University of Chicago

Co-policing Surrounding the University of Chicago

A Thesis Submitted to

The Faculty of the Division of the Social Sciences

In Candidacy for the Degree of

Master of Arts

Department of Computational Social Science

by

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Chicago, IL

June 2020

Abstract

This paper explores the differences between the Chicago Police Department and private campus police operated by the University of Chicago. Both of these departments share a jurisdiction in the community surrounding the University operating under equivalent authority to police the region. This project aims to describe the distinctions between these two departments by understanding how their reactions to reported crimes differ. As colleges and universities across the country expand their police departments, it is increasingly important to understand not only how these departments operate, but how they affect the surrounding community members and municipal policing efforts. We find the University of Chicago Police department supplements municipal policing by primarily focusing on petty crimes and non-criminal incidents that are more likely to affect university students and faculty. However, while the UCPD does collaborate extensively with CPD on more violent crimes, it is again for crimes that impact stakeholders at the university more, such as robberies and assaults. This has serious implications for surrounding neighborhoods, which are predominantely communities of color, who are not being represented by the UCPD in policing practices and have no direct power to hold the University accountable for the actions of its private police force.

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CHAPTER 1

INTRODUCTION

The United States has a complicated history of policing entangled with racial injustices. Police patrols in the United States can trace their roots to slave patrols during the formative years of the country (Capers 2009; Sklansky 1999). These white vigilante groups used fear and intimidation tactics to exert control over slaves and those thought to be helping them (Sklansky 1999). During the period of Jim Crow laws, blacks still endured police intimidation and brutality, justified through laws designed to relegate black Americans to the bottom of the social order (Wynes 1967; Ross 1983). However, these punitive measures were not applied equally, with police rarely charging those who participated in lynch mobs against people of color (Ross 1983). These inequities still echo through policing today, with minorities and inhabitants of low-income areas experiencing documented over-policing, mass incarceration, and increased police violence (Tuch and Weitzer 1997; Weitzer 2000; Alpert et al. 2006).

Across the country public and private policing efforts have grown to counter criminal activity (Strom et al. 2010; Sklansky 1999). Many businesses hire or contract security guards to protect their establishments, goods, and customers (Strom et al. 2010). These personnel typically operate within extremely narrow bounds, with limited jurisdiction and the ability to exert force (Sklansky 1999). These security guards are typically intended to act as a deterrent and trustworthy witness of criminal activity, rather than intervening force (Sklansky 1999).

However, organizations or individuals can hire private police forces that are able to operate with much wider latitude (Sklansky 1999). Many states allow for armed private police with fully equipped patrol cars (Strom et al. 2010; Sklansky 1999). Increasingly, universities are operating their own police departments with this kind of far-reaching authority (Strom et al. 2010; Reaves 2015). Yet, while public universities must maintain some amount of transparency, and are susceptible to FOIA requests, private universities are under no obligation to provide information if requested (Newman 2016). Therefore, private universities have the ability to operatie, in many cases quite large, police forces with little to none accountability and oversight. Under Illinois state law, the police departments of private universities, are only beholden to the university's Board of Trustees, not the communities on or off campus that they police (110 ILCS 1020, n.d.).

Considering the long-running entanglement of racism and violence with policing, the combination of far-reaching authority, lack of accountability and oversight, abundance of resources, and interaction with vulnerable populations typically found at private universities is alarming. There are few better places to study possible inequities as a result of private university policing than at the University of Chicago, which has an extensive history of supporting gentrification efforts to push out people of color in Hyde Park (Sherman 2019; Larson 2012). The campus in Hyde Park is surrounded by lower income neighborhoods, predominantly composed of people of color, which are policed by the University of Chicago Police Department (UCPD) (Sherman 2019). The UCPD has been accused of racially biased policing practices, which have been exhibited in data on stops released by the university (Newman 2016).

While the UCPD provides significant technical and human resources to police Hyde Park and the surrounding area, their jurisdiction is shared with the Chicago Police Department (CPD). This necessitates an understanding, not only of how the UCPD operates, but also of the CPD and the interaction of private police officers employed by the University with public police officers employed by the city. Therefore, in addition to understanding the reports of crimes that both UCPD and CPD receives and responds to, and their outcomes, this project aims to answer how CPD and UCPD crime reports and outcomes vary within the UCPD's jurisdiction, and directly outside of it. Additionally, as some reports of crimes are handled by both the UCPD and CPD in tandem, we also attempt to discern departmental differences from how each agency may handle or report the same "case" in a different manner.

CHAPTER 2

LITERATURE REVIEW

2.1 Inequality in Policing

Since the 1970's, mass incarceration produced by an increase in punitive policing, such as the War on Drugs, have been used to perpetuate racial injustices, with "African Americans are incarcerated at nearly six times the rate of whites, and Hispanics are incarcerated at almost twice the rate of whites" (Fortner 2015). America still lives in segregated communities, leading to separated communities of color exhibiting higher crime rates, not due to residents but the lack of jobs, education, and other opportunities (Capers 2009). The absence of social capital "...that can increase the likelihood of upward mobility is likely to be self-perpetuating..." (Capers 2009). This leads to higher unemployment and lower property values in minority neighborhoods, which coupled with decreased trust and perceived legitimacy of police officers, can exacerbate issues of crime and policing in these communities (Capers 2009).

This creates serious consequences for all people, but especially affects those in society that are already disadvantaged. There is a long history of public policing being racialized or otherwise not applied equally across the population (Alpert et al. 2006; Tuch and Weitzer 1997). Communities of color have been consistently more likely to be subjected to excessive force, exacerbating inequality through social ramifications, like distrust for police and authority (Tuch and Weitzer 1997). Residents in black neighborhoods are also more likely to say that "police stop people in the neighborhood without good reason, verbally abuse neighborhood residents, and and use excessive force against neighborhood residents" (Weitzer 2000). These problems exist in public police departments across the country, but often goes unaddressed, as white people are less likely to think racism in policing exists (Tuch and Weitzer 1997; Weitzer 2000). Yet, in many areas, white officers make up a greater proportion of the police force (Tuch and Weitzer 1997) and are more likely to give out tickets (Alpert et al. 2006). Due to high levels of racial segregation, white police officers are likely to come from predominately white neighborhoods, while predominately interacting with people of color only on patrol, which can reinforce stereotypes and racialized policing (Capers 2009).

Gentrification, while reducing the intensity of policing in the immediate area, can increase policing activity outside of the gentrifying area (Laniyonu 2018). However, despite a decrease in policing, it appears crime actually increases in gentrifying areas (Laniyonu 2018). While Broken Windows policing, which focused on reducing physical disorder in an attempt to reduce crime, was very popular during the 1980's and 1990's, there is contradictory evidence about its effectiveness (Laniyonu 2018). Likely due to the stereotypical associations of people of color and poor with crime, there is strong evidence that the proportion of black Americans in an area is correlated with the distribution of police officers (Laniyonu 2018; Capers 2009)

Typically the decision-making by police officers leading up to a stop is driven by a person appearing "different" or "out of place" (Alpert et al. 2006). As a result, minorities are frequently stopped in white neighborhoods, despite data showing that police suspicions about criminality in most stop and frisks are wrong (Capers 2009). Policing guided by these philosophies invites bias into the policing process, resulting in the targeting of males and minorities (Alpert et al. 2006). Policing that does not adequately address the concerns of the community, expectedly can have as detrimental effects on the community as crime can (Daniel and Moynihan 1970). While crime drives down patronage of businesses, churches, and community organizations, that communities of color revolve around, ineffective policing only increases feelings of danger in the community (Daniel and Moynihan 1970). Policies that emphasize transparency and accountability in policing to the community are not only comforting to residents, but result in more effective enforcement of laws.

2.2 Private Policing

Private policing is a large and growing industry, with companies spending approximately $30 billion in 2015 on private security (Pappas 2012). The United States Department of

Labor estimated that in 2018 1.15 million people in the United States were employed as Security Guards or Gaming Surveillance Officers (US Department of Labor 2018). Guarding represents approximately half of all private security services, with 35 percent of services utilizing armed guards (Strom et al. 2010). Retail, restaurants, and food service was the industry sector with the highest percentage of security officers per employees in 2009 at about 17 percent (Strom et al. 2010). Colleges and universities were ranked tenth with a four percent ratio of security officers to employees (Strom et al. 2010). The State of Illinois requires that any private detective, private security contractor, private alarm contractor, fingerprint vendor, or locksmith be licensed by the state (225 ILCS 447 2004). However, it is likely for these measurements to be *underestimates* of the size of private policing (Sklansky 2011). Quantitatively measuring the scope of private police is incredibly difficult, due to the secrecy and ambiguity surrounding the number of employees performing security work (Sparrow 2014; Sklansky 2011).

With private police these issues with accountability and representativeness become even more difficult to address, especially as they have become a more integral part of society. In the United States, there has been considerable growth in private policing in the last half century, sparking questions about the motivations of these private forces (Shearing 1992). It is now common for public and private police departments to collaborate within their jurisdictions (Shearing 1992; Sparrow 2014), effectively creating a "network of public police and private security that is often overlapping, complimentary [sic] and mutually supportive" (Bouthillier et al. 2006). As governments have sought to cut costs, and private organizations have seen it more cost effective to hire their own workforce for protection, there has been a shift in social control out of the public sphere (Shearing 1992; Joh 2006).

Americans quickly became disillusioned of private policing in the early years of the mining and railroad industries. Private police forces used by the companies in these industries lead to a protection of assets over employees and went against the public interest (Spitzer and Scull 2011; Joh 2006). This resulted in a long period where the state held a "monopoly" on policing. However, starting in the 1960's private policing began to expand, partly in response to a RAND report that re-framed private policing as "an 'industry' providing a 'service' " (Shearing 1992; Joh 2006).

Supporters of this expansion of private police forces claimed that public police had not been provided enough resources to adequately patrol their jurisdictions, creating this "vacuum" which private police were filling. This was framed as a win for everyone, as private police were now performing a role which taxpayers needed but also did not have to fund, and regulations would limit their power (Shearing 1992; Joh 2006). Critics were concerned that now companies could give employees "state authority", and that this cooperation between governments and corporations would only protect the interests of the elite (Shearing 1992).

In recent history, private policing within corporations has shifted to focus on investigative labor (Spitzer and Scull 2011). This shift represents a growing emphasis on obtaining "restitution" versus "revenge" (Spitzer and Scull 2011). Thorough investigations allow for a better likelihood of restitution through legal means, while minimizing the risk of valuable information becoming public (Spitzer and Scull 2011). However, any company's goal is to maximize profits, which means occasionally relying on public police, as that incurs no costs to the company (Spitzer and Scull 2011).

Privatized police officers are particularly problematic when it comes to accountability, as there is a much lower legal standard for how private forces should operate. Private police forces are now under much less government scrutiny, as public police departments rely on the partnership they have with private forces (Joh 2006). Citizens also have fewer legal protections from private police, who are not under any constitutional obligation to follow due process regulations (Sklansky 1999). This means that private police forces are not obligated to provide Miranda warnings before interrogation, and evidence discovered by a search is almost always admissible, although the officer could be charged with assault, trespassing, or false imprisonment (Sklansky 1999).

Yet, despite this lack of regulation, private police officers often have the same or similar powers of public police, over that of which other citizens have (Sklansky 1999). Additionally, private police forces formed by companies are oftentimes allowed to sit in on regional or federal task forces, giving companies access to sensitive information they did not have before (Joh 2006).

This creates far-reaching implications, especially in the case of university police forces, where private police patrol large areas outside of the campus. When these officers have the power to police citizens other than students, there is little to no oversight on whether this power is being exercised fairly and justly, which is antithetical to the strict limitations imposed on police in the Constitution. There will always be instances where the interests of private police are against that of the public's (Sparrow 2014). It is important that citizens understand when these private forces are acting against the public's interests, not only to help protect themselves, but to also spread awareness for this alarming status quo, motivating law makers to more heavily regulate private police forces.

2.3 Campus Policing

Approximately two-thirds of four year colleges or universities with more than 2,500 students employ sworn police officers, with 92 percent of public institutions and 38 percent of private institutions doing so (Reaves 2015). About three quarters of campus officers overall are armed and about eight in ten campus officers could arrest and patrol beyond campus boundaries (Reaves 2015). A larger proportion of police departments at public institutions met regularly with advocacy groups than private institutions (Reaves 2015). The increase in law enforcement personnel has outpaced student enrollment (Reaves 2015). Campuses with sworn officers, on average employed 2.4 full time sworn officers per 1000 students, with private institutions having higher ratios than public institutions (Reaves 2015).

Under the Jeanne Clery Disclosure of Campus Security Policy and Campus Crime Statistics Act of 1990, institutions of higher education that participate in federal financial aid programs must keep and disclose information about crime on and around campus (Reaves 2015; Bauman 2014). On average, overall crime rates are higher at private institutions, both both public and private institutions reported handling about 40 violent crimes per 100,000 students during the 2011-2012 school year (Reaves 2015). Usually, “sworn officers must undergo a considerably more rigorous screening process prior to hiring than their non-sworn counterparts”, but a majority of departments require a college degree for both types of officer (Reaves 2015). While the proportion of minority officers and female officers increased from the previous survey in 2004, the majority of sworn officers were both white and male during the 2011-2012 school year (Reaves 2015).

In some ways, campus police can better serve the public’s interests than public police departments. While campus police work to maintain a “good image” of the school by enforcing campus rules for students (Jacobsen 2015), they can still benefit the public, sometimes more effectively than municipal police departments. Overall, campus police feel their job is to keep students safe and make them feel comfortable (Williams et al. 2016). Police officers employed by universities must undergo Title IX training as all university employees must, and often complete more training about sexual harassment than their municipal counterparts (Smith, Wilkes, and Bouffard 2016). Officers with specialized training pertaining to sexual crimes typically scored lower on scales of rape myth acceptance (Smith, Wilkes, and Bouffard 2016). Perhaps a testament to this focus on safety by campus police, students generally regard their campus as a “protected space” which is safer than other areas and feel that campus police are responsible for this safe environment (Williams et al. 2016; Jacobsen 2015).

Yet, while in a 1998 survey of white college students and faculty only ten percent of respondents felt unsafe on their campus, 36 percent supported arming campus police officers and an additional 26 percent were undecided (Hummer, Austin, and Bumphus 1998). Of the 38 percent of respondents that felt campus police should not be armed, “50 percent felt that”campus life" is not that life-threatening and therefore did not warrant the carrying of firearms by officers" (Hummer, Austin, and Bumphus 1998). 63 percent of respondents who were undecided felt that "the use of firearms should be dependent on the severity of the situation" (Hummer, Austin, and Bumphus 1998).

Campus police officers also play different roles in the lives of those within their jurisdiction. Police on campuses often must play the role of a more parental figure, as most young adults at college are growing into and adjusting to their first experiences living on their own (Williams et al. 2016). Students feel that campus police officers should protect them while simultaneously not interfering with their lives, such as "overreacting" to students participating in under-aged drinking (Jacobsen 2015). This puts campus police officers in an interesting situation, where they are thought of by many students to be "not real cops", while oftentimes still having the same legal powers as public law enforcement officers (Williams et al. 2016). Students also delegitamize campus police by popularizing rumors that campus police are officers that could not get a job with the state or municipal police (Jacobsen 2015) or anecdotes of excessive force (Williams et al. 2016).

This lack of legitimacy of campus police in students' eyes may also stem from the history of campus police. Early campus police in the first half of the twentieth century were little more than security guards, who could investigate and detain, but only refer to the administration for punishment (Sloan 1992). As unrest became widespread on campuses across the country in the late 1960's, college administrators faced losing control of their student populations, and a reliance on outsiders to keep peace on campus (Sloan 1992). Colleges were also growing rapidly during this time, which was accompanied by increases in crime (Sloan 1992). This led to the founding of official campus police departments made up of sworn law enforcers whose training, duties, and organization mirrored that of traditional urban police departments (Sloan 1992).

However, the attitudes of university police officers greatly contrast that of students attending the university. Overwhelmingly, campus police felt that students were, in general, respectful of the rules and cooperative with officers (Sloan 1992). Officers felt that while a minority of students created most of the trouble, outsiders posed the greatest threat to campus security (Sloan 1992). Campus police felt a strong sense of duty towards serving the university community and enforcing campus rules (Gelber 1972). This gives evidence that while campus police officers must police a much different population with different types of crimes than municipal police traditionally do, that they will react and operate in a similar manner.

This commitment to serving is also portrayed through campus police departments' interaction with the community at large. Campus police departments are slightly more likely to have a community policing plan, either written or not, and provide at least eight hours of community police training, when compared to city police (Bromely 2003). Campus and city police departments have roughly the same proportion of full time community police officers, about seven in ten (Bromely 2003). While campus police forces are more likely to have problem solving partnerships with citizens, city departments are more likely to have trained citizens in problem solving (Bromely 2003). Campus officers are overwhelmingly more likely to be assigned to foot or bike patrols than city police officers (Bromely 2003).

