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David Jaeheong Lee April 9, 2025

"Who You Gonna Call?" The Politics of Atlanta's Policing Alternatives and Diversion Initiative

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Abstract

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Americans task the police with many roles and responsibilities. One of them is responding to order-maintenance issues, which tend to result from low-level, even non-criminal offenses. Police often respond in those situations by arresting, jaliing, and sometimes harming people. Some cities however are experimenting with allowing police and non-police responders to divert some people from arrest and jail. Atlanta is one of them. This thesis studies the case of the Policing Alternatives and Diversion (PAD) Initiative in the city of Atlanta. Central to the initiative is the use of non-police responders to resolve some order-maintenance and non-criminal offenses in the city through diversion from arrest and jail. PAD is a result of community activism, interest group mobilization, transformed social constructions, and noncongruent policymaking. Drawing from a mix of interviews with PAD staff, archival research, participant-observation of PAD services and court proceedings, and multivariate analysis of court records, this thesis provides evidence that PAD’s diversion services reduce one’s likelihood of future arrest or rearrest. Specifically, I find that PAD participants are 14.8% less likely to be arrested in the six months after diversion and 24.2% in the twelve months after diversion compared to similar, non-PAD participants. Ultimately, this thesis argues that a shift from the current model of policing for order-maintenance can allow municipalities to arrest and jail less, thereby helping broader efforts to reduce mass incarceration.

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On March 23, 2020, Daniel Prude, a 41 year-old African American man, was visiting his family in Rochester, New York. He experienced a mental health crisis. Joe Prude, his brother, called two times for emergency assistance. A few minutes later, police officers from the Rochester Police Department showed up. They approached Prude with a taser, instructing him to get on the ground. What *were* the *police* doing here? His brother called for them. Normally, we assume the police are the best responders for such situations. That is true in the absence of alternatives to police.

The encounter between Prude and the police escalated. An officer pinned Prude to the ground. For two minutes and fifteen seconds, police crushed Prude's chest against the concrete, forcing him down with a knee in his back. Vomit, foam, and saliva spilled from Prude's mouth. Daniel Prude needed further help. Instead, he was killed. What *were* the police *doing* here?

The death of Daniel Prude is not an isolated incident. It represents just one of countless incidents of the police being ill-equipped to respond to mental health crises. It reminds us that when police encounter civilians, there is always the potential for harm, even death. That is true too for other incidents without criminal conduct by denizens. It is true of simple acts of disorder by denizens. All of that raises questions about the function of police, responses by police, and how we think about the police in our lives. In particular, it asks us to consider if there should be an alternative to police and what the best alternatives could be.

Introduction

"The urban world is a world of police" (Owens 2024). Studying policing draws attention to core concepts and ideas about institutional accountability, discretion, state power, public safety, violence, policy adoption and diffusion, and liberty. As denizens, we expect the police to ensure "public safety." A part of this means being able to walk through the city without worrying about civilian gunfire or assault or theft. It also includes having confidence that when police encounter a crime, or respond to non-criminal related calls, they will not worsen the situation, for instance, by increasing the trauma or harm (Freidman 2020). But insofar as the role of the police and their interactions with denizens are predicated on the potential for "non-negotiably coercive force," harm is always a risk when police are policing, even when calls for police responses may not require it (Bittner 1970, 46). This stems from the fact that police are "street-level bureaucrats" who have wide discretion to enforce their duties (Lipsky 1980). The discretion of police officers to carry out public policy and provide public service is not dissimilar to other public employees like teachers and social workers who represent the "human face" of government policy. What separates the discretion of police from the discretion of other public employees is the former's ability to use physical coercion, even violence, during encounters with the public. Discretion, in this case, becomes a vehicle by which police can escalate (or de-escalate) an encounter, granting police legitimacy and power in every day-to-day interaction (Dowding 1996). Therefore, the safety of some denizens during encounters with the police is precarious.

Understanding whether police actually deliver and maintain public safety starts with focusing on what it is police are tasked with doing. The understanding starts with "disaggregating the policing function" (Freidman 2020, 931). Generally, we task the police with performing multiple tasks. Some tasks they are prepared to perform well. Some tasks they are unprepared to complete. Whether prepared or not, according to James Q. Wilson, police have two primary functions, namely law enforcement and order maintenance. Enforcing the law means detecting and apprehending individuals who commit or are suspected of criminal acts. In these scenarios, making an arrest or initiating other legal processes (like issuing a ticket) often exhausts an officer's responsibilities. Order maintenance focuses on regulating behavior related to "public disturbance" and "disobedience" (for e.g.public drunkenness, disorderly conduct, and loitering). Except for traffic control, police engage in far more instances of order maintenance than law enforcement (Wilson 2009). Sometimes, public "disorder" is criminalized by states and municipalities. For instance, public drunkenness, disorderly conduct, and loitering are all misdemeanors[1] in Georgia. Therefore, police are called for and can arrest for low-level, "victimless" crimes that typically do not endanger anyone directly. This makes control of public disorder the primary function of police.

In the United States, behavior deemed disturbances of public order by police and policymakers are much more heavily concentrated among and policed for politically and economically weak or oppressed groups (Kang 2016). By carrying out police stops, arrests, and use of force disparately, police co-produce social control for the benefit of dominant groups (e.g. racial majorities, property owners, and employers), maintaining their identities and ideologies while fighting "perceived or real threats to social orders or hierarchies" (Owens 2024, 7). Police are, as sociologist Alex Vitale (2020) argues, "fundamentally a tool of social control" used to facilitate the exploitation for the economically and politically weak populations.

This social control function of policing is rooted in the development of modern police in American cities. In the mid 19th and early 20th centuries, some groups were perceived as threats to the established order for their potential for disorder or resistance to authority. These "dangerous classes" included the working poor, immigrants (e.g. the Irish) , African Americans, and other people at the margins of society (Richardson and Harring 1984). Indeed, the rise of

[1] A misdemeanor is a "lesser" criminal act, typically punishable by less than 12 months in jail. Community service, probation, fines, and imprisonment for less than a year are commonly issued punishments for misdemeanors (Legal Information Institute 2021).

modern police was not just about preventing crime. It also involved managing and suppressing "dangerous" classes. Particularly in the post-Civil War era, police were weaponized by elite interests to shut down labor strikes, put down protests, and end other instabilities that disturbed societal orders shaped by race, class, ethnicity, and conduct.

The social control function of policing intensified throughout the latter half of the 20th century amid political pressures to fight crime. Cities launched campaigns to be "tough on crime" by cracking down on frequent, low-level concerns like criminal trespass, loitering, and drug use in "race-class subjugated communities" (Soss and Weaver 2017). These are communities made up of the "racialized poor," people whose intersection of race and class make them especially vulnerable to violence by the state. Expansive and intensive order-maintencane policing in the contemporary period stemmed from the "broken windows" thesis: the notion that visible signs of disorder can lead to a significant decline in a neighborhood's safety and an increase in serious, violent crime (Wilson and Kelling 1982). Under broken windows policing, poor Black and Brown, in particular, experienced coercion, repression, predation, and violence. The over-criminalization of race-class subjugated communities and tough-on-crime policing deepened and widened socio-economic disparities in group experiences with lethal (and nonlethal) police violence. Race, poverty, and place are the strongest predictors of whether a citizen gets stopped, arrested, or killed (Ayres and Borowsky 2008). Moreover, intensified order maintenance policing led to lower levels of political participation, socioeconomic capital, and wellbeing among Black, Brown, and poor people (Ewald 2002; Burch 2013).

In the past decade, protests for police reform have taken place across the country. Protests were catalyzed by police killings of civilians stemming from police stops and calls from the public (Williamson et al. 2018). The deaths included Michael Brown, Eric Garner, Breonna

Taylor, Daniel Prude, Andre Hill, and many others. Demands for police reform following those deaths have called for many things. For instance, the Eight Can't Wait campaign advocates for police departments and cities to adopt eight specific policies that could reduce police violence. Those policies include banning the use of chokeholds, prohibiting police from shooting at moving vehicles, and requiring verbal warnings before police shoot (Yglesias 2020). Others reformers have pushed for ending "stop and frisk" practices, decriminalizing drug possession and sex work, and removing legal immunities that protect police from criminal and civil liability for deaths and other harms of people during police encounters with the public (Human Rights Watch 2020).

But the 2020 murder of George Floyd in Minneapolis by then-officer Derrick Chauvin produced the country's, perhaps the world's, greatest and longest protests to date against the police (Buchanan, Bui, and Patel 2020). One of the main demands of protestors was to "defund" the police, which means taking money away from police and reinvesting it into "vital programs" like housing, healthcare, good jobs, and education (Levin 2020). Advocates have argued that the police are ill-equipped to provide basic public safety, and we need alternative solutions that do not require violence or incarceration. In other words, we need to reduce "the police footprint" by reducing the involvement of police officers in matters that do not require police as the primary response.

The one-size-fits-all of policing, wherein police are expected to deal with domestic violence, mental health episodes, homelessness, substance abuse, and other behavioral concerns with chronic underlying social issues, is ineffective and can be harmful (Friedman 2020). Plus, it fails to address the root problems of extreme poverty and mental illness. Instead, relying on police throws people into a cycle of perpetual police contact and incarceration (McNiel, Binder, and Robinson 2005). Indeed, formerly incarcerated people are nearly ten times more likely than the general public to experience homelessness, and up to 15% of people currently incarcerated were homeless in the year leading up to their arrest (Couloute 2018). Moreover, over 40% of people in jails and prisons have been diagnosed with a mental health disorder (Prison Policy Initiative 2022). Many have not received any treatment since admission. Furthermore, a significant portion of police-denizen interactions involve some sort of public disturbance or order maintenance issue (i.e. homelessness, public drunkenness, panhandling). Accordingly, police are constantly interacting with people suffering from chronic social issues. It is not surprising then, that in 2015, 27% of police shootings involved a mental health crisis.

In an effort to reduce the police footprint in matters of non-violent offenses, reformers call for police to take a backseat to mental health providers and social workers in addressing non-violent, quality-of-life offenses (Lum et al. 2021; Jacobs et al. 2021). Seeking an alternative to police in these behavioral situations, advocates would redraw the boundaries of police work, shrinking the use of police for order maintenance. They propose a greater, perhaps exclusive, reliance on non-police responders to nonviolent and noncriminal disorderliness. They challenge the traditional assumptions about the need for police in producing public safety that has sustained and expanded police forces for over a century (Bell 2021).

Many cities across the nation have adopted or are experimenting with non-law enforcement first-responder models. This is especially true for responding to people experiencing mental health crises. Between January 2020 and July 2022, 19 cities have adopted alternative responder programs. Among them are Los Angeles, Chicago, and Philadelphia (Subramanian and Arzy 2022). The alternatives center diversion from the criminal legal system instead of arresting and channeling people into the criminal legal system.

This thesis is about the politics of diverting low-level “offenders” from arrests and jail by police in American cities. It focuses on policing alternatives. Specifically, it focuses on the politics of municipalities moving away from police as the primary or sole tool for dealing with public disorder and maintaining order. The core of this thesis is a case study of one city and program: Atlanta’s Policing Alternatives and Diversion Initiative (PAD). This initiative is a public-private partnership for order maintenance. It “provides an alternative to police response and diversion from jail for people experiencing extreme poverty, problematic substance use, or mental health concerns” (Atlanta PAD). The initiative pays a non-profit organization to employ private “Community Responders” to respond to pedestrian-initiated “311” non-emergency calls and calls for diversion directly from police officers. Once diverted from arrest, people are paired with private “care navigators,” who, instead of jail, offer human resources to integrate into society, including emergency relief, food, clothing, temporary housing, social welfare subsidies, jobs, and permanent housing.

The thesis has four parts. First, I describe the civil mobilization and political action that led to the formation of PAD in 2015. Specifically, I explain the community mobilization for diversion over police contact and arrests. I identify the actors involved in the conception of the initiative and the demands of community members in Atlanta for alternatives to police responses. Second, I analyze the municipal history of PAD, describing Atlanta’s experiment with diversion. I also explain the legislative origins of diversion as a counter-policy proposal, one intended to reduce police contact and arrests, as well as to fight calls by commercial and other interests for outright banishment of “offenders.” Third, I address the sociopolitical objectives and challenges of implementing and sustaining PAD as a public-private partnership in Atlanta. In doing so, I argue that the adoption of diversion and the formation of PAD was an important instance of “noncongruent policymaking” (Owens and Gunderson 2023, Boushey 2016): elected officials distribute benefits or reduce burdens for to a target group with negative “social constructions” and low political capital (Schneider and Ingram 1997). Typically, policymakers prefer punitive measures for such “deviant” groups. Fourth, I investigate whether PAD “works” as an effective alternative to traditional police-centered order maintenance and law enforcement. I report the results of an original quantitative analysis of diversion via PAD to determine whether its diversion model is statistically associated with a reduction in an individual's chance of future police contact (i.e. arrest or re-arrest). Specifically, I report results from propensity score matching tests I conducted between 337 PAD participants and a carefully selected control group of 911 non-PAD participants. I leveraged administrative data from PAD and the Atlanta Daily Arrest Reports of the Fulton County Superior Court to conduct the matching. After matching techniques, I used linear and logistic regression analyses on the matched pairs. The analyses yielded results that suggest PAD produces statistically significant reductions in future arrests.

This thesis is important for several reasons. Turning our attention to policing alternatives in the United States presents an opportunity for political scientists to return to the study of police/policing. For decades, the discipline has “been diverted from serious political analysis of policing and related criminal justice operations” in the United States (Soss and Weaver 2017, 3). My research contributes to calls for political scientists to scrutinize the varieties of modern policing and contemplate how we can, and even why we should, reduce our country’s reliance on police as first responders to low-level, non-emergency, behavioral “offenses.”

Additionally, the United States has one of the highest incarceration rates in the world. Nearly two million people are behind bars at any given time (Prison Policy Initiative 2024). Fewer than five percent of all arrests are for serious violent crimes (Neusteter and O’Toole

2019). Moreover, from July 2021 to June 2022, according to the U.S. Department of Justice Statistics (2023), jails across the country had 7.3 million admissions. Plus, 70% of the people in jails were yet to be convicted of a crime, awaiting court action on a current charge, or held in jails for other reasons. Moreover, Black citizens were 3.4 times more likely to be in jail compared to white citizens. Accordingly, if municipal leaders adopt policing alternatives, we can reduce the number of people in jail and the racial disparities of jail by diverting people from low-level arrests and towards the treatments they need.

Finally, the American public is uncertain on what it means to reduce the scope of the police (Smith et al. 2024). While only 18% of the public supports "defunding the police," 47% favor reallocating police funds towards social services (Elbeshbishi and Quarshi 2021). Yet, when "defunding the police" is framed as rerouting funds from police towards vital social resources, the public is significantly more likely to support reducing the scale of policing (Smith et al. 2024). Also, nearly two-thirds of Black Americans support reinvesting part of their community's police budget towards healthcare, education, and housing (Cohen 2024). This thesis explores in depth what an alternative to police looks like, bringing more clarity around the topic of police funding and reallocation. Ultimately, its results may help shape public and policymaker preferences and demands about policing alternatives. Maybe it could inform policymakers about the potential of diversion programs to reduce recidivism while maintaining public order.

Literature Review

The implementation of policing alternative programs like PAD is a relatively new occurrence in the story of police and policing in the United States. Understanding the need for policing alternative programs first requires pinpointing the functions and failures of policing and the demand for alternative options among the general public.

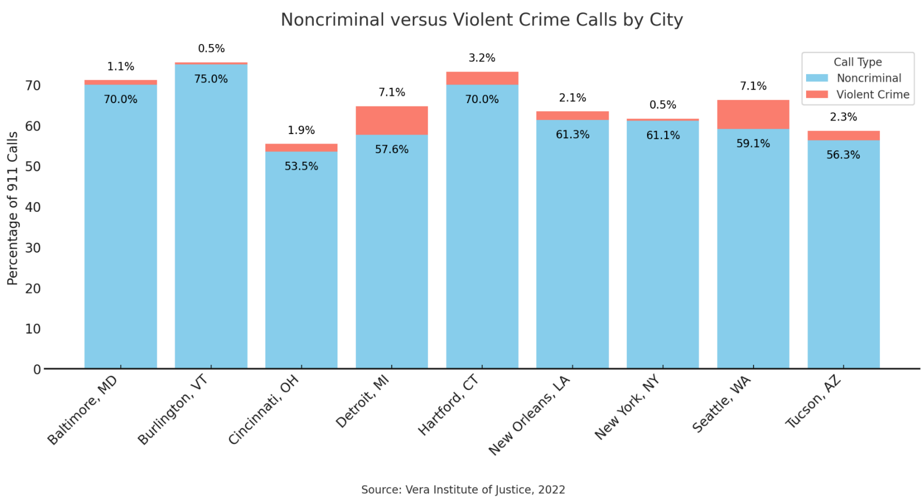
Policing: Functions, Footprint, and Failures

What do police *do* in our urban world? The "varieties of police behavior" include many things, ranging from "fighting crime" to "preserving the peace" (Wilson 2009). At the very least, we imagine police protect the public from "the bad guys" and violence on the streets. The modern cop is often portrayed on television and in films as the crime fighting, justice-dealing type (Grady 2021). Politicians, too, praise police officers as brave, frontline men and women who put their lives on the line everyday for civilians. To be clear, fighting crime *is* one of the roles of urban police. After all, crimes do occur, even violent ones. But armed robberies, assault, homicides, and other violent crimes are relatively low compared to non-violent crimes and order maintenance matters.

According to a study that analyzed 15.6 million 911 calls across nine U.S. cities, nearly two-thirds of all calls involved *noncriminal* situations (Dholakia 2022). Figure 1 shows the most common calls were for "business checks," which include loitering and behavioral concerns, "disturbance," "suspicious" acts, and other miscellaneous, noncriminal complaints. Another study that relies on online police department data portals found that violent crimes only make up around one percent of all calls for service in Baltimore, Cincinnati, New Orleans, San Diego, Seattle, and other major police departments (Asher and Horwitz 2020). Importantly, this includes only crimes that are reported to the police in the first place. Fewer than half of all crimes in the United States are even reported, and most of the crimes that *are* reported never get solved (Pew Research; Gramlich 2024).

Fundamentally, then, there is a "mismatch between what we intend cops to do and what they actually do" (Freidman 2020, 954). Indeed, the police's role is defined more by maintaining order rather than handling serious crime (Wilson 2009). But that has always been true of policing in the United States.

Figure 1. Noncriminal versus Violent Crime Calls by City



Historically, police officers were originally "watchmen" whose job it was to scan the streets and stifle disorder (Wilson 2009). Most of their work involved targeting offenses that harm the broader public domain, or the intangible, "diffuse" victims (Tacher 2014). In Boston, for example, the modern police force grew out of part-time watchmen who kept the streets clear of vagbondage, raucous behavior, public lewdness, and other "obstructions" (Lane 1967). Today, upwards of 30 percent of police duty is spent cruising in patrol cars waiting to deal with minor disturbances and much of the time, police are idle and unproductive (Fritsch et al. 2019; Wilson 2009; and Fassin 2013). But this does not mean there is a lack of police-denizen contact.

Police stops of motorists and pedestrians are the "quintessential encounter" between police and urban denizens (Owens 2024, 5). In 2012, just over 286,000 people between the ages 13 and 25 were stopped by police in New York City (Fratello et al. 2013). In 2020, 21% of U.S. citizens age 16 or older (53.8 million) reported experiencing police contact in the past 12 months (Tapp and Davis 2022). Over one million experienced the threat or use of force; Black people were over two times as likely to report the threat or use of force compared to white people, and males were three times as likely compared to females. Around two million people were stopped on the street, five percent of whom were either searched or arrested. Among stops, traffic stops are the most common; police pull over more than 50,000 drivers on a typical day and over 20 million motorists every year[2] (Stanford Policing Project 2023).

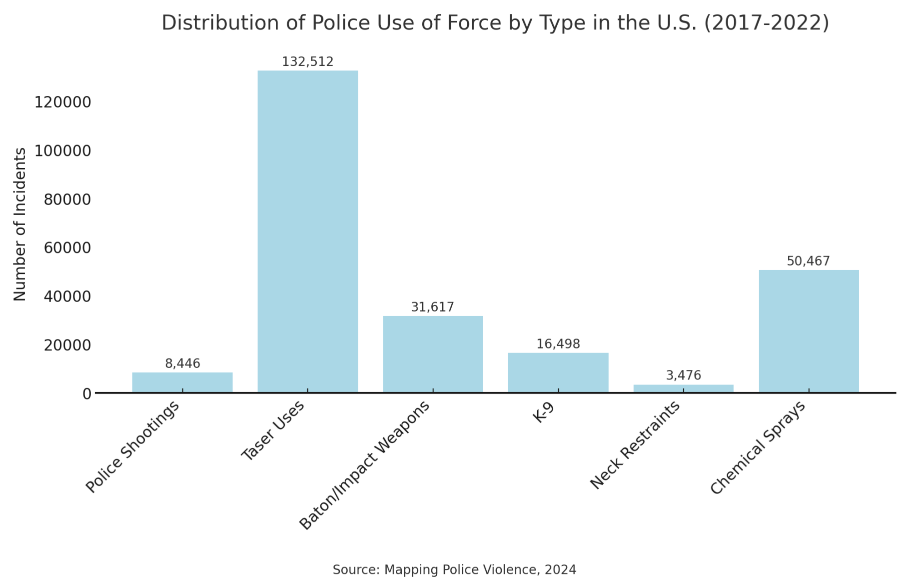
A large portion of police stops are pretextual and unconstitutional (Davis 1997), and they can lead to lasting negative psychological and civic effects. Getting stopped by police is associated with increased symptoms of trauma and anxiety among young men (Geller et al. 2014). People who get pulled over by the police are less likely to vote in the future (Ben-Menachem and Morris 2022), and those who have been stopped more at a young age are less likely to report crimes, even when they are the victims themselves. They are also less likely to have trust in the police, displaying lower levels of comfort seeking help from the police. Furthermore, there are massive racial disparities in police stops. In California, Black people are more than twice as likely to be searched than White people, even though the searches of Black people are slightly less likely to yield contraband and investigative evidence (Lofstrom et al. 2021). Police-denizen contact via stops is a vessel for police use of force and abuse.

According to Egon Bittner, the police's role is best understood as "the distribution of non-negotiably coercive force in accordance with the…situational exigencies" (Bittner 1970, 39). The context behind police stops are often ambiguous and perceived by the officer as unpredictable and potentially dangerous (Wilson 2009). The fact that in these hostile environments police have substantial discretion to respond to any inkling of escalation or danger through the use of force leads to a significant amount of police violence in the US. Based on an

[2] Through traffic stops, police extract revenue sources for the municipal government, oftentimes leading to the practice of "policing for profit." In 2017, at least 482 local governments across the U.S. derived 10% or more of their general revenue from traffic citations (Nastasi 2023).

analysis by Mapping Police Violence (2024) of over one million cases of police use of force across almost 3,000 jurisdictions, it was found that police employ force on approximately 300,000 people every year (Figure 2). In 2023, police killed at least 1,232 people, the most number of homicides by police in over a decade. Moreover, use of force is not spread evenly across demographic populations. Black people are more than twice as likely as White people to experience harm (Harrell and Davis 2018, Wang 2022). Indeed, approximately 96 per 100,000 Black men will be killed in their lifetimes by the police compared to 39 White men (Edwards et al. 2019).

Figure 2. Distribution of Police Use of Force by Type in the U.S. (2017-2022)



Whether they are responding to violent crimes or low-level behavioral disturbances, when police pull over motorists or stop pedestrians, police are the entrypoint of our criminal legal system, facilitating the jailing and imprisonment of millions of people. The U.S. leads the world in incarceration rates. There are over five million people under supervision by correctional systems in the U.S. and two million people currently in a jail or prison (BJS 2022). As of 2022, local U.S. jails held over 663,000 people in custody, with 7.3 million admissions from July 2021 to June 2022 (Zeng 2023). People are put in jail for an average of 32 days, some even longer because they cannot afford bail or are awaiting a hearing. Indeed, of those people in jail, over 80% have yet to be convicted or are awaiting a hearing (Prison Policy Initiative 2024).

Jailing and incarceration at this scale should be alarming. First, 92% of all correctional facilities, including jails, are public, meaning that they accrue costs for taxpayers. In 2017, it was estimated that taxpayers pay around $80.7 billion a year to fund these facilities (Wagner and Rabuy 2017). Plus, jails are often overcrowded, leading to dangerous conditions for the jailed and the officers who oversee them. In 2022, 16% of jails were operating above their rated capacity. In May 2022, the Sheriff of the Fulton County Jail reported that there were 366 people sleeping in temporary beds on the floor of the jail due to overcrowding. Additionally, the US Department of Justice concluded that the jail was violating people's constitutional rights (U.S. DOJ Civil Rights Division 2024). Jails also exacerbate socioeconomic disparities. Black people are 3.4 times more likely to be in jail than white people, and they make up 35% of the entire U.S. jail population (Zeng 2023).

The reason for why jails in the U.S. have so many people (especially people of color) goes back to the role of police. In the pursuit of "maintaining order," police constantly crack down on low-level offenses, filling jails with "offenders" of drug laws and those with behavioral health issues. Nearly a fourth of all people in jails (122,800 people) in 2022 were jailed for a misdemeanor, and there are an estimated 13 million misdemeanor charges every year (Natapoff 2018). The Prison Policy Initiative (2024) found that 247,000 of the 653,000 people in jails were detained for crimes related to drug use or public order. Furthermore, in a report by the U.S. Department of Justice that analyzed jail data from 2011 and 2012, it was shown that one in four inmates reported experiences that "met the threshold for serious psychological distress," and

44% of all jail inmates reported having a mental health disorder. Instead of receiving the treatment they need like substance abuse programs, shelter, medication, and basic food and clothes, far too many people are incarcerated instead, exacerbating their conditions and increasing their likelihood of being re-arrest down the road.

Public Demand for Policing Alternatives

> *Every social failure, we put it off on cops to solve… That's too much to ask. Policing was never meant to solve all those problems.* - Dallas Police Chief David Brown (2016)

Demand for police reform is not new in the U.S. The first era of reform took place in the 1920's in response to the widespread issues of unprofessional conduct and political corruption in police departments (Reiss 1992). Police chiefs like August Vollmer (known as the "father of modern American law enforcement) and Richard Sylvester advocated for increased standards of police training, technology, and professionalism (Go 2020). There was also the "community policing era" of reform from the 1980's to 2000. Against the backdrop of rising crime rates in the 1960's and 1970's and the increased publicization of police violence against civilians, police agencies began to turn to the local communities for collaboration. The goal was to improve the relationship between the police and the people they served, to problem-solve by incorporating the voices of denizens.

