PRE-PUBLICATION COPY

Research Report

SAFE Charlotte: Alternative Response Models and Disparities in Policing

Molly Simmons, Daniel Tapia, Richard H. Donohue, Denis Agniel, Matthew L. Mizel, Lisa Wagner, Amanda Charbonneau, and Danielle Sobol

RAND Social and Economic Well-Being, Justice Policy Program

RR-A1355-1
September 2021
Prepared for the City of Charlotte

This report has not yet been edited or finalized

RAND CORPORATION

For more information on this publication, visit **www.rand.org/t/RRA1355-1**.

Published by the RAND Corporation, Santa Monica, Calif.

About This Report

As part of ongoing efforts to improve policing standards and procedures, the City of Charlotte, North Carolina contracted with RAND to evaluate police-community member contact and propose alternate police response models. RAND was selected to complete this work after a competitive bidding process. RAND began this work on March 3, 2021 and the findings were delivered to the City of Charlotte on June 25, 2021. The recommendations RAND was contracted to respond to were proposed in the SAFE (Safety and Accountability for Everyone) Charlotte report, published by a team of city council members, the City Manager, city leaders, and city government staff. The recommendations that are addressed in the current report include:

Recommendation 2: Work with an external partner to develop a comprehensive recommendation to convert low risk sworn duties to civilian units.

Recommendation 3: Work with an external partner to provide an independent analysis of areas such as police-community member contact, and police calls and responses.

Recommendation 4: Expand the Community Policing Crisis Response Team (CPCRT) and develop a civilian officer responder model for mental health and homeless calls.

Justice Policy Program

RAND Social and Economic Well-Being is a division of the RAND Corporation that seeks to actively improve the health and social and economic well-being of populations and communities throughout the world. This research was conducted in the Justice Policy Program within RAND Social and Economic Well-Being. The program focuses on such topics as access to justice, policing, corrections, drug policy, and court system reform, as well as other policy concerns pertaining to public safety and criminal and civil justice. For more information, email justicepolicy@rand.org.[1]

[1] Shortly after this report was completed, an article was published that addressed many of the same questions we pursued in this text. The paper, Lum, Koper and Wu (2021), reaches similar conclusions to ours.

Abstract

The SAFE Charlotte recommendations were created with the purpose of improving the quality of public safety for the City and Community of Charlotte. These specific recommendations take place within the context of a national movement to restructure policing to better meet the needs of the community. To this end, the RAND Corporation was contracted to conduct analysis in support of three SAFE Charlotte recommendations: Recommendations 2, 3 and 4.

Recommendation 2 is focused on developing recommendations to implement a civilian response for low-risk duties. Recommendation 4 states that CPCRT should be expanded, and a civilian responder model should be explored for those experiencing mental health crisis and homelessness. We approached recommendations 2 and 4 together with a formative evaluation approach. A formative evaluation is a study designed to understand the implementation context, identify potential barriers and facilitators to implementation and determine the feasibility of implementation. We used a mixed methods approach to conduct this formative evaluation and respond to the scope of duties in recommendations 2 and 4.

We found that there is an appetite for alternative response models in Charlotte, however, the development of any intervention must include local stakeholders in every aspect of implementation—from decisions about what people wear to hiring decisions. We are recommending three programs:

1. Expanding the funding and capacity of the Crisis Response Team – wherein police officers are deployed alongside civilian mental health providers to provide critical mental health care.
2. Piloting a new specialized civilian team of clinicians who would deploy in pairs to provide services that could help address substance abuse, mental health, or homelessness.
3. Piloting a team of non-specialized civilians to respond to low-risk, low-priority calls.

Pilot programs for the specialized and non-specialized civilian units should be placed in areas of high demand and with low rates of violent crime. Based on our initial findings, key areas for starting these pilot programs lie within CMPD's Central District and Providence or North Tryon. Pilots programs should begin as city-operated programs for control, coordination, hiring, and safety reasons. These pilot programs should start with daytime working hours. Eventually, the specialized civilian models need to consider moving toward 24/7 operations given the calls for service. We have included a plan for a pilot in the report.

Additionally, Charlotte needs to develop a strong triage model to identify individuals in crisis. This report includes a brief overview of models in use in other cities. This is just one

aspect of a stronger continuum of care for individuals in crisis that needs to be strengthened in Charlotte. We have also included an asset map to identify available resources and gaps in care.

Recommendation 3 of the SAFE Charlotte report requested independent analysis of police/community member contact. Analytic support dedicated to SAFE Recommendation 3 involves quantitative analysis to evaluate the presence and extent to which racial/ethnic bias is evident in policing. We employed set of conventional statistical analyses along with more specialized analyses that are intended to provide more robust tests of statistical bias. Our work for the City of Charlotte as it pertains to this recommendation falls within three analytical tasks: police-community member contacts; identifying police-outliers; and analyzing work and labor demands.

Among more detailed findings, we found that Black residents in Charlotte were more likely to be stopped both by car and as a pedestrian, and when stopped, were more likely to be arrested. This analysis controlled for relevant variables. The same type of disparity was not displayed with other races/ethnicities to the same extent. However, there was insufficient data to determine why the observed racial disparities are present, therefore RAND is providing data recommendations that should enable future analysis. The hope is that these data recommendations would collect data on the wider scope of police activity and provide sufficient contextual information from across different datasets to better identify causes of racial disparities.

Our RAND recommendations around SAFE Charlotte Recommendation 3 stem from our interaction with the data and are intended to facilitate future analysis that should help the department track its own activity and better inform any future pilot programs. We are recommending:

1. CMPD consider clarifying when stop data should be entered in on a call for service and require additional data collection of stops that occur during a call for service.
2. CMPD provide a way for entries in different datasets to be more linkable; specifically, around outcomes of interest (e.g., use of force, complaints, arrests) that could occur during a call for service but were unlinkable to CAD event data. These data should also be validated.
3. CMPD track and make available officer injuries in their internal data sets in order to accurately track risk and inform the deployment of non-sworn individuals through alternative response models recommended in this report.
4. In line with our tasking from the city, Charlotte should consider moving programs to civilians or out of the department entirely if a) a program provides services that are distinct in nature from administering justice; b) a program can maintain or increase the resources and support it receives in its new location; c) program can perform its functions at least as effectively and in line with local regulations without necessarily adhering to regulations or policies followed by the CMPD.
5. CMPD adopt and/or strengthen the use of strategies that move away from aggressive or zero tolerance models as appropriate. CMPD may consider focused deterrence, high visibility enforcement, and broad use of procedural justice techniques.

Under these guidelines in recommendation 4, Animal Care and Control would satisfy all of those conditions provided that they maintain their current level of resource staffing so as not to undermine their provision of services. At this time, we recommend that the Electronic Monitoring Unit remain as-is, since it primarily deals with persons who are subject to electronic monitoring devices as a condition of their release as they await trial. Lastly, the Passenger Vehicles for Hire (PVH) Unit, although administrative in nature, do have a public safety element to them as they are detailed in city ordinances; barring a legislative change we recommend leaving the unit in its status quo.

Table of Contents

Figures

Tables

Summary

The SAFE Charlotte recommendations were created with the purpose of improving the quality of public safety for the City and Community of Charlotte. These specific recommendations take place within the context of a national movement to restructure policing to better meet the needs of the community. To this end, the RAND Corporation was contracted to conduct analysis in support of three SAFE Charlotte recommendations: Recommendations 2, 3 and 4. RAND was awarded the contract in a competitive bidding process.

Recommendations 2 and 4

Recommendation 2 is focused on developing recommendations to implement a civilian response for low-risk duties. Recommendation 4 states that CPCRT should be expanded, and a specialized civilian responder model, where specialized refers to clinical training and/or licensure[2], should be explored for those experiencing mental health crisis and homelessness.

Methods

We approached recommendations 2 and 4 together with a formative evaluation approach. A formative evaluation is a study designed to understand the implementation context, identify potential barriers and facilitators to implementation and determine the feasibility of implementation (Stetler et al., 2006). We used a mixed methods approach to conduct this formative evaluation and respond to the scope of duties in recommendations 2 and 4. This included quantitative analysis of all calls from 2015-2020 and 35 qualitative interviews with community and CMPD stakeholders.

Literature review findings

In order to develop recommendations for Charlotte and draw on existing knowledge about crisis response, we conducted a review of crisis response models being tested across the United. Several states and localities have initiated specialized civilian or co-response team models to respond to low-risk, low-priority calls for service surrounding mental health and homelessness issues. As 7-10% of all police contact involves someone with mental illness (Lord and Bjerregaard, 2014), many of the alternative response models concentrate on mental health services. Several police departments provide specialized training and deploy crisis intervention teams (CIT) of front-line officers directly to provide care, however, research shows that users of

[2] Throughout the report we use the term civilian to refer to all non-sworn responders, inclusive of specialized and non-specialized civilians. Specialized civilians may also be referred to as clinicians or mental health clinicians.

mobile health crisis teams would prefer a mental health professional to a police officer (Boscarato et al., 2014; Klevan, Karlsson and Ruud, 2017). Specialized civilian and co-responder teams, alternatives to officer-only crisis intervention teams, are time-limited units that can perform initial screening, determine next course of action, and potentially provide case management follow-up support. Ideally, they can stabilize an individual to avoid hospitalization or incarceration (Birnbaum et al., 2017).

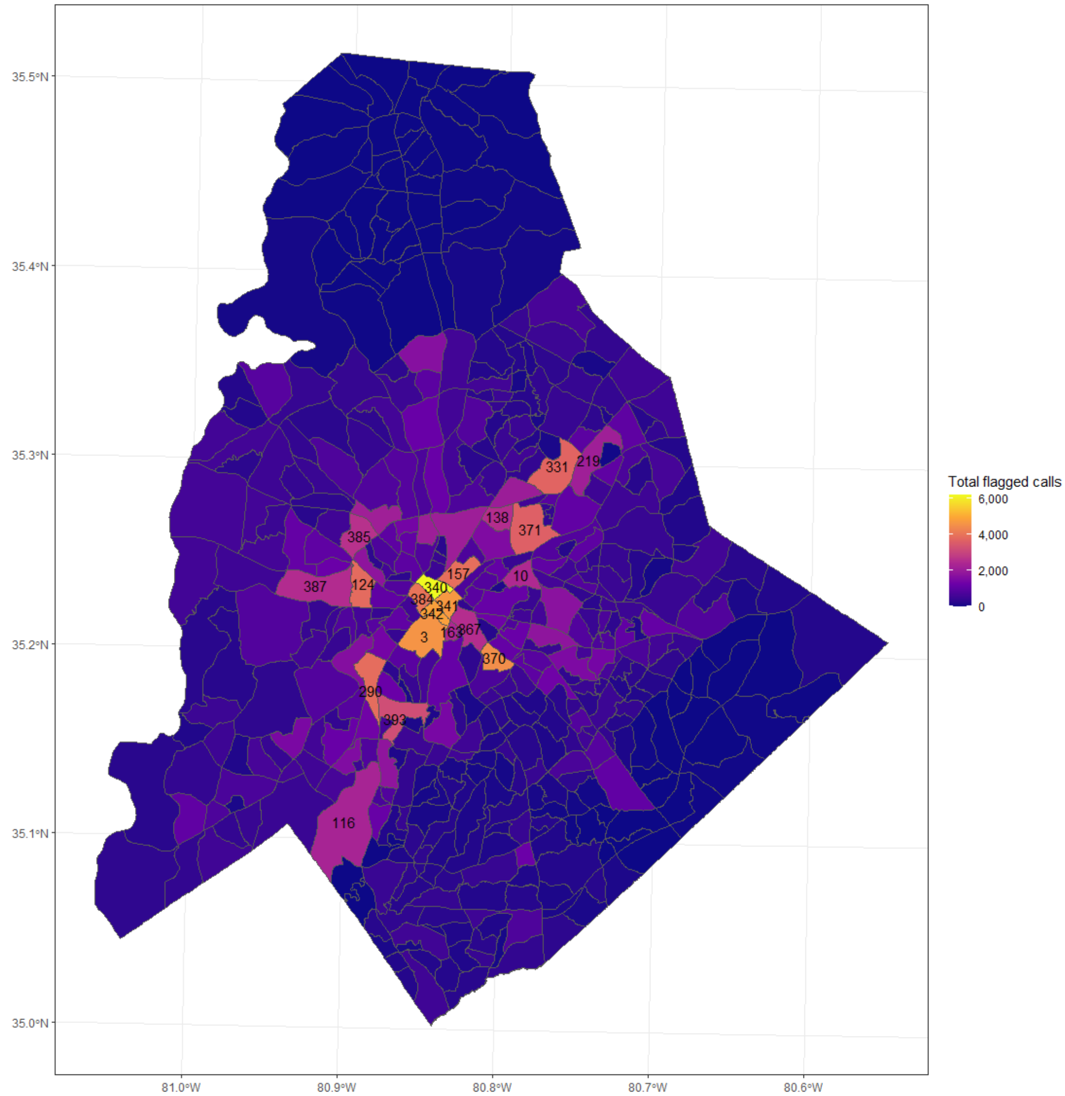
Quantitative Findings

We analyzed all calls for service in the CAD system from 2015-2020 to identify the quantity, type, and spatial-temporal variation of low priority calls for service as well as those calls relating to substance abuse, mental health, and homelessness. The most frequent routine priority call types were noise complaints, traffic accidents and infractions, and larceny from vehicles. Routine priority calls accounted for between 10 and about 20% of calls at all hours of the day, with the lowest share occurring in the early morning and late evening, and the highest share occurring between 7am and 7pm. Between 11am and 2pm, routine priority calls account for about 20% of all calls. There was substantial geographic variation in both the number and proportion of routine priority calls. We identified illegal parking, found property, notify,[3] pick up property or evidence and road blockage as calls associated with the lowest risk.

We flagged a total of 261,439 calls (7% of all calls) that were potentially related to mental health, substance abuse, and homelessness (hereafter, we refer to these calls as a group as "flagged" calls). Calls flagged as potentially related to mental health were overwhelmingly welfare checks (73.6%). Calls flagged for substance abuse were most often overdoses (54.1%). The proportion of flagged calls also increased over time, with the highest percentage (8.6%) occurring in 2020. The volume of flagged calls tended to be lowest in the early morning, after which it increases until its peak at the middle of the day, followed by a slow decrease over the evening. Flagged calls were least likely to be received on weekends, and they were most likely on Mondays and were more frequent in warmer months. Figure S.1 shows a map of the number of flagged calls by neighborhood (numbers on the map represent Neighborhood Statistical Areas):

[3] Typical examples of use involve a caller wanting to share additional information about a previous call and/or case or requests for information and/or guidance that do not fall neatly within another CAD event type

Figure S.1. The Number of Flagged Calls in Each Neighborhood with the Top 20 Neighborhoods Identified



Qualitative Findings: Response to Mental Health Crisis

There were several potential barriers to implementation that we identified, which included racial tension within the city, a lack of continuum of care within Charlotte for behavioral health care, effective ways to triage individuals in need of mental health care who call 911, the potential impact of a shortage of CPCRT/crisis care staff and some tension within the CMPD around civilian intervention. However, we also identified facilitators to implementation that could address many of these barriers. They include hiring the “right” people, collaborating effectively with community organizations and service providers, and disseminating information about intervention programming.

Qualitative Findings: Non-Uniformed Response to Low-Risk Calls

A common theme among stakeholders—by activists, law enforcement, and service providers—was that while there were some potential benefits to civilian personnel,[4] there were also several potential problems. We identified several themes. The most prevalent of these was concerns about how to define "low-risk" and safety of civilian responders. There was also concern of negative reaction to these individuals within the police department. Community members also stated that there were potentially low-risk situations where they would like to have an officer for various reasons. However, many also stated that a uniform has the potential to be upsetting for many community members. We also identified metrics for evaluation. These findings are discussed in more detail in the following section.

Recommendations

We found that there is a need for three potential recommended programs in Charlotte. The first recommended program we evaluated was expanding the funding and capacity of the Crisis Response Team – wherein police officers are deployed alongside mental health clinicians to provide critical mental health care. We are also recommending two pilots: a new team of clinicians who would deploy in pairs to provide services that could help address substance abuse, mental health, or homelessness and a model that delegates low-risk, low-priority calls to non-specialized civilian responders. One main finding of our qualitative research was that it is essential for community stakeholders to be involved in the development and implementation of any of these interventions.

- Estimated costs for recommended program 1, increasing CPCRT: Increase of $718,299 (increase in clinicians only for first year)
- Estimated costs for recommended program 2 (pilot of clinician team): Approximately $850,000 for the first year
- Estimated costs for recommended program 3 (pilot of low-risk, low priority civilian responders): Approximately $1.4M to $1.85M for the first year

We are recommending a community advisory council that be involved in every aspect of implementation of all potential programs—from decisions about what people wear to hiring decisions. This community advisory council will be comprised of residents from communities where the programs are being piloted/expanded. We are recommending that the city ask for recommendations from local community action groups and mental health providers. The council should also include members from community action groups and providers.

In addition to these three recommended programs, we are also recommending specifically with regard to the pilots that:

---

[4] Respondents were asked about varying levels of specialized civilian models and provided input on a range of considerations including where they should be employed (by the police, a city agency, or elsewhere), their qualifications, and even dress or appearance (e.g. CMPD polo, vehicles with CMPD or other markings).

- Pilot programs (recommended programs 2 and 3) for the specialized and non-specialized civilian response models be placed in areas of high demand and low violent crime rates. Based on our initial findings, key areas for starting these programs lie within CMPD's Central District and Providence or North Tryon. By placing these programs in separate locations, evaluation of their effectiveness will be more easily determined.
- Recommended programs should begin as city-operated programs for control, coordination, hiring, and safety reasons. Demand for calls varies across the city and time of day. As such, we have provided maps with the report (see figures in Section 2.3) to show ideal areas for piloting and ongoing deployment of civilian responder models. These programs should start with daytime working hours. Eventually, the specialized civilian models need to consider moving toward 24/7 operations given the calls for service.
- Job requirements should vary for the positions being hired (e.g., mental health clinician vs. non-specialized civilian responder). The teams should have different requirements and training needs, with a focus on mental health, communications, safety, de-escalation, cultural competence, and familiarity with Charlotte and its neighborhoods for the specialized responder units. The non-specialized units still need adequate training in these areas, but due to the nature of the calls they will respond to, require a lesser extent of it and fewer requirements to be hired.
- In order to start the program, in time unit one of the pilots, Charlotte and CMPD should first convene a citizen advisory committee to assist with implementation decisions. Then they should engage in the following: advertising, hiring, and training new civilian employees, modifying policies and procedures, and providing training and education for other sworn and non-sworn staff. Following this period, during time unit two of the pilot, we suggest continual (monthly) examination of performance metrics for the programs followed by a thorough assessment every 6 months during the pilot and at the completion of the pilot.
- In addition to the recommended programs, Charlotte needs to develop a strong triage model to identify individuals in crisis. This is just one aspect of a stronger continuum of care for individuals in crisis that needs to be strengthened in Charlotte. In addition to the need for a strong triage model, assets mapping and qualitative interviews revealed a need for more resources to respond to individuals in crisis, more resources for individuals directly following a crisis, and more robust transitional services to support crisis prevention and early intervention.

Recommendation 3

Recommendation 3 of the SAFE Charlotte report requested independent analysis of police/community member contact. Analytic support dedicated to SAFE Recommendation 3 involves quantitative analysis to evaluate the presence and extent to which racial/ethnic bias is evident in policing. We employed a set of conventional statistical analyses along with more specialized analyses that are intended to provide more robust tests of statistical bias. Our work for the City of Charlotte as it pertains to this recommendation falls within three analytical tasks:

police-community member contacts; identifying police-outliers; and analyzing transition of specific CMPD services.

Methods

The first analytical task was to estimate the extent to which racial/ethnic bias is evident in police interactions. For this, we analyzed stop data, arrest data, and complaint data and employed established methodologies for criminal justice-related data, such as regression analysis, daylight savings time-based benchmarking, search and yield rates. It should be noted that our analyses do not extend farther than the data that we had available for these analyses, and these data were not collected for the purpose of measuring or determining racial bias. Our findings should be interpreted as racial/ethnic disparities in stop- and arrest-related outcomes that do not appear to be explained by other contextual factors in the data, such as the characteristics where the stop took place. Because we did not investigate police body cameras and we have no record of who police chose not to stop or why they chose not to stop them, it was not possible for us to conclusively determine the presence of bias. This difficulty has been discussed in the literature several times.

A second task involved evaluating and identifying individual officers' behavior in several key benchmarks. We leveraged an established framework that uses an internal benchmarking approach for identifying outliers. Briefly, this approach involves, for any given officer, identifying the set of officers that have a similar schedule or patrol area, and weighting those with the most similar profile higher. Then, we estimated regressions with relevant control variables to identity an individual officer's unique coefficient that describes the extent of their deviation from their peers. After we had all officers' coefficients, we considered their distribution to determine whether any individual officer was sufficiently different from the bulk of their peers as to be considered an outlier. We present some summary results for detected outliers below.

A final task is closely tied with tasking associated with Recommendations 2 & 4. This involved a workforce analysis to determine identify how and whether services currently performed by CMPD can be more efficiently delivered by another organization and considered the potential workforce impacts. As the RAND team was responsible for both Recommendations 2, 3, and 4, we conducted a single analysis. For portions of this task solely under SAFE Recommendation 3 this, we relied on interviews to guide our data analysis and evaluate the potential impact of transitioning services out. Rather than specific individual agencies, we identified a set of conditions that – when evaluated for individual programs – would help the City of Charlotte determine whether a set of services would be a candidate for transition outside of the department.

Findings

In Table S.1 below, we summarize the results of our findings. Of particular note, we found that the rate at which Black motorists were stopped was 2-3 times higher than the rate at which White motorists were stopped, and these differences were not explained by the characteristics of the neighborhood where the stop took place. We found that white pedestrians were stopped at much higher rates than Asian or Hispanic pedestrians. We also found Black motorists were requested for a consent to search at much higher rates than White motorists (adjusted odds ratio 1.9, 95% CI 1.6-2.2). We found that Asian motorists were much less likely to be stopped, much less likely to be requested for a consent to search when they were stopped, and less likely to be arrested as a result of a stop.

While we were able to identify some racial disparities, there was insufficient data and information to determine why the observed racial disparities are present. To improve the quality and utility of the data, our recommendations would result in data that better reflect the total scope of police activity and provide sufficient contextual information from across different datasets to better identify causes of racial disparities.

Table S.1. Summary of Identified Statistically Significant Racial/Ethnic Disparities

Outcome of interest	Identified Statistical Racial/Ethnic Disparities
Frequency of vehicle stops	Higher rate of being stopped for Black drivers, Hispanic drivers, and drivers of other or unknown race/ethnicity compared to White drivers, when rates are computed with respect to the population of Charlotte. Lower corresponding rate of being stopped for Asian drivers compared to White drivers. Higher rate of being stopped for Black drivers compared to White drivers, when rates are computed with respect to the population of the neighborhood where the stop took place. Lower corresponding rates for Asian drivers and drivers of other race/ethnicity.
Frequency of pedestrian stops	Higher rates of being stopped for Black pedestrians compared to White pedestrians, when rates are computed with respect to the population of Charlotte. Lower rates of being stopped for Asian pedestrians, Hispanic pedestrians, and pedestrians of other or unknown race/ethnicity, regardless of how rates are computed.
Frequency of no action traffic stops	Greater probability of a no action stop for drivers of other or unknown race/ethnicity relative to White drivers. Lower probability of a no action stop for Hispanic drivers relative to White drivers.
Frequency of no action pedestrian stops	Greater probability of a no action stop for Hispanic pedestrians relative to White pedestrians.
Result of Vehicle Stops	Greater probability of being arrested and lower probability of receiving a written warning for Black drivers relative to White drivers.

	Greater probability of being issued a citation and lower probability of receiving a written warning for Hispanic drivers relative to White drivers. Lower probability of being arrested, lower probability of being issued a citation, and lower probability of receiving a written warning for Asian drivers relative to White drivers. Lower probability of being arrested and lower probability of receiving a written warning for drivers of other or unknown race/ethnicity relative to White drivers.
Result of Pedestrian Stops	Lower probability of being issued a citation for Hispanic pedestrians relative to White pedestrians.
Request for Consent to Search	Greater probability that a Black driver would be requested for consent to search the vehicle relative to White drivers. Lower probability that an Asian driver or a driver of other or unknown race/ethnicity would be requested for consent to search the vehicle relative to White drivers.
Consent given for search	Insufficient data.
Yield rates and contraband, vehicle stops	Lower probability of finding contraband during a search for Hispanic drivers relative to White drivers.
Yield rates and contraband, pedestrian stops	No statistically significant findings.
Decision to use force, vehicle stops	Greater probability of Black drivers experiencing a use of force during a stop relative to White individuals. Supplemental analysis of the probability that Black arrestees were more likely to have experienced a use of force compared to White arrestees was inconclusive. Lower odds of Hispanic arrestees to experience a use of force relative to non-Hispanic arrestees.
Severity of force	When force was used against a pedestrian or driver, there was a greater probability that the force was lethal (firearms) or less lethal (tasers, batons, sprays) when the pedestrian/driver was Asian or of other/unknown race/ethnicity compared to White pedestrians/drivers than physical force (holds, punches, kicks). When force was used against a pedestrian or driver, there was a greater probability that the force was lethal (firearms) when the pedestrian/driver was Asian, Hispanic, or of other/unknown race/ethnicity compared to White pedestrians/drivers than physical force (holds, punches, kicks).
Severity of force on unarmed individuals	When force was used against an unarmed pedestrian or driver, there was a greater probability that the force was lethal (firearms) or less lethal (tasers, batons, sprays) when the pedestrian/driver was Black or of other/unknown race/ethnicity compared to White pedestrians/drivers than physical force (holds, punches, kicks). When force was used against a pedestrian or driver, there was a greater probability that the force was lethal (firearms) when the pedestrian/driver was Hispanic or of other/unknown race/ethnicity compared to White pedestrians/drivers than physical force (holds, punches, kicks).

Recommendations

Our recommendations stem from our interaction with the data and are intended to facilitate future analysis that should help the department track its own activity and better inform any future pilot programs. Additionally, with a data set that's more representative of police activity and more easily connected with other datasets to integrate contextual information, the potential for explaining specific causes of racial disparities will be greater. They are summarized below.

- To better determine the causes of racial disparities and better capture and evaluate policing activity, CMPD should consider clarifying when stop data should be entered in on a call for service. As it stands, it is not necessarily always true that individuals stopped during a call for service will be entered into the stop data set. We recommend that when CMPD stop or otherwise detain individuals at all – even on a call for service – they be entered into the stop dataset. This would enable the analysis of uses for force for every police officer-civilian interaction.
- CMPD should improve linkages for entries in different datasets within their own datasets; specifically around outcomes of interest (e.g., use of force, complaints) that could occur during a call for service but were unlinkable to CAD event data. This would facilitate analysis of uses of force if we could connect CAD events to use of force incidences. This includes validating data entry between different dataset to ensure the correct information is available (e.g. linked use of force and arrest records).
- CMPD should track and make available officer injuries and narrative data in their internal data sets in order to accurately track risk and inform the deployment of non-sworn individuals through alternative response models like the ones we recommend as pilots in this report. As it currently stands, we cannot tell if a UOF incident involved an assault on a police officer and can only tell if the subject possessed weapons at the time of a UOF incident.
- When using outlier detection methods, CMPD should not rely solely on the method and use additional administrative data to inform discussions with the flagged individuals. Additionally, once CMPD remedies or otherwise addresses outlier behavior, information relevant to the outlier behavior should be then disseminated through communications or by revised policies, practices, or procedures.
- In line with our tasking from the city, we also considered whether any individual services provided by the CMPD should be transitioned out to alternative agencies. We developed guidelines that would identify when a program is a candidate for transition out of the department and into another agency. If: a) a program provides services that are distinct in nature from administering justice; b) a program can maintain or increase the resources and support it receives in its new location; c) program can perform its functions at least as effectively and in line with local regulations without necessarily adhering to regulations or policies followed by the CMPD, then we would recommend the City and Department consider the program for transition out of CMPD. Animal Care and Control would satisfy all of those conditions provided that they maintain their current level of resource staffing so as not to undermine their provision of services. At this time, we recommend that the Electronic Monitoring Unit and Private Vehicle for Hire remain as-is.

- Additionally, we noted a lack of trust between minority communities and CMPD in interviews, and therefore recommend that CMPD implement programs to increase trust and legitimacy, perceptions of police, and treatment of citizens in general. Specific recommendations involve engaging in positive, non-enforcement actions with citizens and training officers in procedural justice. Additionally, re-prioritizing traffic stops and enforcement to focus on crash reductions can improve disparities and public safety, and move away from aggressive or zero tolerance models as appropriate. More details on these interventions can be found in the RAND's *Better Policing Toolkit.*[5] These may assist CMPD in focusing on crime and public safety while improving relations with and engaging the community.

[5] The toolkit is located at https://www.rand.org/pubs/tools/TL261/better-policing-toolkit.html

Acknowledgments

This research was supported by the City of Charlotte, North Carolina through contract 2021000922. We thank our colleagues from Charlotte, specifically Julia Martin, Lauren Ruvalcaba, Kellie High-Foster, and Monica Nguyen, who provided insight and expertise that greatly assisted the authors in understanding the procedures and protocols of the Charlotte Mecklenburg Police Department.

This report would not be possible without the input from the many stakeholders across Charlotte who shared their experiences and opinions with us. We appreciate their time and candor.

We thank the many individuals within RAND who support both the research that we do and help in the preparation of the final report. Kayla Howard helped to turn our writing into a properly formatted report. We would also like to thank John Hollywood and Daniel Lawrence for comments that greatly improved this report. We are immensely grateful for their comments on the draft of the manuscript; any errors are our own and should not reflect our colleagues' effort and guidance. Thanks also go to Christine Edwards at Amplify Consulting for her assistance managing the interviews and who provided thoughtful comments and insights along the way.

Abbreviations

CAHOOTS	Crisis Assistance Helping out on the Streets
CDCP	Child Development Community Policing
CFIR	Consolidated Framework for Implementation Research
CIT	Crisis Intervention Team
CMPD	Charlotte Mecklenburg Police Department
CPCRT	Community Policing Crisis Response Team
CRESS	Community Response for Equity, Safety, and Service
EMT	Emergency Medical Technician
EPD	Eugene Police Department
IVC	Involuntary Commitment
MCAT	Mobile Crisis Assistance Team
NEPS	Non-Emergency Police Services
NSA	Neighborhood Statistical Areas
PIC	Person in Crisis
PRN	Promise Research Network
PSAP	Public-Safety Answering Point
PSW	Police Social Work Liaison
PVH	Passenger Vehicle for Hire
SEW	Social and Economic Well-Being
SMART	Systemwide Mental Assessment Response Team
SQ	Status Quo
STAR	Support Team Assisted Response
VFH	Vehicle for Hire

1. Background

The City of Charlotte released the SAFE Charlotte report on October 26, 2020. The report was a collaborative effort between the Charlotte City Council, city leadership, residents and community leaders to create a safer city. A central element of the SAFE Charlotte report is the promotion of safe policing and the goal of reimagining the Charlotte Mecklenburg Police Department (CMPD) (SAFE, 2021), where roughly 1900 sworn officers respond to an average of 597,080 calls for service per year (Charlotte-Mecklenburg Police Department, n.d.). RAND was awarded this contract through a competitive bidding process. Work began in March of 2021 and was completed in July of 2021.

Community-police relations across the country are suffering (Saunders and Kilmer, 2021). High-profile fatal encounters between law enforcement and Black Americans over the past few years have sparked large-scale protests against police as well as calls to defund, or even abolish, police departments. CMPD Chief Jennings has commented that the current level of distrust nationally, especially in Black communities, is the highest that he's ever seen (Gordon and Alexander, 2021). Per community organizers, the relationship between the CMPD and the community in Charlotte has not escaped this dilemma (Morabito, 2020). A number of high-profile police-involved deaths (Gordon and Alexander, 2021; Morabito, 2020; Silverman, Burnside and Chavez, 2020), the CMPD's difficulties in securing witnesses in the aftermath of a 2020 mass shooting event (Foster, 2020), and videos that appear to show CMPD officers intentionally cornering and firing tear gas on protesters during a summer 2020 protest highlight these tensions (Kuznitz, Clasen-Kelly and Lindstrom, 2020).

The CMPD is working towards the goal of a safe, trusting relationship with the community and have achieved a number of milestones in this effort. The department has achieved full compliance with Campaign Zero's "8 Can't Wait" initiative (Charlotte-Mecklenburg Police Department, 2020b), formalized a policy against "no-knock" warrants, banned the use of CS gas for crowd dispersal during protests, and enhanced body-worn camera technology and automatic reporting (SAFE, 2021). They plan to implement a customer service curriculum in an effort to shift police culture to one where community members are treated as customers as opposed to as victims or suspects (Gordon and Alexander, 2021), as well as to require cultural competence training of officers. The department is also working to empower a Citizens Review Board to review cases where an officer witnesses another officer using excessive force (SAFE, 2021).

In addition to these achievements, the CMPD is, and has been, working towards a more robust response to behavioral health crises. In 2005 the State of North Carolina introduced Crisis Intervention Training for police officers ("Crisis Intervention Teams,"), a 40-hour training where officers are trained to respond to behavioral health crises and work with community partners to divert those in crisis from the criminal justice system and towards health care services (Charlotte-Mecklenburg Police Department, 2016). As of April 2019, 28% of the department

(690 officers) had attended the 40-hour CIT training (Charlotte-Mecklenburg Police Department, 2019), and CMPD is in the process of expanding this number (SAFE, 2021). The department also offers an 8-hour mental health first aid training where officers are provided with general information about mental health issues as well as practical skills for approaching and supporting someone in crisis (Charlotte-Mecklenburg Police Department, 2016).

In April 2019, CMPD launched the Community Policing Crisis Response Team (CPCRT). It includes CIT trained officers and Masters-level mental health clinicians who respond collaboratively to calls concerning a behavioral health crisis (Charlotte-Mecklenburg Police Department, 2019). In addition, the team assigns cases for proactive follow up (Morabito, 2020). Preliminary data has shown CPCRT has promise in its ability to divert community members involved in mental health and homelessness calls for service from jail or psychiatric hospitals (SAFE, 2021), however, challenges remain in addressing the mental health care needs of the population in Charlotte. For example, law enforcement is frequently utilized as transport for psychiatric patients between hospitals. This requires that the patient be involuntary committed to the hospital and the potential that they are restrained in the car, introducing an interaction with the legal system and potential trauma to a patient who may have willingly checked in for care (Knopf, 2020).

In response to these lingering issues, recommendations 2 and 4 of the SAFE Charlotte report call for the expansion of CPCRT, the development of a civilian responder model for mental health and homelessness calls and the development of recommendations for converting low-risk sworn duties to nonuniform units. Recommendation 3 calls for an analysis of police-community members contact data in order to assess the presence of bias that may be encouraging poor relationships with the community, as well as to identify services that could more efficiently be delivered by an alternative agency or organization.

2. SAFE recommendations 2 and 4: Alternative responses for low-risk calls and CPCRT Expansion

2.1. Introduction

In this chapter we are responding to the SAFE Charlotte report recommendations 2 and 4. Recommendation 2 is focused on developing recommendations to implement a civilian response for low-risk duties. Recommendation 4 states that CPCRT should be expanded, and a non-sworn officer responder model should be explored for those experiencing mental health crisis and homelessness. Within these recommendations, there were specific tasks:

- Task 1: Analysis of calls for service data, with a focus on low-risk, low-priority calls for service and calls related to mental health crises, substance abuse, and homelessness. This analysis will include a separate breakdown of low-risk, low-priority calls for service, and calls related to mental health, substance abuse, and homelessness crises by examining the quantity, type, and spatial-temporal variation of calls that can be responded to by:
  i. CMPD's Community Policing Crisis Response Team;
  ii. A unit of civilian mental health clinicians, social workers, and/or EMTs; and
  iii. A unit of non-specialized civilian community safety technicians.
- Task 2: Engagement with the Charlotte community, in partnership with the city, to determine residents' opinions of potential recommendations.
- Task 3: Asset mapping of resources in Charlotte, both internal and external to the city, that have capacity to respond to or assist with such calls. This will involve interviews with city and county public safety departments, local mental healthcare providers, and other organizations.
- Task 4: Recommending options for implementing civilian response models for:
  i. Mental health, substance abuse, and homelessness calls for service; and
  ii. Other low-risk, low-priority calls for service

Task 1 was addressed using quantitative analysis of police data. Tasks 2 and 3 were addressed using a qualitative approach. In the methods section, we will provide more details about how we addressed these tasks. Task 4 is recommendations, and as such the response to task 4 is included in the Rand Recommendations section of this report (Chapter 4). To guide our response to these tasks, we also conducted a literature review on alternative response models for individuals in crisis.

2.2. Background on Alternative Response Models

In order to develop recommendations for Charlotte and draw on existing knowledge about crisis response, we conducted a review of crisis response models being tested across the United States. Several states and localities have initiated civilian or co-response team models to respond to low-risk, low-priority calls for service surrounding mental health and homelessness issues. As 7-10% of all police contact involves someone with mental illness (Lord and Bjerregaard, 2014), many of the alternative response models concentrate on mental health services. Several police departments provide specialized training and deploy crisis intervention teams (CIT) of front-line officers directly to provide care, however, research shows that users of mobile health crisis teams would prefer a mental health professional to a police officer (Boscarato et al., 2014; Klevan, Karlsson and Ruud, 2017). Civilian and co-responder teams, alternatives to officer-only crisis intervention teams, are time-limited units that can perform initial screening, determine next course of action, and potentially provide case management follow-up support. Ideally, they can stabilize an individual to avoid hospitalization or incarceration (Birnbaum et al., 2017). Response by these teams is often initiated when the police or 911 is contacted to report a person in need. The decision to deploy the team may be made by a licensed mental health professional—as is the case in New York—or it may be up to the caller to define their situation as an emergency requiring psychological intervention, which is what occurs in Connecticut (Vanderploeg et al., 2016).

Co-Response Models

Co-response units generally include a mental health professional, or at least an individual with some training in mental health crisis intervention, paired with a sworn officer. While impact evaluations of such teams are limited, cities where evaluations or case studies have taken place indicate that these teams can be successful in responding to low-risk calls. In Los Angeles, the Systemwide Mental Assessment Response Team (SMART) is co-deployed with an officer unit and has been shown to both allow individuals in crisis to access a greater range of treatment options and to allow patrol units to respond to other calls, instead of acting as hospital transport or waiting at a hospital for staff to assess and admit a patient (Lopez, 2016). In Indianapolis, an evaluation of the Mobile Crisis Assistance Team (MCAT) program in its pilot phase has similar outcomes and provides useful insight into designing a co-response unit. The MCAT team serves primarily as a first responder unit and is made up of police, paramedics, and masters-degree level behavioral health clinicians. Stakeholders attribute the success of the MCAT pilot to interagency communication and dialogue, particularly the ability to utilize the systems and software of multiple agencies to compare criminal justice and healthcare records when dispatching to the scene of an emergency. The biggest barriers to MCAT success were in communicating and coordinating MCAT goals and responsibilities with external actors in the community, as well the lack of treatment services for referral; stakeholders wished that more resources would have been spent on inventorying and expanding treatment services to support MCAT (Bailey et al., 2018).

Specialized Civilian Response Models

For the purposes of this document, we have separated specialized civilian response models from other approaches. Examples of specialized civilians are emergency medical technicians (EMTs), social workers and mental health clinicians. Civilian response units may be made of civilian police employees or of civilian teams without police affiliation.

In Birmingham, Alabama the Community Service Officer team is made up of civilians trained in social work or related fields who provide crisis intervention and some follow-up assistance in mental health emergencies or on social service-related calls, such as in cases of domestic violence, needs for transportation or shelter, or other general service requests. This force has been found to be particularly active and adept at on-scene crisis intervention, though the small force limits their availability (Steadman et al., 2000). Alternatively, these civilian teams may be funded through or partnered with the police department but made up of team members who are not police employees. The Eugene, Oregon Crisis Assistance Helping out on the Streets (CAHOOTS) team is likely the best-known example of this model. CAHOOTS units are two-person teams of crisis workers and medics, and staff carry a police radio that 911 and non-emergency call-line dispatchers use to request their response on a special channel. Depending on the call type, a CAHOOTS team may be the only responder on scene, or they may be part of a joint response (CAU, 2020). Per a 2020 impact report, the CAHOOTS program has diverted 5-8% of calls to the Eugene Police Department (EPD) and utilized about 2% of the department's budget. CAHOOTS staff and EPD collectively developed criteria for calls that might be routed to a CAHOOTS team, and they credit being embedded in the emergency communications and public safety infrastructure with much of their impact (CAU, 2020; Beck, Reuland and Pope, 2020). In Denver, Support Team Assisted Response (STAR), a trauma-informed approach modeled on the CAHOOTS program, consists of a mental health clinician and EMT. A 2021 evaluation of the STAR pilot program estimates that it could reduce Denver Police service calls by 2.8%[6] (Blick et al., 2021). This program is still in a pilot phase.

In some cases, mental health crisis response units respond to calls for service that involve co-occurring substance use disorders and/or homelessness (Reuland, 2010), or take on calls and activities that involve homelessness as part of their scope of services (CAHOOTS does this). There are some police departments have specialized homelessness co-responder units, such as The Philadelphia Police Department's Service Detail, where units are made up of homeless service providers and/or social workers and law enforcement officers who are available to provide basic public safety. Civilian partnerships to respond to issues of homelessness exist as well - residents of Syracuse, NY are asked to call an alternate number to request street outreach

[6] STAR teams respond to 911 CAD codes for: Assist, intoxicated person, suicidal series, welfare check, indecent exposure, trespass unwanted person, Syringe disposal when there is no evidence of criminal activity, disturbance, weapons, threats, violence, injuries, or serious medical needs

services instead of police, as are those in San Francisco and Rockford, Illinois (Batko et al., 2020).

Other Civilian-Only Models

For the purposes of this document, and to align with the SAFE Charlotte recommendation, we have focused this section on civilian response models that do not explicitly require highly trained personnel such as social workers or clinicians. However, this is not to say that they do not possess skills that enable them to provide services to the community. For example, in programs using “violence interrupters,” personnel are not clinicians or EMTs but possess skills that make them “credible messengers” (Gaherty and Asdourian, 2020). In these cases, community responders can use credibility, relationships, and training to mediate conflict (Irwin and Pearl, 2020). However, a recent report by the Center for American Progress (2020) indicates that models such as these are not dispatched via 911.

In other cases, there are recent moves toward using civilians to handle calls for service that typically do not involve conflict that the police have historically responded to. Examples are included below in table 1.1.

Table 1.1 Examples of Civilian Response Models

Location	Population of Interest	Details
Ithaca/Tompkins County, NY	Varies	Reimagining public safety plan and resolution detail a new Department of Public Safety, some of whom will be unarmed civilians who will respond to calls; call types to be determined.
Northampton, MA	Varies	Proposed Department of Community Care integrated with 911 that may be comprised of: peer responders, co-responders, or civilian advocates
Amherst, MA	Unclear	Proposed Community Responders for Equity, Safety, and Service comprised of peer specialists to respond to police calls; additional details unclear.
Fort Worth, TX	Low level incidents	First group of responders trained and deployed in 2021 to respond to quality-of-life issues
Brooklyn Center, MN	Traffic	Bill proposed (May 2021) for unarmed civilians to enforce all non-moving traffic violations
Berkeley, CA	Traffic	Police to be diverted away from low-level traffic offenses, future creation of unarmed Department of Transportation.

SOURCE: (City of Ithaca, 2021; Northampton Policing Review Commissioners, 2021; Community Safety Working Group, 2021; McKinney, 2021; Associated Press, 2020; City Clerk, n.d.; Office of the Mayor, 2021)

Although these non-specialized civilian response models may be promising, there is little or no evidence that they are effective, as all of the programs in Table 1.1 above are currently proposed or under development, except for Forth Worth. Further, there has been substantially more effort in the area of unarmed, specialized responses to mental health, substance use, and homelessness than other call for service types. Nonetheless, we have included them in this section as they describe the trend Charlotte and other municipalities are strongly considering while examining the future of public safety services.

As discussed above, data on the implementation, functioning, and impact of alternative response models is scarce. With that in mind, a number of lessons can be gleaned from the models where such reports exist. A defining factor of the successful civilian and co-responder models discussed is interagency cooperation and communication, with clear criteria and procedures for identifying service call types where an alternative response is appropriate. A case where more of this is needed is that of Brattleboro, Vermont's Police Social Work Liaison (PSW) Program. The PSW program, funded through the Department of Mental Health and the Division of Alcohol and Drug Abuse Programs, is not embedded within Brattleboro Police Department operations and in fact has no MOU with department. A 2020 evaluation of the program concluded that it did not achieve any desired outcomes, having found "no evidence that this program plays any role in diverting incarceration or hospitalization" (Witzberger and Megas-Russell, 2020), likely in part due to the siloed nature of the program. Other factors leading to successful models include external communications to encourage community stakeholders to trust and utilize services and collaborative creation of protocols between health care, crisis response, and police departments (Bailey et al., 2018; Beck, Reuland and Pope, 2020). The lessons from these programs helped us to execute this study and shape our recommendations within this report.

2.2. Methods for Recommendations 2 and 4

We approached recommendations 2 and 4 with a formative evaluation approach. A formative evaluation is a study designed to understand the implementation context, identify potential barriers and facilitators to implementation and determine the feasibility of implementation (Stetler et al., 2006). We used a mixed methods approach to conduct this formative evaluation and respond to the scope of duties in recommendations 2 and 4.

In order to guide this formative evaluation, we drew on the Consolidated Framework for Implementation Research (CFIR), a widely used implementation research model. CFIR is flexible so that it can be applied to any implementation effort, has a comprehensive set of interview questions that can be tailored, and has a large body of evidence showing links between CFIR-identified barriers and facilitators and implementation outcomes. There are five CFIR domains: Intervention Characteristics, Individual Characteristics, Implementation Process, Inner Setting, and Outer Setting. Within each domain there are subdomains. Intervention characteristics include subdomains such as complexity and cost of the intervention. Individual characteristics include the subdomains such as individual stage of change and self-efficacy. Implementation process includes subdomains such as planning and change champions. Inner settings include subdomains such as access to resources, leadership buy-in and organizational culture. Outer settings include aspects such as external policies and peer pressure. It is not necessary to utilize all five domains as the framework can be tailored to the research goals and setting. It just provides a roadmap to evaluate potential barriers and facilitators to implementation (Damschroder et al., 2009).