Traditionally, while public universities are considered an extension of the state, private universities are not considered state actors, even when university police forces are involved (Jahnig 2015). The Supreme Court of North Carolina determined that religious colleges do not violate the Establishment Clause, which designates the separation of religious institutions and the law, as long police officers from religious colleges are enforcing the laws of the state, and therefore not advancing one religion through their actions (Hopkins and Neff 2014). However, the Ohio Supreme Court ruled in May 2015 that the police department of Otterbein University, a private institution, was a public office that can be compelled to release records as "its officers are sworn, state-certified police officers who exercise plenary police power", which goes against the traditional legal precedent in this regard (142 Ohio St.3d 535 2015).

Under the federal 1033 program, municipal police departments, including departments operated by universities can receive military surplus for only the cost of shipping and receiving (Bauman 2014). At least 124 colleges have received equipment through this program, ranging from outer-wear to assault rifles, grenade launchers and armored vehicles (Bauman 2014). Campus police personnel claim these are only for “serious incidents”, but critics argue the equipment is unnecessary and concerning, especially in the wake of incidents of police brutality, like those that occurred in Ferguson (Bauman 2014). While departments must show proof that officers have received training to use any new weapon, vehicle, or tool to maintain accreditation from the International Association of Campus Law Enforcement Administrators, there is no requirement for campus police departments to attain accreditation (Bauman 2014).

Institutions of higher education cannot create their own police departments without some kind of state authorization (Hopkins and Neff 2014). At least 44 states have authorized campus policing, but the method and the degree to which these policing powers are vested to universities and colleges varies greatly by state, with some states granting full policing powers to campus officers, while others force campuses to have their officers deputized by municipal departments (Hopkins and Neff 2014). In Illinois, the Private College Campus Police Act gives private colleges and universities the power to appoint members of a campus police department with “. . . the powers of municipal peace officers and county sheriffs, including the power to make arrests. . . for violations of state statutes or municipal or county ordinances, including the ability to regulate and control traffic on the public way contiguous to the college or university property. . . in the county where the college or university is located” (110 ILCS 1020, n.d.).

2.4 The University of Chicago

The University of Chicago Police Department (UCPD) is the largest private police force in Chicago (Reaves 2008), encompassing a jurisdiction of approximately 6.5 miles and 65,000 people (Larson 2012). The University of Chicago had the twelfth largest campus police force by number of full time employees in the country during the 2011-2012 school year (Bureau of

Justice Statistics 2015). UCPD officers, like those on many other campuses across the United States, are fully accredited, armed, and sworn (Heaton et al. 2016) and authorized to operate throughout all of Cook County (Sherman 2019). The UCPD patrols Hyde Park and five surrounding neighborhoods, sharing the area with Chicago Police patrols (Sherman 2019).

The University of Chicago has a rich history of using the policing of “things”, through urban renewal policies, and the policing of people to further their own agenda (Sherman 2019; Larson 2012). The university created their own police department in the 1960’s in response to parents’ concern about the safety of their children, and the administration’s concern about enrollment (Sherman 2019; Larson 2012). While the university started by convincing the Chicago police commissioner to deputize their officers, an Illinois law passed in 1989 gave universities the power to swear in their own police officers (Sherman 2019; Larson 2012).

Racial tensions surrounding the UCPD have persisted to this day. Students of color attending The University of Chicago have reported carrying a backpack and frequently wearing UChicago branded clothing to avoid being hassled by UCPD (Honig 2014; Gold 2014). A bill in introduced by a representative for the Hyde Park area in the Illinois General Assembly requiring universities to release information died in committee after the University of Chicago promised to release policing data (Newman 2015). In response to community outcries about racial profiling and transparency, the University agreed to publicly release information on the UCPD and their interactions with civilians in 2015, despite having no legal obligation to do so (The University of Chicago 2015; Newman 2016). However, the released data does not appear to clear the UCPD of racial bias, as “African-Americans make up approximately 59 percent of the population in UCPD’s patrol area but 93 percent of UCPD’s field interviews” (Newman 2016). These well-documented systematic issues within the UCPD warrant additional research to better equip activists and policy makers seeking to make policing in the surrounding community more equitable and in the interest of the public.

Modern campuses, have spread beyond buildings owned by the university, to residences and businesses that students frequent, necessitating extended jurisdictions beyond campus (Hopkins and Neff 2014). While the Chicago Police Department has entered into jurisdiction agreements with the University of Chicago Police Department and Northwestern University Police Department, whereas those agencies generally patrol defined geographical areas, the CPD still retains the authority to provide "all required police services" in these jurisdictions (Chicago Police Department 2017).

CHAPTER 3

DATA AND METHODS

3.1 Data

[Table 1 about here.]

[Table 2 about here.]

[Table 3 about here.]

[Table 4 about here.]

[Table 5 about here.]

[Table 6 about here.]

The merged and processed data has 769230 observations, although for the models only 58988 observations that are within UCPD's defined boundaries are used. All crimes in the data were reported to have occurred between 2010-07-01 and 2019-12-02 23:59:00. Within UCPD's patrol boundaries, approximately 84.1% of reported crimes were responded to by CPD alone. Crimes in UCPD's patrol area were reported to be on average in areas with a household size of 1.567 people, a median age of 26.622 years, 0.15 of households containing families. Crimes are reported in areas where the people are, on average, 40% female, 46% black, 20% white, 4% Asian, 3% Latino, and 14% are minors.

3.1.1 Retrieval

This project combines data from three sources, the University of Chicago, the Chicago Police Department, and the United States Census Bureau. The University of Chicago publishes data on incidents responded to by the University of Chicago Police Department on the website for the university's department of Safety and Security (The University of Chicago n.d.a). While this data is publicly view-able, the university does not provide an option to download the data in an easy to analyze format, so the data was web-scraped using the `rvest` package in R. Data on reported incidents published by the university and the city include time, location, descriptions, and outcomes of crimes reported to both agencies. However, as neither agencies publish demographic data of suspects or victims involved with a reported crime, this is inferred from the characteristics of the census block where the crime was reported to have happened. The University of Chicago publishes the UCPD's "area of patrol" via a PDF map online (The University of Chicago n.d.b). This was copied by hand into a shape-file via Google Maps, to geocode whether a crime was reported to have happened in the area the UCPD regularly patrols. Crime Reports from CPD were retrieved from the City of Chicago's data portal through their Socrata API with the `RSocrata` package. 2010 decennial census block level data was retrieved from the US Census API using the `tidycensus` package.

3.1.2 Processing

Data from the University of Chicago included incidents that the UCPD responded to that were not possible crimes, such as medical emergencies, which were removed from the data-set used for analysis. However incidents that could be related to a crime, such as "missing property" or "information [related to a possible crime]" were kept in the data-set for analysis. Categories were hand-coded and collapsed into as few matching categories between data from the University and the city as much as possible, with any categories that only appeared in the data from one department re-categorized as "other". The University of Chicago includes a hand-entered location for each report, typically a street corner or a city block. This provided location data was geocoded into coordinates with the Google Maps API using the `ggmap` package. Date-time information was stored as text for both data-sets, necessitating the use of the `lubridate` package to parse out when crimes were reported to have occurred.

Data from the University of Chicago specifies whether a crime responded to by UCPD was also responded to by CPD. In the comments section, the majority of these reports marked as handled by both departments by the UCPD, there is also a CPD case number, which allowed for those cases to be matched in the data from the CPD. Unfortunately, not all cases could be matched, meaning some amount of crime reports from the CPD are mismarked as handled only by CPD. Even after matching categories of attributes for reported crimes for each department, some reports matched by CPD case number had different information for, allegedly, the same incident. Therefore, all reports marked as responded to by both departments from both departments were kept. Census block data was converted from raw counts of people or housing units with a given demographic trait in the block to proportions. Since the `tidycensus` package includes geometry data with the Census variables, the data on crime reports could be merged with the Census data based on geographic location. Using the `st_within()` function from the `sf` package, it was determined which census block each crime was reported to have occurred in, linking the attributes of that block to the reported crime.

3.2 Methods

All of the analyses were conducted in RStudio version 1.2.5033 using R version 3.6.3. All R packages and their information used throughout this project are listed below.

[Table 7 about here.]

3.2.1 Visual Analysis

Especially in the case of geo-temporal data, such as crime reports, a visual analysis is an essential tool to study the data. Finding relationships and patterns in a data-frame of numbers is a much harder task for humans compared to performing the same task with numbers and shapes (Tory and Möller 2004; Keim et al. 2006). Therefore, we broke down several dimensions of our crime report data into much easier to understand visualizations using the `ggplot2` package in R.

3.2.2 Lasso Regression

Due to the large number of variables in the data-set, a modeling method with built-in feature selection was essential. Lasso regressions, and more recently, Random Forest models have proved very effective for feature selection (Tibshirani 1996; Bühlmann and Zürich 2006) on top of modeling relationships in crime report data (Kadar et al. 2018; Chalfin et al. 2019). Their popularity not only stems from their performance, but also their ease of use and compatibility with a wide selection of different categorical outcomes. However, there can be variance between models fit on the same data, which for significant robustness, necessitates the use of boot-strapping with lasso regression models (A Alves, Ribeiro, and Rodrigues 2018). However, bootstrapped lasso models using the `bootLasso()` in the `HDCI` produced models with only one variable for predicting whether an arrest had occurred, and no variables for other models, resulting in the use of Lasso regression without bootstrapping.

The lasso models were built using the `glmnet` package in R, specifically using the `cv.glmnet()` function which performs k-fold cross-validation to determine the optimal lambda value. The default value of 10 folds for cross validation were used. For binary outcomes logistic lasso regression was used, with cross-validation optimizing on the area under the receiver operator characteristic (ROC) curve, while for multiple-categorical outcomes multinomial lasso regression was used, optimizing on the misclassification rate. Lasso models with continuous outcomes used the default optimization metric of mean squared error. Data was partitioned into a 75/25 training/testing split using the `caret` package.

3.2.3 General Additive Models

While lasso regression models perform well with feature selection, other linear-based models such as General Additive Models (GAMs) are superior for predictive performance (Kadar et al. 2018). GAMs are well suited for research applications due to their flexibility, quick building times (especially compared to ensemble methods like Random Forests), and ease of interpretation. GAMs increase predictive performance by accounting for non-linear relationships while also using a smoother to avoid over-fitting, having been used with crime data with promising results (Hastie and Tibshirani 1987; Mitchell, Brown, and Conklin 2007; Gedeborg et al. 2017). The output of a GAM in R is very similar to those for other linear models using the `lm()` and `glm()` functions, making the results accessible to anyone already familiar with linear models. For this project, GAMs were built using the `mgcv` package in R, using variables selected using the previously generated lasso regression models. For the models predicting arrests and responding department, only the 10 most influential variables from the lasso regression model were used to reduce training time. All continuous variables were fitted using smoothers, with smoothing parameters selected using the default Generalized Cross Validation method. Data was partitioned into a 75/25 training/testing split using the `caret` package.

3.2.4 Assessing Performance

For both models predictive performance assessment depends on the type of outcome variable. For binary outcomes the area under the ROC curve was assessed, while categorical outcomes used classification accuracy, and for continuous outcomes, root mean square error. Predictive performance was determined using the testing data that was partitioned before the modeling process.

CHAPTER 4

RESULTS

4.1 Visual Analysis

[Figure 1 about here.]

Crime typically ebbs and flows temporally, with some relation to the natural day-night rhythms of people. Naturally overall crime are more likely to occur when more people are out and about, although certain types of crimes may contradict these patterns. For example, burglaries frequently happen at night, as the darkness and lack of people about gives cover to a criminal attempting to surpass theft prevention devices. For all crimes in UCPD's patrol area we see a distinct offset in the peak times of reported crimes, even though both departments are responding to the same exact geographical space. The lull in reported crimes for UCPD, while covering a similar interval, starts much earlier than for city police. On weekdays, this nightly lull starts around 1 AM and lasting until about 5 AM for the University, but goes from about 6 AM to 10 AM for CPD. This drop in reports is much shorter and later on the weekends for city officers, from about 10 AM to 12 PM, but only slightly later for UCPD from about 4 AM to 8 AM.

[Figure 2 about here.]

Over a larger temporal scale, crimes reported to the city show a stronger seasonal effect than those handled by the University. While most types of crimes seem to increase and decrease similarly for both departments, incidents involving narcotics or robbery appear to be more independent. While the CPD has seen a large steady decrease in narcotics related crimes, the UCPD has actually seen a slight uptick in recent years, with robberies following a similar but less divergent pattern. As expected, the University handles a much smaller volume of reported crimes across the board than CPD does in the same area.

[Figure 3 about here.]

[Table 8 about here.]

Within the same area, departments proportionally respond to different types of crimes with varying frequencies. The CPD alone responds to a larger proportion of violent crimes, such as burglary, battery, and assault in contrast to University officers. The UCPD alone responds to a large proportion of thefts and "other" crimes, the latter of which is likely more an artifact of the data collection process than the incidents themselves. Interestingly, despite each department alone responding to a similar proportion of thefts and robberies, when both departments respond, it is overwhelmingly likely to be a robbery instead of a theft, in stark contrast to the reports each department receives on their own.

[Figure 4 about here.]

Overall, both departments respond very similarly to crimes, when it comes to making an arrest. Thefts, harassment, damage to property, burglary, and deceptive practice, all have similarly low arrest rates among both departments, while interference with a public officer is very likely to end in arrest regardless of who responds. However, the UCPD appears to be much more lenient with crimes involving, substance abuse, as for both narcotics crimes and liquor law violations, the CPD has quite a high arrest rate, while University officers are much less likely to perform an arrest. However, the UCPD does have a slightly greater tendency to make an arrest for trespassing and battery than officers from the city.

[Figure 5 about here.]

[Figure 6 about here.]

As we might expect, responses involving just University officers are tightly confined to campus, while those involving city officers typically do not. However, reported crimes where both departments responded are spread evenly across the entirety of the UCPD's patrol area. Similarly most types of crime are reported to have occurred all across the UCPD's patrol area. Reports of deceptive practice occur with much higher density around "downtown" Hyde Park on the east end of 53rd street, with burglaries happening on the west end of 53rd by Washington Park. Violent crimes and narcotics offenses are commonly reported north and south of Hyde Park, concentrated along Cottage Grove Avenue. Overall, the campus seems to have much lower reported crime rates than the surrounding area, especially with reports of violent crimes.

[Figure 7 about here.]

These differences in departmental responses also exist in the demographics of the areas each department responds to. The UCPD is more likely to respond to reports in their jurisdiction in areas with higher proportions of whites and Asians, while handling fewer reports in areas with a greater black population. Conversely, CPD is more likely to respond to areas with a greater proportion of blacks, while tackling fewer reports in white and Asian areas. A report is slightly more likely to be responded to by both departments in white areas than neighborhoods with a greater proportion of black residents.

[Figure 8 about here.]

[Figure 9 about here.]

While, there are only small racial differences in a report ending in an arrest, dispositions vary greatly by department. The probability of an arrest occurring varies little across differing neighborhood demographics, when CPD responds either alone or with the UCPD. Only areas that are almost entirely white have a much greater risk of arrest by CPD. In contrast, there is a clear trend of racialized differences in arrests to reports responded to by the UCPD. Areas with a higher proportion of people of color, tend to have greater probabilities of an arrest occurring by UCPD, while ares with a larger white population exhibit a decreased probability of arrest.

[Figure 10 about here.]

[Figure 11 about here.]

Racialized differences can also be observed in the types of crimes that are reported and the responses to those reports by police officers. Overall, greater numbers of reports per capita come from white areas than predominately black areas. This is especially true for thefts. However for some more violent crimes like weapons violations and assaults, more reports per capita come from black neighborhoods. Similarly, while some types of crimes like those involving narcotics and interference with public officer are universally likely to end in arrest, other categories have clear racial disparities. In the case of a reported public peace violations and liquor law violations, if the report came from a black area there is a much higher chance of arrest than in white neighborhoods. In contrast reports of weapons violations, theft, and arson are more likely to end in arrest when they are reported in predominately white areas compared to black neighborhoods.

4.2 Model Analysis

4.2.1 Arrests

[Table 9 about here.]

The lasso regression model determined that the type of reported crime to be most influential in predicting whether an arrest would occur, especially when the reported crime was a crime involving narcotics, interference with a public officer, a weapons violation, trespassing, public peace violation, or homicide, which all increased the chance of an arrest occurring. Crimes such as burglary, deceptive practice, and theft, areas with a higher proportion of Asians and homeowners were associated with a lower chance of arrest. As latitude increased, or as the location of a crime was reported to be farther north, the chance of arrest also decreased significantly. Areas with a higher proportion of two-parent households were associated with an increased chance of arrest. This model had a ROC AUC of 0.852.