Since the early 2010's, the Black Lives Matter movement, along with other police reformers and police abolitionists, have sought to alter the scope, scale, and consequences of police encounters with denizens.[3] The goals are to reduce police violence and increase individual

[3] Some have called to "abolish the police." Activists like Mariame Kaba, the founder of a grass-roots group that works to end youth incarceration, argue that the only way to reduce police violence is to reduce the number of police officers. Citing over a century of "failed" police reform, advocates of abolishing the police push for replacing all police officers with trained community care workers who could employ "restorative-justice models" instead of arresting people (Kaba 2020).

and department accountability. They have helped change police practices across municipal America. The changes include the adoption of implicit bias trainings, body-worn cameras, and bans on no-knock warrants (Brookings 2022). They also have sparked federal investigations of municipal police departments (for example, Ferguson, Louisville, and Memphis) by the U.S. Department of Justice. The investigations have focused on problematic, violent, and biased policing (U.S. DOJ Civil Rights Division 2015). Efforts like Campaign Zero have advocated for ending "broken windows" policing, demilitarizing the police, making officer training more robust, and abolishing for-profit policing (Campaign Zero 2025).

Support for police reform spiked after the murder of George Floyd in May 2020. As of late 2020, 85% of the U.S. public strongly supported clarifying use of force standards and requiring body cameras. Most Americans also believed that racial bias is a problem in policing, and those who did reported greater support for police reforms (Hanink and Dunbar 2022). Furthermore, according to a 2021 national poll, the majority of the public favored increasing accountability and oversight of police agencies (e.g. adopting more civilian oversight boards and mandating investigations into police shootings (Mancini et al. 2024)). Additionally, some advocates of police reform have pushed to revise police training curricula to include recognizing and responding to mental health episodes and behavioral health concerns. The National Alliance on Mental Illness has suggested "creating a culture that focuses on reducing the use of force" among police departments. Indeed, one study cited by the Department of Justice found that de-escalation training can have marginally positive effects on police use of force (Engel et al. 2020).

Beyond changing the *way* police perform their duties, one underlying goal of modern police reform has been to shrink the footprint of the police as a whole–both the *function* of police and our reliance on it. Since 2020, advocates have pushed harder than ever to defund the police. Put simply, to "defund the police" means to "take financial resources from the police and devote them to the real needs of struggling communities" (Freidman 2020, 932). This includes investing money that would otherwise go to police departments into youth programs, affordable housing, healthcare, and education. One of the primary motivations for reducing the scope of police is the seeming failure of police to be solutions to the underlying problems of the crimes they respond to. As mentioned earlier, police respond to all sorts of crimes and disorderliness, many of which are violent and require law enforcement.

But the police are also tasked with responding to calls related to behavioral issues involving mental health and substance abuse. It is this latter function that proponents of police reform, both those favoring continued funding of police and those favoring defunding the police, have scrutinized, as people experiencing these issues are especially vulnerable to police harm. It is estimated that people with serious mental health illnesses are over ten times as likely to experience use of force in interactions with police compared to those without them (Laniyonu and Goff 2021). Between 2015 and 2020, a fourth of all fatal police shootings involved someone with a mental illness.

The killings of Daniel Prude and other victims across the nation symbolize the inability of police to respond to mental health crises proactively rather than reactively, and to respond with empathy and compassion rather than deadly force. Based on a 2021 national poll, over half of the public believed that the police are either not doing "very well" or "not well at all" in dealing with mental health crises (Mancini and Metcalfe 2023). The public felt even stronger against the criminal legal system broadly ("judges, prosecutors, jail or prison administrators"), with over 70% of Americans reporting that the system is doing an unacceptable job in handling people's mental health.

Police are also ill-equipped to properly deal with issues related to homelessness and extreme poverty. People who are unhoused are sucked into a "gyre" of poverty, arrest, and incarceration (Harrell and Nam-Sonenstein 2023). In a study by the California Policy Lab, people experiencing unsheltered homelessness reported an average of 21 police contacts in the past six months, ten times the number compared to sheltered people (Rountree et al. 2019). Another study in San Francisco found that between 10 percent and 24 percent of people in jail were homeless at the time of the arrest (Herring et al. 2019). Furthermore, people incarcerated more than once are 13 times more likely to experience homelessness than those who are not (Couloute 2018).

There are several reasons for this overrepresentation of the unhoused in police-denizen encounters. First, unhoused individuals are significantly more likely to experience serious mental health illnesses, including schizophrenia, anxiety, and depression, as well as substance use disorder (Sousa et al. 2022, Padgett 2020). Pairing these conditions with the unavoidable–and criminalized– aspects of homelessness, like sleeping in public places, loitering, and vagrancy, leads to an increased number of interactions with the police and hence arrests. Once released from incarceration, individuals are left in a worse position than before: a criminal conviction severely decreases the chance of obtaining employment (Couloute 2018), and individuals still face barriers to healthcare resources and quality care that they lacked before (Kulkarni et al. 2010). Moreover, unpaid fines, missed court dates, and probation violations easily trigger warrants and arrests (Bailey 2020).

While the slogan “Defund the police” has become popularized throughout the country, the current literature shows mixed results about people’s feelings towards allocating money away from the police. Pew Research (2020) found that in June 2020, only 25 percent of Americans supported decreasing police funding. Another study reported support up to 43.3 percent among Americans (Baranauskas 2022). In terms of racial divide, a study done by Gallup found that more Black adults supported reducing the scope of the police compared to the rest of the U.S. population in 2022: while 61% of Black adults believed in eliminating officer enforcement of nonviolent crimes, only 45% of the non-Black Americans did (McCarthy 2022). However, a different research design found Black adults were less supportive of reallocating funds than White respondents, predominantly due to fears about increases in crimes and riots (Capers et al. 2024).

Ba et al. (2024) investigates whether or not a lack of public demand for policing alternatives can be attributed to insufficient information among the public about the availability of such alternatives. The authors found that exposing respondents to information on a particular website detailing alternative response options to specific scenarios significantly reduced demand for police in nonviolent situations. This effect remained across political lines. What is apparent is that people’s preference towards policing alternatives depends on a myriad of factors, including whether they live in areas with more crime (McClelland et al. 2024), are suffering from substance abuse disorder (Barberi and Taxman 2019), are socioeconomically advantaged, have high levels of racial resentment (Mancini et al. 2024), and how much information they have about policing alternatives (Ba et al. 2024).

Perhaps most importantly, *how* people define “defunding the police” matters more than how they *feel* about it. An experimental study by Smith et al. (2024) found that framing the issue in terms of reallocating and redirecting funds increased the likelihood of support for defunding the police. Specifically, when people were told that defunding the police meant redirecting police funds to social services, people were more likely to support the policy compared to those who were told that defunding meant eliminating the police.

One reason why people may oppose the reallocation of funds to other actors is because of the belief that this redirection will lead to more disorder, crime, and violence. This fear is intuitive when we consider that we have traditionally viewed the role of the police to be that of peacekeeping and order maintenance. So answering the question of whether diversion programs actually reduce crime is crucial to both informing policymakers' decisions and shaping public demand.

Diversions from Policing: Municipal Models from Across the U.S.A.

Some denizen encounters with police result in their arrest (Figure 3). Some denizens however, may be diverted from arrest. Diversion is a broad term that refers to "exit ramps" that move people away from the criminal legal system without a criminal conviction (Wang and Quand 2021). There are three basic modes of diversion: civilian-initiated diversion, police-initiated diversion, and post-booking diversion.

Under civilian-initiated diversion, a "disorderly" or "criminally-acting" person can be diverted prior to an arrest. This is known as pre-arrest diversion. It requires the discretion of a non-police civilian or a law enforcement officer. Civilians can initiate diversions by utilizing designated crisis hotlines to call non-law enforcement officers to respond to disturbances, eliminating the potential for arrest. These community responders are usually health professionals and trained crisis workers who have experience in de-escalation and mental health encounters (Figure 4).

Figure 3. Standard Police Arrest

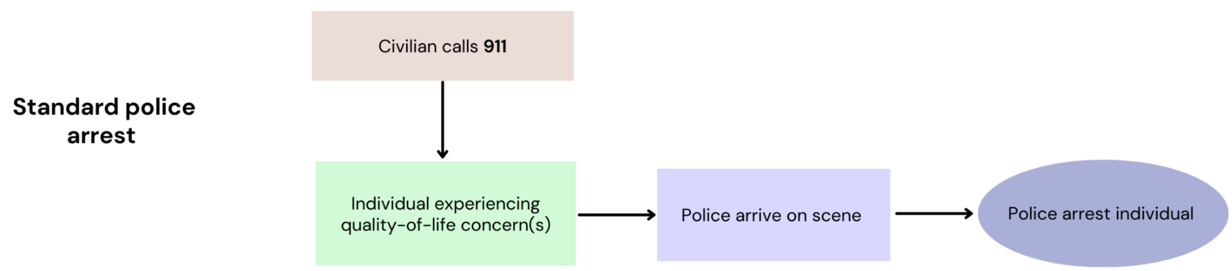
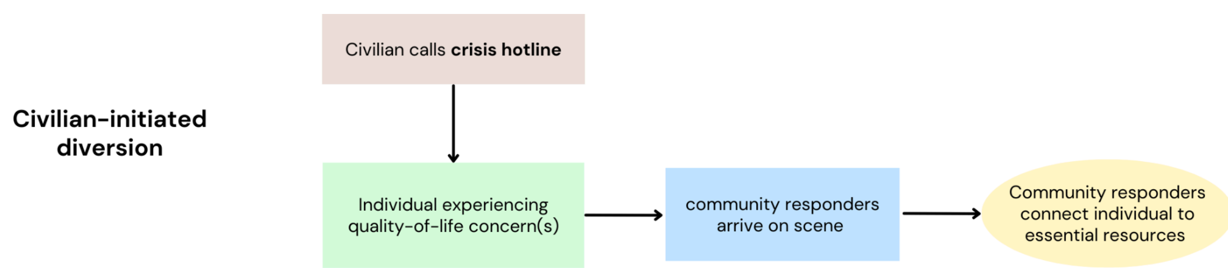
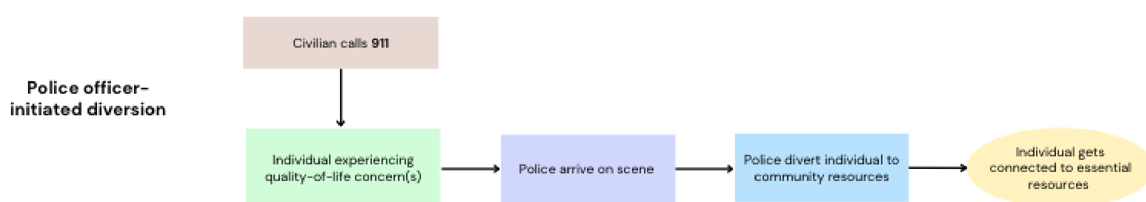


Figure 4. Mode of Diversion: Civilian-Initiated



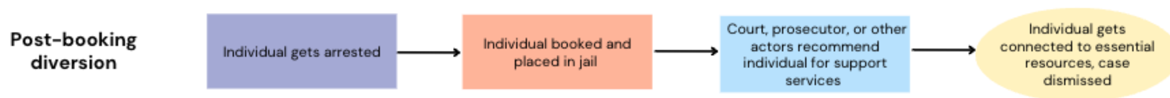
Under police officer-initiated diversion, police officers choose not to arrest a "disorderly" or "criminally-suspect" subject. Instead, the police officer redirects the subject to support services that provide the subject with resources for addressing substance use, mental health challenges, and/or homelessness or other matters of precarious shelter (Figure 5).

Figure 5. Mode of Diversion: Police officer-Initiated diversion.



In some cases, other actors in the criminal legal system can divert a "disorderly" or "criminally-suspect" subject *after* their arrest by a police officer. Such diversion is referred to as “post-booking” or “pre-charge” diversion. Such diversions are often part of diversion programs administered by courts, prosecutors, solicitor generals, law enforcement agencies, and even nonprofits. Those diversion programs redirect an individual towards targeted support plans rather than moving forward with a charge (either a charge is never filed, or the initial charges get dismissed with a trial).

Figure 6. Mode of Diversion: Post-Booking



Regardless of the mode of diversion, The goal of diversion is to target the root problems of low-level crimes and ultimately increase public safety[4]. Police arrest and incarceration, by exacerbating issues of homelessness, substance use disorder, and mental health, prime individuals to repeat low-level offenses and make contact with the police over and over. Allow us to imagine a “continuum of public safety (Owens, Michael Leo 2020),” wherein community responders and alternative support services exist on the left end and police exist on the right. In this continuum, non-police community response services are never violent, while police are potentially violent. If we believe that police violence and arrests of low-level crimes decrease community safety, we should aim to go as far to the other end of the spectrum as possible, where the threat of harm against the individual is nonexistent. In other words, while officer-led

[4] While traditionally “public safety” has been defined by the government as protecting individuals from violent harm to person or property, from third parties, and natural elements (Friedman 2021), sociologists, criminologists, and other scholars have pushed for a more nuanced and encompassing approach to this term. Public safety in the context of policing and diversion includes physical protection from violence, but it also encapsulates overall physical and mental wellbeing derived from access to mental health resources, housing, food, and other basic needs.

diversions reduce harm, diversion without the presence of police offers the most direct path towards increasing community safety.

Diversion from arrest (and/or incarceration after convictions for charges) is not new in the U.S. It first emerged in 1967 when the President's Commission on Law Enforcement and Administration of Justice sought to provide an alternative route for first-time offenders, as well as the youth (Farrell et al. 2018). Youth diversion programs (youth courts) were intended to eliminate the psychological damage and stigma associated with incarceration. Then in 1989, the first "drug courts" appeared. These are court-supervised diversions for drug-related cases that offer individuals the opportunity to enter long-term substance treatment instead of receiving a jail sentence (National Treatment Court Resource Center 2023). More than 2,500 such programs exist nationwide today (Office of National Drug Control Policy 2025). Over the last decade, many U.S. cities and jurisdictions have implemented police-led diversions that seek to assist people experiencing mental health concerns, homelessness, and other vulnerable groups like people engaging in sex work (Beckett 2023, Harmon-Darrow et al. 2023). The Appendix provides a list of all municipal-level diversion programs in the U.S. as of March 2025.

Seattle's Law Enforcement Assisted Diversion Program (LEAD) was one of the first established police-led diversion programs in the country. Created in 2011, LEAD sought to divert people suspected of low-level drug and prostitution offenses to social and legal services instead of putting them in jail. Over time, the pool of people eligible for LEAD diversion expanded to include individuals engaging in misdemeanor theft, misdemeanor property destruction, criminal trespass, unlawful bus conduct, and obstruction of a law enforcement officer (Beckett, 2023 p10). The LEAD model works as follows: a police officer arrests an individual as usual and brings them to the police precinct. There, the officer screens the individual for LEAD eligibility, and they give eligible individuals the option of participating in LEAD instead of undergoing further criminal booking and prosecution. A LEAD case manager then connects with the individual, providing outreach and social services to put them on a path towards recovery from homelessness, substance abuse, and other issues.

A 2017 nonrandomized control trial of the program found that LEAD participants exhibit 60% lower odds of arrest during the six months subsequent to diversion compared to the control group. In the long term (post-two years), participants show 58% lower odds of arrest and 39% lower odds of being charged with a felony (Collins et al. 2017). LEAD's significant benefits could be attributed to the case managers' long-term, tailored case management that provides support for housing stability, job attainment, and sobriety. Since its creation in 2011, the "LEAD" model has scaled across the country. As of 2021, 42 communities in 21 states have established law enforcement assisted diversions (The LAPPA "LEAD" Report 2021). Cities that have adopted LEAD models include Albany, Santa Fe, Baltimore, Philadelphia, and New Haven.

There also exist many civilian-initiated diversion programs. The first program of this kind is Crisis Assistance Helping Out on the Streets (CAHOOTS) in Eugene, Oregon. Founded in 1989, the program allows civilians to either call a non-emergency number in Eugene or call 911 like a normal emergency call that could result in a police response. For the latter, dispatchers are trained to recognize non-violent situations with a behavioral concern and route those calls to CAHOOTS. It then dispatches two-person teams of crisis workers for non-emergency situations, and if the scene involves a crime in progress or violence, police tag along as co-responders (White Bird Clinic, 2020). The CAHOOTS responders–upon receiving consent from the affected individual–make referrals to behavioral health services, counseling, housing resources, and other channels of support. Similar programs exist elsewhere.

In Olympia, Washington, the Crisis Response Unit (CRU) launched in April 2019, funded after a public safety referendum passed by voters in 2017. CRU made over 500 contacts with people in just three months (Thompson 2020). In Denver, Colorado, the Support Team Assisted Response (STAR) program started in June 2020. As of December 2023, STAR engaged with at least 4,435 individuals. Three-fourths of its calls were identified as mental health concerns (Gillespie et al. 2024). In Phoenix, Arizona, its Crisis Response Network (CRN) has existed since 2001. It sends mobile crisis teams of clinicians to intervene in mental health concerns about denizens of the city. CRN dispatches teams 1,400 times per month (Beck et al. 2020). Minneapolis, too, has an alternative response program. Its Behavioral Crisis Response (BCR) program began its design in 2017 and launched in 2021. Since then, BCR mental health professionals have responded to at least 16,000 emergency calls. Moreover, the Minneapolis Police Department lauds BCR for effectively de-escalating behavioral episodes, reducing the "need" for arrests by Minneapolis police officers (Phelps 2024, Collins 2024).

A third diversion model is the co-responder model. This response involves the pairing of police with at least one mental health professional that jointly responds to calls for service related to behavioral concerns. Typically, the mental health professional rides along with the police, arriving at the scene concurrently. In Douglas County, Colorado, they launched its Community Response Team in 2017 as a partnership between police, county commissioners, Fire/EMS services, and mental health providers. Between 2017 and 2019, it engaged in 208 diversions from jails and saved the city $4.9 million. A similar program started in Gainesville, Florida in April 2018. In its first year alone, its co-responder pairs handled 635 calls, saving the city $240,000.

There are underlying themes to this model of programs. One of them is that all of their diversions are funnelled through a centralized call center. In each location, a civilian can call either the designated non-emergency line, or 911. In the latter case, the 911 call center dispatcher identifies if the concern is a non-emergency behavioral issue and diverts the response to the respective alternative response team accordingly. Additionally, all of these programs receive funding, in part, by government expenditures. STAR, for instance, is primarily funded through the city of Denver's Department of Public Health and Environment, buttressed by a grant from the nonprofit Caring for Denver Foundation. Olympia's CRU is funded by a local tax source and grant from the Washington Association of Sheriffs and Police Chiefs. Phoenix's CRN is supported by the Regional Behavioral Health Authorities (AHCCCS 2021).

Eugene's CAHOOT is worth noting separately. Its mobile response team is funded by the City of Eugene. Moreover, the bulk of its municipal funding is through the Eugene Police Department budget (City of Eugene 2025). The city allocates annual funds from its police department to this alternative response team. Not only does CAHOOTS reduce the scope and footprint of the Eugene Police Department, it manifests a degree of "defund the police" by transferring a portion of police funding to diversion managed by a non-police entity.t. Meanwhile,Euguene enjoys a more cost and energy efficient system, given that CAHOOTS diverts five to eight percent of Eugene's 911 calls from the police and arrests/jailing. This annually saves the city of Euguene up to $1.23 million (Waters 2021).

There is a dearth of documented evidence on the effectiveness of diversion programs. According to a review of 31 databases from 1985-2016 of studies on the diversion of Class A drug from the criminal legal system, evidence of reduction in recidivism among diverted individuals is uncertain (Hayhurst et al. 2017). A review from 2009 that identified 21 publications or research papers that examined the "criminal justice outcomes of various diversion models" found little evidence that diverting people significantly reduced recidivism. Most recently, a systematic review of health, human services, legal, and criminal justice databases for empirical research on police-initiated pre-arrest diversion of adults from 2000-2022 found 47 relevant studies (Harmon-Darrow et al. 2022). While the authors found that police diversion programs were associated with reducing recidivism and lowering costs, only ten articles, based on six studies, employed quasi-experimental research designs that had a comparison group. The results of these studies were mixed.

Atlanta's Policing Alternatives and Diversion Initiative

PAD was the product of complex political processes in the city of Atlanta that required community organizing, public demand, government cooperation, and other municipal actors to be implemented. It started as a collective response by advocates and community leaders in 2013 to the punitive efforts by the city to target and banish sex workers and low-level offenders. Although the PAD's development is relatively new, it fits squarely in a much deeper context of Atlanta's political economy and past (and present) efforts nationwide to criminalize public disorder.

Criminalizing "Disorder" in the "City Too Busy to Hate"

Atlanta as a modern "growth machine" city (Molich 1976) was shaped heavily in the mid to late 20th century by coalitions of business and political elites (Stone 1989). The political economy of Atlanta and its growth machine coalitions prioritized commercial development and economic growth. This came amid Atlanta becoming a majority Black city, coupled with the election of its first Black mayor, and nothing but Black mayors and generally majority-Black city councils since then. All of that Black municipal empowerment allowed Atlanta to assume the title of “The Black Mecca” of the South (Ebony Magazine 1971; Hobson 2017). During this time, Atlanta’s Black and White elites found a mutual interest in attracting and maintaining investment via financial capital through its political and social capital.

With Black people becoming the majority of Atlanta’s residents, starting in the 1970s, the election of Maynard Jackson as mayor, along with prominent Black business leaders to positions of power in the city government, Atlanta held its head high as the “Black Mecca of the South.” To sustain a harmonious and profitable relationship with their White counterparts, Black municipal and civic leaders (and middle-class Black Atlantans) knew they had to maintain respectability. Respectability is the process whereby people in marginalized groups appeal to the cultural-political identities of the dominant social groups in order to achieve assimilation and social mobility (Jefferson 2023). At a minimum, this meant ensuring that their neighborhoods and streets were clean and welcoming. Middle-class Black reformers bought into the “germ theory of crime and immorality,” which posited that unkempt neighborhood conditions invited a slew of vice and criminal activity (Galishoff 1985). The reformers believed that crime and immorality, as well as disorder, would tarnish the image of the city, especially amid Black municipal empowerment. Hence, longstanding Black civil society organizations like the Atlanta Urban League and the Atlanta chapter of the NAACP organized neighborhood cleanups and community-driven sanitation campaigns (Wiggins 2020).

By far the biggest proponents of respectability and order maintenance were business leaders in the commercial districts. To attract business from across the nation and sustain the “growth machine,” Atlanta needed to be a reputable commercial terminal. A part of that meant making sure that disorder and crime weren’t prevalent on streets of Midtown and Downtown. So when the Federal Bureau of Investigation in 1973 declared Atlanta the “murder capital of the

U.S.A.," Black and White city leaders turned frantic. Multiple crime waves hit Atlanta, as it did across the country at the time. Crime dramatically increased throughout the 1970s. And at a period when annually over a million people were travelling to Atlanta's downtown for conventions, business leaders felt they had to salvage their city (Wiggins 2020).

Despite the uptick in homicides, break-ins, robberies, and assaults, businesses in the city complained primarily about low-level disorders (Auburn Avenue Revitalization Committee 1979). They felt that the prostitution, homeless people, and public drunks scared customers away and drove down business. They demanded greater police presence on the streets to put away sex workers and panhandlers and the homeless. Quickly, the majority-Black Atlanta City Council sought to remove as many undesirable people from the business district as possible, criminalizing all sorts of disorderly behavior that threatened the flow of commerce in the city. Black business owners also successfully pushed the Department of Public Safety to sign a Police/Community agreement that doubled the beat patrol in their districts to heighten surveillance on people engaging in sex work and panhandling (Wiggins 2020).

The dramatic increase in the use of police officers to try to arrest low-level offenses through arrest and jailing during the late 20th century, for the sake of protecting economic investment and development, reveals the powerful role commercial interests play in the adoption of punitive policymaking to combat disorder. This has been the case from then until now. It explains much of the origins of the community mobilization against policing disorder and for diversion from arrests through PAD.

PAD began as a community campaign in Atlanta in 2013 against the criminalization of sex work. Around that time, business owners who had been frustrated with the rising prostitution and drug activity around their buildings brought their concerns to the Atlanta City Council. This led the city to introduce an ordinance that would ban convicted sex workers from "areas of prostitution" or even the entire city after a second prostitution conviction. The council voted unanimously (14-0) to move the banishment ordinance, "Stay Out of Areas of Prostitution" (SOAP), to its Public Safety and Legal Administration Committee. It also drew the support of several business entities in Midtown and Downtown, including the Midtown Ponce Security Alliance (MPSA). Around this time, banishment–"a punishment inflicted upon criminals, by compelling them to quit a city, place, or country for a specified period of time" (Black 1951)–grew. As sociologists Katherine Beckett and Steve Herbert (2010) noted, "banishment [was] back". In Seattle specifically, Beckett observed that "Stay Out of Drug" orders increased from 7 percent to 30 percent between 2001 and 2005. This led to a concurrent increase in trespass cases filed in the Seattle Municipal Court, constituting 10 percent of all case filings by 2005.

MPSA's vice president at the time, Steve Gower, said that the sex work banishment in Atlanta would be "instrumental in addressing the problem" (The Georgia Voice 2013). The banishment also gained the support of then-Atlanta Police Chief George Turner and then-Mayor Kasim Reed. "We are not trying to put people in jail," said Mayor Reed. "We simply ask that they not come back to where they were caught or convicted" (AJC 2013). Despite Mayor Reed's claims, community advocates and sex workers vehemently opposed the ordinance. Moki Macías, the current-Executive Director of PAD, originally raised the ordinance to community leaders in the Pittsburgh area of Atlanta. According to Macías (2024), advocates argued that the banishment would disproportionately impact Black transgender women. Soon enough, civic leaders from Racial Justice Action Center, Women on the Rise, LaGender, and Trans(forming) galvanized to create the "Solutions not Punishment" Coalition (SNaPCO) to stop the ordinance.

The people involved in this campaign were those who were personally impacted by the criminalization of sex work–people who were formerly incarcerated, had lived experience in sex work and recovery, and were previously subject to frequent police interactions.

According to the Southern Center for Human Rights, SNaPCO worked to empower people targeted and profiled by the criminal justice system, especially trans and gender non-conforming people of color. “The idea was that we really just needed another solution,” according to Macías.[5] “Services, not sentences; jobs, not jail. Just trying to get at: ‘there’s got to be another way.’ People are just doing what they can to survive.” Indeed, people engaging in “survival sex work” (exchanging sex for money, dugs, or other commodities for survival) are vulnerable to a host of physical and mental risks, including HIV, depression, and suicidality (Marshall et al. 2012), and throwing these people in jail only deprives them of essential financial and health resources.

SNaPCO aggressively pushed back against the banishment. It signed on to a letter to the city of Atlanta that opposed the ordinance. The letter was clear: “The ordinance is rooted in homophobia, transphobia, and racism… We fall prey to a myriad of allegations that are baseless simply because we are viewed as ‘different.’ By and large, engaging in sex work is an act of survival, not of choice.” (Georgia Voice 2013). The coalition was successful. The city council put the ordinance indefinitely on hold. It has never resurfaced. SNaPCO won that battle. But it recognized that there was more work to do. Its ultimate goal was to address the core issues of the criminal legal system. The fact that the police were the only first responders to concerns like littering, disorderly conduct, littering, and criminal trespass–concerns that are prevalent for sex workers–remained a problem.

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[5]As a part of my research for this, I conducted interviews with Moki Macías and other PAD staff I mention throughout this thesis.