In the following sections we detail the steps we took to conduct a formative evaluation with the ultimate goal of improving police policies to manage low-risk calls and individuals with mental illness/experiencing homelessness/substance use disorder. This section specifically details the methods used to respond to the tasks outlined in the introduction of this chapter.

Methods to Respond to Task 1

We first analyzed all calls for service according to both their priority and their listed call type. We focused primarily on the initial priority and the initial call type because these initial designations would be the most influential for resource allocation. We identified all 240 call types observed during the 2015-2020 study period. From this list, we categorized calls according to their likelihood to be related to substance abuse, mental health, and homelessness. This was accomplished through the following process:

- Reviewing the call code in the CAD system. The first step consisted of identifying the CAD code for the CFS. This was done by examining the TYPE_CODE_ORIG_DESC (type of call code by its original description).
- With any CFS that were unclear as to their meaning, we confirmed with CMPD their definitions, circumstances for use, and any associated risks. For example, "ASSIST MEDIC" was not clear in its description. Following discussions with CMPD, this was clarified as a situation where police are called to assist EMS that typically involves risk of danger (i.e., weapon present or assault/threat of assault)
- We then flagged and confirmed calls for service that were potentially related to homelessness or mental health (e.g. overdose, possession of drugs/paraphernalia, loitering or trespassing related to homeless individual call types).

Two other sources of information were used to categorize calls. Calls where the crisis response team or the crisis intervention team were dispatched were flagged as potentially mental health related, and there was a subset of calls where CMPD had separately flagged them as being related to homelessness.

Based on this information, we documented the volume of each categorized call type and priority overall and by neighborhood, as well as by time of day, day of week, month, and year.

When considering classifying low-risk calls, we relied on proxies for risk since we were unable to determine the injury rate for different types of calls because we did not have access to officer injury data. We assume that calls are a high risk to the safety of the responder if 1) their priority changes during the course of their service, and 2) they require more than a single unit on scene. Priority 5 calls that do not escalate and can be managed by a single unit are considered to be ideal for non-sworn responders since it is unlikely they: 1) will call for sworn-backup and be unable to address the call by themselves.

Methods to Respond to Tasks 2 and 3

In order to respond to tasks 2 and 3 used qualitative interviews, literature review and targeted web searches.

Study Sample

We identified and interviewed representatives from city and county public safety departments, local mental healthcare provider organizations, community action organizations and local social service providers. Details on the sample are included in table 2.13 of this chapter, in the results section.

Recruitment

We conducted 35 interviews. This number of interviews has been shown to achieve saturation (Simmons et al., 2017). Saturation is when no new information is yielded through additional interviews (Yin, 2015). We used both purposeful and snowball-type sampling to identify appropriate people. Purposeful sampling is when participants are pre-selected at the outset of the projects and snowball sampling is when additional participants with particular knowledge relevant to the project are identified during the course of research (Yin, 2015). We worked with the city to identify the purposeful sample. We then asked enrolled participants to identify additional potential participants at the end of each interview for snowball sampling. Community participants received $50 for their participation, when feasible and appropriate.

Interview Guide and Data Collection

Participants were interviewed once for approximately 60 minutes. In light of the coronavirus pandemic, all interviews were conducted via Zoom. Interview questions were guided by the research questions and CFIR (Damschroder et al., 2009). Constructs from CFIR included in the interview guide are detailed in Table 2.1. These questions not only adhere to the CFIR construct, but also collect critical information for asset mapping (task 3).

Table 2.1 CFIR Constructs

Construct	Description
Intervention Characteristics	Attributes of the intervention which may impact implementation. These include cost, complexity, design and quality
Outer Settings	External threats to implementation. These include: external policies, racial issues, resources in the community
Inner Settings	Attributes internal to the organization which potentially impact implementation. These include: culture, training, tension for change
Characteristics of Individuals	Attributes of the individuals implementing the intervention. These include personal attributes, belief in the intervention

Process	The implementation processes. These include: planning, stakeholder buy-in, evaluation of intervention

The complete interview guide is included in Appendix A.

Analysis

We analyzed interviews using Dedoose (Version, 2018), a qualitative data analysis software and led by two senior research staff (MS, MM). All interviews were de-identified to ensure anonymity of participants. Interviews were recorded and transcribed and detailed notes were taken during the interviews. Interview notes were imported into Dedoose for analysis and then specific quotes were pulled from transcriptions when they were identified as significant from the notes (Version, 2018). The codebook was largely developed with *a priori* codes based on implementation science literature with thematic codes emerging through the data (Utarini, Winkvist and Pelto, 2001; Sobo et al., 2002). A complete copy of the codebook is included in Appendix B.

Two experienced coders (MS, MM) lead the coding effort. In order to achieve consistent coding, three interviews were double coded for inter-rater reliability and the team discussed results to resolve minor disagreements that emerged. From that point each remaining transcript was coded by a primary coder with spot checks by MS.

We also used the interviews, targeted google searches and two community tools, The One Charlotte Health Alliance website and NC211.com, to develop an asset map of mental health, substance abuse disorder, and homelessness/housing resources. “Asset mapping,” or “asset-based” or “strengths-based” planning, is viewed as a superior approach to needs assessment while occasionally seen as a complement rather than an alternative to needs assessment (Beaulieu, 2002). In addition to mapping the type of asset, we also collected information about the location of the asset and how to access it (e.g., relevant contacts, application procedures, etc.). We mapped the exact location of the asset geographically, and produced a visualization where a map of the community showing where the assets are located by type was overlaid on a map of calls flagged as potentially related to behavioral health or homelessness. The map allowed us to assess any gaps in service needs and location, and is included in the recommendation section of this chapter. In addition, we placed each of the behavioral health resources along a continuum of behavioral health care in order to assess any gaps in levels of care available. Finally, we created a resource guide with the types of assets grouped conceptually. This guide can be found in Appendix D.

2.3. Findings

Calls for service

Routine priority calls

We analyzed all calls for service in the CAD system from 2015-2020 to identify the quantity, type, and spatial-temporal variation of low priority calls for service as well as those calls relating to substance abuse, mental health, and homelessness.

We found that routine priority (priority 5) calls for service made up about 16% of all calls for service – see Table 2.2 for the frequency of all priority levels. Routine priority calls for service were the second most frequent priority level, much lower than immediate priority calls (priority 3, 64% of all calls) but much higher than either emergency priority (priority 1, 8%) or priority 2 (9%).

Table 2.2. All Calls for Service by Priority Type

Priority	Description	Total calls for service	% of all calls
0	Officer in Trouble	1,367	0.04%
1	Emergency priority	289,548	8.13%
2	Priority calls - suspect on scene	305,145	8.57%
3	Immediate priority	2,261,214	63.51%
4	Officer crime scene calls	7	<0.01%
5	Routine priority	581,226	16.32%
6	Animal control emergency priority	1,161	0.03%
7	Animal control immediate priority	565	0.02%
8	Animal control routine priority	349	0.01%
9	Appointments or non-timed response	119,835	3.37%

The most frequent routine priority call types were noise complaints, traffic accidents and infractions, and larceny from vehicles. See Table 2.3 for the 20 most frequent routine priority call types. The 20 most frequent routine priority (priority 5) call types, with frequency and percentage of all routine priority calls are included.

Table 2.3. The 20 Most Frequent Routine Priority (Priority 5) Call Types, with Frequency and Percentage of All Routine Priority

Call type	Total N of routine calls	% of all routine calls	Cumulative %
Noise Complaint	56,596	9.7%	9.7%

Accident, Non-Roadway, Property Damage	51,615	8.9%	18.6%
Larceny from Vehicle	44,760	7.7%	26.3%
Hit & Run, Non-Roadway, Property Damage	34,426	5.9%	32.2%
Illegal Parking	28,941	5.0%	37.2%
Break/Enter, Residential – Unoccupied	23,445	4.0%	41.3%
Suspicious Vehicle, Unoccupied	21,491	3.7%	45.0%
Larceny	20,317	3.5%	48.4%
Child Development Community Policing (CDCP) Clinician Visit	17,496	3.0%	51.5%
Accident in Roadway, Property Damage	14,735	2.5%	54.0%
Injury to Real/Personal Property	14,117	2.4%	56.4%
Found Property	13,956	2.4%	58.8%
Abandoned Vehicle	13,643	2.3%	61.2%
Missing Person	13,377	2.3%	63.5%
Attempt to Locate	13,305	2.3%	65.8%
Escort	12,468	2.1%	67.9%
Pick up property or evidence	11,471	2.0%	69.9%
Notify	11,179	1.9%	71.8%
Domestic property recovery	10,323	1.8%	73.6%
Serve legal papers	8,703	1.5%	75.1%

We also examined how rates of routine priority calls changed over time. The share of all calls that were assigned routine priority stayed relatively stable over time, with the highest rate in 2016 (more than 104,000 calls, 17.5% of all calls) and the lowest rates occurring in 2015 (15.3%) and 2020 (15.5%). Descriptive statistics of routine priority calls by year are given in Table 2.4. It is also notable that the total routine priority call volume was much lower in 2020 compared to any other year (about 79,000 calls compared to more than 98,000 in all other years). This drop is likely due to the COVID-19 pandemic.

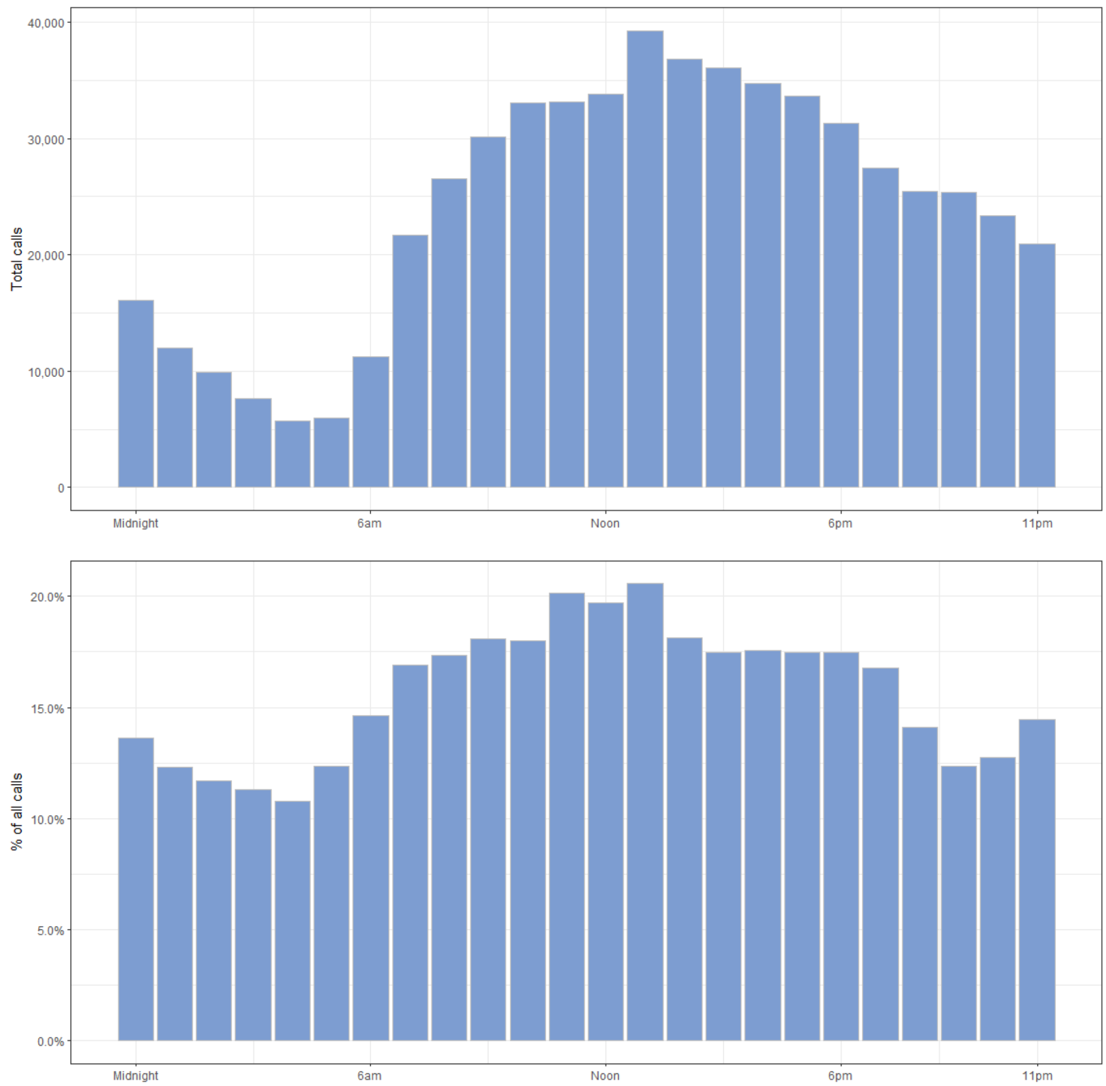
Table 2.4. Routine Priority Calls by Year

Year	Total calls	% of all calls within year	% of all routine priority calls
2015	97,778	15.3%	16.8%
2016	104,553	17.5%	18.0%
2017	101,299	16.4%	17.4%
2018	98,363	16.5%	16.9%

2019	99,484	16.6%	17.1%
2020	79,749	15.5%	13.7%

There was significant variation in the volume of routine priority calls by time of day. See Figure 2.1. The top panel shows the number of routine priority calls. The bottom panel shows the proportion of all calls at that hour of the day that were routine priority.

Figure 2.1. Routine Priority Calls by Hour of the Day



Routine priority calls accounted for between 10 and about 20% of calls at all hours of the day, with the lowest share occurring in the early morning and late evening, and the highest share occurring between 7am and 7pm. Between 11am and 2pm, routine priority calls account for about 20% of all calls.

We did not find substantial variation in the number or proportion of calls by day of week or by month. See Figures 2.2 and 2.3. In each figure, the top panel shows the number of routine priority calls, and the bottom panel shows the proportion of all calls on that day of the week or month that were routine priority.

Figure 2.2. Routine Priority Calls by Day of Week

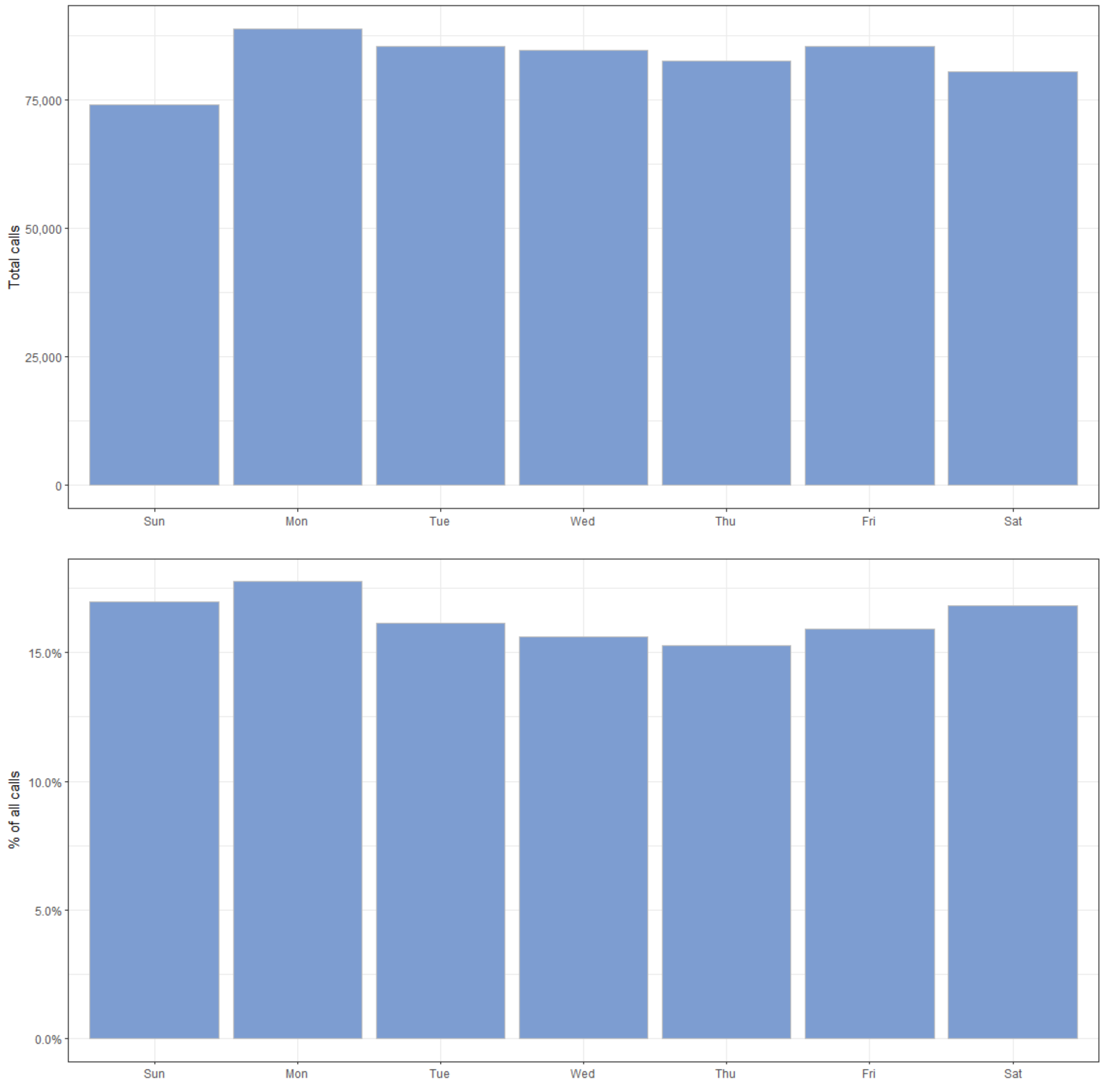
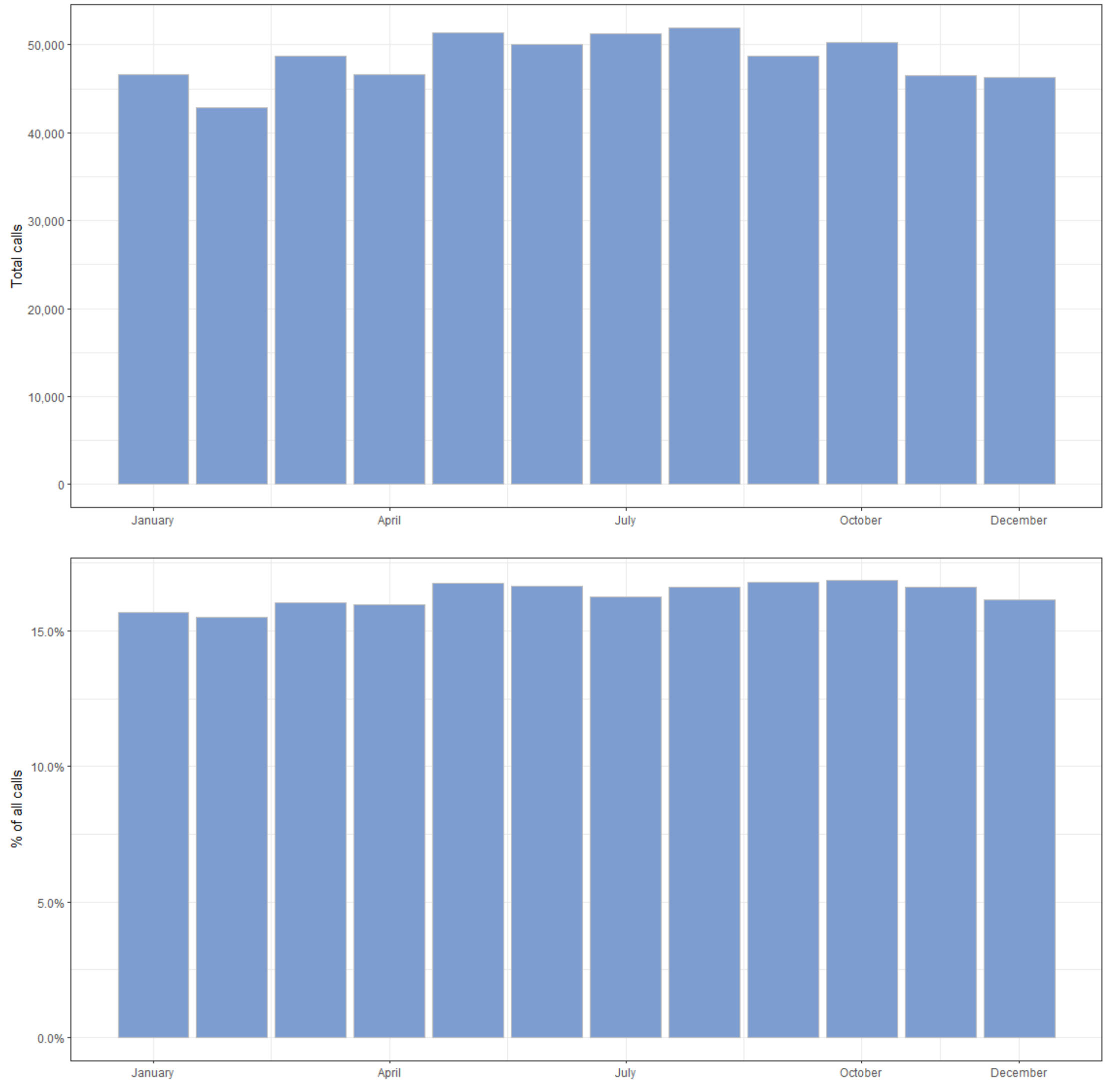
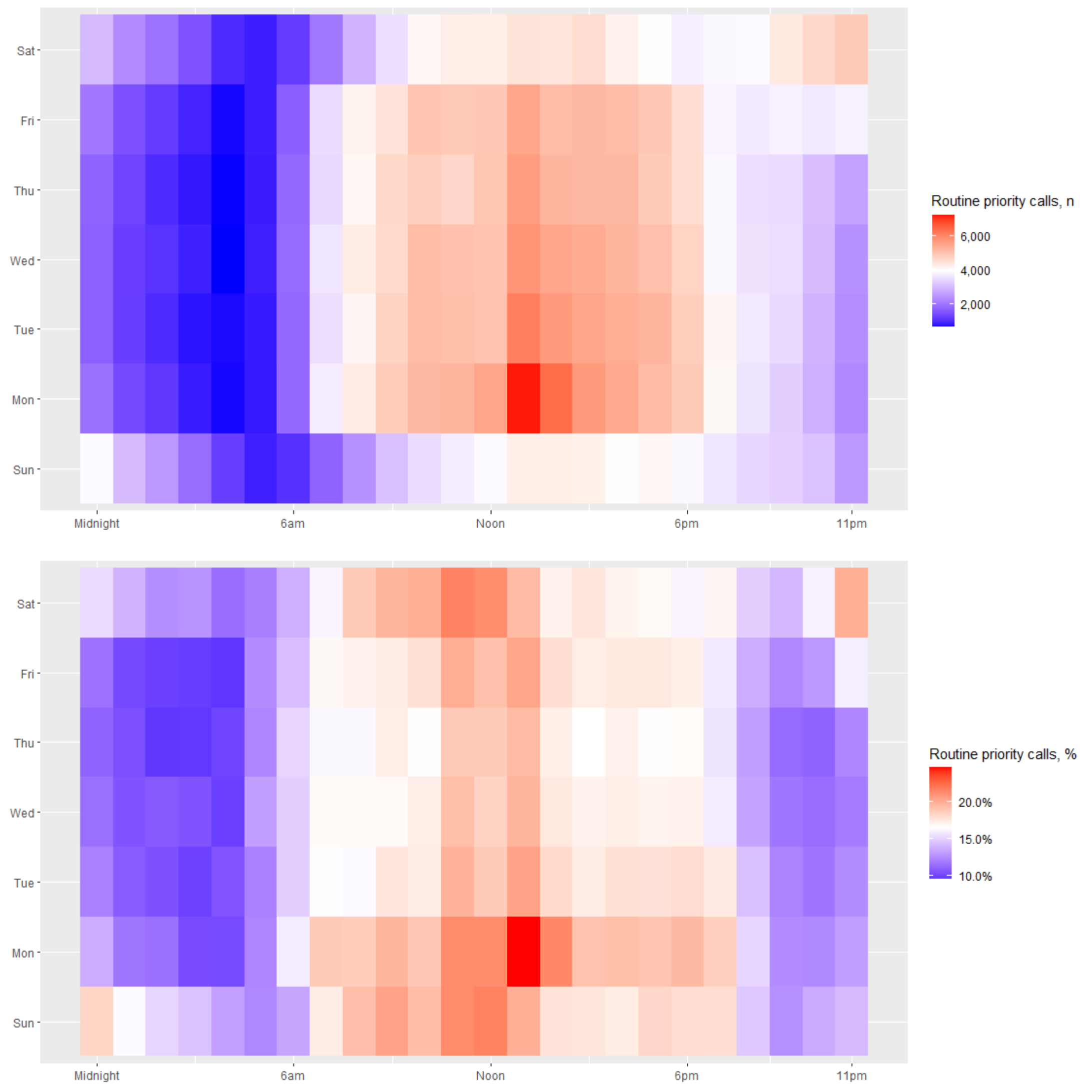


Figure 2.3. Routine Priority Calls by Month



Looking in more detail at variation by time of day and day of week together, Figure 2.4 shows that routine priority calls are most likely on Monday afternoon, with substantial volume of calls during business hours during the week and late at night on the weekend.

Figure 2.4. Routine Priority Calls by Hour of Day and Day of Week



There was substantial geographic variation in both the number and proportion of routine priority calls. See Figure 2.4 for maps showing routine calls by neighborhood. The 20 neighborhoods with the most routine priority calls are given in Table 2.5. Neighborhood statistical area 3 had the most routine priority calls (13,050), and about 19% of all calls in this neighborhood were routine priority. More than 30% of the calls in neighborhood statistical area 64 were routine priority. The left panel shows the number of routine priorities calls in each neighborhood. The right panel shows the proportion of all calls from that neighborhood that were routine priority (minimum 500 calls).

Figure 2.4. Routine Priority Calls by Neighborhood

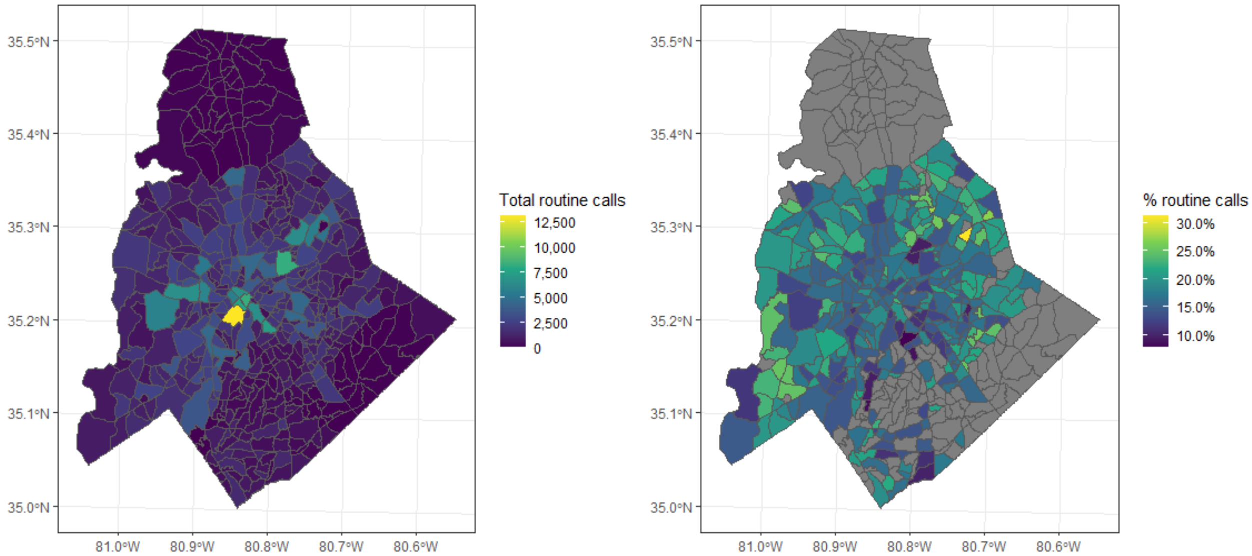


Table 2.5. Routine Priority Call Volume and Proportion for the 20 Neighborhoods with the Most Routine Priority Calls

Neighborhood statistical area	Total Number of Routine Calls	% Routine Calls
3	13,050	19.1%
341	8,173	16.0%
371	8,140	12.8%
342	7,608	15.6%
370	7,115	15.5%
340	6,559	14.2%
387	6,461	16.0%
367	6,407	19.9%
331	6,244	14.3%
124	5,934	15.6%
122	5,775	12.1%
219	5,630	18.1%
384	5,629	16.6%
385	5,256	16.4%
64	4,997	31.2%
72	4,505	21.2%
164	4,501	12.6%
290	4,489	11.9%
363	4,485	16.9%
389	4,478	15.7%

In the absence of officer injury data, we defined low risk as calls for which1) their priority did not change during the course of their service, and 2) they did not require more than a single unit on scene. Table 2.6 provides top 24 lowest-risk calls by this metric. Illegal parking, found property, notify,[7] pick up property or evidence and road blockage were the lowest risk calls by this metric.

Table 2.6. Lowest Risk Calls, sorted by highest percentage of single-unit calls and lowest priority-escalation

Original Call Type	Low Risk %	Priority Escalation %	Required Multiple Units %	Total Calls
Illegal Parking	85.123	0.048	14.349	28,991
Found Property	83.78	0.071	15.365	14,032
Notify	82.677	4.578	12.816	11,205
Pick Up Property or Evidence	80.369	0.113	19.291	11,487
Road Blockage	79.895	0	17.016	1,716
Accident Non-Roadway-Property Damage	79.647	0.008	19.534	51,684
Accident in Roadway-Property Damage	78.417	0.034	19.536	14,757
Abandoned Vehicle	78.099	0.029	20.481	13,666
Hit & Run-Non-Roadway-Property Damage	77.047	0.032	22.41	34,458
Vehicle Disabled Not in Roadway	76.541	0.106	18.958	2,822
Larceny from Vehicle	74.834	0.029	24.737	44,791
Hit & Run-In Roadway-Property Damage	74.583	0	23.912	7,377
Fraud/Forgery	73.483	0.029	25.751	6,788
Missing Persons Recovery	72.629	0	27.105	6,010
Alcohol Beverage Control Violations-Citations	72.273	0.39	26.623	1,540
Suspicious Vehicle Unoccupied	71.184	0.037	27.874	21,554
Injury to Real/Personal Property	70.955	0.057	28.245	14,130
Break/Enter Commercial	68.853	0.067	30.598	7,471

[7] Typical examples of use involve a caller wanting to share additional information about a previous call and/or case or requests for information and/or guidance that do not fall neatly within another CAD event type

Assist Other Agency	68.582	0.104	28.299	6,700
Suspicious Property	67.63	0.0412	30.8422	2,422
Larceny	67.317	0.064	31.755	20,362
Vehicle Recovery	64.832	0.082	34.251	8,502
Missing Person	64.754	0.06	34.200	13,383
Missing Person-Runaway	64.593	0.018	34.84	5,465

Calls relating to mental health, substance abuse, and homelessness

We flagged a total of 261,439 calls (7% of all calls) that were potentially related to mental health, substance abuse, and homelessness (hereafter, we refer to these calls as a group as "flagged" calls). These, presented in Table 2.7, included more than 89,000 potentially related to homelessness, more than 160,000 potentially related to mental health, and more than 12,000 potentially related to substance abuse.

Table 2.7. Calls Flagged as Potentially Related to Mental Health, Substance Abuse, and Homelessness

Total Flagged Calls	% Flagged	Homelessness: Total Calls	Mental Health: Total Calls	Substance Abuse: Total Calls
261,439	7%	89,317	163,490	12,732

Calls flagged for homelessness were most frequently related to loitering (see Table 2.8). All call types accounting for more than 1% of calls flagged for homelessness are included.

Table 2.8. Most Frequent Call Types of Calls Flagged as Potentially Related to Homelessness

Call Type	Total Calls	% Of All Homelessness Calls
Loitering for Money	**34,778**	**38.9%**
Loitering	**20,350**	**22.8%**
Homeless People	**5,455**	**6.1%**
Disturbance	**4,867**	**5.4%**
Welfare Check	**3,368**	**3.8%**
Suspicious Property	**2,580**	**2.9%**
Suspicious Person/Prowler	**2,385**	**2.7%**
Citizen Contact	**2,320**	**2.6%**
Trespass	**1,288**	**1.4%**

Abandoned Property	**985**	**1.1%**
Assist Medic	**985**	**1.1%**

Calls flagged as potentially related to mental health were overwhelmingly welfare checks. See Table 2.9. All call types accounting for more than 1% of calls flagged for mental health are included.

Table 2.9. Most Frequent Call Types of Calls Flagged as Potentially Related to Mental Health

Call Type	Total Calls	% Of All Mental Health Calls
Check the Welfare Of	120,374	73.6%
CDCP Clinician Visit	17,496	10.7%
Suicide-Threat	15,712	9.6%
Suicide-Attempt	4,536	2.8%

Calls flagged for substance abuse were most often overdoses. See Table 2.10. All call types accounting for more than 1% of calls flagged for substance abuse are included.

Table 2.10. Most Frequent Call Types Of Calls Flagged As Potentially Related To Substance Abuse

Call Type	Total Calls	% Of All Substance Abuse Calls
Overdose	6,893	54.1%
Loitering-Sale/Purchase Drugs	4,727	37.1%
Drug Paraphernalia-Found/Pickup	1,112	8.7%

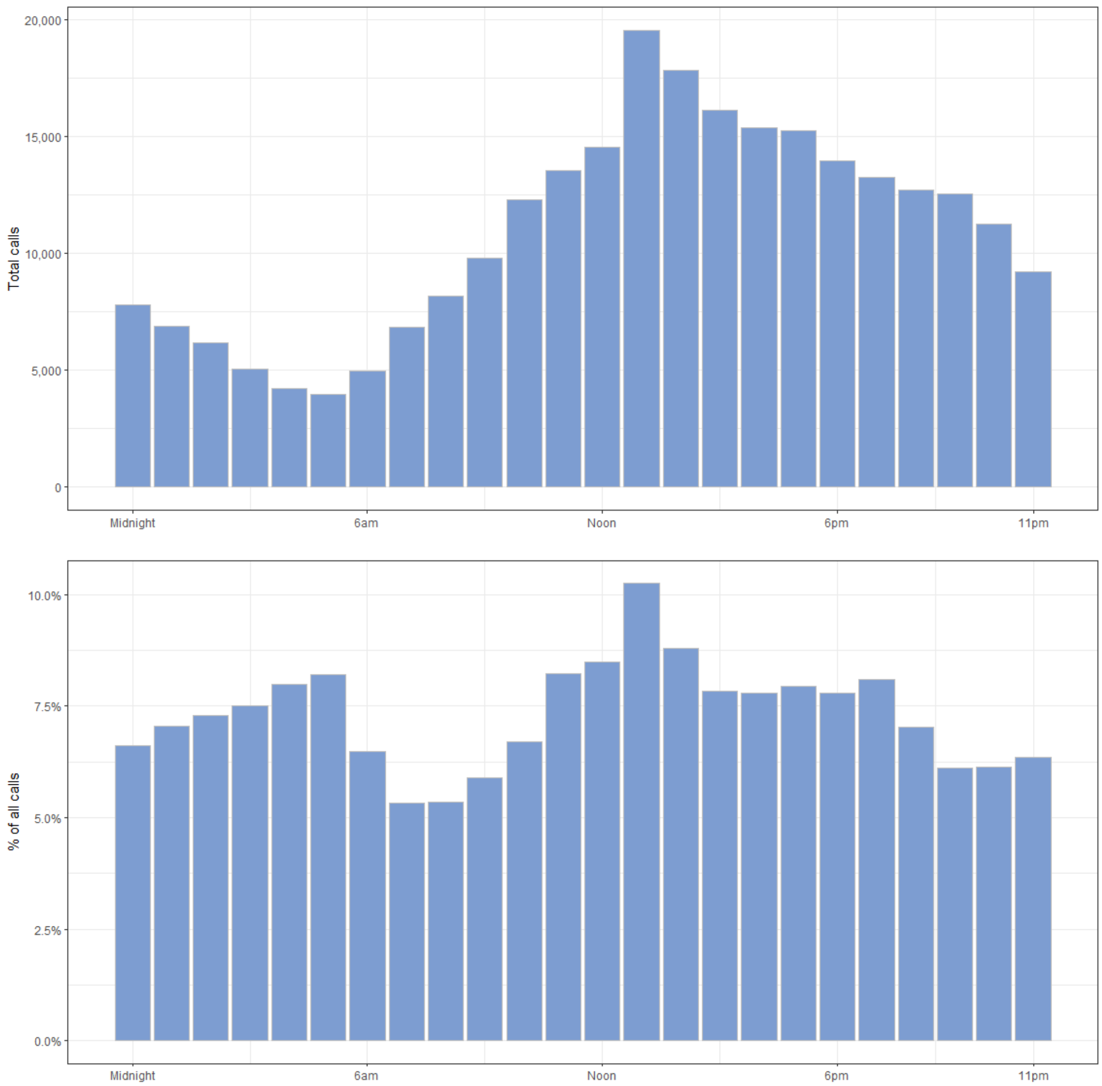
We also examined how rates of flagged calls changed over time. Call volume and share of all calls increased over the study period, as can be seen in Table 2.11. The lowest flagged call volume (relative to all calls) was in 2015, when 6% of all calls were flagged (37,125 flagged calls), and they increased each year until reaching a peak share of 8.6% of all calls in 2020 when 43,960 calls were flagged.

Table 2.11. Flagged Calls (Relating To Substance Abuse, Mental Health, And Homelessness) By Year

Year	Total calls	% of all calls within year	% of all flagged calls
2015	37,125	5.8%	14.2%
2016	41,441	6.9%	15.9%
2017	45,248	7.3%	17.3%
2018	45,802	7.7%	17.5%
2019	47,863	8.0%	18.3%
2020	43,960	8.6%	16.8%

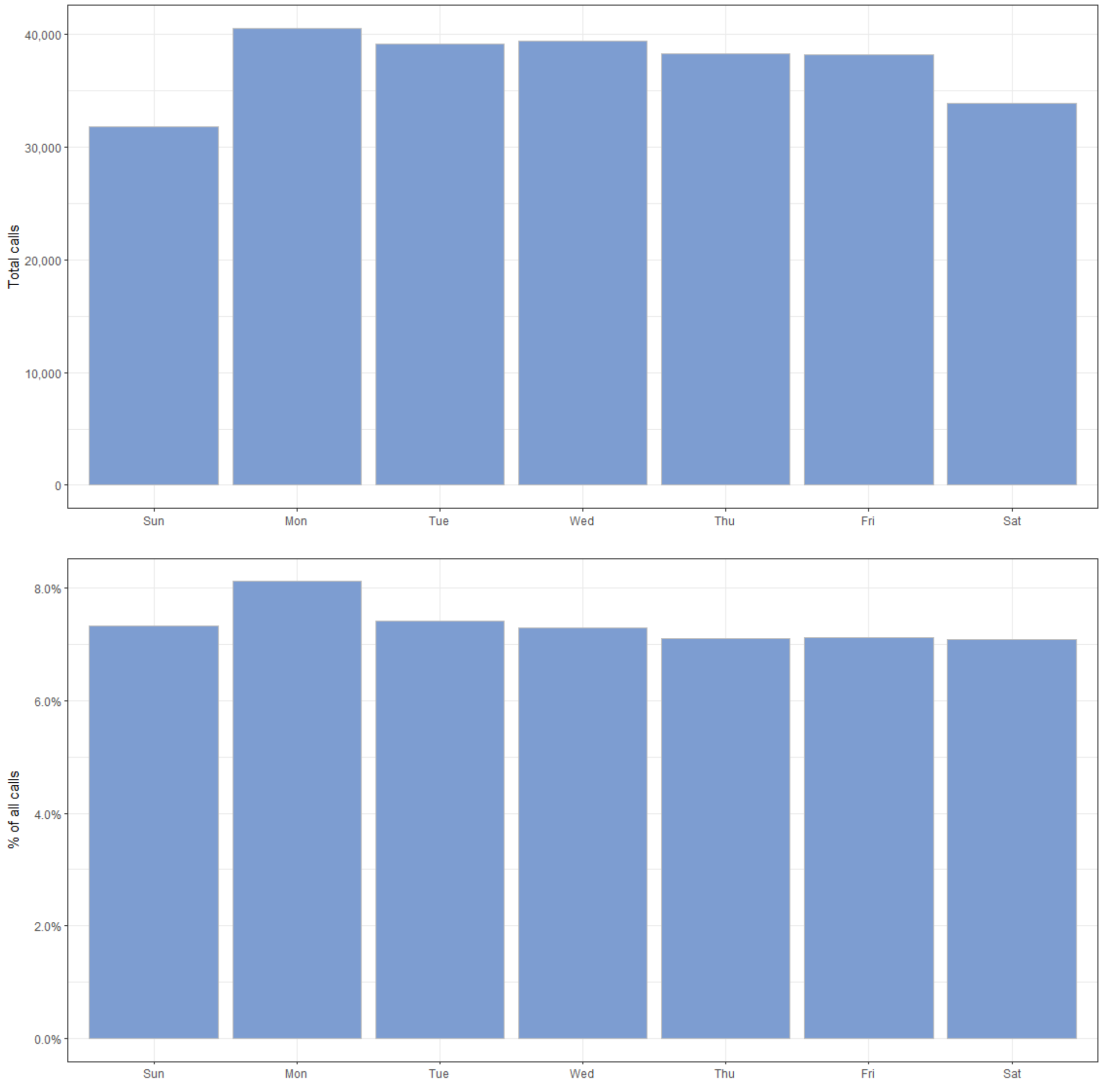
Flagged calls reach their peak, both in terms of call volume and share of all calls, in the middle of the day. See Figure 2.5 for variation by time of day. The top panel shows the number of flagged calls. The bottom panel shows the proportion of all calls at that hour of the day that were flagged. The volume of calls tends to be lowest in the early morning, after which it increases until its peak at the middle of the day, followed by a slow decrease over the evening.

Figure 2.5. Flagged Calls (Relating to Substance Abuse, Mental Health, and Homelessness) By Hour of the Day



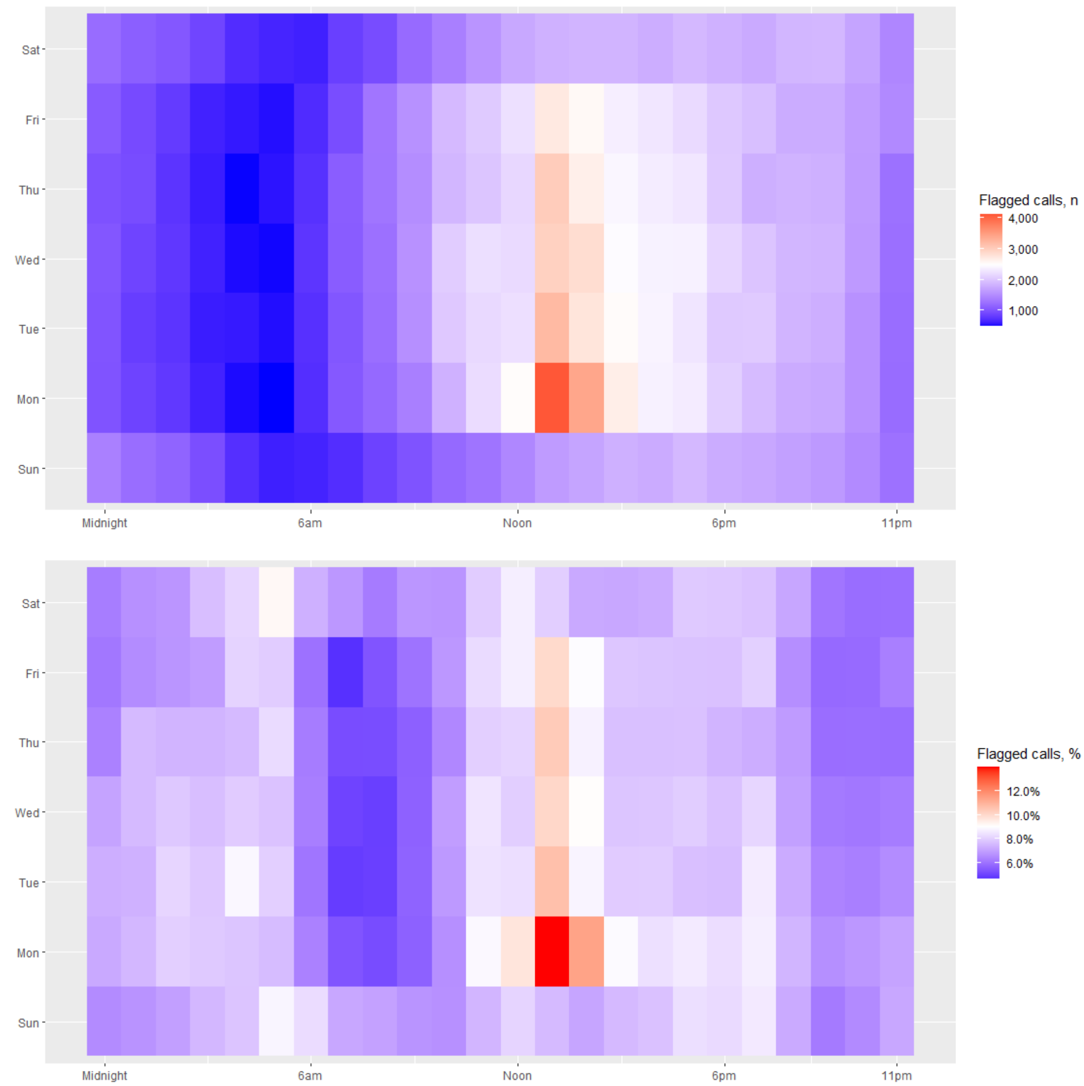
Flagged calls were least likely to be received on weekends, and they were most likely on Mondays. See Figure 2.6. The top panel shows the number of flagged calls. The bottom panel shows the proportion of all calls at that hour of the day that were flagged.