[Table 10 about here.]

[Table 11 about here.]

[Figure 12 about here.]

Similarly, the most significant coefficients in the GAM model are primarily types of violent crimes. Interference with a public officer has a predicted 92% chance of ending in arrest. Crimes involving narcotics have a similarly high 94% chance. Interestingly, crimes where the suspect was reported as being armed have a very low probability of ending in arrest, at 4%. This appears to indicate that instigators of weapons violations are less likely to be aprehended following the crime. While the nonlinear terms are all highly significant, except for proportion of one person households, none of them have a very strong relationship with the dependent variable. This model had a ROC AUC of 0.839, indicating good predictive performance.

4.2.2 Responding Department

UCPD Versus CPD

[Table 12 about here.]

From this lasso regression model, it appears the UCPD is less likely to respond to incidents to the north and west, in areas where there are more families and blacks, and to domestic crimes. However it appears that officers from the university are more likely to respond to crimes reported where there is a higher proportion of any other race than black, and to crimes involving liquor law violations and harassment. This model had a ROC AUC of 0.872, indicating good predictive performance.

[Table 13 about here.]

[Table 14 about here.]

[Figure 13 about here.]

The estimates from the lasso closely match those from the GAM model. Crimes reported to have involved a domestic incident, liquor law violation, and deceptive practice are all significant. There is an estimated 57% probability of UCPD responding to a liquor law violation, estimated 0% probability of responding to an incident of deceptive practice, and a 0% chance of responding to a domestic incident. While the nonlinear terms are all highly significant, none of them have a very strong relationship with the dependent variable. This model had a ROC AUC of 0.869, indicating good predictive performance.

Both Departments Versus Each Department

[Table 15 about here.]

The lasso regression model indicates that both departments are less likely to respond to crimes toward the south and east, crimes located in areas with higher proportions of blacks, and crimes involving domestic incidents, deceptive practice, or liquor law violations. However, both departments are more likely to respond to reported crimes involving homicide, robbery, and to a lesser degree burglary and weapons violations. Crimes that were reported to have occurred in areas with higher populations of Asians or Latinos are also more likely to have both departments respond. This model had a ROC AUC of 0.836, indicating good predictive performance.

[Table 16 about here.]

[Table 17 about here.]

[Figure 14 about here.]

However, while the GAM model had a ROC AUC of 0.742, indicating good predictive performance, it appears that this model is not very accurate. Many of the linear estimates for this GAM model are wildly large and highly insignificant. This could be due, in part, to a number of variables specified as non-linear terms that should be linear terms. The smooth estimates for proportion Asian and proportion black both have estimated degrees of freedom close to 1, indicating they should be linear terms, not non-linear terms. While the nonlinear terms are all highly significant, except for proportion black, Asian, and Latino, none of them have a very strong relationship with the dependent variable.

4.2.3 Race

[Table 18 about here.]

[Table 19 about here.]

[Table 20 about here.]

[Figure 15 about here.]

[Table 21 about here.]

[Table 22 about here.]

[Table 23 about here.]

[Figure 16 about here.]

[Table 24 about here.]

[Table 25 about here.]

[Table 26 about here.]

[Figure 17 about here.]

[Table 27 about here.]

When predicting racial makeup of an area where a crime occurred, it appears that other demographic variables account for most of the variation in the outcome. Proportion Asian and black both have a significant negative relationship with the responding department being UCPD. However, this accompanies only a small change of a few tenths of a percentage less of each race in the areas where UCPD responds to reported crimes. For the proportion of whites, the only significant relationships are with the reported crime type being homicide or interference with a public officer. Both account for approximately 1% less white people in the areas where those types of crimes occur.

CHAPTER 5

DISCUSSION

It is clear that the actions of each department reflect the community for which they are policing. The UCPD is more likely to respond to a liquor law violation, but much less likely to make an arrest for it. While the UCPD handles an equivalent proportion of crimes involving narcotics as the CPD, they proportionally also made much fewer arrests. While both departments handle a large amount of thefts on their own, UCPD responds to a larger proportion of theft, and many other incidents such as missing property where a crime may have occurred. It appears that the UCPD does try to fit this "parental" role as referenced by Williams et al. (2016). Instead of being excessively punitive, as they could for petty crimes like liquor law violations, they appear to simply respond and nothing more in the vast majority of cases. Likely campus officers are administering verbal warnings for crimes like under-aged drinking, that university students are likely to engage in, but pose little threat to other community members.

However, there are some cases where UCPD officers appear to be equally or more punitive than their city counterparts. Officers from either department are highly likely to make an arrest when someone is interfering in their policing activities. Furthermore, when campus police respond to crimes of trespassing or sex crimes there is a higher likelihood of an arrest being made. Again, this seems to be indicative of differences in the communities each department polices. Especially at a private university, there are many amenities only accessible to the university community, and not the public at large. University officers may be more likely to punish people who are not affiliated with the university, trespassing on private university property, to reinforce the exclusivity of those spaces. Additionally, University members are unlikely to be sympathetic to these trespassers, who students and faculty are likely to see as taking resources that outsiders are not entitled to.

Sex crimes could be a similar situation, where stakeholders in the community view the issue as one warranting more putative measures. Serious sexual crimes such as sexual assault and rape are more likely to occur on college campuses than in the general population (Fisher, Cullen, and Turner 2000; DeKeseredy and Kelly 1993; Koss, Gidycz, and Wisniewski 1987). This alone could account for a higher proportion of arrests, but university officers may also be more likely to make an arrest. Bringing a suspect into custody can aid in the investigation and building a case against an offender, but also prohibit additional possible attacks from the offender, or even negative PR about the university. Certainly, the university not only wants to maintain an image of safety, but also to not appear to be protecting a possible sexual offender.

Relationships between race and reported crimes, also appear to be an artifact of the different populations each department polices. There is a strong positive relationship between the proportion of Asians and whites living in an area where a crime occurred and the likelihood that UCPD responded to a crime, while crimes happening in areas where blacks live are less likely to have campus officers respond. Considering that the UCPD is more likely to make an arrest in black neighborhoods, but typically respond alone to non-violent crimes, this suggests that UCPD officers are over-policing or being overly puntative when operating in predominantely black areas (Laniyonu 2018; Capers 2009). The university community is not representative of the surrounding community, with the tendency of a much higher proportion of whites and Asians, and lower proportion of blacks, to attend and work at the university than to live in the area surrounding the university (Results, Block, and Greenland 2016, @CMAP2019). As the UCPD does not police much outside of the Hyde Park / Kenwood area, they do not interact with as many black community members as CPD patrols who patrol the entire area, perhaps reinforcing racial biases.

[Table 28 about here.]

CHAPTER 6

CONCLUSION

Certainly we could expect the University of Chicago to prioritize the concerns of university members over the surrounding community. However, this becomes particularly problematic when these two communities differ so greatly. Whether purposeful or coincidental, the university's policing practices appear to be reinforcing discriminatory norms, which municipal police have been more effective at avoiding within the same jurisdiction. This provides some evidence that despite CPD's history with discriminatory policing practices, governmental oversight has been decently successful in steering the department away from such traditions.

It is unclear why the police departments private of universities have been given such wide latitude to operate under Illinois state law. Americans widely supported the restriction of private policing when it was performed by railroads, and considered them to be working against the public good (Spitzer and Scull 2011; Joh 2006). Yet, private universities are allowed to create their own police force, with the full authority of munincipal departments, with the only requirement being that officers must meet minimum training qualifications (110 ILCS 1020, n.d.). The UCPD overwhelmingly responds to reports of non-violent crimes reported to have occurred on or immediately surrounding campus. Rarely do university officers respond alone to reports of violent crimes farther off campus, instead relying on city police officers to handle more serious safety concerns in the surrounding area. If the focus of a campus police force is keep university members and their property safe, then it appears the UCPD can accomplish that goal without the far-reaching powers they currently possess.

In 2016, UCPD's police chief declined to confront the department's current issues with racial profiling, deflecting the issue by claiming that "two-thirds of investigatory stops are initiated by community members, rather than UCPD officers" (Newman 2016). While the UCPD appears to be addressing the needs of university community members, it remains unclear if they are listening to residents from surrounding communinties, who are more likely to be negatively impacted by the university's policing efforts. In 2017, 94% of people stopped by the University of Chicago Police Department were black, compared to 72% of all stops conducted by CPD (IDOT 2017). While the University of Chicago has made great progress towards becoming more transparent about their policing practices, it has only done so under the threat from community activists of forced transparency through a proposed state law (Newman 2016).

Illinois state law specifically states that private universities may use their police departments "for the protection of of students, employees, visitors and their property, and the property branches, ***and interests of the college or university***" (110 ILCS 1020, n.d.). Considering the university's racialized policing and their historical efforts to promote urban renewal at the expense of residents of color in Hyde Park, it seems the UCPD is as much a tool to protect the interests of university, as it is intended to protect university community members and their property. There remains a chance that community activists can persuade the university to curtail their own powers, just as they convinced university leaders to release data on the UCPD's practices. However, as long as these broad private policing powers for universities remain enshrined in state law, the risk of purposeful abuse or negelectful misuse of those to powers to sustain social stratification will continue to persist.