Despite the defeat of the banishment ordinance, Mayor Reed remained determined to thwart prostitution in the city. He created the Working Group to Reduce Prostitution (WGRP). It was composed of fifteen members. It included the City Solicitor, City of Atlanta Chief of Staff, President of the Midtown Ponce Security Alliance, and leaders of advocacy groups like the Racial Justice Action Center and Georgia Equality. From April 2013 to July 2013, the working group held four meetings to discuss potential alternatives to banning sex workers. While the minutes from these meetings are not posted on the city of Atlanta's "publicly available" meetings page, a blog post from July 28, 2013 on Patch offers details from the July session. According to the post, SNaPCO participated in the meeting, and alongside the Racial Justice Action Center, called for "Atlanta Pre-Arrest Diversion" (APAD). The idea was to create a diversion program for street level sex work offenses. Eventually in 2020, the name was changed to the "Policing Alternatives and Diversion Initiative" also known as PAD. This program would redirect sex workers to community-based treatment and support services instead of the traditional route of jail.

SNaPCO's leaders modeled the proposal for PAD after Seattle's Law Enforcement Assisted Diversion (LEAD) program. LEAD is a public-private partnership. It began as a four-year pilot program in the Belltown neighborhood of Seattle in 2011.[6] It diverts low-level drug and sex work offenders away from jail and the criminal legal system. Police officers choose to redirect individuals engaging in drug use and sex work towards care provided by Evergreen Treatment Services, a private nonprofit founded in 1973 that develop and execute intervention plans for LEAD participants. Although LEAD started with an annual $950,000 funding from

[6] The multi-agency collaboration involves "The Defender Association's Racial Disparity Project, the Seattle Police Department, the ACLU of Washington, the King County Prosecuting Attorney's Office, the Seattle City Attorney's office, the King County Sheriff's Office, Evergreen Treatment Services, the King County Executive, the Washington State Department of Corrections, and others" (Beckett 2014).

private sources, it has received grants from the City of Seattle, King County, Washington State, and federal awards over the last decade (Green 2011, Washington State HCA 2024).

At the July 2013 working group meeting in Atlanta, several members expressed a desire to implement the proposal for APAD. SNaPCO's proposal moved forward when the Ford Foundation, the philanthropy that helped fund Seattle's LEAD back in 2011, offered to finance a study trip for SNaPCO members and city officials to travel to Seattle to witness first-hand how their pre-booking program works. In 2015, Councilman Kwanza Hall, County Commissioner Marvin Arrington, City Solicitor Ronda Graham and SNaPCO leaders traveled to Seattle to glean information on LEAD. Meanwhile, leaders back in Atlanta stayed busy. SNaPCO attended public safety town halls and police-community forums, held public rallies and press conferences, and delivered a thousand postcards to the mayor in support of APAD.

SNaPCO was actively trying to build community and City Council support for legislation that would authorize a design team for APAD. They started with the sponsorship of eight council members for the legislation. From August to December 2015, SNaPCO packed four City Council meetings to deliver public comments, and by December, the Atlanta City Council and the Fulton County Board of Commissioners unanimously voted to establish a 62-person design team for the Atlanta Pre-Arrest Diversion. This design team launched in June 2016. According to the "Pre-Arrest Diversion Initiative Design Team" document released by Fulton County, the design team would be responsible for envisioning the guiding principles for the initiative, the location of the pilot program and the target population, program eligibility, including charges and background, and other criteria that would later makeup the core components of the PAD we know today. I obtained many of the names[7] of the design team members from the certificates of appreciation PAD awarded them on March 8, 2017, which I received from Director Macías.

One major responsibility of the PAD design team was to determine eligibility criteria for its diversions and help create the pilot program in 2017. The pilot program would engage in diversions in eight APD beats in Zones 5 and 6, Midtown, Downtown, and Old Fourth Ward. In designing the pilot, PAD analyzed APD data related to quality of life, narcotics, and prostitution-related crimes to determine the top calls for service, most common arrest charges, and demographics of potential PAD participants in APD Zones 3, 5, and 6. See Figures 7 and 8 for PAD's data on the most common calls for service and arrests from 2016-2017. The design team also conducted "focus groups" with 40 APD officers from Zones 5, 6, and the COPS Unit, according to an APD training powerpoint from June 23, 2017.

[7] The design team included the following individuals: Mona Bennett, The Honorable Keith Gammage, Judge Lillian Caudle, Roni Graham, Eunice Cho, Rabbi Joshua Lesser, Judge Alford Dempsey, Brenda Muhammad, Dr. Anna Pollack, Anna Roach, Dr. Sarah Vinson, Dr. Glenda Wrenn, Kim Anderson, The Honorable Marvin S. Arrington, Jr., Frankie Atwater, Judge Diane E. Bessen, Xochitl Bervera, Emily Brown, BT, Neil Campbell, Ms. DeeDee Chamblee, George Chidi, The Honorable Andre Dickens, LaTrina Foster, Dr. Liz Frye, Pierre Gaither, The Honorable Kwanza Hall, The Honorable Paul L. Howard, Jr., Kevin A. Jefferson, Rosalie Joy, Mary Signey Kelly-Harbert, Judge Cassandra Kirk, Chief Patrick Labat, Cathryn Marchman, David McCord, Vernon Pitts, Kelly Prejean, Tiffany Roberts, Amber Robinson, Major Marisha Shepherd, Chief Erika Shields, Holiday Simmons, Judge Christopher E. Ward, Marilynn B. Winn, and Dr. Mojgan Zare.

Figure 7. Calls for Service by Category, July 2015 - July 2016 (PAD 2017)

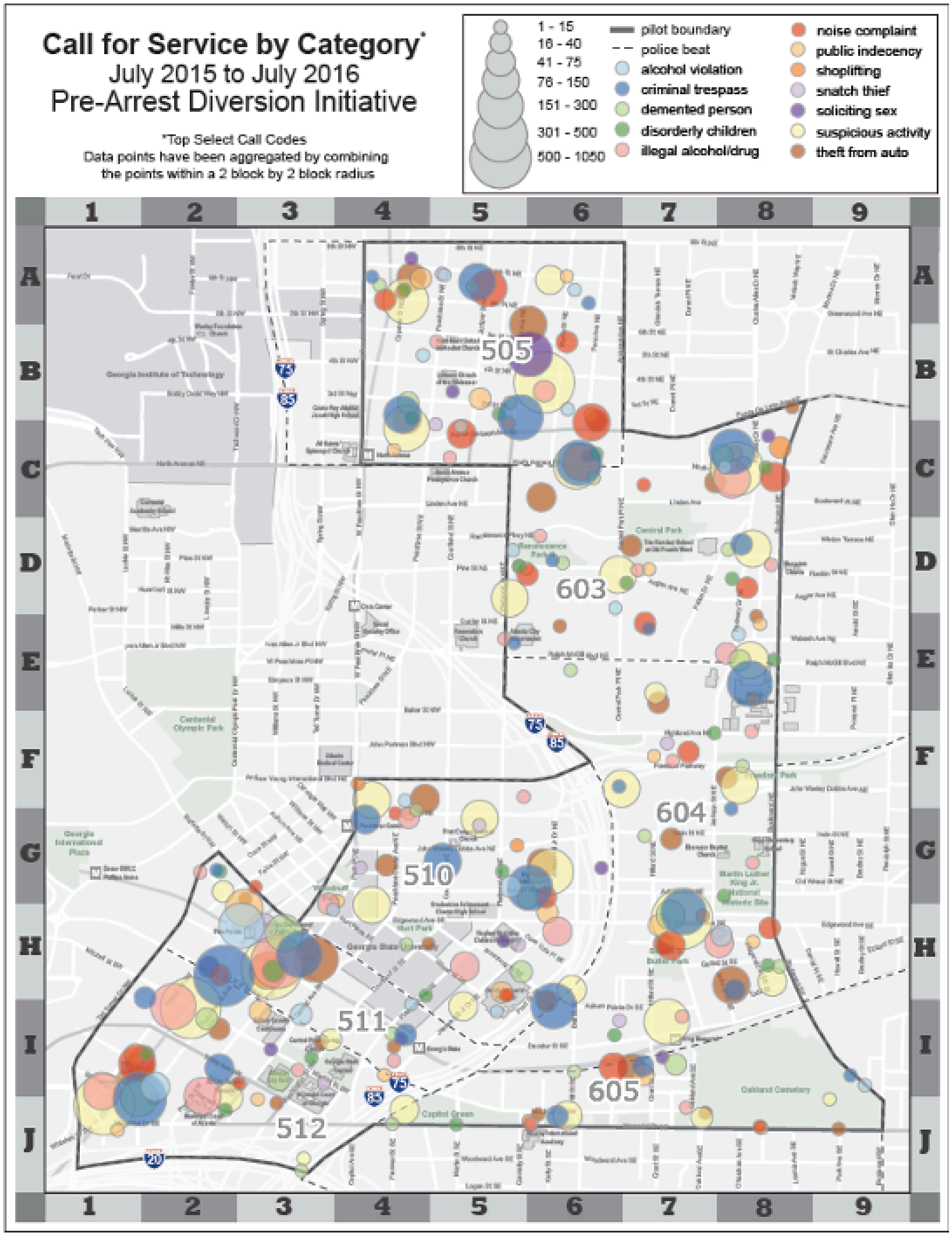
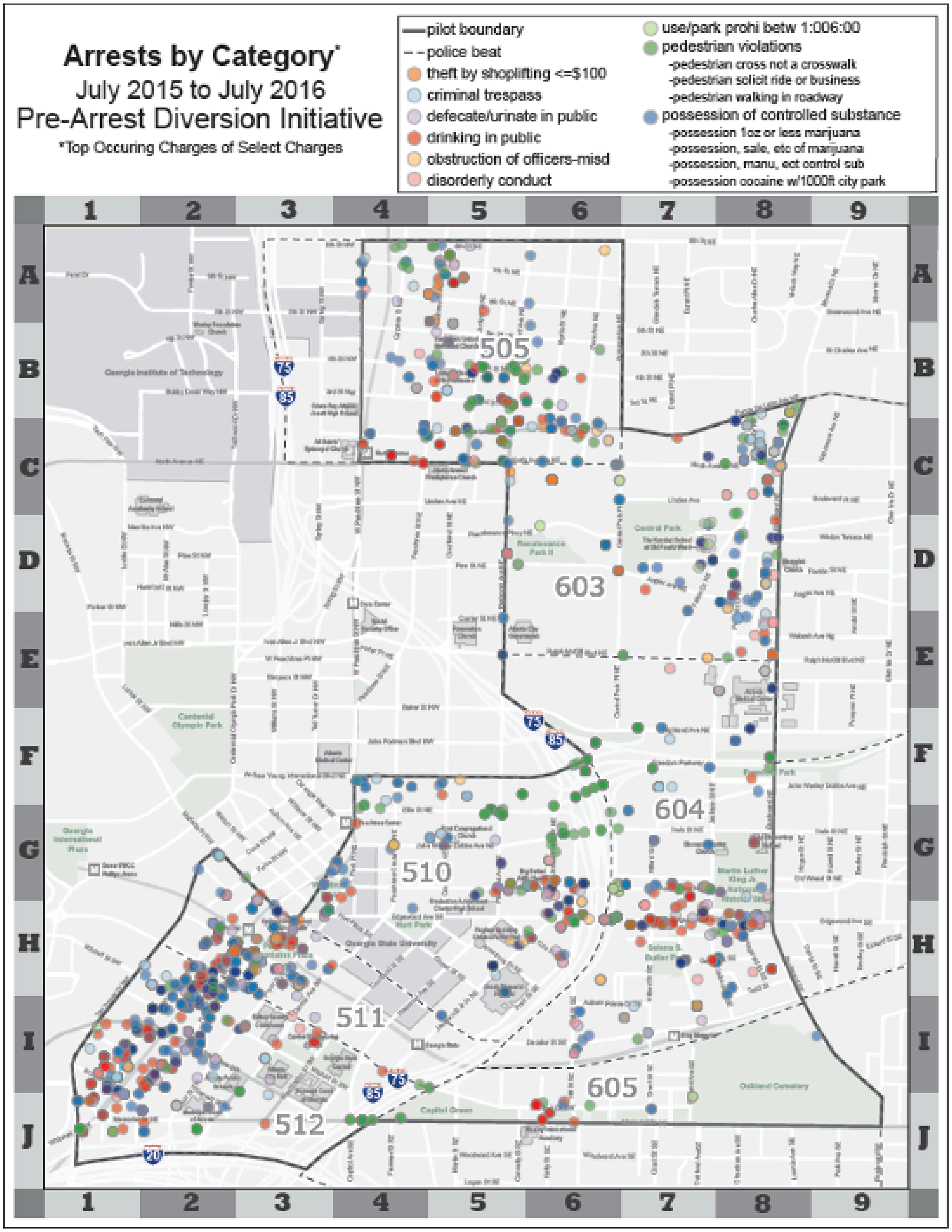


Figure 8. Arrests by Category, July 2016 - July 2017 (PAD 2017)



Creating the multi-agency collaboration among private social welfare providers and public institutions required overcoming hurdles. According to Macías, “I think initially, there was a lot of concern with the idea that if you could punish people but choose not to, that… it was a get out of jail free card." As evidenced by the 2013 attempt to banish sex workers, municipal officials (and police officers) felt that "disorderly" people and low-level, nonviolent "offenders" needed to be punished to fix their ways. The ideological opposition to PAD as an approach to policing and order-maintenance was palpable. The words of Michael Bond, who chaired the Public Safety Committee of the Atlanta City Council, illustrate it: "Should we provide more services? Of course. But this isn't a Lifetime movie where every hooker has a heart of gold. We still need to get tough on the problem of prostitution" (Los Angeles Times 2013). Furthermore, even during the process of designing PAD' operations, there were municipal concerns about eligibility for diversions. PAD sought to give people several chances at recovery and progress. But many municipal officials believed that PAD should exclude from diversions people with arrest records.

In the end, after a few years of debate and agreement, a city council that initially sought to banish sex workers and drug users from Atlanta unanimously supported diversions from arrests. It was unsurprising, according to Moki Macías: "There was a year and a half of organizing–educating council members, involving them in the process of learning from LEAD." Sharing the stories of people who would benefit from diversion was a big part of getting the municipal officials to understand the potential of PAD. Personal narratives became important to the issue framing of and for diversion as an alternative to arrest and jail.

During the campaign, SNaPCO collected written and video testimonials of people who were in or had gone through the criminal legal system. It used the testimonials to craft composites of individual stories to illuminate and humanize people's experiences with arrests and jailings. For example, viewers would be shown the story of a person named "Joe." They would learn about his backstory, his family, and how he ended up in a particular neighborhood in

Atlanta. The video would talk about what Joe's challenges may have been before encountering a police officer and getting arrested. Macías explained it this way: "When you start talking about 'Joe' and understand his story and see what would have resulted in a 'terroristic threat' against a police officer, it became clear that these situations are really complex and the people who need help the most are those who need PAD…" Such stories, coupled with community outreach and activism by SNaPCO, helped develop a diversion protocol that continues to serve denizens in the city of Atlanta. See Figure 9 for an example of written testimonials shared by PAD to stakeholders.

Figure 9. Written Testimonials by PAD

PAD Potential Participants

Marcus is a 52-year old Black Veteran who was born and raised in the Old Fourth Ward, Atlanta and was trained as a third-generation mechanic who works on and off. Fifteen years ago he was diagnosed with Bipolar disease and self-medicates with alcohol to manage his symptoms.

Marcus has been homeless on and off for the past 10 years, sometimes staying with his daughter in O4W but spending most of his nights sleeping on the streets downtown. Marcus has been arrested over 30 times for public intoxication, drinking within 1000 feet of a package store, and urinating in public, and was arrested five years ago for assault after getting into a bar fight.

Marcus is stopped near Grady Hospital for public intoxication and criminal trespass…

David is a 23-year old Black man who moved to Atlanta four years ago to look for work after being released from probation in Alabama and lives with his mother and girlfriend in the Pittsburgh neighborhood.

David has been using heroin for the past three years after getting addicted while in prison and sometimes sells small amounts of heroin to support his habit. He has been arrested six times in the past three years for possession of marijuana and shoplifting and he is looking for work after getting fired from his job as a bus boy.

David is stopped at Five Points Station for possession of heroine…

Monica is a 30-year old Black Trans woman who grew up in New Orleans and moved to Atlanta eight years ago after her family kicked her out of the house for being transgender. Although she has a B.A .and some training as a nurse, Monica has been unable to find work in Atlanta (she was fired once when her employer discovered she was trans) and has no family in Georgia.

She is HIV + and has been arrested five times for idling and loitering, public indecency, and prostitution. She does not have a stable place to live though she finds temporary apartments and rooms for rent and she occasionally does sex work in Midtown to survive.

Monica is stopped in Midtown for idling and loitering...

The Political Origins of PAD

In many ways, the adoption of PAD in the city of Atlanta was a marvel. In 2013, the idea that a police officer could choose to redirect an individual from handcuffs into the hands of community-led service providers and resources was a fairly radical idea. At that point, one of the only officer-led diversion models that existed in the United States was Seattle's LEAD program. Indeed, by the time PAD got to accepting diversions in 2017, the city of Atlanta had "one of the most progressive pre-arrest protocols in the country," according to Macías.

To better understand the local politics and municipal adoption of PAD as a response to the call for order-maintenance via diversion, it is useful to view it through the "multiple streams" framework John Kingdon (1995). Kingdon theorizes that, at any given point, there is an almost unlimited number of policy problems that could reach the top of the policy agenda. Given that policymakers have limited resources, answering Harold Laswell's (1936) famous question of "Who gets what, when, and how?" requires rational decision making. That involves a thorough contemplation of benefits, risks, and available knowledge. According to Kingdon, three "streams" – problems, policies, and politics – must come or be brought together at the right time for a policy to be adopted.

First, in the problem stream policy entrepreneurs try to get their problem or issue the agendas of policymakers. Problems in Atlanta around 2013 were prostitution and drug use around neighborhoods and business districts. According to then-Atlanta Police Chief George Turner, APD had received numerous complaints from residents and businesses about those two issues. For example, the president of the MPSA, Peggy Denby, spoke openly about wanting male transgender prostitutes out of her neighborhood (Georgia Voice 2013). According to Denby, "[Atlanta's] biggest problem has been prostitution…(in two areas where) those people have been coming to the same area for 30 years…the only way to get rid of them is to banish them" (Robinson 2013). A downtown businessman named Mr. Miller went on Channel 2 news and reported concern about how prostitutes would leave condoms and needles in front of doorways. He said of the last 48 years his pharmacy had been open on Broad Street, the past 10 years have experienced a marked decline in conditions (WSB-TV Atlanta 2013). According to WSB Atlanta, law enforcement had arrested 300 "johns" (male prostitution clients) and made more than 1,400 arrests that could fall under prostitution.

Second, in response to the problems of sex work and drug use, there were several proposed solutions in the local "policy stream." Kingdon states that policy solutions swirl around in a "primeval soup," which grows as different actors (community leaders, experts, consultants) add their proposed policy ingredient. Whether a solution is "consumed" by policy makers depends on its technical feasibility, value acceptability within the policy and public communities, and anticipated costs (Kingdon 1984, 138). One solution was banishment. It was originally proposed by APD Chief Turner and supported by business owners and residents like Mr. Miller. The banishment was an iteration of the same story told in the American municipalities since the late 1900s, a product of the infamous "broken windows" approach to crime first introduced by Kelling and Wilson in 1982. It empowered police officers to increase their foot patrol and crack down on the disorder that threatened to compound every day it was left unchecked.

But advocates of diversion knew that a punitive approach to sex work was not going to alleviate those issues. In fact, by the time this banishment was initially proposed, the city had already tried to fight the prevalence of sex work and drug use by investing large amounts of resources on punitive tactics. In February of 2012 for example, APD Chief Turner had signed into the APD Policy Manual in 2012 the implementation of "Vice Operations." They dedicated an entire operation on sending undercover cops in "take-down vehicles" to single out petty street-level activities such as prostitution, illegal sale, and consumption of alcohol. Yet, people who would go to jail for these low-level crimes would come back out and relapse into the same behavior, but with fewer resources than before. Hence, community leaders offered diversion as an alternative solution.

Not only was there aggressive advocacy in support of PAD's diversion services, there already existed a functioning model in the United States to go off of. "We were really leaning on the work of LEAD in Seattle," as Macías recalled for me. "Nationally, we were seeing LEAD shift the conversation." The fact that a diversion program existed for four years by the time the PAD design team was proposed meant that Atlanta just needed to look at what Seattle was doing with LEAD and take what was working. If there was any doubt about the technical feasibility of such a program, which there certainly was at the time, city officials like Councilman Hall visiting Seattle to observe the mechanisms of LEAD surely pushed back some of those concerns.

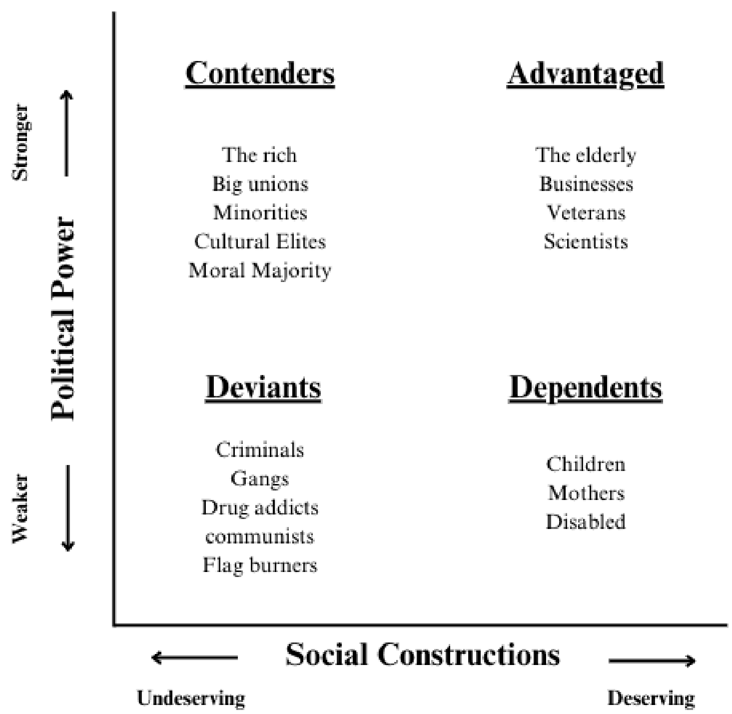
Third, the politics stream includes the existing political climate, public opinion about an issue, upcoming elections, and other forces that shape public attention and responses to problems. In 2013 Atlanta had municipal elections. That meant that city council members and the mayor were up for reelection. It mattered for the adoption of PAD. As Macías put it, "I think that [reelection] is always a part of the equation," shaping the different incentives elected officials might have had in supporting PAD. When organizations banded together to create political coalitions like SNaPCO, city leaders recognized a growing body of community-based political capital. They saw the broad support for diversion across different constituencies, the ability of people to build a coalition, and considered their own political futures.

Taken together, the three streams coalesced to create a "window of opportunity" for PAD to come to life. "Basically," according to Kingdon (1995), "a window opens because of a change in the political stream." Plus, as Kingdon contends, "there are also occasions during which a problem becomes pressing, creating an opportunity for advocates of proposals to attach their solutions to it." The problems of sex work and drug use were well understood, a viable solution had already existed, and city leaders had the political will to adopt an alternative solution. Ultimately, the controversial introduction of the banishment ordinance opened the "window of opportunity" for community advocates of alternatives to policing to push the idea for PAD to the forefront of the political municipal agenda.

Apart from the framework offered by Kingdon, there is another important aspect of public policy making, which is the social perception of people and groups in our world. PAD advocates challenged people to reorient their views on people engaging in low-level crimes, especially crimes associated with meeting basic needs and survival. Historically, these people have had specific statuses or "social constructions" attached to them from members of society. Helen Schneider and Ann Ingram (1997, 107) define social construction as "the process through which values and meaning become attached to events, people, patterns of action, or any other phenomena." These characteristics are normative and evaluative, portraying groups in positive or negative terms through stories, symbolism, and metaphors (Edelman 1988). The social construction of target populations is important because it provides rationale for determining who public policymakers choose to burden or benefit through policy adoption. Ultimately, social construction, in part, explains who wins and who loses from distributive politics.

Depending on society's perceptions of them, different groups receive different treatment from policymakers. Indeed, when elected officials decide which target populations receive benefits or burdens, they have a propensity to distribute benefits to the powerful, positively-viewed groups in society (i.e. the middle class and businesses). Labeled by Schneider and Ingram as the "advantaged," these groups possess lots of political power and are seen by the public as good and deserving. In contrast are the politically weak, negatively-constructed populations (e.g., criminals and the homeless). Such "deviants" have little to no political power, and they are viewed as undeserving of benefits (Figure 10). While Schneider and Ingram only theorized what groups belonged to which quadrants stemming from the intersection of social constructions and political resources, empirical scholarly work has confirmed where "target populations" fall into their framework. Most significantly, Rebecca Kreitzer and Canids Watts Smith (2018), by surveying 1,572 people to "appraise" the social constructions of 73 different groups, mapped out exactly how the public perceives different groups. As predicted by Schneider and Ingram, people perceive others with criminal records and drug addictions, along with the unhoused and sex workers, as "deviants" with negative social constructions and limited political resources.

Figure 10. Schneider and Ingram's (1997) Social Construction of Target Populations Framework



Insofar as policymakers have a "distributive tendency" (Weingast et al. 1981) and are motivated by reelection, social constructions of target populations fit squarely into public officials' re-election calculus. Elected officials have a strong incentive to cater to the needs and desires of the advantaged because they have the most political capital. Providing good public policy to the advantaged not only leads the target population to respond positively, but it garners support from others who "approve of the beneficial policies being conferred on deserving people" (Schneider and Ingram 1993). Elected officials likewise derive enormous benefit from punishing "deviants" as politically weak target populations.

Elected officials do not fear electoral retaliation from depriving these groups of benefits because they have the least political power. Moreover, society believes that deviants deserve to be punished: their problems are their own personal responsibilities, and the government should yield little respect to their situations. Compare this to the problems faced by the advantaged, which are seen as important public problems that the government should treat with respect. The notorious "tough-on-crime" policies of the War on Crime enacted across the nation in the 20th century that led to the mass incarceration of Black communities illustrate the tendency of the government to punish politically weak and negatively-viewed groups (Alexander 2010, Taifa 2021). Specifically in Atlanta, which was true elsewhere, Black leaders – civic and municipal – often called for the active punishment of low-level offenders to maintain respectability among their White counterparts and facilitate commerce in the growth machine (Wiggins 2020; Forman 2017).

On the social level, the nation-wide ethos of ending urban violence communicated that everyday citizens should adopt "get tough" attitudes and levy informal social control on deviants (Garland 2001). The message was that disorderly conduct is not tolerated, and the broader public should increase personal surveillance and intervene to stymie the destructive lifestyles of "deviants" and the public disorder they created and constituted. Hence, policies that aggressively punished criminals both fueled the social construction of criminals as undeserving and painted policymakers as the heroes who served the interests of the public.