Figure 2.6. Flagged Calls (Relating To Substance Abuse, Mental Health, And Homelessness) By Day Of The Week



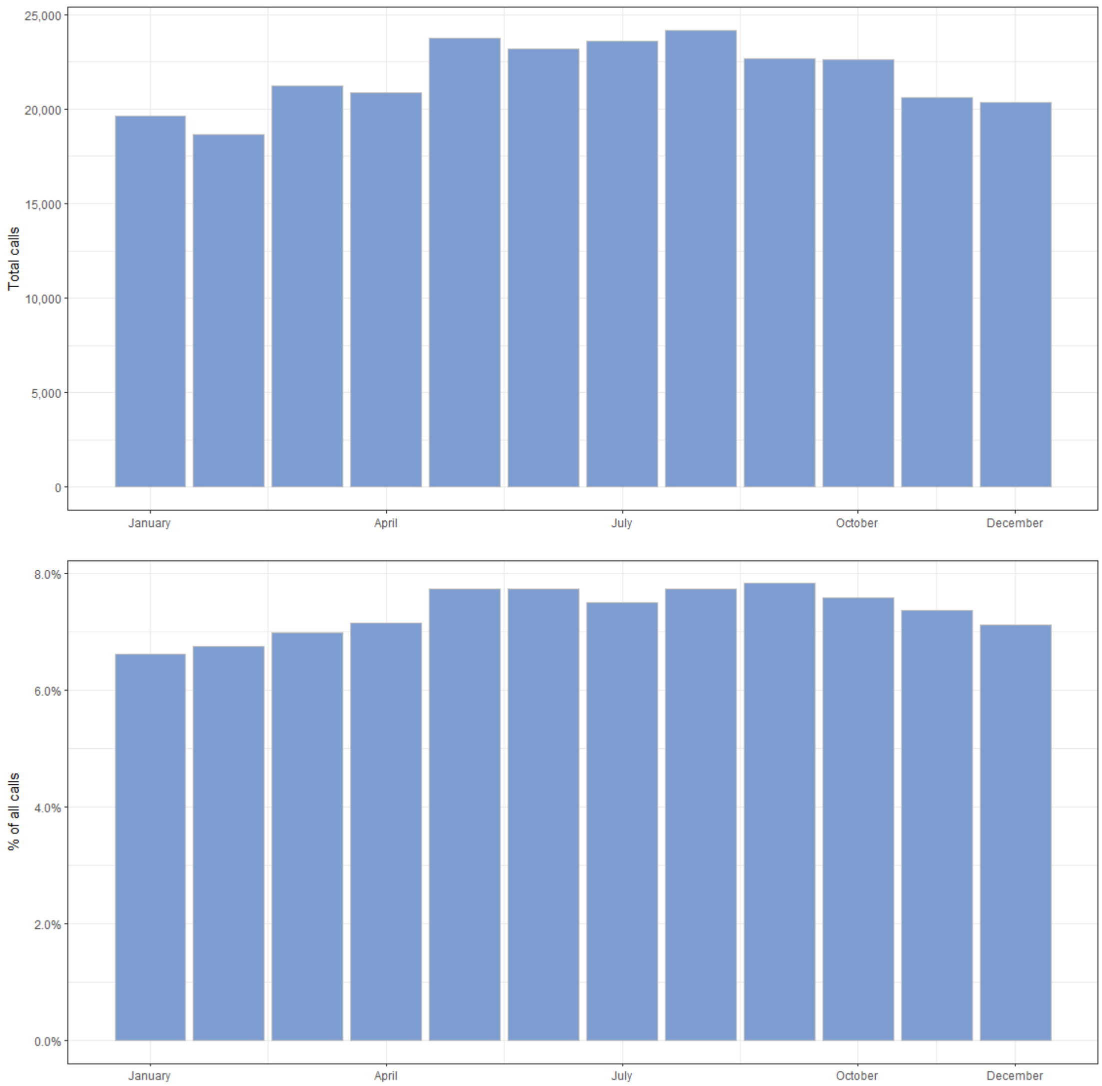
Looking in more detail at variation by time of day and day of week together, Figure 2.4 shows that flagged calls were most likely in the afternoon, particularly on Monday.

Figure 2.7. Flagged Calls (Relating To Substance Abuse, Mental Health, And Homelessness) by Hour of Day and Day of Week



Flagged calls tended to be more frequent during warm weather months (see Figure 2.7). In the figure, the top panel shows the number of flagged calls. The bottom panel shows the proportion of all calls in that month that were flagged.

Figure 2.7. Flagged Calls (Relating to Substance Abuse, Mental Health, and Homelessness) By Month



Flagged calls were most likely to occur in NSA 340 (6,169 flagged calls), where more than 13% of all calls were flagged as potentially relating to mental health, substance abuse, or homelessness. See Figure 2.8 for maps of flagged call variation by neighborhood (the left panel shows the number of flagged calls in each neighborhood, and the right panel shows the proportion of all calls from that neighborhood that were flagged, minimum 500 calls), and see Table 2.12 for a listing of the top 20 neighborhoods in terms of flagged call volume. Figure 2.9 zooms in on the left panel of Figure 2.8 and labels the top 20 neighborhoods listed in Table 2.12. Two other neighborhoods in Table 2.12 had both a sizable call volume and about 13% of all calls flagged – Neighborhood Statistical Areas (NSA) 157 (3,891 flagged calls) and 163 (2,386 flagged calls). While the table lists the NSA, the location of these NSAs can be found on the map in figure 2.8.

Figure 2.8. Flagged Calls by Neighborhood

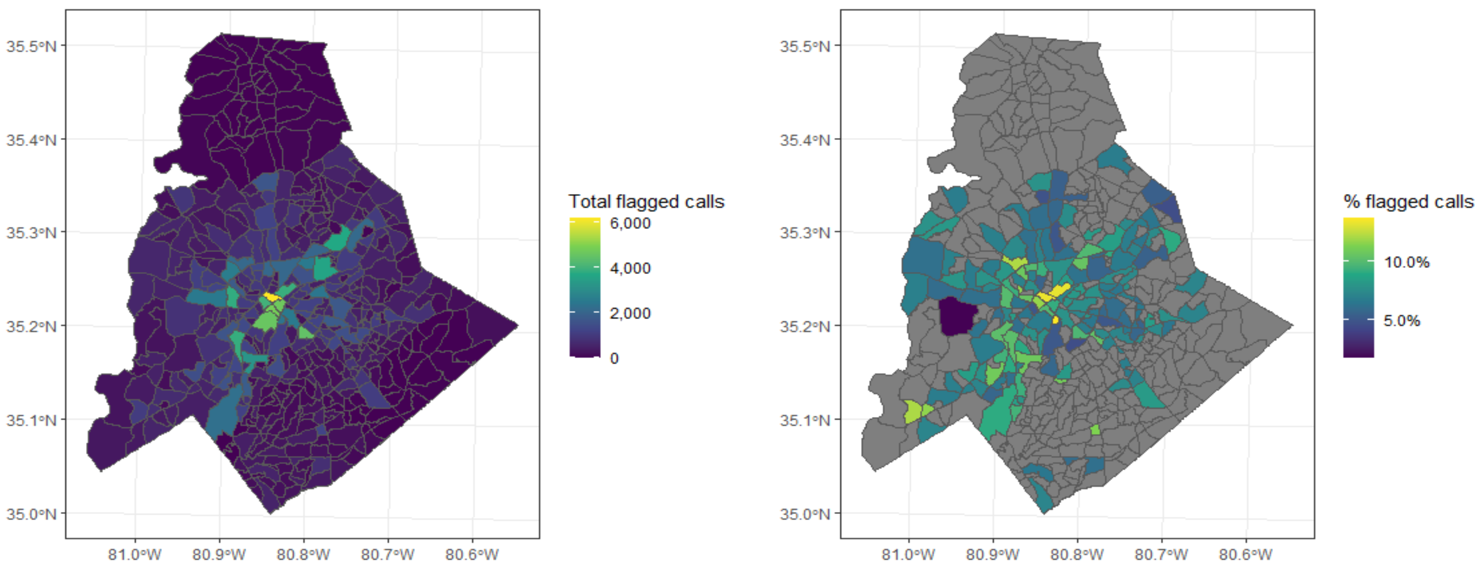
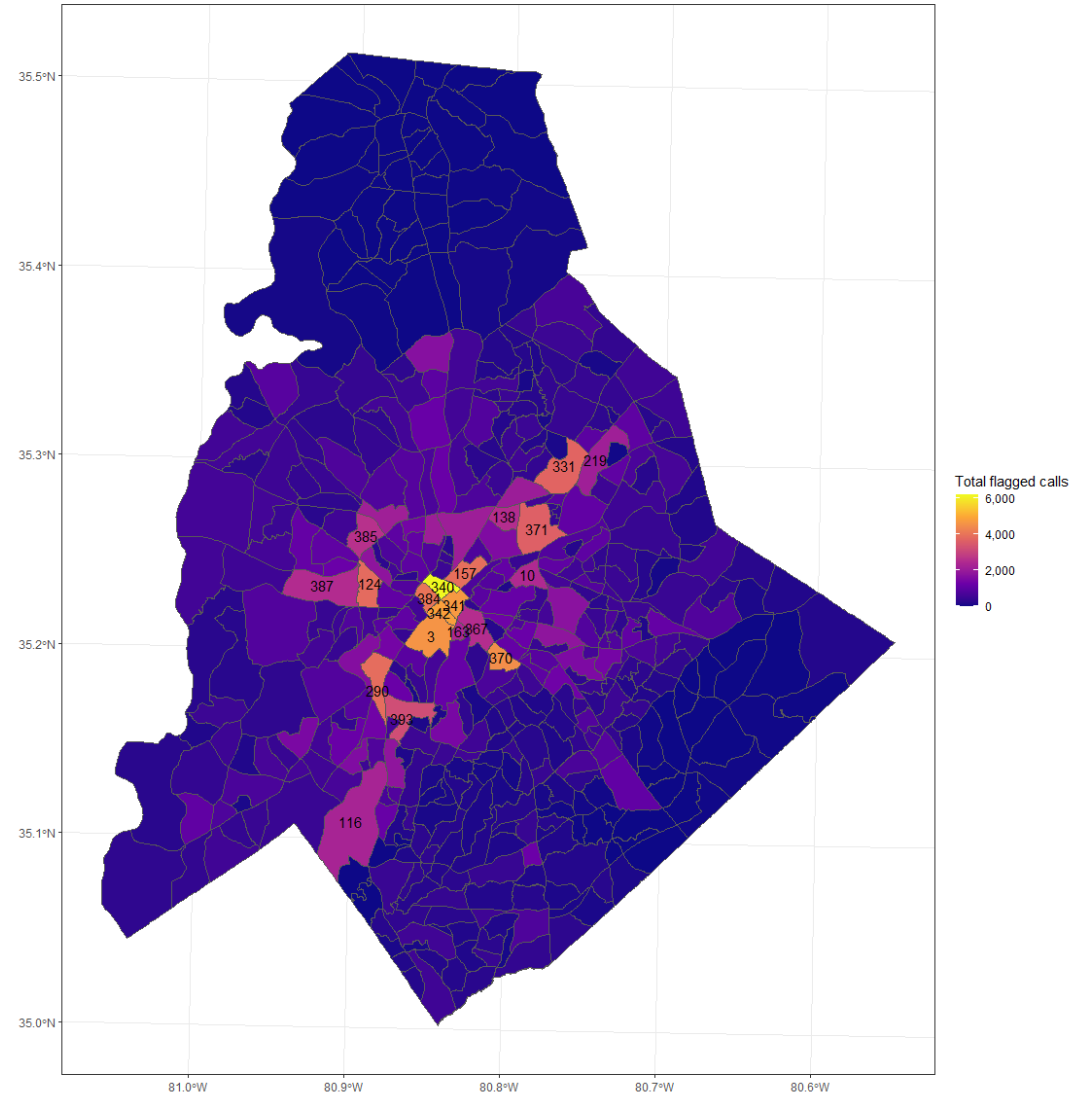


Table 2.12. Flagged Call Volume and Proportion for the 20 Neighborhoods with the Most Flagged Calls

Neighborhood Statistical Area	Total Flagged Calls	% Flagged Calls
340	6,169	13.4%
342	4,827	9.9%
341	4,685	9.2%
3	4,592	6.7%
370	4,469	9.8%
384	3,993	11.8%
157	3,891	13.3%
290	3,857	10.2%
124	3,821	10.0%
331	3,703	8.5%
371	3,602	5.7%
393	3,199	10.8%
385	2,596	8.1%
367	2,528	7.8%

138	2,523	10.6%
387	2,484	6.1%
10	2,431	7.8%
163	2,386	13.7%
116	2,270	9.1%
219	2,120	6.8%

Figure 2.9. The Number of Flagged Calls in Each Neighborhood with the Top 20 Neighborhoods Identified



Stakeholder Input and Implementation Considerations

We also aimed to gather perspectives from stakeholders, such as community members, members of the CMPD and service providers on existing interventions and potential alternative interventions. We conducted 35 interviews over a 6-week period (March 2021-April 2021). Table 2.13 presents stakeholder representation within our sample.

Table 2.13 Interview Stakeholders

Interview Stakeholders	**n**
Law Enforcement	9
First Responder	3
Government Employee/Stakeholder	4
Service Providers	16
Community Members	3
Total	**35**

As discussed in the methods section, this is a formative evaluation, meaning our goal was to understand the implementation climate and identify barriers and facilitators to implementation. This section is divided into two sections. First, we will discuss our findings on civilian/co-response models for mental health, homelessness and substance use and then we will discuss non-uniform/non-sworn officer response for calls for service. Within each section we will discuss community perspectives and implementation climate. As discussed in the methods section, we used the CFIR implementation framework to guide the interview questions and analysis approach.

Civilian/co-response models for mental health, homelessness and substance use

We identified several themes within the qualitative interviews that have the potential to impact implementation of a civilian/co-response model to respond to mental health/substance use/homelessness calls. There were several potential barriers to implementation that we identified, which included racial tension within the city, a lack of continuum of care within Charlotte for behavioral health care, effective ways to triage individuals in need of mental health care who call 911, the potential impact of a shortage of CPCRT/crisis care staff and some tension within the CMPD around civilian intervention. However, we also identified facilitators to implementation that could address many of these barriers. They include hiring the “right” people, collaborating effectively with community organizations and service providers, and disseminating information about intervention programming. We also identified areas for evaluation of programming. These findings are detailed in the following section, beginning with a discussion of the backdrop of racial tension in Charlotte.

As we consider expansion of CRT and development and implementation of any additional crisis intervention approaches, we must acknowledge the racial tension that exists in Charlotte. As one participant stated, you ‘see a different customer service expectations in different parts of the city and economic situations.’ Several Black participants discussed fear of police that exists in their communities. One participant went as far as to say that if he was pulled over by police, he would fear for his life. Several participants pointed out this tension as a barrier that must be addressed in order to successfully work with individuals of all backgrounds in crisis. While some of the aspects of this tension, such as disparities in health care and education and centuries old institutional racism, are beyond the scope of this study, they are still an important backdrop to consider when developing and implementing an intervention. For instance, we heard from several participants that uniforms and police vehicles have the potential to scare or incite some individuals due to past experiences, even when not in crisis. CPCRT has made attempts to address this by utilizing officers in polo shirts. This has been applauded by community members; however, it was noted that they are not available 24 hours a day. Furthermore, these individuals are likely to be needed at night when they are not on duty.

Due to this tension, there was emphasis on hiring the “right” people. Respondents reported that individuals needed to understand the community and reflect the community. They have to build trust. This meant hiring individuals from communities that frequently utilize services or individuals willing and excited to deeply enmesh themselves in the community. One participant described how involvement in the community meant the individual not only needed to be willing to hold listening sessions with the communities they serve but also attend BBQs and other community events. One potential way to address community involvement that was raised by stakeholders was contracting or consulting with community organizations during the hiring process. Not only is hiring important, but so is training. Individuals must be trained to use culturally competent language, recognize truly risky situations, and avoid unnecessary escalation of other situations.

It is also essential that any crisis intervention approach collaborate with community organizations when in the field. There are some shining examples of when this has been done successfully. Roof Above described their collaboration with the CPCRT team as deeply constructive and collaborative. Roof Above cited the fact that CPCRT let them take the lead and advise CPCRT in crisis situations and that this was essential to their success. Despite this example, other community organizations were not aware of CPCRT and did not know how to access it. The type of working relationship described by Roof Above will be necessary for the success of any intervention. These organizations must be a part of the team implementing any crisis intervention. However, there is a tension that exists for community groups when they work with police. This can have a negative impact on the community’s perceptions of the organization. This is another reason that community organizations be active leaders in the development of interventions. Finally, because these relationships and visibility within the community are so essential, it is also important that crisis response teams be geographically specific and focus on one or a limited number of neighborhoods.

Participants indicated that increased community outreach must also include dissemination of information about CPCRT and any other crisis intervention. Some of this will come through greater involvement in the community. However, participants reported CMPD must also hold events in neighborhoods and distribute information to community organizations. It was widely discussed that not many people know about CPCRT. One participant also discussed the possibility of having celebrities, such as musicians and athletes, discuss mental illness and crisis intervention in an effort to disseminate information about CPCRT. This includes dissemination of a non-emergency number.

Another major issue in Charlotte, which community organizations who provide services can help to alleviate, is a lack of continuum of care. Participants reported that there were limited options for existing CPCRT staff. They could either take someone to jail or involuntary commitment. Involuntary commitment (IVC) can be traumatic and feel like a different version of incarceration, though. Jail or IVC should be the last resorts and not the primary options. Participants reported a need for step down services, such as crisis stabilization centers and 23-hour respites. As one participant stated, IVC and jail are overused because "when all you have is a hammer, everything looks like a nail." Participants voiced concern that too many organizations do not collaborate but rather work within their own silos. Having multiple entities, both CMPD and CBOs, will improve the quality of response and service. The resource guide in Appendix D and the maps presented in the asset map section of this chapter also detail organizations that can be potential partners for locations to refer individuals in crisis, however, funding is needed to support these resources.

Another issue along the continuum of care that needs to be addressed is triage to identify individuals in crisis. Participants reported that there is not a consistent system to identify individuals who may benefit from crisis intervention in the 911 call center. We identified no policy as to how these individuals in crisis are identified and when to send the CPCRT team through the 911 call center. Furthermore, the vast majority of crisis calls to 911 are actually routed through fire and medical emergency who do not currently have crisis intervention staff with the same level of training. However, CrySis does have their own internal systems to manage these calls. Collaboration within city entities may be warranted to improve services overall.

Another issue on the continuum of care that needs to be addressed is knowledge of when and where hospitals have availability to manage a person in crisis. Research shows that being held in an emergency room can be detrimental to those in mental health crisis (Zeller and Rieger, 2015). The ambulance service in Charlotte, CrySis, currently keeps a running list of which hospitals have availability. They began doing this in March 2020 at the beginning of the Coronavirus pandemic. Participants reported that a formalization of this system and integration into the police and 911 system could be beneficial.

One important theme we identified through interviews is the need for more crisis staff at more hours of the day. There is the impression that teams take too long to arrive on the scene, and the fact that they are not available 24 hours a day is problematic. Respondents reported that this meant that even those who know about CPCRT teams can be reluctant to request them through 911 if they know there is going to be a delay. Furthermore, limiting the geography of teams into neighborhood-based teams will increase the need for teams overall across the city.

One complicating factor in this need to increase the number of teams is that respondents reported a shortage of social workers and therapists in Charlotte. North Carolina currently is a designated Mental Health Counselor Shortage Area by the Federal Health Resources and Services Administration (Health Resources & Services Administration, n.d.). And participants reported that this shortage may make it difficult to retain staff if adequate compensation is not provided.

Finally, we identified some limited tension within the department to non-police crisis intervention. There were concerns raised about safety of the mental health professionals. While it was generally agreed on that no therapist should be first to enter a scene when there was a weapon present, there is potential that these therapists may need some level of training to recognize when a situation is unsafe. However, other law enforcement participants reported that they love the CPCRT team because it frees them to do the job they are actually trained to do. Nevertheless, some participants wondered whether CMPD would maintain support for CPCRT if or when someone was hurt, which is a very real possibility regardless of working with mental health professionals. In addition, participants outside CMPD had mixed impressions of whether the rank-and-file as well as leadership valued mental health considerations—whether that be through engaging in mental health training or incorporating citizen's mental health in how they handle calls. Using a mental health informed perspective is different than many aspects of traditional police training.

We also asked several questions to determine how crisis intervention should be evaluated. We received several suggestions which included:

- number of discretionary arrests going up or down
- number of calls that result in resolution with no arrest or hospitalization
- Does emergency department utilization of mental health rise or fall?
- rise or fall in mental health related hospital admissions
- number of people who utilize crisis intervention that receive follow up
- A community survey with knowledge and impressions of the program
- If medication issues are resolved
- If individuals are placed in non-hospital mental health services
- Percentage who refused care
- Descriptive statistics of who was served
- Evaluation done on a three-month cycle
- More CPCRT/crisis intervention data needs to be collected above was is currently collected
- Must control for socio-economic variables

Civilian Response for Calls for Service

A common theme among stakeholders—by activists, law enforcement, and service providers—was that while there were some potential benefits to civilian responders, there were also several potential problems. In this section we will discuss the model of civilians to respond to low-risk situations. We identified several themes. The most prevalent of these was concerns about how to define "low-risk" and safety of civilian responders. There was also concern of negative reaction to these individuals within the police department. Community members also stated that there were potentially low-risk situations where they would like to have an officer for various reasons. However, many also stated that a uniform has the potential to be upsetting for many community members. We also identified metrics for evaluation. These findings are discussed in more detail in the following section.

Participants voiced that defining "low-risk" and "non-uniform police" (what we have been referring to as civilian response) are critical to this strategy. Not only did participants themselves have a variety of conceptions of each, but they also recognized that many different definitions exist. As such, a civilian would have to be carefully thought out to make it effective. Nevertheless, A potential benefit of the civilian response model is that it would free up police for calls and work that require their unique skillset.

Respondents also identified as another potential benefit that the regular police uniform and squad cars can be upsetting or antagonizing, especially for communities of color and the trans community. However, it was emphasized that a "non-uniform" response could not simply be an officer who had their uniform removed. As one participant stated, "you can't unlearn the things you learned in the academy." Participants recognized the importance of proper training for this new model to work and that the organization needed to incentivize relationship building to be effective. Both staff and supervisors also need to embrace the model and be motivated to work in the community, as the success of the effort depends on such an orientation. Moreover, it is important to fairly compensate the civilian staff so that they stay on the job and do not quickly leave for other opportunities in the hospital or school systems. Respondents emphasized that they wanted these units to "reflect the community."

Despite the potential benefits, there were several concerns raised by both community and police stakeholders. Several participants pointed out that while a situation may at first appear to be low risk, it can escalate quickly. One way to address this is to secure community buy-in. Outreach to communities to spread awareness about this program and to secure help in implementing it is important. Several community members expressed optimism that civilian response would be well-received by communities of color, especially if it improved racial equity, which would greatly help it succeed.

Another potential issue is stigma within CMPD. As one participant stated, "Some police feel either you're a badge or you're not. So, we need to show civilians can do stuff too and can represent the department in a great way. So, house them together, so sworn can see amazing situations of non-sworn responding great, making better calls. Important to make them equals." Placing sworn and civilian together and fostering mutual respect and collaboration is important for gaining police officer buy-in. Research is needed on how to accomplish this as it has not been widely used before.

Community stakeholders also responded that they wanted uniformed police to respond in certain instances, even if the situation is low-risk. One member of the community provided a specific example in which her house had been broken into. She called the police to come and take a report, and while this was a low-risk situation where an officer was likely not needed, she wanted those in the community to know she had taken this seriously and called the police. Thus, the police can be seen as protective in certain instances, and low-risk situations are an opportunity to be seen serving the community in a positive way. Removing officers from these duties may mean that they are only seen engaging in threatening activities in some neighborhoods. Conversely, communities that do not have a history of conflict with the police may not want or see the need for civilian response when they make calls for service. Navigating roll-out of a civilian response across the varied neighborhoods of Charlotte is a challenge to be addressed.

Finally, recognizing the challenges of making a civilian response model work, some community members were concerned that CMPD would abandon the effort when challenges arose. They believed that the police focus on the "worst case scenario" as a reason that civilian response would not work. In addition, they believed that taxpayers do not want to pay for what is perceived as "Black and Brown services." Thus, these participants worried that what could be an effective approach would not get a fair chance to succeed. While there are potential drawbacks, situations cited by interview participants as possible low risk situations include:

- Road closures
- Removal of drug paraphernalia from a public place
- Larceny report
- Break-in reports
- "Fender benders"
- Truancy

In order to evaluate this program, participants reported they would like to see reporting on staff safety and workload, officer morale, community awareness and response and a reduction in the number of complaints against the CMPD. One participant also stated that they would like to see on-going evaluation every three months.

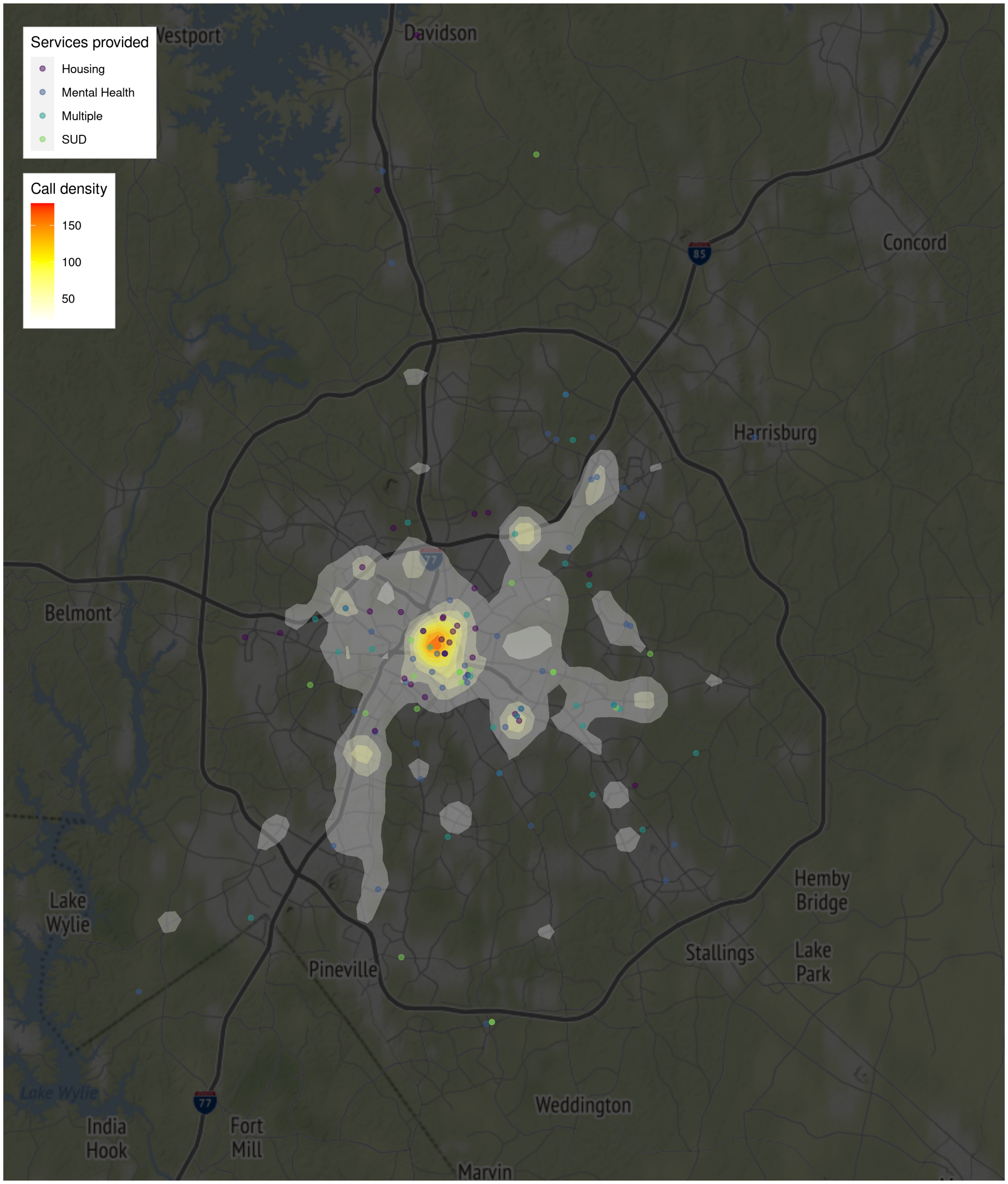
Asset mapping

We took an 'asset-based' or 'strengths-based' approach to assessing the needs of the Charlotte community, assembling a resource guide of 142 service providers in 124 locations in The City of Charlotte and surrounding areas. Our search focused on crisis services and accessible on-going support services for mental health needs (80 resources), substance abuse disorders (47 resources), and housing and homelessness services (41 resources). We did not include private practices that offer clinical counseling or psychiatric care but did include for-profit providers of more extensive wrap-around services (including medication management for substance abuse disorders) or for-profit providers that provide free care for vulnerable populations, as well as for-profit substance abuse rehabilitation centers. We excluded private providers because assessing the availability and quality of these providers was beyond the scope of this study. We also wanted to avoid duplicative work as this information can be found elsewhere (The One Charlotte Health Alliance website[8], as an example, is an excellent resource).

The asset map in Figure 2.10 maps the location of each resource, overlaid on a density map of calls that we have flagged as potentially related to mental health, substance abuse, and homelessness. The map shows a concentration of homelessness services near the area with the highest call volume, with mental health and substance abuse disorder resources falling slightly outside of the areas of greatest need. The map also implies that the areas of greatest need do not feature providers that offer multiple services – these are scattered in lower call volume areas. While some of these resources offer mobile services, this map implies a mismatch between the areas of greatest need and where service providers, particularly those providing behavioral health services, are located.

[8] http://www.oneclthealth.org/

Figure 2.10. Locations of Housing and Behavioral Health Resources in Relation to 911 Call Density



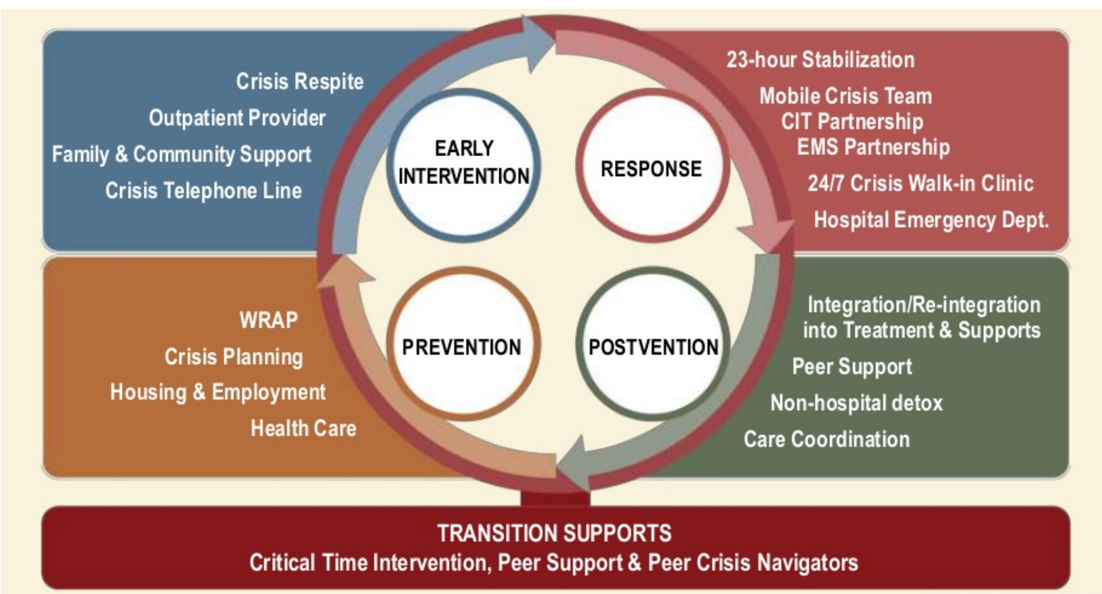
Of the 142 service providers that we identified, just four provide resources through a government agency. The majority of providers (85) are local, regional, or national non-profit organizations, while the remainder are hospital and health care groups or for-profit clinical service providers. Overall, the asset mapping exercise revealed a number of gaps in service provision for the behavioral health and housing needs of Charlotteans. Positively, we did find a large network of resources for youth and teens in the Charlotte area.

Our qualitative interviews indicated the need for a more robust continuum of behavioral health care services in Charlotte. In order to assess this, we have categorized services along the continuum of crisis care, as defined by the Substance Abuse and Mental Health Services Administration's National Guidelines for Behavioral Health Crisis Care (Substance Abuse and Mental Health Services Administration, 2015), presented in figure 2.11.

The vast majority of behavioral health care services in Charlotte fall into the Early Intervention area of the continuum. 76 of these resources provide counseling services and support groups; roughly one-third of which are offered through private, for-profit organizations or individuals. While it is encouraging to see this level of care most represented, a city the size of Charlotte would ideally have a higher concentration of community based, accessible resources. In addition to outpatient services, Charlotte has 8 crisis telephone lines (not including 9-1-1) to provide early intervention services to residents in acute crisis.

Moving on to response, Charlotte has a mobile crisis team funded by the county, CIT trained officers, and 3 crisis receiving and stabilization facilities. There is one dedicated Psychiatric Emergency Department, provided through Atrium Health, and two hospitals that provide psychiatric inpatient units, provided through Atrium Health and Novant.

Figure 2.11. SAMHSA Continuum of Crisis Care



Postvention services include residential services, peer support services, intensive in-home services, and partial hospitalization or intensive outpatient treatment (where an individual goes home every night but is essentially "hospitalized" during the day). There is a gap in this level of care in Charlotte. We find 24 such services in Charlotte, and just 14 of these serve the adult population. Further, 10 of the 23 that we found are for-profit entities, which may restrict access for low-income populations.

Homelessness and housing services, which fall into the prevention category, are mostly offered through local or national non-profit organizations. The resources that we have mapped offer a range of homelessness and housing services, including financial assistance, temporary housing, and quality-of-life services for unhoused Charlotteans. However, many of these services are siloed from behavioral health and substance abuse care: just seven of the 41 homelessness and housing resources in our guide provide services for both housing needs and mental health or substance abuse disorder needs, which often co-occur, and just one, Quality Comprehensive Health Center, provides services for all three. Note that we concentrated on homelessness and housing in the prevention category and did not map access to health care or employment services. In addition, many of the providers mapped in the 'early intervention' category provide crisis planning services, which fall into the prevention category on the continuum.

Finally, wrapped around all of these services are transition supports, which include peer support, Critical Time Intervention (CTI) and Assertive Community Treatment (ACT), where a team of professionals provides a mix of services in vivo, meaning in the setting and context in which problems arise, as opposed to in a clinical setting (Phillips et al., 2001). Charlotte has a limited number of transition support resources, with two providers of ACT and CTI services (Cardinal Innovations and Monarch Behavioral Health Services), and one peer support provider (The Promise Resource Network).

Taken together, our asset map and resource guide describe a system with gaps in response, postvention, and transitional behavioral health care and where the private sector and non-profit organizations carry much of the burden. No organization provides the full continuum of care through one resource, though Cardinal innovations is represented at all levels. That said, Cardinal has historically had a somewhat problematic relationship with Mecklenburg county, and the county is in the process of disengaging its contracts with them (Kuznitz, 2020). Additionally, we see room for a higher number of comprehensive wraparound services for homeless and housing insecure individuals who struggle with behavioral health and substance abuse issues.

Last, we do find an encouraging number of services for teen and youth populations: 35 of the providers listed in the resource guide concentrate on servicing youth and teen populations. Behavioral health services for this population as represented along the continuum of care discussed above as are those for adults, and a number of homelessness and housing resources concentrate on the youth and teen population as well.

3. SAFE Recommendation 3: Analysis of Police-Community Member Contact and Police Calls and Responses

3.1. Introduction

Recommendation 3 of the SAFE Charlotte report requested independent analysis of police/community member contact. Analytic support dedicated to SAFE Recommendation 3 involves quantitative analysis to evaluate the presence and extent to which racial/ethnic bias is evident in policing. We employed set of conventional statistical analyses along with more specialized analyses that are intended to provide more robust tests of statistical bias. Our work for the City of Charlotte as it pertains to this recommendation falls within three tasks: police-community member contacts; identifying police-outliers; and analyzing work and labor demands.

The first tasks involved estimating the extent to which racial bias is evident in police interactions. For this, we analyzed stop data, arrest data, and complaint data and employed established methodologies for criminal justice-related data, such as regression analysis, daylight savings time-based benchmarking and analysis of search and yield rates of contraband during police stops.

A second task involved evaluating and identifying individual officers' behavior in several key benchmarks. We leveraged an established framework that uses an internal benchmarking approach for identifying outlier officer behavior. Briefly, this approach evaluates a given officer by comparing them to a weighted combination of all other officers, where the weights are chosen to make the comparison group as similar as possible to the evaluated officer. Then, we estimated regressions with relevant control variables to identity an individual officer's performance in comparison to other officers. After we had all officers' estimated performance, we considered their distribution to determine whether any individual officer was sufficiently an outlier, while controlling for the fact that we were making comparisons over many officers and wanted to limit the risk of finding an outlier by chance.

A final task is closely tied with tasking associated with Recommendations 2 & 4. This involved a workforce analysis to determine and identify whether services currently performed by CMPD can be more efficiently delivered by another organization and considered the potential workforce impacts. For this, we relied on interviews to guide our data analysis and evaluate the potential impact of transitioning services out of CMPD. Rather than identify specific individual agencies, we identified a set of conditions that – when evaluated for individual programs – that can help the City of Charlotte determine whether a set of services would be an ideal candidate for transition outside of the department.

In the next section we describe in detail our methodologies for each of these tasks. Following that, we describe the findings in detail. Recommendations from this can be found in the recommendations chapter of this report. In Appendix C, you can find additional detail about our models.

3.2. Methods

Analysis of Police-Community Member Contacts

We conducted analysis of police-community member contacts in order to ascertain if statistically significant evidence of racial disparities exist after controlling for neighborhood contexts. We employed three different methodologies to determine the extent to which there is statistically significant evidence of racial disparities in policing. Note that we distinguish between racial bias and racial disparities. Our analyses do not extend farther than the data that we had available for these analyses, and these data were not collected for the purpose of measuring or determining racial bias. Racial disparities are defined here as measurable differences in outcomes that are associated with a racial or ethnic identity group compared to a reference group. Meanwhile, racial bias refers to the attitudes, beliefs, or practices that an individual might have for or against an identity group. Identifying and estimating racial disparities is possible through statistical analysis, whereas the identification of racial bias is difficult because bias is internal and there is not sufficient evidence – statistical or otherwise – to determine whether any individual is acting on racial bias. This is an issue that has been identified as problematic in police/community member contact. That said, disparities can in principle be estimated and we focus our analysis in this way.

Furthermore, in general we cannot rule out the possibility that the disparities we estimate are due to factors that are not measured in the administrative data. We have attempted to mitigate this possibility by controlling for contextual factors in our analysis, such as the characteristics of the neighborhood in which stops took place, but we do not have all relevant information about each event and thus our findings must be interpreted in light of the possibility of unmeasured factors influencing the magnitude of disparities.

For the first subtask, we conducted descriptive statistics and fit a series of generalized linear models. Descriptive statistics are used to give a broad overview of how often an event occurs. We did this to address the following questions selected by the City of Charlotte:

i. Are there racial disparities in decisions to use force among perceived race/ethnicity of persons stopped when controlling for age, gender, offense type, and neighborhood context (e.g., crime, poverty)?
ii. Are there racial disparities in levels of severity of force used among perceived race/ethnicity of persons stopped when controlling for age, gender, offense type, and neighborhood context (e.g., crime, poverty)?

iii. Are there racial/ethnic disparities in use of less lethal or lethal force among of unarmed individuals on whom this level of force was used when controlling for age, gender, and neighborhood context (e.g., crime, poverty)?
iv. Are there racial disparities in the frequency of no action stops across perceived race/ethnicity of persons stopped when controlling for neighborhood context (e.g., crime, poverty)?
v. Are there racial disparities in the yield rates of contraband found among perceived race/ethnicity of persons stopped when controlling for neighborhood context (e.g., crime, poverty)?
vi. Are there racial disparities between perceived race/ethnicity of persons stopped and the result of the stop when controlling for neighborhood context (e.g., crime, poverty)? If so, what is the relationship between perceived race/ethnicity of persons stopped and their rate of arrest?
vii. Are there racial disparities in rate of officer requests for consent to search based on the perceived race/ethnicity of persons stopped when controlling for neighborhood context (e.g., crime, poverty)?
viii. Are there racial disparities in rate of consent given to search by the perceived race/ethnicity of persons stopped when controlling for neighborhood context (e.g., crime, poverty)?
ix. Are there racial disparities between the number of pedestrian and vehicle stops across perceived race/ethnicity of persons stopped compared to their representation in the population when controlling for neighborhood context (e.g., crime, poverty)?
x. Is the frequency of pedestrian stops by perceived race/ethnicity equivalent to the proportion of those races/ethnicities represented in the community when controlling for neighborhood context (e.g., crime, poverty)?
xi. Is the frequency of vehicle stops by perceived race/ethnicity equivalent to the proportion of those races/ethnicities represented in the community when controlling for neighborhood context (e.g., crime, poverty)?
xii. What is the proportion of the number of citizen complaints in the neighborhood to the number of police stops in the same neighborhood when controlling for neighborhood context (e.g., crime, poverty)?
xiii. What is the proportion of the number of citizen complaints alleging racial or identity profiling to the number of police stops in the community when controlling for neighborhood context (e.g., crime, poverty)?

As different questions required different types of data to answer them, we used binary logistic regression for analyses where the outcome of interest was a binary yes/no variable (i, ii, iii, iv, v, vii, and viii); we used multinomial logistic regression when the outcome of interest included multiple unordered categories (vi); and Poisson regression when the outcome was a rate (ix, x, xi, xii, and xiii). These regression models allowed us to take into account factors related to the stop as well as contextual information about the neighborhood where the stop occurred. All generalized linear models used cluster-robust standard errors to account for the fact that repeated observations within the same neighborhood may be correlated over time.

We supplemented the regression analyses for question xi with an additional approach called the "veil of darkness" technique that relies on daylights saving time changes to compare differences in the decision to stop before and after the time shift in order to determine if conditions of low visibility or high visibility lead to different outcomes in policing (RTI International, n.d.; Grogger and Ridgeway, 2006; Worden, McLean and Wheeler, 2012; Taniguchi et al., 2017; Stacey and Bonner, 2020). The intuition of the veil of darkness technique is that the population and demographics of drivers on the road remains constant between daylight savings time changes. While the drivers on the road would be more or less the same, a key difference would be whether a stop takes place during daylight. If it is the case that members of a given identity group are being stopped at a greater rate during the time of year when their commute occurs during daylight relative to when it is dark – then the only difference would be the higher visibility during daylight savings and we can consider that evidence of racial disparities. However, if it is the case that daylight makes no difference in the numbers of drivers being stopped, then that suggests that there is no disparity.

Finally, for question v we analyzed the yield rates of searches by different perceived racial group; yield rates are taken as proxies for the amount and quality of information that officers use to conduct searches, with low yield rates taken to suggest the use of poor or inaccurate information in some cases. Table 3.1 summarizes the methods and data sources we used.

Additionally, we also asked questions from the community concerning race relations and stop data. We coordinated with the team leading interviewing communities and stakeholders for Recommendations 2 and 4 to assess CMPD's collection of data practices and considered how CMPD's efforts compare to other law enforcement agencies in order to inform recommendations.

The different datasets we used were extracted from CMPD's internal database. Stop Data is an internal version of the publicly available traffic and pedestrian stop data with officer-specific identifiers to facilitate other analysis of individuals. Internal Affairs (IA) Use of Force (UOF), IA UOF Employee Weapons, IA UOF Subject Weapons, and IA Complaints data are internal affairs-specific datasets. We use these datasets to connect force incidents to the type of force used and whether any subjects possessed weapons. Additionally, we use CAD data to link stop data to a City of Charlotte dataset on quality of life (Quality of Life dataset) for information on neighborhood characteristics, as we discuss below.

Table 3.1: Summary of Methods and Data Sources for Recommendation 3, Task 1.

