 6. These models, too, depend on the strength of the covariates included. While each chapter makes a strong case for the specification of all the models within it, it is certainly possible that important covariates were omitted.

Finally, because this dissertation employed only quantitative methods, it cannot speak to the specific motivations of police officers; differences in zone leadership and working group cohesion; the factors that go into the decision to serve a warrant or conduct an order maintenance stop; and variation in the decision-making processes of officers in Red Dog, data-driven units, and other APD units. Information on each of these factors would be useful for better understanding the patterns described in this dissertation. Obtaining such information requires a robust qualitative design, such as officer interviews, focus groups, or field observations (Frankfort-Nachmias & Nachmias, 2007). As such, future researchers should pursue qualitative investigations into the motivations of police officers in making arrests and variation therein across zones/precincts/districts, tactics, and units.

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Appendix A: Police Stop Codes

Primary Codes – Secondary Codes

Arrest Warrant – Failure to Appear in Court
Arrest Warrant – Probation Violation
Arrest Warrant – Drug crime
Arrest Warrant – Violent Crime
Arrest Warrant – Non-Violent Crime
Arrest Warrant – Unknown/Other

Search Warrant – Drug crime
Search Warrant – Violent Crime
Search Warrant – Non-Violent Crime
Search Warrant – Unknown/Other

Prostitution Sting – [None]

Dispatched to Scene – Traffic Accident
Dispatched to Scene – Disorder
Dispatched to Scene – Suspicion of Drug Activity
Dispatched to Scene – Criminal Trespass
Dispatched to Scene – Non-Violent Crime
Dispatched to Scene – Violent Crime
Dispatched to Scene – Suspicious Person
Dispatched to Scene – Suspicious Vehicle
Dispatched to Scene – Unknown/Other

Surveillance Detail – Disorder
Surveillance Detail – Drug Activity
Surveillance Detail – Suspected Drug Deal
Surveillance Detail – Witnessing a Drug Deal
Surveillance Detail – Non-Violent Crime
Surveillance Detail – Violent Crime

Directed Patrol – Disorder
Directed Patrol – Traffic Stop
Directed Patrol – Suspicious Vehicle
Directed Patrol – Suspicious Person
Directed Patrol – Pedestrian Check
Directed Patrol – Suspected Drug Activity
Directed Patrol – Suspected Drug Deal
Directed Patrol – Witnessing Drug Activity
Directed Patrol – Witnessing a Drug Deal
Directed Patrol – Non-Violent Crime

Directed Patrol – Violent Crime
Directed Patrol – Criminal Trespass
Directed Patrol – Call for Help

Routine Patrol – Disorder
Routine Patrol – Traffic Stop
Routine Patrol – Traffic Stop, at an Approved Checkpoint
Routine Patrol – Suspicious Vehicle
Routine Patrol – Suspicious Person
Routine Patrol – Pedestrian Check
Routine Patrol – Suspected Drug Activity
Routine Patrol – Suspected Drug Deal
Routine Patrol – Witnessing Drug Activity
Routine Patrol – Witnessing a Drug Deal
Routine Patrol – Non-Violent Crime
Routine Patrol – Violent Crime
Routine Patrol – Criminal Trespass
Routine Patrol – Call for Help

Probation/Parole Check – [None]

Processing an Inmate – [None]

Types of Disorder (Tertiary Codes)

Blocking Sidewalks/Roadways
Darting into Streets
Harassment
Jaywalking
Loitering
Panhandling
In Park after Hours
Public Drinking
Public Intoxication
Public Urination
Underage Drinking

Appendix B: Police Stop Coding Procedures

General rules

1) Code from the perspective of the officer
2) Code the initial contact rationale with arrestee (i.e. code what brought this officer to interact with this arrestee)
3) Code the rationale for the stop, but note all cases where context is **in a known drug location** as a sub-code
4) In instances of two or more options for coding, select drug-related code if any of the rationales could be captured by one of the drug-related codes
5) When there are multiple offenses identified in the narrative, select the sub-code of the more serious offense (for example, in the case of longer narratives in which there is a disorder or traffic offense [e.g. loitering] mentioned as well as something more serious [e.g. drug, non-violent, or violent crime], code the latter)

Code-specific rules

6) **Traffic stop** should only be coded when the pretext for the stop is a traffic violation and nothing else; approved checkpoints include security checkpoints, DUI checkpoints, safety checkpoints, license checkpoints, speed traps, and roadblocks
7) **Non-violent sub-codes** include all Part I and II property crimes, fraud, etc. – i.e. felony-type offenses that are not violent; treat any non-property, non-violent, non-criminal trespass crimes as '**other**'

8) Code **Dispatched to Scene** when a 911 call, other officer, other law enforcement agency (LEA), other non-LEA (e.g., hospital, fire department), or an unknown agency/individual dispatches the officer to the scene of a particular disturbance or offense

9) Use sub-code **suspicious vehicle** or **disorder** when the suspicions are non-drug related and/or no other information about the grounds for suspicion are provided (i.e. use sub-code **non-violent crime**, for example, when the officer is dispatched to the scene because a suspicious person is standing by cars, looking into car windows, breaking into cars, etc.)