The policies borne out of the War on Crime were beneficial for policymakers for another reason. While punishing the deviants, elected officials simultaneously bolstered the police, creating a two-way stream for political capital. Historically, the police have enjoyed a positive social construction and possessed political power. Television shows like Dragnet, The Untouchables, and Adam 12 depicted the white cop as the hero that defeats the bad guys, and the police lived in the minds of affluent, suburban property owners as the infatigable blue line that ensured order. Moreover, the police had–and still maintain–political clout. Over 55% of police officers in the United States are union members and 57.5% of police officers are covered by collective-bargaining contracts (DiSalvio 2021). Through funding and endorsing campaigns, police unions can have significant sway over elections (Zoorob 2019), making political backing from the police a valuable asset for elected officials. By militarizing the police and spending enormous amounts of money on municipal police departments, elected officials likely gained the support of police agencies and unions, invigorating their chances of reelection.

Applying the social construction framework to the case of PAD, it appears intuitive that elected officials would have an incentive to oppose its formation. Given that PAD calls for the reduction in scope of the police and keeping “deviants” out of the criminal legal system, its goals are at odds with the traditional values we expect the public and policymakers to hold. After all, part of the social construction of “deviants” is that they respond mainly to punishment. But the fact that the city adopted PAD in 2015 demonstrates “noncongruent policy making,” a phenomenon where elected officials choose policies that deliberately mismatch assumptions about the deservingness of groups (Owens and Gunderson 2023, Boushey 2016). An example of this phenomenon is the adoption of "Ban the Box" (BTB) policies across cities in the U.S.

BTB was a political demand for municipal governments to adopt policies that end or embargo the disclosure of criminal records on job applications. The idea was that people with criminal records—a politically and socially disadvantaged group–should not be further disadvantaged in obtaining future employment (NCSL 2021). Owens and Gunderson (2023) reveal important municipal contexts behind BTB adoptions across the U.S. They found that working-class community organizing correlated strongly with cities choosing to adopt BTB policies. Moreover, they found that descriptive representation, in this case Black representation in city leadership, increased the chances of BTB adoption by cities. Finally, they report that "BTB policy adoptions are associated with other cities adopting them first."

We can apply municipal adoptions of BTB to the adoption of PAD by the city of Atlanta. Not only was there intense organizing from politically and economically marginalized groups for the policy solution, Atlanta had a majority Black City Council (11 of 16 members were Black) and a Black mayor (Kasim Reed) in 2015, signifying high levels of descriptive representation for the communities most likely to produce a great number of people needs diversion and communities benefiting from diversion as public policy. Furthermore, the city adopted PAD because of municipal policy learning, especially learning of the lesson that diversion did not worsen disorder and crime. The lesson came from observing Seattle's LEAD program. Consistent with BTB policy adoptions, PAD was an example of noncongruent policymaking made possible by the presence of all these factors at the right time.

PAD exemplifies noncongruent policymaking in another way. Elected officials went onboard with the policy because advocates were able to successfully shift the social construction of sex workers and low-level offenders. According to Schneider and Ingram, social constructions are subject to change over time. They are mutable under some conditions. Consider same-sex couples in the United States.

In 1996, just 27 percent of Americans believed that same-sex couples should be recognized by the law (Gallup “LGBTQ+ Rights”). Today, around 69 percent of Americans support gay rights. The gay rights movement has certainly grown to capture the interests of elected officials and to have their voices included in important policy decisions. Similarly, people living with AIDS were initially perceived to be deviants; not only did existing sodomy laws in the South, for instance, legally discriminate against sex between people of the same sex, people at the time stigmatized AIDS as merely a product of sinful behavior. But that social construction began to change when activists shed light on the stories of people suffering from the disease.

The news that basketball star Magic Johnson had AIDS revealed that anyone, even heterosexual people, could suffer from AIDS. Combined with the medical advancements in the treatments available for the disease, the public quickly accepted it as a broader public health issue. Victims of AIDS were no longer seen as deviants, but as “dependents,” people with relatively low political power but now considered deserving by the public of benefits (Donovan 2001).

Similar to the perception of people in the LGBTQ+ community and victims of AIDS, public views about homeless people have slowly shifted. In a recent nationwide poll, researchers from the National Alliance on Ending Homelessness found that an increasing number of people believe that homelessness is caused by economic factors like the cost and availability of housing, inflation, and low wages. This represents a “significant shift” in the public’s understanding of homelessness that is likely informed by personal experiences about the cost of living (NAEH

2024, 5). When asked about solutions to homelessness, more than half (54%) showed support for government policies that fund programs that provide services and shelter for people experiencing homelessness. 47% of respondents reported support for increased investments in mental health and substance use prevention. Crucially, 86% of respondents did not believe that increased law enforcement could solve homelessness or keep people from sleeping outdoors on public property.

Most people today do not believe law enforcement can effectively address some of the crimes that are policed the most such as criminal trespass. This kind of non-punitive, service-oriented approach to homelessness suggests that the public may view homeless people less as "deviants" (as traditionally seen according to Shneider and Ingram) and more as "dependents" who deserve greater care and benefits, assisted by public policies. Indeed, 70% of respondents strongly or somewhat agreed with the statement: "Homelessness is caused by social or economic policies that leave people economically vulnerable and without the support to live stably. It can be solved by policies that better protect vulnerable people" ((NAEH 2024). This contrasts sharply with the "personal responsibility" ethos historically weaponized in addressing homelessness, along with crime and disorder associated with homelessness.

Returning to Atlanta, leaders of SNaPCO used community organizing and advocacy, amid various changes in the three streams of problems, policies, and politics, to shift how public policymakers thought about sex work, drug use, and homelessness. They did it to shift those target populations from "deviants" to "dependents," where the latter has more positive social constructions and a bit more political resources that may permit policymakers to at least burden them less, especially through arrests and jailings. In particular, "Organizing was incredibly important," according to Macías. In her view, community organizing and advocacy moved more municipal leaders to take a more thoughtful, even if still paternalistic, view of the people on the street. Policymakers slowly moved to favor or at least accept diversion and rehabilitation through social services over just relying on arrests and punishment. With this shift in social construction and perceptions of rising political influence came a municipal abandonment of solely relying on punitive approaches like banishment.

Before, policymakers signaled messages towards sex workers and drug users like "'Your' problems are your own personal responsibility" and "Government should treat you with disrespect and hate." With the adoption of PAD, the elected officials embraced a different message: "'Your' problems are the responsibility of the private sector" and "Government should treat you with pity." Seen as "dependents" instead of "deviants," to some degree, sex workers, drug users, and the homeless could experience fewer burdens and maybe more benefits by way of diversion over arrests, even if if required policymakers to accept that sometimes "disorderly" people and people who resort to low-level crime to stay afloat on the streets needed second, third, or more chances to try to turn their lives around.

Implementation of PAD

PAD is a hybrid model of diversion. It employs pre-arrest diversions and post-booking diversion. In this section I describe the implementation of PAD. Specifically, I explain how the initiative operates, starting with diversion and moving through case management in PAD's hopes of reducing recidivism.

Diversion

Imagine David is in downtown Atlanta. He experiences a "non-emergency quality of life concern related to mental health, substance use, or extreme poverty." Such concerns may include public disturbances, public indecency, welfare (asking for food or help), mental health, substance use, basic needs, and public health. Someone observes David in the moment of concern. They call ATL311, which is a hotline in the city of Atlanta that receives community calls for non-emergency services and makes referrals to municipal agencies and social welfare organizations. In the case of David, an ATL311 Supportive Service agent would ask the caller a series of questions to determine if the concern was appropriate for a PAD referral. Assume it is. The agent would contact PAD's Referral Coordination Team. There is a caveat: PAD is not on a 24-hour service. It only operates between the hours of 7AM and 7PM.

PAD would dispatch a two-person Community Responder Team (See Figure 11) to the location of David. These community responders have different backgrounds with a variety of qualifications. This includes experience in law enforcement, CPR and narcan training, mental health and behavioral services, and substance use services. Additionally, some of PAD's community responders have personal experiences with homelessness, recovery from substance abuse, and the criminal legal system that equip them with the skills to provide compassion and appropriate care to those they serve.

Figure 11. PAD Community Responders (PAD 2025)

Typically, according to PAD, a Community Response Team will arrive on the scene within 30 minutes. Upon reaching the scene, PAD responders would engage David by conducting an initial intake interview. The interview allows the responders to identify and assess the immediate needs of David. This might include a meal, clean clothes, a shower, or shelter. It also will include, based on the identified needs, where to take David for further assistance. He could, for instance, be transported to overnight shelter, respite, a MARTA station, or alcohol and drug rehabilitation.

A core value of PAD, in contrast to a policing agency like the Atlanta Police Department, is honoring "dignity and self-determination." PAD makes it clear that it will only transport David if he consents to receive assistance from PAD. PAD will never coerce David or use a threat of coercion (e.g., seeking his arrest) to take specific actions. Compare that to police officers for whom coercion and the threat of the use of force are inherent to their roles when it comes to order-maintenance and law enforcement.

The PAD diversion of David that I described follows the community-responder model, where a police officer or other order-maintenance or law enforcement agent is not involved in the process. But, some scenarios involving PAD involve the police.

Imagine David, again. He is experiencing a quality of life concern. Perhaps David is "disturbing the peace." Someone observes David. Instead of calling ATL311, the observer calls 911, which is for emergency calls for assistance from the police or other protective service (e.g., the fire department). A 911 dispatcher will refer the call about David to the nearest police officers. The police officers will go to the location of David.

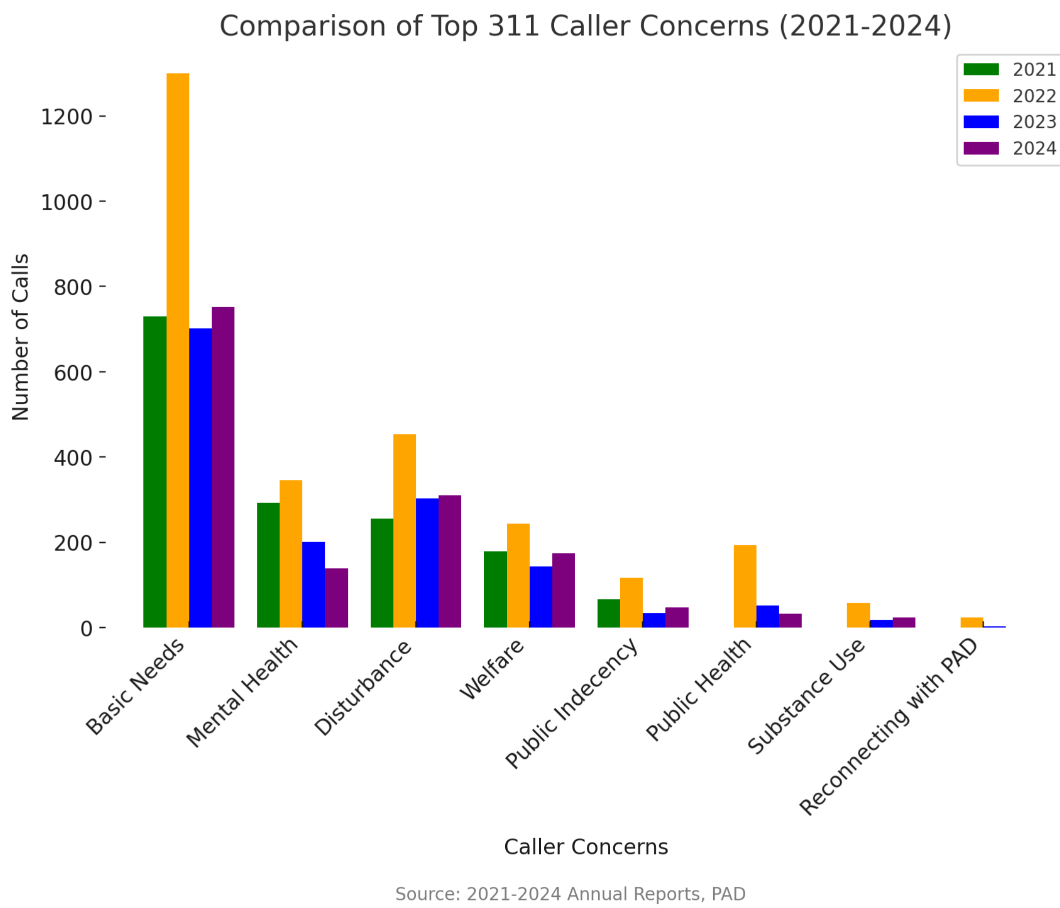
When they arrive on the scene, the police officers will engage David. They will assess the situation. If the situation is a non-emergency concern, the officers use their discretion to divert David to PAD, instead of arresting David and booking him into jail. Specifically, a police officer calls the PAD Referral Coordination Team. PAD then dispatches a two-person Community Responder Team to the scene. Community Responders arrive and conduct an initial intake interview with David. Meanwhile, the police officers stay on the scene until PAD either transports David to receive services or David refuses the assistance of PAD. In this scenario, whether to divert or "pass the baton" to PAD is up to the discretion of the police officers, combined with the choice of David to accept the service of PAD.

In both scenarios, observers, dispatchers, police, and PAD employees co-produce the policy we call diversion. However, there are countless missed opportunities for diversion on any given day. One reason is , to reiterate, PAD only operates its diversion services between 7am and 7pm. Another reason is that many officers use their discretion but choose to not divert. As I will describe later in the thesis, the majority of individuals who qualify for diversion in the city of Atlanta get arrested and jailed.

What sets PAD apart from other diversion programs in the United States is its ability to accept individuals into its services after they have already been arrested and booked into jail. In other words, there can be diversion after arrest. PAD partners with the Office of the City Solicitor and the Office of the Public Defender to identify individuals who have been arrested for a divertable charge and offer them an opportunity for diversion through PAD. When an individual is identified, a PAD Care Navigator visits the jail and screens them for PAD eligibility. If the individual has not been charged with an offense yet but they consent to a diversion, they are released to PAD the following morning. Or an individual can be diverted through PAD after they have been charged with an offense. At that point, they could have been in custody anywhere from days to months before being referred by the Solicitor or Public Defender to PAD's services. In either situation, once a person is diverted to/through PAD their cases are dismissed or closed without any mandated conditions.PAD's public Monthly Report data provides diversion statistics.

Generally, PAD averages about 300 diversions per year. In 2023, PAD completed 264 diversions. There were a total of 1,498 PAD *requests* through 311. These are calls for PAD made by observers or 311 dispatchers. One reason for the discrepancy between the number of requests for PAD and the number of actual diversions might be that some individuals do not consent to being diverted and enrolled in PAD's services. In this case, the community responders would just hand the individual basic needs like food, water, and a MARTA card. Another reason might be that by the time PAD arrives at the scene, the individual no longer behaves concerningly or is in need of assistance. Figure 12 shows the makeup of 311 calls by concern type over time. As we see, the most common reasons for 311 calls are basic needs, disturbances, and mental health.

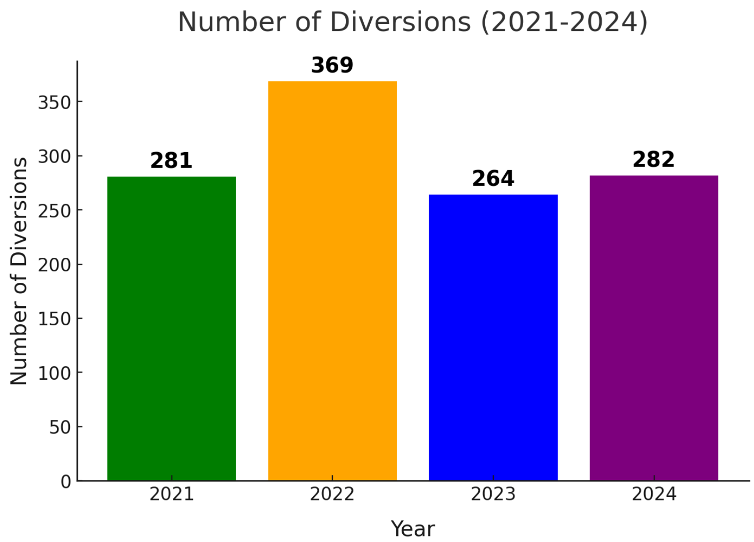
Figure 12. Non-Emergency 311 Calls by Type (2021-2024)



Of the 264 diversions, 129 (49 percent) diversions were street-level, pre-booking diversions, 97 (37 percent) were post-booking diversions, and 38 (14 percent) were "re-referrals."[8] Notably, the year 2022 had significantly more diversions than the other three years. In terms of the locations of diversions, diversions tend to occur most frequently in Zone 5 of the Atlanta Police Department (APD). Zone 5 covers most of Downtown Atlanta, the neighborhood of Ansley Park, Piedmont Park, and other areas (Atlanta Police Department 2025). Figure 13 and Figure 14 show the number of diversions over time and the number of divisions by APD Zone.

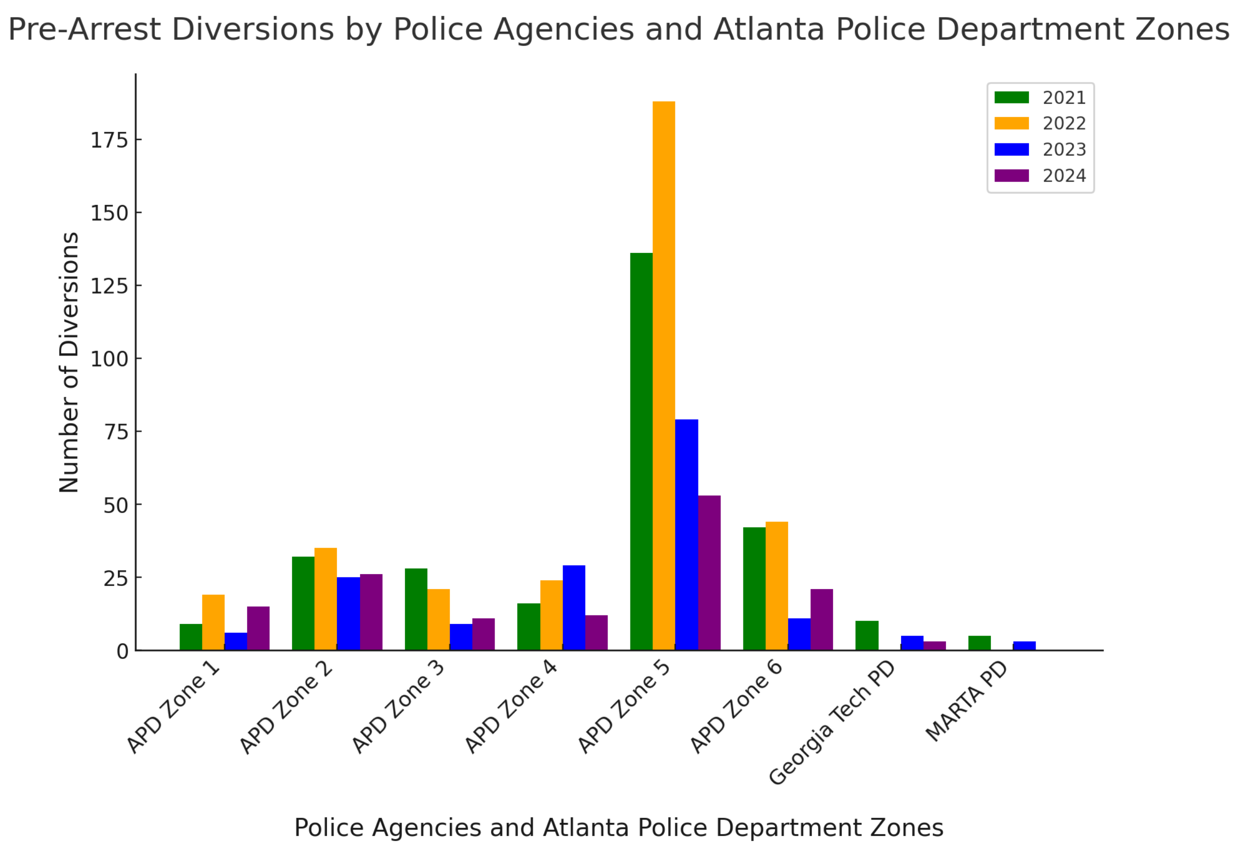
Figure 13. Number of Diversions by Year

[8] "Re-referrals" refer to the diversions of individuals who have been diverted to PAD before.



Includes post-booking referrals, except for 2021 which had no post-booking referrals.
Source: 2021-2024 Annual Reports, PAD

Figure 14. Diversions by Policing Agency and Zone



Source: 2021-2024 Annual Reports, PAD

The monthly data reports also disaggregate PAD participants by demographics . Figure 15 and Figure 16 show the demographic characteristics of the 952 PAD participants from 2022 through 2024. (Demographic information is unavailable before 2022).

Figure 15. PAD Participants by Race/Ethnicity

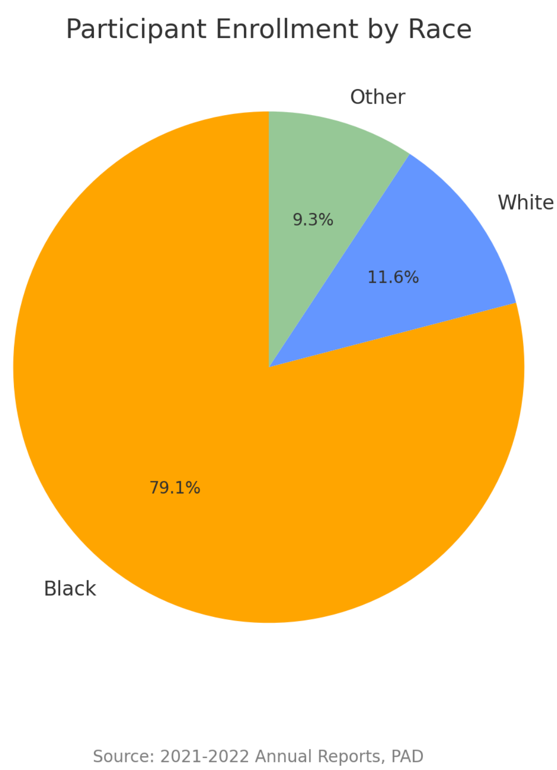


Figure 16. PAD Participation by Age

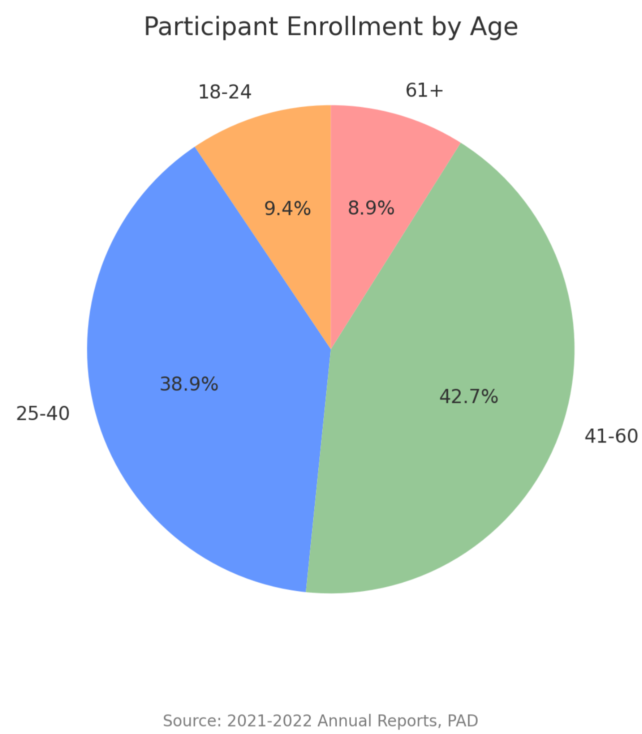
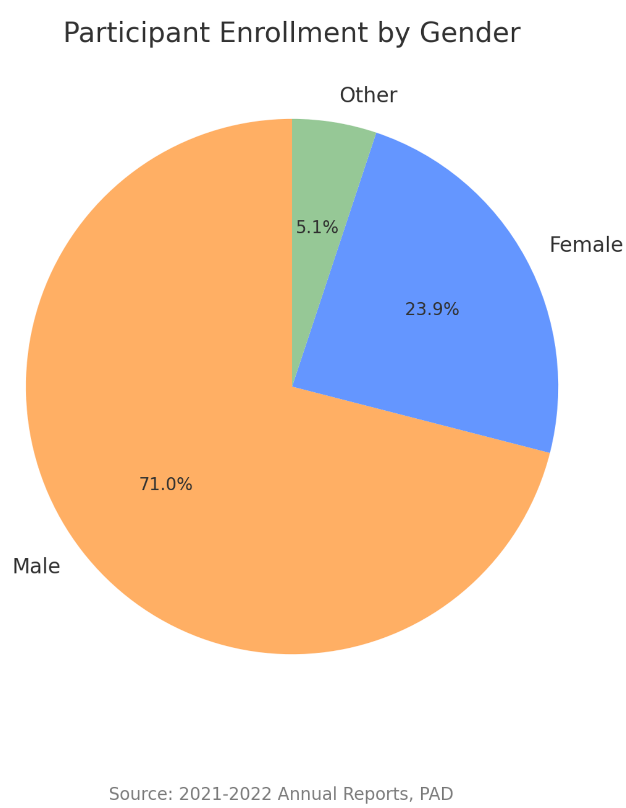


Figure 17. PAD Participants by Gender



Case Management

After an individual gets diverted and becomes a PAD participant, they get paired with a Care Navigator. A Care Navigator provides ongoing case management and meets with their participants every other week to set goals and connect them with the resources they need. This could include securing long-term housing, addressing open court cases, reconnecting with family, and finding a job. Based on an interview I conducted with Stacy Piper, the PAD Operations Coordinator, getting a participant proper documentation is one of the most important parts of PAD's case management. Oftentimes, a participant lacks identification (e.g. a driver's license, social security card, birth certificate). Those documents are necessary and required to obtain resources like medication, rehabilitation, and housing. Hence, one of the first things PAD does is make sure a participant receives those documents.