Research Question	Methods	Data Sources
Point i. Racial disparities in decisions to use force	Binary Logistic	Stop data, CAD data, Quality of Life data

Point ii. racial disparities in levels of severity of force	Binary Logistic	IA Use of force data, IA UOF Employee Weapons, Quality of Life data
Point iii. racial disparities in use of less lethal or lethal force among of unarmed individuals	Binary Logistic	IA Use of force data, IA UOF Employee Weapons, IA UOF Subject Weapons, Quality of Life data
Point iv. disparities in the frequency of no action stops	Binary Logistic	Stop data, CAD data, Quality of Life data
Point v. racial disparities in the yield rates	Binary Logistic	Stop data, CAD data, Quality of Life data
Point vi. racial disparities between perceived race/ethnicity of persons stopped and the result of the stop	Multinomial Logit	Stop data, CAD data, Quality of Life data
Point vii. racial disparities in rate of officer requests for consent to search	Binary Logistic	Stop data, CAD data, Quality of Life data
Point viii. racial disparities in rate of consent given to search	Binary Logistic	Stop data, CAD data, Quality of Life data
Point ix. racial disparities between the number of vehicles stops across perceived race/ethnicity of persons	Poisson Regression	Stop data, CAD data, Quality of Life data
Point x. pedestrian stops by perceived race/ethnicity	Poisson Regression,	Stop data, CAD data, Quality of Life data
Point xi. vehicle stops by perceived race/ethnicity	Poisson Regression, Veil of Darkness Benchmarking	IA Complaints data, Quality of Life data
Point xii. proportion of the number of citizen complaints	Poisson Regression	IA Complaints data, Quality of Life data
Point xiii. proportion of the number of citizen complaints alleging racial/ethnic or identity profiling	Poisson Regression	IA Complaints data, Quality of Life data

For all regressions, we used a set of control variables to capture the neighborhood context to help more accurately estimate the association between individuals' racial and ethnic identity and law enforcement outcomes. This neighborhood-level data was collected by the City of Charlotte within the Quality of Life dataset and we rely on it for our geographic units of analysis and neighborhood variables (City of Charlotte, 2021). We rely on this dataset since it provides fine grained, neighborhood level data that is easily connected to CAD and CMPD data sets and allows us to control and adjust for neighborhood contextual variables. We included the following neighborhood-level variables in adjusted regression models: median household income, number of residents receiving public nutrition assistance, the percentage of adults employed ("employment rate"), jobs per acre ("job density"), violent offenses per 1,000 residents ("violent crime rate"), property offenses per 1,000 residents ("property crime rate"), disorder-related calls per 1,000 residents ("disorder call rate"), and nuisance violations per 100 housing units ("nuisance violation rate"). Not all variables were available for all neighborhoods and all years. For example, the median household income was only recorded in 2017 and 2018, while the study period for this analysis was 2015-2020. Furthermore, in a given year, even when information was available for many neighborhoods, some neighborhoods may still be missing data.

Missingness was low (<2%) for economic variables but was higher for property and violent crime rates (2-9%) and higher still for disorder call rates (6-13%) and nuisance violation rate (8-12%). We used imputation to fill in missing data when it was missing.[9]

Supplemental Analysis: Use of Force and Arrested Individuals

In addition to our analysis of use of force incidents during police stops, we also evaluated the uses of force on individuals who were arrested. These decision was based on the understanding that use of force during stops represents a small proportion of all uses of force, and that CMPD's main dataset on uses of force was their internal affairs data. However, conducting an analysis on this dataset alone would be inappropriate since it would not be possible to determine the effect of identity on incidences where use of force occurred or did not occur because the dataset is composed of only cases where force was used. To establish a baseline, we use consider the effect of racial and ethnic identity on use of force when an individual is arrested. It bears keeping in mind that this is a different question than is being asked with respect to police stops. Analyzing use of force in police stops involves estimating the likelihood of use of force given a traffic stop; whereas the supplemental analysis is estimating the likelihood of use of force given the fact that subject was arrested on a charge. We adopt two methods for conducting this supplemental analysis: a conventional logistic regression and a casual inference matching scheme. The conventional logistic regression will be conducted in an identical fashion as is done for other tests here; relationships between the outcome (use of force) and variables of interest (identity, crime, patrol division context, whether the subject had weapons) will be directly estimated.[10]

Causal inference matching is a type of research design that attempts to replicate the conditions that give controlled experiments their power (Ho et al., 2007). Briefly, the intuition behind a matching research design is to accurately estimate the relationship of a variable of interest by taking a subset of the data where the group that has the binary variable (called the "treatment" group) looks almost identical to the group that does not (called the "control" group). Put differently: this process finds two groups (say, White and non-White arrestees), selects and weights individuals within the two groups such that they look similar on every possible dimension (age, sex, criminal charge, location of arrest, neighborhood context) except for the "treatment" variable – here White versus non-White identity for arrestees.[11] When the two groups have similar values for all variables we decide to control for, we consider the data

---

[9] To account for missingness, we used an imputation model to fill in missing data in years where missingness occurred for some neighborhoods (e.g., 2017 and 2018 for median household income). Specifically, we used a fully conditional specification and predictive mean matching via the mice package in R to perform a single imputation. Then, for years where no information was available, the closest available year was used to fill in the missing data. This means, for median household income, using the 2018 value for 2018, 2019, and 2020 and using the 2017 value for 2015, 2016, and 2017.

[11] For neighborhood context at the patrol division level, we took a weighted average of its constituent NSA quality of life indicators.

"balanced". The specific matching technique we use is coarsened exact matching – which is beneficial since it also balances for correlations between variables that might otherwise be ignored by methods that focus on univariate balance between the groups (Iacus, King and Porro, 2012). Our approach to utilizing this technique is to match on scenario and neighborhood specific variables for different identities. This involves – for every identity group – selecting a subset of the data that closely resembles that group. For example, to match for Black arrestees, we would try to find a group of non-Black arrestees who resemble the Black arrestees to the greatest extent possible. We would also do this for Hispanic, and White arrestees.[12] We include our illustrations of covariate balance in the statistical appendix. Note that balanced datasets which use regressions to estimate coefficients do not require additional variables *unless* there remains a significant imbalance after the data is matched. Figures in the appendix show balanced datasets between the treatment and control, so we can run a simple model unadjusted for additional covariates.

Internal Benchmarking of Officers

Analysis under this task is concerned with metrics and methods to identify individual officers rather than the behavior of CMPD as a whole. Indeed, while policy changes may be useful in affecting general behaviors and outcomes of the department, identifying individual officers for intervention to prevent problems from arising can likely be more effective in some cases. This is borne out by the literature that provides evidence for the presence and disproportionate impact of a small number of personnel (Ridgeway and MacDonald, 2012).

Efforts under this task revolve around using quantitative analysis centered on individual officers. First, we employed a doubly robust internal benchmarking method that compare officers to others with similar attributes and attempts to identify outliers, and second, to identify whether officer characteristics were associated with policing outcomes, we used logistic regression for policing outcomes and officers characteristics (race/ethnicity, age, sex, years of experience) in addition to incident or event-relevant control variables when appropriate (stop-related control variables such as driver demographics and reasons for stop).

Methodology to Identify and Address Outliers Who May Exhibit Bias

Our methodology described here has been employed in other cities for outlier detection. We employed an internal benchmarking method to identify officers who were outliers compared to their peers in terms of policing outcomes[13]. Internal benchmarks measure individual officer

[12] There are insufficient numbers of Asian, Native American, and Other/Unknown individuals groups in our merged data set to run this analysis on.

[13] Doubly robust refers to the two ways that this methods attempts to create valid comparisons and accurate estimates of individuals' differences from the group. The first method is through weighting more similar observations higher with propensity score weighting, while the second method is to include additional variables in regressions to control for the influence of other factors (e.g. stop specific context).

activity with reference to a comparable peer group. These peer groups are assembled based on a range of factors, like the similarity in their work schedules or patrol areas. To develop internal benchmarks, we examined how frequently they stopped drivers of a given race/ethnicity in relation to the distribution of their peers. This first entails identifying the peer-groups of every individual officer, and then calculating their relevant stop rates.

The specific approach we adopted is outlined in Ridgeway and MacDonald (2012). Their methodology is advantageous because it considers joint distributions in the assembly of their peer groups – which stated differently – means that it would be able to capture the fact that two officers that both work at 11:00 PM at night may not be grouped together if one is on shift on Tuesdays and the other works Fridays at 11:00 PM. The effect of specific combinations of variables can imply vastly different contexts. The peer group was created as a weighted combination of all other officers stops, with weights determined by how similar their characteristics (shift, work schedule, patrol areas) are to the target officer. To create the weights, we used a machine learning model called gradient boosted models to find the most accurate weights and peer group for each officer.

Finally, Ridgeway and MacDonald (2012) note that the rate of false positives is significant in conventional internal benchmarking. To mitigate against the prevalence of false positives, they control the false discovery rate, which is the proportion of identified outliers who are falsely identified as outliers due to random chance. The final result is then a probability that the racial/ethnic distribution of an officer's stops is outside the norm compared to similar peer officers. Sufficiently high probabilities may indicate an opportunity for intervention.

Work Force Analysis and Recommendations

In this task, we focused on the roles and responsibilities of CMPD and the extent to which alternative arrangements or staffing arrangements can lead to a more efficient and effective provision of services to the public. To this end we conducted an analysis of CMPD staffing; an analysis of CMPD programs; and working in partnership of consultants of recommendations 2 and 4 to determine overall impact of alternative response model.

Analysis of CMPD staffing

Our approach in this regard was to determine how alternative staffing models or workforces could change following a change in policy, as determined by an alternative response model. The first stop was to interview individuals within CMPD to determine the assigned roles and responsibilities of sworn and civilian personnel. Using interview data, we would then turn to the data and analyze how workloads would change if work were somehow reallocated among personnel. However, the lack of comparable precedents and rigorously evaluated programs and the challenges of projecting what this program would look like if fully implemented meant that we relied on the interviews with CMPD and community stakeholders to determine the impact on the CMPD workforce.

Analysis of specific CMPD programs and partners

In addition to evaluating police data for evidence of racial/ethnic disparities, we were also asked to evaluate whether programs operated under the auspices of CMPD and community partners could be transitioned to other agencies. These specific programs and partners will be considered in terms of the services they provide to the community and the match between these services and the low-risk, transferable, duties of sworn personnel. This analysis will also be considering the source of funding, and the implications of transitioning those duties. This is to help determine realistic reallocation strategies that CMPD could pursue to better serve public safety and assist in the provision of broader public services.

3.3. Findings

In this section, we will review the individual results of every analysis specified by the city in its request for proposals. Our analysis fits under 4 general categories: police-community member contacts analysis; individual officer analysis; CMPD policies and strategies; and roles and responsibilities of CMPD. Our interpretation of these analyses will be presented at the end of this chapter. The summary of our findings is below. We discuss each finding in detail in the following sections.

Table 3.2. Summary of Identified Statistically Significant Racial/Ethnic Disparities

Statistical Test	Identified Statistical Racial/Ethnic Disparities
Frequency of vehicle stops	Higher rate of being stopped for Black drivers, Hispanic drivers, and drivers of other or unknown race/ethnicity compared to White drivers, when rates are computed with respect to the population of Charlotte. Lower corresponding rate of being stopped for Asian drivers compared to White drivers. Higher rate of being stopped for Black drivers compared to White drivers, when rates are computed with respect to the population of the neighborhood where the stop took place. Lower corresponding rates for Asian drivers and drivers of other race/ethnicity.
Frequency of pedestrian stops	Higher rates of being stopped for Black pedestrians compared to White pedestrians, when rates are computed with respect to the population of Charlotte. Lower rates of being stopped for Asian pedestrians, Hispanic pedestrians, and pedestrians of other or unknown race/ethnicity, regardless of how rates are computed.
Frequency of No action traffic stops	Greater probability of a no action stop for drivers of other or unknown race/ethnicity relative to White drivers. Lower probability of a no action stop for Hispanic drivers relative to White drivers.
Frequency of No action pedestrian stops	Greater probability of a no action stop for Hispanic pedestrians relative to White pedestrians.

Result of Vehicle Stops	Greater probability of being arrested and lower probability of receiving a written warning for Black drivers relative to White drivers. Greater probability of being issued a citation and lower probability of receiving a written warning for Hispanic drivers relative to White drivers. Lower probability of being arrested, lower probability of being issued a citation, and lower probability of receiving a written warning for Asian drivers relative to White drivers. Lower probability of being arrested and lower probability of receiving a written warning for drivers of other or unknown race/ethnicity relative to White drivers.
Result of Pedestrian Stops	Lower probability of being issued a citation for Hispanic pedestrians relative to White pedestrians.
Request for Consent to Search	Greater probability that a Black driver would be requested for consent to search the vehicle relative to White drivers. Lower probability that an Asian driver or a driver of other or unknown race/ethnicity would be requested for consent to search the vehicle relative to White drivers.
Consent given for search	Insufficient data.
Yield rates and contraband, vehicle stops	Lower probability of finding contraband during a search for Hispanic drivers relative to White drivers.
Yield rates and contraband, pedestrian stops	No statistically significant findings.
Decision to use force, vehicle stops & arrests	Greater probability of Black drivers experiencing a use of force during a stop relative to White individuals. Supplemental analysis of the probability that Black arrestees were more likely to have experienced a use of force compared to White arrestees was inconclusive. Lower odds of Hispanic arrestees to experience a use of force relative to non-Hispanic arrestees.
Severity of Force	When force was used against a pedestrian or driver, there was a greater probability that the force was lethal (firearms) or less lethal (tasers, batons, sprays) when the pedestrian/driver was Asian or of other/unknown race/ethnicity compared to White pedestrians/drivers than physical force (holds, punches, kicks). When force was used against a pedestrian or driver, there was a greater probability that the force was lethal (firearms) when the pedestrian/driver was Asian, Hispanic, or of other/unknown race/ethnicity compared to White pedestrians/drivers than physical force (holds, punches, kicks).
Severity of Force on Unarmed Individuals	When force was used against an unarmed pedestrian or driver, there was a greater probability that the force was lethal (firearms) or less lethal (tasers, batons, sprays) when the pedestrian/driver was Black or of other/unknown race/ethnicity compared to White pedestrians/drivers than physical force (holds, punches, kicks). When force was used against a pedestrian or driver, there was a greater probability that the force was lethal (firearms) when the pedestrian/driver was Hispanic or of other/unknown race/ethnicity compared to White pedestrians/drivers than physical force (holds, punches, kicks).

Police-Community Member Contacts Analysis

As listed in the first section of this chapter and listed in Table 3.1, we conducted 13 different statistical analyses. In each, we used a set of control variables like neighborhood and interaction-specific contexts to evaluate the extent to which racial/ethnic disparities were evident. Note that in this section we only include model estimates for the variables of primary interest, but we include estimates for the full set of control variables in Appendix C.

Interpretation of statistical results

What follows in this paragraph is a guideline for interpreting statistical measures of association in our analysis, taking as an example the odds ratio (OR), which is used in all logistic regression analyses. In these analyses, ORs associated with specific racial/ethnic groups for a specific outcome can be interpreted as the relative odds that an individual in that group experienced the outcome compared to a baseline group, after controlling for other factors included in the model. The baseline group across all of our analyses is set as White individuals, meaning all other races/ethnicity outcomes were compared to White individuals. Odds ratios lower than 1 mean that a group is estimated to be less likely than White individuals to experience the outcome. Odds ratios higher than 1 mean that a group is estimated to be more likely than White individuals to experience the outcome. ORs near 1 indicate similar rates of experiencing the outcome to White individuals. If the OR for use of force corresponding to Asian motorists is estimated to be 1.50 – it can be interpreted as follows: "When stopped, the odds of an Asian individual being subject to a use of force was 1.50 times (or 50.0%) higher than the odds for a White individual, after controlling for neighborhood characteristics and stop-related contextual variables." Importantly, we also include in our results tables a measure of statistical uncertainty of our estimates (called a 95% confidence interval, denoted 95% CI or CI) in parentheses. The CI can be interpreted as all of the ORs that are consistent with the data based on the model. Suppose that the confidence interval around the Asian motorist's odds ratio was listed as: (0.45, 4.10). In this case for Asian individuals, the lower bound of their CI would be 0.45, which is less than 1 and represents having odds of experiencing use of force about half as large as White motorists. Correspondingly, the upper bound of the CI would be 4.10, which can be interpreted as having odds of experiencing use of force more than four times as large as White motorists. Because the CI for Asian individuals includes a lower bound that indicates they may be less likely than White individuals to experience the outcome and an upper bound that shows they may be much more likely than White individuals to experience an outcome, this example analysis would not provide strong evidence for racial/ethnic bias either in favor or against Asian individuals, nor would it rule it out. Analyses where the CI includes 1 are often called "non-significant."

On the other hand, if the CI for Asian motorists' OR extended instead from 1.05 to 1.75, both the lower and upper bound would then be greater than 1, and they would both suggest that Asian motorists were more likely than White motorists to experience the outcome. In this case, the CI would suggest that Asian motorists have anywhere from 5% to 75% higher odds of experiencing the outcome. Note that because the CI does not overlap 1, this is traditionally considered "statistically significant," and we draw attention to these coefficients using bolded text in the tables of this report. However, in all cases, the magnitude of estimated effects and spread of CIs remain important regardless of statistical significance. All related logistic regressions (binomial logit, multinomial logit) are interpreted in a similar way. We also report rate ratios (see the next section), which can be interpreted as how much higher the rate of a particular outcome are for a given racial/ethnic group compared to the rate in White citizens. Confidence intervals for rate ratios can be interpreted in the same way as for ORs.

Frequency of vehicle and pedestrian stops

To analyze the frequency by which different racial/ethnic groups were subjected to stops, we conducted several analyses. The first analyses used Poisson regression to estimate how the rate of stops differed between racial/ethnic groups after accounting for the neighborhood characteristics where the stop took place. The *rate* at which stops occurred is a function of both the number of stops of those of a particular race/ethnicity and the representation of the racial/ethnic group in the community. We considered two ways to measure this representation: either as (i) the stops per 100,000 citizens in the racial/ethnic group in Charlotte as a whole or (ii) the stops per 100 citizens in the racial/ethnic group in the neighborhood where the stop took place. The second rate was not computable for all neighborhoods and racial/ethnic groups because some neighborhoods due to lack of data[14]. For each analysis, we fit an unadjusted model, which does not control for neighborhood characteristics, as well as an adjusted model, which does.

We estimate that White citizens were stopped at a rate of 0.79 stops per 100,000 White citizens per month. We estimate that the rates for citizens of the other races/ethnicities were either much lower (for Asian people, 0.42 per 100,000 Asian citizens) or much higher (for Black people, 2.37 per 100,000, Hispanic people, 1.13 per 100,000, and those of other or unknown race/ethnicity, 1.67 per 100,000). After adjusting for seasonality (month and year) as well as the characteristics of the neighborhood, we find essentially the same increased and decreased rates as in the unadjusted analysis. See Table 3.3 for all rates, rate ratios, and confidence intervals.[15]

[14] Two neighborhoods were missing racial/ethnic population data altogether. Among the rest, 5 neighborhoods (1%) had 0 White population, 27 (6%) had 0 Black population, 49 (11%) had 0 Hispanic population, 117 (25%) had 0 Asian population, and 408 (89%) had 0 population of other races/ethnicities.

[15] In various datasets that CMPD made available to us, there was a field for individuals with an "other/unknown" identity.

Table 3.3. Rates of pedestrian and vehicle stops by racial/ethnic group per 100,000 citizens of that group per month.

Race/ethnicity	Total stops	Unadjusted rate/100k	Unadjusted RR, (95% CI)	Adjusted rate/100k	Adjusted RR, (95% CI)
Asian	8,258	0.421	**0.53, (0.49-0.57)**	0.365	**0.53, (0.49-0.57)**
Black	260,914	2.368	**2.99, (2.62-3.41)**	2.053	**2.99, (2.62-3.41)**
Hispanic	49,913	1.127	**1.42, (1.22-1.66)**	0.978	**1.42, (1.22-1.66)**
Other	9,781	1.666	**2.1, (1.95-2.26)**	1.446	**2.1, (1.93-2.29)**
White*	134,666	0.792	NA	0.687	NA

*Reference group
Clustered standard errors by neighborhood statistical area. Bolded text indicates statistical significance

The second analysis instead standardized rates to the population within each neighborhood. Note that some neighborhoods have a "0" population for a particular race/ethnicity and thus cannot be included in this analysis – compare the total stops in Table 3.2 to those in Table 3.3. Notably, almost half of the stops of those of other/unknown race/ethnicity were not analyzable for this analysis because they occurred in neighborhoods that were listed as having only White, Black, Hispanic, and Asian residents.

The unadjusted analysis still shows that Black and Hispanic drivers were stopped at higher rates than White people (unadjusted rate ratios of 2.95 and 1.37 respectively), while those of other/unknown race/ethnicity were stopped at similar rates to White people (unadjusted rate ratio 0.97), and Asian people were stopped at much lower rates. After adjusting for the neighborhood characteristics, the differences between the rates among White people and Hispanic people largely go away (adjusted rate ratio 1.05 (95% CI 0.92-1.19)), but Black people were still found to be stopped at a disproportionate rate (adjusted rate ratio 2.07 (95% CI 1.80-2.39)) as is shown in Table 3.4.

Taking the two analyses together, we find that Asian people were stopped less frequently than White people, Black people were stopped more, and these differences do not appear to be explained by the characteristics of the neighborhoods where these stops took place. Both of these results were statistically significant in both the adjusted and unadjusted models. In the case of Hispanic people, we find that they were also stopped significantly more frequently than White people compared to the population of Hispanic and White people in Charlotte overall. However, we found that with respect to the Hispanic and White populations in the neighborhoods where the stops took place, Hispanics were stopped at about the same rates, after adjusting for neighborhood characteristics.

Table 3.4. Rates of pedestrian and vehicle stops by racial/ethnic group per 100 citizens of that group in the neighborhood of the stop per month.

Race/ethnicity	Total stops*	Unadjusted rate/100	Unadjusted RR, (95% CI)	Adjusted rate/100	Adjusted RR, (95% CI)
Asian	6,891	0.162	**0.45, (0.39-0.51)**	0.155	**0.4, (0.35-0.45)**
Black	256,113	1.069	**2.95, (2.64-3.31)**	0.808	**2.07, (1.8-2.39)**
Hispanic	47,879	0.497	**1.37, (1.2-1.57)**	0.408	1.05, (0.92-1.19)
Other	4,461	0.349	0.97, (0.84-1.11)	0.286	**0.73, (0.62-0.87)**
White*	133,679	0.362	NA	0.390	NA

*Reference group
Clustered standard errors by neighborhood statistical area. Bolded text indicates statistical significance

Frequency of pedestrian stops by race/ethnicity in communities

The analysis of pedestrian stops follows the same lines as the previous analysis of all stops. First, we analyzed rates with respect to all city residents of a particular racial/ethnic group and, second, we analyzed rates with respect to residents of a particular racial/ethnic group within the neighborhood of the stop. Full results are given in Tables 3.5 and 3.6.

We estimate that White pedestrians were stopped at a rate of 0.007 stops per 100,000 White Charlotte citizens per month. We estimate that the rates for pedestrians of the other races/ethnicities were either much lower (for Asian pedestrians, 0.001, Hispanic pedestrians, 0.004, and pedestrians of other/unknown race/ethnicity 0.003) or much higher (for Black pedestrians, 0.014). The ratios of these rates to one another were basically unchanged after adjusting for neighborhood characteristics. On the other hand, when computing rates based on the population of the racial/ethnic group within neighborhood, we find that, after controlling for neighborhood characteristics, rates of pedestrian stops were either similar (Black pedestrians) or much lower for all non-White racial/ethnic groups. This may suggest that the increased rate among Black pedestrians is due to increased pedestrian stop frequency in Black neighborhoods that is not explained by crime rates/other neighborhood characteristics.

Table 3.5. Rates of pedestrian stops by racial/ethnic group per 100,000 citizens of that group per month.

Race/ethnicity	Total stops	Unadjusted rate/100k	Unadjusted RR, (95% CI)	Adjusted rate/100k	Adjusted RR, (95% CI)
Asian	15	0.0007652	**0.11, (0.06-0.21)**	0.0000396	**0.11, (0.06-0.21)**
Black	1,548	0.0140464	**2.07, (1.62-2.65)**	0.0007249	**2.08, (1.61-2.65)**
Hispanic	199	0.0044915	**0.66, (0.48-0.91)**	0.0002322	**0.66, (0.48-0.92)**
Other	18	0.0030655	**0.45, (0.27-0.76)**	0.0001516	**0.43, (0.26-0.71)**

White*	1,154	0.0067895	NA	0.0003508	NA

*Reference group
Clustered standard errors by neighborhood statistical area. Bolded text indicates statistical significance

Table 3.6. Rates of pedestrian stops by racial/ethnic group per 100 citizens of that group in the neighborhood of the stop per month.

Race/ethnicity	Total stops	Unadjusted rate/100	Unadjusted RR, (95% CI)	Adjusted rate/100	Adjusted RR, (95% CI)
Asian	14	0.0003285	**0.11, (0.06-0.2)**	0.0000201	**0.09, (0.05-0.16)**
Black	1,538	0.0064196	**2.07, (1.58-2.67)**	0.0002505	1.08, (0.73-1.6)
Hispanic	190	0.0019726	**0.63, (0.45-0.88)**	0.0000902	**0.39, (0.24-0.62)**
Other	9	0.0007051	**0.23, (0.11-0.47)**	0.0000329	**0.14, (0.07-0.29)**
White*	1,153	0.0031205	NA	0.0002325	NA

*Reference group
Clustered standard errors by neighborhood statistical area. Bolded text indicates statistical significance

Frequency of vehicle stops by race/ethnicity in communities

Because there are vastly more vehicle stops than pedestrian stops, the analysis of vehicle stops is essentially identical to the analysis of all stops (vehicle and pedestrian) above. We include the tables for vehicles stops here in Tables 3.7 and 3.8. All effect estimates and conclusions are similar to the analysis above.

Table 3.7. Rates of vehicle stops by racial/ethnic group per 100,000 citizens of that group per month.

Race/ethnicity	Total stops	Unadjusted rate/100k	Unadjusted RR, (95% CI)	Adjusted rate/100k	Adjusted RR, (95% CI)
Asian	8,243	0.4205003	**0.54, (0.5-0.58)**	0.3650083	**0.54, (0.5-0.58)**
Black	259,366	2.3534611	**3, (2.62-3.42)**	2.0422124	**2.99, (2.62-3.42)**
Hispanic	49,714	1.1220525	**1.43, (1.22-1.67)**	0.9742888	**1.43, (1.22-1.67)**
Other	9,763	1.6626890	**2.12, (1.97-2.28)**	1.4450500	**2.12, (1.94-2.31)**
White*	133,512	0.7855089	NA	0.6819444	NA

*Reference group
Clustered standard errors by neighborhood statistical area. Bolded text indicates statistical significance

Table 3.8. Rates of vehicle stops by racial/ethnic group per 100 citizens of that group in the neighborhood of the stop per month.

Race/ethnicity	Total stops	Unadjusted rate/100	Unadjusted RR, (95% CI)	Adjusted rate/100	Adjusted RR, (95% CI)
Asian	6,877	0.1613756	**0.45, (0.39-0.51)**	0.1546665	**0.4, (0.35-0.45)**
Black	254,575	1.0625945	**2.96, (2.64-3.32)**	0.8048212	**2.08, (1.81-2.4)**
Hispanic	47,689	0.4951200	**1.38, (1.21-1.58)**	0.4068447	1.05, (0.92-1.2)
Other	4,452	0.3487712	0.97, (0.85-1.11)	0.2858365	**0.74, (0.63-0.87)**
White*	132,526	0.3586656	NA	0.3864875	NA

*Reference group
Clustered standard errors by neighborhood statistical area. Bolded text indicates statistical significance

In addition to the analysis of vehicle stop rates above, we also fit a "veil of darkness" model to assess the racial/ethnic disparity in stop frequency. The results of the analysis are presented in Table 3.9. Based on these results, it appears to be the case that no individual identity group is significantly more likely to be stopped in high visibility conditions. Hispanic individual are only slightly less likely to be stopped in high visibility conditions – specifically, we estimate the OR to be 0.991 (95% CI 0.985 – 0.997), which is robust to the inclusion of control variables with 0.932 times lower odds in high visibility conditions (95% CI 0.824 – 0.994).

Table 3.9. Relative Odds that Stopped Driver Belongs to Given Identity Group when Stop Occurs During Daylight vs. when Stop Occurs At Night, vehicle stops

Identity Group	Unadjusted OR	Adjusted OR
White	1.008 (0.998, 1.017)	1.009 (0.961, 1.058)
Black	1.003 (0.992, 1.014)	1.033 (0.988, 1.081)
Hispanic	**0.991 (0.985, 0.997)**	**0.932 (0.824, 0.994)**
Other/Unknown*	0.998 (0.995, 1.001)	0.903 (0.782, 1.043)
Asian	1.000 (0.997, 1.002)	0.989 (0.851, 1.569)

Confidence Intervals in parentheses.
* We included Native Americans into the Other/Unknown category in regressions given their small sample size
Clustered standard errors by neighborhood statistical area.
Bolded Text indicates statistical significance

Frequency of No Action Stops

For this analysis, we focused on stop data to analyze the frequency with which no action stops – that is, stops that did not result in a citation, warning, or arrest – occurred across different racial/ethnic groups. The regression results and frequency table for vehicle stops is presented in

Table 3.10 below. To evaluate the probability of no action stops we used logistic regression.[16] We found that Hispanic individuals were significantly less likely than White individuals to be subject to a no action stop, after controlling for the characteristics of the neighborhood and stop context where the stop took place. Relative to White individuals, Hispanic individuals were estimated to have about half the odds of having a no action stop (0.551 times – or 44.9% less – that of White individuals, 95% CI 0.496 – 0.612). Meanwhile, individuals who belong to other or unknown identity groups are 6.66 (95% CI 5.718 – 7.758) times more likely to experience a no action stop.

Table 3.10. Relative Odds of No Action Stops, Vehicle Stops (Relative to White Individuals)

Identity Group	Adjusted OR	Total Stops	No action Stops
Asian	0.956 (0.794, 1.151)	9,655	170
Black	0.906 (0.854, 0.961)	298,006	6,672
Hispanic	**0.551 (0.496, 0.612)**	57,239	1,075
Other	**6.660 (5.718, 7.758)**	11,177	1,113
Native American*	NA	320	6
White**	NA	162,248	2,972

Confidence Intervals in parentheses.
* We present Native Americans as a category separately here, but included it with the Other/Unknown category in regressions given their small sample size
** White individuals are the baseline for comparisons, and so their estimate is omitted.
Clustered standard errors by neighborhood statistical area.
Bolded Text indicates statistical significance

With respect to pedestrian stops, we found that Hispanic pedestrians had 1.543 times the odds (95% CI 1.059 – 2.249) - or 54.3% (95% CI 5.9% - 124.9%) higher odds – of experiencing a no action stop as compared to a White individual, after controlling for neighborhood characteristics, as shown in Table 3.11. This result is significant.

Table 3.11. Relative Odds of No Action Stops, Pedestrian Stops (Relative To White Individuals)

Identity Group	Adjusted OR	Total Stops	No Action Stops
Asian	2.279 (0.637, 8.152)	15	12
Black	1.042 (0.832, 1.306)	1,641	772
Hispanic	**1.543 (1.059, 2.249)**	208	129

[16] In this model we also included the reason for the stop as a control variable. For this variable, we combined checkpoint- and DUI-related stops into the “Other” category.

Other	1.354 (0.460, 3.987)	20	12
Native American*		4	2
White**		1,188	525

Confidence Intervals in parentheses.
* We present Native Americans as a category separately here, but included it with the Other/Unknown category in regressions given their small sample size
** White individuals are the baseline for comparisons, and so their estimate is omitted.
Clustered standard errors by neighborhood statistical area. Bolded Text indicates statistical significance

Result of Stops

A tabular summary of the relationship between stops and different racial/ethnic groups is presented below in Table 3.10 for vehicle stops and 3.11 for pedestrian stops.

Table 3.12. Frequency of Vehicle Stop Result by Race/Ethnicity

	Asian	Black	Hispanic	Native American	Other/Unknown	White
Arrest	101	8,244	1,230	11	54	2,053
Citation Issued	3,682	109,301	26,829	136	4,631	62,982
No Action Taken	170	6,672	1,075	6	1,117	2,972
Verbal Warning	5,203	161,954	26,178	146	4,758	83,167
Written Warning	499	11,835	1,927	21	621	11,074

Table 3.13. Frequency of Pedestrian Stop Result by Race/Ethnicity

	Asian	Black	Hispanic	Native American	Other/Unknown	White
Arrest	0	195	22	1	0	76
Citation Issued	0	257	13	0	4	270
No Action Taken	12	772	129	2	10	525
Verbal Warning	3	409	43	1	2	310
Written Warning	0	8	1	0	0	7

In order to consider neighborhood and other contextual effects, we used multinomial logistic regression. Resulting ORs can be interpreted in a similar way to ORs computed for a binary outcome, with the exception that there is an additional reference baseline outcome: a no action stop. Each OR is now specific to both a race/ethnicity (compared to White community members) and to a stop result (compared to a no action stop). Taking a specific example, we would interpret the OR for Asian community members for the stop result of arrest in Table 3.14 in the following way: during a stop, the odds that a stop resulted in arrest rather than no action for an Asian motorist were 0.83 times those same odds for a White motorist.

We found that, after controlling for neighborhood characteristics, Asian individuals had 24.9% lower odds (95% CI 16.7% - 32.4%) of receiving a written warning instead of a no action stop than a White individual did. Asian individuals were also estimated to have 7.8% (95% CI 2.2% - 13.0%) lower odds than White individuals to receive a citation rather than a no action stop. Finally, Asian individuals were estimated to have 29.3% (95% CI 11.7% - 43.4%) lower odds of being arrested as a result of a stop relative to White individuals. Black individuals had 0.821 times the odds of (95% CI 0.769 – 0.878) - or approximately 17.9% (95% CI 12.2% - 23.1%) lower odds than - White individuals to receive a written warning rather than have a no action stop, and 64.9% higher odds (95% CI 51.1% - 78.0%) to be arrested as a result of a stop. Meanwhile, Hispanic individuals had 20.0% lower odds (95% CI 12.7% - 26.6%) of receiving a written warning rather than no action stop and 1.550 times the odds (95% CI 1.454 - 1.653 to receive a citation rather than a no action stop compared to White individuals. Individuals who were perceived to be of another or unknown ethnicity were estimated to have significantly lower odds of experiencing a stop that results in an arrest (OR 0.315 95% CI 0.235 – 0.423) or written warning (OR 0.873 95% CI 0.783.- 0.927) rather than a no action stop.

Table 3.14. Odds Ratios for Result of Vehicle Stop by Race/ethnicity, White community member and no action stops as baseline

	Asian	Black	Hispanic	Other/Unknown*	White**
Arrest	**0.707 (0.566, 0.883)**	**1.649 (1.511, 1.780)**	1.089 (0.969, 1.223)	**0.315 (0.235, 0.423)**	
Citation Issued	**0.922 (0.870, 0.978)**	1.019 (0.984, 1.054)	**1.550 (1.454, 1.653)**	0.956 (0.902, 1.101)	
No Action Taken***					
Written Warning	**0.751 (0.676, 0.833)**	**0.821 (0.769, 0.878)**	**0.800 (0.734, 0.873)**	**0.873 (0.783, 0.927)**	

Confidence Intervals in parentheses.
* We include Native Americans with the Other/Unknown category in regressions given their small sample size
** White individuals are the baseline for identity group comparisons, and so their estimate is omitted
*** No Action taken is the baseline outcome. In this category we included verbal warnings.
Clustered standard errors by neighborhood statistical area.
Bolded Text indicates statistical significance

When investigating pedestrian stop data, the relatively small sample size presented a challenge for estimation. Because of the small sample size for Asian individuals (n = 15), we group them in the Other category along with Native American individuals. Written warnings were omitted from the pedestrian analysis, due to the small sample size and resulting unstable estimates. Given the relatively small sample size, there is more uncertainty in many of these ORs as is evident in Table 3.15. We found that Hispanic pedestrians had significantly lower odds of receiving a citation (OR 0.438, 95% CI 0.240 - 0.798) rather than a no action stop relative to White pedestrians.

Table 3.15. Odds Ratios for Result of Pedestrian Stop by Race/ethnicity, White community members and no action stops as baseline

	Black	Hispanic	Other/Unknown*
Arrest	1.301 (0.907, 1.865)	0.986 (0.545, 1.783)	0.269 (0.031, 2.272)
Citation Issued	1.092 (0.851, 1.400)	**0.438 (0.240, 0.798)**	1.545 (0.565, 4.222)
No Action Taken***			
Written Warning****			

Confidence Intervals in parentheses.
* We included Asian and Native Americans into the Other/Unknown category in regressions given their small sample size
*** No Action taken is the baseline outcome.
**** Omitted given small sample size. Clustered standard errors by neighborhood statistical area. Bolded Text indicates statistical significance

Requests to search during stops

In total, White motorists received a total of 1,230 requests for consent to search out of a total of 134,487 total stops that could be linked to CAD data, corresponding to 0.91% of all stops with such a request. Black motorists were about 2.6 times more likely to receive a request for consent to search (6,175 requests in 260,489 total stops), and Hispanic motorists were about 1.5 times more likely (673 requests in 50,069 total stops). Asian motorists received such requests in only 0.6% of stops. These results were significant. Full results are shown in Table 3.16.

After adjusting for the characteristics of the neighborhood where the stop took place, Black motorists were still found to be requested for a consent to search at significantly higher rates than White motorists (adjusted OR 1.9, 95% CI 1.6-2.2). The OR for Hispanic motorists was attenuated after adjusting for neighborhood characteristics to 1.14 (95% CI 0.97-1.34), which is not significant. Asian motorists were found to receive such requests for consent at even lower rates after adjusting for neighborhood (adjusted OR 0.6, 95% CI 0.4-0.8). See Table 3.14 for full results.

Table 3.16. Requests for consent to search during vehicle stop by driver race/ethnicity.

Race/ethnicity	Total stops	Requests for consent	Percent of stops with request	Unadjusted OR	Adjusted OR
Asian	8,302	48	0.58%	**0.63, (0.47-0.84)**	**0.57, (0.43-0.76)**
Black	260,489	6,175	2.37%	**2.63, (2.26-3.06)**	**1.88, (1.63-2.16)**

Hispanic	50,069	673	1.34%	**1.48, (1.25-1.74)**	1.14, (0.97-1.34)
Native American*	293	5	1.71%	NA	NA
Other	9,529	35	0.37%	**0.44, (0.32-0.62)**	**0.39, (0.28-0.54)**
White**	134,487	1,230	0.91%	NA	NA

*Grouped with "Other" in logistic regression models.
**Reference group
Clustered standard errors by neighborhood statistical area. Bolded text indicates statistical significance

Consent for search given and racial/ethnic disparities

We could not analyze whether there were racial/ethnic disparities in how often consent was given to search when it was requested because such data were unavailable. We explored the possibility that data for requests for consent to search (see previous section) could be cross-referenced with available information on the type of search. One of the search types in the data available to us was "Consent." We hypothesized that an indication that the search type was "Consent" could be used as a marker that consent was given when it was requested.

However, we did not find that these two sources of data could be reconciled. See the breakdown in Table 3.17 of stops where a vehicle search was performed and the two data sources could be linked (only 7,058 of 8,166 requests for consent could be linked to search type data). In some cases, there were indications that the type of search was "Consent," but we have no indication from the request data that consent to search was requested. Conversely, there are many instances where a consent to search was requested but a different search type was listed (e.g., "Probable Cause" or "Search Incident to Arrest").

Table 3.17. Frequency of indicated type of search and whether there was an indication of a request for consent to search among stops where there was a vehicle search.

Type of search	Consent to search requested	n
Consent	No	1,506
Consent	Yes	4,488
Probable Cause	No	12,074
Probable Cause	Yes	2,422
Protective Frisk	No	299
Protective Frisk	Yes	72
Search Incident to Arrest	No	1,009
Search Incident to Arrest	Yes	70
Search Warrant	No	19
Search Warrant	Yes	6

Yield Rates of Contraband

An analysis of yield rates (the rate at which contraband is discovered) could be interpreted as a test of racial/ethnic disparities. The theoretical understanding is that officers gather information and act once they believe they have a sufficient amount. If officers rely on sufficient information, then you would expect higher yield rates. If officers are acting on insufficient information, then yield rates should be lower. It may be the case that officers have different information requirements that vary by different group which leads to disparities – *unless* it is the case that officers have a minimum information threshold that results makes it so that a great many people can be considered worthwhile to search (Ayres, 2002). In such a case, this test can still be used to evaluate a disparate impact on different identity groups given the relatively low accuracy of searches on them (Ayres, 2002). Our analysis yield rates by racial/ethnic identities are included in the table below for vehicle related stops along with the relevant regression results adjusted for neighborhood characteristics.

The results of the regression analysis, presented in Table 3.18, shows that Hispanic motorists have 21.2% (95% CI 9.7% - 31.7%) lower odds than White individuals of holding contraband when searched. This result was significant. Yield rates for Black motorists and Asian motorists were estimated to be nearly identical to White motorists (with statistically insignificant odds ratios of 0.96 and 0.94, respectively) after adjusting for neighborhood factors. There were comparatively few searches among pedestrians, as is evident in Table 3.19, and thus all estimates had a great deal of uncertainty.

Table 3.18. Relative Odds of Finding Contraband when Searched, Vehicle Stops (Relative to White individuals)

Identity	Total Searches	Contraband Found	Yield Rates	Adjusted OR
Asian	135	56	41.5%	0.937 (0.632, 1.394)
Black	18,919	8,851	46.7%	0.959 (0.879, 1.046)
Hispanic	2,095	895	42.7%	**0.788 (0.683, 0.907)**
Other	59	105	56.2%	0.802 (0.530, 1.216)
Native American	14	5	45.0%	NA
White	3,182	1,421	44.7%	NA

Confidence Intervals in parentheses.
* We present Native Americans as a category separately here, but included it with the Other/Unknown category in regressions given their small sample size
** White individuals are the baseline for comparisons, and so their estimate is omitted
Clustered standard errors by neighborhood statistical area. Bolded Text indicates statistical significance

Table 3.19. Relative Odds of Finding Contraband when Searched, Pedestrian Stops (Relative to White individuals)

Identity	Total Searches	Contraband Found	Yield Rates	Adjusted OR
Asian	0	0	NA	NA
Black	501	143	28.5%	1.451 (0.872, 2.416)
Hispanic	54	14	25.9%	1.328 (0.663, 2.658)
Other	4	2	50.0%	4.992 (0.617, 40.369)
Native American	2	1	50.0%	NA
White	158	NA	22.8%	NA

Confidence Intervals in parentheses.
* We present Native Americans as a category separately here, but included it with the Other/Unknown category in regressions given their small sample size
** White individuals are the baseline for comparisons, and so their estimate is omitted
Clustered standard errors by neighborhood statistical area. Bolded Text indicates statistical significance

Decisions to Use Force

We again used logistic regression to model the probability that force would be used during a stop. Since there were only 6 incidences of use of force among pedestrian stops, we focus our analysis on vehicle stops.[17] The results of our analysis are presented in Table 3.20 below.

The odds of use of force were found to be nearly twice as high for Black individuals compared to White individuals (OR 1.944), and the CI included ORs as low as 1.301 and as high as 2.905. This suggests that there is strong evidence that the odds of force being used against a Black individual during a vehicle stop are higher than the odds for a White individual, after controlling for neighborhood characteristics and stop-related context variables. To further analyze the relationship between identity and use of force, we also ran the model again and controlled for whether the stop led to an arrest, measuring arrest as a binary variable. After controlling for stops that result in arrest, the estimated odds of Black individuals being subject is still higher than White individuals (OR 1.599, 95% CI 1.060 – 2.411).

Table 3.20. Relative Odds of Use of Force during a vehicle stop (Relative to White individuals)

Identity Group coefficients	Total Cases	UoF Incidents	Adjusted OR, not controlling for arrest	Adjusted OR, controlling for arrest
Asian	8,243	3	1.332 (0.395, 4.489)	1.547 (0.455, 5.256)

[17] Note: we grouped Native Americans in with Other/Unknown group, and bear in mind that the baseline category is White individuals, so these odds should be interpreted as the odds of force being stopped relative to a White stopped individual.

Black	259,983	206	**1.944 (1.301, 2.905)**	**1.599 (1.060, 2.411)**
Hispanic	49,722	21	1.023 (0.574, 1.822)	1.167 (0.651, 2.089)
Other/Unknown	9,763*	2	0.649 (0.154, 2.741)	1.001 (0.236, 4.241)
Native American*	320	0	NA	NA
White**	133,590	36	NA	NA

Confidence Intervals in parentheses.
* We present Native Americans as a category separately here, but included it with the Other/Unknown category in regressions given their small sample size
** White individuals are the baseline for comparisons, and so their estimate is omitted.
Clustered standard errors by neighborhood statistical area. Bolded Text indicates statistical significance.

To provide further context for the relatively small number of uses of force (250 total), we explored the reason for the stops that resulted in use of force and tabulated these reasons for all drivers and for Black drivers specifically in Table 3.21. Note that within the stop data, there are a number of unknowns: we do not know the type of force used during the stop, whether and the extent to which the driver resisted, or if the officer sustained any injuries, or if the driver had a warrant that caused the situation to escalate. Further information about individual stops are necessary. Note that Black drivers were subject to uses of force most often for stops related to vehicle regulations. This may suggest that CMPD should consider the relative risk of pursuing these types of stops across the board as it exposes both drivers and police officers to risk.

Table 3.21. Reasons for Stop when Stop Resulted in a Use of Force, all and Black drivers.

Reason for Stop	All Drivers	Black Drivers
Investigation	30	25
Other	20	13
Safe Movement	14	12
Seat Belt	3	3
Speeding	46	27
Stop Light/Sign	25	16
Vehicle Equipment	36	16
Vehicle Regulatory	76	60
Total	250	189

Supplemental Analysis: Uses of Force on Arrestees

Although we were tasked to analyze uses of force as it occurs during police stops, we also conducted a supplemental analysis of uses of force as applied to incidences of arrests. Additionally, we connected CMPD's internal use of force dataset with their arrest records to evaluate whether the there were disparities in the use of force in cases where an individual was arrested. Our specific unit of analysis in this case is the officer-arrest with our outcome of interest being whether a specific officer during an arrest used force. It should be noted that the vast majority of uses of force are physical and do not include weapons – lethal or otherwise. To conduct this analysis, we merged the internal use of force with arrest records wherein the age, sex, identity, patrol division, and involved officers matched. In the use of force data, we found only 27 duplicates based on this merging scheme. These rows seemed to be data entry errors since all males and females across all duplicates shared the same age. For arrest data, we identified 2,657 non-unique rows on the basis of subject demographics out of the total arrest dataset of 95,793. In order to justify the merger of these two datasets, we require completely unique combinations of identifying data, and we also make the assumption that if use of force is to precede an arrest, it occurs on the same day with an identical officer who uses force being recorded as involved in the arrest (either in an assisting, arresting, or transporting capacity). Based on this strategy, we were able to connect 1,202 use of force incidents directly to arrests. This means that – on the basis of our assumptions above – 1,259 uses of force were not associated with an arrest. This is likely due to a data collection errors; data for use of force incidents and arrests are entered by separate CMPD personnel with no validation between them. This means that if a police supervisor enters in a different age for a subject in a use of force incident than is filed for the arrest record, the record will not match.[18] For this reason we recommend that CMPD improve the ability to link and validate information across different datasets.