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CHAPTER 7

APPENDICES

Figures

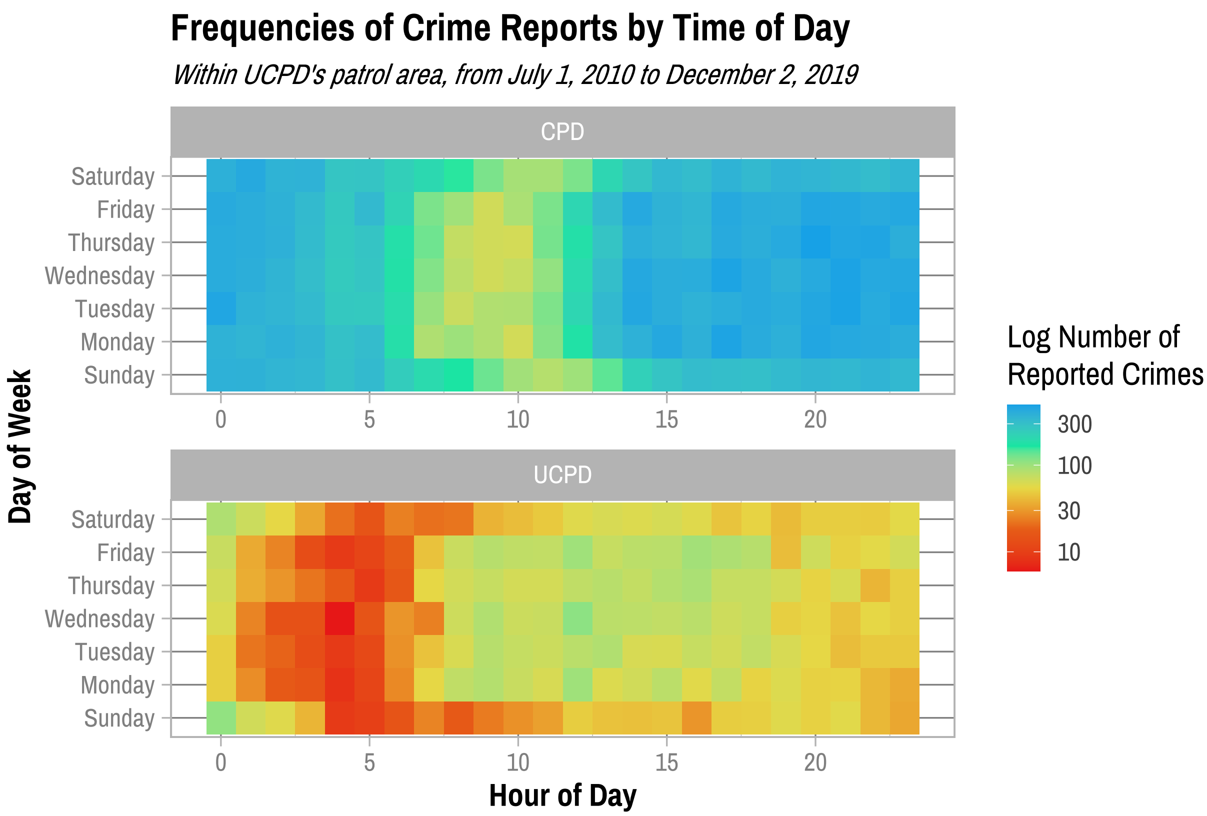

Figure 7.1: Frequencies of Crime Reports by Time of Day

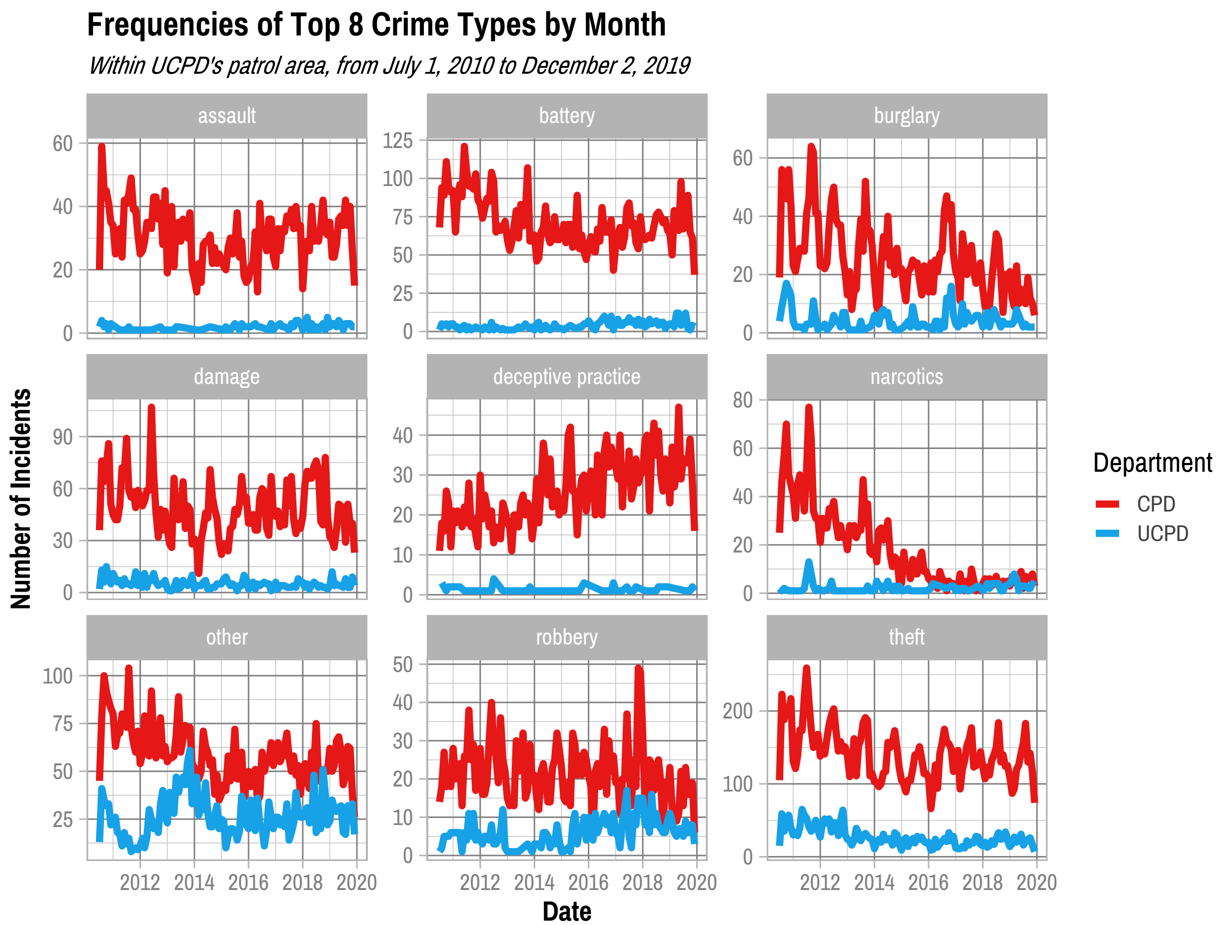

Figure 7.2: Frequencies of Crime Reports by Month

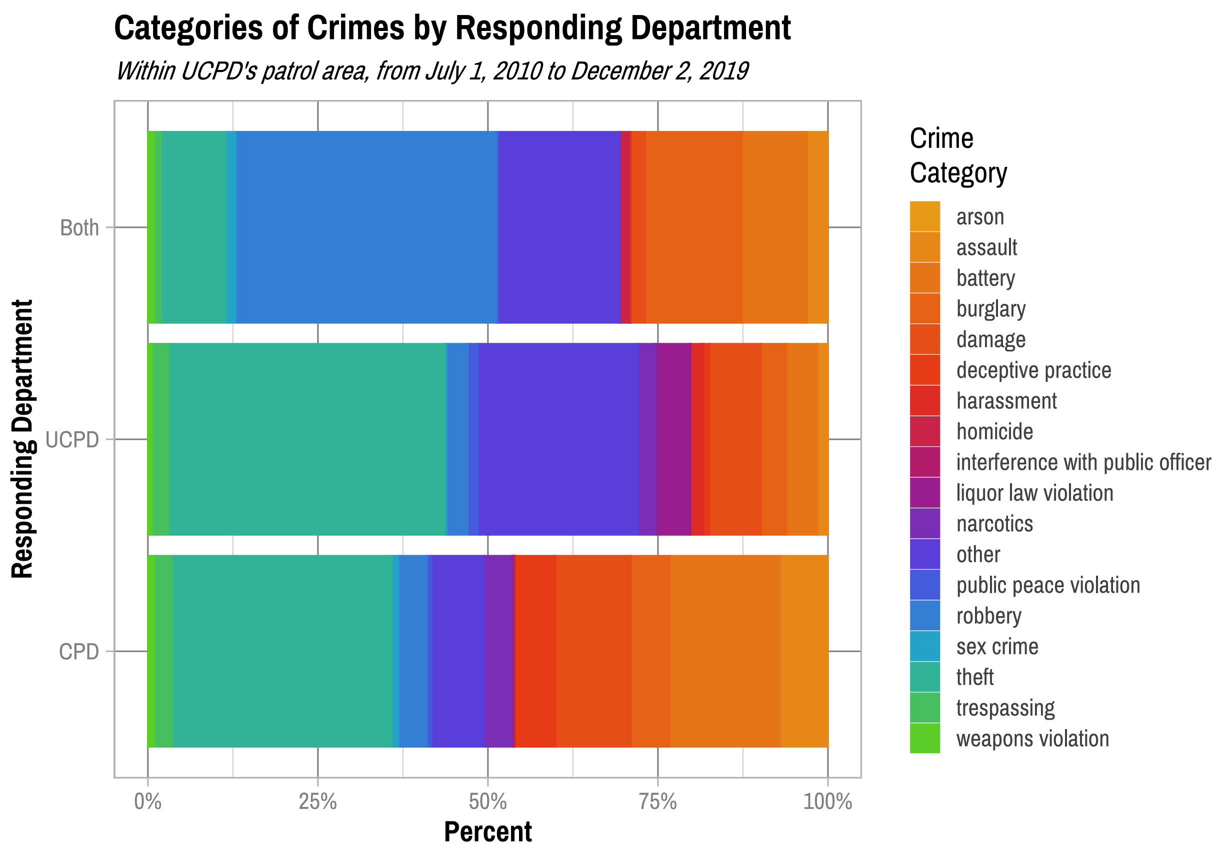

Figure 7.3: Categories of Crime Reports by Responding Department

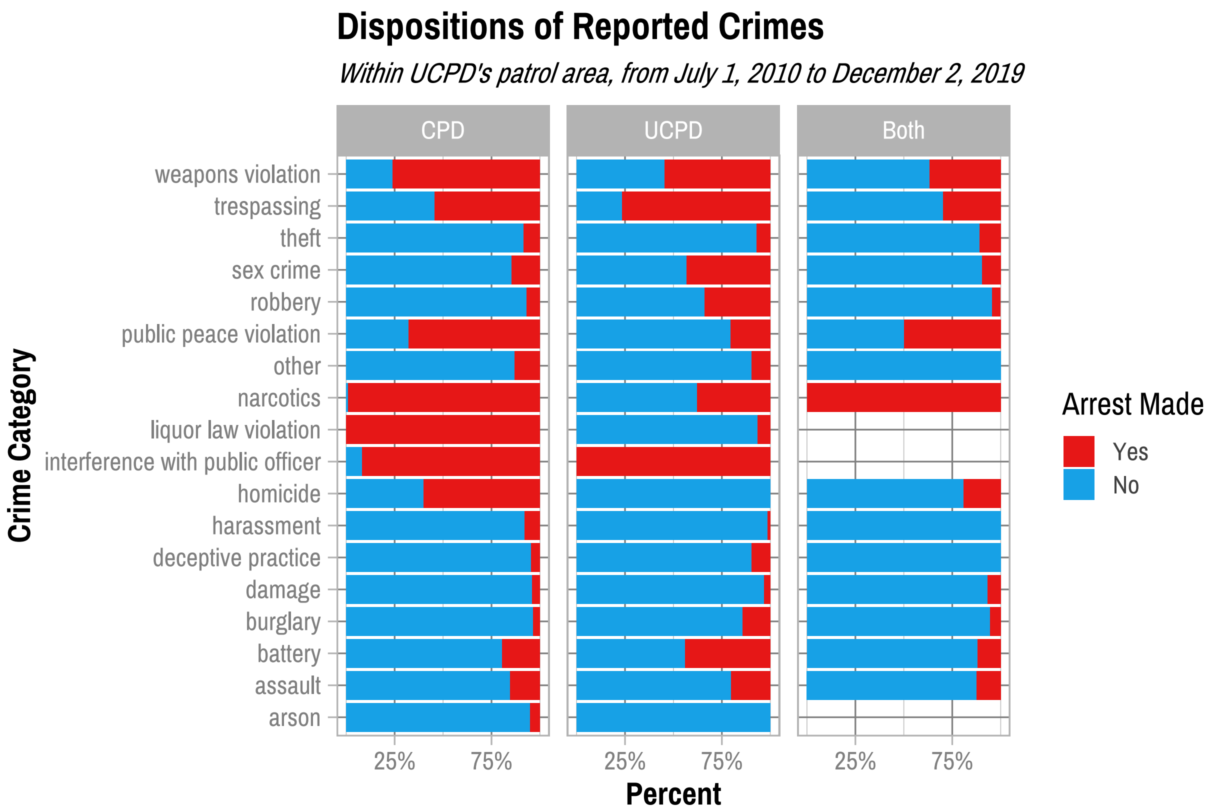

Figure 7.4: Dispositions of Reported Crimes

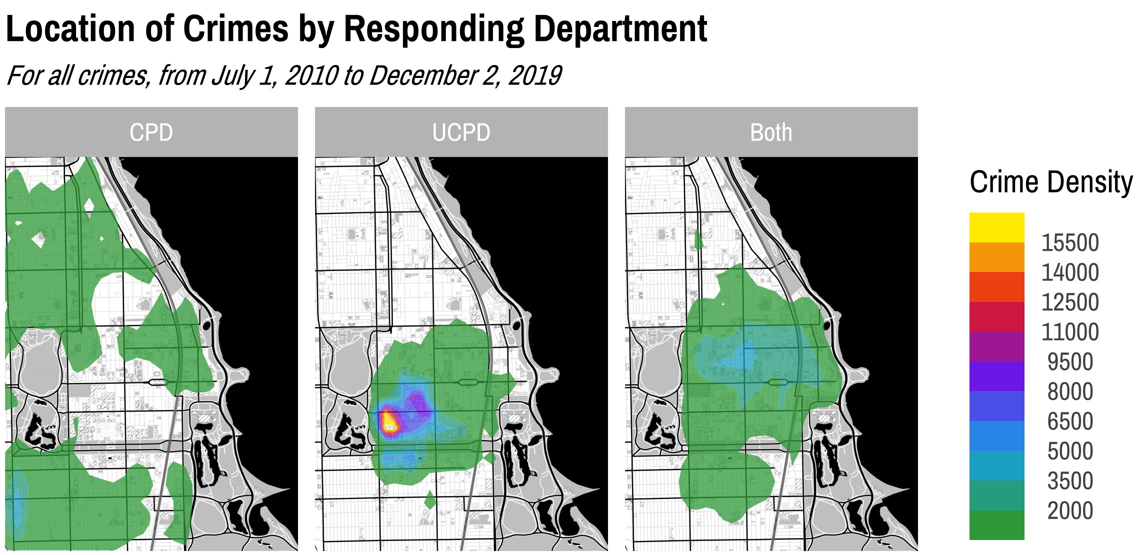

Figure 7.5: Location of Crimes by Responding Department

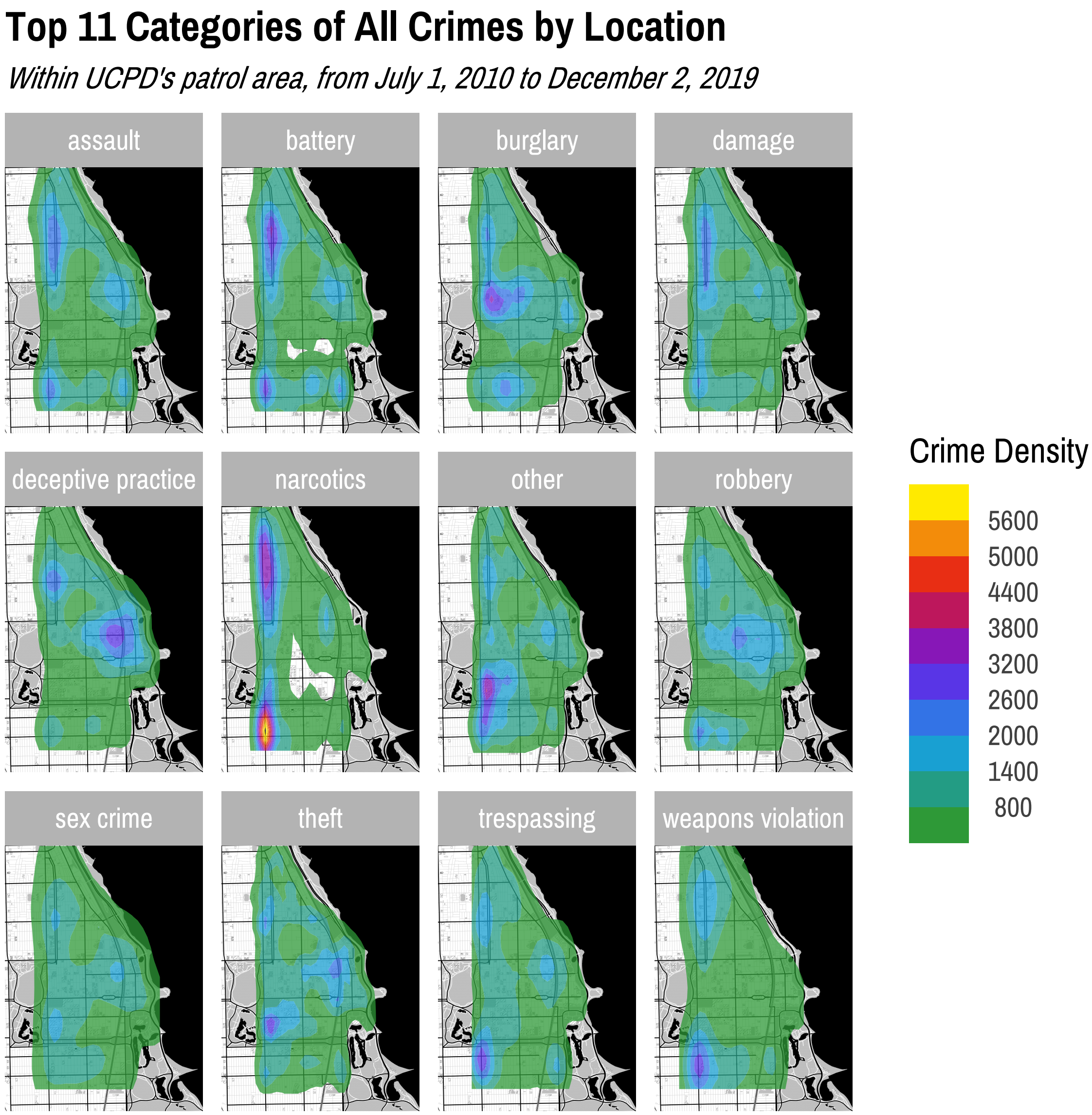

Figure 7.6: Location of Crimes by Category

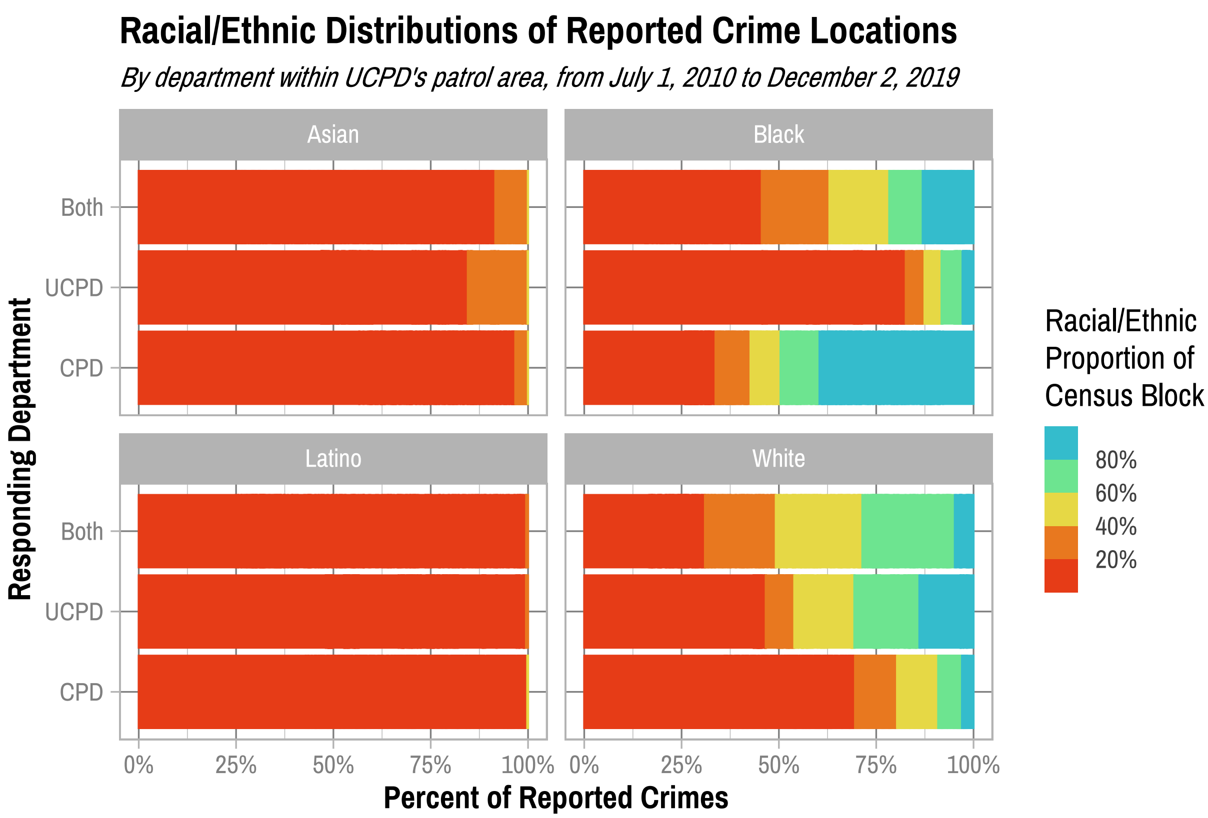

Figure 7.7: Racial/Ethnic Distributions of Department Responses

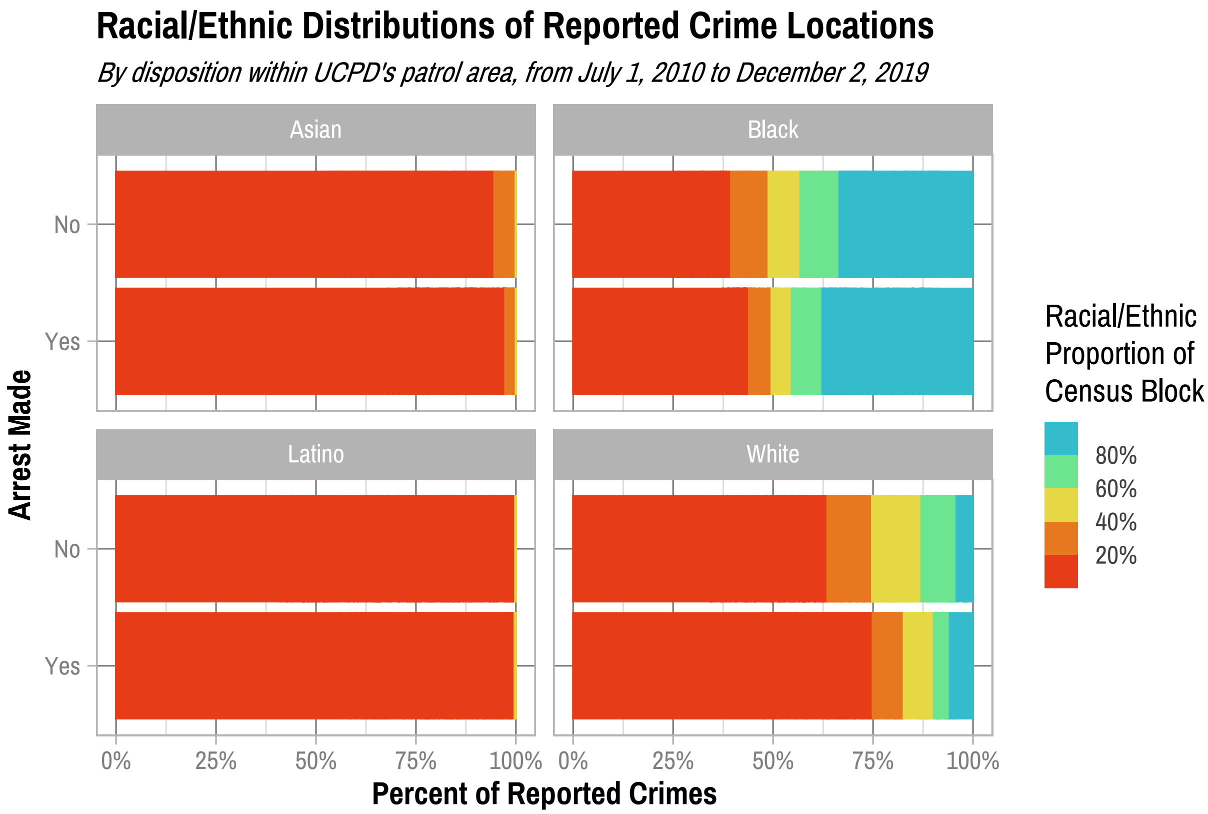

Figure 7.8: Racial/Ethnic Demographics of Report Dispositions