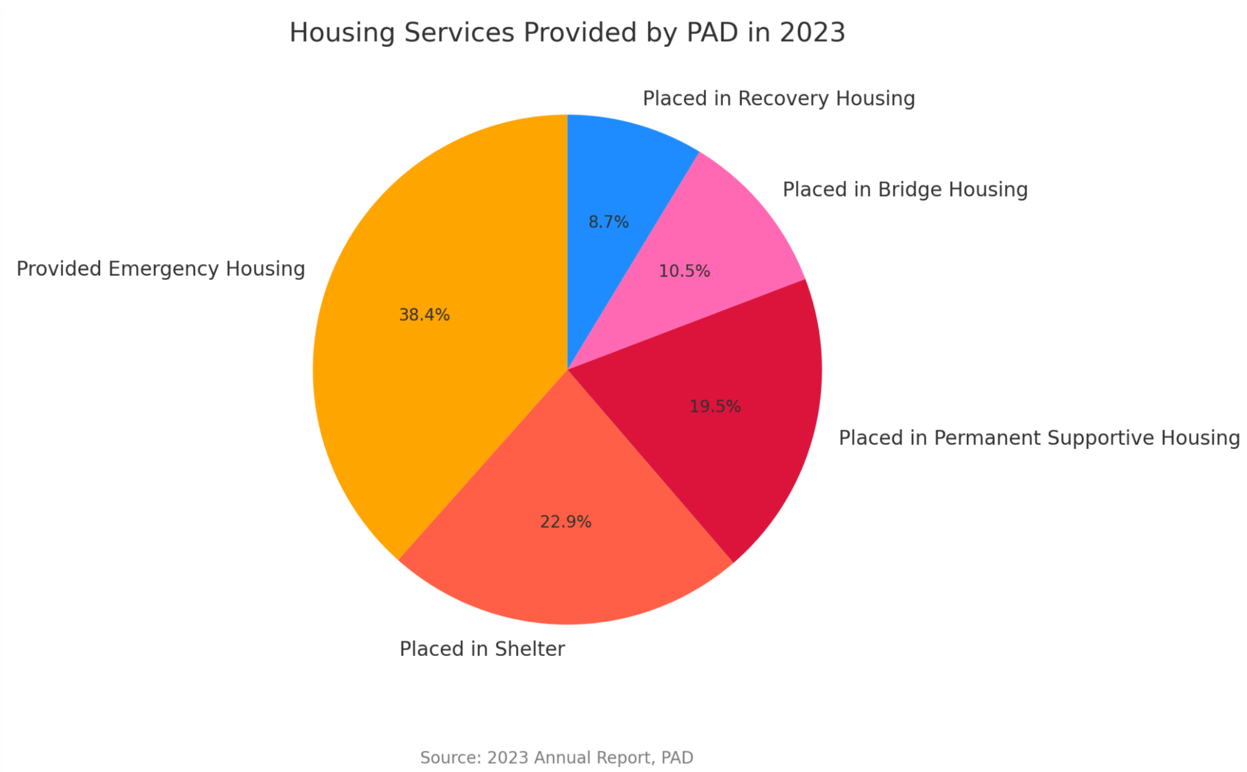
Another important part of a Care Navigator's work is providing respite and getting the participant off the street into a safer environment: "Just to relax and…think about what it is you really want. You can't do that when you worry about your safety," according to Piper. The simple act of offering a constant, reliable support system guarantees a temporary reset. "People are in jail mostly for criminal trespass or shoplifting," according to Erice Monteiro, PAD's Legal Navigation Manager. "We provide resources like food and shelter so that they don't need to shoplift." Whatever basic needs a participant may need, PAD's Care Navigators work hard to provide them.

Care Navigators also advocate for participants. In particular, they are legal advocates. If a participant gets arrested for a quality of life crime, their Care Navigator shows up to court at their First Appearance Hearing to advocate for the participant's release. "When the judge sees that there are support systems and services set in place, they are more likely to let them go," according to Monteiro. As a part of this research, I conducted first-hand observations of PAD's courtroom advocacy at the Fulton County Superior Court. From June 1, 2024 to August 23, 2024, I sat in on the First Appearance Hearings of five different PAD participants. In two of the hearings, the judge asked the Care Navigator, who sat in the spectator bench in the back, to stand up and testify to their participant's involvement in PAD. For the first participant, the Care Navigator mentioned how they had been making progress in their substance use and mental health well-being. For the second participant, the Care Navigator testified to their reconnection with family and attainment of Food Stamps. Both times, the judge released the participant and dropped the charges.

The point of case management is not to solve participants' problems overnight. Care Navigators understand that a lot of the struggles participants face are deep-rooted and even chronic. Addressing conditions like addiction, homelessness, and mental health concerns requires patience, bonding, and empathy. The reason Care Navigators, Community Responders, and everyone else involved in the program are able to do the work they do is because many of them have lived experiences of their own. Some members of the PAD team were formerly incarcerated. Others were once homeless or experiencing drug addiction. They bring to the job a level of expertise and empathy that only those who have been in their participants' shoes can have. "Recovery takes a while. PAD follows them in this process. Someone to love you and care for you and forgive you if you happen to step backwards for a bit...PAD holds on until they get where they need to be," according to Piper.

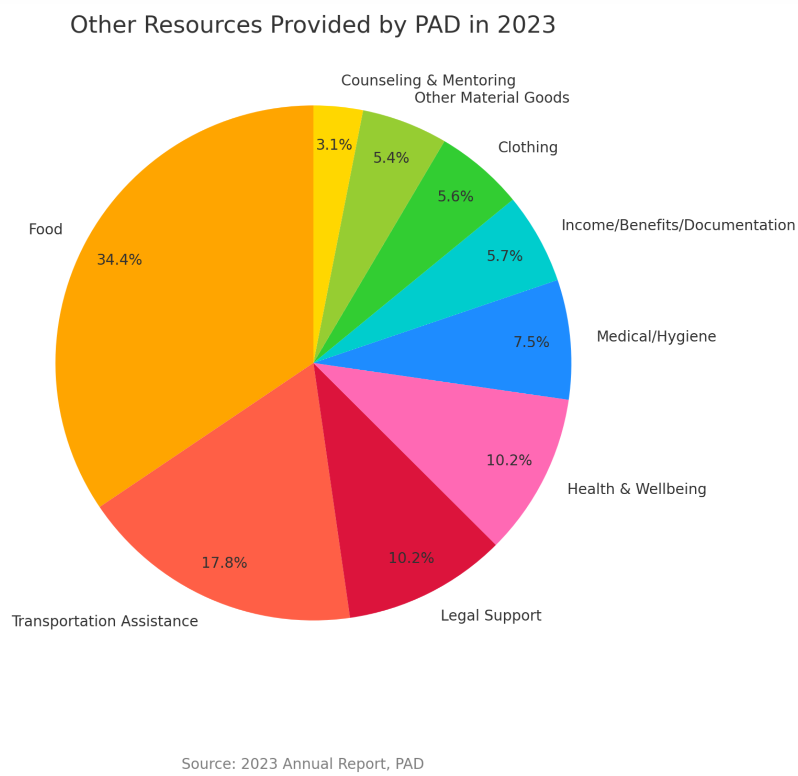
PAD offers housing and health support that can alleviate chronic problems faced by its participants. In 2023, PAD assisted 380 participants in obtaining housing. Specifically, it assisted participants in obtaining emergency housing (38%), permanent supportive housing (19%), and basic shelter (23%) (Figure 18).

Figure 18. Housing Services Provision for PAD Participants, 2023



Beyond housing support, PAD both its participants and non-participants to other types of social care . Such social care includes emergency relief in the forms of food, medicines, clothing, and cash or income subsidies. Figure 19 illustrates it.

Figure 19. Emergency Relief Associated with PAD, 2023



Another way PAD offers care to its participants is through legal support. People who are diverted by PAD frequently have ongoing or open court cases. Such legal issues present barriers for people to find stability and recovery, including inducing extreme stress and mental health deterioration (Nam-Sonenstein 2023). Moreover, missing a court date frequently leads to "Failure to appear" warrants and arrests, throwing that person back into jail. PAD's Legal Navigation Manager keeps an updated list of all open court cases of its participants and notifies each person's Care Navigators if that participant needs to show up to court for a case. That Care Navigator then goes to court with that participant, showing support and making sure that those cases get resolved. Offering legal assistance this way removes one of the key barriers participants face towards getting back on their feet.

Municipal Doubts about Diversion

Diversion programs like PAD can raise many hesitations. Elected officials could have concerns about such programs being unfavorable among the public. They could anticipate drawing backlash from the police. City leaders could also have doubts about their efficacy–whether they would lead to an increase in crime because of their non-punitive nature, causing denizens to feel less safe in their cities. In Atlanta, some elected officials have doubts about PAD.

In 2024, PAD's municipal funding was in peril, mainly because some city council members and the mayor had doubts about the efficacy of PAD. Around a third (32%) of PAD's funding comes from the city of Atlanta (CCI 2024). In April 2024, the city of Atlanta issued a request for proposals for mobile response to community diversion. PAD applied, and after negotiating the scope of work, budget, and contract language, was awarded a $5 million multi-year contract on July 26. At its October 30th meeting of the Finance Committee there was an agenda item. PAD was the agenda item. During the meeting, Councilman Alex Wan reported that instead of moving forward with the newly awarded PAD contract, the mayor's office had initiated a new procurement process (Weill-Greenberg 2024). The process would occur over fourteen days and be closed to the public.

PAD, according to Macías, was not informed in advance about the proposed new process, which included PAD not being invited to apply. When PAD inquired to learn more about this procurement process, the city refused to provide additional information. Even city council members were blindsided and confused. Councilman Amir Farokhi, for instance, reported feeling "disappointed that things have fallen apart" (Bagby 2025). According to Devin Franklin, the Senior Movement Policy Council for the Southern Center for Human Rights, "The city launched a secret special procurement process that effectively subverted and undermined the lawful award to PAD” (SCHR 2024).

The Legal Defense Fund, ACLU of Georgia, and other organizations filed letters of support to the City Council and Mayor’s office urging the continued funding of PAD. Indeed, since July 2024, PAD staff had been operating without a formal contract, unsure of whether their services would ever be funded. “With additional delays,” Macías wrote in an email to community members, “we will be unable to continue providing these services.” PAD mobilized community members to contact the city council. It also mobilized community members to give formal comments before the city council. Approximately 50 supporters of PAD appeared before the city council on October 3rd and pressed the city to extend the contract to PAD. The advocacy by PAD seemed to make a difference. Soon after the public testimonies in support of PAD, the Mayor’s office on November 6th cancelled the new procurement process. The City Council then voted on the contract, awarding to PAD as all had originally expected. On January 6, 2025, in another email sent by Macías to the community, it was discovered that the City Council signed off on the award, marking the first ever multi-year contract between PAD and the city of Atlanta.

Lying at the core of the funding strife was municipal uncertainty about PAD’s efficacy. According to a press release by the Mayor’s office on January 2, 2025 , “the previous agreement lacked the necessary performance metrics that would ensure taxpayers were getting the services for which they paid” (City of Atlanta 2025). In an interview I conducted with Councilman Alex Wan, he stated that support for PAD among the City Council was much higher in 2015. But after seeing the money and time it takes for PAD to improve conditions, support “eroded.” At a glance, Councilman Wan stated that support was likely around 60/40 in support of PAD. One of the big concerns was the “repetitive nature of how PAD is needed.” The fact that PAD isn’t a one-time fix for an individual's chronic underlying issues instilled doubt in the minds of some city leaders about PAD's usefulness. He stated that to relieve resistance and skepticism, there needs to be more robust data in the monthly, quarterly, and annual reports to help measure and understand PAD's efficacy.

Assessing PAD as a Public-Private Partnership

One of the primary motivations of this thesis is to derive empirical findings about PAD's effects from diversion data, which may positively influence future municipal support for PAD. I utilize administrative data from PAD's internal database. The database is called Apricot. Additionally, I draw from daily Atlanta arrest reports from the Fulton County Superior Court Administration. Plus, I leverage records from the Fulton County Georgia Inmate Records. The records are part of a public database that includes histories of arrest and jail for residents of Fulton County. I was able to utilize each source for the purposes of this study with permission from PAD's Legal Navigation Manager. The goal was to assess the treatment effect of PAD on participant arrests in the six months and 12 months after diversion. To do this, I matched 337 PAD participants to a control group gathered from the daily arrest reports.

Data

Treatment Group

I collected anonymized information about PAD participants through PAD's internal database system Apricot. At the time I collected data (January 1, 2025), PAD had diverted a total of 1,391 unique individuals since the program started. I narrowed the pool of participants to only those who were diverted *before* January 1, 2024, seeing as one outcome I sought to measure was the arrest history of an individual one year after diversion. Given that at least one year would not have passed between an individual's diversion anytime after January 1, 2024 and the time of this study, I had to exclude them from this study. That left a total of 1,108 potential participants. This included individuals who were 1) still active in the PAD program (i.e., had been meeting with their care navigator bi-weekly since their diversion date), 2) considered “outreach” (i.e., had not been in contact with their care navigator for thirty days), and 3) considered “inactive” (i.e., had not been in contact with their care navigator for ninety days).

I chose to include only individuals who were either still active or in outreach status. The reason is because the treatment effect of PAD—as defined by this study—encapsulates not just the singular act of diverting an individual from arrest, but providing them with continual care and resources after diversion Individuals who were no longer receiving care, therefore, would not have accurately reflected the treatment as previously defined. From the 340 remaining individuals remaining, there were three whose gender was listed as “other.” I excluded those people from the study, as there were no individuals in the control with a gender listed as “other.”

The treatment group ultimately consisted of 337 anonymized PAD participants. Using Apricot, I looked into how each of those participants were diverted: 54 were diverted through people calling 311, 239 were Law Enforcement Assisted Diversions (LEAD), and 44 were from post-booking diversions or third-party community organization referrals. I then coded demographic information of each individual (age, race, gender). See Appendix A for a sample of people in the treatment group. Apricot does not provide information on the specific crime of each diverted individual. Therefore, I was unable to match individuals on the exact crime they were diverted/arrested for. Apricot also does not provide records of specific resources or care services each PAD participant received. Accordingly, identifying the intermediate variable between the treatment and outcome is impossible..

Control Group

The control group consists of individuals who were not diverted through PAD but who were arrested and charged with a crime(s) that fell under PAD's definition of "divertible" crime(s). According to PAD, divertible crimes include: Criminal Trespass, Disorderly Conduct, Drinking in Public, Fare Evasion, Jay walking, Loitering / Prowl, Panhandling, Pedestrian in the roadway, Possession of Illegal Substance, Possession of Drug Related Object, Public Indecency, Public Intoxication, Shoplifting (misdemeanor), Soliciting in roadway, Theft of Services (misdemeanor), Theft by shoplifting (misdemeanor), Urban Camping, and Willful Obstruction of Law Enforcement Officer.

The control group consists of individuals pulled from the city of Atlanta's daily arrest report. The daily arrest report is a document that gets sent every morning to PAD through a partnership with the Superior Court of Fulton County in Atlanta. Each report provides a list of arrests that occurred in the city of Atlanta from the previous day. It details the names, date of birth, gender, race, charges, and other miscellaneous information about each arrested individual. See Figure 20 for an example of an anonymized arrest report page. For this study, the earliest arrest report I had access to was from April 17, 2023, meaning the control group included only individuals arrested within the nine-month time frame of April 17, 2023 and December 31, 2023. Within that time frame, PAD received an arrest report for 147 days. The total number of arrests based on those reports is 9,779.

Figure 20. Example of an Arrest Report (Anonymized)

Inmate Bookings Report GAFULTONPROD

Date Range: Monday, June 12, 2023 Sort By: Date/Time of Confinement

Nodes: Fulton County Jail; Bellwood Jail; Alpharetta Jail; Out of County Inmates; Courts; South Annex; Marietta Annex; Atlanta City Detention Center

Fulton County Jail

SO # / Inmate's Name	DOB / Description	Confined	Arresting Agency	Charges	Warrant #/Issuing Authority	Bond Amt./Type	Image
[redacted]	[redacted] BF 5'00"125	06/12/2023 12:27 AM	APD	Foreign County	2023964WF/HCSO	No Bond	Yes
[redacted]	[redacted] WM 5'08"160	06/12/2023 1:32 AM	GSP	Safety Equipment Not Used Properly	NA/NA	0.00/Signature Bond	Yes
				Failure to Have License on Person	NA/NA	0.00/Signature Bond	
				VGCSA -Possession Of Methamphetamine	EW-0405836/Downtc	3500.00/Surety Bond	
			GSP	Foreign County	2022279WF/HCSO	No Bond	
				Foreign County	22-001719/COLUMB	No Bond	
[redacted]	[redacted] BF 5'04"155	06/12/2023 1:46 AM	APD	Battery - Family Violence (1St Offense) Misd	EW-0405839/Downtc	3000.00/Pre-Trial Relea	Yes
[redacted]	[redacted] BM 5'08"140	06/12/2023 1:56 AM	GDPS	Reckless Driving	EW-0405862/Downtc	0.00/Pre-Trial Release	Yes
				Reckless Conduct	EW-0405863/Downtc	0.00/Pre-Trial Release	
				Driving - Speeding	EW-0405864/Downtc	0.00/Pre-Trial Release	
				Driving- Fleeing Or Attempting To Elude A Police Offi	EW-0405860/Downtc	0.00/Pre-Trial Release	
				Driving-Child Or Youth Restraint Not Used Properly	EW-0405861/Downtc	0.00/Pre-Trial Release	
[redacted]	[redacted] BF 5'08"218	06/12/2023 2:08 AM	APD	CRIMINAL DAMAGE TO PROPERTY - 2ND DEGRE	EW-0405850/DOWN	2500.00/Surety Bond	Yes
				WILLFUL OBSTRUCTION OF LAW ENFORCEMEN	EW-0405851/DOWN	500.00/Surety Bond	
			PTS	BATTERY-FAMILY VIOLENCE (1ST OFFENSE)	23CR000508A/FULT	4000.00/Surety Bond	
[redacted]	[redacted] BM 6'01"180	06/12/2023 3:05 AM	APD	Criminal Trespass	EW-0405852/Downtc	1000.00/Signature Bon	Yes
				Interference With Government Property - Misdemean	EW-0405854/Downtc	Not Set	
				Willful Obstruction Of Law Enforcement Officers - Mis	EW-0405853/Downtc	1000.00/Signature Bon	
[redacted]	[redacted] BM 6'00"217	06/12/2023 3:15 AM	MARTAPD	CRIMINAL DAMAGE TO PROPERTY - 2ND DEGRE	EW-0405859/DOWN	0.00/Signature Bond	Yes
[redacted]	[redacted] BM 6'03"206	06/12/2023 3:22 AM	APD	CRIMINAL TRESPASS AND DAMAGE TO PROPER	EW-0405869/Downtc	500.00/Surety Bond	Yes
				Entering Automobile Or Other Motor Vehicle With Inte	EW-0405870/Downtc	5000.00/Surety Bond	
			FCSO	Foreign County	2022-10-1972/JEFFE	No Bond	

Printed on 06/13/2023 10:23 AM Page 1 of 8

I first narrowed that list by filtering individuals based on charges. One of the matching criteria I employed was crime type (i.e., whether an individual was charged with a crime considered divertible by PAD). I selected individuals who were only charged with a crime(s) that are considered divertible. This filter narrowed down the potential control group to 919 individuals. From there, I cleaned the data by first identifying anyone in the control group who happened to be a PAD participant. This prevented the same individual from appearing in both the treatment group and control group. I found four individuals who were enrolled in PAD and I removed them from the control group. I then identified anyone who appeared more than once. The outcome measure for this study is whether an individual was arrested in the 6 months and twelve months after diversion or arrest. The issue with an individual appearing multiple times in the control group is that their recidivism or outcome status becomes dependent on which date is chosen as the starting point of the evaluation. Imagine an individual gets arrested on June 1, 2023 and again on August 1, 2023 and has no subsequent arrest history after August 1, 2023. If the first arrest date is used as the baseline, that individual will be counted as a recidivating due to their August arrest date. If the August 1, 2023 arrest is used, that individual will not be counted. There were three individuals who appeared more than once (twice). To resolve this issue, I randomly selected one of their two arrest dates as the baseline evaluation date, removing the other appearance. The ultimate control group consisted of 911 individuals. See Appendix A for a sample of the control group.

Methods

I conducted a propensity score matching test, where I paired individuals based on four covariates, generating 337 matched pairs. After conducting balancing checks to ensure that the distribution of covariates between the two groups is statistically similar, I ran linear and logistic regression models to analyze the outcomes of both groups.

I started by matching individuals based on four covariates: race, gender, age at the time of evaluation, and number of previous arrests. Others have identified those attributes to be strong predictors of future arrests (Yukheneko et al. 2019, Abramson 2023, Stolzenberg et al. 2020, OICS 2014). The first three covariates were listed on Apricot for the treatment group and the daily arrest reports for the control group. To identify the arrest history for each individual, I relied on the public Fulton County Georgia Inmate Records. This public website allows one to enter the name and date of birth of an individual and find that person's complete arrest and jail history in the Fulton County Jail. Figure 21 provides an example of an anonymized jail record of an individual.

Figure 21. Jail record example (anonymized).

Jail Records Search Results

Skip to Main Content Logout My Account Search Menu New Jail Search Refine Search Help

Record Count: 8
Search By: Defendant **Last Name:** redding **First Name:** tajuana **Date of Birth:** 1/8/72

Booking Number	Defendant Name	Booked	Released	Arresting Agency	Charge(s)
[redacted]	[redacted]	05/07/2013	05/16/2013	Atlanta Police Department	U/S PED SOL CONTRIBU
[redacted]	[redacted]	11/12/2013	11/21/2013	Atlanta Police Department Atlanta Police Department Atlanta Police Department	Pedestrian Cross Not A Crosswalk/Jay Walking Pedestrian Soliciting Rides or Business Pedestrian Walking In Roadway
[redacted]	[redacted]	10/09/2014	11/22/2014	Atlanta Police Department	Sale Of Cocaine
[redacted]	[redacted]	02/05/2016	02/19/2016	Atlanta Police Department	Probation Violation (Sale Of Cocaine)
[redacted]	[redacted]	06/08/2017	06/15/2017	Atlanta Police Department	PROBATION FELONY - Sale Of Cocaine
[redacted]	[redacted]	09/19/2017	03/29/2018	Atlanta Police Department Atlanta Police Department Atlanta Police Department Fulton County Sheriff's Office	Possession And Use Of Drug Related Objects Possession of Cocaine PROBATION VIOLATION-Sale Of Cocaine BEHAVIOR HEALTH COURT
[redacted]	[redacted]	09/13/2018	10/24/2018	Atlanta Police Department Atlanta Police Department Fulton County Sheriff's Office Fulton County Sheriff's Office	PROBATION WARR - Poss And Use Of Drug Related Ob PROBATION WARR - Possession of Cocaine BEHAVIORAL HEALTH COURT PROGRAM Sale Of Cocaine
[redacted]	[redacted]	03/07/2019	05/25/2019	Fulton County Sheriff's Office Fulton County Sheriff's Office	PROBATION VIOLATION - Possession And Use Of Drug PROBATION VIOLATION - Possession of Cocaine

I determined how many previous arrests an individual had in the control group at the time of evaluation by identifying their date of arrest from the arrest report and finding it on the jail record. I counted how many previous arrests they had prior to that specific arrest. For the treatment group, I first identified an individual's diversion date from Apricot. Individuals who were diverted from arrest by a police officer or through a "311" call had no arrest record online. Therefore, I looked at how many arrests they had prior to the date of *diversion.* Appendix A

Propensity Score Matching

Randomized controlled trials are considered the "gold standard" for estimating the effect of a treatment. In randomized control trials, the random treatment allocation ensures that a subject's treatment status will not confound with measured or unmeasured baseline characteristics. This allows one to estimate the treatment effect by directly comparing the outcomes between the treated and control groups (Greenland et al. 1999, Hariton and Locascio 2018). In observational studies however, treatment is not randomized. This biases the treatment selection because it is often influenced by subject characteristics (Glesby and Hoover 1996, Austin and Platt 2010).

Utilizing propensity scores can remove the effects of treatment-selection bias in observational studies. An individual's propensity score is the "probability of treatment assignment conditional on observed baseline characteristics" (Austin 2011). The propensity score is a balancing score: treated and untreated subjects with the same propensity score will have the same multivariate distribution of measured baseline covariates (Rosenbaum and Rubin 1983). Propensity scores are most commonly estimated by regressing treatment status on observed baseline characteristics through a logistic regression model.

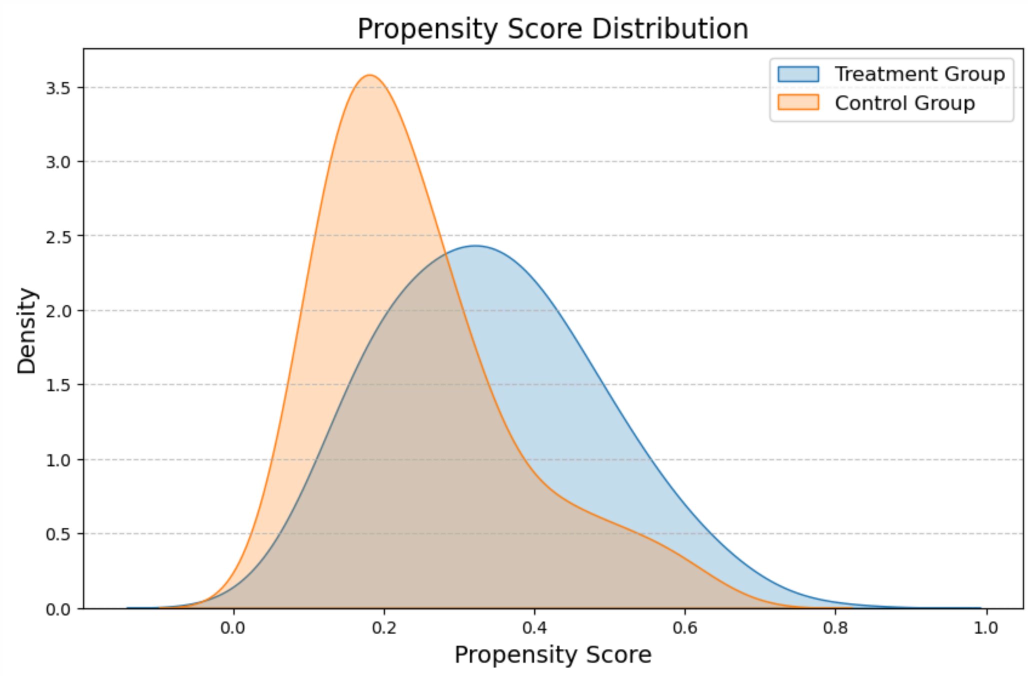
The predicted probability of treatment derived from the fitted regression model is the propensity score. Matching on propensity scores, wherein treated and untreated subjects are matched based on similar propensity scores, is one way of estimating the effect of treatment on individuals. If the outcome is binary, which it is in this study (1=arrest, 0=no arrest), the effect of treatment is estimated as the difference between the proportion of subjects who experience the outcome. Using Python, I generated the propensity scores for each individual by regressing treatment status (i.e., whether an individual was diverted through PAD) on the covariates of race (1=Black, 0=White, 2=other), gender (1=male, 0=female), age at the time of diversion/arrest, and number of previous arrests.

Appendix A provides a sample of the propensity scores of each individual. Table 1 shows the coefficients for each covariate derived from the logistic regression function. I also include a graph (Figure 22) illustrating the distribution of propensity scores by group before matching.