We first analyze the effect of subject race/ethnicity on the use of force using a conventional logistic regression, controlling for cause for arrest, whether subject had weapons, and patrol division characteristics. Results for this regression analysis are show below in Table 3.22. As Table 3.22 shows, the estimated odds ratios for all identity groups are statistically insignificant.

Table 3.22. Logistic Regression, Use of force in merged UOF and Arrest data

Variable Name	Estimated Odds Ratio	Lower Bound	Upper Bound

[18] This could be problematic for our conventional logistic regression analysis if the accuracy of data entry is correlated with other variables (e.g. race, age, type of crime) because this would ultimately produce a biased sample. Even so, our causal inference matching method mitigates against this concern by drawing as balanced and unbiased of a dataset subset as possible to estimate as accurate of odds ratios as possible.

Black	0.905	0.684	1.199
Hispanic	0.507	0.253	1.015
Other identity	0.151	0.022	1.034

Our results are included below in Table 3.23.

Table 3.23 indicates that Black arrestees are 19.3% (95% CII 2.9% - 39.1%) more likely than non-Black arrestees to have experienced a use of force connected to an arrest. Meanwhile, Hispanic arrestees are 46.4% *less* likely (95% CI 27.8% - 59.9%) than non-Hispanic arrestees to experience a use of force during a stop on the same day as the arrest. Both of these results were significant. On the other hand, we did not find that there was strong evidence that White arrestees were more or less likely than non-White arrestees to have experienced a use of force during a stop on the same day as the arrest (OR 1.04, 95% CI 0.88 – 1.23).

Table 3.23. Use of Force on Arrestees; Logistic Regression on Matched Data

Group	Arrests	Arrests Coinciding with Force	(95% Confidence Interval)
Black	67,400	913	**1.193 (1.029, 1.391**)
Hispanic	7,637	64	**0.544 (0.401, 0.722)**
White	18,952	220	1.041 (0.879, 1.228)

Cluster robust standard errors used to construct the 95% confidence intervals.

Taken all together, Our results in Table 3.22 and 3.23 suggest that there is inconclusive evidence for racial/ethnic discrepancies in uses of force for Black arrestees given the initial null result in Table 3.22 and the confidence interval that borders on a null result (1.193 95% CI 1.029 – 1.391), however there is some evidence that Hispanic arrestees are less likely to receive force given the relatively robust confidence interval (0.544 95% CI 0.401 – 0.722) though we would have greater confidence in this finding had it been evident in Table 3.22.

Severity of Force

This analysis used the IA use of force data to analyze severity of force. For this analysis, we examined how – when force is employed – the severity of the force differs based on the identity of recipients. To conduct this analysis, we grouped force into several types: physical force, less lethal force, and lethal force. Physical force entails any force that is used to restrain or otherwise hold subjects – without the use of any equipment, including hands and fists. Less lethal force involves using equipment not intended to kill subjects but otherwise inflict pain or discomfort, including K9 units. Firearms are considered a separate (“lethal”) category of force. In the analyses below, we analyze the probability of experiencing “more than physical force,” which means less lethal or lethal force, as well as the probability of experiencing lethal force. See Table 3.24 for the breakdown of all indicated types of force and their categorization into these three groups of force. Because there were so few recorded uses of forces in this database, we did not adjust for contextual neighborhood factors or use logistic regression, as the variability of our estimates is already quite high before adjustment. We simply computed the difference in probability of each event and characterized variability of these estimates in terms of confidence intervals based on inverting the score test for a difference in proportions (Brown and Li, 2005).

Table 3.24. Categorization of Officer Use of Force Into Three Categories: Physical Force, Less Lethal Force, And Lethal Force

Force category	Specific force used	n
Physical Force	Hands/Fists	1,374
	Tackling	572
	Pressure Points	127
	Knee Strike	117
	Feet/Kicking	62
	Elbow Strike	31
Less Lethal Force	Taser	258
	Canine	155
	Pepper spray	121
	Other Weapons	103
	Baton	13
	Launcher	8
	Flashlight	4
Lethal Force	Firearm	35

Among those interactions where force was used, those involving White civilians were the least likely to involve more than physical force (21% of 600 force episodes) and the least likely to involve lethal force (0.7%). The proportion of incidents involving more than physical force was slightly higher when Black civilians (24%, 3 percentage points higher than for White civilians) and Hispanic civilians (26%, 5 percentage points higher) were involved. The confidence intervals suggest that we cannot rule out the possibility that White civilians actually experience this level of force at a higher rate than these groups because the CIs include values less than 0. Almost half of the 13 episodes where force was used with Asian civilians involved more than physical force (26 percentage points higher than White civilians, 95% [3, 51]), and more than half of the 31 such episodes involved more than physical force with civilians of unknown or other race/ethnicity (28 percentage points higher than White civilians, 95% CI [12, 45]). Despite these rates being much higher than the 21% when White civilians were involved, the precision of these estimates is low because there are so few episodes of force for some of these races/ethnicities. See Table 3.25 for all estimates.

Similarly, lethal force was found to be used at higher rates among non-White civilians, but the precision of these estimates is much lower still. For example, we found that lethal force was used in about 5 of the 186 (2.7%) force episodes involving Hispanic civilians compared to 4 in

601 episodes involving White civilians (0.7%), for a risk difference of 2 percentage points (95% CI [0.2, 5.5]). The confidence interval suggests that this difference is significant. We found that the risk of lethal force being used against an Asian civilian was about 7 percentage points higher than for White civilians, though this was computed on a very small number of total episodes (13) and only a single lethal force episode, yielding a very wide confidence interval including relatively small and improbably large differences (95% CI [0.6, 32.7]), reflecting the great deal of uncertainty in this estimate. Similar results with a similarly wide CI were found for civilians of other or unknown race/ethnicity.

Table 3.25. Use of Less Lethal and Lethal Force in Police-Community Member Contacts, Where Force Was Used

Race/ethnicity	Force episodes	n, more than physical force***	%, more than physical force	Risk difference, more than physical force	n, lethal force	%, lethal force	Risk difference, lethal force
Asian	13	6	46.2%	**25.69, (2.44, 50.65)**	1	7.7%	**7.03, (0.64, 32.68)**
Black	2,150	506	23.5%	3.07, (-0.75, 6.63)	22	1.0%	0.36, (-0.72, 1.04)
Hispanic	186	48	25.8%	5.34, (-1.37, 12.74)	5	2.7%	**2.02, (0.23, 5.51)**
Native* American	2	0	0.0%	--	0	0.0%	--
Other	31	16	51.6%	**28.02, (11.66, 44.66)**	3	9.7%	**8.43, (2.41, 22.93)**
White**	601	123	20.5%	--	4	0.7%	--

Confidence Intervals in parentheses.
Bolded text indicates significance
*Grouped with "Other" in logistic regression models.
**Reference group
*** "More Than Physical Force" means the use of Less Lethal or Lethal force.

Use of Less Lethal or Lethal Force on Unarmed Individuals

For this analysis, we considered whether community members listed in the Internal Affairs database had associated weapons. If none of the following weapons were associated with the community member, then they were considered to have been unarmed in the incident: firearm, knife, taser, baton, flashlight, "other weapons."

Our results for this question are presented in Table 3.26. As in the previous section of all force episodes, White civilians were again found to have the lowest rates of more than physical force (16% of 530 episodes), and differences and 95% confidence intervals for using more than physical force were found to be similar with similar levels of precision. The risk of more than physical force was found to be about 4 percentage points higher among unarmed Black civilians than among unarmed White civilians (95% CI [0.5, 7.7]), and this difference was found to be significant. Lethal force was never used in the 530 interactions with unarmed White civilians or the 10 interactions with unarmed Asian civilians, while it was used in 3 of the 1,894 interactions with unarmed Black civilians, in 2 of 156 interactions with unarmed Hispanic civilians, and in 2 of the 29 interactions with unarmed civilians of other or unknown race/ethnicity.

Table 3.26. Use of less lethal and lethal force in police-community member contacts where force was used, and community member was unarmed.

R324864 race/ethnicity	Force episodes	n, more than physical force***	%, more than physical force	Risk difference, more than physical force	n, lethal force	%, lethal force	Risk difference, lethal force
Asian	10	3	30.0%	13.77, (-5.83, 44.3)	0	0.0%	0, (-0.72, 27.79)
Black	1,894	388	20.5%	**4.26, (0.46, 7.73)**	3	0.2%	0.16, (-0.56, 0.46)
Hispanic	156	28	17.9%	1.72, (-4.54, 9.09)	2	1.3%	**1.28, (0.35, 4.56)**
Native* American	1	0	0.0%	--	0	0.0%	--
Other	29	14	48.3%	**30.44, (13.65, 47.95)**	2	6.9%	**6.67, (1.85, 21.34)**
White**	530	86	16.2%	--	0	0.0%	--

*Grouped with “Other” in logistic regression models.
**Reference group
Clustered standard errors by neighborhood statistical area. Bolded text indicates statistical significance.

Proportion of citizen complaints in communities

We examined how complaint volume was related to the volume of vehicle and pedestrian stops in the neighborhood using Poisson regression. We found that for every additional 500 stops in a neighborhood, the number of complaints was estimated to increase by about 16% (95% CI (12%, 21%)). These rates were virtually unchanged when adjusting for neighborhood characteristics.

Racial/ethnic profiling complaints in communities

We examined all of the descriptions for the rule of conduct that was potentially violated in the complaint data. Only 29 instances potentially refer to racial/ethnic profiling. We did not have sufficient data to estimate the relationship between the number of police stops in the community and the number of racial/ethnic profiling complaints with so few instances of such complaints.

Individual Officer Analysis

As discussed in our methodology section, we used a doubly robust internal benchmarking approach to identify officers who are outliers in their behaviors relative to their peers.[19] We used this approach first to establish appropriate comparisons for all officers based on their shifts, beats, and other factors (e.g., years of experience) and weight them accordingly. Second, we used a weighted logistic regression model to estimate how much more often the target officer stopped individuals of a given race/ethnicity than comparison officers, adjusting for characteristics of the stop. For example, for determining if an officer is stopping a driver of a specific group disproportionately, we controlled for the reason for the stop (e.g., speeding, moving violation, investigation) as well as neighborhood contextual variables (neighborhood crime and socioeconomic variables). Finally, we determined whether the target officer was engaging in the behavior much more frequently than comparison officers if a specific officer had a statistically significant difference from his/her comparison group after controlling the false discovery rate at 20%. A plot that may help illustrate this is presented below in Figure 3.1.[20]

[19] While this methodology can be useful, it should be kept in mind that this method should be used alongside additional administrative data, and additionally CMPD can modify its application of the method to include more factors and more data.

[20] Produced with the locdfr package for R (Efron et al., 2015)

Figure 3.1. Illustration of Distribution of Officer Coefficients and fdr plot

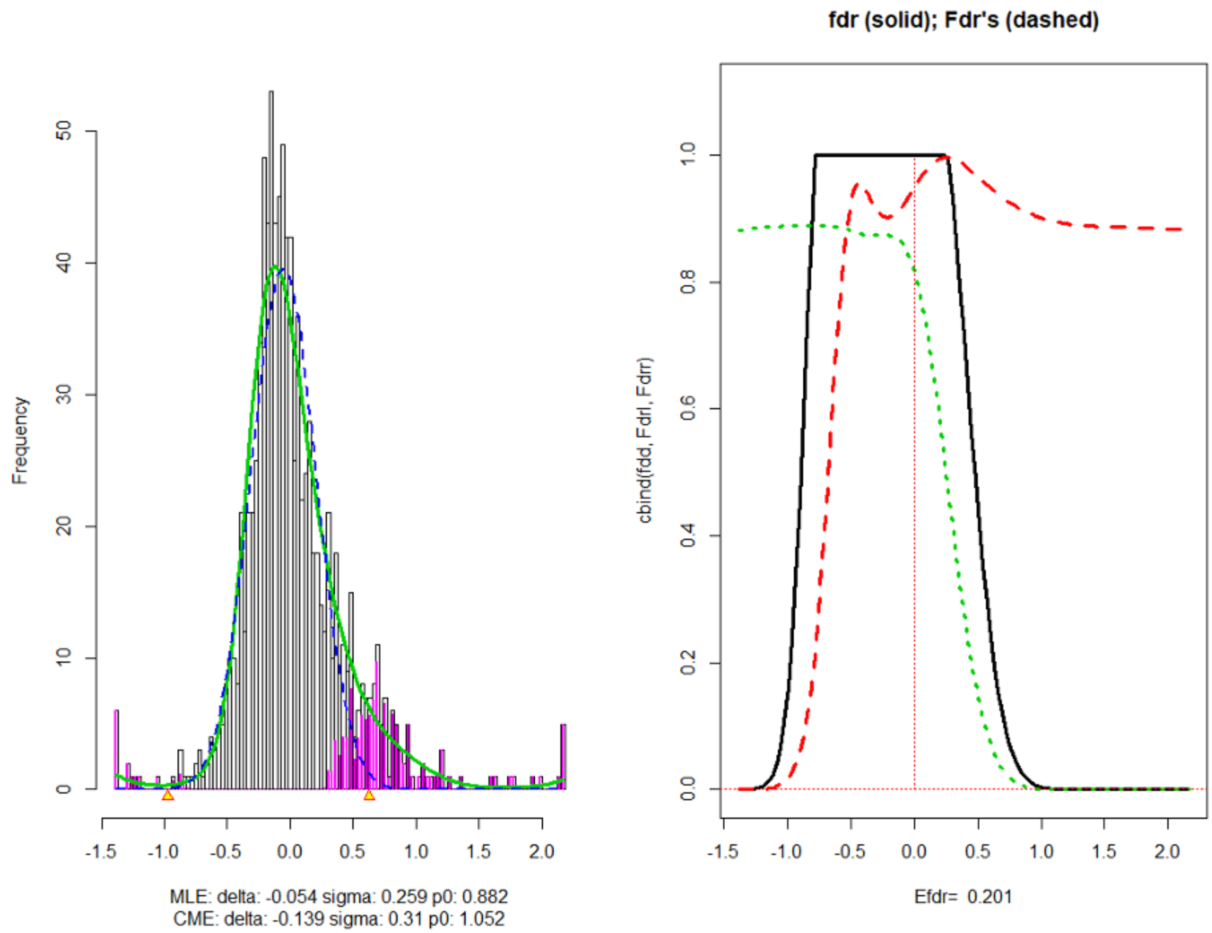


Figure 3.1 has two panels; the left panel graphs the distribution of individual officer coefficients with a histogram. The coefficients correspond to the standardized log odds ratio for stopping an individual of a given race/ethnicity compared to other similar officers. Under the null hypothesis that the officer is similar to their comparison officers, coefficients would be normally distributed (following a bell curve) around zero. If the officer is very different from their comparison group, they will depart from this distribution. The false discovery rate (fdr) is the probability that a given z-statistic deviates from the benchmark null distribution. The small triangles indicate where the differences between the officer and their comparison group are sufficiently large as to ensure that the fdr is less than 0.20. The right panel graphs the fdr as a solid black line. Note how at the center of the distribution is when the fdr is the highest, and as it moves to either extreme, the fdr decreases This means that if we set our threshold near the center of the distribution, most of the officers we identified as outliers would be "false discoveries" or not truly outliers. Our threshold would identify the number of cases that have a fdr of less than 0.20.

We applied this technique to a 5-year stop data set. Using officers' shifts, schedule, division, beat, and month we were able to weight the similarity between officers' stops.[21] Then, we regressed the probability that one officer stops an individual of a given ethnic group using logistic regression and controlling for neighborhood variables. We evaluated whether there was any discrepancy with respect to vehicle stops of Asian drivers, Black drivers, Hispanic drivers, White drivers, or drivers of other or unknown race/ethnicity.[22] For each, we show the distribution of all officers' z-scores (standardized log ORs) as it pertains to a given group. Based on this, we identified the number of officers that could be considered outliers and examined summary statistics about officers who were flagged as outliers. In total, 1,046 different officers had conducted a more than 100 stops to estimate and analyze their coefficients.

The distribution of officers' z-scores for stopping Asian drivers is represented in Figure 3.2. Following the convention from Figure 3.1, the purple-shared regions of the histogram represent count of individuals whose scores appear not to be drawn from the central distribution. This figure is also a good illustration of the point that this detects outliers who either stop significantly more or fewer than their peers. All told, 47 outliers were detected for stopping Asian individuals, all of whom stopped fewer Asian drivers than their peers and had most of their stops take place in Providence (46.5%; 3% Asian) and Westover (18.8%; 3.3% Asian). This should also serve to convey the point that while this is useful for identifying outlier behavior it should accompany other procedures to identify and remedy behaviors.

[21] Of the variables used, the variable with the consistently high relative influence were geographic variables (e.g. beat, division). This raises a potential additional analysis could be carried out by drawing comparisons between officers and their peers who operate in the same geographic area rather than the entire city.

[22] We attempted to detect outliers for Native Americans as well, however the sample size of stopped Native Americans was insufficient, but may be possible for the entire dataset rather than a 5-year period.

Figure 3.2. Histogram of Officer coefficients, stopped Asian individuals

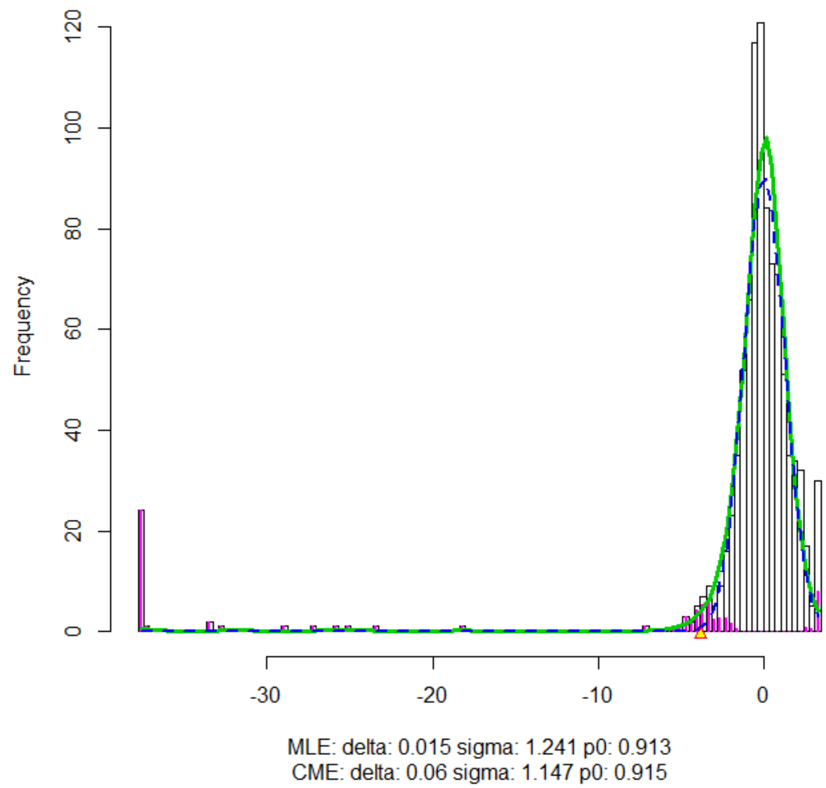


Figure 3.3 presents the distribution of z-scores for stops of Black drivers. Note that in this case there are outliers who stop both more and fewer Black drivers than their peers. Explanations for stops below the distribution could be similar to those for Asian individuals – they may be on assignment in a location where there are relatively few Black drivers. All told, we have identified 15 outliers, 7 of which stopped more than their peers. For the individuals who stopped fewer Black drivers than their peers, over 50% of their stops occurred in Providence (34.4%; 20% Black) and Steele Creek (20.4%; 36% Black). For outliers with more stops of Black drivers than their peers, the majority occurred in North Tyron (21.7%; 52% Black), Central (18.2%; 24.7% Black), and Westover (14.6%; 45% Black).

Figure 3.3. Histogram of Officer coefficients, stopped Black individuals

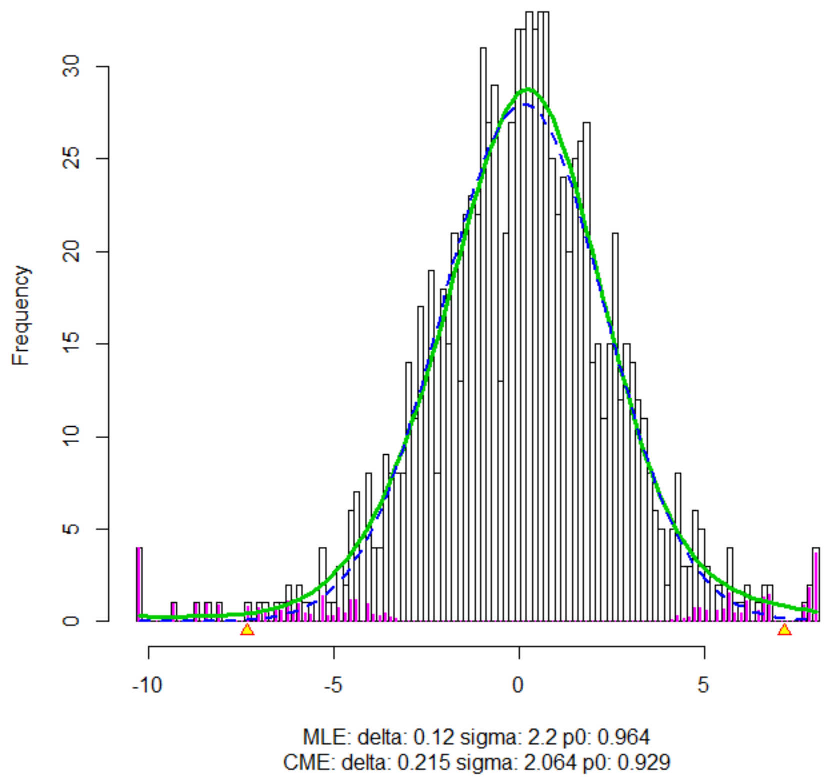


Figure 3.4 presents the distribution of officers' z-scores for stopping Hispanic drivers. As is the case with Black drivers, this distribution is symmetric and there exists officers who stop disproportionately greater and lower numbers of Hispanic drivers. Based on the analysis of Hispanic drivers, we found 38 outliers, 29 of which stopped more than their peers. For individuals who stopped fewer Hispanic individuals than their peers, over half of their stops took place in North (36.9%; 6.9% Hispanic) and Steele Creek (34.6%; 27.8% Hispanic) divisions. For those stopping more than their peers, most of their stops took place across Eastway (22.8%; 17.1% Hispanic), South (19.8%; 7.5% Hispanic), and Hickory Grove (18.9%; 24.0% Hispanic).

Figure 3.4. Histogram of Officer coefficients, stopped Hispanic individuals

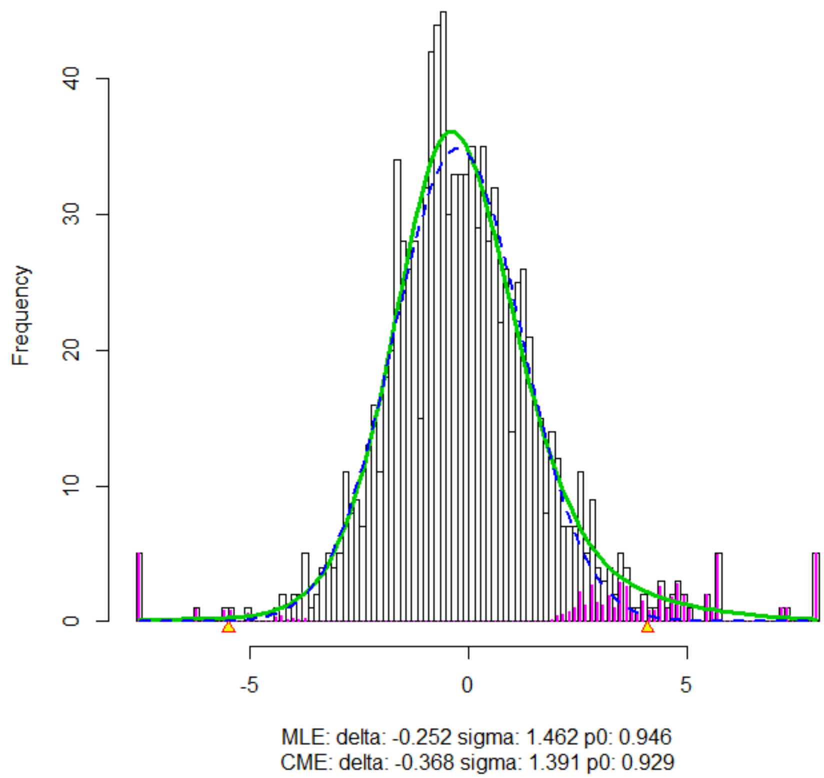
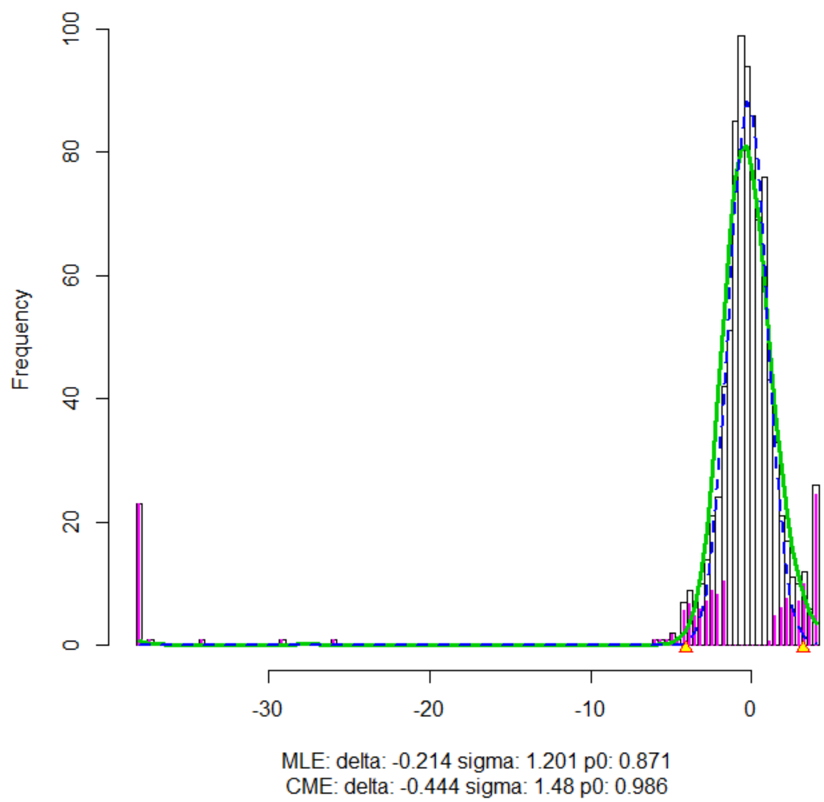


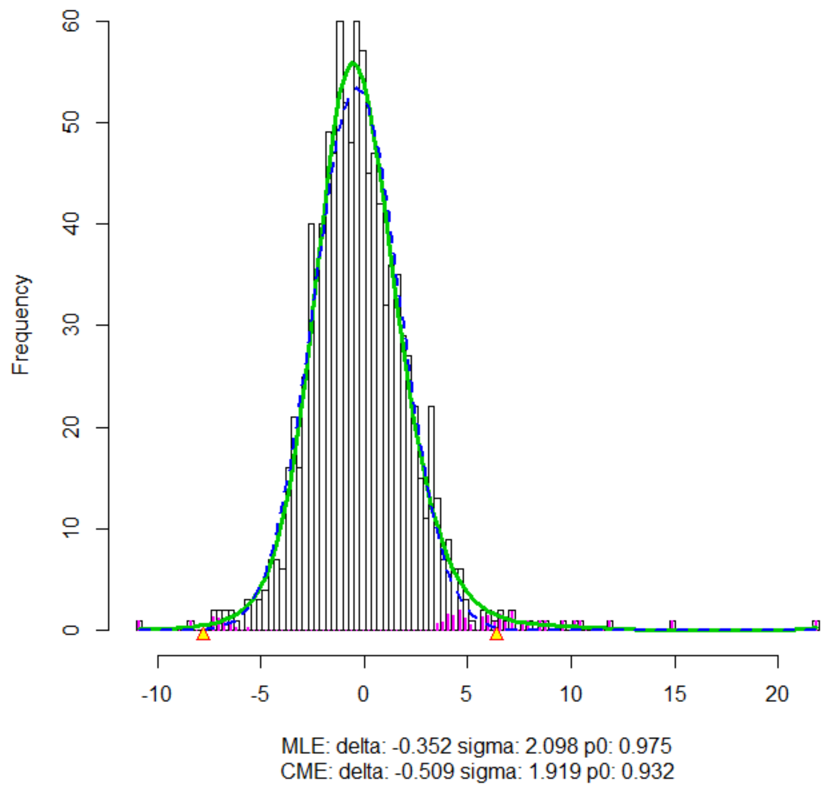
Figure 3.5 presents the distribution for officers' stops of individuals who are considered to belong to another or unknown identity group. Here there is a similarity to the plot for Asian drivers where there is a left skew to graph, suggesting a significant number of individuals who are stopping a significantly fewer number of individuals belonging to another or unknown identity group. However, unlike the plot for Asian individuals, there is a number of individuals who stop significantly more than the average officer. All told, we identify 78 outliers for stops of other or unknown drivers, 40 of which stopped more than their peers. For the 38 that stopped fewer than their peers, most of their stops took place in Steele Creek (32.7%; 0.3% Other) and Freedom divisions (29.0%; 0.06% Other). For those that stopped more than their peers, the majority of their stops took place in North (21.3%; 0.15% Other), Independence (12.4%; 0.141% Other), Westover (10.1%; 0.03% Other), and Providence (10.1%; 0.009% Other).

Figure 3.5. Histogram of Officer coeffients, stopped Other/Unknown individuals



Finally, we consider the extent to which officers stop disproportionately more or fewer White drivers in Figure 3.6. Figure 3.6 shows a generally symmetric distribution, much like the case for Black and Hispanic drivers. For white individuals, we detected 17 outliers, 15 of which stopped more than their peers. For the 2 outliers who stopped fewer than their peers, most of their stops occurred in Eastway (53.2% of all their stops; 42.4% White). For those that stopped more than their peers, the majority of their stops occurred in Providence (31.1%; 70.2% White) and Steele Creek (19.3%; 25.47% White).

Figure 3.6. Histogram of Officer's coefficients, stopped White individuals



We consider two types of outliers: outliers that stopped any individuals at a lower rate than their peers (low outliers) and those that stop individuals at a greater rate (high outliers). Individuals who stopped any group lower than their peers as a group collectively had 50% of their stops within the Providence (17.6%), Eastway (12.9%), Steele Creek (12.3%), and North (12.0%) Divisions. Meanwhile, individuals who stopped any group at a higher rate than their peers had 50% of their stops in South (14.7%), Providence (14.3%) , Westover (9.5%), Eastway (9.5%), and Steele Creek (9.1%) Divisions. For context, we include a summary Table 3.27 below illustrate the demographic distribution across all divisions, along with a measure of diversity which measures the probability that any two randomly selected individuals will be a different ethnic groups. Most frequently, it seems reasonable that outlier detection is identifying where officers tend to patrol, but there are a few instances where some outliers stop more individuals of a specific group in a division wherein they are underrepresented, e.g., Central Division for Black drivers; South Division for Hispanic drivers; Providence division for drivers with an Unknown/Other identity; and Steele Creek division for White individuals.

Table 3.27. Demographics and Diversity by Division

Division	White (%)	Black (%)	Asian (%)	Hispanic (%)	Other (%)	Diversity
Steele Creek	25.470	36.427	7.204	27.783	0.319	0.720
Independence	33.813	34.148	5.967	21.557	0.141	0.719
Eastway	42.439	30.570	5.382	17.104	0.227	0.694
Hickory Grove	20.175	48.443	4.982	23.977	0.193	0.665
University City	33.064	46.871	8.284	7.937	1.236	0.658
Westover	33.760	45.882	3.371	15.177	0.031	0.651
Freedom	21.352	52.868	6.303	16.329	0.060	0.644
North Tyron	12.687	52.820	3.045	29.443	0.145	0.617
North	29.438	55.599	3.021	9.389	0.149	0.594
Central	58.919	24.744	4.734	6.851	0.027	0.585
Airport	18.559	60.795	3.103	14.497	0.001	0.574
South	70.808	8.672	9.618	7.520	0.241	0.476
Providence	70.233	20.311	3.008	4.092	0.009	0.463
Metro	12.444	79.690	1.083	4.203	0.028	0.348

Table 3.28 provides additional information about individual stops and their reasons for the stop – distinguishing between high outliers, officers which stop more individuals than their peers, and low outliers, who stop fewer, as well as the collection of all other stops made by officers who were not identified as outliers. The numbers in the individual cells represents the total number of stops made by officers who are flagged as either high or low outliers for stops involving drivers belonging to those specific groups. The numbers in parentheses provide the percentage of stops with that specific reason out of all stops made by the outlier group. Note that the individual officers within these groups do not have to be the same across all group; it is possible for an officer to be an outlier towards one group but to be normal otherwise. Based on Table 3.28, outliers for White drivers seem to differ based on the rate at which they stop speeding drivers and the extent to which stops are made for equipment-related reasons. Meanwhile, for Black drivers, high outliers make a greater percentage of stops related to speeding and vehicle regulations – with the greater percentage of vehicle regulatory stops being different between low and high. High outliers for Hispanic drivers meanwhile tended to have a higher proportion of stops due to investigations, whereas low outliers tended to make a greater number of stops for speeding related reasons. For individuals with another/unknown identity, investigation related reasons seem to be higher a percentage, as well as speeding relative to the baseline. Low outliers for Asian drivers seem to be under-stopped on the basis of vehicle-related stops but have a greater percentage of stops related to speeding.

While it is likely not the case in every instance – a substantial number of differences between outliers and their peer group seem to involve vehicle equipment or regulatory reasons for stops.

If it is the case that officers are emphasizing enforcement of equipment or regulatory violations, then these may be disproportionately affecting drivers by stopping them at higher rates than other groups who have a greater occurrence of these violations.

Table 3.28. High and Low Outlier stops by Reason for Stop and Group

Outlier Type (n)	Investigation	Other	Safe Movement	Seat Belt	Speeding	Stop Light/Sign	Vehicle Equipment	Vehicle Regulatory
				White				
High (15)	70 (0.3%)	439 (1.9%)	1132 (4.8%)	292 (1.2%)	14836 (63%)	2142 (9.1%)	692 (2.9%)	3964 (16.8%)
Avg. (882)	1703 (1.7%)	2549 (2.6%)	7346 (7.5%)	599 (0.6%)	27721 (28.4%)	13679 (14%)	10174 (10.4%)	33702 (34.6%)
Low (2)	4 (0.5%)	3 (0.4%)	31 (4.2%)	19 (2.6%)	426 (57.7%)	43 (5.8%)	95 (12.9%)	117 (15.9%)
				Black				
High (7)	109 (1.3%)	71 (0.9%)	185 (2.2%)	122 (1.5%)	1915 (23%)	285 (3.4%)	1247 (14.9%)	4408 (52.8%)
Avg. (882)	4972 (2.5%)	4296 (2.1%)	11968 (6%)	2112 (1.1%)	35162 (17.6%)	17210 (8.6%)	28029 (14%)	96548 (48.2%)
Low (8)	96 (0.7%)	207 (1.6%)	550 (4.2%)	159 (1.2%)	9355 (72%)	653 (5%)	78 (0.6%)	1890 (14.6%)
				Hispanic				
High (29)	1433 (16.6%)	278 (3.2%)	296 (3.4%)	46 (0.5%)	3138 (36.4%)	477 (5.5%)	837 (9.7%)	2113 (24.5%)
Avg. (882)	1554 (4.5%)	1365 (3.9%)	2977 (8.5%)	274 (0.8%)	7518 (21.6%)	4158 (11.9%)	5336 (15.3%)	11638 (33.4%)
Low (9)	2 (0.1%)	40 (2.1%)	128 (6.7%)	17 (0.9%)	1331 (69.3%)	143 (7.4%)	33 (1.7%)	226 (11.8%)
				Other				
High (40)	110 (5%)	62 (2.8%)	144 (6.5%)	24 (1.1%)	1052 (47.8%)	226 (10.3%)	128 (5.8%)	456 (20.7%)
Avg. (882)	135 (2.2%)	301 (4.9%)	528 (8.6%)	37 (0.6%)	2100 (34.1%)	880 (14.3%)	714 (11.6%)	1472 (23.9%)
Low (38)	4 (1.3%)	8 (2.5%)	25 (7.9%)	6 (1.9%)	220 (69.4%)	20 (6.3%)	14 (4.4%)	20 (6.3%)
				Asian				
Avg. (882)	106 (1.7%)	148 (2.4%)	573 (9.3%)	37 (0.6%)	1968 (32%)	1145 (18.6%)	775 (12.6%)	1397 (22.7%)
Low (47)	1 (0.3%)	5 (1.7%)	32 (10.7%)	1 (0.3%)	179 (60.1%)	30 (10.1%)	19 (6.4%)	31 (10.4%)
				Baseline (Non-outliers)				
All non-outliers	8474 (2.5%)	8663 (2.5%)	23407 (6.8%)	3061 (0.9%)	74513 (21.6%)	37103 (10.8%)	45054 (13.1%)	144820 (42%)

Officer characteristics and policing outcomes

We also evaluated the associations between specific officer characteristics (e.g. experience, age, identity) and policing outcomes, such as stops, arrests, and complaints. These results are presented in Tables 3.28, 3.29. and 3.30. We found that Asian officers were much less likely to record an arrest as a result of a stop (OR 0.589, 95% CI 0.474 – 0.732) than their White counterparts, after controlling for the context of the stop. Black officers were similarly less likely to record an arrest (OR 0.696, 95% CI 0.642 – 0.753) compared to their White colleagues. Additionally, stops involving male officers were more likely to result in an arrest (1.328 95% CI 1.22 – 1.446) compared to those involving female officers. Finally, older officers were found to be less likely to arrest individuals as a result of a stop (OR 0.976, 95% CI 0.972 – 0.981) as were more experienced officers (OR 0.978, 95% CI 0.971 – 0.982). However, we would point out the relatively small sample sizes in these cases and that arrests for stops often occur when an outstanding warrant for the stopped driver is discovered. Asian officers (OR 1.719, 95% CI 1.341 – 2.202) and Black officers (OR 1.3 95% CI 1.174 – 1.439) more often issued a citation as a result of a stop compared to White officers. Additionally, Hispanic officers (OR 0.885, 95% CI 0.803 – 0.976), Native American officers (OR 0.57, 95% CI 0.429 – 0.756), and officers considered to have another or unknown identity (OR 0.821, 95% CI 0.753 – 0.895), all had lower odds of issuing a citation as a result of a stop. Male officers were also less likely to issue a citation (OR 0.806, 95% CI 0.763 – 0.85). Additionally, we found that officer age (OR 1.028, 95% CI 1.023 – 1.033) was associated with increased odds of a stop resulting in a citation. We did not find strong evidence of any associations with use of force, as there were so few use of force incidents and resultingly large confidence intervals for all ORs.

For analysis of officer characteristics on arrest and complaints data, we considered the association between variables with specific types of arrests or complaints. The question we ask: given that there is an arrest/complaint, what is the estimated relationship between officer characteristics and specific types of complaints or arrests? With respect to arrests for specific offenses, we only found that male officers were more likely to have arrested individuals for speeding (OR 1.423 95% CI 1.067 – 1.899) and that Black officers were more likely to arrest individuals for communication of threats (OR 1.195 95% CI 1.072 – 1.332). Finally, with respect to complaints, we found that Black officers were less likely to receive a complaint involving an arrest, search or seizure than their White counterparts (OR 0.368, 95% CI 0.218 – 0.622). Male officers were found to be much more likely than female officers to have a complaint about an arrest, search or seizure (OR 2.891, 95% CI 1.314 – 6.362) and to have a complaint related to use of force (OR 2.653, 95% CI 1.165 – 6.039), and officers with greater years of experience are expected to have a lower probability of receiving a complaint (OR 0.956 95% CI 0.923 – 0.99).

Table 3.29: Odds Ratios, Officer Characteristics, Stops, by Result

	Arrests				Citation				Use of Force			
	N	Odds Ratio Est.	Lower Bound	Upper Bound	N	Odds Ratio Est.	Lower Bound	Upper Bound	N	Odds Ratio Est.	Lower Bound	Upper Bound
Officer, Asian	433	**0.589**	**0.474**	**0.732**	15,539	**1.719**	**1.341**	**2.202**	12	1.05	0.575	1.918
Officer, Black	1,263	**0.696**	**0.642**	**0.753**	38,627	**1.3**	**1.174**	**1.439**	34	0.942	0.614	1.444
Officer, Hispanic	542	0.943	0.821	1.083	6,079	**0.885**	**0.803**	**0.976**	6	0.581	0.252	1.339

Officer, Native American	47	1.356	0.895	2.055	333	**0.57**	**0.429**	**0.756**	1	1.111	0.141	8.769
Officer, Other	1,013	**0.886**	**0.816**	**0.963**	8,014	**0.821**	**0.753**	**0.895**	18	0.943	0.567	1.567
Officer, male	10,764	**1.328**	**1.22**	**1.446**	191,571	**0.806**	**0.763**	**0.85**	229	0.854	0.515	1.415
Officer, White	8,395				138,969				179			
Officer, female	929				15,990				21			
Officer age		**0.976**	**0.972**	**0.981**		**1.028**	**1.023**	**1.033**		0.993	0.969	1.018
Officer years of service		**0.978**	**0.971**	**0.984**		1.006	0.998	1.014		1.016	0.987	1.046

Clustered standard errors were used to compute 95% CIs.
Bolded numbers indicate statistical significance.

Table 3.30: Odds Ratios, Officer Characteristics, Arrests by Charge

	Speeding				Public Intoxication				Communication of Threats			
		Odds Ratio Est.	**Lower Bound**	**Upper Bound**		**Odds Ratio Est.**	**Lower Bound**	**Upper Bound**		**Odds Ratio Est.**	**Lower Bound**	**Upper Bound**
Officer, Asian	56	1.134	0.69	1.862	11	1.245	0.517	3	86	0.962	0.704	1.314
Officer, Black	271	1.087	0.868	1.363	41	0.939	0.623	1.415	528	**1.195**	**1.072**	**1.332**
Officer, Hispanic	75	0.834	0.566	1.23	15	0.996	0.619	1.604	180	1.169	0.98	1.394
Officer, Native American	4	0.684	0.246	1.9	1	0.932	0.125	6.961	10	0.955	0.479	1.905
Officer, Other	103	0.647	0.486	0.861	15	0.6	0.367	0.982	297	1.142	0.983	1.326
Officer, White	1,089				195				1,979			
Officer, male	1,489	**1.423**	**1.067**	**1.899**		1.042	0.622	1.745	2,767	0.926	0.813	1.054
Officer, female	109				254				312			
Officer age		1.012	0.998	1.026		1.014	0.992	1.036		1.003	0.996	1.01
Officer years of service		0.964	0.946	0.982		0.99	0.965	1.016		0.995	0.986	1.004

Clustered standard errors by neighborhood statistical areas were used to compute 95% CIs.
Bolded numbers indicate statistical significance.

Table 3.31: Odds Ratios, Officer Characteristics, Complaints, by source and type

	External Complaint				Arrest, Search, Seizure				Use of Force			
		Odds Ratio Est.	**Lower Bound**	**Upper Bound**		**Odds Ratio Est.**	**Lower Bound**	**Upper Bound**		**Odds Ratio Est.**	**Lower Bound**	**Upper Bound**
Officer, Asian	11	0.928	0.23	3.742	5	1.128	0.355	3.578	6	2.601	0.838	8.078
Officer, Black	90	0.726	0.487	1.083	12	**0.368**	**0.218**	**0.622**	20	0.717	0.35	1.465
Officer, Hispanic	35	1.092	0.495	2.412	10	0.63	0.218	1.815	9	0.591	0.19	1.84

Officer, Native American	4				1				0	NA	NA	NA
Officer, Other	29	1.272	0.535	3.02	11	0.57	0.07	4.625	9	0.573	0.19	1.732
Officer, White	289				72				77			
Officer, male	402	1.295	0.977	1.716	104	**2.653**	**1.165**	**6.039**	113	2.766	1.094	6.991
Officer, female	56				7				8			
Officer age		0.997	0.975	1.02		0.995	0.963	1.028		0.983	0.945	1.023
Officer years of service		1.009	0.987	1.032		**0.956**	**0.923**	**0.99**		1.009	0.98	1.04

Clustered standard errors by division of occurrence were used to compute 95% CIs.
Bolded numbers indicate statistical significance.

CMPD Policies and Strategies That May Be Affecting Disparities

Given our identification of statistically significant racial/ethnic disparities, we considered whether any policies or strategies may be driving these results. We reviewed CMPD's current Interactive Directives Guide as part of this effort. While we were able to identify no specific policies or strategies that may drive racial/ethnic disparities we observe in our results, we have suggestions for CMPD. To better identify the cause of these racial/ethnic disparities and determine if they in fact are driven by bias, we suggest that CMPD gather more data. As police-initiated stops and their results are up to the individual officers' discretion, CMPD may need to gather information about their decision-making processes and what their information is for conducting a stop or resolving it in a certain way. Other data sources, like body cam footage, may be a fruitful resource in this case. Once CPMD is better informed, it can establish guidelines that seek to minimize racial/ethnic bias-driven disparities and more effectively contribute to the public safety. In the future, CMPD should consider community input to their written directives, which was also noted in the National Police Foundation (NPF) report for CMPD (Straub et al., 2018). CMPD should also review available training (including effectiveness of training and policies) as they relate to bias. One area that may not receive as much attention is bias-based calls to the police.[23]

We also examined CMPD's directives to determine if certain other criteria were addressed. For example, with respect to "choke holds" (or similar) the current policy dictates the following:

H. Officers will not use the following tactics unless deadly force is reasonably necessary:

1. Any hold with or without a device that restricts a person's airway.
2. Any hold with or without a device that restricts blood flow to a person's brain.[24]

Restricting this type of tactic is consistent with the International Association of Chiefs of Police's (IACP) National Consensus Policy and Discussion Paper on Use of Force (International Association of Chiefs of Police, 2020).