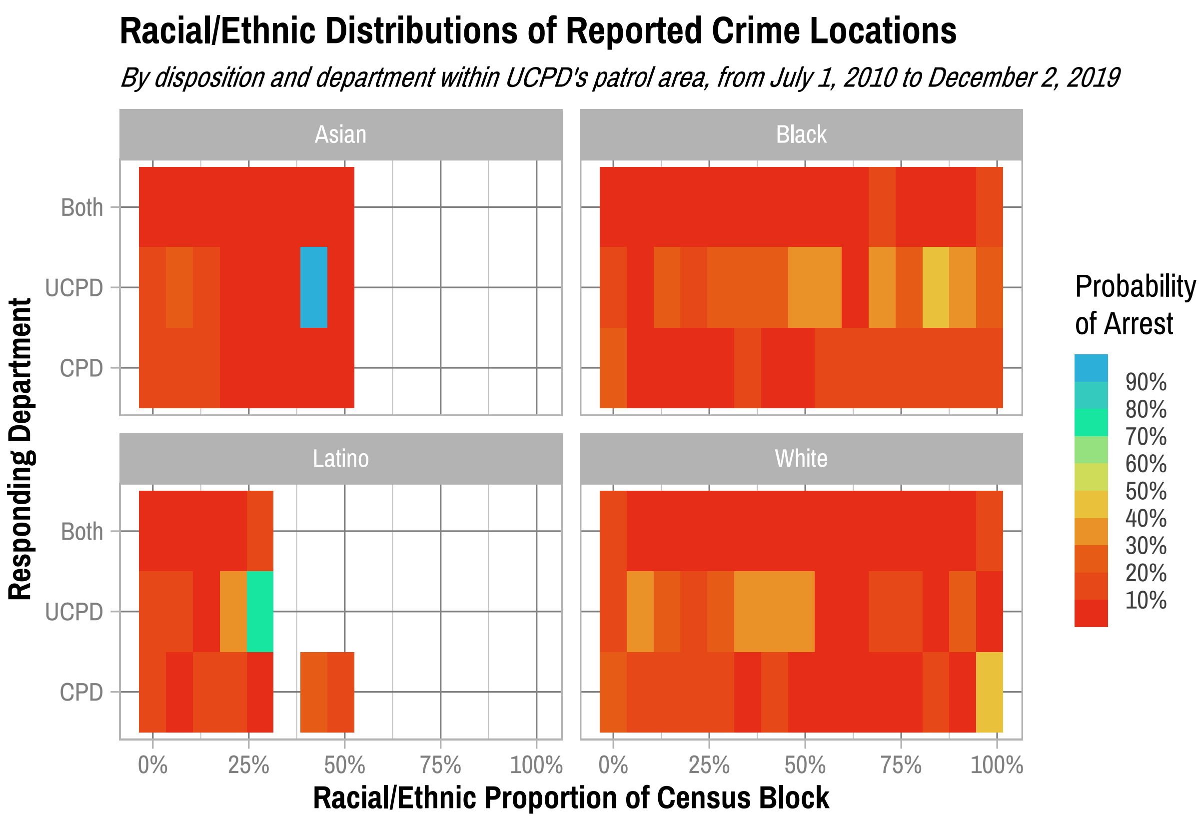

Figure 7.9: Racial/Ethnic Distributions of Report Dispositions by Department

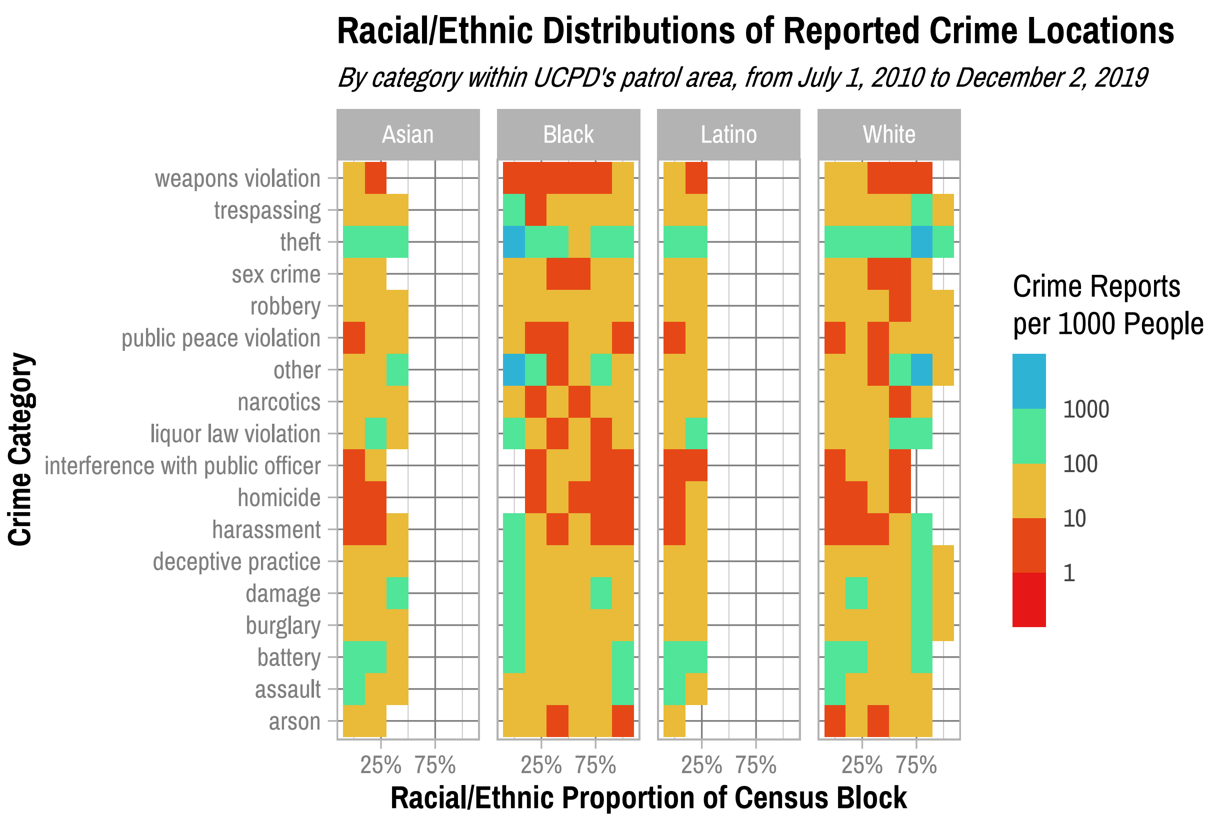

Figure 7.10: Racial/Ethnic Distributions of Report Categories

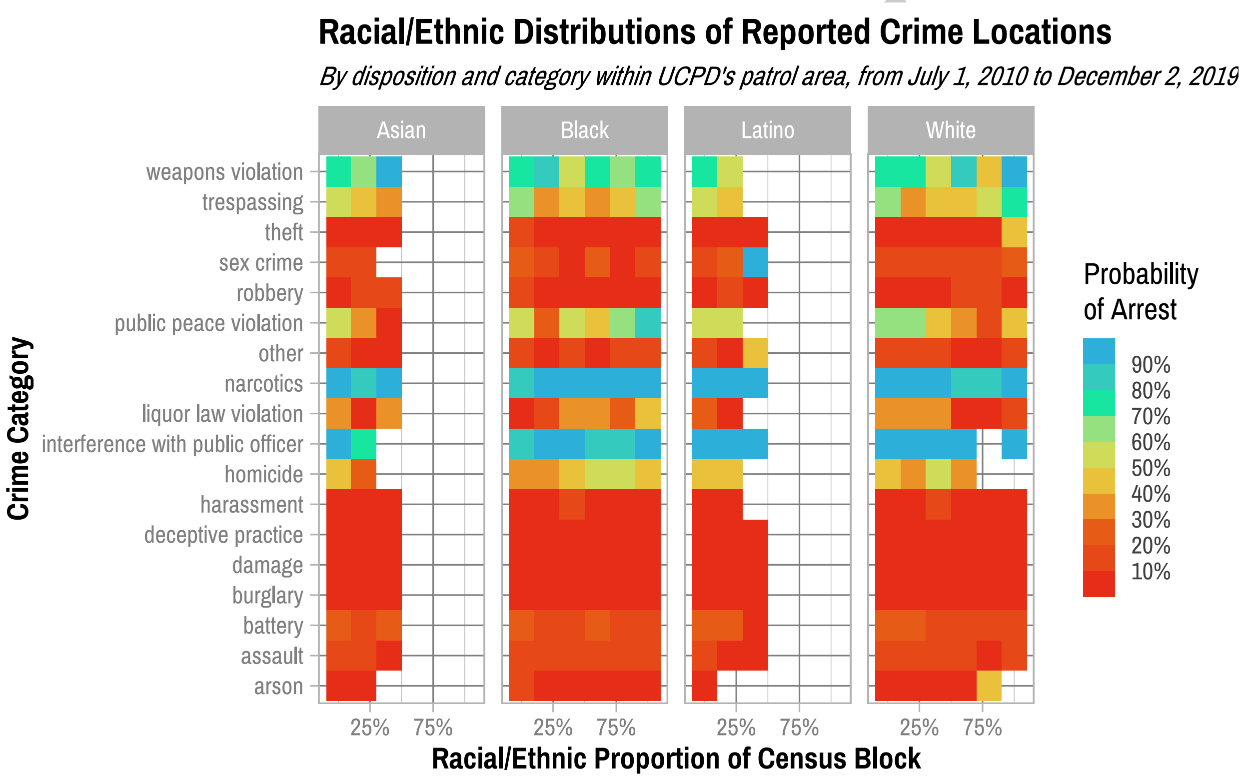

Figure 7.11: Racial/Ethnic Distributions of Report Category Dispositions

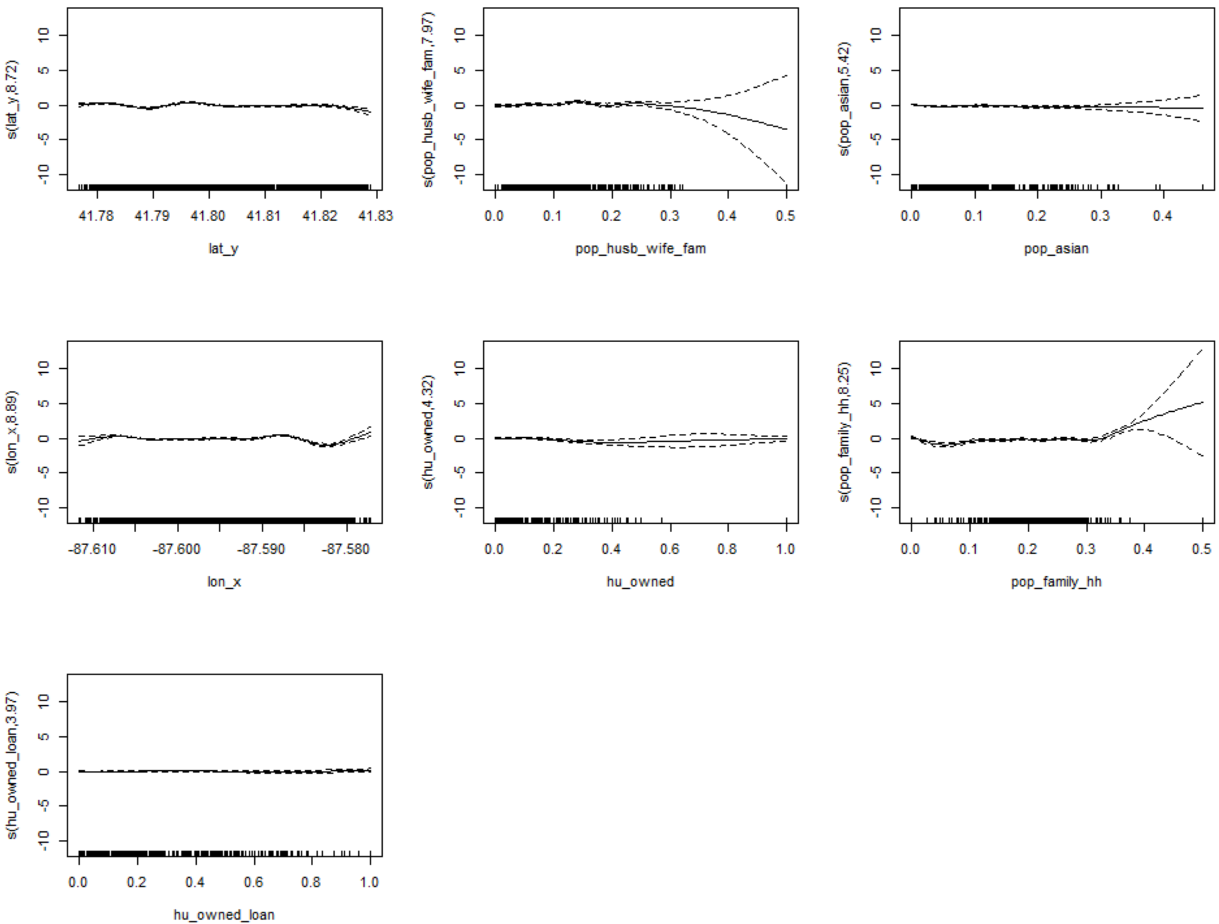

Figure 7.12: Arrest Model - Plots of Nonlinear GAM Covariates

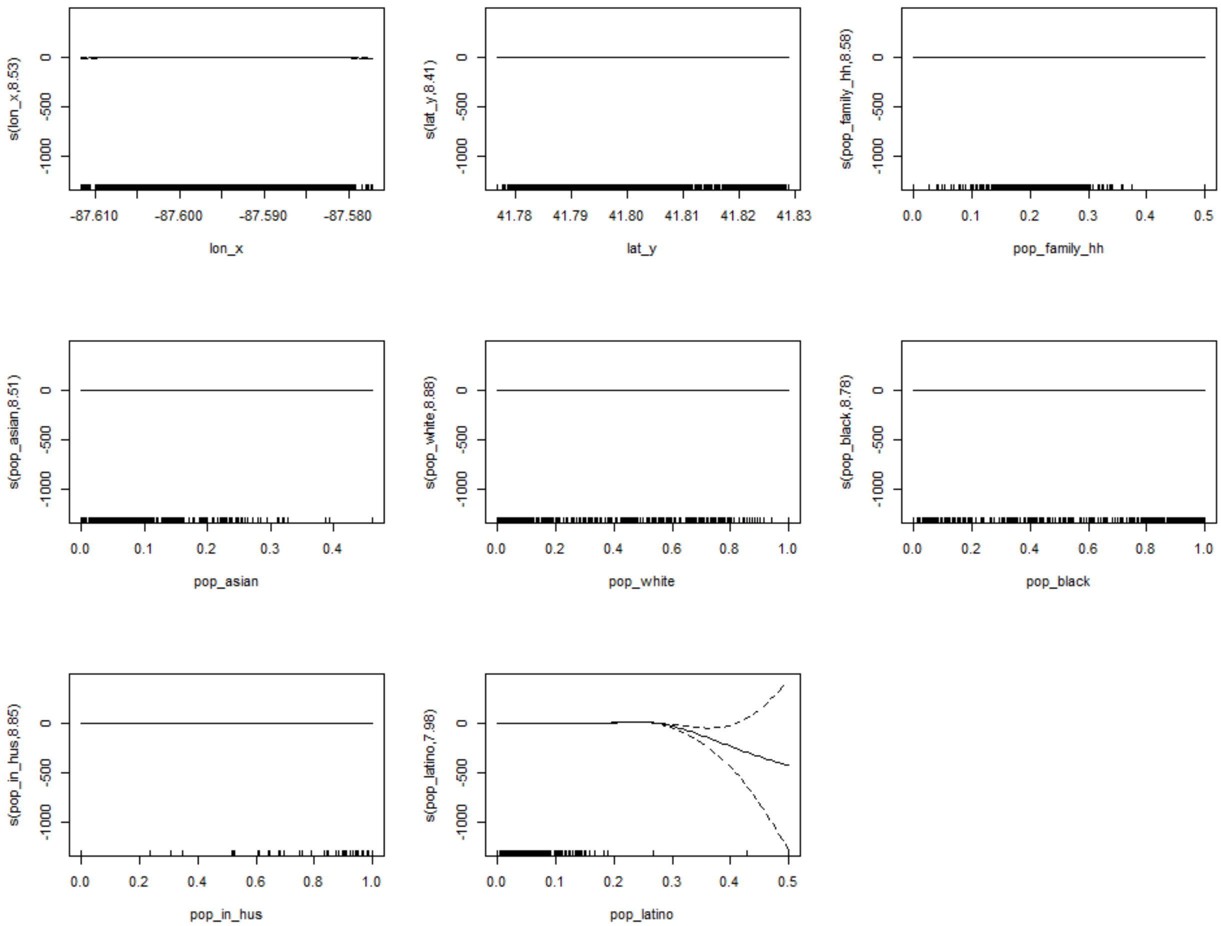

Figure 7.13: UCPD vs. CPD - Plots of Nonlinear GAM Covariates

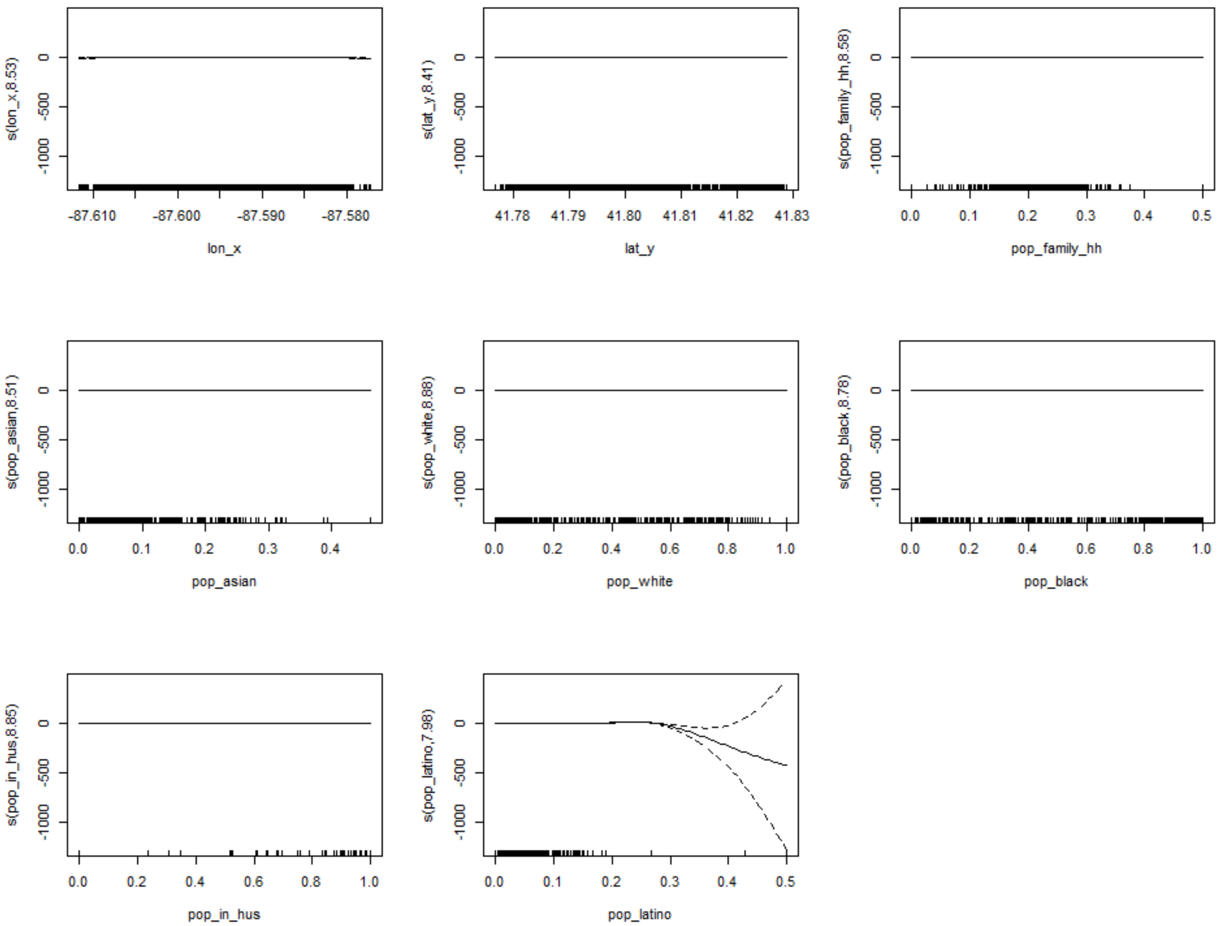

Figure 7.14: Both vs. Each - Plots of Nonlinear GAM Covariates

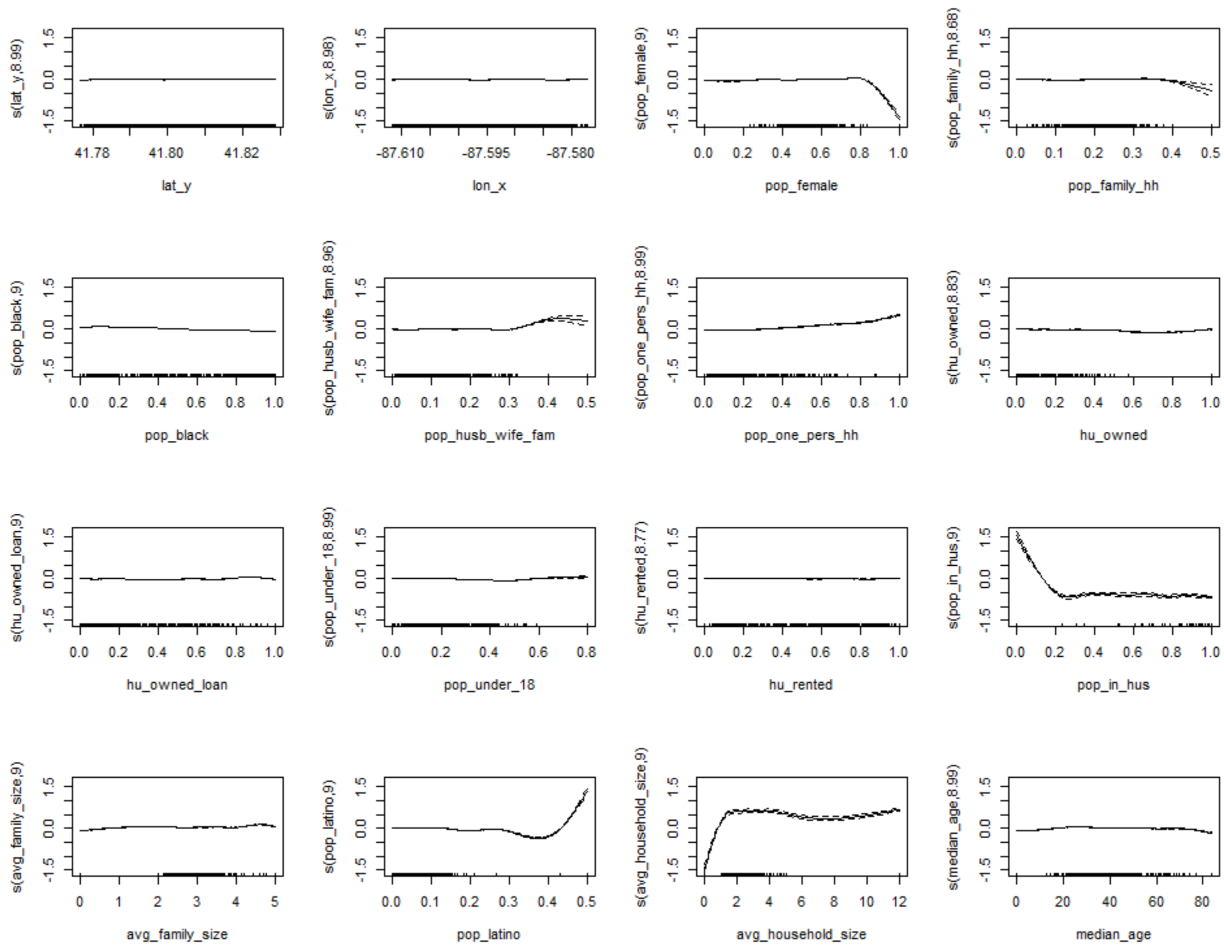

Figure 7.15: Asian Model - Plots of Nonlinear GAM Covariates

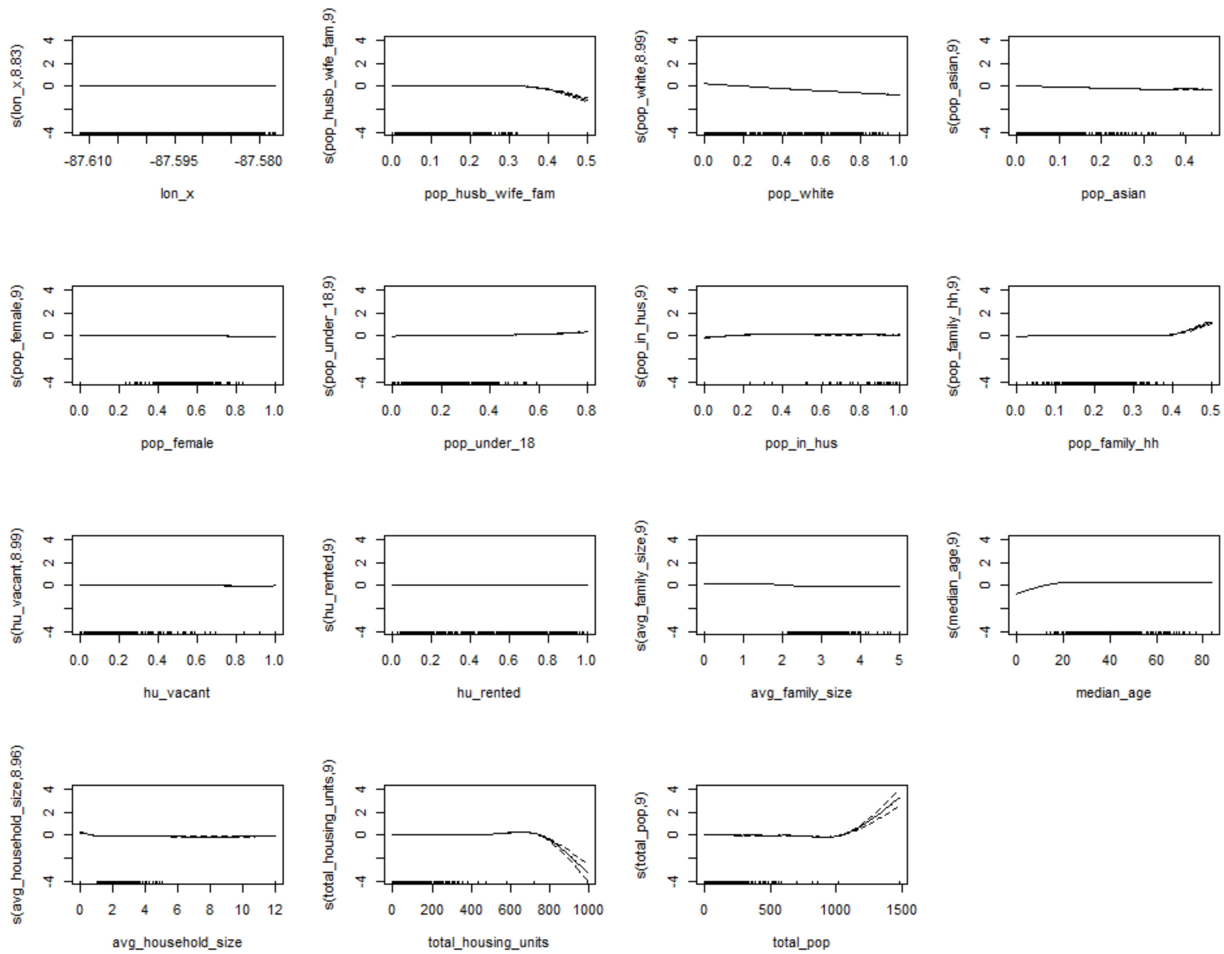

Figure 7.16: Black Model - Plots of Nonlinear GAM Covariates

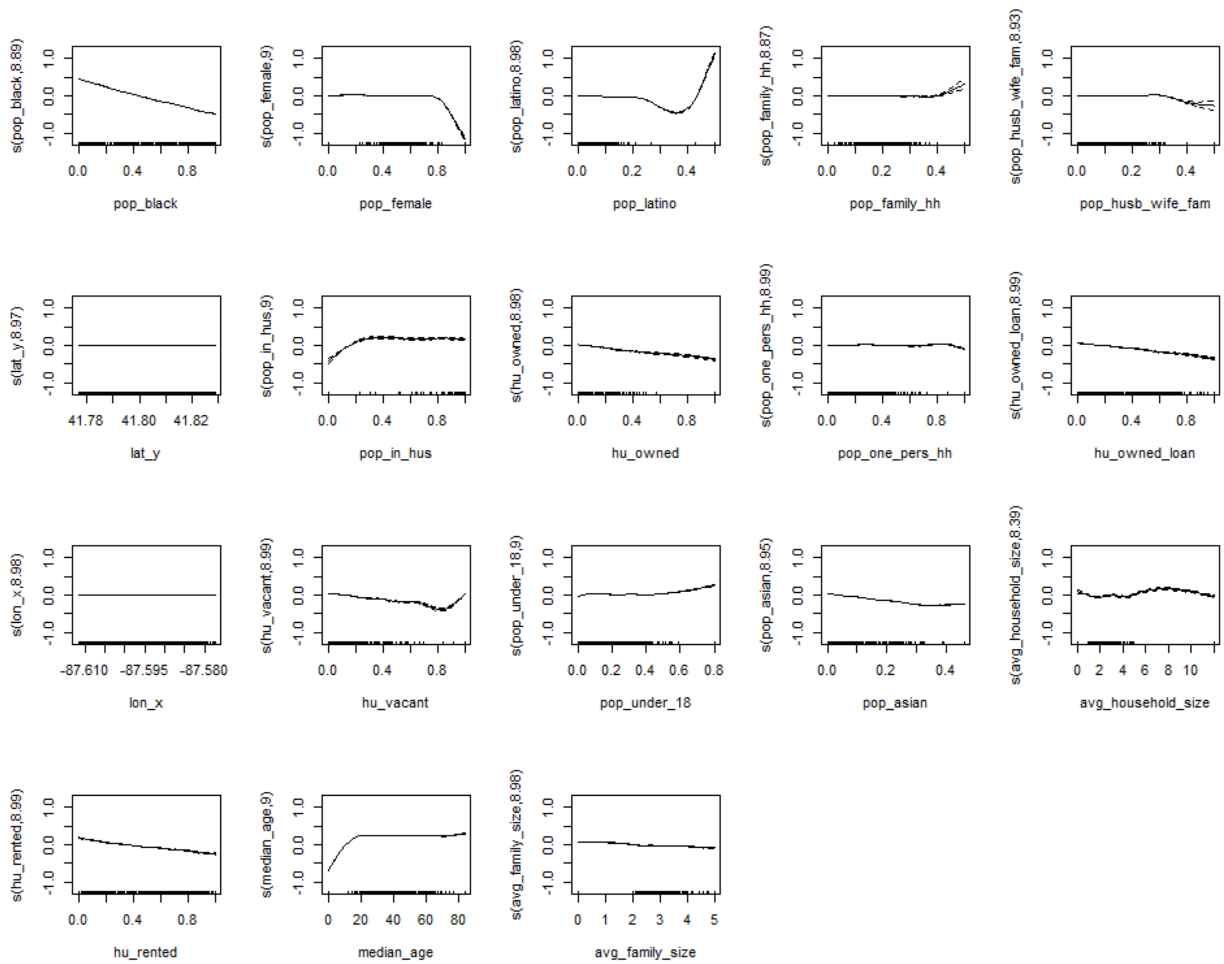