Table 1. Coefficients of Covariates from Propensity Score Logistic Regression Model

	Variable	Coefficient	Std. Error	P-Value
0	const	-3.0867	0.3044	0.0000
1	Age	0.0446	0.0053	0.0000
2	Gender	-0.6497	0.1506	0.0000
3	Race	0.8096	0.1914	0.0000
4	Num_of_arrests	0.0074	0.0051	0.1427

Figure 22. Distributions of Propensity Scores



There were several criteria I used to inform my matching on propensity scores. First I created matched pairs without replacement. In this scenario, once an untreated subject is selected to pair with a treated subject, that untreated subject is no longer in the pool for consideration as a potential match for subsequent treated subjects (Rosenbaum 2002). Matching with replacement is more often used when there are few control subjects compared to treatment subjects. In this study, because there were 911 control subjects and 337 treated subjects, I chose to match without replacement. Second, I utilized "greedy matching" rather than "optimal matching." In greedy matching, a treated subject is selected at random and is paired with the untreated subject whose propensity score is closest to that of the selected treated subject. This process is repeated until every treated subject is matched to its nearest unmatched subject. Optimal matching entails forming pairs to minimize the total within-pair difference of the propensity score. It was shown that there is no significant difference in creating balanced matched pairs between the two methods (Gu and Rosenbaum 1993).

Finally, I formed matched pairs both with and without considering the common area of support. The common support in propensity score matching refers to the overlap in the propensity score distribution between the treated and untreated groups. The assumption of common support holds that if the two groups have no overlapping characteristics, a counterfactual condition cannot be generated through matching (Silver 2021). In this study, there were only a few subjects who had propensity scores outside the area of common support. Hence, my primary analysis relied on forming matched pairs without excluding those individuals. However, I still formed matched pairs and ran analyses on those within the area of common support (See Appendix A).

Balancing Test

After matching, it is important to evaluate whether there remain systemic differences in baseline covariates between the treated and untreated subjects. (Austin 2011). To do this, I first illustrated the distribution of covariates between the two groups. Figure 23 and Figure 24 compare the distribution of gender and race across the treatment and control groups. Figure 25 and Figure 26 permit comparisons of the distribution of subjects by age and prior arrests.

Figure 23. Comparison of Gender by Group (1 = male, 0 = female)

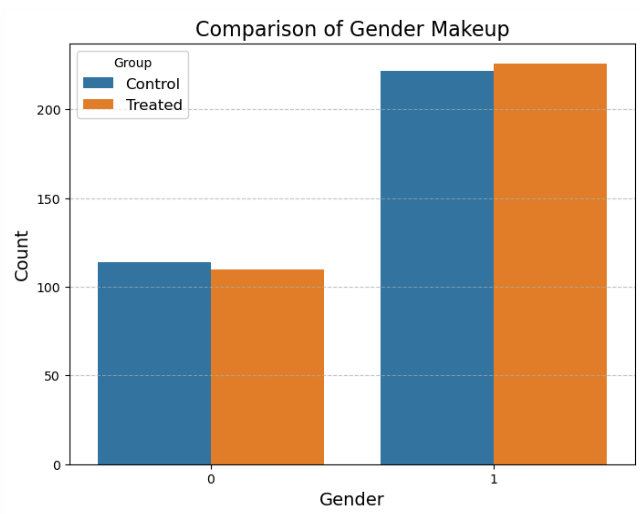


Figure 24. Comparison of Race by Group (0 = White, 1 = Black, 2 = other)

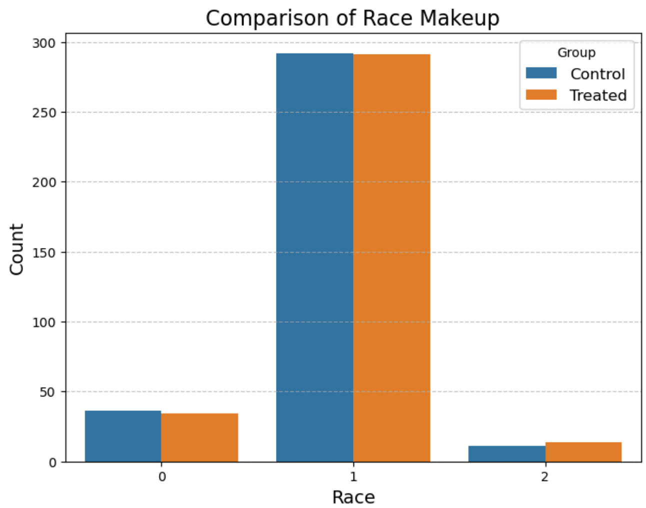


Figure 25. Age Distribution by Prior Arrest

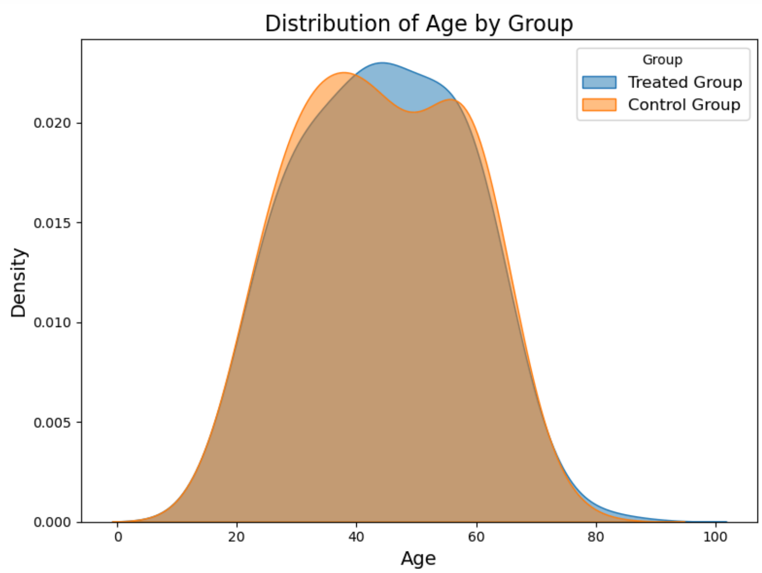
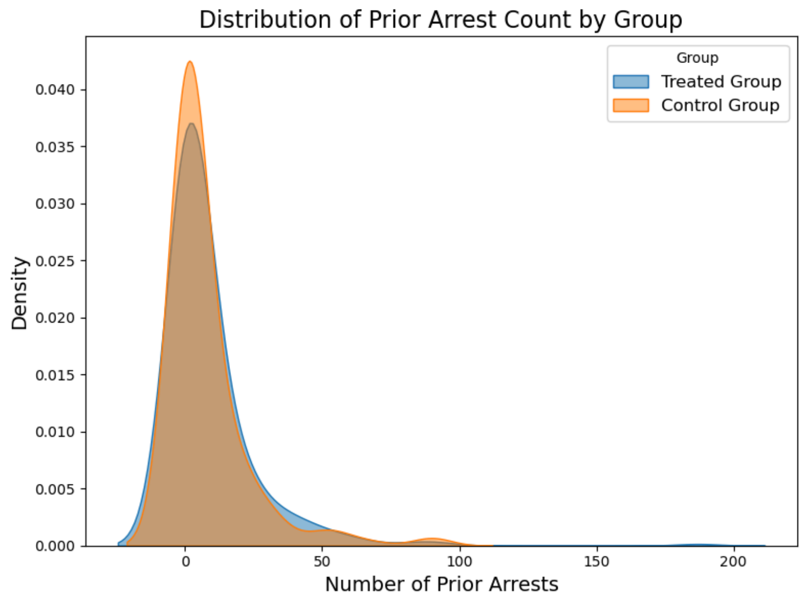


Figure 26. Distribution of Prior Arrest Counts



Additionally, I conducted a t-test for the continuous covariates, along with a chi-square test of significance, for the categorical covariates. The results suggest there were no significant differences in the makeup of any covariates at the p = .05% significance level. Table 2 presents the results.

Table 2. T-test for Continuous Covariates

T-Test Results for Continuous Covariates:

	Covariate	Treated Mean	Control Mean	T-Statistic	P-Value
0	Age	44.267857	44.002976	0.255988	0.798039
1	Num_of_arrests	8.619048	7.690476	0.740629	0.459183

Table 3. Chi-square Test for Categorical Covariates

Chi-Square Test Results for Categorical Covariates:

	Covariate	Chi2 Statistic	P-Value	Degrees of Freedom
0	Gender	0.060268	0.806073	1
1	Race	0.352997	0.838200	2

Data Limitations

The primary limitation to this data is the possibility of unobservable covariates biasing the treatment effect. Although I matched on the covariates of race, gender, age, and arrest history, there are several covariates that I could not account for. Those include individuals' housing situation, mental health history, family history, physical health conditions, education, income, and other physical and mental health characteristics that might affect one's likelihood of being arrested in the future. According to a metaanalysis done on studies that investigate risk factors for recidivism, educational problems (i.e. not having a high school diploma), substance abuse, low income, and unemployment are all significant risk factors for recidivism (Yukheneko et al. 2019). Indeed, any systematic differences in these covariates between the two groups would bias the estimated effect of PAD on future arrest rates.

Another significant unobservable factor is the environment or situational circumstance of the arrest or diversion. A key assumption of this study is that individuals who got arrested for divertible crimes were just as eligible for diversion as someone who was diverted. Although it may be true that individuals in the control group were all arrested for a divertible crime(s), we have no information on the circumstance around which they were arrested. There may have been systematic differences in the behaviors of individuals between the two groups that cannot be accounted for by just the charges. For example, individuals in the control group may have been more hostile, unstable, and "unsuited" for diversion in the eyes of the responding officers, whereas those who were diverted were more calm, compliant, and generally more responsive to de-escalation. These differences are important because they could suggest something about the likelihood of an individual being arrested again in the future or engaging in the same low-level crimes.

Finally, there was an element of artificial selection that occurred in compiling the control group. To obtain the control group, I manually picked individuals on the daily arrest reports who were charged for crimes considered divertible. Due to the very nature of the control group being a hand-selected sample, there may have been potential human biases or errors that impacted the selection. In the future, a more sophisticated method of comparing a treatment and control group is .

Results

I conducted several different analyses on the data. I ran linear and logistic regression analyses to estimate the treatment effect of PAD both *before and after* matching subjects on propensity scores. I also estimated the treatment effect across the subgroups race, gender, and age.

Results of Pre-Matching Analysis

The outcome of interest of this study is whether an individual is arrested in the six months and twelve months after the diversion/arrest date. If an individual in the treatment or control group had an arrest history within six months after the arrest or diversion, the outcome was coded as "1" in both the six months and one year-post column. If they had an arrest in the period between six months and one year after, the outcome was coded as "0" in the six months-post column and "1" in the one year-post column. If they had no arrest history following the evaluation date or had an arrest after one year, the outcome was coded as "0" in both columns. See Appendix A for a sample of all outcomes.

Before evaluating the effect of the PAD treatment on matched pairs, I ran simple and multilinear regressions on the entire sample of treatment and control subjects (n=1248). Table 4 and Table 5 present the results of the simple linear regression models. The models estimated the treatment effect of PAD, without controlling for any covariates and without matching for the periods of six months and one year post-evaluation. Table 6 and Table 7 present the results of multilinear regression models that control for covariates race, gender, age, and arrest history.

Table 4. Linear Regression Results, Pre-Matching (six months-post)

```
Linear Regression Model for Arrested_Six_Months_Post (Unadjusted, Before Matching):

                            OLS Regression Results
==============================================================================
Dep. Variable:     Arrested_Six_Months_Post   R-squared:                 0.037
Model:                                  OLS   Adj. R-squared:            0.036
Method:                       Least Squares   F-statistic:               48.08
Date:                      Mon, 07 Apr 2025   Prob (F-statistic):     6.54e-12
Time:                              23:10:26   Log-Likelihood:          -579.08
No. Observations:                      1247   AIC:                       1162.
Df Residuals:                          1245   BIC:                       1172.
Df Model:                                 1
Covariance Type:                  nonrobust
================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const             0.2360      0.013     18.488      0.000       0.211       0.261
PAD_Treatment    -0.1705      0.025     -6.934      0.000      -0.219      -0.122
==============================================================================
```

Table 5. Linear Regression Results, Pre-Matching (twelve months-post)

```
Linear Regression Model for Arrested_Twelve_Months_Post (Unadjusted, Before Matching):

                            OLS Regression Results
=================================================================================
Dep. Variable:     Arrested_Twelve_Months_Post   R-squared:                 0.069
Model:                                     OLS   Adj. R-squared:            0.068
Method:                          Least Squares   F-statistic:               91.84
Date:                         Mon, 07 Apr 2025   Prob (F-statistic):     4.89e-21
Time:                                 23:10:26   Log-Likelihood:          -731.74
No. Observations:                         1247   AIC:                       1467.
Df Residuals:                             1245   BIC:                       1478.
Df Model:                                    1
Covariance Type:                     nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
const             0.3557      0.014     24.651      0.000       0.327       0.384
PAD_Treatment    -0.2664      0.028     -9.583      0.000      -0.321      -0.212
==============================================================================
```

Table 6. Multilinear Regression Results, Pre-Matching (six months-post)

```
Multiple Linear Regression Model for Arrested_Six_Months_Post (Controlling for Covariates):

                            OLS Regression Results
==================================================================================
Dep. Variable:     Arrested_Six_Months_Post   R-squared:                       0.092
Model:                                  OLS   Adj. R-squared:                  0.089
Method:                       Least Squares   F-statistic:                     25.27
Date:                      Mon, 07 Apr 2025   Prob (F-statistic):           2.51e-24
Time:                              23:10:46   Log-Likelihood:              -542.26
No. Observations:                      1247   AIC:                             1097.
Df Residuals:                          1241   BIC:                             1127.
Df Model:                                 5
Covariance Type:                  nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const            0.1797      0.045      4.015      0.000       0.092       0.267
PAD_Treatment   -0.1783      0.025     -7.083      0.000      -0.228      -0.129
Age             -0.0013      0.001     -1.480      0.139      -0.003       0.000
Gender           0.0795      0.025      3.210      0.001       0.031       0.128
Race             0.0120      0.027      0.437      0.662      -0.042       0.066
Arrests          0.0065      0.001      7.270      0.000       0.005       0.008
==============================================================================
```

Table 7. Multilinear regression model pre-matching (twelve months-post)

```
Multiple Linear Regression Model for Arrested_Twelve_Months_Post (Controlling for Covariates):

                            OLS Regression Results
====================================================================================
Dep. Variable:     Arrested_Twelve_Months_Post   R-squared:                       0.142
Model:                                     OLS   Adj. R-squared:                  0.139
Method:                          Least Squares   F-statistic:                     41.11
Date:                         Mon, 07 Apr 2025   Prob (F-statistic):           3.15e-39
Time:                                 23:10:46   Log-Likelihood:              -680.55
No. Observations:                         1247   AIC:                             1373.
Df Residuals:                             1241   BIC:                             1404.
Df Model:                                    5
Covariance Type:                     nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const            0.2599      0.050      5.198      0.000       0.162       0.358
PAD_Treatment   -0.2705      0.028     -9.616      0.000      -0.326      -0.215
Age             -0.0019      0.001     -1.970      0.049      -0.004   -8.29e-06
Gender           0.1354      0.028      4.895      0.000       0.081       0.190
Race             0.0267      0.031      0.869      0.385      -0.034       0.087
Arrests          0.0079      0.001      7.911      0.000       0.006       0.010
==============================================================================
```

Lastly, I generated linear probability models using propensity scores as weights before actually matching on the propensity scores. Tables 8 and 9 display the results of the models.

Table 8: Linear probability model with propensity score weighting (six months-post)

```
Weighted Linear Probability Model for Arrested_Six_Months_Post (Using Propensity Score Weights):

                            WLS Regression Results
==============================================================================
Dep. Variable:     Arrested_Six_Months_Post   R-squared:                       0.064
Model:                                  WLS   Adj. R-squared:                  0.064
Method:                       Least Squares   F-statistic:                     85.61
Date:                      Mon, 07 Apr 2025   Prob (F-statistic):           9.26e-20
Time:                              23:11:02   Log-Likelihood:                -537.12
No. Observations:                      1247   AIC:                             1078.
Df Residuals:                          1245   BIC:                             1088.
Df Model:                                 1
Covariance Type:                  nonrobust
================================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const          0.2381      0.014     17.330      0.000       0.211       0.265
PAD_Treatment -0.1804      0.019     -9.252      0.000      -0.219      -0.142
==============================================================================
```

Table 9: Linear probability model with propensity score weighting (twelve months-post)

```
Weighted Linear Probability Model for Arrested_Twelve_Months_Post (Using Propensity Score Weights):

                            WLS Regression Results
==============================================================================
Dep. Variable:     Arrested_Twelve_Months_Post   R-squared:                    0.102
Model:                                     WLS   Adj. R-squared:               0.101
Method:                          Least Squares   F-statistic:                  141.5
Date:                         Mon, 07 Apr 2025   Prob (F-statistic):        5.47e-31
Time:                                 23:11:02   Log-Likelihood:             -709.08
No. Observations:                         1247   AIC:                          1422.
Df Residuals:                             1245   BIC:                          1432.
Df Model:                                    1
Covariance Type:                     nonrobust
================================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const          0.3559      0.016     22.564      0.000       0.325       0.387
PAD_Treatment -0.2663      0.022    -11.897      0.000      -0.310      -0.222
==============================================================================
```

Results of Post-Matching Analysis

I first ran a multilinear regression model on the matched pairs data holding the covariates constant. Below are the multilinear equation, the results of the regression from six months and one year-post evaluation, and the respective bar graphs illustrating the results. I also conducted logistic regressions and calculated the logistic marginal effects for the treatment, which can be found in Appendix.

Figure 27. Multilinear Regression Model.

$$Y = \beta_o + \beta_1 PAD + \beta_2 Age + \beta_3 Gender + \beta_4 Arrests + \upsilon$$

Table 4: Multilinear Regression Results (six months-post).

```
Linear Probability Model for Arrested_Six_Months_Post:

                            OLS Regression Results
==================================================================================
Dep. Variable:     Arrested_Six_Months_Post   R-squared:                     0.114
Model:                                  OLS   Adj. R-squared:                0.107
Method:                       Least Squares   F-statistic:                   17.14
Date:                      Mon, 07 Apr 2025   Prob (F-statistic):         5.67e-16
Time:                              23:00:31   Log-Likelihood:              -195.25
No. Observations:                       672   AIC:                           402.5
Df Residuals:                           666   BIC:                           429.6
Df Model:                                 5
Covariance Type:                  nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const            0.1365      0.061      2.242      0.025       0.017       0.256
PAD_Treatment   -0.1483      0.025     -5.911      0.000      -0.198      -0.099
Age              0.0005      0.001      0.534      0.594      -0.001       0.002
Gender           0.0264      0.027      0.963      0.336      -0.027       0.080
Race            -0.0102      0.037     -0.274      0.784      -0.083       0.063
Arrests          0.0053      0.001      6.399      0.000       0.004       0.007
==============================================================================
```

Table 5: Multilinear Regression Results (twelve months-post).

```
Linear Probability Model for Arrested_Twelve_Months_Post:

                            OLS Regression Results
==============================================================================
Dep. Variable:     Arrested_Twelve_Months_Post   R-squared:                       0.169
Model:                                 OLS   Adj. R-squared:                  0.163
Method:                      Least Squares   F-statistic:                     27.05
Date:                     Mon, 07 Apr 2025   Prob (F-statistic):           5.90e-25
Time:                             23:00:31   Log-Likelihood:                -284.07
No. Observations:                      672   AIC:                             580.1
Df Residuals:                          666   BIC:                             607.2
Df Model:                                5
Covariance Type:                 nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const            0.2920      0.069      4.203      0.000       0.156       0.428
PAD_Treatment   -0.2418      0.029     -8.446      0.000      -0.298      -0.186
Age             -0.0018      0.001     -1.610      0.108      -0.004       0.000
Gender           0.1175      0.031      3.761      0.000       0.056       0.179
Race            -0.0128      0.042     -0.302      0.763      -0.096       0.070
Arrests          0.0061      0.001      6.503      0.000       0.004       0.008
==============================================================================
```

Figure 28. Average treatment effect six months-post

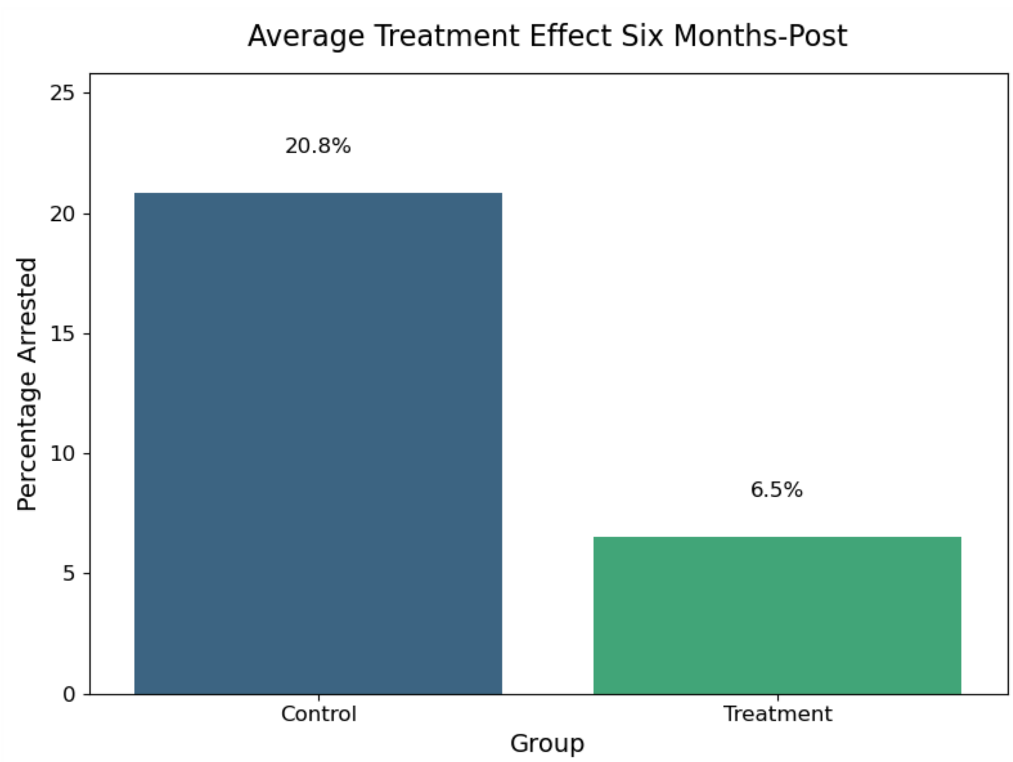
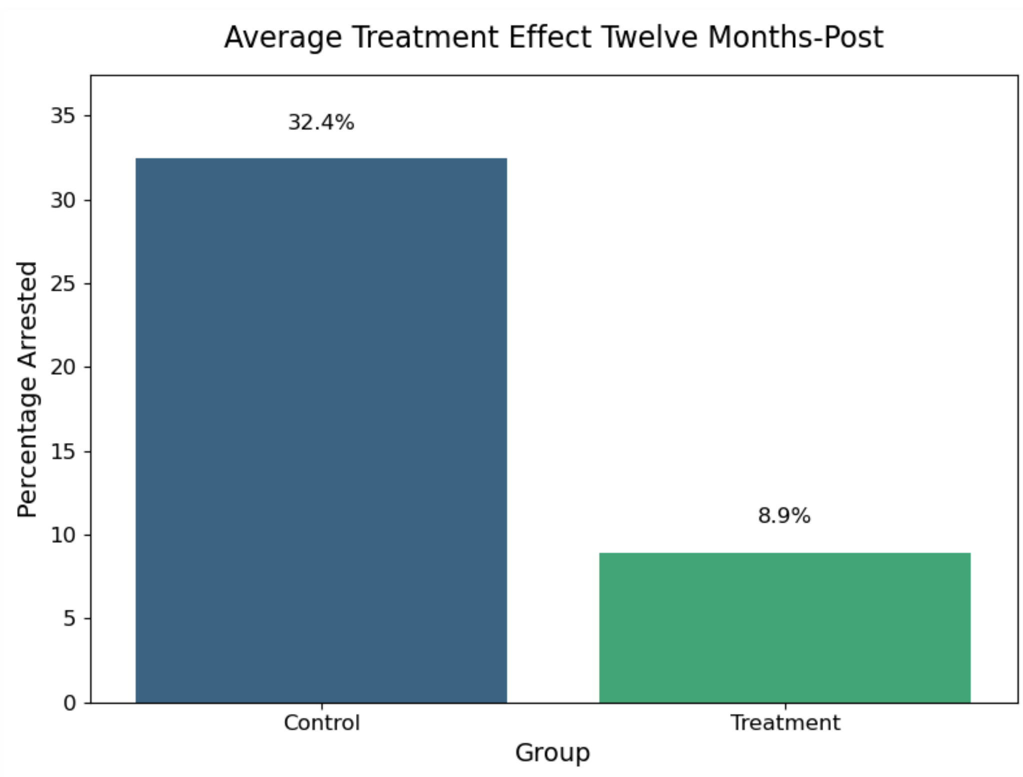


Figure 29. Average treatment effect one year-post



Additionally, I estimated a model of the treatment effect by subgroup, looking at how the treatment effect varies across gender, race, and age. See Figures 30-33 for results. The results of those linear regression models can be found in Appendix A. Plus, , I ran linear regression models that include an interaction term between race and treatment, as well as gender and treatment, which can also be found in the Appendices.

Figure 30. Average Treatment Effect by Gender and Race (six months-post).

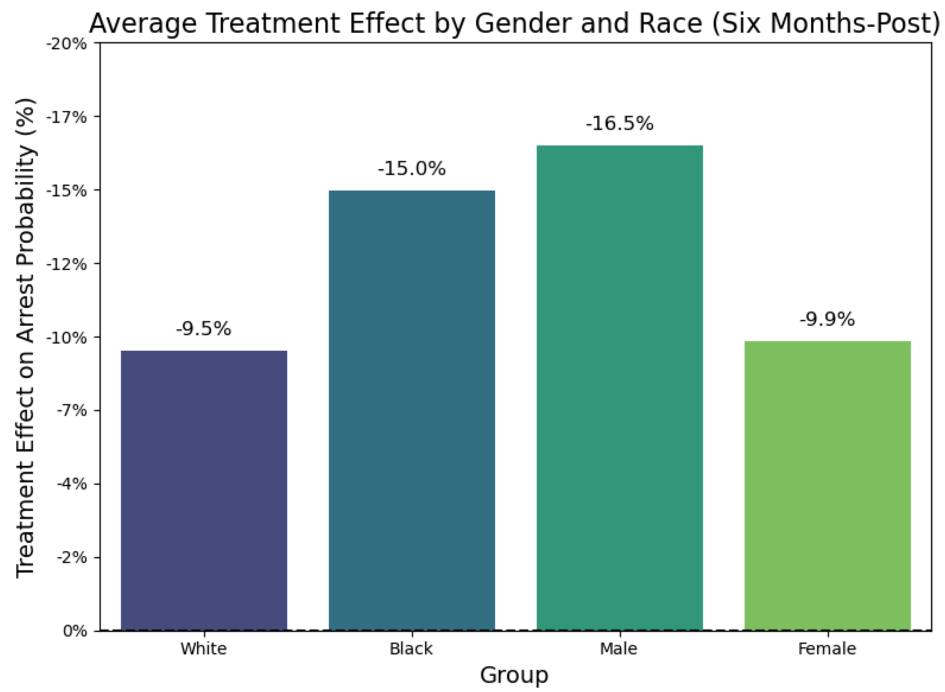


Figure 31. Average Treatment Effect by Gender and Race (twelve months-post).