---

[23] See concerns noted by the Commission on Accreditation for Law Enforcement Agencies (CALEA, 2020)

[24] CMPD Directive 600-019, Response to Resistance

CMPD Directive 600-019 also includes the following language: “The CMPD recognizes and respects the integrity and paramount value of human life. The Department believes that human life is sacrosanct and the goal of any encounter with the public is girded by the unwavering commitment to the preservation of life. Consistent with this belief is the Department’s full commitment to a culture of guardianship that embraces a warrior spirit in protecting the community.” The sanctity of life is consistent with the Police Executive Research Forum’s (PERF) first guiding principle on use of force (PERF, 2016). However, CMPD may want to reconsider the use of the term “warrior,” as it could inoculate officers with friction toward the communities they serve .[25]

CMPD also specifically addresses profiling in Directive 600-017 *Arbitrary Profiling*. This section explicitly dictates that officers will not use arbitrary stereotypes as:

1. A factor in the selection of whom to stop and search.
2. A motivation for the decision to initiate a police activity.
3. A motivation to conduct a police activity differently than they normally would.
4. An assumption regarding an individual’s immigration status.

It should also be noted that, consistent with past reports (i.e. NPF, 2018), CMPD takes a proactive approach in transparency by publishing its department directives online at https://charlottenc.gov/CMPD/Documents/Resources/CMPDDirectives.pdf. There is also a web portal for submitting complaints and commendations, including outlines of the processes that follow (https://charlottenc.gov/CMPD/Pages/Commendation-Complaint_Process.aspx). CMPD provides the public with open data in the form of traffic stops and officer involved shootings; additional data on police-public interactions, including use of force could be beneficial for the department and community (Charlotte-Mecklenburg Police Department, 2020a).[26] Lastly, CMPD is a participant in the FBI’s National Use of Force Data Collection initiative. For 2020, only 5,030 of 18,514 law enforcement agencies nationwide contributed data to this effort (FBI, n.d.).

Roles and Responsibilities of CMPD and Workforce Analysis

In our analysis of CMPD roles and responsibilities, we consulted with the team leading Recommendations 2 & 4 in exploring alternative response models and their impacts on patrol officers’ workload in response. We identified a number of different calls for service could potentially be delegated to non-sworn staff or specialized clinicians, provided guidelines were identified to assure the safety of these staff. In our discussions with CMPD however, we heard several things: 1) Overall policing staffing levels were unlikely to change after duty re-allocation given CMPD staffing requirements; 2) The need to maintain response times; 3) The need of

---

[25] Much has been written about the warrior vs. guardian mindset in policing, but see, for example (Rahr and Rice, 2015).

[26] This would be in addition to the annual internal affairs reports published and made public by CMPD.

having patrol units available for these calls. In our own research of similar programs in similar cities, we identified similar concerns (See Ft. Worth, TX). As a result, the budget implications of these re-allocations are not likely to lead to significant cost savings from reducing patrol staffing. In fact, depending on assumptions concerning the efficiency with which non-sworn staff clear specific calls, re-allocation efforts may lead to a cost increase stemming from having to field additional staff. Since many civilian or alternative-response model programs are only beginning to be considered across the United States, rigorous, program evaluation evidence is sparse – which is simply to say that there are very few precedents that can be used to draw inform a detailed examination of the direct budget implications of a staffing model – let alone the wider costs of providing care or intangible costs or benefits of those models. This leads to our recommendation that the City of Charlotte pursue a pilot program (discussed in the recommendations section) to evaluate alternative response models and use the resulting data to provide estimates that would be most appropriate for the city.

In addition to alternative response models for sworn patrol officers, we also considered whether some services provided by CMPD could be re-allocated to other entities. Based on our interviews with representatives from Animal Care and Control, Electronic Monitoring, and Private Vehicle for Hire. While, the compressed project schedule and logistic challenges of obtaining data were challenges, our discussions enable us to define guidelines that could inform whether and how programs provided by the CMPD should be provided under the auspices of another body. Briefly, our guidelines are that if:

- A program provides services that are distinct in nature from administering justice;
- A program can maintain or increase the resources and support it receives in its new location;
- A program can perform its functions at least as effectively and in line with local regulations without necessarily adhering to regulations or policies followed by the CMPD;

then it follows that the program in question is a viable candidate for being transitioned out of CMPD and to another authority. However, we would stress that the question of effectiveness with which any program provides services to the community is key: it would be counter-productive to transition a program out of CMPD if it means it receives fewer resources due to policies, statutes, or other funding limitations as a result. Ensuring that programs receive support once transitioned out of CMPD. Based on these guidelines, CMPD’s Animal Care and Control (ACC) and control is a potential candidate for transitioning out of CMPD, provided it maintains funding levels. Meanwhile, we would caution against transitioning electronic monitoring outside of CMPD as it deals with individuals charged of violent crimes and so would benefit from CMPD’s practices and procedures.

4. RAND Recommendations

Based on our research into community policing and the context that the City and community of Charlotte find themselves, we have identified several recommendations that should help CMPD better meet the needs of its residents and improve public safety for the wider community. As the RAND team was working on two different sets of recommendations, we present them each in turn (2 and 4 together followed by 3). These recommendations were based on information and data from stakeholders as well as our analysis. Our primary recommendation that speaks to SAFE Charlotte's Recommendations 2 & 4 is to establish a pilot program with the intent of evaluating it and tailoring it for expanded use in Charlotte should it prove successful. However, it is essential to note that any pilot *must* include community input and a strong evaluation plan. Our primary recommendations pertaining to Recommendation 3 center around data and its potential use in improving policing as well as providing general guidelines for transitioning CMPD services to different agencies.

4.1. Recommendation 2 & 4

Three recommended programs

We are recommending an expansion of CPCRT, a pilot of non-specialized civilians to respond to low priority calls, and a separate pilot of and a pilot of a specially trained civilian unit like CAHOOTS, but tailored to Charlotte specifically. In this section we will provide details for these recommended programs, beginning with low priority calls.

It should be noted that for the pilot of low-risk/low-priority calls, that the call types must be carefully selected. This is a difficult task due to the limitations of the data—we did not have officer injury data. The safety of civilian responders is a prevailing concern throughout all of the qualitative interviews. Additionally, since there is inherent risk in every call, there should be a procedure in place for sworn officers to assist a civilian responder in the cases where a low-risk, low-priority call escalates or is otherwise unsafe. Under these circumstances, specifying the universe of calls that could be diverted in every case is difficult given the inherent risk present and variation in context between calls. However, given proper support, researchers could collect better data and utilize more advanced models, such as machine learning models, to identify low-risk/low-priority events. In addition, implementation of any program may result in some changes to dispatch-related policies and training, so it is likely more beneficial to specify guidelines that can accommodate changes rather than a fixed list of call types. Generally, types of calls that are the least likely to escalate or require multiple units on scene to resolve a situation are the best possible candidates for diverting to civilian responders.[27] In the data, calls related to road blockages and illegal parking had no incidences of escalation (Table 2.6) and often were manageable by a single unit, which makes these calls amenable to diversion to a non-specialized civilian team, when legally permissible. Additional calls may involve those that are primarily report-taking calls, such as some vehicle or traffic related calls, accidents involving property damage, or other property crimes. However, some priority 5 calls with a higher likelihood to escalate may be best left to sworn officers, even if they are relatively low priority (e.g., intoxicated individuals, suspicious persons or vehicles, noise complaints or domestic disturbances, missing persons cases). Indeed, because there is risk to any call, a short-term mitigation strategy is necessary to ensure that these civilian responders are not sent to calls that escalate and to ensure that backup is readily accessible should the need arise during initial calls in the pilot phase. Proper training to manage an unsafe situation would be essential in the instances where a call could escalate and present a dangerous environment for all involved. Additional concerns about a civilian unit found in the qualitative data included that having a civilian responding to a call for service may not meet the expectations of community members and may not make people feel safe. Finally, there were also concerns it removes many opportunities for police to be seen in the community contributing in a positive way.

With regard to the expansion of CPCRT and a pilot of specialty trained civilians, it is clear from the qualitative data that any intervention that is implemented *must* involve community organizations at every step. This means collaboration on the specifics of the intervention (who is hired, how people in crisis are identified, what staff wears, etc.…). This also means addressing the lack of continuum of care in Charlotte through collaboration with community organizations. Many of these organizations have care options available, such as peer respite. However, asking community organizations to assist with the continuum of care must also come with funding for these organizations. We provided more detail on these services in the resource map section of chapter 2. However, there is a problematically low capacity for step down treatment options in Charlotte and while this issue needs to be noted, it is beyond the scope of this study. It is also clear from the qualitative data that hiring the "right" individuals are essential to the implementation of any intervention. This would mean hiring people representative of the community or subcontracting to a community organization (and housing them within the CMPD). Time must also be given to allow these representatives to enmesh themselves within the community, meaning they not only hold listening sessions but also attend community events. It would also be potentially beneficial to limit the geography these teams work in to allow them time to get to know the community. These teams must also be available 24 hours a day, to

[27] It should clearly be noted that there is an element of risk associated with almost every call type, with the exception of reports taken over the phone. Such risks were highlighted in interviews, and risk is still present even with the most thorough screening of calls by dispatch/call taking personnel.

effectively serve the community. We will provide more detail on the geography and timing of all interventions in the following section.

Finally, while there is one major benefit to housing any intervention pilot external to the CMPD, namely it bypasses potential tension between community members and the police, we are recommending that these pilots be a CMPD program. This will facilitate sharing of resources, information and dispatch. Other programs nationally that have attempted to remove these programs from the police department have not been successful at coordinating response services and avoiding jail or hospitalization for community members (Witzberger and Megas-Russell, 2020).

Geographic Location for Pilots and Types of Calls

Non-Specialized Civilian Response for Low-Priority/Low-Risk calls

Based on our analysis of where routine priority calls are located, we recommend the city consider weighing the deployment of the pilot two-person non-specialized civilian teams in areas that have high concentrations of these low priority calls for service. These are not calls where behavioral health services are needed, but tasks identified in chapter 2 as lower risk. These include: illegal parking, found property, notify, pick up property or evidence and road blockage. However, it should be noted that our lack of data on officer injury limits the strength of these data to fully identify risk. Our analysis in Table 4.1 shows the Neighborhood Statistical Areas (NSA) with the highest average numbers of Priority 5 calls per week over the last five years. There is no empirical evidence for the number of teams that should be piloted. Note that these numbers represent all calls which may not all be divertible. Assuming it takes about an hour for a team of two to clear a divertible call and a fraction of calls will be diverted, one team should be sufficient per NSA. However, note that the geographic size of NSAs varies widely and is by no means uniform. Additionally, racial/ethnic and social equity concerns is a valid consideration in deploying a pilot program, so we leave the identification of specific geographic areas to policymakers and community representatives based on the evidence we are providing here.

Table 4.1 Top 10 NSAs for Priority 5 Calls, 2015-2020

Neighborhood Statistical Area (NSA)	Divisions	Neighborhood	Count	Approx. Calls Per week
3	Providence, Central	Dilworth	13,050	42
341	Central	Downtown Charlotte	8,173	26
371	North Tyron	Hidden Valley	8,140	26
342	Central	Downtown Charlotte	7,608	24
370	Providence	Grier Heights	7,115	23

340	Central	Downtown Charlotte	6,559	21
387	Freedom, Airport	Wick City	6,461	21
367	Providence, Eastway, Central	Elizabeth	6,407	21
331	University City	University City / Mineral Springs	6,244	20
124	Metro, Freedom	Ashley Park	5,934	19

Specialized Civilian Response

In terms of pilot deployment of the specialized civilian response, we have provided the average calls per week for homelessness, substance abuse, and mental health calls that were also flagged as Priority 5 based on six years of data. These are located in Table 4.2 below. If the City of Charlotte decides to move forward with this program, it should consider selecting NSAs and related police service areas to deploy these teams. We have identified 12 potential locations for pilot teams to be located based on call volume. It should be noted that, in order to allow for ease of evaluation, these teams should not be co-located with the other non-specialized civilian response team. The final selection of the location should be made by policymakers with feedback from community representatives.

Table 4.2 NSAs with Highest Average Homelessness, Substance Abuse, and Mental Health Low Priority Calls per Week, 2015-2020

		Homelessness		
NSA	***Divisions***	***Neighborhood***	***Count***	***Approx. Calls/Week***
340	Central	Downtown Charlotte	823	3
341	Central	Downtown Charlotte	510	2
384	Central	Downtown Charlotte	502	2
342	Central	Downtown Charlotte	463	1
3	Providence, Central	Dilworth	396	1
		Substance Abuse		
NSA	***Divisions***	***Neighborhood***	***Count***	***Approx. Calls/Week***
122	Airport, Westover, Freedom	Charlotte International Airport[28]	44	<1

[28] While this is the NSA with the greatest number of substance abuse related calls, we would like to comment that a pilot in other neighborhoods might be better suited to provide services to the community.

341	Central	Downtown Charlotte	37	<1
340	Central	Downtown Charlotte	27	<1
178	Steel Creek, Westover	Greenbrier Woods	25	<1
3	Providence, Central	Dilworth	20	<1
		Mental Health		
NSA	**Divisions**	**Neighborhood**	**Count**	**Approx. Calls/Week**
370	Providence	Grier Heights	483	2
371	Providence	Hidden Valley	450	1
21	North Tyron	Sugar Creek / Atanado Junction	368	1
385	Freedom, Metro	Thomasborough / Hoskins	324	1
389	Eastway, Hickey Grove, North Tyron	Windsor Park	247	1

Cost benefit analysis of Pilots

We will also combine the information gained in tasks 1, 2 and 3 of SAFE Charlotte recommendations 2 and 4 to develop a cost benefit analysis for the interventions. This included program resources and inputs (e.g., staff training, time needed to screen and identify eligible pilot program participants, labor costs for program staff). Inputs such as labor were measured in time and wages per unit of time.

Whereas inputs/resources are the immediate drivers of cost, these resources can in turn produce outputs and outcomes that may yield further cost differentials between participant and individuals not served by a civilian responder. Regarding outputs, we considered factors such as jail diversion and other similar outcomes. To the extent possible, we requested information related to various costs directly from the city of Charlotte. As needed, we supplemented this with estimates of the social and economic costs of justice involvement as found in the literature. We used this information, in combination with data from the larger population served by CMPD, to understand the costs and benefits potentially associated with these pilot programs.

Non-Specialized Civilian Response to Low-Priority, Low-Risk Calls

We will begin by considering the cost-benefit of non-specialized civilians responding to low-priority, low-risk calls. Costs and benefits will depend on which Priority 5 calls are diverted as well as the hours and geography covered but can generally be expected to be along the lines of those listed in Tables 4.3 and 4.4. These tables, presented below, provide an overview of the program inputs and outputs that were considered in the development of the cost benefit analysis for alternate call response model pilot programs.

Table 4.3. Program Inputs and Change Relative To Status Quo

Input	Projected Change	Considerations
Personnel	Savings	• Salary and benefits • Shifts covered • Number/type of calls diverted
Training	Short term cost, long term savings	• New initial program (cost) • Length of time of training (cost) • Potential long-term savings relative to police officer training (savings)
Equipment	Savings	• Radios, vehicles, non-police uniforms, protective equipment • Some initial costs with long-term savings relative to *status quo*
Evaluation	Cost	• Rigorous, independent evaluation of pilot program can help determine effectiveness and path forward

Table 4.4. Program Outputs and Change Relative To Status Quo

Output	Projected Change	Considerations
Citations/Arrests	Decrease	• Rare outcomes for Priority 5 calls • Subsequent decreases in jail time, hospitalizations possible but rare
Safety	Unclear: More research is needed	• Risks should be low, but are not always apparent at the time of dispatch[29] • Civilian response is expected to reduce the likelihood of escalation • Civilian responders may be under-equipped to respond to situations that do escalate • Dispatch can mitigate some risks, but situations may change on arrival threatening safety
Police-Community Relations	Unclear: More research is needed	• Residents may favor a civilian response, but preferences will vary by type of call and across individuals/communities • Could reduce both negative and positive interactions between sworn officers and civilians • Degree to which civilian response unit is associated with CMPD will play a role
Police Morale	Mixed: More research is needed	• Administrative duties likely to decrease for sworn officers • Effects on wellness unclear, could increase/decrease based on exposure to negative calls for service • Perceived lack of confidence in officers by community and city leadership

Scenarios

The scenarios listed below are simplified across several dimensions for the purposes of comparison. Given the uncertainty regarding civilian response times, we provide a wide range of

[29] Safety concerns have been raised in interviews and focus groups.

scenarios, starting from the average total service time for the current response model. Response duration will best be predicted based on pilot data from the newly created program.[30]

Scenario A: One civilian representative responds to a Priority 5 call, assuming half the response duration as in the *status quo* (37 minutes).

Status Quo (SQ): Current response to Priority 5 calls by one or more sworn police officers. In 2020, the average total service time[31] was approximately 74 minutes, rounded up to the nearest minute.

Scenario 1: Civilian representatives respond to a Priority 5 call, assuming 2 times the *status quo* response duration (148 minutes). *This scenario is also likely when there is a two-person civilian response team handling a call for service. Similar to co-responder programs, such as the CPCRT and others across the country, as well as CAHOOTS and other pilot programs, civilians are often paired together.*

Scenario 2: Two civilian representatives respond to a Priority 5 call, assuming a call time comparable to Denver's Support Team Assisted Response (STAR) program duration. In this case, STAR response shortened ***on-scene*** time by approximately 27.7%.[32] This would reduce total time on scene to 57 minutes per civilian responder, or a total of 114 minutes.

Wage Estimates

In Table 4.5 below, we further simplify the scenarios described above by assuming one responder per call and estimate wage costs per Priority 5 call. The average wage of one sworn officer is used to represent the *status quo*. It should be noted, any cost savings are inflated due to using the average salary which could mix in supervisors/those on higher pay scales. For the four civilian response scenarios, we provide several possible hourly wages for comparison. These include two "new roles," one of which is equivalent to 10 percent less than an entry-level police officer (Step 1 on the pay scale), and the other which is 10 percent less than a Step 2 police officer. We have included New Role 2 because of the proposed elimination of Step 1 per the City of Charlotte FY 2021 Compensation and Benefits (City of Charlotte, 2020). For comparison, we

[30] Additional considerations for response time: travel and dispatch time could increase due to the size of the civilian response unit relative to the number of patrol officers. Differences in response options (e.g., citations, arrests, escorting to services) and administrative requirements (e.g., required reports) could increase or decrease the response time relative to the *status quo*.

[31] Sum of service time for each unit assigned/dispatched, averaged over all Priority 5 calls.

[32] Denver's STAR program is more comparable to the third option we discuss, as the team serves mental health and non-violent police calls. However, the estimates are helpful as it is a two-person non-sworn team (Blick et al., 2021).

also include the wages for a CMPD Police Investigative Technician[33] and a Social and Human Service Assistant (U.S. Bureau of Labor Statistics, n.d.-b). Note that, for these estimates, Scenario 3 could be considered to double the response time *or* double the number of responders to the call relative to the *status quo*. Similarly, Scenario A could be considered to halve the response time *or* halve the number of responders to the call relative to the *status quo*.

Table 4.5 Wage Costs by Scenario Relative to Status Quo ($/Call)

Role	Hourly Wage	Scenario A cost (Change from SQ)	*Status Quo* cost	Scenario 1 cost (Change from SQ)	Scenario 2 cost (Change from SQ)
Sworn Officer[a]	$34.70	n/a	$42.79	n/a	n/a
New Role 1[b]	$19.80	$12.21 (-30.58)	n/a	$48.84 (+6.05)	$37.62 (-5.17)
New Role 2[c]	$20.79	$12.82 (-29.97)	n/a	$51.28 (+8.49)	$39.50 (-3.29)
Police Investigative Technician	$17.42	$10.74 (-32.05)	n/a	$42.97 (+0.18)	$33.10 (-9.69)
Social and Human Service Assistant[d]	$18.38	$1.33 (-31.46)	n/a	$45.34 (+2.55)	$34.92 (-7.87)

[a]Average CMPD Officer
[b]10% below CMPD Officer Step 1
[c]10% below CMPD Officer Step 2
[d]Source, for comparison's sake, is the national median for this position according to the Bureau of Labor Statistics

In most scenarios, a net savings in wages would be expected and could be substantial when aggregated over the total number of calls. However, if the number of responders or the duration of the response were to double relative to the *status quo*, wage costs could increase relative to the current model. Additional considerations include the possibility of high turnover at lower wages and the differences in benefits packages for non-sworn and sworn personnel.

While we are able to estimate wage savings and costs, it is not possible, prior to a pilot and its related developments and adjustments to procedure, to estimate a total savings overall annually because it is unclear what proportion of calls can be diverted given their varying contexts and the dispatchers' evaluation of them. Some Priority 5 calls could be diverted to the specialized civilian team developed under other response models for Recommendation 4 (e.g., 984 "homeless people" calls) and some may require a sworn officer response (e.g., if the team arrives on the scene and there is a firearm present) and therefore be inappropriate for the civilian response unit. Additionally, we are also unable to anticipate which scenarios and their related

[33] City stakeholders stated that Police Investigative Technicians would have a similar salary to the proposed non-sworn responders (Interview 2)

assumptions are going to emerge during the program pilot. As a simplified example, assume the following: 1. A civilian representative in a new role earns 10% less than a Step 2 CMPD officer; 2. The number of responders and total service time remain constant in the new response model (i.e., equal to the *status quo*); 3. A pilot program of 10 individuals assigned to 5 two-person teams working 40 hours a week.

Based on other pilot programs, co-responder models, and CMPD's own CPCRT, teams typically deploy in pairs. Thus, it is critical to examine the costs relative to two civilians responding in place of one officer. Scenarios 1 and 2 then lend useful information for planning purposes. Under Scenario 1, where two civilians respond and take the same amount of time as an officer, the costs are *higher,* leading to a cost increase of **$35,793.84**.[34] However, there is some evidence that civilian responders may be *more* efficient than sworn responders, which is reflected in Scenario 2. Under these circumstances, cost *savings* would be approximately **$18,006.17**.[35]

Pilot of a similar program in Fort Worth, Texas

The Fort Worth Police Department in Texas recently undertook a similar set of reforms: expanding its existing crisis response team and developing a specialized civilian response team for low-risk, low-priority calls. Ten members of the pilot Civilian Response Unit recently completed training and will work 7am-7pm in limited areas of the city.[36] The line item in the FY2021 budget that corresponds specifically to this limited pilot program is $808,669. Adjusting this for a 5% increase in cost of living in Charlotte, **an initial estimate for a similar year-long pilot is approximately $850,000,** with the variables noted in previous sections affecting the real total cost considerably. However, the Fort Worth Civilian Response Unit responds to calls during a limited window and does not run 24 hours a day. Interview data has clearly indicated that stakeholders report that any pilot or program in Charlotte should be 24 hours. According to the City of Fort Worth, Texas FY 2021 Salary Schedule (City of Fort Worth, 2021), the wages for this position are presented in Table 2.16 below.

---

[34] 5 teams x 40 hours = 200 hours a week. 200 / (148/60) Priority-5 clearance time = 81.08 calls / week, 81.08 * 52 = 4,216.21. Rounded, 4,216 * 8.49 increased costs per call = $35,793.84.

[35] 5 teams x 40 hours = 200 hours a week. 200 / (114/60) Priority-5 clearance time = 105.26 calls / week, 105.26 * 52 = 5,473.68. Rounded, 5,473 * 3.29 savings per call = $18,006.17.

[36] Budget available here: https://police.fortworthtexas.gov/CCPD/ccpd-quarterly-reports. Program Description: "The FY21 budget provides funding for the creation of the Community Service Officer Program. This is a pilot team of 10 nonsworn civilians to answer nonviolent calls for service. The Community Service Officers will handle lower priority calls, which frees up sworn officers to handle the emergency calls for service and focus more on crime prevention. In addition, community/police relations improve with the interactions from a Community Service Officer answering non-violent calls. It is a softer approach for the community to receive basic police services such as completing reports, information requests, and community concerns."

Table 4.6 Civilian Responder Wages

Minimum		Midpoint		Maximum	
$/hr	Annual	$/hr	Annual	$/hr	Annual
$17.20	$35,774.00	$21.50	$44,718.00	$25.80	$53,662.00

Table 4.7 compares an entry level civilian responder's hourly rate to that of an officer at various career steps in Fort Worth. Police officer base pay is greater in Fort Worth than it is in Charlotte; applying the same proportion of officer wages to civilian responders in Charlotte would result in low wages (Table 4.8). It should be noted that low pay could lead to higher turnover and other staffing challenges, which may be more costly over time.

Table 4.7 Civilian Responder Wages as a Proportion of Police Wages in Fort Worth

Location	Step 1 (56%)	Step 2 (52.4%)	Step 3 (50.8%)	Step 4 (48.4%)
Charlotte	$21.99	$23.10	$24.25	$26.74
Fort Worth	$30.69	$32.22	$33.83	$35.52

NOTE: We only include the steps, not the time in grade required for the steps.

Table 4.8 Applying the Proportional Wages in Fort Worth to Charlotte Police Officer Wages

	Step 1	Step 2	Step 3	Step 4
Charlotte	$21.99	$23.10	$24.25	$26.74
Non-sworn Responder Proportion	56.0%	53.4%	50.8%	48.4%
Estimated Hourly Wage	$12.32	$12.33	$12.33	$12.95

We have provided the details above to show comparisons that Charlotte should consider when examining both officer and civilian responder wages that may ensure professional workforces. However, the City should rely on estimates in Table 4.5 for planning purposes.

Other Pilot Programs

There are additional programs under discussion or consideration throughout the country. Amherst, Massachusetts (population: 39,924 (U.S. Census Bureau, 2019), 47 sworn police officers (Amherst Police Department, n.d) is considering a Community Response for Equity, Safety, and Service (CRESS) team to replace some police functions. Although the program is still in development, recent talks indicated that $2.2 million is budgeted for CRESS, with up to 18 staff in one proposal (Merzbach, 2021).

The City of Ithaca and Tompkins County, NY, recently completed a reimagining public safety report that includes a completely new Department of Public Safety in lieu of a traditional police department. Elements from this plan include civilian responders, and budget information was available on a small-scale pilot. Budget estimates for Ithaca/Tompkins County include the following (City of Ithaca and City of Tompkins County, 2021):

- $75,500 salary and benefits for each Community Solutions Officer (includes $500 for sworn), exact number of officers to be determined.
- $70,320.18 salary and benefits for civilian staff in sheriff's office x 3 positions = $210,960.54

These relevant pilots are included here to demonstrate the cost of comparable implementations. If Charlotte is to pursue civilian response teams, these comparisons could guide the pay and benefits for a professional model.

Cost Benefit Analysis for Mental Health Crisis interventions

Expansion of CPCRT

One approach outlined by the city to respond to SAFE Charlotte's fourth recommendation is to double the number of clinical staff involved in co-responding with sworn officers to higher risk mental health calls. The primary cost consideration is the contract for clinical services. CMPD may also need to consider whether additional sworn officers need to be trained in order to support increased call volume and whether there is current capacity in the service provider community. To provide the City of Charlotte as much information as possible, we provide estimates and information on expanding CPCRT.

The main outcome of the CPCRT expansion will be the likely increase in the number of calls to which CPCRT responds, and there may be both costs (e.g., CPCRT calls are longer on average) and benefits (e.g., fewer community members in jail, fewer hospital stays) associated with this change in volume. While we understand that costs for time spent in jail are borne by the county and health care costs are borne by the state, this is a community cost that deserves consideration. CPCRT responded to 2,894 calls in 2020, and we have assumed that the call volume will roughly double with the doubling of staff, given that there were more than 22,000 calls per year with a mental health component in 2018-2020. Table 4.9 summarizes the estimated costs and benefits.

Table 4.9 Costs and Benefits Associated with the Expansion of CPCRT

Input	Change from status quo	Cost or Savings
Contracted Clinicians	Increase from 6 to 12	Cost of $718,299/yr[a]
Increased duration of response	Increase of 145 min for officers[b]	$83.85/additional call x 2,900 calls per year = cost of $243,189/yr
Jail time avoided	8% of additional calls	Savings of approximately $87,241/yr[c]

[a]Based on a doubling of Year 3 contract fees, assuming that most contract costs double with the doubling of staff
[b]CPCRT calls with a documented disposition took, on average, 207 minutes to resolve. Non-CPCRT officers spent 62 minutes, on average, responding to calls with a mental health component. Cost estimate is derived from officer salaries without benefits and healthcare, assuming that the cost is additional time spent rather than hiring of additional staff. CMPD will need to consider whether additional officers are required to meet increased call load associated with hiring of additional clinical staff.
[c] A SAFE presentation notes that 8% of CPCRT calls resulted in jail time avoided. The savings listed represent a continuation of that trend for the additional calls and assumes an average of 2 days of jail time avoided. In a 2014 survey (Henrichson, Rinaldi and Delany, 2015), the reported average daily cost per inmate in Mecklenburg County was $166.04. Adjusted for inflation[37] to March 2021, this is $188.02 per person per day. 0.08 avoid jail x 2,900 calls x 188.02 per day x 2 days = $87,241.28

Lower-Risk Mental Health Calls, Homelessness, Welfare Checks

Charlotte is also exploring diverting calls pertaining to lower-risk mental health issues, homelessness, and welfare checks to a response pair of a mental health clinician and an EMT (potentially paired with a mental health counselor), which in combination with CPCRT is similar to that of the CAHOOTS program in Eugene and Springfield, Oregon.[38]

Table 4.10 describes the potential costs and savings associated with this response model.

Table 4.10 Costs and Savings Associated With Medic/Counselor Response Programs

Input/Output	Change	Considerations/Examples
Personnel	EMT/Medic and counselor in place of officers	• Calls Diverted (20% of all calls in Eugene, OR[39] 2.8% reduction in all calls in Denver pilot[40])

[37] (U.S. Bureau of Labor Statistics, undated)

[38] "CAHOOTS provides immediate stabilization in case of urgent medical need or psychological crisis, assessment, information, referral, advocacy & (in some cases) transportation to the next step in treatment. Any person who reports a crime in progress, violence, or a life-threatening emergency may receive a response from the police or emergency medical services instead of or in addition to CAHOOTS" (White Bird Clinic, undated).

[39] (Shapiro, 2020)

[40] (Blick et al., 2021)

		• Officer back-up for some diverted calls (0.63% of calls in Eugene, OR)[41] • Approximately $270,000 to staff one mobile crisis team for a year[42]
Training	Extensive safety and response training	• CAHOOTS training, is intended to be the basis of MACRO training: 40-hour class time, OPD ride along, 500 hours mentor-guided field training, continued training and education • MACRO also bases program on CAHOOTS safety training to include scene awareness, risk identification, communication and radio communication, defensive driving, de-escalation, debriefings[43]
Equipment	Vans in place of patrol vehicles	• Alterations (e.g., wheelchair lifts) • Maintenance • Sprinter Crew Vans start at $41,375[44]
Response duration	Potential savings	• Shorter response duration in Denver pilot (25 vs. 34min)[45]
Jail time	Savings	• No clear estimates of how often this occurs • For CPCRT, SAFE estimates that jail time is avoided in 8% of calls[46]
Hospitalizations	Savings	• Small evaluation in Dekalb County Georgia: 55% of calls resolved without hospitalization vs. 28% with police response[47]
Outpatient mental health services	Short term cost with potential savings in the long term	• 15 percentage point increase in outpatient mental health service utilization following an interaction with the Crisis Stabilization service in Minnesota[48] • Could reduce long-term use of other services

Similar Programs in Other Cities

Estimates of costs and benefits in other cities deploying similar programs or pilots can provide a high-level estimate of what Charlotte should expect. Cost estimates for pilot programs range from $1.4M to $1.85M. Eugene and Springfield, Oregon, report spending $2.1M and saving $15M per year on their long-running program that includes both a co-responder model and a medic/counselor only model. It should be noted that Charlotte is a different setting both geographically and demographically than Springfield and Eugene Oregon, so there will need to be modifications to the program. Interview data has also suggested the possibility of including a peer with these response teams. Although rigorous evaluations are lacking, many cities provide basic estimates of calls to which civilian teams responded, their outcomes, and the cost of the program. Few cities provide estimates of benefits, which are typically more difficult to assess.

---

41 *See supra* note 13

42 (Crisis Now, undated)

43 (Urban Strategies Council, 2020)

44 See https://www.mbvans.com/en/sprinter#lineup

45 *See supra* note 14

46 (Blick et al., 2021, p.20)

47 (Scott, 2000)

48 (Bennett and Diaz, 2013)

Table 4.11 Medic/Counselor Response Programs

Location	Estimate	Additional Details
Denver, CO[49]	Cost $1.4M	• Pilot program • 6 teams, 4 vans, 24/7, limited geographically
Eugene and Springfield, OR[50]	Cost: $2.1M per year Estimated Savings: $15M per year	• Cahoots model, running ~30yrs • Police budget totals $90M • Savings: ER, officer, and EMS diversion • Uses both joint response model and Cahoots-only response
Chicago, IL[51] (Sweeney, 2020)	Cost: $1.7M	• Pilot program includes 3 clinicians in 911 call center • Started with a co-responder model only and added the $1.7M alternate, nonpolice pilot
Dekalb County, GA[52]	Savings of $443 per case	• Small evaluation of 131 cases.
Minnesota[53]	Benefit to cost ratio = $3.90, or $1,280 per person	• Mobile crisis response team • Benefits include reduced hospitalization and crime victimization
Metro Areas in Midwest[54]	Benefit to cost ratio = $1.16, or $201 per person	• Specific to psychiatric emergencies
Oakland, CA[55]	Start-up cost: $1.85M	• Mobile Assistance Community Responders, pilot program

There is considerable uncertainty in estimating costs and benefits associated with a new program and its potential effects. We have relied primarily on estimates of specific costs and benefits from existing programs in other cities. It is important to note, however, that while there are many cities employing similar response models, there is very little rigorous research on their effects and costs. Charlotte could gain additional information by running a carefully designed and evaluated pilot program in order to understand the effects of the program, its costs and benefits, and necessary adjustments to maximize benefits.

Limitations of Cost Benefit Analysis

Additional analyses of call data and refining the details of each program will inform more precise estimates of costs and benefits, but some parameters will remain unknown until a pilot program is adopted and evaluated. It is difficult to predict whether and how the outcomes of calls

---

[49] *See supra* note 14

[50] *See supra* note 13

[51] (Sweeney, 2020)

[52] *See Supra* note 20

[53] (Minnesota Department of Human Services, 2018)

[54] (Washington State Institute for Public Policy, n.d.; Washington State Institute for Public Policy, 2014)

[55] (Kamisher, 2021)

will differ with a civilian response model. Furthermore, some of the risks and opportunities associated these programs are unpredictable or do not translate to monetary value. Police-community relations, public safety, and well-being are all important outcomes that can be difficult to measure.

The assumptions we have described in this report can significantly affect the estimates of benefits and costs. There may also be costs that we have not anticipated, such as administrative meetings with 911 dispatch or other affected agencies. In addition, we have not considered longer term impacts, nor benefits that accrue to individuals and groups not associated with CMPD. For example, an individual who is not arrested because of the civilian response to a call may retain employment that would have been lost if they were arrested; we have not accounted for benefits/costs to community members affected by the response. We have heard in several interviews that community outreach is needed, but the extent and cost of that outreach is not addressed in the current study. We have also not included the costs for evaluation of a pilot program. We also have not accounted for longer-term costs and benefits to Charlotte; there could be longer term increases in demand for behavioral health services that cannot be met with the existing services available. It has been noted in interviews and confirmed in the asset mapping that Charlotte lacks an effective continuum of care for mental health patients and increased mental health services may make awareness of this shortfall more acute. The cost estimates from cities with longstanding programs provide concrete information about ongoing costs and sustainability that may not be incorporated in a simple tally of cost information.

Additional Considerations for Cost Benefit Analysis

The City and police department need to prepare for a multiyear transition period to fully get to the new system if the initiatives are continued past a pilot period. During this time, additional issues may need to be addressed including, but not limited to: civilian and officer attrition, safety risks to civilian responders, the need for ongoing training, career progression pipelines (or lack thereof), pay differential for working nights/evenings, and determining future geographic areas to continue/discontinue programs. Further, the City should solicit input from patrol officers, and in cases where new programs are adopted, educate and train them on how to interact with and support these initiatives.

In addition to these logistical considerations, program evaluation will be key to deciding whether and how to expand programs. As the context in which these programs are piloted is one in which other efforts are concurrently active, disentangling the specific effect of any program can be difficult. It would be possible to determine the overall impact across all programs, but this would be uninformative as it pertains to individual programs. Additionally, understanding the social context in which these programs will be piloted is important for success and special consideration should be paid to social justice and racial/ethnic equity. Traditional evaluation programs require decisionmakers to choose where the programs will be implemented and thereby raise the question of fairness in their decisions. However, there are evaluation strategies that are capable of addressing questions of fairness, equity, and evaluation. We employed a statistical analysis with more specialized analysis that are intended to provide tests of statistical bias, along with more specialized statistical analysis that are intended to provide more robust tests of statistical bias. Our work for the City of Charlotte as it pertains to these recommendations falls within three analytical tasks: police-community member contacts; identify outliers within the police department; and analyzing work and labor demands.

Staffing requirements to respond to the current volume of such calls.

As this is a pilot program, we provide baseline estimates for the response times and numbers of calls that are able to be accommodated by civilian responders. Based on our estimates, five civilian responder teams could feasibly respond to between 81 and 105 calls per week in the specialized-civilian team (EMT and clinician).

It is reasonable to assume that five teams of non-specialized civilians could respond to the higher end of that spectrum (roughly 105 calls per week) when dispatched to non-emergency, low priority calls. Currently, there is no additional established basis for time estimates for this model. However, the metrics we have provided, combined with outputs from the early stages of the pilot should guide this effort in the future.

It should be noted however, that interview data indicate that enmeshing mental health providers within the communities they service is essential. This means it would be best to limit the size of the geographic area these individuals respond to, so they have this opportunity. It also means that time for community outreach is required for these teams.

Hours teams are available

The deployment of mental health teams has to benefit civilians in need by providing needed services and also free up patrol units to service higher priority calls, Therefore, we recommend that teams be available during hours where peak need occurs or where mental health, substance abuse, or homelessness related calls are more frequent than the daily average. For mental health, substance, and homeless related calls, the peak volume of the day occurs around 1:00PM extending to 10:00PM. These times coincide with increases in other call types, and mental health, substance, and homelessness related calls represent about 7-10% of all calls during this period. However, between 12:00AM-6:00AM, these calls still represent a similar share (6-8%) of all calls that CMPD may receive. To take advantage of the double benefit, the City should consider fielding the team 24 hours a day. Qualitative data also indicated a community desire for 24-hour services from both types of teams. See Figure 2.4 for an illustration of calls by hour of the day.

Performance measures

The following table outlines three types of metrics for evaluating the new models. Process measures will provide insight into what the new units are doing, how often they are acting, and how much time it is taking them to do so. Outcome measures provide insight into how well the new model is achieving the goals of both diverting calls from CMPD and of connecting individuals in crisis to appropriate resources or resolving the issue. Impact measures track the ways in which the models are impacting the community, including reducing the number of person-crisis events and reducing CMPD costs.

Tracking these metrics will require adding new indicators to the existing CAD system. CMPD may also be able to incorporate these measures in the same manner that CPCRT performance is measured, or they may be most efficiently tracked through the creation of a tool that functions in parallel to the CAD system. For example, the Eugene Police Department (EPD) Crime Analysis Unit in Eugene, OR, created two interactive tools that pull data from the EPD CAD system to measure the performance of the CAHOOTS units. The table references the possible creation of such a tool when 'analysis tool' is mentioned.

We have drawn the following metrics from the CAHOOTS program analysis (CAU, 2020), The Denver STAR program evaluation (Blick et al., 2021), Rochester's Person in Crisis team pilot plan (City of Rochester Department of Recreation and Human Services, 2021), and relevant academic articles (Bailey et al., 2018; Currier, Fisher and Caine, 2010; Dyches et al., 2002; Scott, 2000; Guo et al., 2001). This is supplemented by the materials and data provided by Charlotte and CMPD, as well as through our qualitative interviews. We believe these metrics are key for measuring success and that CMPD and Charlotte should re-visit them periodically while including community support/input.

Table 4.12 Performance Measures for Intervention Evaluation

Type	Measure	Evaluation method	Appropriate for specially trained crisis response	Appropriate for non-specialized civilian unit
Process Measure	Call types that the unit responded to	Flagged in CAD system	X	X
Process Measure	Number of calls the unit responded to as percent of all calls	Flagged in CAD system	X	X
Process Measure	Number of calls escalated to CMPD	Flagged in CAD system	X	X
Process Measure	Time spent at the scene	Flagged in CAD system	X	X
Process Measure	Response time	Flagged in CAD system	X	X
Outcome Measure	Number of calls diverted from police response as percent of all calls. A call is considered diverted from CMPD when no CMPD sworn officer resources are dispatched to a call nature that would have required a	Analysis Tool	X	X

	police response before the unit was created.			
Outcome Measure	Number of calls resolved by non-sworn unit.	Flagged in CAD system	X	X
Outcome Measure	Number of individuals diverted from hospitalization as percent of all relevant call types (i.e., suicidal subject, disorderly subject) An individual is considered diverted from the hospitalization when relevant call types do not result in psychiatric hospitalization.	Analysis Tool	X	
Outcome Measure	Number of individuals connected to community services as percent of all calls. A service connection is established when the individual has a confirmed appointment or is transported directly to a community resource.	Analysis Tool	X	
Impact Measure	Repeat encounters as percent of all crisis unit calls.	Analysis Tool	X	
Impact Measure	Individual engaging with community resources and/or treatment	Follow-up Analysis Tool	X	
Impact Measure	Cost savings to CMPD	See CBA	X	X
Impact Measure	Knowledge of the services in the community	Community survey		

Job Descriptions

RAND reviewed job descriptions for mental health clinician and EMT response teams, where available, as well as limited publicly available documentation for other civilian response models. For the EMT roles, and obvious requisite qualification as an EMT. Similarly, we recommend at least master's level training for the clinician.

Additional basic information, yielded from a review of other, similar models, co-response models, and interviews highlighted the need for the team to have knowledge and ties to Charlotte and the neighborhoods they work in, strong communications skills, a drivers' license and interest in enmeshing themselves in the communities they serve.

There are additional considerations that also apply and would behoove Charlotte and CMPD as they strive to attract candidates. First, a willingness to work with law enforcement. Since the positions are expected to eventually become 24/7, this expectation should be included in the job description as well, including any shift differential pay. Further, the job description should be clear in what CMPD, and Charlotte's background investigation process is for this position. We have included sample job descriptions from CAHOOTS in Appendix E. However, the job description from Charlotte should be tailored to the city with input from community advisors.

For the non-specialized civilian response models not requiring a trained clinician or EMT to handle low-risk, low priority calls for service, the Fort Worth job description is an excellent resource for the City of Charlotte to consider. We have included that job description in Appendix E. Highlights to consider include:

- Specific references to types of calls civilian responders will answer. For Fort Worth, this includes responding to lost/stolen/found property, minor motor vehicle incidents, and theft.
- Knowledge, skills, and abilities related to communications skills, problem solving, and customer service. Although the job description includes a knowledge of laws, statutes, and general orders for Fort Worth PD, these could be taught/trained for new employees in a Charlotte-specific team.
- Required to have at least a high school diploma/GED, valid driver's license, and other department/state requirements

Based on our interviews, the idea of having "peers" respond to calls or be part of Charlotte's public safety plan should also be considered in a job description (Youth Alive!, n.d.; Springfield Urban League, n.d).

Training for new hires (for either model) will be a foundation for each program. We suggest a program similar to Oakland's MACRO effort, which consists of the following based on CAHOOTS:

> CAHOOTS training, effective and based on extensive experience, will be the basis of MACRO cohort training with 40-hour class time, OPD ride-along, 500 hours mentor-guided field training, a strong ongoing training & continuing education program with skills labs, in-services, and staff meetings which include a reporting/discussion of cases. CAHOOTS safety training includes scene awareness, risk identification, communication with work partners, radio communication, defensive driving, de-escalation, self-care/clinical debrief, intuition, and decision-making autonomy (Urban Strategies Council, 2020).

The Promise Research Network (PRN) put together a Stakeholder Feedback and Development Report that also discusses potential training needs specific to a mental health and paramedic co-responder unit. PRN's findings argued for the following: "crisis intervention, de-escalation, suicide intervention, emotional CPR, local social service resources, and cultural awareness" (2021, p. 16). RAND concurs with PRN's identification of these training and education needs. We also strongly suggest safety/safety identification training, familiarization with policies and procedures, and training in use of CMPD equipment (i.e., radios, vehicles). For the non-specialized units responding to low-risk calls, the training needs will be substantially lower.

Review of CMPD Policies

RAND reviewed the CMPD Interactive Directives Guide to determine what changes, if any, would be needed with the formation and inclusion of civilian response models. While there are many directives that will need to be changed, we have highlighted significant areas below. It should be noted that in many cases, and throughout the directives, that adding definitions of civilian responders will flow through the document.

Table 4.13 Integration of Crisis Intervention into Existing CMPD Policy from Interactive Directives Guide

Section	Title	Recommendation
100	Organization	Addition of the use, roles, and police interaction with civilian response models
100-0005	Patrol Services	Addition of civilian responders and location within its command-and-control structure, shift assignments
300-001	Scheduling, Timekeeping, and Attendance	Add and define civilian responders and their pay, scheduling, and attendance
300-005	Workers' Compensation	Include new civilian employees
300-006	Light Duty Policy	Determine if light duty is possible for civilian responders and where they can work during this period.
300-007	Secondary Employment	General change to include new civilian responders in policy
300-008	Personnel Records	General change to include new civilian responders in policy
300-009	Employee Drug and Alcohol Testing	Determine if civilian responder positions are "safety sensitive" and warrant inclusion for random testing protocols
400-001	Uniform and Grooming Standards	Modify grooming standards if needed based on roles for civilian responders
500-003	Management of Subjects with Mental Illness/ Extreme Distress	Change and add any new resources for officers (based on RAND's resource mapping); add any new civilian co-responder team options and definitions.
600	Operations	Clear incorporation of all new models into operations
800-001	Use of Public Records and Department Information	Clarify if civilian responders can access records.
800-002	Media Relations	Clarify where and how this applies to civilian responders
900-005	Naloxone Nasal Spray	Add civilian responders to this policy
900-008	Cardiopulmonary Resuscitation	Add CPR & AED provision for civilian responders.