10) Choose **suspicious vehicle** sub-code when the person(s) is(are) in a vehicle and something about the vehicle ignites the officer's suspicion

11) Use sub-code **suspected drug deal** when the officer witnesses behavior s/he believes is indicative of a drug deal, but does not see an actual exchange of drugs (such as witnessing someone going to the window of a home that is known for drug sales and emerging two minutes later, without the officer ever actually witnessing the drug transaction)

12) Use sub-code **Dispatched to scene - suspicion of drug activity** when drug activity constitutes even some of the grounds for suspicion/reason to alert police, except in cases where the officer is called for a more serious offense (e.g. violent or non-violent crime)

13) All **witnessing drug activity** sub-codes refer to drug activity that falls short of witnessing a hand-to-hand drug transaction, but the officer's suspicions are initially ignited by physically seeing drugs, drug-influence, or drug paraphernalia

(i.e. may include seeing someone with drug paraphernalia, suspecting someone of being high, indication that person sells but no transaction is witnessed, or trafficking-related movement of drugs, for example)

14) Use sub-code **Routine patrol - suspected drug activity** or **Directed patrol – suspected drug activity** when the officer notes a behavior s/he believes is indicative of trying to conceal drugs, but s/he does not explicitly see drugs or drug paraphernalia, such as a person's hands being clenched or quickly throwing something away (falls short of 'witnessing')
15) **Search warrant – drug crime** should only be coded when the search warrant type is drug-specific
16) **Surveillance detail – drug activity** should be coded for all drug activity that falls short of witnessing or suspecting a hand-to-hand transaction (drug deal)
17) The difference between **surveillance details** and **buy-bust operations** is that surveillance details do not involve proactive action on the part of officers to initiate a drug deal (by an undercover or CI) and instead involve surveillance of a specific location and reactive policing when activity is observed
18) Use **surveillance detail** when *other* undercover officers or surveillance teams dispatch this officer to the scene, or when referred by another officer who witnesses drug activity or another offense; this means that surveillance detail includes both actual surveillance *and* law enforcement notifications about drug activity to arresting officers
19) Prioritize **arrest warrant** over **search warrant** when narrative includes both

20) Code illegal gambling (dice games) as **disorder** – this logic holds for offenses that are largely misdemeanor, even if not technically a quality of life offense

21) Code **call for help** when officer is flagged down for an injury, suspicious vehicle, specific crime, or unknown situation

22) Code **directed patrol** for all narratives that include 'directed patrol,' 'crime suppression unit,' or 'Field Investigation Team (FIT),' or 'APEX'– note that many of these cases are warrants and buy-busts which should be coded as such

23) Treat 'wanted persons' as **arrest warrant**

24) In cases where the officer is called for a dispute, code this as **disorder** rather than **violent crime** (as dispute is a less serious characterization than fight or assault)

Disorder-specific sub-codes

25) Code sub-categories of disorder by prioritizing activity like **loitering, jaywalking, public drinking, public urination**, and **dispute**

26) Code the disorder sub-category as **noise complaint** only when the noise complaint is not dispute-related (i.e. loud music)

27) Code the disorder sub-category as **pedestrian check** when there is no indication that anything specific raises the officer's suspicion, but the officer stops the person anyway

28) Code the disorder sub-category as **suspicious person** when the person's presence, activity, behavior, or gestures, etc., ignite police suspicions

Appendix C: Missing Data Tables

Table C1. Sources of Missing Data

	2005 (n=3,017)	2012 (n=1,197)	Total (n=4,214)
Missing or Incomplete Narrative Only	29 (0.96%)	171 (14.29%)	200 (4.75%)
Missing Address Data Only	228 (7.56%)	36 (3.01%)	264 (6.26%)
Missing or Incomplete Narrative and Missing Address Data	2 (0.07%)	3 (0.25%)	5 (0.12%)
Total Missing	259 (8.58%)	210 (17.54%)	469 (11.13%)