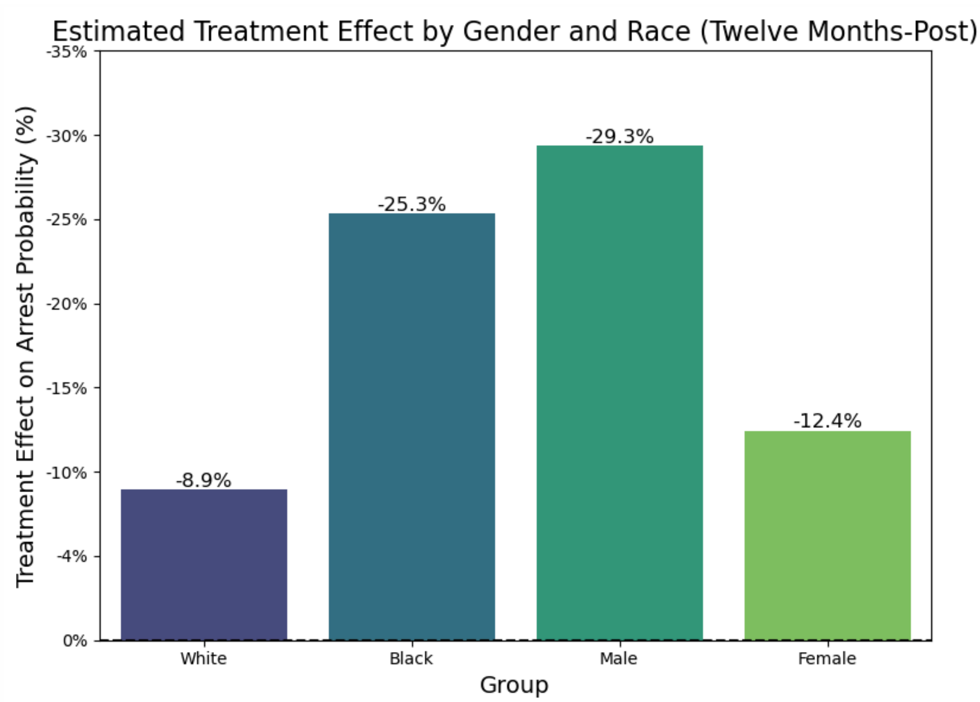


Figure 32. Average Treatment Effect by Age Group (six months-post)

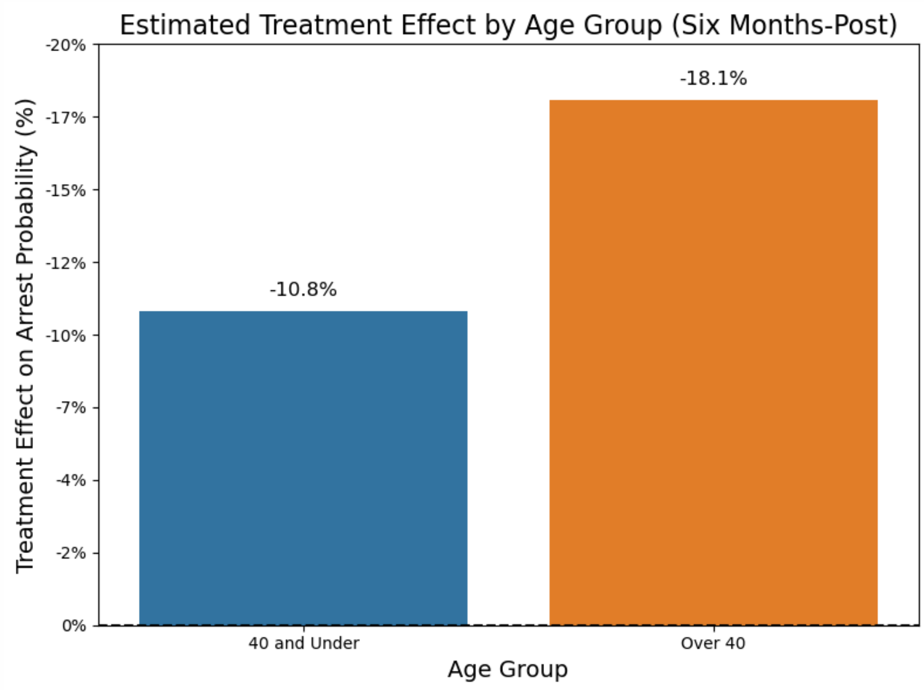
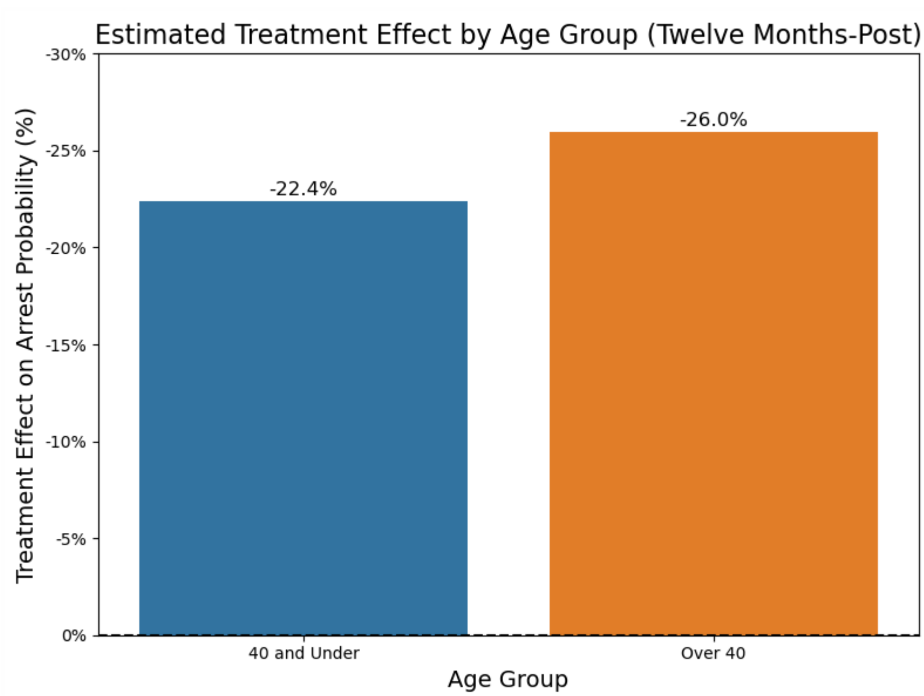


Figure 33. Average Treatment Effect by Age Group (twelve months-post).



Discussion of Empirical Results

The evidence from my empirical study of diversion through PAD suggests that at both the six months and twelve months after diversion through PAD, participants exhibited a significant reduction in arrests. All else equal, individuals who were diverted through PAD were approximately 15% less likely to be arrested in the next six months and about 24% less likely in the twelve months compared to the control group. This negative correlation is consistent with the findings from an evaluation of the Seattle LEAD program (Collins et al. 2017).

I found that the treatment effect of PAD was similar and significant both before and after creating matched groups based on propensity scores. In the six months after diversion, the treatment effect was -0.17 ($p<0.005$) before matching and -0.148 ($P<0.005$) after matching. This is important for at least two reasons. First, regressions control for covariates linearly while matching controls for covariates non-parametrically. Propensity score matching is more "conservative" because it ensures covariate balance in a way that does not rely on the functional form assumptions of a linear regression. It ensures that there is no difference between the covariate distributions between the treated and control groups. The fact that there was a statistically significant treatment effect before and after matching indicates that a more conservative approach still detected an effect, and the functional form assumptions of the linear regression were not a major deal in the first place.

Second, the consistency in results increases the generalizability of the findings. The pooled sample before matching contained a broader group of individuals that may be more representative of the population, while the matched group focused on a specific subset of individuals. Given that the treatment effect was similar and significant in both cases, it suggests that PAD's treatment effect could be extended to a broader population outside of just the individuals studied.

The propensity score analysis added robustness to my study. However, the propensity score analysis has its limits. In particular, it l cannot account for unobservable characteristics among the subjects in the study. As discussed earlier, I could only match individuals on observable attributes and covariates. Specifically, I could only match them by race, gender, age, and arrest history. That is important to keep in mind and it tempers my findings. This is especially the case because one the largest set of potential confounders stem from the circumstances that led to the call for and arrival of police officers. Many factors produce the moments when an individual encounters a police officer and influence the discretion of police officers to choose diversion or arrest. There might have been systematic differences in the behaviors, actions, and responses of those subjects the police diverted compared to those subjects the police arrested. While we know that individuals in the control group and treatment group were exclusively engaged in "divertible" crimes or behaviors at the times police officers encountered them, we cannot be certain that the contexts, including the choices of those engaged in divertible actions and the environments where those choices occurred, as well as the perceptions and behaviors of police officers on the scene, were similar. Yet, it is unlikely that such unobservable conditions are the primary reason individuals were arrested rather than diverted.

Based on the 2023 Atlanta arrest reports covering 147 days, police made 9,779 arrests that could have been diverted. But in a span of four years, from 2021-2024, there were only 1,196 diversions associated with PAD. That big gap between potential diversions versus actual diversions might suggest that police officers simply chose not to divert individuals suitable by policy for diversion (or the police officers somehow were unaware of the option to divert). In line with that possibility, I attempted to empirically understand the perspectives and choices of police officers when it came to diversion. I especially wanted to understand their awareness and comprehension of "divertible" behaviors, as well as to understand the logic they use to decide between arrest and diversion. To be clear, my hope was to interview Atlanta police officers and their supervisors, including the Chief of Police, to grasp their opinions about diversion generally and PAD specifically. But lack of access to and unresponsiveness from members of the Atlanta Police Department prohibited me from studying and incorporating the perspectives of the police. Future studies addressing diversion, specifically those studying PAD, should prioritize efforts to identify and understand police perspectives about diversion.

Nonetheless, my empirical results suggest that diverting an individual through PAD and enrolling them in supportive services produces an intervention that slows the "revolving door" of jailing for oder-maintenance related offenses. This is likely attributable to the combination of diversion with ongoing case management by PAD staff and the provision of social support by organizations that partner with PAD. People who engage in low-level, divertible crimes typically have underlying mental and physical health issues, as well as quality-of-life problems stemming from extreme poverty or homelessness (Jones and Sawyer 2019). By receiving, in addition to diversion, resources like food, housing, and job security that help alleviate those underlying concerns, individuals would be less likely to engage in behavioral "disturbances" and resort to low-level crimes to stay afloat.

Additionally, I found significant treatment effects of diversion via PAD for subgroups by race, age, and gender. Diversion compared to arrest led to a bigger decrease in re-arrests of Black individuals than White individuals. The treatment also had a larger effect on males than females. This difference in outcomes by race and gender makes sense in the context of the systemic inequalities prevalent in the United States. Scholars have long investigated the lasting impact of centuries of racist policies like slavery, segregation, and incarceration; over time, these discriminatory practices have led to racial disparities in intergenerational mobility, education, access to healthcare, and trauma, all factors that contribute to future incarceration rates (Alexander 2010, Western and Pettit 2010, Wacquant 2001, The National Research Council 2014, Skiba et al. 2011, Crenshaw et al. 2015).

Because these structural disadvantages tend to target Black Americans, we would expect that interventions that directly address those inequalities such as diversion from arrest have a greater impact on Black Americans than White Americans. Indeed, existing literature supports this theory. Early childhood education programs, earned income tax credit expansions, minimum wage increases, Medicaid expansion, and improved housing opportunities were all shown to positively impact Black Americans more than White Americans (Currie and Thomas 1995, Deming 2009, Hoynes and Patel 2018, Sommers et al. 2017, Chetty et al. 2016, Rothstein 2017). A diversion program like PAD, which not only interrupts the cycle of incarceration for participants but provides continual care for underlying concerns, would likewise target the consequences of discriminatory practices that disproportionately affect Black men.

Across all subgroups, the treatment had a bigger effect in the twelve months after diversion compared to the six months after diversion. This result can be explained by the fact that programs targeting structural inequalities often have positive impacts that actualize or cascade in the long run. Deming (2009) demonstrated that the early childhood education program Head Start led to test score improvements that faded after a few years but significant gains in employment levels later on in life. Chetty et al. (2016) found that children who moved to a more affluent area before age 13 were more likely to attend college and experience higher earnings as adults. Even improved healthcare opportunities are shown to increase long-term survival rates and economic stability (Sommers et al. 2017, Currie and Almond 2011).

For PAD, one explanation for the increased benefits in the longer run is that breaking the cycle of incarceration, including jailing (both pre-trial and post-conviction) takes time and sustained effort (Blumstein and Nakamura 2009, Langan and Levin 2002). Diverting an individual once does not guarantee that they will show sudden, immense improvement in their ability to desist from order-maintenance disturbances or criminal behavior. It is possible, even likely, that they recidivate and be re-arrested for the same or similar low-level crimes as before. But with continual care, empathy, and resources, that individual gets closer to finding stability and integrating into the general population.

Taking a step back from the findings, while keeping them in mind, PAD could benefit far more people than it currently does. However, it faces several limitations that prevent its services from reaching more people. First, there are the constrained resources of PAD, which limit its daily operations. Currently, PAD's diversion services only operate from 7AM to 7PM. Twelve hours of operation might seem like a significant amount of time for doing diversion. But many low-level disturbances and crimes occur late at night and early in the morning. For example, a homeless individual might have the police called on them at 2AM because they are sleeping on private property, leading to a Criminal Trespass charge. The fact that PAD's services do not extend to these hours of the day significantly reduces the number of diversions they can engage in. Second, the Atlanta Police Department could do more to support diversion. Its police officers do not divertas many individuals as they could to PAD. Again, whether the under-utilization of diversion in favor of arrest by police is due to a lack of information or program buy-in by the police are unclear, due to the challenges of ascertaining the perspectives of the Atlanta Police

Department about diversion and PAD.

One major way PAD could overcome these obstacles to expanding diversion is through more funding, both municipal and non-municipal. With more revenue PAD could hire more staff to extend its daily hours of operations. Additionally, PAD staff and "champions" (allies) could increase their community presence by more regularly attending APD Zone meetings, other policing events, and more community gathering. By doing so, PAD could increase awareness of diversion among and buy-in from police officers as well as educate more officers on how to divert to PAD. Plus, it would help PAD make the broader community aware of and hopefully supportive of diversion, especially through PAD.

Funding is a critical part of public policy. The decision on where to distribute benefits and burdens lies at the core of policymaking. This thesis has the potential to guide elected officials in the city of Atlanta in their decisions to continue supporting PAD. This is especially relevant given that a large reason the Mayor's Office delayed the financial award to PAD in late 2024 was uncertainty around the efficacy around PAD. With novel empirical insight showing positive effects of PAD, policymakers will be able to make more grounded, well-informed resolutions on how to fund PAD moving forward. This thesis also has implications for policing alternative programs in other municipalities across the U.S. Since 2020, policing alternative models have begun to scale across the country amidst calls for police reform and abolition. For example, in April 2024, Kansas City Kansas City allocated $1.26 million into their "REACH" program, following PAD's model (The Kansas City Defender, 2024). But this scaling, as well as others, has occurred largely without the empirical data offering evidence of its effectiveness. This thesis adds onto the dearth of program evaluations done on policing alternative programs, showing results that support their efficacy.

Conclusion

The purpose of this thesis was to understand the politics of diversion, focusing on how municipalities can move away from relying on police as the primary (and sometimes only) tool for addressing public disorder and maintaining order. I did that through a case study on Atlanta's PAD, from analyzing the social, legislative, and political history of its origins, to conducting an original quantitative study to gauge its efficacy.

PAD began as a grassroots organization seeking to push back against Atlanta's prostitution banishment in early 2013. It relied on the advocacy of community leaders in marginalized groups to fight the punitive ordinance. After defeating the banishment, the leaders formed the "Solutions Not Punishments" Coalition (SNaPCO), introducing diversion to city officials as the solution to reducing the number of low-level offenses in the city. The coalition worked with the city council and Mayor Reed's office to develop a program mirroring Seattle's LEAD program. After two years of educating elected officials and the public on the potential for diversion (including bringing city leaders to Seattle to witness LEAD's operations, advocating in public hearing at the city council, and sharing testimonies of previously incarcerated individuals), SNaPCO gained the support of the city in 2015 to design the city's first ever diversion program.

By exploring PAD's mission, conception, funding, public support, and impact, my thesis contributes to the literature on the politics of public policy. Specifically, my thesis broadens our understanding of "noncongruent policy making," whereby subgroups or target populations that traditionally have little political power and negative social constructions ("deviants") receive benefits (or less burdens) by elected officials. In this instance, the lessening of burdens for those encountered by the police for "disturbing the peace" happens through diversions. As I reveal from Atlanta, such noncongruent policymaking can happen due to a combination of several factors, including a high level of descriptive representation in the city, alternatives ways of framing the issues of “disorder,” preexistence of a policy solution to “disorder,” and an increasing public demand for alternatives to arrest and jailing. In Atlanta, noncongruent policy making was also made possible by community activism and mobilization to change the social construction of the “disorderly” as a target population from “deviants” to “dependents,” maybe even to “contenders,” over time.

Amidst changes in the three streams of problems, policies, and politics in Atlanta, community leaders in SNaPCO and other coalitions advocated relentlessly and educated elected officials on the importance of diversion. Not only did these political coalitions increase the political capital of the homeless, sex workers, and drug users, they led elected officials to view them under a more positive social construction. This led to the municipal abandonment of relying solely on punitive approaches like banishment and arrest for dealing with “disorder.”

Furthermore, my thesis invites more political scientists to return to the study of police/policing. As police have physically harmed, even killed, countless people experiencing mental health crises or substance abuse problems (and placed millions more in jail), the American public has increasingly placed its attention on reforming the police over the last decade, with some calling for the defunding or complete abolition of police. At the core of this topic is whether or not police ensure “public safety” the way we expect them to. This is relevant to Political Science because the police are the “street-level” bureaucrats authorized to detain, arrest, and use violence on behalf of the government who we entrust to keep denizens safe in routine parts of everyday life. Although that means protecting people from civilian gunfire or preventing the theft of local businesses, that also involves responding effectively to non-criminal related calls and not increasing the trauma or harm when arriving at the scene. Yet, one-fourth of all fatal police encounters involve people experiencing a mental health crisis, and nearly 40 percent of people in jail in 2024 were arrested for crimes related to drug use or pubic disorder (Prison Policy Initiative 2024).

The fact that physical coercion and violence are key functions of police make police work inherently punitive, which only exacerbates the underlying issues of poverty, substance abuse, and homelessness. This thesis asks political scientists to revisit the core function of police and question if their primary function of "order maintenance policing" actually delivers the promise of "public safety." In order to achieve a more just system that reduces the number of needless arrests and killings, we must invest in a first-responder model rooted in interventions that disrupt the cycle of crime and get people back on their feet. In the "continuum of public safety," we need to go towards the opposite direction of police–towards non-police community response services that are never punitive. Atlanta's PAD offers a footprint for other municipalities to follow.

Appendix A. Municipal Diversion Programs in the U.S.A. (Source: Frazier 2023)

Cities with Law Enforcement Assisted Diversions

Alaska	**Georgia**	**Kentucky**	**North**	**New York**	**Tennessee**
Anchorage	Atlanta	Louisville	Carolina	Buffalo	Chattanooga
	Savannah		Durham	New York	Memphis
			Raleigh	Syracuse	Murfreesboro

Alabama	**Iowa**	**Louisiana**	**North** Dakota	**Ohio**	**Utah**
Huntsville	Cedar Rapids	Baton Rouge	Fargo	Cleveland	Salt Lake City
		New Orleans		Columbus	West Valley
		Shreveport		Dayton	City

Arizona	**Idaho**	**Massachusetts**	**Nebraska**	**Oklahoma**	**Virginia**
Chandler	Boise	Cambridge	Omaha	Norman	Alexandria
Gilbert		Lowell		Oklahoma City	Chesapeake
Phoenix		New Bedford			Hampton
Scottsdale					Norfolk

California	**Illinois**	**Michian**	**New**	**Oregon**	**Wisconsin**
Corona	Aurora	Lansing	**Hampshire**	Portland	Milwaukee
Oxnard	Rockford		Manchester		
San	Springfield				
Francisco					
San Jose					
Ventura					

Colorado	**Indiana**	**Minnesota**	**New Mexico**	**Pennsylvania**	**Texas**
Aurora	Evansville	Rochester	Albuquerque	Philadelphia	Allen
Pueblo	Fort Wayne	St. Paul	Las Cruces		Amarillo
	Indianapolis		Rio Rancho		Corpus Christi
					Dallas

Florida	**Kansas**	**Missouri**	**Nevada**	**Rhode Island**	**El Paso**
Coral	Overland PArk	Independence	Sparks	Providence	Fort Worth
Springs	Topeka	Kansas City			Frisco
Davie		Lee’s Summit			Lewisville
Fort		St. Louis			Lubbock
Lauderdale		**Montana**			**Plano**
Gainesville		Billings			Richardson
Miami					San Antonio
Orlando					

Cities with Co-Responder Models

Alabama	**California**	**Kansas**	**North**	**Oregon**	**Texas**
Mobile	Burbank	Olathe	**Carolina**	Gresham	Amarillo
	Carlsbad	Overland Park	Greensboro	Portland	Austin
	Chila Vista				Grand Prairie
	Concord				Houston
	Daly				Irving

	Downey				Laredo
	El Cajon				
	Elk Grove				
	Escondido				
	Fontana				
Arizona	Fremont	**Massachusetts**	**Nebraska**	**Pennsylvania**	**Virgina**
Chandler	Fresno	Boston	Omaha	Pittsburgh	Virginia Beach
	Glendale	Lowell			
	Huntington Beach	New Bedford			
	Los Angeles				
	Moreno Valley				
	Murrieta				
	Riverside				
	Roseville				
	San Diego				
	Torrance				
Colorado	**Idaho**	**Maryland**	**New Hampshire**	**South Carolina**	**Washington**
Arvada	Meridian	Baltimore	Manchester	Columbia	Bellevue
Aurora					Seattle
Boulder					Spokane
Centennial					Vancouver
Colorado Spring					

Fort Collins

Greeley

Longmont

Westminster

Florida	**Illinois**	**Michigan**	**New York**	**Tennessee**	**Wisconsin**
Gainesville	Naperville	Grand Rapids	Rochester	Knoxville	Green Bay
		Lansing		Nashville	Madison

Cities with Community Responder Models

Alabama	**California**	**Florida**	**Maryland**	**New York**	**Virgina**
Birmingham	Anaheim	Orlando	Baltimore	Rochester	Newport News
	Antioch				
	Berkeley				
	Fairfield				
	Garden Grove				
	Irvine				
	Oakland				

Arizona	**Colorado**	**Massachusetts**	**Minnesota**	**Oregon**
Mesa	Denver	Boston	Minneapolis	Eugene
Phoenix		Lynn		
Scottsdale				
Tucson				

Appendix B. Institutional Review Board

The Institutional Review Board (IRB) of Emory University determined on October 16, 2024 that this research fell outside the category of "Human Subject Research." It was determined to be "Program Evaluation." As a result, IRB review was not required.

Appendix C. Qualitative data

As a part of this thesis, I conducted interviews with several PAD staff to better understand the organization's history, values, operations, successes, and limitations. I interviewed Stacy Piper (Operations Coordinator) on 11/5/24, Erice Monteiro (Legal Navigation Manager) on 11/11/24, Tamia Dame (Director of Communications) on 11/14/24, and Moki Macías (Executive Director) on 11/14/24. I also interviewed Atlanta City Councilman Alex Wan on 12/2/24.

Having worked as PAD's legal Navigation Intern since July 2023, I have engaged in participant observation. I have been on several "ride-alongs" with PAD's Community Responders in Atlanta. I observed how they interact with individuals when responding to calls for service, and I witnessed the process of intaking new participants on the streets. I also assisted with post-booking diversions on two separate occasions: 7/3/24 and 8/8/24. Both times, I went to Fulton County Jail with a Care Navigator and met with a potential PAD participant. I observed the screening process to determine participant eligibility, which involved casual but structured questions about that individual's health, housing, and other personal circumstances. Furthermore, I sat in on several court hearings of PAD participants. From June 1, 2024 to August 23, 2024, I observed the First Appearance Hearings of five different PAD participants. In two of the hearings, the Care Navigator I was with was called by the judge to speak on the participant's progress with PAD. After the Care Navigator testified to the participant's involvement with PAD, the judge dismissed the case and let them go.

I also conducted archival research for this thesis. I searched the AJC archives to find statements by former Mayor Reed, the MPSA, and other actors involved in the prostitution banishment proposed in 2013. I relied on a 2013 blog post from Patch to find statements from SNaPCO leaders when they pushed back against the ordinance and first introduced the concept of diversion. I also requested PAD for any documents from 2013-2017 that would be helpful in understanding PAD's origins and advocacy work during its conception. I received the written testimonials of participants used to inform stakeholders on PAD's impact, slideshows used in APD training sessions from 2017 that include details on PAD's pilot program, and the certificates of appreciation given to each member of the original design team. Taken together, these documents helped me tell the story of PAD's conception over the last decade.