In addition, we reviewed other files provided by CMPD, especially where applicable to dispatch. These are critical as they 1) identify where, when, and how civilian responders should be dispatched, and 2) safety considerations in doing so. In order to do so, we highlight recommendations below.

Table 4.14 Integration of Crisis Intervention into Additional CMPD Policies

Document Number	Title	Recommendation
100-204	Call Entry Procedure	Incorporation of options for sending civilian responders to non-emergency calls. Addition of specific requirements for non-police units, similar to the

		details for CIT-related calls.
105	Citizen Demand	Inclusion of civilian responders as an option if caller requests them instead of police.
110	Non-Emergency Police Services (NEPS) and 311	Inclusion of civilian responders as an option if caller requests them instead of police. Specific inclusion of call types (additional calls, others that can be or cannot be diverted) and when civilian responders can handle them in the field.
115	Event Remarks	Information on why civilian responder needs to respond should be added, similar to IV.C. for officers.
118	CMPD Priorities	No changes need to be made unless specific language is requested that designates civilian responders as an option for some priority calls.
412	Mobile crisis team	Modify as needed as certain units and civilian response options become available.

It should also be noted that during a pilot period CMPD staff are aware of the capabilities and locations of civilian response assets.

Potential Dispatch Models

The city of Charlotte needs to develop a model for identifying individuals in crisis that may need an alternative response model. RAND reviewed established and emerging dispatch models for various civilian response models. In general, these fell into areas where they came into a Public Safety Answering-Point (PSAP) via 911, or were sent to a 211/311 number, and, in some cases, were redirected to other organizations.

Krider, Huerter, Gaherty, and Moore (2020) outlined how, using a sequential intercept model, 911 is utilized to direct calls/response to local law enforcement, crisis lines, or a crisis care continuum. For the sites selected in their report, Colorado Springs diverts calls from 911 to a community response team, consisting of a sworn officer, a medical provider, and a clinician. Meanwhile, Harris County, TX uses a crisis call diversion program (Houston Police Department, n.d.), where calls come in to 911, but specially trained staff have the ability to handle and assist persons in need of services.[56] The Vera Institute for Justice also outlined how services such as 211, 311, and crisis hotlines are alternatives for using the 911 system. For example, 211 has typically been used for health and community services, while 311 systems are a [rare] alternative to 911 for filing complaints about or making reports for a variety of services (Neusteter et al., 2019).

New and emerging changes in policing and public safety have led to the consideration of different dispatch models. San Francisco's Crisis response Street Team required a marketing strategy to educate the public about the program and whom to call. In this case, 311 and 911 are used, with 911dispatching the calls for service to the new teams (Mental Health San Francisco Implementation Working Group, 2021; City of San Francisco Office of the Mayor, 2020). Rochester's plan is to use 211 and 911 for their Person in Crisis (PIC) Team, with 211 being the

[56] These personnel, "tele-counselors" are trained to handle non-emergency mental health calls.

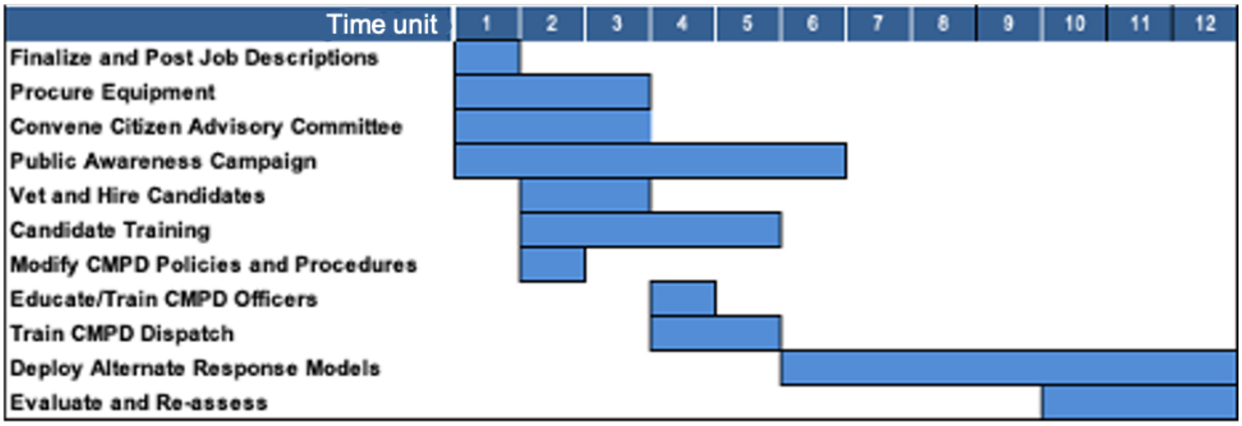
"publicized" number for call taking, but dispatching personnel through 911 (City of Rochester Department of Recreation and Human Services, 2021).

While all have strengths and weaknesses, at this time we recommend that the program(s) be dispatched via Charlotte's 911 PSAP. The reasoning behind this recommendation is two-fold. First, it answers the safety questions raised in the interviews. Several law enforcement stakeholders we interviewed noted they were concerned about the safety of any type of unarmed civilian responder, especially with a new program. Through keeping the dispatching of these personnel in the same dispatch and CAD system, CMPD can mitigate potential safety issues. Secondly, keeping the pilot programs in the 911 call system allows for efficiency in terms of citizen awareness, equipment (i.e., radios), and in the number of personnel working for CMPD and the City. However, more work needs to be done to identify how 911 can better identify individuals in crisis and, metrics would need to be developed to identify low-risk calls that do not require mental health intervention. Additionally, keeping both the call-taking and dispatching functions at a central location/number will ease the burden on the city to market and educate the populace on new phone numbers and dispatch options.

Timeline for Implementation

We have included a recommended program implementation timeline in 4.1 below. We have included "time units" which should be three to twelve weeks, depending on department constraints. We have factored in several areas that may take some time and effort that should be considered that were somewhat outside the scope of this engagement. For example, if new radios and vehicles need to be procured, we have factored in an allowance of time at the beginning of the pilot timeframe. During the time unit, Charlotte and CMPD should make the public aware of the programs being offered/piloted. We have also included a community advisory team, which will need to be convened prior to the beginning of any pilot. Literature on these types of programs and interview data indicate having community partners is essential to the success of these interventions (Suarez-Balcazar, Francisco and Rubén Chávez, 2020). It should also be noted that this timeline is a tool/guide and can be compressed or lengthened based on hiring needs.

Figure 4.1. Pilot Timeline



There are additional details that should also be addressed. First, our timeline shows alternate responses coming online at the six-month mark, to start for at least six months. We assume that due to the investment in the program, they will continue after their first six months in operation. We have also shown an end-of-pilot evaluation and re-assessment timeframe. Based on our metrics developed in Table 4.1 above, there should also be the ability to assess the program on a monthly basis.

Summary for Pilot Development

Based on our reviews of comparable new and existing programs across the US, the needs and desires of the Charlotte community, and the dispersion of calls for service, we recommend the following high-level conclusions for the development of the pilot program.

- Pros and cons for having a city-operated model vs. a partner-operated model are by placing it within the city infrastructure (either as individuals directly hired by the city or a subcontractor to the city) it increases capacity for organization, oversight of the program, dispatch and sharing resources (such as data systems). The major benefit to housing the program external to the city is that there is a tension between CMPD and many communities in Charlotte. However, there are ways to achieve this without housing the response model pilot program external to the city. Community involvement in the development and implementation of the pilot is essential to overcoming this barrier.
- Pilot programs for the specialized and non-specialized civilian response models should be placed in areas of high demand and low violent crime. Based on our initial findings, key areas for starting these programs lie within CMPD's Central District and Providence or North Tryon. By placing these programs in separate locations, evaluation of their effectiveness will be more easily determined.
- Response model pilot programs should begin as city-operated programs for control, coordination, hiring, and safety reasons.
- Charlotte should consider two separate programs; one specialized unit of clinicians paired with EMTs, and a second unit comprised of non-specialized responders, in

addition to the planned expansion of CPCRT. Based on budgets and experiences in other areas, these units should start with 10-12 personnel each. Our estimates show that teams could handle between 81 and 105 calls per week. These figures should be consistently evaluated and monitored as the program matures.

- Demand for calls ("flagged calls" in our report) varies across the city and time of day. As such, we have provided maps to show ideal areas for piloting and ongoing deployment of civilian responder models. These programs should start with daytime working hours. Eventually, the specialized civilian models need to consider moving toward 24/7 operations given the calls for service.
- To accommodate new models of service, CMPD must overhaul their policies and procedures. This is a foundational step in ensuring the safety of civilian responders, what their expectations are, how they interact with the public, and how they interact with members of the department. We have highlighted several top-level areas that are necessary starting blocks for this effort.
- While we recognize that calls and dispatch could be done through a 211/311, 911, or a separate public or non-public line, we recommend calls be routed through Charlotte's PSAP for the initial pilot program. This will allow for metrics to be gathered in the CAD system, allow for citizens to be given the opportunity to request or be offered alternate response models, and will allow for CMPD to monitor situations for safety. However, systems need to be developed within the 911 call center to better identify mental health crisis calls.
- We propose 13 performance metrics across process, outcome, and impact measures. The majority of these measures should be accommodated through the CAD system, although some require a specific tool to compile data to examine performance. Knowledge of the program itself should be measured using a community survey apart from CMPD itself. These measures can also be done in tandem with the outputs for CMPD's overall performance.
- Job requirements should vary for the positions being hired (e.g., mental health clinician vs. civilian responder). The teams should have different requirements and training needs, with a focus on mental health, communications, safety, de-escalation, cultural competence, and familiarity with Charlotte and its neighborhoods for the specialized responder units. The non-specialized units still need adequate training in these areas, but due to the nature of the calls they will respond to, require a lesser extent of it and fewer requirements to be hired. We have provided sample job descriptions from programs across the US including CAHOOTS and the Fort Worth model however, any job description for Charlotte must be tailored to the city and must be developed with community input, potentially from an advisory committee.
- In order to start the program, Charlotte and CMPD should engage in the following: advertising, hiring, and training new civilian employees, modifying policies and procedures, and providing training and education for other sworn and non-sworn staff and convening a citizen advisory committee to assist with implementation decisions. These efforts are expected to take approximately six months. Following this period, we suggest an initial timeframe of six months with continual (monthly) examination of performance metrics for the programs followed by a thorough assessment in months five and six of program deployment (11 and 12 of the complete program).

- According to our projections, our bottom-line estimates for increasing CPCRT and piloting the two new models are the following:
  - Estimated costs for pilot 1, increasing CPCRT: Increase of $718,299 (increase in clinicians only for first year)
  - Estimated costs for pilot 2 (clinician team): Approximately $850,000 for the first year
  - Estimated costs for pilot 3 (low-risk, low priority civilian responders): Approximately $1.4M to $1.85M for the first year

4.2. Recommendation 3

Improving field collection of data at community member-officer contacts

In our interviews with stakeholders that had experience with police data or were directly involved in law enforcement, we asked for their opinions and thoughts concerning stop data collection. We believed there might be a desire for this data to collect more information than is correctly collected. However, none of the individuals in interviews expressed a need or desire for more or different types of data collection, so our recommendations stem from our interaction with the data.

First, we recommend that CMPD consider the practices that determine whether and when data is entered into the stop data set. From our understanding in interviews, police stops were logged so long as they occurred and were officer-initiated. However, when police officers are dispatched to a call for service and they happen to hold or stop individuals while attending to that call, their decision about whether or not to enter the data into the stop data set is at their own discretion. However we recommend that CMPD collect stop data even if an officer is stopping someone in response to a call for service and include a field to let users of the data know whether a stop was completely officer-initiated of it occurred during a call for service. Individuals stopped for a police initiated traffic or pedestrian stop will only represent a portion of police activity. However, individuals stopped during a call for service may be subject to the same factors that drive racial/ethnic disparities during police initiated stops. At the present, stopped individuals it seems to be the case that individuals stopped during a call for service is not currently collected. So the issue could be that the data underestimates how often individuals are stopped, however, being explicit about the number of individuals that were interacted with during a call for service, would then enable better analysis of use of force.

Second, one of the challenges we faced when attempting to evaluate racial/ethnic bias was that some police outcomes of interest (e.g., use of force, complaints) was could not be connected to CAD event data. While it is possible to link some CAD events and arrests to use of force incidents, not all were an exact match. Establishing some internal method of directly connecting CAD events to use of force incidents would provide a more complete understanding of different police activities and how they relate to race/ethnicity. It should be noted that while we found evidence of racial/ethnic disparities, we found no conclusive evidence of racial/ethnic bias.

Finally, we recommend that the police department track and make available officer injuries and narrative data in their internal data sets. We were unable to conduct a thorough risk analysis because we lacked this information and had to rely on proxies (e.g. number of units on scene; whether the priority escalates). If we had information about officer injury rates, we could more reliably identify the types of calls that should not be delegated to non-sworn or civilian staff, which is vital information when considering when to send non-sworn civilian staff to calls under alternative response models. Information about officer injuries would also inform use of force analysis as well; capturing data on assaults on police officers during a call for a service would provide greater context for a use of force.

Identifying and addressing officers who exhibit bias

CMPD's ability to identify and address individual officers who exhibit bias is determined by their available data and the interconnectivity between them. As it stands, the city could evaluate whether any individual officer exceeds internal benchmarks (e.g., officers with similar years of experience, beats, patrols) and conduct the same doubly robust internal benchmarking technique we apply here and make their own modifications by including more data and factors. Additionally, it could conduct the internal benchmarking method across a variety of different outcomes (arrests, stops, uses of force), and focus on officers who exhibit a high probability of being outliers in multiple areas.

CMPD's ability to address these officers is another question. As we understand it, the department has a protocol in place to interact with officers exhibiting disproportionate outcomes and engaging with the officer in question to find out more information. The remedy for any individual officer is likely to be different, and we recommend that CMPD leverage its relevant data to determine why any individual officer is exhibiting outlier behavior, and use that engagement to inform department-wide mitigation efforts to provide racial/ethnic bias-driven disparities. By using some outlier detection methodology on a consistent basis, CMPD would be able to monitor the behaviors and outcomes of its officers, intervene and address outliers, and use the information gleaned from direct engagement with the officer to clarify policies or set guidelines so that current and future officers are less likely to demonstrate outlier behavior where the behavior is unwarranted. This would enable a feedback cycle where CMPD is consistently monitoring, addressing, and establishing guidelines to provide individual officers from unwarranted outlier behavior.

Optimal and efficient allocation of CMPD staff

Across the groups working on Recommendations 2 and 4 and Recommendation 3, we evaluated alternative response models for CMPD staff that include a re-allocation of labor to non-specialized civilian and specialized staff. Based on interviews with department leadership and our understanding of the risks, department response times, and dynamics that occur at any given call for service, we concluded that any substantial shift or reallocation to an alternative response model would not affect staffing so much as it would affect the availability of currently available officers. This conclusion was informed by our exploration of a potential pilot program for the City of Charlotte and our understanding of CMPD staffing requirements. Given all of these, we only recommend that the City pursue a *pilot* program to determine and fine tune an alternative response model for the city. Our understanding of the budget implications of this and further developments leads us to believe that this may not lead to lower cost but may improve provision of public safety at large. After piloting these programs, the City and CMPD should assess whether further expansion is warranted or if programs should be terminated.

Transitioning identified CMPD services to alternate agencies or organizations

Similarly, to discussions concerning alternative response models, we also considered whether any individual services provided by the CMPD should be transitioned out to alternative agencies. To gain information, we reached out to CMPD's Animal Care and Control, Passenger Vehicle for Hire (PVH), and Electronic Monitoring programs. Understandably, CMPD may want to consider other programs, and so we developed guidelines that would identify when a program is a candidate for transition out of the department and into another agency. If: a) a program provides services that are distinct in nature from administering justice; b) a program can maintain or increase the resources and support it receives in its new location; c) program can perform its functions at least as effectively and in line with local regulations without necessarily adhering to regulations or policies followed by the CMPD, then we would recommend the City and Department consider the program for transition out of CMPD. Under these guidelines, Animal Care and Control would satisfy all of those conditions provided that they maintain their current level of resource staffing so as not to undermine their provision of services. At this time, we recommend that the Electronic Monitoring Unit remain as-is, since it primarily deals with persons who are subject to electronic monitoring devices as a condition of their release as they await trial. These persons are suspects in crimes that often involve violence; shifting these duties may present a threat to public safety. Lastly, the PVH Unit generally supports the administrative functions set forth in Chapter 22 in the Code of Ordinances for the City of Charlotte (Order of the City Council, 2003). These functions, although administrative in nature, do have a public safety element to them as they are detailed in city ordinances; barring a legislative change we recommend leaving the unit in its status quo

Additional Considerations

Our research identified several areas that offer areas for improvement for CMPD and community relations, especially regarding the quantitative analyses. For example, Table 3.5 indicated Black individuals were more likely to be subject to more than physical force (i.e. the use of less lethal instruments or greater) when compared to White individuals. Although our analysis did not include a deep examination of *every* use of force incident there are potential causes and steps that can be examined. Going forward, narrative data and officer injury data should be collected during these incidents to better understand the circumstances. The interviews also highlighted a lack of trust between minority communities and CMPD, echoing previous academic studies (see, for example, Tyler and Jackson, 2014).

Combining these outputs with research on cooperation and compliance with police (which may affect use of force outcomes, among other measures), in addition to the recommended outreach to communities we suggest CMPD can implement programs to increase trust and legitimacy, perceptions of police, and treatment of citizens in general. Initiatives that show promise are police engaging in positive, non-enforcement actions with citizens (Peyton, Sierra-Arévalo, and Rand, 2019) and training officers in procedural justice (see, for example, Wood, Tyler, and Papachristos, 2020).

Additionally, vehicle stop and search data presents another strategy for consideration. The Fayetteville, NC police department re-prioritized traffic stops and enforcement to focus crash reductions to attempt to improve racial/ethnic disparities and improve public safety from 2013-2016 (Fliss, Baumgartner, Dalamater, Marshall, Poole, and Robinson, 2020). Fliss, et al. (2020) found that the intervention can be a "stop gap" to reduce racial/ethnic disparities, and its measures showed improvements in negative traffic outcomes such as crashes and fatalities.[57]

Lastly, we recommend CMPD adopt and/or strengthen the use of strategies that move away from aggressive or zero tolerance models as appropriate. CMPD may consider *focused deterrence*, *high visibility enforcement*, and broad use of *procedural justice* technique. More details on these interventions can be found in the RAND's *Better Policing Toolkit.*[58] These may assist CMPD in focusing on crime and public safety while improving relations with and engaging the community.

4.3. Conclusion

These recommendations are made with the intention of improving public safety in Charlotte through different means. Through a pilot program, we hope the City is able to evaluate the effectiveness of these alternative response models and modify the chosen model as necessary to suit the needs of the community. By deploying pilot programs, the city will have another means by which to extend support to residents who are most in need of services while also improving CMPD's ability to address higher priority calls, should the program be found successful and subsequently expanded. In a similar vein, our recommendation that the City follow guidelines concerning CMPD staffing, and services are made with the intention that CMPD could benefit from a greater focus with the realization that provision of services could potentially be more efficient under other agencies. Our data-related recommendations are intended to facilitate future

[57] It should also be noted that crime was relatively unaffected by these changes.

[58] The toolkit is located at https://www.rand.org/pubs/tools/TL261/better-policing-toolkit.html

analysis and allow the city to better leverage data. The city graciously shared its resources with the team, which were instrumental in conducting our analysis.

References

Amherst Police Department, "Homepage," n.d. https://www.amherstma.gov/3558/Police

Associated Press, "Berkeley Moves Toward Removing Police From Traffic Stops," *U.S. News & World Report*, July 15, 2020. https://www.usnews.com/news/us/articles/2020-07-15/berkeley-moves-toward-removing-police-from-traffic-stops

Ayres, Ian, "Outcome Tests of Racial Disparities in Police Practices," *Justice Research and Policy,* Vol. 4, No. 1-2, December, 2002, pp. 131-142. https://journals.sagepub.com/doi/abs/10.3818/JRP.4.1.2002.131

Bailey, Katie, Staci Rising Paquet, Bradley R. Ray, Eric Grommon, Evan M. Lowder, and Emily Sightes, "Barriers and facilitators to implementing an urban co-responding police-mental health team," *Health & Justice,* Vol. 6, No. 1, November 22, 2018, p. 21. https://doi.org/10.1186/s40352-018-0079-0

Batko, Samantha, Sarah Gillespie, Katrina Ballard, Mary Cunningham, Barbara Poppe, and Stephen Metraux, *Alternatives to Arrests and Police Responses to Homelessness: Evidence-Based Models and Promising Practices*, Washington, D.C.: Urban Institute, October, 2020. https://www.urban.org/sites/default/files/publication/103158/alternatives-to-arrests-and-police-responses-to-homelessness.pdf

Beaulieu, Lionel J., *Mapping the Assets of Your Community: A Key Component for Building Local Capacity*, Mississippi State, MS: Southern Rural Development Center, 2002. https://files.eric.ed.gov/fulltext/ED467309.pdf

Beck, Jackson, Melissa Reuland, and Leah Pope, *Case Study: CAHOOTS Eugene, Oregon*, Brooklyn, NY: Vera Behavioral Health Crisis Alternatives, November, 2020. https://www.vera.org/behavioral-health-crisis-alternatives/cahoots

Bennett, Amy Leite, and Jose Diaz, "Crisis Stabilization Claims Analysis: Technical Report Assessing the Impact of Crisis Stabilization On Utilization of Healthcare Services," *Amherst H. Wilder Foundation*, April, 2013. https://www.wilder.org/wilder-research/research-library/crisis-stabilization-claims-analysis-technical-report-assessing

Birnbaum, Michael L., Asra F. Rizvi, Jamie Confino, Christoph U. Correll, and John M. Kane, "Role of social media and the Internet in pathways to care for adolescents and young adults with psychotic disorders and non-psychotic mood disorders," *Early Intervention in Psychiatry,* Vol. 11, No. 4, August, 2017, pp. 290-295. https://www.ncbi.nlm.nih.gov/pubmed/25808317

Blick, Brian, Vinnie Cervantes, Blake Christianson, W. Andrew Dameron, Terese Howard, Matthew Lunn, Zach McDade, Christopher Quinn, Lisa Raville, Chris Richardson, Carleigh Sailon, Jennifer Schwartz, Tracesea Slater, and Janet Vvan der Laak, *STAR Program Evaluation*, January 8, 2021. https://wp-denverite.s3.amazonaws.com/wp-content/uploads/sites/4/2021/02/STAR_Pilot_6_Month_Evaluation_FINAL-REPORT.pdf

Boscarato, Kara, Stuart Lee, Jon Kroschel, Yitzchak Hollander, Alice Brennan, and Narelle Warren, "Consumer experience of formal crisis-response services and preferred methods of crisis intervention," *International Journal of Mental Health Nursing,* Vol. 23, No. 4, August, 2014, pp. 287-295. https://www.ncbi.nlm.nih.gov/pubmed/24575860

Brown, Lawrence, and Xuefeng Li, "Confidence intervals for two sample binomial distribution," *Journal of Statistical Planning and Inference,* Vol. 130, No. 1, March, 2005, pp. 359-375. https://www.sciencedirect.com/science/article/pii/S037837580400271X

CALEA, "Bias-based Calls to the Police," January 8, 2020. https://www.calea.org/news/announcements/bias-based-calls-police
CAU, *CAHOOTS Program Analysis*, Eugene, Oregon: Eugene Police Department, August 21, 2020. https://www.eugene-or.gov/DocumentCenter/View/56717/CAHOOTS-Program-Analysis
Charlotte-Mecklenburg Police Department, *CMPD Crisis Intervention Team (CIT)*, YouTube, September 20, 2016. https://www.youtube.com/watch?v=nGkgGZFb7nA&t=31s
———, "Community Wellness: Community Policing Crisis Response Team (CPCRT)," 2019. https://charlottenc.gov/CMPD/Organization/Documents/SupportSvcs/CMPD_CITdoc.pdf
———, *Internal Affairs 2020 Annual Report*, 2020a. https://charlottenc.gov/CMPD/Organization/Documents/OfcoftheChief/InternalAffairs/IA_anlrpt2020.pdf
———, "Response to "8 Can't Wait"," 2020b. https://charlottenc.gov/CMPD/Documents/Newsroom/CMPD-RESPONSE-TO_8-CANT-WAIT-DETAILED.pdf
———, "Jobs," n.d.
City Clerk, "Reimagining Public Safety Task Force," n.d. https://www.cityofberkeley.info/home.aspx
City of Charlotte, *FY 2021 Compensation and Benefits*, Charlotte, North Carolina, 2020. https://charlottenc.gov/budget/FY2021/9Compensation_and_Benefits-fixed.pdf
———, "Charlotte-Mecklenburg Quality of Life Dataset," 2021. As of March 25, 2021: https://mcmap.org/qol/
City of Fort Worth, "Civilian Response Specialist Job Description," Fort Worth, TX, 2020. https://www.fortworthtexas.gov/files/assets/public/hr/documents/job-descriptions/c/civilian-response-specialist.pdf
———, *FY2021 Salary Schedule*, Texas, 2021. https://www.fortworthtexas.gov/departments/hr/administration/prr/salary-schedule
City of Ithaca, *A Resolution Adopting and Authorizing Mayor to Submit the Reimagining Public Safety Plan Pursuant to New York Stae Executive Order 203*, Ithaca, NY, 2021. https://www2.tompkinscountyny.gov/files2/2021-04/Master%20Final%20Document%20City%20of%20Ithaca.pdf
City of Ithaca, and City of Tompkins County, *Budget Estimates for the Reimagining Public Safety Draft Report*, New York, 2021. https://www2.tompkinscountyny.gov/files2/2021-03/RPS%20Report%20Budget%20Estimates%20-%20Revised%203.29.21.pdf
City of Rochester Department of Recreation and Human Services, *Person In Crisis Team Pilot Plan Executive Summary*, Rochester, NY, January 4, 2021. https://www.cityofrochester.gov/uploadedFiles/Departments/Drys/21%20DRHS%20Person%20in%20Crisis%20ERA%20format%20Plan%20FINAL%20020321.pdf
City of San Francisco Office of the Mayor, "San Francisco's New Street Crisis Response Team Launches Today," San Francisco, Calif, November 30, 2020. https://sfmayor.org/article/san-franciscos-new-street-crisis-response-team-launches-today
Community Safety Working Group, *Report in Fulfillment of Part A and Part B of Contract to the Town of Amherst*, Seven Generations Movement Collective, May 4, 2021. https://www.amherstma.gov/DocumentCenter/View/55902/7GenMC-Final-Report-to-the-CSWG-552021
Crisis Now, "Tools: Crisis Resource Need Calculator," n.d. https://crisisnow.com/tools/

Currier, Glenn W., Susan G. Fisher, and Eric D. Caine, "Mobile Crisis Team Intervention to Enhance Linkage of Discharged Suicidal Emergency Department Patients to Outpatient Psychiatric Services: A Randomized Controlled Trial," *Academic Emergency Medicine,* Vol. 17, No. 1, January, 2010, pp. 36-43. https://onlinelibrary.wiley.com/doi/full/10.1111/j.1553-2712.2009.00619.x
Damschroder, Laura J., David C. Aron, Rosalind E. Keith, Susan R. Kirsh, Jeffery A. Alexander, and Julie C. Lowery, "Fostering implementation of health services research findings into practice: a consolidated framework for advancing implementation science," *Implementation science,* Vol. 4, August 7, 2009, pp. 1-15. https://implementationscience.biomedcentral.com/track/pdf/10.1186/1748-5908-4-50.pdf
Dyches, Hayne, David E. Biegel, Jeffrey A. Johnsen, Shenyang Guo, and Meeyoung Oh Min, "The Impact of Mobile Crisis Services on the Use of Community-Based Mental Health Services," *Research on Social Work Practice,* Vol. 12, No. 6, November, 2002, pp. 731-751. https://journals.sagepub.com/doi/10.1177/104973102237470
locfdr: Computes Local False Discovery Rates, version 1.1-8, 2015. https://cran.r-project.org/web/packages/locfdr/index.html
FBI, "Crime Data Explorer," n.d. https://crime-data-explorer.app.cloud.gov/pages/le/uof
Foster, David, *Incoming CMPD Chief Jennings wants to ensure community trust*, YouTube: Charlotte Observer, July 2, 2020. https://www.youtube.com/watch?v=KUCl5rxCMKo
Gaherty, Kirby, and Elijah Asdourian, "How Interrupters Face the Epidemic of Violence in Cities Head On," National League of Cities, 2020. https://www.nlc.org/article/2020/08/31/how-interrupters-face-the-epidemic-of-violence-in-cities-head-on/
Gordon, Michael, and Ames Alexander, "Charlotte chief says trust in police is the worst he's ever seen. But he has a plan.," *Charlotte Observer*, April 23, 2021. https://www.charlotteobserver.com/news/politics-government/article250836869.html
Grogger, Jeffrey, and Greg Ridgeway, "Testing for Racial Profiling in Traffic Stops From Behind a Veil of Darkness," *Journal of the American Statistical Association,* Vol. 101, No. 475, September, 2006, pp. 878-887. https://www.tandfonline.com/doi/abs/10.1198/016214506000000168
Guo, Shenyang, David E. Biegel, Jeffrey A. Johnsen, and Hayne Dyches, "Assessing the Impact of Community-Based Mobile Crisis Services on Preventing Hospitalization," *Psychiatric Services,* Vol. 52, No. 2, February, 2001, pp. 223-228. https://ps.psychiatryonline.org/doi/full/10.1176/appi.ps.52.2.223
Health Resources & Services Administration, "Shortage Areas," Last updated June 3, 2021, n.d. https://data.hrsa.gov/topics/health-workforce/shortage-areas
Henrichson, Christian, Joshua Rinaldi, and Ruth Delany, *The Price of Jails: Measuring the Taxpayer Cost of Local Incarceration*, Brooklyn, NY: Vera Institute of Justice, May, 2015. https://www.vera.org/publications/the-price-of-jails-measuring-the-taxpayer-cost-of-local-incarceration
Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth A. Stuart, "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference," *Political Analysis,* Vol. 15, No. 3, 2007, pp. 199-236. https://www.cambridge.org/core/article/matching-as-nonparametric-preprocessing-for-reducing-model-dependence-in-parametric-causal-inference/4D7E6D07C9727F5A604E5C9FCCA2DD21
Houston Police Department, "Crisis Calll Diversion Program (CCD)," n.d. https://www.houstoncit.org/ccd/

Iacus, Stefano M., Gary King, and Giuseppe Porro, "Causal Inference without Balance Checking: Coarsened Exact Matching," *Political Analysis,* Vol. 20, No. 1, 2012, pp. 1-24. https://www.cambridge.org/core/article/causal-inference-without-balance-checking-coarsened-exact-matching/5ABCF5B3FC3089A87FD59CECBB3465C0

International Association of Chiefs of Police, *National Consensus Policy and Discussion Paper on Use of Force*, July, 2020. https://www.theiacp.org/sites/default/files/2020-07/National_Consensus_Policy_On_Use_Of_Force%2007102020%20v3.pdf

Irwin, Amos, and Betsy Pearl, "The Community Responder Model: How Cities Can Send the Right Responder to Every 911 Call," *Center for American Progress*, October 28, 2020. https://www.americanprogress.org/issues/criminal-justice/reports/2020/10/28/492492/community-responder-model/

Kamisher, Eliyahu, "Oakland Takes First Steps Toard Directing Some 911 Calls to Community Responders," *Appeal*, April 20, 2021. https://theappeal.org/oakland-macro-911-non-law-enforcement-emergency-response/

Klevan, Trude, Bengt Karlsson, and Torleif Ruud, ""At the extremities of life"–Service user experiences of helpful help in mental health crises," *American Journal of Psychiatric Rehabilitation,* Vol. 20, No. 2, April, 2017, pp. 87-105. https://www.tandfonline.com/doi/full/10.1080/15487768.2017.1302370

Knopf, Taylor, "More NC psych patients are ending up handcuffed in a police car. Why?," *North Carolina Health News*, December 14, 2020. https://www.northcarolinahealthnews.org/2020/12/14/more-nc-psych-patients-are-ending-up-handcuffed-in-a-police-car-why/

Kuznitz, Alison, "Mecklenburg wants to break ties with a healthcare agency. Here's what happens next," *Charlotte Observer*, November 4, 2020. https://www.charlotteobserver.com/news/politics-government/article246973002.html

Kuznitz, Alison, Fred Clasen-Kelly, and Lauren Lindstrom, "'Wave goodbye, the're all about to get gassed': CMPD planned tear gas attach, video shows," August 26, 2020. https://www.charlotteobserver.com/news/local/article245270810.html

Lopez, Hector, *A Descriptive Study of LAPD's Co-Response Model for Individuals with Mental Illness*, ProQuest: California State University, Long Beach, 2016. https://www.equitasproject.org/wp-content/uploads/2017/06/Lopez-Thesis-on-Co-responder-model.pdf

Lord, Vivian B, and Beth Bjerregaard, "Helping persons with mental illness: Partnerships between police and mobile crisis units," *Victims & Offenders,* Vol. 9, No. 4, October 16, 2014, pp. 455-474. https://www.tandfonline.com/doi/full/10.1080/15564886.2013.878263

McKinney, Matt, "Unarmed traffic stops part of Brooklyn Center mayor's police reform plan," *Star Tribune*, May 8, 2021. https://www.startribune.com/unarmed-traffic-stops-part-of-brooklyn-center-mayor-s-police-reform-plan/600055064/

Lum, Cynthia, Christopher S. Koper, and Xiaoyun Wu. "Can We Really Defund the Police? A Nine-Agency Study of Police Response to Calls for Service." *Police Quarterly*, (July 2021). https://doi.org/10.1177/10986111211035002.

Mental Health San Francisco Implementation Working Group, *Street Crisis Response Team Issues Brief*, San Francisco Department of Public Health, February, 2021. https://www.sfdph.org/dph/files/IWG/SCRT_IWG_Issue_Brief_FINAL.pdf

Merzbach, Scott, "Alternative police services option proposed in Amherst," *Daily Hampshire Gazette*, April 24, 2021. https://www.gazettenet.com/Community-responders-team-sought-in-Amherst-budget-40131259

Minnesota Department of Human Services, *Mobile Crisis Mental Health Services*, March, 2018. https://mn.gov/dhs/assets/mobile-crisis-services_tcm1053-333826.pdf

Morabito, Nate, "More than a year later, some Safe Coalition NC, NAACP requests of CMPD unmet," *WCNC Charlotte*, June 1, 2020. https://www.wcnc.com/article/news/investigations/investigators/some-safe-coalition-nc-naacp-requests-cmpd-unmet/275-3f7e8dbc-700c-4e8d-857a-5e7f3793b340

Neusteter, S. Rebecca, Maris Mapolski, Mawia Khogali, and Megan O'Toole, *The 911 Call Processing System: A Review of the Literature as it Relates to Policing*, Vera Institute of Justice, July, 2019. https://www.vera.org/downloads/publications/911-call-processing-system-review-of-policing-literature.pdf

Northampton Policing Review Commissioners, *Reimagining Safety Report*, 2021. https://www.northamptonma.gov/DocumentCenter/View/16810/Reimagining-Safety---Northampton-Policing-Review-Commission-Report

Office of the Mayor, *Motion: Report and Recommendations from Mayor's Fair and Impartial Policing Working Group*, Berkeley, CA, City of Berkeley, 2021. https://www.berkeleyside.org/wp-content/uploads/2021/02/Motion-Item-1-Fair-and-Impartial-Policing.pdf

Order of the City Council, *Code of Ordinances for the City of Charlotte, North Carolina: Chapter 22 - Vehicles for Hire*, 2003. https://library.municode.com/nc/charlotte/codes/code_of_ordinances?nodeId=PTIICOOR_CH22VEHI

PERF, *Guiding Principles on Use of Force*, Washington, D.C., March, 2016. https://www.policeforum.org/assets/30%20guiding%20principles.pdf

Phillips, Susan D., Barbara J. Burns, Elizabeth R. Edgar, Kim T. Mueser, Karen W. Linkins, Robert A. Rosenheck, Robert E. Drake, and Elizabeth C. McDonel Herr, "Moving Assertive Community Treatment Into Standard Practice," *Psychiatric Services,* Vol. 52, No. 6, June, 2001, pp. 771-779. https://ps.psychiatryonline.org/action/showCitFormats?doi=10.1176%2Fappi.ps.52.6.771

Rahr, Sue, and Stephen K. Rice, *From Warriors to Guardians: Recommitting American Police Culture to Democratic Ideals*, Washington, D.C.: National Institute of Justice, April, 2015. https://www.ojp.gov/pdffiles1/nij/248654.pdf

Reuland, Melissa, "Tailoring the police response to people with mental illness to community characteristics in the USA," *Police Practice and Research,* Vol. 11, No. 4, August 6, 2010, pp. 315-329. https://doi.org/10.1080/15614261003701723

Ridgeway, Greg, and John M. MacDonald, "Doubly Robust Internal Benchmarking and False Discovery Rates for Detecting Racial Bias in Police Stops," *Journal of the American Statistical Association,* Vol. 104, No. 486, January, 2012, pp. 661-668. https://www.tandfonline.com/doi/abs/10.1198/jasa.2009.0034

RTI International, "The RTI-STAR Traffic Stop Analysis," n.d. https://www.rti.org/impact/rti-star-traffic-stop-analysis-tool

SAFE, *SAFE Charlotte: Safety and Accountability for Everyone*, City of Charlotte, 2021. https://citycharlottencgov.azureedge.net/Safe_Charlotte_Digital.pdf

Saunders, Jessica, and Beau Kilmer, "Changing the Narrative: Police–Community Partnerships and Racial Reconciliation," *Justice Quarterly,* Vol. 38, No. 1, January, 2021, pp. 47-71. https://www.tandfonline.com/doi/full/10.1080/07418825.2019.1568520
Scott, Roger L., "Evaluation of a Mobile Crisis Program: Effectiveness, Efficiency, and Consumer Satisfaction," *Psychiatric Services,* Vol. 51, No. 9, September, 2000, pp. 1153-1156. As of 2021/06/03: https://ps.psychiatryonline.org/doi/full/10.1176/appi.ps.51.9.1153
Shapiro, Ari, "'CAHOOTS': How Social Workers And Police Share Responsibilities In Eugene, Oregon," in *All Things Considered*: National Public Radio, June 10, 2020. https://www.npr.org/2020/06/10/874339977/cahoots-how-social-workers-and-police-share-responsibilities-in-eugene-oregon
Silverman, Hollie, Tima Burnside, and Nicole Chavez, "A North Carolina man overdosed in police custody. He was along and crying out for help before collapsing," *CNN*, October 2, 2020. https://www.cnn.com/2020/10/02/us/harold-easter-death-charlotte-police/index.html
Simmons, Molly M., Benjamin G. Fincke, Mari-Lynn Drainoni, Bo Kim, Tom Byrne, David Smelson, Kevin Casey, Marsha L.. Ellison, Christy Visher, and Jessica Blue-Howells, "A two-state comparative implementation of peer-support intervention to link veterans to health-related services after incarceration: a study protocol," *BMC health services research,* Vol. 17, No. 1, September 12, 2017, p. 647. https://bmchealthservres.biomedcentral.com/articles/10.1186/s12913-017-2572-x
Sobo, Elisa J., Glenn Billman, Lillian Lim, J. Wilken Murdock, Elvia Romero, Donna Donoghue, William Roberts, and Paul S. Kurtin, "A rapid interview protocol supporting patient-centered quality improvement: hearing the parent's voice in a pediatric cancer unit," *The Joint Commission Journal on Quality and Patient Safety,* Vol. 28, No. 9, September, 2002, pp. 498-509. https://www.sciencedirect.com/science/article/abs/pii/S1070324102280554?via%3Dihub
Springfield Urban League, Inc., "Job Description: CeaseFire Violence Interrupter," n.d. https://www.springfieldul.org/Custom/Library/1/documents/SULEmployment/JobDescriptionViolenceInterrupter.pdf
Stacey, Michele, and Heidi S. Bonner, "Veil of Darkness and Investigating Disproportionate Impact in Policing: When Researchers Disagree," *Police Quarterly,* Vol. 24, No. 1, March, 2020, pp. 55-73. https://journals.sagepub.com/doi/full/10.1177/1098611120932905
Steadman, Henry J., Martha Williams Deane, Randy Borum, and Joseph P. Morrissey, "Comparing Outcomes of Major Models of Police Responses to Mental Health Emergencies," *Psychiatric Services,* Vol. 51, No. 5, May, 2000, pp. 645-649. https://ps.psychiatryonline.org/doi/abs/10.1176/appi.ps.51.5.645
Stetler, Cheryl B., Marcia W. Legro, Carolyn M. Wallace, Candice Bowman, Marylou Guihan, Hildi Hagedorn, Barbara Kimmel, Nancy D. Sharp, and Jeffrey L. Smith, "The role of formative evaluation in implementation research and the QUERI experience," *Journal of general internal medicine,* Vol. 21, No. Suppl 2, February, 2006, pp. S1-S8. https://link.springer.com/article/10.1007/s11606-006-0267-9
Straub, Frank, Jeffrey Brown, Roberto Villasenor, Jennifer Zeunik, Ben Gorban, Blake Norton, and Eddie Reyes, *Advancing Charlotte: A Police Foundation Assessment of the Charlotte-Mecklenburg Police Department Response to the September 2016 Demonstrations*, Police Foundation, February, 2018. https://www.policefoundation.org/wp-content/uploads/2018/02/Advancing-Charlotte-Final-Report.pdf

Suarez-Balcazar, Yolanda, Vincent T. Francisco, and Noé Rubén Chávez, "Applying Community-Based Participatory Approaches to Addressing Health Disparities and Promoting Health Equity," *American Journal of Community Psychology,* Vol. 66, No. 3-4, December 29, 2020, pp. 217-221. https://onlinelibrary.wiley.com/doi/10.1002/ajcp.12487
Substance Abuse and Mental Health Services Administration, "Current Federal Initiatives Promoting Crisis Services," edited by McKeon, Rishard, 2015. https://www.slideshare.net/davidwcovington/supercharge-crisis-services-vijay-ganju-natcon15-47169905?from_action=save
Sweeney, Annie, "Chicago revises mental health response plan to include responder teams without police," *Chicago Tribune*, November 29, 2020. https://www.ems1.com/mental-health/articles/chicago-revises-mental-health-response-plan-to-include-responder-teams-without-police-KJESD1anKl7usYLA/
Taniguchi, Travis A., Joshua A. Hendrix, Alison Levin-Rector, Brian P. Aagaard, Kevin J. Strom, and Stephanie A. Zimmer, "Extending the Veil of Darkness Approach: An Examination of Racial Disproportionality in Traffic Stops in Durham, NC," *Police Quarterly,* Vol. 20, No. 4, December, 2017, pp. 420-448. https://journals.sagepub.com/doi/full/10.1177/1098611117721665
U.S. Bureau of Labor Statistics, "Consumer Price Index Inflation Calculator," n.d.-a. https://www.bls.gov/data/inflation_calculator.htm
———, "Social and Human Service Assistants," Last updated April 9, 2021, n.d.-b. https://www.bls.gov/ooh/community-and-social-service/social-and-human-service-assistants.htm
U.S. Census Bureau, "Amherst town, Hampshire County, Massachusetts Population Estimates," 2019. https://www.census.gov/quickfacts/amhersttownhampshirecountymassachusetts
Urban Strategies Council, *Report on Feasibility and Implementation of a Pilot of Mobile Assistance Community Responders of Oakland (MACRO)*, June, 2020. https://urbanstrategies.org/wp-content/uploads/2020/06/USC-MACRO-REPORT-6_10_20.pdf
Utarini, Adi, Anna Winkvist, and Gretel H. Pelto, "Appraising studies in health using rapid assessment procedures (RAP): Eleven critical criteria," *Human Organization,* Vol. 60, No. 4, Winter, 2001, pp. 390-400. https://www.jstor.org/stable/44127503?seq=1
Vanderploeg, Jeffrey J., Jack J. Lu, Timothy M. Marshall, and Kristina Stevens, "Mobile crisis services for children and families: advancing a community-based model in Connecticut," *Children and youth services review,* Vol. 71, December, 2016, pp. 103-109. https://www.sciencedirect.com/science/article/pii/S0190740916303589
Version, Dedoose, "8.0. 35. Web application for managing, analyzing, and presenting qualitative and mixed method research data ", Los Angeles, CA: SocioCultural Research Consultants, LLC, 2018.
Washington State Institute for Public Policy, *Mobile Crisis Response: Benefit-Cost Results*, Olympia, WA, May, 2014. https://www.wsipp.wa.gov/BenefitCost/ProgramPdf/289/Mobile-crisis-response
———, "Benefit-Cost Results: Techincal Document," Last Updated December, 2019, n.d. https://www.wsipp.wa.gov/BenefitCost
White Brid Clinc, "CAHOOTS," n.d. https://whitebirdclinic.org/cahoots/
Witzberger, Shea, and Emily Megas-Russell, *Final Report on the Community Safety Review Process*, December 31, 2020. https://www.brattleboro.org/vertical/Sites/%7BFABA8FB3-EBD9-4E2C-91F9-C74DE6CECDFD%7D/uploads/CSRT_Final_Report_12-31-201232.pdf

Worden, Robert E., Sarah J. McLean, and Andrew P. Wheeler, "Testing for Racial Profiling With the Veil-of-Darkness Method," *Police Quarterly,* Vol. 15, No. 1, March, 2012, pp. 92-111. https://journals.sagepub.com/doi/full/10.1177/1098611111433027
Yin, Robert K., *Qualitative research from start to finish*: Guilford Publications, 2015.
Youth Alive!, "Job Description: Violence Interrupter," n.d. https://www.youthalive.org/wp-content/uploads/2015/07/Violence-Interrupter-Job-Description-2018.pdf
Zeller, Scott L., and Sarah M. Rieger, "Models of Psychiatric Emergency Care," *Current Emergency and Hospital Medicine Reports,* Vol. 3, No. 4, December, 2015, pp. 169-175. https://link.springer.com/article/10.1007/s40138-015-0083-9

Appendix A. Interview Protocols

Community Advocates Focus Group / Interview Guide

1. **Tell me a little about yourself and your position.**

Community Policing Crisis Response Teams

The community policing crisis response team includes a 24-hour call center, a mobile mental health crisis team and crisis incident stress management. Within this unit, the Mobile Crisis Team is a group of qualified professionals with experience in mental health, developmental issues and substance abuse. They have experience in emergency psychiatric or family intervention and can assist officers or families with involuntary commitments.]