Figure 7.17: White Model - Plots of Nonlinear GAM Covariates

Tables

Table 7.1: Categorical Variables

skim_variable	n_missing	complete_rate	ordered	n_unique	top_counts
id	78	1.000	FALSE	769145	18-: 2, A00: 2, B00: 2, B00: 2
case_number	7972	0.990	FALSE	760374	HY3: 4, HZ4: 4, JA2: 4, HT5: 3
responding_dept	5	1.000	FALSE	3	cpd: 759539, ucp: 7522, bot: 2164
reporting_dept	0	1.000	FALSE	2	cpd: 760324, ucp: 8906
primary_type	0	1.000	FALSE	18	the: 167026, bat: 163686, dam: 83409, nar: 62008
description	1	1.000	FALSE	8375	dom: 86660, sim: 84451, $50: 61210, to : 44853
location_description	3681	0.995	FALSE	996	str: 176155, apa: 137314, res: 136059, sid: 78357
day_of_week	0	1.000	FALSE	7	wed: 112163, fri: 111581, tue: 111118, thu: 110729
month	0	1.000	FALSE	12	jul: 78676, aug: 76577, sep: 70474, oct: 70089
block_id	12	1.000	FALSE	9052	170: 2645, 170: 2149, 170: 1881, 170: 1763