Appendix D. Variables Used in Regression Models

- Gender: 1 = Male, 0 = Female
- Race: 1 = African American, 0 = White
- PAD Treatment: 1 = Received PAD diversion, 0 = Did not receive PAD diversion
- Arrested Before: 1 = Yes, 0 = No
- Six Months Post: 1 = Arrested six months after diversion/arrest, 0 = Not arrested
- One Year Post: 1 = Arrested six months after diversion/arrest, 0 = Not arrested

Appendix E. Sample of the Treatment Group

Individual	Diversion Date	Date of Birth	Age	Gender	Race	PAD Treatment	Arrested Before	Prior Arrests	Six Months Post	One Year Post	Propensity Scores
2IAJ	1/2/18	3/2/66	51	1	1	1	1	22	1	1	0.38058381
116N	2/24/18	7/17/69	53	0	1	1	1	2	0	0	0.5258142
BTOL	4/1/18	6/30/62	60	1	1	1	1	2	0	0	0.44178741
GFA1	4/18/18	1/8/72	50	0	1	1	1	6	0	0	0.49978904
YGYM	1/8/19	12/20/78	43	0	1	1	0	0	0	0	0.41148168
FVD5	2/8/19	7/9/86	36	0	1	1	0	0	0	0	0.33843414
ZX4B	2/18/19	3/18/63	59	1	1	1	1	5	0	0	0.4362825
51Q9	6/21/19	9/13/87	35	0	1	1	0	0	0	0	0.32851398
EJE7	7/9/19	3/11/55	68	1	1	1	1	16	0	0	0.55654213

Appendix F. Sample of the Control Group

Individual	Diversion Date	Date of Birth	Age	Gender	Race	PAD Treatment	Arrested Before	Prior Arrests	Six Months Post	One Year Post	Propensity Scores
H450	5/15/23	8/28/66	56	1	1	0	1	4	0	0	0.40189107
UV45	5/15/23	1/11/83	40	1	1	0	0	0	0	0	0.24205586
NRUE	5/15/23	9/8/82	40	0	1	0	1	3	1	1	0.38474329
3WIL	5/16/23	6/16/65	57	1	0	0	0	0	0	0	0.23285015
AWNT	5/16/23	5/10/89	34	0	1	0	0	0	0	0	0.3187445
2BIC	5/16/23	7/20/56	66	1	1	0	0	0	1	1	0.50475915
LHBE	5/16/23	11/22/85	37	0	1	0	0	0	0	0	0.34849839
E0C5	5/16/23	9/12/91	31	1	1	0	0	0	0	0	0.17607852
J2NG	5/16/23	6/20/62	60	1	1	0	0	0	0	0	0.43812737
6ICP	5/17/23	6/2/69	53	1	1	0	0	0	0	0	0.36326939

Appendix G. Sample of Matched Pairs from the Treatment and Control Groups

Treated Individual	Propensity Score	Control Individual	Propensity Score
2IAJ	0.3805838	DH4K	0.3809465
116N	0.5258142	FTYP	0.5236589
BTOL	0.4417874	5JE1	0.4423795
GFA1	0.499789	SBZN	0.5010104
YGYM	0.4114817	JBHL	0.4114817
FVD5	0.3384341	OLFO	0.3384341
ZX4B	0.4362825	VMU9	0.4344567
51Q9	0.328514	JCAG	0.328514
EJE7	0.5565421	0QPM	0.5565073

Appendix H1. Supplemental Logistic Regression Analyses

```
Logistic Regression for Arrested_Six_Months_Post:

                           Logit Regression Results
==================================================================================
Dep. Variable:     Arrested_Six_Months_Post   No. Observations:              672
Model:                                Logit   Df Residuals:                  666
Method:                                 MLE   Df Model:                        5
Date:                      Mon, 07 Apr 2025   Pseudo R-squ.:              0.1293
Time:                              23:02:00   Log-Likelihood:            -233.63
converged:                             True   LL-Null:                   -268.33
Covariance Type:                  nonrobust   LLR p-value:             1.357e-13
================================================================================
                    coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const            -2.1545      0.630     -3.419      0.001      -3.390      -0.919
PAD_Treatment    -1.4849      0.275     -5.408      0.000      -2.023      -0.947
Age               0.0068      0.010      0.696      0.486      -0.012       0.026
Gender            0.3517      0.281      1.253      0.210      -0.198       0.902
Race             -0.0529      0.391     -0.135      0.892      -0.818       0.713
Arrests           0.0334      0.007      4.808      0.000       0.020       0.047
================================================================================
```

Logistic Regression for Arrested_Twelve_Months_Post:

Logit Regression Results

Dep. Variable:	Arrested_Twelve_Months_Post	No. Observations:	672
Model:	Logit	Df Residuals:	666
Method:	MLE	Df Model:	5
Date:	Mon, 07 Apr 2025	Pseudo R-squ.:	0.1743
Time:	23:02:00	Log-Likelihood:	-282.86
converged:	True	LL-Null:	-342.55
Covariance Type:	nonrobust	LLR p-value:	4.235e-24

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.0909	0.540	-2.022	0.043	-2.148	-0.033
PAD_Treatment	-1.8326	0.245	-7.495	0.000	-2.312	-1.353
Age	-0.0142	0.009	-1.658	0.097	-0.031	0.003
Gender	0.9990	0.260	3.849	0.000	0.490	1.508
Race	-0.0353	0.344	-0.103	0.918	-0.709	0.638
Arrests	0.0383	0.007	5.239	0.000	0.024	0.053

Appendix H2. Logistic Marginal Effects

Marginal Effects for Arrested Six Months Post Outcome:

Logit Marginal Effects

Dep. Variable:	Arrested_Six_Months_Post
Method:	dydx
At:	overall

	dy/dx	std err	z	P>|z|	[0.025	0.975]
PAD_Treatment	-0.1539	0.028	-5.445	0.000	-0.209	-0.098
Age	0.0007	0.001	0.696	0.486	-0.001	0.003
Gender	0.0364	0.029	1.253	0.210	-0.021	0.093
Race	-0.0055	0.040	-0.135	0.892	-0.085	0.074
Arrests	0.0035	0.001	5.020	0.000	0.002	0.005

Marginal Effects for Arrested Twelve Months Post Outcome:

Logit Marginal Effects

Dep. Variable:	Arrested_Twelve_Months_Post
Method:	dydx
At:	overall

	dy/dx	std err	z	P>|z|	[0.025	0.975]
PAD_Treatment	-0.2460	0.029	-8.408	0.000	-0.303	-0.189
Age	-0.0019	0.001	-1.669	0.095	-0.004	0.000
Gender	0.1341	0.034	3.973	0.000	0.068	0.200
Race	-0.0047	0.046	-0.103	0.918	-0.095	0.086
Arrests	0.0051	0.001	5.629	0.000	0.003	0.007

Appendix I. Linear Regression Analyses by Subgroup

```
Linear Probability Model for Race: White Subset (Arrested_Six_Months_Post):

                                OLS Regression Results
==================================================================================
Dep. Variable:     Arrested_Six_Months_Post   R-squared:                     0.675
Model:                                  OLS   Adj. R-squared:                0.658
Method:                       Least Squares   F-statistic:                   40.18
Date:                      Mon, 07 Apr 2025   Prob (F-statistic):         3.52e-14
Time:                              23:08:19   Log-Likelihood:               27.537
No. Observations:                        62   AIC:                          -47.07
Df Residuals:                            58   BIC:                          -38.57
Df Model:                                 3
Covariance Type:                  nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
Intercept        0.0265      0.065      0.405      0.687      -0.105       0.158
PAD_Treatment   -0.0951      0.042     -2.284      0.026      -0.178      -0.012
Age           3.169e-05      0.001      0.026      0.979      -0.002       0.002
Arrests          0.0821      0.008      9.931      0.000       0.066       0.099
==============================================================================

Linear Probability Model for Race: Black Subset (Arrested_Six_Months_Post):

                                OLS Regression Results
==================================================================================
Dep. Variable:     Arrested_Six_Months_Post   R-squared:                     0.105
Model:                                  OLS   Adj. R-squared:                0.101
Method:                       Least Squares   F-statistic:                   22.98
Date:                      Mon, 07 Apr 2025   Prob (F-statistic):         4.44e-14
Time:                              23:08:19   Log-Likelihood:              -192.57
No. Observations:                       591   AIC:                           393.1
Df Residuals:                           587   BIC:                           410.7
Df Model:                                 3
Covariance Type:                  nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
Intercept        0.1556      0.052      3.011      0.003       0.054       0.257
PAD_Treatment   -0.1497      0.028     -5.406      0.000      -0.204      -0.095
Age              0.0004      0.001      0.376      0.707      -0.002       0.003
Arrests          0.0052      0.001      5.986      0.000       0.003       0.007
==============================================================================
```

Linear Probability Model for Race: White Subset (Arrested_Twelve_Months_Post):

OLS Regression Results

Dep. Variable:	Arrested_Twelve_Months_Post	R-squared:	0.663
Model:	OLS	Adj. R-squared:	0.646
Method:	Least Squares	F-statistic:	38.05
Date:	Mon, 07 Apr 2025	Prob (F-statistic):	1.00e-13
Time:	23:08:51	Log-Likelihood:	17.084
No. Observations:	62	AIC:	-26.17
Df Residuals:	58	BIC:	-17.66
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0949	0.078	1.225	0.226	-0.060	0.250
PAD_Treatment	-0.0893	0.049	-1.811	0.075	-0.188	0.009
Age	-0.0012	0.001	-0.848	0.400	-0.004	0.002
Arrests	0.0976	0.010	9.975	0.000	0.078	0.117

Linear Probability Model for Race: Black Subset (Arrested_Twelve_Months_Post):

OLS Regression Results

Dep. Variable:	Arrested_Twelve_Months_Post	R-squared:	0.149
Model:	OLS	Adj. R-squared:	0.145
Method:	Least Squares	F-statistic:	34.28
Date:	Mon, 07 Apr 2025	Prob (F-statistic):	1.99e-20
Time:	23:08:51	Log-Likelihood:	-273.23
No. Observations:	591	AIC:	554.5
Df Residuals:	587	BIC:	572.0
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.3690	0.059	6.231	0.000	0.253	0.485
PAD_Treatment	-0.2535	0.032	-7.986	0.000	-0.316	-0.191
Age	-0.0018	0.001	-1.358	0.175	-0.004	0.001
Arrests	0.0064	0.001	6.453	0.000	0.004	0.008

Linear Probability Model for Gender: Female Subset (Arrested_Six_Months_Post):

```
                               OLS Regression Results
====================================================================================
Dep. Variable:     Arrested_Six_Months_Post   R-squared:                       0.421
Model:                                  OLS   Adj. R-squared:                  0.414
Method:                       Least Squares   F-statistic:                     53.42
Date:                      Mon, 07 Apr 2025   Prob (F-statistic):           5.56e-26
Time:                              23:08:19   Log-Likelihood:                 19.595
No. Observations:                       224   AIC:                            -31.19
Df Residuals:                           220   BIC:                            -17.54
Df Model:                                 3
Covariance Type:                  nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept         0.0494      0.053      0.941      0.348      -0.054       0.153
PAD_Treatment    -0.0986      0.030     -3.293      0.001      -0.158      -0.040
Age               0.0007      0.001      0.534      0.594      -0.002       0.003
Arrests           0.0196      0.002     11.206      0.000       0.016       0.023
==============================================================================
```

Linear Probability Model for Gender: Male Subset (Arrested_Six_Months_Post):

```
                               OLS Regression Results
====================================================================================
Dep. Variable:     Arrested_Six_Months_Post   R-squared:                       0.081
Model:                                  OLS   Adj. R-squared:                  0.075
Method:                       Least Squares   F-statistic:                     13.12
Date:                      Mon, 07 Apr 2025   Prob (F-statistic):           3.17e-08
Time:                              23:08:19   Log-Likelihood:                -165.37
No. Observations:                       448   AIC:                             338.7
Df Residuals:                           444   BIC:                             355.2
Df Model:                                 3
Covariance Type:                  nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept         0.2249      0.062      3.630      0.000       0.103       0.347
PAD_Treatment    -0.1652      0.033     -4.967      0.000      -0.231      -0.100
Age              -0.0005      0.001     -0.384      0.701      -0.003       0.002
Arrests           0.0038      0.001      3.986      0.000       0.002       0.006
==============================================================================
```

Linear Probability Model for Gender: Female Subset (Arrested_Twelve_Months_Post):

```
                                OLS Regression Results
=========================================================================================
Dep. Variable:     Arrested_Twelve_Months_Post   R-squared:                       0.371
Model:                                     OLS   Adj. R-squared:                  0.362
Method:                          Least Squares   F-statistic:                     43.24
Date:                         Mon, 07 Apr 2025   Prob (F-statistic):           5.24e-22
Time:                                 23:08:51   Log-Likelihood:                -3.0734
No. Observations:                          224   AIC:                             14.15
Df Residuals:                              220   BIC:                             27.79
Df Model:                                    3
Covariance Type:                     nonrobust
==================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
Intercept        0.1237      0.058      2.127      0.035       0.009       0.238
PAD_Treatment   -0.1244      0.033     -3.755      0.000      -0.190      -0.059
Age             -0.0005      0.001     -0.381      0.704      -0.003       0.002
Arrests          0.0196      0.002     10.101      0.000       0.016       0.023
==============================================================================
```

Linear Probability Model for Gender: Male Subset (Arrested_Twelve_Months_Post):

```
                                OLS Regression Results
=========================================================================================
Dep. Variable:     Arrested_Twelve_Months_Post   R-squared:                       0.147
Model:                                     OLS   Adj. R-squared:                  0.141
Method:                          Least Squares   F-statistic:                     25.51
Date:                         Mon, 07 Apr 2025   Prob (F-statistic):           3.04e-15
Time:                                 23:08:51   Log-Likelihood:                -229.00
No. Observations:                          448   AIC:                             466.0
Df Residuals:                              444   BIC:                             482.4
Df Model:                                    3
Covariance Type:                     nonrobust
==================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
Intercept        0.5094      0.071      7.133      0.000       0.369       0.650
PAD_Treatment   -0.2934      0.038     -7.654      0.000      -0.369      -0.218
Age             -0.0034      0.001     -2.278      0.023      -0.006      -0.000
Arrests          0.0048      0.001      4.426      0.000       0.003       0.007
==============================================================================
```

Linear Probability Model for Age: 40 and Under Subset (Arrested_Six_Months_Post):

```
                               OLS Regression Results
===================================================================================
Dep. Variable:     Arrested_Six_Months_Post   R-squared:                       0.095
Model:                                  OLS   Adj. R-squared:                  0.085
Method:                       Least Squares   F-statistic:                     9.399
Date:                      Mon, 07 Apr 2025   Prob (F-statistic):           6.30e-06
Time:                              23:09:41   Log-Likelihood:                -39.394
No. Observations:                       272   AIC:                             86.79
Df Residuals:                           268   BIC:                             101.2
Df Model:                                 3
Covariance Type:                  nonrobust
================================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
Intercept       0.1367      0.095      1.440      0.151      -0.050       0.324
PAD_Treatment  -0.1080      0.034     -3.147      0.002      -0.176      -0.040
Age            -0.0007      0.003     -0.222      0.824      -0.007       0.005
Arrests         0.0146      0.003      4.419      0.000       0.008       0.021
============================================================================
```

Linear Probability Model for Age: Over 40 Subset (Arrested_Six_Months_Post):

```
                               OLS Regression Results
===================================================================================
Dep. Variable:     Arrested_Six_Months_Post   R-squared:                       0.125
Model:                                  OLS   Adj. R-squared:                  0.118
Method:                       Least Squares   F-statistic:                     18.80
Date:                      Mon, 07 Apr 2025   Prob (F-statistic):           2.02e-11
Time:                              23:09:41   Log-Likelihood:                -144.51
No. Observations:                       400   AIC:                             297.0
Df Residuals:                           396   BIC:                             313.0
Df Model:                                 3
Covariance Type:                  nonrobust
================================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
Intercept       0.2054      0.118      1.741      0.082      -0.027       0.437
PAD_Treatment  -0.1809      0.035     -5.180      0.000      -0.250      -0.112
Age            -0.0001      0.002     -0.067      0.946      -0.004       0.004
Arrests         0.0049      0.001      5.496      0.000       0.003       0.007
============================================================================
```

Linear Probability Model for Age: 40 and Under Subset (Arrested_Twelve_Months_Post):

```
                                OLS Regression Results                               
=====================================================================================
Dep. Variable:     Arrested_Twelve_Months_Post   R-squared:                       0.142
Model:                                     OLS   Adj. R-squared:                  0.132
Method:                          Least Squares   F-statistic:                     14.79
Date:                         Mon, 07 Apr 2025   Prob (F-statistic):           6.14e-09
Time:                                 23:09:42   Log-Likelihood:                -111.24
No. Observations:                          272   AIC:                             230.5
Df Residuals:                              268   BIC:                             244.9
Df Model:                                    3                                         
Covariance Type:                     nonrobust                                         
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept         0.3203      0.124      2.592      0.010       0.077       0.564
PAD_Treatment    -0.2239      0.045     -5.009      0.000      -0.312      -0.136
Age              -0.0021      0.004     -0.541      0.589      -0.010       0.006
Arrests           0.0203      0.004      4.733      0.000       0.012       0.029
==============================================================================
```

Linear Probability Model for Age: Over 40 Subset (Arrested_Twelve_Months_Post):

```
                                OLS Regression Results                               
=====================================================================================
Dep. Variable:     Arrested_Twelve_Months_Post   R-squared:                       0.178
Model:                                     OLS   Adj. R-squared:                  0.172
Method:                          Least Squares   F-statistic:                     28.62
Date:                         Mon, 07 Apr 2025   Prob (F-statistic):           9.05e-17
Time:                                 23:09:42   Log-Likelihood:                -174.16
No. Observations:                          400   AIC:                             356.3
Df Residuals:                              396   BIC:                             372.3
Df Model:                                    3                                         
Covariance Type:                     nonrobust                                         
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept         0.3581      0.127      2.819      0.005       0.108       0.608
PAD_Treatment    -0.2598      0.038     -6.907      0.000      -0.334      -0.186
Age              -0.0015      0.002     -0.657      0.511      -0.006       0.003
Arrests           0.0061      0.001      6.281      0.000       0.004       0.008
==============================================================================
```

J. Linear Regression Analyses with Interaction Terms

```
Linear Probability Model for arrested_six_month_post (With Race-Treatment Interaction):

                               OLS Regression Results
==================================================================================
Dep. Variable:     arrested_six_month_post   R-squared:                       0.115
Model:                                 OLS   Adj. R-squared:                  0.107
Method:                      Least Squares   F-statistic:                     14.33
Date:                     Mon, 03 Mar 2025   Prob (F-statistic):           2.10e-15
Time:                             23:35:38   Log-Likelihood:                -195.07
No. Observations:                      672   AIC:                             404.1
Df Residuals:                          665   BIC:                             435.7
Df Model:                                6
Covariance Type:                 nonrobust
=============================================================================================
                                coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------
const                         0.1600      0.072      2.209      0.027       0.018       0.302
PAD_Treatment                -0.1898      0.074     -2.582      0.010      -0.334      -0.045
Race                         -0.0168      0.027     -0.624      0.533      -0.070       0.036
treatment_race_interaction    0.0443      0.074      0.600      0.549      -0.101       0.189
Age                           0.0005      0.001      0.513      0.608      -0.001       0.002
Gender                        0.0255      0.027      0.931      0.352      -0.028       0.079
Race                         -0.0168      0.027     -0.624      0.533      -0.070       0.036
Num_of_arrests                0.0053      0.001      6.398      0.000       0.004       0.007
==============================================================================
```

```
Linear Probability Model for arrested_one_year_post (With Race-Treatment Interaction):

                              OLS Regression Results
==================================================================================
Dep. Variable:     arrested_one_year_post   R-squared:                       0.169
Model:                                OLS   Adj. R-squared:                  0.161
Method:                     Least Squares   F-statistic:                     22.51
Date:                    Mon, 03 Mar 2025   Prob (F-statistic):           3.23e-24
Time:                            23:35:38   Log-Likelihood:                -284.06
No. Observations:                     672   AIC:                             582.1
Df Residuals:                         665   BIC:                             613.7
Df Model:                               6
Covariance Type:                nonrobust
=============================================================================================
                                coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------
const                         0.2864      0.083      3.465      0.001       0.124       0.449
PAD_Treatment                -0.2319      0.084     -2.764      0.006      -0.397      -0.067
Race                         -0.0036      0.031     -0.116      0.907      -0.064       0.057
treatment_race_interaction   -0.0106      0.084     -0.126      0.900      -0.176       0.155
Age                          -0.0018      0.001     -1.604      0.109      -0.004       0.000
Gender                        0.1177      0.031      3.760      0.000       0.056       0.179
Race                         -0.0036      0.031     -0.116      0.907      -0.064       0.057
Num_of_arrests                0.0061      0.001      6.497      0.000       0.004       0.008
==============================================================================
```

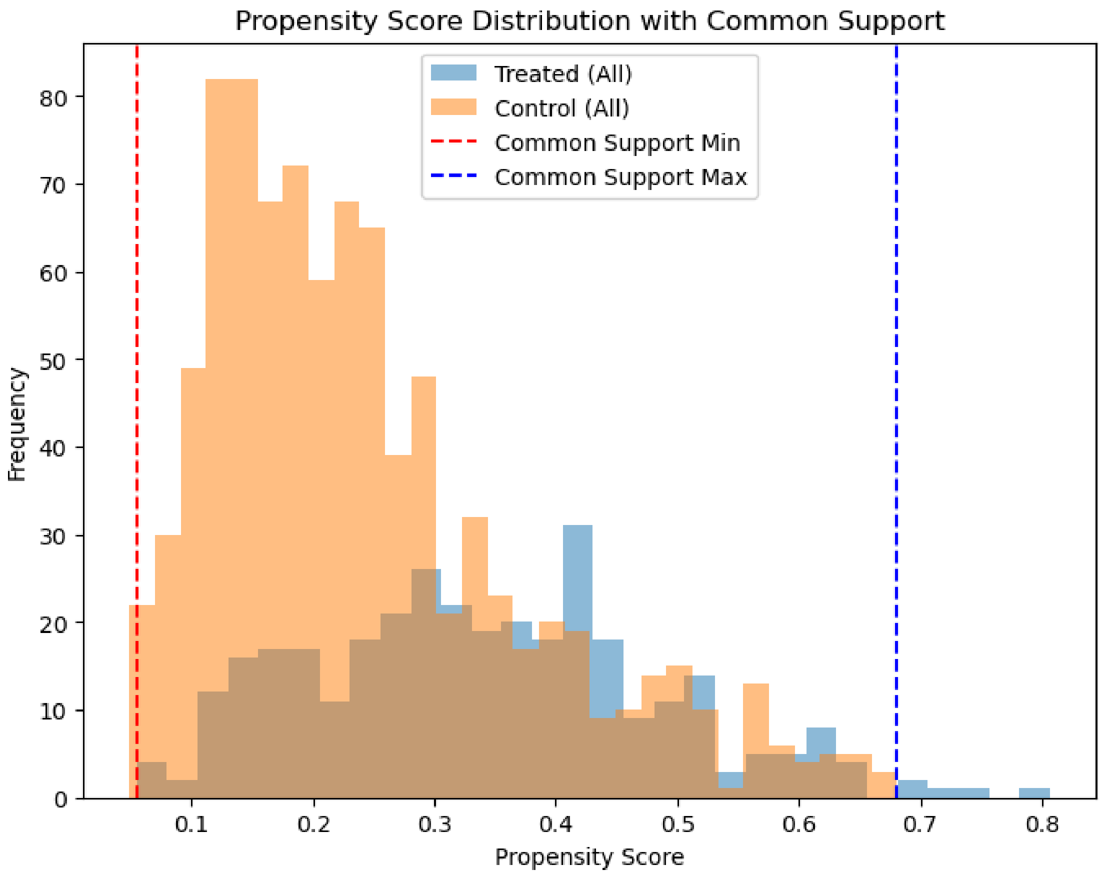
Linear Probability Model for Arrested_Six_Months_Post (With Race-Treatment Interaction):

```
                               OLS Regression Results
==================================================================================
Dep. Variable:     Arrested_Six_Months_Post   R-squared:                       0.115
Model:                                  OLS   Adj. R-squared:                  0.107
Method:                       Least Squares   F-statistic:                     14.33
Date:                      Mon, 07 Apr 2025   Prob (F-statistic):           2.10e-15
Time:                              23:10:02   Log-Likelihood:                -195.07
No. Observations:                       672   AIC:                             404.1
Df Residuals:                           665   BIC:                             435.7
Df Model:                                 6
Covariance Type:                  nonrobust
=============================================================================================
                                coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------
const                         0.1600      0.072      2.209      0.027       0.018       0.302
PAD_Treatment                -0.1898      0.074     -2.582      0.010      -0.334      -0.045
Race                         -0.0168      0.027     -0.624      0.533      -0.070       0.036
treatment_race_interaction    0.0443      0.074      0.600      0.549      -0.101       0.189
Age                           0.0005      0.001      0.513      0.608      -0.001       0.002
Gender                        0.0255      0.027      0.931      0.352      -0.028       0.079
Race                         -0.0168      0.027     -0.624      0.533      -0.070       0.036
Arrests                       0.0053      0.001      6.398      0.000       0.004       0.007
==============================================================================
```

Linear Probability Model for Arrested_Twelve_Months_Post (With Race-Treatment Interaction):

```
                                OLS Regression Results
=====================================================================================
Dep. Variable:     Arrested_Twelve_Months_Post   R-squared:                       0.169
Model:                                     OLS   Adj. R-squared:                  0.161
Method:                          Least Squares   F-statistic:                     22.51
Date:                         Mon, 07 Apr 2025   Prob (F-statistic):           3.23e-24
Time:                                 23:10:02   Log-Likelihood:                -284.06
No. Observations:                          672   AIC:                             582.1
Df Residuals:                              665   BIC:                             613.7
Df Model:                                    6
Covariance Type:                     nonrobust
=============================================================================================
                                coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------
const                         0.2864      0.083      3.465      0.001       0.124       0.449
PAD_Treatment                -0.2319      0.084     -2.764      0.006      -0.397      -0.067
Race                         -0.0036      0.031     -0.116      0.907      -0.064       0.057
treatment_race_interaction   -0.0106      0.084     -0.126      0.900      -0.176       0.155
Age                          -0.0018      0.001     -1.604      0.109      -0.004       0.000
Gender                        0.1177      0.031      3.760      0.000       0.056       0.179
Race                         -0.0036      0.031     -0.116      0.907      -0.064       0.057
Arrests                       0.0061      0.001      6.497      0.000       0.004       0.008
==============================================================================
```

Appendix K. Propensity Score Distribution with Common Support Indicators



Appendix K1. Linear Regression Analysis of Matched Pairs Excluding Individuals Outside Area of Common Support

```
Linear Regression Model for Arrested_Six_Months_Post (Matched Pairs, Post Common Support):

                            OLS Regression Results
==============================================================================
Dep. Variable:     Arrested_Six_Months_Post   R-squared:                       0.119
Model:                                  OLS   Adj. R-squared:                  0.112
Method:                       Least Squares   F-statistic:                     17.68
Date:                      Mon, 07 Apr 2025   Prob (F-statistic):           1.85e-16
Time:                              23:15:26   Log-Likelihood:                -175.88
No. Observations:                       662   AIC:                             363.8
Df Residuals:                           656   BIC:                             390.7
Df Model:                                 5
Covariance Type:                  nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
const             0.1747      0.060      2.914      0.004       0.057       0.292
PAD_Treatment    -0.1311      0.025     -5.316      0.000      -0.179      -0.083
Age              -0.0006      0.001     -0.554      0.580      -0.003       0.001
Gender            0.0395      0.027      1.442      0.150      -0.014       0.093
Race             -0.0332      0.036     -0.917      0.359      -0.104       0.038
Arrests           0.0064      0.001      7.032      0.000       0.005       0.008
==============================================================================
```

Linear Regression Model for Arrested_Twelve_Months_Post (Matched Pairs, Post Common Support):

```
                               OLS Regression Results
=====================================================================================
Dep. Variable:     Arrested_Twelve_Months_Post   R-squared:                       0.174
Model:                                     OLS   Adj. R-squared:                  0.168
Method:                          Least Squares   F-statistic:                     27.60
Date:                         Mon, 07 Apr 2025   Prob (F-statistic):           2.10e-25
Time:                                 23:15:26   Log-Likelihood:                -251.00
No. Observations:                          662   AIC:                             514.0
Df Residuals:                              656   BIC:                             541.0
Df Model:                                    5
Covariance Type:                     nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
const             0.2594      0.067      3.863      0.000       0.128       0.391
PAD_Treatment    -0.1957      0.028     -7.086      0.000      -0.250      -0.141
Age              -0.0021      0.001     -1.835      0.067      -0.004       0.000
Gender            0.1212      0.031      3.950      0.000       0.061       0.181
Race             -0.0295      0.041     -0.727      0.467      -0.109       0.050
Arrests           0.0078      0.001      7.634      0.000       0.006       0.010
==============================================================================
```

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