Table C2. Arrestee-Case Level Variables by Missingness

	Non-Missing	Missing
	Mean (SD)/Proportion	Mean (SD)/Proportion
2005 (n=3,017)		
Black[1]	90.54%	89.58%
Non-White[2]	91.41%	91.51%
Male[3]	88.29%	91.12%
Age at Arrest	32.71 (10.91)	33.3 (11.02)
Top Charge on Arrest[4]		
Possession	52.72%	51.74%
Intent to Sell	39.88%	42.47%
Sales, Trafficking, Manufacturing	7.40%	5.79%
Drug Involved in Arrest[5]		
Methamphetamine/Amphetamines	3.73%	2.70%
Cocaine	71.39%	76.06%
Heroin	3.37%	3.47%
Marijuana	24.91%	22.39%
Hallucinogens/Party Drugs	3.77%	2.32%
Unspecified Controlled Substance	5.15%	3.86%
2012 (n=1,197)		
Black[1]	86.42%	85.24%
Non-White[2]	87.34%	86.67%
Male[3]	88.86%	85.71%
Age at Arrest***	37.51 (12.20)	33.42 (10.28)
Top Charge on Arrest[4]***		
Possession	62.01%	37.14%
Intent to Sell	26.85%	42.38%
Sales, Trafficking, Manufacturing	11.14%	20.48%
Drug Involved in Arrest[5]		
Methamphetamine/Amphetamines	4.15%	3.33%
Cocaine	55.83%	52.86%
Heroin	8.61%	7.62%
Marijuana***	26.95%	42.38%
Hallucinogens/Party Drugs	2.53%	4.29%
Unspecified Controlled Substance	12.77%	14.29%

+p<.10, * p<.05, ** p<.01, *** p<.001
[1]Reference category: non-black.

[2]Reference category: white, non-Hispanic.
[3]Reference category: female or other gender.

[4]Reference category: possession.

[5]Categories not mutually exclusive.

Appendix D: List of Hypotheses

"Tough on Crime" Analyses

H1: If the Red Dog Unit contributed disproportionately to the racial disparities observed in the "tough on crime" era, then drug arrests by Red Dog officers will be more likely to involve black (or other non-white) arrestees and occur in neighborhoods with higher levels of black (or other non-white) residents than will arrests by other APD officers.

H2: If order maintenance stops a contributed disproportionately to the racial disparities observed in the "tough on crime" era, then drug arrests conducted using order maintenance tactics will be more likely to involve black (or other non-white) arrestees and occur in neighborhoods with higher levels of black (or other non-white) residents than will arrests involving other tactics.

H3: If search and arrest warrants contributed disproportionately to the racial disparities observed in the "tough on crime" era, then drug arrests conducted using search and arrest warrants will be more likely to involve black (or other non-white) arrestees and occur in neighborhoods with higher levels of black (or other non-white) residents than will arrests involving other tactics.

"Smart on Crime" Analyses

H1: If data-driven tactics contributed disproportionately to the racial disparities observed in the "smart on crime" era, then drug arrests by officers on directed patrol or in any of these units will be more likely to involve black (or other non-white) arrestees and occur in neighborhoods with higher levels of black (or other non-white) residents than will arrests by other APD officers.

H2: If order maintenance stops a contributed disproportionately to the racial disparities observed in the “smart on crime” era, then drug arrests conducted using order maintenance tactics will be more likely to involve black (or other non-white) arrestees and occur in neighborhoods with higher levels of black (or other non-white) residents than will arrests involving other tactics.

H3: If search and arrest warrants contributed disproportionately to the racial disparities observed in the “smart on crime” era, then drug arrests conducted using search and arrest warrants will be more likely to involve black (or other non-white) arrestees and occur in neighborhoods with higher levels of black (or other non-white) residents than will arrests involving other tactics.

Era Comparison Analyses

H1: If the shift from “tough on crime” tactics to “smart on crime” tactics resulted in an attenuation of racial disparities, then the “smart on crime” era will be associated with reductions in the black (or other non-white) arrest rate and reductions in racial disparities for drug arrests.

H2: If a reduction in the use of specialized units contributed to the attenuation of racial disparities across eras, then the effect of specialized units within the “smart on crime” era will be associated with reductions in the black (or other non-white) arrest rate and reductions in racial disparities for drug arrests relative to the “tough on crime” era.

H3: If a reduction in the use of order maintenance stops contributed to the attenuation of racial disparities across eras, then the effect of order maintenance stops within the “smart on crime” will be associated with reductions in the black (or other non-white) arrest rate and reductions in racial disparities for drug arrests relative to the “tough on crime” era.

H8: If a reduction in the use of search and arrest warrants contributed to the attenuation of racial disparities across eras, then the effect of warrants within the “smart on crime” will be associated with reductions in the black (or other non-white) arrest rate and reductions in racial disparities for drug arrests relative to the “tough on crime” era.