Table 7.2: Binary Variables

skim_variable	n_missing	complete_rate	mean	count
arrest	5	1	0.252	FAL: 575195, TRU: 194030
domestic	2	1	0.196	FAL: 618224, TRU: 151004
armed	2	1	0.023	FAL: 751247, TRU: 17981
aggravated	2	1	0.070	FAL: 715763, TRU: 53465
attempted	2	1	0.011	FAL: 760555, TRU: 8673
weekend	0	1	0.277	FAL: 555791, TRU: 213439
in_ucpd_bound	0	1	0.077	FAL: 710242, TRU: 58988

Table 7.3: Continuous Variables

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
time	0	1	12.245	7.653	0.000	4.517	14.000	19.000	23.983	<U+2587><U+2585><U+2583><U+2587><U+2587>
year	0	1	2014.317	2.779	2010.000	2012.000	2014.000	2017.000	2019.000	<U+2587><U+2587><U+2586><U+2586><U+2586>
avg_family_size	12	1	2.750	1.537	0.000	2.500	3.120	3.670	14.000	<U+2585><U+2587><U+2581><U+2581><U+2581>
avg_household_size	12	1	2.251	1.330	0.000	1.670	2.480	3.110	14.000	<U+2587><U+2585><U+2581><U+2581><U+2581>
median_age	12	1	29.063	16.903	0.000	22.000	30.800	39.500	93.500	<U+2583><U+2587><U+2585><U+2581><U+2581>
total_housing_units	12	1	42.116	64.457	0.000	7.000	23.000	48.000	993.000	<U+2587><U+2581><U+2581><U+2581><U+2581>
hu_occupied	12	1	0.654	0.345	0.000	0.552	0.788	0.907	1.000	<U+2583><U+2581><U+2581><U+2585><U+2587>
hu_owned	12	1	0.064	0.098	0.000	0.000	0.022	0.095	1.000	<U+2587><U+2581><U+2581><U+2581><U+2581>
hu_owned_loan	12	1	0.165	0.198	0.000	0.000	0.101	0.258	1.000	<U+2587><U+2582><U+2581><U+2581><U+2581>
hu_rented	12	1	0.425	0.301	0.000	0.154	0.455	0.656	1.000	<U+2587><U+2585><U+2587><U+2586><U+2583>
hu_vacant	12	1	0.172	0.187	0.000	0.000	0.126	0.257	1.000	<U+2587><U+2583><U+2581><U+2581><U+2581>
total_pop	12	1	85.071	121.708	0.000	15.000	55.000	102.000	1483.000	<U+2587><U+2581><U+2581><U+2581><U+2581>
pop_asian	12	1	0.014	0.071	0.000	0.000	0.000	0.000	1.000	<U+2587><U+2581><U+2581><U+2581><U+2581>
pop_black	12	1	0.709	0.413	0.000	0.294	0.961	1.000	1.000	<U+2583><U+2581><U+2581><U+2581><U+2587>
pop_family_hh	12	1	0.183	0.103	0.000	0.152	0.218	0.250	0.500	<U+2583><U+2582><U+2587><U+2581><U+2581>
pop_female	12	1	0.448	0.227	0.000	0.441	0.529	0.584	1.000	<U+2582><U+2581><U+2587><U+2582><U+2581>
pop_husb_wife_fam	12	1	0.059	0.059	0.000	0.000	0.050	0.087	0.500	<U+2587><U+2582><U+2581><U+2581><U+2581>
pop_in_hus	12	1	0.806	0.390	0.000	1.000	1.000	1.000	1.000	<U+2582><U+2581><U+2581><U+2581><U+2587>
pop_islander	12	1	0.000	0.003	0.000	0.000	0.000	0.000	0.250	<U+2587><U+2581><U+2581><U+2581><U+2581>
pop_latino	12	1	0.056	0.167	0.000	0.000	0.000	0.023	1.000	<U+2587><U+2581><U+2581><U+2581><U+2581>
pop_latino_asian	12	1	0.000	0.004	0.000	0.000	0.000	0.000	0.200	<U+2587><U+2581><U+2581><U+2581><U+2581>
pop_latino_black	12	1	0.005	0.021	0.000	0.000	0.000	0.000	1.000	<U+2587><U+2581><U+2581><U+2581><U+2581>
pop_latino_islander	12	1	0.000	0.000	0.000	0.000	0.000	0.000	0.059	<U+2587><U+2581><U+2581><U+2581><U+2581>
pop_latino_native	12	1	0.001	0.007	0.000	0.000	0.000	0.000	0.429	<U+2587><U+2581><U+2581><U+2581><U+2581>
pop_latino_other_race	12	1	0.027	0.099	0.000	0.000	0.000	0.000	1.000	<U+2587><U+2581><U+2581><U+2581><U+2581>
pop_latino_two_plus_races	12	1	0.003	0.018	0.000	0.000	0.000	0.000	1.000	<U+2587><U+2581><U+2581><U+2581><U+2581>
pop_latino_white	12	1	0.020	0.075	0.000	0.000	0.000	0.000	1.000	<U+2587><U+2581><U+2581><U+2581><U+2581>
pop_male	12	1	0.376	0.198	0.000	0.357	0.431	0.488	1.000	<U+2582><U+2582><U+2587><U+2581><U+2581>
pop_native	12	1	0.002	0.011	0.000	0.000	0.000	0.000	0.714	<U+2587><U+2581><U+2581><U+2581><U+2581>
pop_one_pers_hh	12	1	0.120	0.157	0.000	0.016	0.080	0.156	1.000	<U+2587><U+2581><U+2581><U+2581><U+2581>
pop_other_race	12	1	0.027	0.099	0.000	0.000	0.000	0.000	1.000	<U+2587><U+2581><U+2581><U+2581><U+2581>
pop_rural	12	1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	<U+2581><U+2581><U+2587><U+2581><U+2581>
pop_two_plus_races	12	1	0.015	0.051	0.000	0.000	0.000	0.016	1.000	<U+2587><U+2581><U+2581><U+2581><U+2581>
pop_under_18	12	1	0.213	0.150	0.000	0.077	0.234	0.320	0.833	<U+2586><U+2587><U+2583><U+2581><U+2581>
pop_urban	12	1	0.824	0.381	0.000	1.000	1.000	1.000	1.000	<U+2582><U+2581><U+2581><U+2581><U+2587>
pop_urban_areas	12	1	0.824	0.381	0.000	1.000	1.000	1.000	1.000	<U+2582><U+2581><U+2581><U+2581><U+2587>
pop_urban_clusters	12	1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	<U+2581><U+2581><U+2587><U+2581><U+2581>
pop_white	12	1	0.056	0.155	0.000	0.000	0.000	0.016	1.000	<U+2587><U+2581><U+2581><U+2581><U+2581>
lon_x	0	1	-87.621	0.040	-102.282	-87.650	-87.622	-87.599	-80.791	<U+2581><U+2581><U+2581><U+2587><U+2581>
lat_y	0	1	41.776	0.028	39.879	41.753	41.771	41.795	43.429	<U+2581><U+2581><U+2587><U+2581><U+2581>

Table 7.4: Date-time Variables

skim_variable	n_missing	complete_rate	min	max	median	n_unique
date	0	1	2010-07-01	2019-12-02 23:59:00	2014-08-04 20:17:30	487977

Table 7.5: Counts of Reports by Department and Category

primary_type	CPD	UCPD	Both
arson	38	2	NA
assault	3473	113	64
battery	8040	334	199
burglary	2828	271	297
damage	5479	557	43
deceptive practice	2959	62	4
harassment	74	139	4
homicide	50	1	26
interference with public officer	85	6	NA
liquor law violation	17	370	NA
narcotics	2050	193	2
other	3830	1718	371
public peace violation	332	107	6
robbery	2085	229	799
sex crime	472	23	31
theft	16038	2967	198
trespassing	1277	179	20
weapons violation	462	42	19
TOTAL	49589	7313	2083

Table 7.6: Mean Values for Crimes in UCPD's Patrol Area

Variable	Mean
arrest	0.156
domestic	0.126
armed	0.025
aggravated	0.044
attempted	0.014
time	12.793
weekend	0.258
year	2014.395
in_ucpd_bound	1.000
avg_family_size	2.013
avg_household_size	1.567
median_age	26.622
total_housing_units	83.496
hu_occupied	0.607
hu_owned	0.044
hu_owned_loan	0.171
hu_rented	0.392
hu_vacant	0.113
total_pop	159.350
pop_asian	0.043
pop_black	0.465
pop_family_hh	0.150
pop_female	0.397
pop_husb_wife_fam	0.074
pop_in_hus	0.683
pop_islander	0.000
pop_latino	0.029
pop_latino_asian	0.000
pop_latino_black	0.005
pop_latino_islander	0.000
pop_latino_native	0.000
pop_latino_other_race	0.007
pop_latino_two_plus_races	0.003
pop_latino_white	0.013
pop_male	0.348
pop_native	0.001
pop_one_pers_hh	0.158
pop_other_race	0.009
pop_rural	0.000
pop_two_plus_races	0.024
pop_under_18	0.141
pop_urban	0.745
pop_urban_areas	0.745

Table 7.7: R Packages

Name	Version	From
beachball	0.1.0	github.com/tonofshell
Cairo	1.5.10	CRAN
caret	6.0.85	CRAN
cowpoke	0.1.0	github.com/tonofshell
doParallel	1.0.15	CRAN
extrafont	0.17	CRAN
ggmap	3.0.0	CRAN
glmnet	3.0.2	CRAN
HDCI	1.0.2	CRAN
jsonlite	1.6.1	CRAN
kableExtra	1.1.0	CRAN
knitr	1.28	CRAN
lubridate	1.7.4	CRAN
mgcv	1.8.31	CRAN
pROC	1.16.1	CRAN
rmarkdown	2.1	CRAN
RSocrata	1.7.10.6	CRAN
scales	1.1.0	CRAN
sf	0.8.1	CRAN
skimr	2.1	CRAN
tictoc	1.0	CRAN
tidycensus	0.9.6	CRAN
tidyverse	1.3.0	CRAN
treemapify	2.5.3	CRAN

Table 7.8: Categories of Crime Reports by Responding Department

Crime Category	CPD	UCPD	Both
arson	0%	0%	NA
assault	7%	2%	3%
battery	16%	5%	10%
burglary	6%	4%	14%
damage	11%	8%	2%
deceptive practice	6%	1%	0%
harassment	0%	2%	0%
homicide	0%	0%	1%
interference with public officer	0%	0%	NA
liquor law violation	0%	5%	NA
narcotics	4%	3%	0%
other	8%	23%	18%
public peace violation	1%	1%	0%
robbery	4%	3%	38%
sex crime	1%	0%	1%
theft	32%	41%	10%
trespassing	3%	2%	1%
weapons violation	1%	1%	1%

Table 7.9: Arrest Model Coefficient Estimates - Lasso Regression

Variable	Est.
(Intercept)	60.011
primary_type.narcotics	4.426
primary_type.interference with public officer	3.557
primary_type.weapons violation	2.847
primary_type.trespassing	2.204
pop_asian	-2.017
primary_type.public peace violation	1.973
pop_husb_wife_fam	1.953
primary_type.homicide	1.470
lat_y	-1.446
primary_type.damage	-0.828
hu_owned	-0.779
primary_type.burglary	-0.636
primary_type.deceptive practice	-0.573
primary_type.battery	0.559
primary_type.theft	-0.336
pop_one_pers_hh	-0.286
aggravated.TRUE	0.277
hu_owned_loan	-0.248
primary_type.assault	0.222
armed.TRUE	-0.149
hu_vacant	0.102
primary_type.robbery	-0.078
avg_family_size	-0.042
primary_type.sex crime	0.040
month.mar	0.019
responding_dept.cpd	0.012
primary_type.harassment	-0.010
time	0.003
date	0.000
total_pop	0.000

Table 7.10: Arrest Model Linear Coefficient Estimates - GAM

Variable	Est.	Std. Error	Z Value	P Value
(Intercept)	-2.786	0.736	-3.787	0.000
primary_typeassault	0.975	0.737	1.322	0.186
primary_typebattery	1.294	0.736	1.758	0.079
primary_typeburglary	-0.263	0.741	-0.355	0.723
primary_typedamage	-0.418	0.739	-0.565	0.572
primary_typedeceptive practice	-0.324	0.742	-0.437	0.662
primary_typeharassment	-0.511	0.865	-0.590	0.555
primary_typehomicide	2.675	0.783	3.415	0.001
primary_typeinterference with public officer	5.252	0.871	6.031	0.000
primary_typeliquor law violation	1.034	0.757	1.367	0.172
primary_typenarcotics	5.517	0.742	7.434	0.000
primary_typeother	0.801	0.737	1.087	0.277
primary_typepublic peace violation	2.817	0.744	3.788	0.000
primary_typerobbery	0.483	0.741	0.651	0.515
primary_typesex crime	1.091	0.747	1.461	0.144
primary_typetheft	0.227	0.736	0.308	0.758
primary_typetrespassing	3.038	0.738	4.116	0.000
primary_typeweapons violation	3.764	0.744	5.060	0.000
aggravatedTRUE	0.327	0.061	5.323	0.000
armedTRUE	-0.428	0.152	-2.812	0.005

Table 7.11: Arrest Model Smooth Coefficient Estimates - GAM

Variable	Est. Df	Chi Sq.	P Value
s(pop_asian)	3.804	66.364	0.000
s(pop_husb_wife_fam)	8.337	56.245	0.000
s(lat_y)	8.780	189.897	0.000
s(hu_owned)	7.941	24.806	0.002
s(pop_one_pers_hh)	1.009	3.855	0.051
s(hu_owned_loan)	7.658	34.673	0.000
s(hu_vacant)	8.761	90.288	0.000

Table 7.12: UCPD vs. CPD Model Coefficient Estimates - Lasso Regression

Variable	Est.
(Intercept)	-3543.027
lon_x	-64.122
lat_y	-49.665
pop_family_hh	-4.773
pop_asian	3.659
primary_type.liquor law violation	3.474
primary_type.harassment	2.113
pop_white	1.852
domestic.TRUE	-1.579
primary_type.other	1.484
pop_latino	1.300
primary_type.deceptive practice	-1.069
pop_black	-1.004
primary_type.assault	-0.617
pop_in_hus	-0.490
primary_type.public peace violation	0.407
pop_one_pers_hh	0.368
aggravated.TRUE	-0.287
primary_type.theft	0.272
primary_type.sex crime	-0.218
primary_type.narcotics	-0.217
primary_type.battery	-0.182
hu_vacant	-0.107
month.jun	-0.093
month.dec	-0.056
month.nov	0.052
avg_family_size	-0.036
avg_household_size	-0.030
weekend.TRUE	-0.027
month.oct	0.002
date	0.000

Table 7.13: UCPD vs. CPD Linear Coefficient Estimates - GAM

Variable	Est.	Std. Error	Z Value	P Value
(Intercept)	-3.667	1.225	-2.992	0.003
primary_typeassault	-1.299	0.961	-1.351	0.177
primary_typebattery	-0.572	0.955	-0.599	0.549
primary_typeburglary	-0.678	0.956	-0.709	0.478
primary_typedamage	-0.632	0.954	-0.662	0.508
primary_typedeceptive practice	-2.483	0.966	-2.571	0.010
primary_typeharassment	1.914	1.001	1.912	0.056
primary_typehomicide	-85.991	11032629.281	0.000	1.000
primary_typeinterference with public officer	-0.079	1.130	-0.070	0.944
primary_typeliquor law violation	3.951	1.017	3.884	0.000
primary_typenarcotics	-0.061	0.959	-0.063	0.949
primary_typeother	1.098	0.953	1.152	0.250
primary_typepublic peace violation	1.118	0.971	1.151	0.250
primary_typerobbery	-0.089	0.957	-0.093	0.926
primary_typesex crime	-2.092	0.994	-2.105	0.035
primary_typetheft	-0.599	0.952	-0.629	0.530
primary_typetrespassing	-0.337	0.961	-0.351	0.725
primary_typeweapons violation	0.239	0.982	0.243	0.808
domesticTRUE	-2.337	0.141	-16.522	0.000

Table 7.14: UCPD vs. CPD Smooth Coefficient Estimates - GAM

Variable	Est. Df	Chi Sq.	P Value
s(lon_x)	8.812	1214.799	0
s(lat_y)	8.085	1803.070	0
s(pop_family_hh)	8.300	98.541	0
s(pop_asian)	8.386	64.780	0
s(pop_white)	8.722	36.337	0
s(pop_latino)	8.000	106.972	0
s(pop_black)	8.642	75.161	0
s(pop_in_hus)	8.908	100.549	0

Table 7.15: Both vs. Each Model Coefficient Estimates - Lasso Regression

Variable	Est.
(Intercept)	1443.750
lat_y	-21.004
lon_x	6.651
primary_type.homicide	4.525
primary_type.robbery	2.781
pop_latino	1.954
domestic.TRUE	-1.942
primary_type.burglary	1.734
primary_type.other	1.679
primary_type.deceptive practice	-1.375
primary_type.weapons violation	1.208
aggravated.TRUE	1.193
pop_asian	1.124
primary_type.liquor law violation	-1.047
pop_black	-1.045
hu_owned	1.033
primary_type.sex crime	0.997
primary_type.battery	0.607
pop_white	0.592
pop_family_hh	-0.513
arrest.TRUE	-0.494
pop_in_hus	0.394
primary_type.theft	-0.342
primary_type.damage	-0.327
hu_rented	0.275
armed.TRUE	0.218
avg_family_size	0.153
month.feb	-0.144
day_of_week.sat	0.120
month.jun	0.085
day_of_week.tue	0.074
hu_owned_loan	0.073
hu_vacant	-0.040
day_of_week.mon	-0.036
month.oct	0.024
pop_one_pers_hh	0.016
time	0.008
month.dec	-0.001
date	0.000

Table 7.16: Both vs. Each Linear Coefficient Estimates - GAM

Variable	Est.	Std. Error	Z Value	P Value
(Intercept)	-143.060	11863283.204	0.000	1
primary_typeassault	138.273	11863283.204	0.000	1
primary_typebattery	139.054	11863283.204	0.000	1
primary_typeburglary	139.823	11863283.204	0.000	1
primary_typedamage	137.634	11863283.204	0.000	1
primary_typedeceptive practice	135.880	11863283.204	0.000	1
primary_typeharassment	137.862	11863283.204	0.000	1
primary_typehomicide	142.977	11863283.204	0.000	1
primary_typeinterference with public officer	103.806	14169879.447	0.000	1
primary_typeliquor law violation	102.909	12479963.403	0.000	1
primary_typenarcotics	136.128	11863283.204	0.000	1
primary_typeother	139.918	11863283.204	0.000	1
primary_typepublic peace violation	138.072	11863283.204	0.000	1
primary_typerobbery	141.095	11863283.204	0.000	1
primary_typesex crime	139.454	11863283.204	0.000	1
primary_typetheft	137.688	11863283.204	0.000	1
primary_typetrespassing	138.281	11863283.204	0.000	1
primary_typeweapons violation	139.712	11863283.204	0.000	1
domesticTRUE	-2.506	0.243	-10.312	0
aggravatedTRUE	1.151	0.102	11.330	0

Table 7.17: Both vs. Each Smooth Coefficient Estimates - GAM

Variable	Est. Df	Chi Sq.	P Value
s(lat_y)	6.715	193.487	0.000
s(lon_x)	8.916	79.787	0.000
s(pop_latino)	1.148	1.451	0.218
s(pop_asian)	1.002	0.091	0.764
s(pop_black)	1.000	0.010	0.922
s(hu_owned)	5.221	26.383	0.000
s(pop_white)	7.145	23.967	0.003

Table 7.18: Asian Model Coefficient Estimates - Lasso Regression

Variable	Est.
(Intercept)	-9.264
lat_y	-0.309
lon_x	-0.253
pop_female	0.168
pop_family_hh	-0.157
pop_black	-0.133
pop_husb_wife_fam	0.088
pop_one_pers_hh	0.077
hu_owned	0.058
pop_under_18	-0.048
hu_owned_loan	0.042
pop_in_hus	0.029
hu_rented	0.027
avg_family_size	0.009
responding_dept.ucpd	0.006
pop_white	-0.006
primary_type.liquor law violation	0.005
responding_dept.cpd	-0.003
arrest.TRUE	-0.003
primary_type.battery	-0.002
primary_type.damage	0.002
attempted.TRUE	0.002
avg_household_size	-0.002
primary_type.assault	-0.001
primary_type.burglary	0.001
primary_type.harassment	0.001
primary_type.interference with public officer	0.001
primary_type.public peace violation	-0.001
primary_type.robbery	0.001
primary_type.theft	0.001
month.mar	-0.001
median_age	-0.001
primary_type.other	0.000
time	0.000
weekend.TRUE	0.000
total_housing_units	0.000
hu_vacant	0.000
total_pop	0.000
pop_latino	0.000

Table 7.19: Asian Linear Coefficient Estimates - GAM

Variable	Est.	Std. Error	Z Value	P Value
(Intercept)	0.039	0.004	8.678	0.000
responding_deptcpd	0.000	0.001	0.478	0.633
responding_deptucpd	-0.003	0.001	-3.991	0.000
primary_typeassault	0.002	0.004	0.450	0.652
primary_typebattery	0.002	0.004	0.556	0.579
primary_typeburglary	0.005	0.004	1.027	0.304
primary_typedamage	0.004	0.004	0.887	0.375
primary_typedeceptive practice	0.004	0.004	0.923	0.356
primary_typeharassment	0.006	0.005	1.257	0.209
primary_typehomicide	0.001	0.006	0.240	0.810
primary_typeinterference with public officer	0.006	0.005	1.223	0.221
primary_typeliquor law violation	0.006	0.005	1.297	0.195
primary_typenarcotics	0.002	0.004	0.428	0.669
primary_typeother	0.003	0.004	0.570	0.568
primary_typepublic peace violation	0.003	0.005	0.693	0.488
primary_typerobbery	0.003	0.004	0.752	0.452
primary_typesex crime	0.001	0.005	0.296	0.767
primary_typetheft	0.003	0.004	0.714	0.475
primary_typetrespassing	0.002	0.004	0.402	0.688
primary_typeweapons violation	0.003	0.005	0.600	0.549
arrestTRUE	0.000	0.000	-0.522	0.602
attemptedTRUE	0.002	0.001	1.680	0.093
monthfeb	0.000	0.001	0.733	0.464
monthmar	0.000	0.001	-0.623	0.533
monthapr	0.000	0.001	0.492	0.623
monthmay	0.000	0.001	0.078	0.938
monthjun	0.000	0.001	0.431	0.666
monthjul	0.000	0.001	0.791	0.429
monthaug	0.001	0.001	1.646	0.100
monthsep	0.000	0.001	-0.601	0.548
monthoct	0.000	0.001	0.495	0.621
monthnov	0.000	0.001	0.862	0.389
monthdec	0.000	0.001	0.474	0.636

Table 7.20: Asian Smooth Coefficient Estimates - GAM

Variable	Est. Df	Chi Sq.	P Value
s(lat_y)	8.989	2156.164	0
s(lon_x)	8.988	1410.353	0
s(pop_female)	8.994	14032.740	0
s(pop_family_hh)	9.000	1175.940	0
s(pop_black)	9.000	18758.123	0
s(pop_husb_wife_fam)	8.954	1822.599	0
s(pop_one_pers_hh)	8.975	3024.511	0
s(hu_owned)	8.983	2331.405	0
s(pop_under_18)	8.967	760.068	0
s(hu_owned_loan)	8.999	2070.522	0
s(pop_in_hus)	8.995	3010.942	0
s(hu_rented)	8.981	1696.386	0
s(avg_family_size)	8.992	2410.041	0
s(pop_white)	8.995	19489.786	0
s(avg_household_size)	8.999	3071.478	0

Table 7.21: Black Model Coefficient Estimates - Lasso Regression

Variable	Est.
(Intercept)	-139.691
lon_x	-1.595
pop_husb_wife_fam	-0.781
pop_white	-0.702
pop_asian	-0.679
pop_female	0.432
pop_under_18	0.411
pop_in_hus	0.171
pop_family_hh	0.049
hu_vacant	0.041
hu_rented	0.031
avg_family_size	0.029
primary_type.liquor law violation	0.012
median_age	0.008
avg_household_size	0.004
primary_type.damage	0.001
hu_owned	-0.001
responding_dept.ucpd	0.000
primary_type.robbery	0.000
total_housing_units	0.000
total_pop	0.000

Table 7.22: Black Linear Coefficient Estimates - GAM

Variable	Est.	Std. Error	Z Value	P Value
(Intercept)	0.473	0.004	125.550	0.000
primary_typeassault	-0.003	0.004	-0.812	0.417
primary_typebattery	-0.003	0.004	-0.757	0.449
primary_typeburglary	-0.002	0.004	-0.516	0.606
primary_typedamage	-0.001	0.004	-0.367	0.713
primary_typedeceptive practice	-0.004	0.004	-1.190	0.234
primary_typeharassment	-0.002	0.004	-0.454	0.650
primary_typehomicide	-0.008	0.005	-1.713	0.087
primary_typeinterference with public officer	-0.003	0.004	-0.611	0.541
primary_typeliquor law violation	-0.004	0.004	-0.969	0.333
primary_typenarcotics	-0.004	0.004	-0.964	0.335
primary_typeother	-0.002	0.004	-0.579	0.563
primary_typepublic peace violation	-0.003	0.004	-0.746	0.456
primary_typerobbery	-0.005	0.004	-1.284	0.199
primary_typesex crime	-0.004	0.004	-0.998	0.318
primary_typetheft	-0.003	0.004	-0.779	0.436
primary_typetrespassing	-0.003	0.004	-0.690	0.490
primary_typeweapons violation	-0.003	0.004	-0.748	0.454
responding_deptcpd	0.000	0.001	-0.859	0.390
responding_deptucpd	-0.002	0.001	-2.907	0.004

Table 7.23: Black Smooth Coefficient Estimates - GAM

Variable	Est. Df	Chi Sq.	P Value
s(lon_x)	8.802	941.665	0
s(pop_husb_wife_fam)	9.000	1743.744	0
s(pop_white)	8.987	450051.920	0
s(pop_asian)	8.995	78584.357	0
s(pop_female)	9.000	4841.490	0
s(pop_under_18)	9.000	5669.525	0
s(pop_in_hus)	8.994	1204.399	0
s(pop_family_hh)	9.000	1647.345	0
s(hu_vacant)	8.989	5133.575	0
s(hu_rented)	8.995	3717.724	0
s(avg_family_size)	8.994	3369.513	0
s(median_age)	8.994	393682.436	0
s(avg_household_size)	8.986	3180.626	0
s(hu_owned)	8.991	2646.879	0
s(total_housing_units)	9.000	1937.170	0
s(total_pop)	9.000	1532.429	0

Table 7.24: White Model Coefficient Estimates - Lasso Regression

Variable	Est.
(Intercept)	18.617
pop__black	-0.719
pop__female	0.570
pop__latino	0.416
pop__husb__wife__fam	0.289
pop__family__hh	-0.261
lat__y	-0.251
pop__in__hus	0.158
hu__owned	0.149
pop__one__pers__hh	-0.110
hu__owned__loan	-0.105
lon__x	0.089
hu__vacant	0.067
pop__under__18	-0.067
avg__household__size	0.041
pop__asian	-0.021
responding__dept.ucpd	0.019
responding__dept.cpd	-0.014
primary__type.narcotics	-0.013
primary__type.liquor law violation	0.009
primary__type.burglary	0.008
median__age	0.006
primary__type.weapons violation	-0.005
hu__rented	0.005
primary__type.interference with public officer	-0.004
avg__family__size	-0.002
primary__type.assault	-0.001
primary__type.battery	-0.001
arrest.TRUE	-0.001
month.aug	-0.001
primary__type.harassment	0.000
primary__type.robbery	0.000
primary__type.theft	0.000
month.apr	0.000
month.oct	0.000
year	0.000
total__housing__units	0.000
total__pop	0.000

Table 7.25: White Linear Coefficient Estimates - GAM

Variable	Est.	Std. Error	Z Value	P Value
(Intercept)	0.204	0.003	75.507	0.000
responding_deptcpd	-0.001	0.000	-1.941	0.052
responding_deptucpd	0.000	0.000	0.354	0.723
primary_typeassault	-0.004	0.003	-1.317	0.188
primary_typebattery	-0.003	0.003	-1.284	0.199
primary_typeburglary	-0.004	0.003	-1.350	0.177
primary_typedamage	-0.003	0.003	-1.127	0.260
primary_typedeceptive practice	-0.004	0.003	-1.523	0.128
primary_typeharassment	-0.004	0.003	-1.280	0.201
primary_typehomicide	-0.010	0.003	-2.992	0.003
primary_typeinterference with public officer	-0.007	0.003	-2.051	0.040
primary_typeliquor law violation	-0.007	0.003	-2.474	0.013
primary_typenarcotics	-0.004	0.003	-1.659	0.097
primary_typeother	-0.004	0.003	-1.344	0.179
primary_typepublic peace violation	-0.004	0.003	-1.398	0.162
primary_typerobbery	-0.004	0.003	-1.602	0.109
primary_typesex crime	-0.003	0.003	-1.058	0.290
primary_typetheft	-0.004	0.003	-1.317	0.188
primary_typetrespassing	-0.004	0.003	-1.514	0.130
primary_typeweapons violation	-0.004	0.003	-1.529	0.126

Table 7.26: White Smooth Coefficient Estimates - GAM

Variable	Est. Df	Chi Sq.	P Value
s(pop_black)	8.984	683578.889	0
s(pop_female)	9.000	6720.006	0
s(pop_latino)	8.998	14533.160	0
s(pop_husb_wife_fam)	8.933	1388.254	0
s(pop_family_hh)	8.978	781.874	0
s(lat_y)	8.977	1918.108	0
s(pop_in_hus)	9.000	1546.135	0
s(hu_owned)	8.984	1542.512	0
s(pop_one_pers_hh)	8.995	3480.792	0
s(hu_owned_loan)	8.991	2887.830	0
s(lon_x)	8.988	1881.473	0
s(hu_vacant)	9.000	3364.801	0
s(pop_under_18)	9.000	4482.106	0
s(avg_household_size)	8.554	3021.173	0
s(pop_asian)	8.806	131339.315	0
s(median_age)	9.000	269867.070	0
s(hu_rented)	8.994	5282.521	0
s(avg_family_size)	8.983	1321.425	0

Table 7.27: Performance of Race Models

Model	RMSE
Asian Lasso	0.038
Asian GAM	0.025
Black Lasso	0.086
Black GAM	0.020
White Lasso	0.087
White GAM	0.016

Table 7.28: Race/Ethnicity Comparison of UChicago and Surrounding Areas

Race/Ethnicity	UC Students	UC Academics	UC Staff	Hyde Park	Woodlawn	Kenwood	Washington Park
Asian	14%	18%	10%	13%	3%	9%	0%
Black	4%	3%	17%	28%	83%	68%	94%
Hispanic	8%	2%	6%	8%	3%	2%	2%
White	41%	61%	60%	46%	9%	17%	1%
Other	33%	16%	7%	5%	2%	4%	3%