2. **Tell me what you know about Community Policing Crisis Response Teams.**
    - What are your thoughts on Community Police Response Teams?
3. **How do you think Community Policing Crisis Response Teams are working in your community?**
    - Are they effective?
        - How would we know if Community Policing Crisis Response Teams are working?
        - How would we know if they are not?
    - Walk me through what they are doing now.
        - How common are they?
    - What has been the community response?
    - Walk me through how you would like to see them function from a practical perspective.
4. **Tell me about why Community Policing Crisis Response Teams are or are not important to your community.**
    - How might they impact racial/ethnic equity?

Non-uniformed response model for low-risk situations

[One of the recommendations of the SAFE Charlotte report was to develop a model to convert low risk sworn duties to non-uniform units. To address this recommendation, we are working with Charlotte to create safe roles for nonuniform representatives to respond to lower priority calls. This will free be sworn officers to focus their energy on building relationships with the community and preventing crime.]

5. **Tell me what you know about a non-uniformed response model.**

6. **What are your thoughts on non-uniformed responders for low-risk situations? These situations include mental illness and homelessness calls.**
    - What do you think would work with a non-uniformed model?
    - What do you think wouldn't work about a non-uniformed response model?
    - Walk me through how you would like to see it function from a practical perspective.
    - What do you think would be the community response to it?

7. **How would we know if Community Policing Crisis Response Teams are working?**
    - How would we know if they are not?

8. **Tell me about why a non-uniformed response for low-risk calls model is or is not important to your community.**
    - How might they impact racial/ethnic equity?

General evaluation

9. **What do you think is the best approach to engaging community in providing feedback to evaluate and improve either of these models we have discussed?**

Police Data

10. **How would you characterize the average experience of police interactions with CMPD?**
    - Is it generally positive or negative? Why?
    - When it occurs, what do you think racial/ethnic bias looks like in interactions with CMPD**?**
    - When are community members most likely to come into contact with officers? In their own neighborhood or another one?

11. **What types of crime are you most concerned about in your community?**
    - What types of crime do you feel are most prevalent in your community?

Service Provider Focus Group / Interview Guide

1. **Tell me a little about yourself, your position, and your organization.**

Community Policing Crisis Response Teams:

The community policing crisis response team includes a 24-hour call center, a mobile mental health crisis team and crisis incident stress management. Within this unit, the Mobile Crisis Team is a group of qualified professionals with experience in mental health, developmental issues and substance abuse. They have experience in emergency psychiatric or family intervention and can assist officers or families with involuntary commitments.

2. **Tell me what you know about a Community Policing Crisis Response Teams.**
    - What are your thoughts on Community Policing Crisis Response Teams?

3. **How do you think Community Policing Crisis Response Teams are working in the Charlotte community?**
    - Are they effective?
        - How would we know if Community Policing Crisis Response Teams are working?
        - How would we know if they are not?
    - Walk me through what they are doing now.
        - How common are they?
    - What has been the community response?
    - Walk me through how you would like to see them function from a practical perspective

4. **How would you like the city to evaluate Community Policing Crisis Response Teams?**

5. **Tell me about why Community Policing Crisis Response Teams are or are not important to Charlotte.**
    - How might they impact racial/ethnic equity?

Non-uniformed response model for low-risk situations:

One of the recommendations of the SAFE Charlotte report was to develop a model to convert low risk sworn duties to non-uniform units. To address this recommendation, we are working with Charlotte to create safe roles for nonuniform representatives to respond to lower priority calls. This will free be sworn officers to focus their energy on building relationships with the community and preventing crime.

6. **Tell me what you know about a non-uniformed response model.**
7. **What are your thoughts on non-uniformed responders for low-risk situations? These situations include mental illness and homelessness calls.**
    - What do you think would work with a non-uniformed model?

- What do you think wouldn't work about a non-uniformed response model?
- Walk me through how you would like to see it function from a practical perspective.
- What do you think would be the community response to it?

8. **What kind of staff would you need to support a non-uniformed response model if your organization were to become part of it?**
   - How would you use current staff to fill this need?
   - Tell me about the feasibility of hiring appropriate staff?
   - Tell me about the feasibility of managing this staff?
   - How would you ensure this staff is effectively doing their job?

9. **What are some of the costs associated with a non-uniformed response model if your organization were to participate in it?**
   - How would you cover these costs?

10. **How would you like the city to evaluate a non-uniformed response for low-risk calls model?**

11. **Tell me about why a non-uniformed response for low-risk calls model is or is not important to the Charlotte community.**
    - How might it impact racial/ethnic equity?

12. **How do you think city leadership would feel about implementing a non-uniformed response model for low-risk calls?**

Law Enforcement and City Representatives Focus Group / Interview Guide

1. **Tell me a little about yourself and your position.**

Community Policing Crisis Response Teams:

The community policing crisis response team includes a 24-hour call center, a mobile mental health crisis team and crisis incident stress management. Within this unit, the Mobile Crisis Team is a group of qualified professionals with experience in mental health, developmental issues and substance abuse. They have experience in emergency psychiatric or family intervention and can assist officers or families with involuntary commitments.

2. **[POLICE, first ask: Do you work with Community Policing Crisis Response Teams?] What are your thoughts on Community Policing Crisis Response Teams?**

3. **How do you think Community Policing Crisis Response Teams are working in Charlotte?**
    - Are they effective?
        - How would we know if Community Policing Crisis Response Teams are working?
        - How would we know if they are not?
    - Walk me through what they are doing now.
        - FOR POLICE: How have they affected how police do their job?
    - What has been the community response?
    - Walk me through how you would like to see them function from a practical perspective.
    - How might they impact racial/ethnic equity?

4. **How should the city evaluate Community Policing Crisis Response Teams?**

Non-uniformed response model for low-risk situations:

5. **Tell me what you know about a non-uniformed response model?**

6. **What do you define as a "low-risk situation?"**

7. **What are your thoughts on non-uniformed responders for low-risk situations? These situations include mental illness and homelessness calls.**
    - What do you think would work with a non-uniformed model?
    - What do you think wouldn't work about a non-uniformed response model?
    - What risk do you perceive in using this model?
        - Risks to the police officer?
        - Risks to the community?
    - What are the benefits in using this model?
        - Benefits to the police officer?
        - Benefits to the community?

- Walk me through how you would like to see it function from a practical perspective.
- What do you think would be the community response to it?
- How might it impact racial/ethnic equity?

8. **What do you think is the best approach for achieving buy in from Charlotte community in a non-uniformed response for low-risk calls model?**

9. **How should the city evaluate a non-uniformed response for low-risk calls model?**

10. **How do you think city leadership would feel about implementing a non-uniformed response model for low-risk calls?**

11. **What kind of staff is needed to support a non-uniformed response model?**
    - How would you use current staff to fill this need?
    - Tell me about the feasibility of hiring appropriate staff?
    - Tell me about the feasibility of managing this staff?
    - How would you ensure this staff is effectively doing their job?

Police Data

12. **[POLICE] Please explain any changes you would like to make to data collection forms, so they more accurately capture data.**

Appendix B. Qualitative Codebook

Code Tree

- Background Information
- CPCRT
  - Overall thoughts/perspective/experience/knowledge
  - Individual characteristics
  - Intervention characteristics
  - Outer settings
  - Inner settings
  - Process
- Non-uniform response
  - Overall thoughts/perspective/experience/knowledge
  - Individual characteristics
  - Intervention characteristics
  - Outer settings
  - Inner settings
  - Process
- General implementation
  - Overall thoughts/perspective/experience/knowledge
  - Individual characteristics
  - Intervention characteristics
  - Outer settings
  - Inner settings
  - Process
- Services Provided
- CIT
- Mental health
- Homelessness
- Improve data collection on calls and stops
- Notable quote / information
- Miscellaneous, worth flagging

Appendix C. Statistical Annex

This section provides the full set of results we used in our analysis. The intention of this section is to be transparent about our methods and cumulative results. While we provide interpretations of key independent variables in the main body of text, short descriptions of the models will accompany each table to contextualize the analysis.

Table D.1 is a logistic regression that estimates the relationship between each variable and whether force was used in a stop. For estimation of the upper and lower bounds of the 95% confidence interval, we used clustered standard errors by neighborhood statistical area.

Table D.1: Use of Force, Vehicle Stops, Logistic Regression

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Asian	1.332	0.395	4.489
Black	1.944	1.301	2.905
Hispanic	1.023	0.574	1.822
Other	0.649	0.154	2.741
Driver Age	0.999	0.989	1.009
Driver Male	1.94	1.454	2.589
Other Reason	0.949	0.513	1.757
Safe Movement	0.223	0.108	0.458
Seat belt	0.189	0.043	0.819
Speeding	0.181	0.105	0.311
Stop Light/Stop Sign	0.27	0.147	0.497
Vehicle Equipment	0.279	0.165	0.472
Vehicle Regulatory	0.187	0.117	0.299
Job Density	1	0.986	1.013
Employment Rate	1.021	0.996	1.046
Household Income	1	1	1
Public Nutrition Assistance	1.01	0.995	1.025
Nuisance Violation Rate	1.004	0.996	1.012
Property Crime Rate	0.999	0.995	1.004
Disorder Call Rate	0.999	0.998	1
Violent Crime Rate	1.015	0.992	1.04
Asian Population (%)	0.956	0.904	1.012
Black Population (%)	0.973	0.932	1.015
Hispanic Population (%)	0.967	0.927	1.009
White Population (%)	0.965	0.923	1.009

N:	460,598
McFadden's R-squared:	0.0328

Table D.2 is another logistic regression very similar to Table D.2, with the exception that we include a binary variable indicating whether a stopped driver was arrested as a result of the stop. Note that the variable for arrest is extremely large and highly significant and vastly improves model fit. Note that this finding means that if individuals are arrested, they are estimated to be 40.9 times more likely to have suffered a use of force.

Table D.2: Use of Force, Vehicle Results with Arrest Control Variable, Logistic Regression

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Asian	1.547	0.455	5.256
Black	1.599	1.06	2.411
Hispanic	1.167	0.651	2.089
Other	1.001	0.236	4.241
Driver Age	1.012	1.002	1.023
Driver Male	1.226	0.916	1.64
Other Reason	1.061	0.569	1.977
Safe Movement	0.607	0.298	1.237
Seat belt	0.491	0.111	2.175
Speeding	0.708	0.412	1.216
Stop Light/Stop Sign	0.889	0.5	1.582
Vehicle Equipment	0.803	0.483	1.336
Vehicle Regulatory	0.58	0.368	0.913
Job Density	1	0.987	1.012
Employment Rate	1.014	0.99	1.039
Household Income	1	1	1
Public Nutrition Assistance	1.007	0.992	1.022
Nuisance Violation Rate	1.003	0.995	1.011
Property Crime Rate	1	0.996	1.004
Disorder Call Rate	0.999	0.998	1.001
Violent Crime Rate	1.01	0.987	1.033
Arrest Stop Result	41.955	30.836	57.082
Asian Population (%)	0.954	0.904	1.006
Black Population (%)	0.969	0.93	1.009
Hispanic Population (%)	0.965	0.926	1.005
White Population (%)	0.964	0.924	1.005
N:	460,598		

McFadden's R-squared: 0.1625

Table D.3 presents the results for use of force on the merged use of force and arrest datasets with a conventional logistic regression. Use of force and arrest datasets were merged on the basis of unique observations of individuals according to age, sex, race/ethnicity, location, and involved officer in both datasets. The results for this analysis is listed in Table D.3.

Table D.3. Use of Force, Logistic Regression Analysis on UOF-Arrest merged data

Variable Name	Estimated Odds Ratio	Lower Bound	Upper Bound
Black	0.905	0.684	1.199
Hispanic	0.507	0.253	1.015
Other identity	0.151	0.022	1.034
Age	0.995	0.989	1
Male	2.162	1.692	2.763
Aggravated Assault with gun	0.361	0.211	0.617
Carrying Concealed Weapon, Weapons Violations	0.613	0.217	1.736
Disorderly Conduct	2.555	1.591	4.105
Distribution Drugs, Controlled Substances	0.897	0.437	1.841
Driving While Impaired	0.34	0.156	0.74
Hit and Run, Traffic Fatality	0.157	0.025	0.982
Liquor Violation	2.283	0.892	5.847
Murder & Non-negligent Manslaughter	0	0	0
Non-aggravated Assault	1.056	0.66	1.688
Possession, Drugs, Controlled Substances	0.836	0.527	1.327
Property Crimes, Theft	0.686	0.46	1.024
Property Crimes, Theft, Violent	0.547	0.325	0.922
Rape, Sex offenses	0.159	0.018	1.377
Soliciting	0	0	0
Traffic Violation	0.611	0.258	1.447
Violation of State Statute, Other Charge	0.446	0.295	0.673
Subject used physical force	3.951E+12	3.374E+11	4.625E+13
Subject used less lethal force	6.184E+8	2.973E+9	1.245E+10
Subject used a knife	9.341E+9	3.579E+9	2.438E+10
Subject used a firearm	7.934E+9	3.706E+9	1.699E+10
Disorder Call Rate, patrol division	1.019	0.984	1.056
Employment Rate, patrol division	0.944	0.88	1.013
Household Income, patrol division	1	1	1
Job Density, patrol division	1.397	1.137	1.717
Nuisance Call Rate, patrol division	1.194	0.946	1.506

Public Nutrition Assistance, patrol division	1.013	0.85	1.206
Property Crime Rate, patrol division	0.952	0.863	1.049
Violent Crime Rate, patrol division	0.708	0.381	1.314
N =	191,998		
McFadden's R-squared=	0.432		

Figure D.1 presents the results of our coarsened exact matching for Black arrestees and use of force. On the left, the different variable names are listed, and on the right, their balance improvement is graphed. The closer the absolute standardized mean distance – which is a measure for how different two samples (e.g. treatment and control) are on a single variable – is to zero, the more similar they are. The further away the values are from zero, the greater the discrepancy between two groups. The original differences between the two groups is visualized by a circle with no fill, whereas the matched differences are denoted by a black circle. If the black circle is left of the circle with no fill, then comparisons between groups on the matched data can be said to be less driven by differences on these control variables – because the control variables have been made more similar in the matched dataset. In this case, the high absolute standardized mean distance for "crimeDriving While Impaired" means that Black arrestees and non-Black arrestees were very different on that variable. Figures D.2 and D.3 are similar to D.1, and all of them show that the matching process was successful in achieving balance across all variables, meaning we can run tests on the binary treatment variable and the outcome without including them into the regression equation. The "age" variable is an integer variable that provided the age of the individual. Sex refers to the biological sex of the individual. The crime variable identifies whether the crime the arrestee was charged with was Aggravated Assault, Disorderly Conduct, and so on. Variables prefixed by "sub_" indicate whether the subject used physical force, less lethal force, a knife, or a firearm. Variables with a "_div" suffix like "disorder_div" are the neighborhood level control variables we use in other models but averaged using population weights for every NSA in the patrol district.

- disorder_div : disorder call rate
- employmet_div : employment rate
- hhincome_div: household income
- jobdensity_div : job density
- nuisance_div: nuisance violations
- pna_div : public nutrition assistance
- property_div: property crime rate
- violent_div: violent crime rate respectively.

The variables are same for every analysis in Figures D.1 through D.3.

Figure D.1 Balance Matching, Black Arrestees and Force

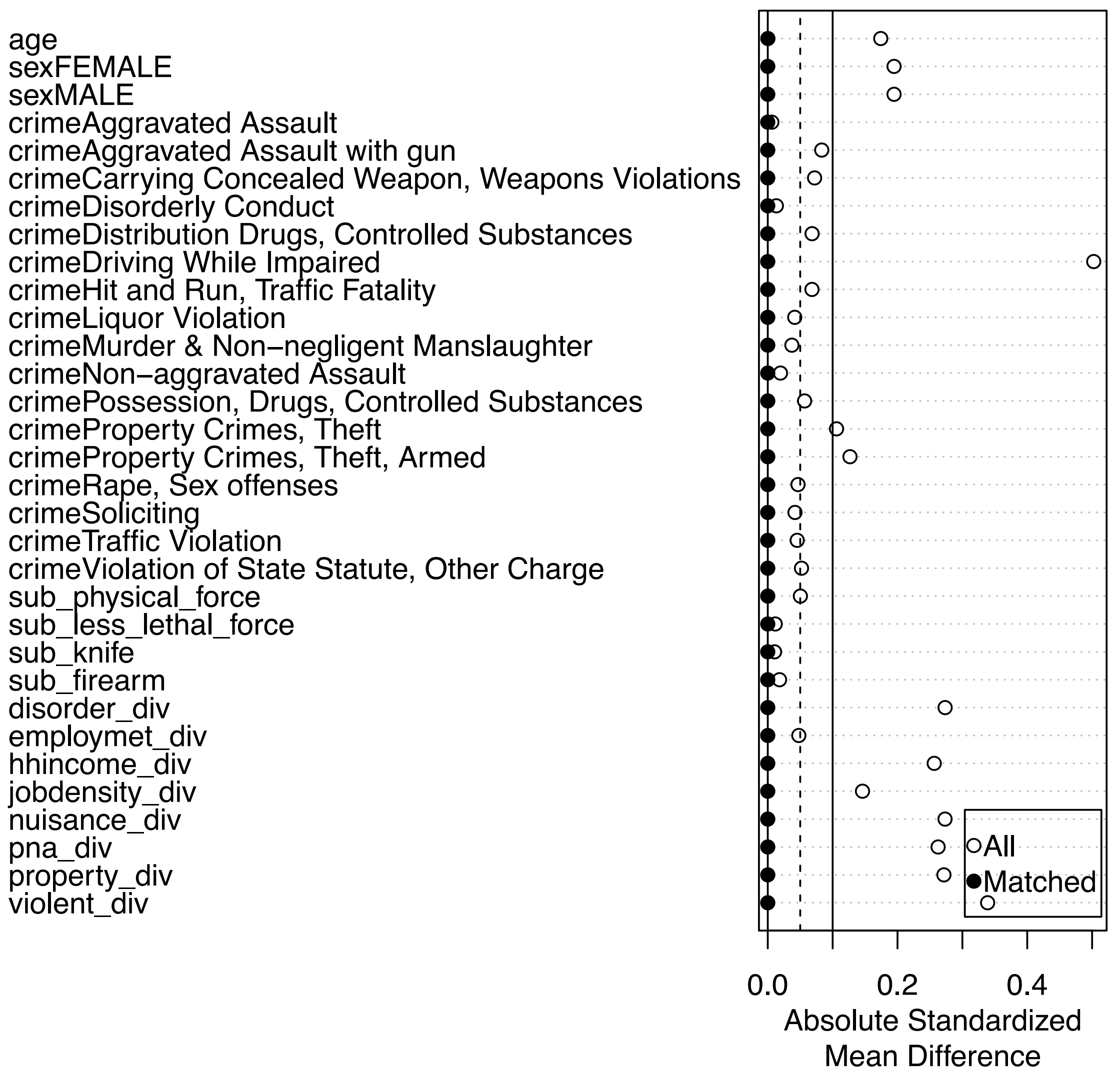


Table D.4 is a logistic regression comparing use of force on Black arrestees to use of force on non-Black arrestees. We used cluster robust standard errors to derive the confidence intervals here and for Tables D.5 and D.6 as well.

Table D.4. Results of Logistic Regression, Black Arrestees and Force, Matched Data

Variable	Odds Ratio Estimate (95% Confidence Interval)
Intercept	**0.005 (0.004, 0.005)**
Black	**1.193 (1.028, 1.391)**
N:	152,294
McFadden's R-squared:	0.0001

Figure D.2 Balance Matching, Hispanic Arrestees and Force

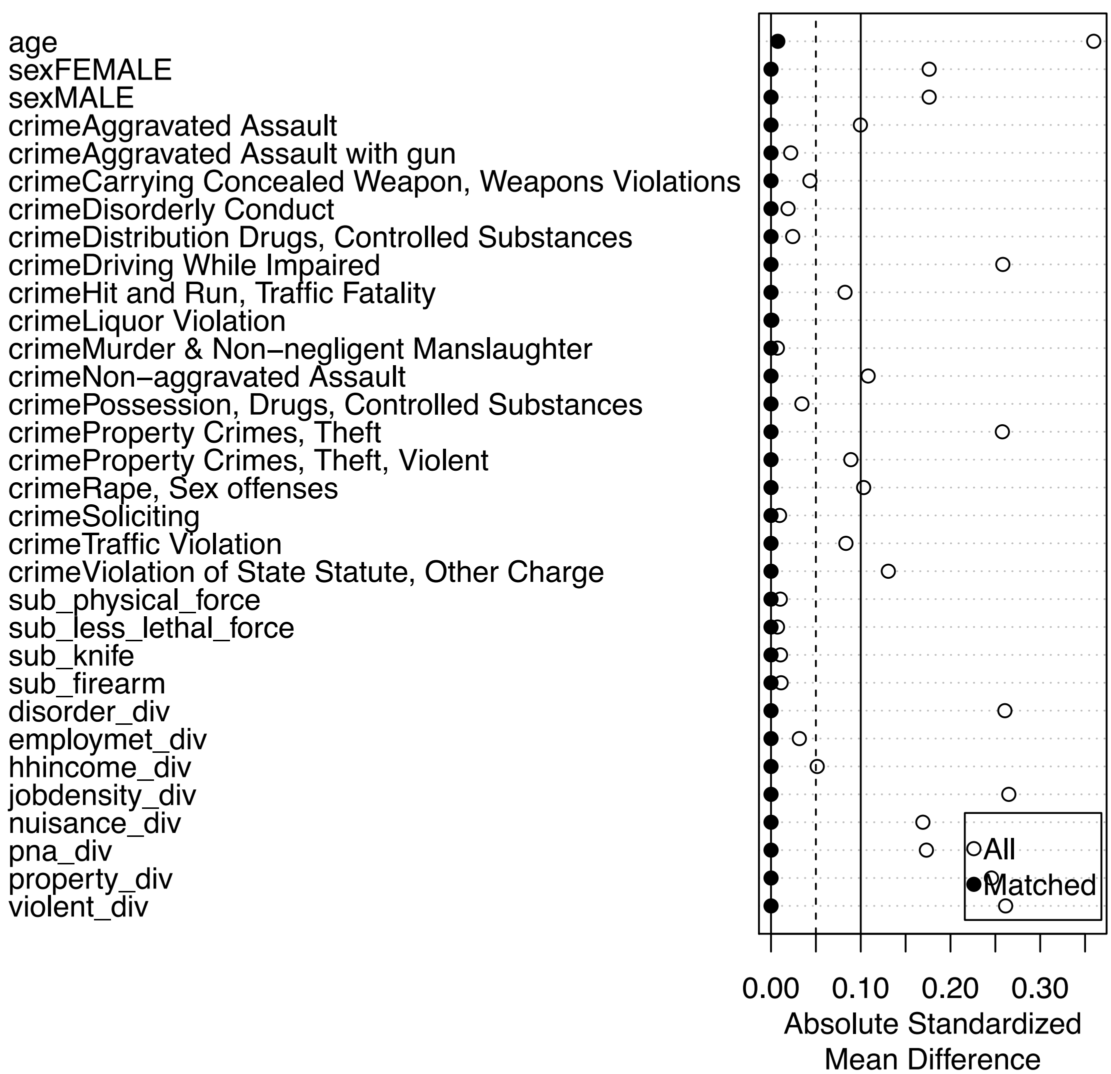


Table D.5. Results of Logistic Regression, Hispanic Arrestees and Force, Matched Data

Variable	Estimate (95% CI)
Intercept	**0.006 (0.006, 0.007)**
Hispanic	**0.545 (0.401, 0.721)**
N:	97,812
McFadden's R-squared	0.0019

Figure D.1 Balance Matching, White Arrestees and Force

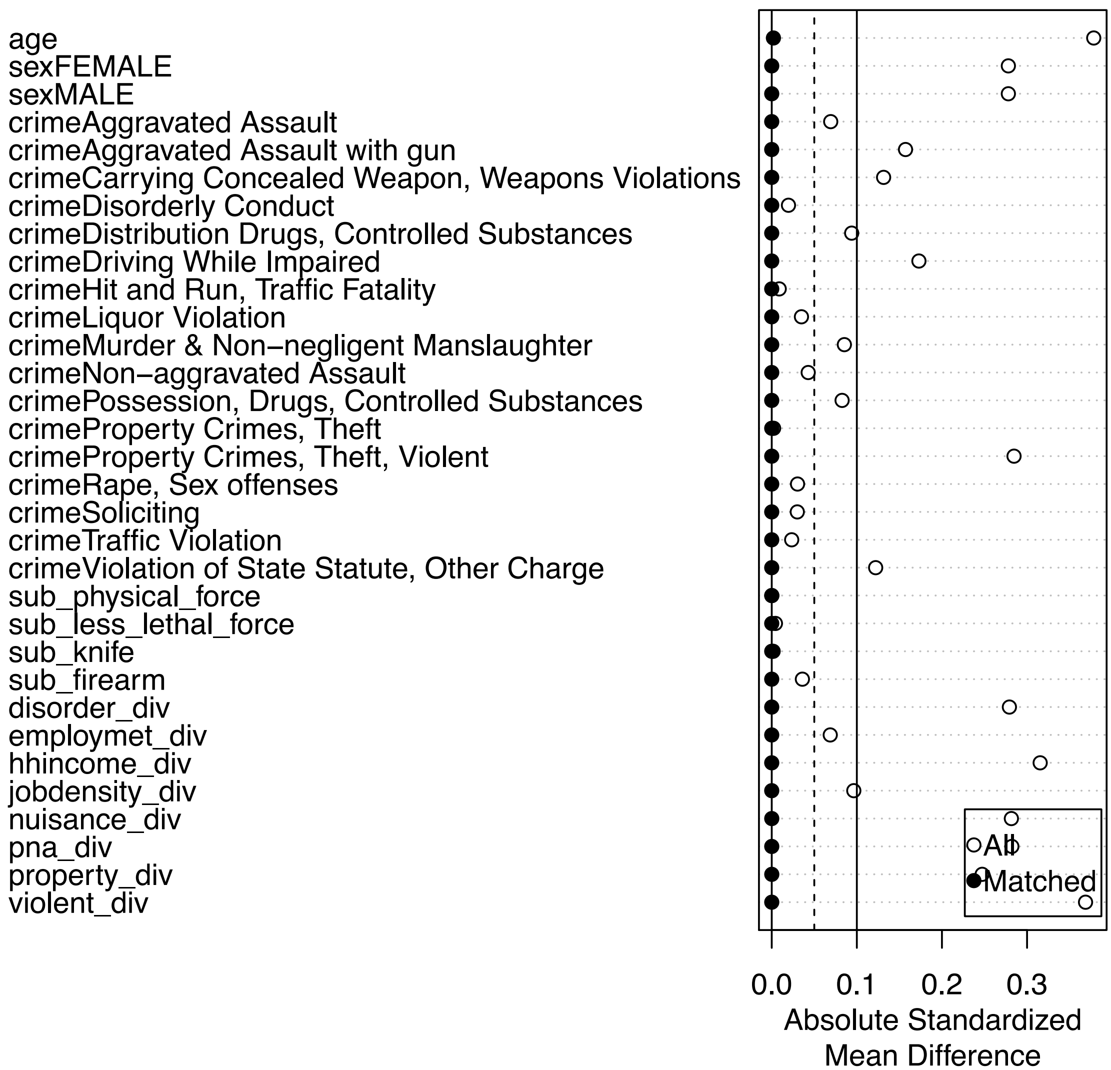


Table D.6. Results of Logistic Regression, White Arrestees and Force, Matched Data

Variable	Estimate (95% CI)
Intercept	**0.006 (0.005, 0.006)**
White	1.041 (0.879, 1.228)
N:	136,052
McFadden's R-squared:	-0.0004

Tables D.7 and D.8. are no action stops for pedestrians and traffic stops respectively. Both analyses are logistic regressions, and used clustered standard errors on neighborhood statistical areas to derive the confidence intervals.

Table D.7. No Action Stops, Pedestrian Results

Variable	**Estimated Odds Ratio**	**Lower Bound**	**Upper Bound**
Intercept	2.795	0.01	772.799
Asian	2.279	0.637	8.152
Black	1.042	0.832	1.306
Hispanic	1.543	1.059	2.249
Other	1.354	0.46	3.987
Pedestrian Age	1.001	0.992	1.01
Pedestrian Male	0.781	0.613	0.996
Crime in Progress	0.036	0.018	0.069
Other Reason	1.409	0.98	2.024
Job Density	0.986	0.974	0.998
Employment Rate	1.017	0.991	1.044
Household Income	1	1	1
Public Nutrition Assistance	0.998	0.981	1.015
Nuisance Violation Rate	0.993	0.982	1.004
Property Crime Rate	0.999	0.995	1.002
Disorder Call Rate	0.999	0.998	1
Violent Crime Rate	1.038	1.013	1.063

Asian Population (%)	0.975	0.918	1.035
Black Population (%)	0.975	0.925	1.028
Hispanic Population (%)	0.977	0.926	1.031
White Population (%)	0.975	0.923	1.031
N	2,934		
McFadden's R-squared:	0.2047		

Table D.8. No Action Stops, Vehicle Results

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Asian	0.956	0.794	1.151
Black	0.906	0.854	0.961
Hispanic	0.551	0.496	0.612
Other	6.66	5.718	7.758
Driver Age	1.001	0.998	1.003
Driver Male	1.302	1.239	1.368
Other Reason	0.424	0.379	0.475
Safe Movement	0.059	0.052	0.068
Seat belt	0.042	0.032	0.057
Speeding	0.022	0.019	0.025
Stop Light/Stop Sign	0.033	0.027	0.04
Vehicle Equipment	0.068	0.062	0.076
Vehicle Regulatory	0.091	0.083	0.099
Job Density	1.003	0.999	1.007
Employment Rate	1.007	0.999	1.014
Household Income	1	1	1
Public Nutrition Assistance	0.998	0.994	1.003
Nuisance Violation Rate	1	0.996	1.004
Property Crime Rate	0.999	0.998	1
Disorder Call Rate	1	1	1.001
Violent Crime Rate	0.993	0.986	1.001
Asian Population (%)	1	0.986	1.014
Black Population (%)	1.008	0.996	1.02
Hispanic Population (%)	1.005	0.994	1.018
White Population (%)	1.002	0.99	1.014
N:	460,598		
McFadden's R-squared:	0.1360		

Tables D.9 and D.10 are logistic regressions that attempt to predict whether a conducted search results in the discovery of contraband. Here again, we used clustered standard errors on neighborhood statistical areas to derive the confidence intervals.

Table D.9. Contraband Discovery Rate, Pedestrian Results

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Black	1.4512	0.8716	2.4162
Hispanic	1.3277	0.6633	2.6576
Other	4.9918	0.6173	40.3689
Pedestrian Age	0.9871	0.9699	1.0045
Pedestrian Male	0.4694	0.2617	0.842
Crime in Progress	1.8054	1.0582	3.0802
Other Reason	0.4919	0.2893	0.8362
Job Density	0.9912	0.9783	1.0042
Employment Rate	0.978	0.9331	1.0252
Household Income	1	1	1
Public Nutrition Assistance	0.9867	0.96	1.0142
Nuisance Violation Rate	0.9789	0.961	0.9972
Property Crime Rate	0.9996	0.9927	1.0066
Disorder Call Rate	1.0017	1.0004	1.0031
Violent Crime Rate	0.9716	0.9392	1.0051
Asian Population (%)	0.9309	0.8576	1.0105
Black Population (%)	0.9344	0.8676	1.0065
Hispanic Population (%)	0.9088	0.8443	0.9782
White Population (%)	0.9235	0.8582	0.9937
N:	623		
McFadden’s R-squared:	0.049		

Table D.10. Contraband Discovery Rate, v, Vehicle Results

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Asian	0.9386	0.6318	1.3943
Black	0.9588	0.8791	1.0458
Hispanic	0.7881	0.6828	0.9096
Other Identity	0.8024	0.5296	1.2157
Driver Age	0.9846	0.9816	0.9876
Driver Male	1.1743	1.0943	1.2602

Other Reason	0.7655	0.6683	0.8768
Safe Movement	1.0356	0.9005	1.191
Seat belt	1.2487	0.9878	1.5784
Speeding	1.0122	0.8858	1.1565
Stop Light/Stop Sign	1.2579	1.099	1.4398
Vehicle Equipment	1.0802	0.973	1.1992
Vehicle Regulatory	1.0119	0.921	1.1117
Job Density	0.9971	0.9941	1.0001
Employment Rate	1.0178	1.0108	1.0248
Household Income	1	1	1
Public Nutrition Assistance	0.9932	0.9885	0.9979
Nuisance Violation Rate	1.0013	0.9985	1.0041
Property Crime Rate	0.9997	0.9987	1.0008
Disorder Call Rate	0.9998	0.9994	1.0002
Violent Crime Rate	1.0129	1.0044	1.0215
Asian Population (%)	0.9999	0.9831	1.0169
Black Population (%)	1.0051	0.9904	1.02
Hispanic Population (%)	1.0003	0.9854	1.0153
White Population (%)	0.9985	0.9833	1.0138
N:	21,703		
McFadden's R-squared:	0.0110		

Tables D.11 and D.12 are multinomial logistic regressions that attempt to estimate the relationship between the set of variables below and the result of the stop. Please note that the variable coefficients change between different outcomes; what may be positive and statistically significant for one variable may be negative for another. Thus, all of the estimates are sectioned off by the specific outcome they attempt to predict.

Table D.11. Result of Stop by Identity group, Vehicle Stops

	Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Arrest				
	Asian	.707216	.5664034	.8830358
	Black	1.649072	1.510966	1.799802
	Hispanic	1.08867	.9690447	1.223063
	Other Group	.3151151	.2346093	.4232461
	Driver Age	.9692649	.9668851	.9716505
	Driver Male	2.671525	2.509298	2.84424

Other Reason for Stop	.9687417	.843449	1.112646
Safe Movement	.1847793	.1591969	.2144727
Seat Belt	.2808445	.2300314	.3428821
Speeding	.1761901	.1552195	.1999939
Stop Light/Sign	.1252887	.1090538	.1439405
Vehicle Equipment	.1436072	.128227	.1608322
Vehicle Regulatory	.1673259	.1514644	.1848484
Job Density	.9992313	.995783	1.002692
Employment Rate	1.011699	1.005486	1.017949
Household Income	.9999965	.9999944	.9999986
Public Nutrition Assistance	1.005877	1.00157	1.010203
Violent Crime Rate	1.004014	.9961563	1.011934
Nuisance Violations Rate	1.001584	.998842	1.004333
Property Crime Rate	.999623	.9984078	1.00084
Disorder Call Rate	1.000061	.9997235	1.000398
Asian Population (%)	1.009052	.9925032	1.025876
Black Population (%)	1.007977	.9943089	1.021833
Hispanic Population (%)	1.006876	.9937187	1.020208
White Population (%)	1.003464	.9897592	1.017358
Intercept	.0138117	.0031687	.0602032
Citation Issued			
Asian	.9224355	.8698248	.9782284
Black	1.018879	.9843147	1.054657
Hispanic	1.550364	1.454011	1.653102
Other Group	.9564539	.9021824	1.01399
Driver Age	.992467	.9912575	.9936781
Driver Male	.954126	.9308299	.9780053
Other Reason for Stop	.9961726	.7868048	1.261253
Safe Movement	.547188	.4255407	.70361
Seat Belt	1.63954	1.234904	2.176763
Speeding	3.751934	3.025381	4.65297
Stop Light/Sign	.6804173	.5507863	.8405578
Vehicle Equipment	.3107203	.2507722	.3849992
Vehicle Regulatory	1.026064	.8364484	1.258663

Job Density	.9977737	.9953525	1.000201
Employment Rate	.9990212	.9937335	1.004337
Household Income	.9999982	.9999968	.9999997
Public Nutrition Assistance	.9999717	.9943589	1.005616
Violent Crime Rate	.9919142	.9842182	.9996704
Nuisance Violations Rate	.9990252	.9941525	1.003922
Property Crime Rate	1.001886	1.000741	1.003033
Disorder Call Rate	.9998301	.9994363	1.000224
Asian Population (%)	.9940661	.9801192	1.008212
Black Population (%)	.9858641	.9729049	.9989959
Hispanic Population (%)	.9895601	.9764729	1.002823
White Population (%)	.9868697	.9740276	.9998811
Intercept	3.186518	.8264909	12.28555
No Action Taken	(base outcome)		
Written Warning			
Asian	.7506669	.6763976	.8330911
Black	.8214504	.7688043	.8777016
Hispanic	.8004402	.73356	.8734181
Other Group	.8725002	.7830615	.9721543
Driver Age	1.010698	1.008778	1.012622
Driver Male	.7788784	.749933	.808941
Other Reason for Stop	3.176455	2.038998	4.948442
Safe Movement	2.488627	1.64965	3.754289
Seat Belt	4.173789	2.697583	6.457823
Speeding	7.622397	5.115036	11.35885
Stop Light/Sign	2.761871	1.858027	4.105395
Vehicle Equipment	1.407447	.9611296	2.06102
Vehicle Regulatory	1.676189	1.144428	2.455034
Job Density	.9941746	.9864953	1.001914
Employment Rate	.9891163	.9693219	1.009315
Household Income	1.000003	.999999	1.000007
Public Nutrition Assistance	1.020716	1.011448	1.030069

Violent Crime Rate	1.001397	.9886587	1.014299
Nuisance Violations Rate	.9948235	.9884981	1.001189
Property Crime Rate	1.003911	1.000557	1.007275
Disorder Call Rate	.9991026	.9982153	.9999906
Asian Population (%)	1.031378	1.001337	1.062321
Black Population (%)	1.021348	.9949157	1.048483
Hispanic Population (%)	1.030788	1.002723	1.059637
White Population (%)	1.037727	1.00878	1.067504
Intercept	.0030445	.0001139	.0813706
N	460,598		
McFadden's R-squared	0.0981		

Table D.12. Result of Stop by identity group, pedestrian

Results	Estimated Odds Ratio	Lower Bound	Upper Bound
Arrest			
Black	1.300972	.907301	1.865454
Hispanic	.9860808	.545439	1.782702
Other Group	.2692756	.0319085	2.272414
Pedestrian Age	.9782647	.966379	.9902965
Pedestrian Male	1.664339	1.106368	2.503709
Investigation	.3542719	.2106991	.5956769
Other Reason for Stop	1.065754	.566821	2.003862
Job Density	1.010196	.9980507	1.02249
Employment Rate	.98528	.9518566	1.019877
Household Income	.9999955	.9999838	1.000007
Public Nutrition Assistance	.9949889	.9739812	1.01645
Violent Crime Rate	1.018662	.9905442	1.047577
Nuisance Violations Rate	.9920877	.9796866	1.004646
Property Crime Rate	1.001597	.9978115	1.005397
Disorder Call Rate	.9992213	.9981056	1.000338

Asian Population (%)	1.047847	.9569228	1.147411
Black Population (%)	1.059492	.9786687	1.146991
Hispanic Population (%)	1.047743	.9676014	1.134523
White Population (%)	1.048118	.9663398	1.136817
Intercept	.0051211	1.23e-06	21.39747
Citation Issued			
Black	1.091789	.8514423	1.399981
Hispanic	.4381035	.2404796	.7981331
Other Group	1.544855	.565216	4.222417
Pedestrian Age	1.004838	.9940605	1.015732
Pedestrian Male	.9077343	.6577146	1.252795
Investigation	.0998048	.0656885	.15164
Other Reason for Stop	.0416691	.0184677	.0940189
Job Density	1.01619	1.009039	1.023391
Employment Rate	1.024012	.9924159	1.056613
Household Income	.9999994	.9999929	1.000006
Public Nutrition Assistance	.9685665	.951052	.9864035
Violent Crime Rate	.9788549	.9492537	1.009379
Nuisance Violations Rate	1.01294	1.003908	1.022052
Property Crime Rate	.9962808	.9931497	.9994218
Disorder Call Rate	1.001182	1.000108	1.002257
Asian Population (%)	.9613546	.9095982	1.016056
Black Population (%)	.9822621	.9397411	1.026707
Hispanic Population (%)	.9825777	.9405823	1.026448
White Population (%)	.9629205	.9226955	1.004899
Intercept	2.705183	.0071585	1022.279
No Action Taken	(base outcome)		

N	2,919
McFadden's R-squared	0.2138

Table D.13 is a logistic regression that attempts to predict when an officer asks for a stopped individuals consent to search their effects, property, or vehicle. Here again, we used clustered standard errors for the neighborhood statistical area that the stop took place in.

Table D.13. Racial/Ethnic Disparities in Requests for Consent to Search

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Asian	0.572	0.431	0.758
Black	1.879	1.635	2.161
Hispanic	1.141	0.971	1.340
Other	0.392	0.282	0.544
February	0.962	0.865	1.069
March	0.982	0.884	1.090
April	0.918	0.822	1.024
May	0.968	0.867	1.080
June	0.924	0.819	1.043
July	0.914	0.816	1.025
August	0.938	0.848	1.038
September	0.927	0.823	1.045
October	0.860	0.767	0.964
November	0.860	0.759	0.974
December	1.280	1.158	1.416
Year, 2016	5.097	4.302	6.039
Year, 2017	6.091	5.047	7.351
Year, 2018	5.867	4.822	7.138
Year, 2019	4.646	3.835	5.629
Year, 2020	5.678	4.637	6.953
Disorder Call Rate	1	1	1.001
Employment Rate	1.011	0.999	1.023
Household Income	1	1	1
Job Density	1.004	0.998	1.010
Nuisance Violation Rate	1.006	1	1.012
Public Nutrition Assistance	1.020	1.012	1.028
Property Crime Rate	0.998	0.996	1
Violent Crime Rate	0.997	0.982	1.012
N	463,168		
McFadden's R-squared	0.04931619		

Tables D.14 through D.17 estimate the frequency with which pedestrians and vehicle stops occur in a specific neighborhood and their association with specific variables. These are Poisson regression models with yearly and monthly fixed effects which use clustered standard errors on the neighborhood statistical areas. They differ in whether they estimate pedestrian, vehicle, or both stops, and whether they are predicted with reference to their local neighborhoods or the city.

Table D.14. Frequency of pedestrian and vehicle stops by perceived race/ethnicity per 100,000 citizens of Charlotte

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Asian	0.5316284	0.4939594	0.5721700
Black	2.9867361	2.6168189	3.4089452
Hispanic	1.4221247	1.2159692	1.6632318
Other	2.1041152	1.9302091	2.2936898
February	0.9279337	0.9031281	0.9534207
March	0.9207917	0.8950476	0.9472762
April	0.8558890	0.8271795	0.8855950
May	0.7885124	0.7650012	0.8127462
June	0.7287942	0.7050268	0.7533629
July	0.8347854	0.8072711	0.8632375
August	0.8306335	0.8028382	0.8593912
September	0.7185974	0.6950714	0.7429197
October	0.7659030	0.7389820	0.7938047
November	0.7600301	0.7359203	0.7849298
December	0.8397763	0.8139817	0.8663883
Year, 2016	1.5812512	1.4890950	1.6791108
Year, 2017	1.9162444	1.7668364	2.0782866
Year, 2018	1.6661202	1.5190788	1.8273947
Year, 2019	1.9600431	1.7479300	2.1978963
Year, 2020	1.2494282	1.1219752	1.3913594
Disorder Call Rate	0.9997452	0.9991220	1.0003689
Employment Rate	0.9990581	0.9866683	1.0116034
Household Income	0.9999950	0.9999891	1.0000010
Job Density	0.9976386	0.9775922	1.0180961
Nuisance Violation Rate	1.0042955	0.9976730	1.0109620
Public Nutrition Assistance	1.0107532	1.0005013	1.0211102
Property Crime Rate	1.0039692	0.9981731	1.0097991
Violent Crime Rate	1.0047293	0.9858878	1.0239309
N	165,600		
McFadden’s R-squared	0.2088565		

Table D.15. Rate of pedestrian and vehicle stops by perceived race/ethnicity per 100 citizens within the neighborhood where the stop occurred

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Asian	0.381	0.335	0.433
Black	1.936	1.684	2.225
Hispanic	0.984	0.864	1.122
Other	0.701	0.596	0.824
February	0.931	0.906	0.957
March	0.934	0.905	0.964
April	0.861	0.832	0.892
May	0.792	0.768	0.817
June	0.748	0.723	0.774
July	0.835	0.807	0.864
August	0.834	0.807	0.863
September	0.720	0.695	0.745
October	0.752	0.726	0.780
November	0.730	0.708	0.752
December	0.740	0.717	0.764
Year, 2016	0.740	0.696	0.787
Year, 2017	0.884	0.816	0.957
Year, 2018	0.726	0.661	0.796
Year, 2019	0.850	0.761	0.949
Year, 2020	0.548	0.494	0.607
Disorder Call Rate	1	1	1.001
Employment Rate	1.002	0.990	1.015
Household Income	1	1	1
Job Density	0.997	0.984	1.010
Nuisance Violation Rate	1.005	0.997	1.013
Public Nutrition Assistance	1.006	0.996	1.016
Property Crime Rate	1.004	1	1.008
Violent Crime Rate	0.998	0.981	1.015
N	135,612		
McFadden’s R-squared	0.2427147		

Table D.16. Frequency of vehicle stops by perceived race/ethnicity by population

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Asian	0.515	0.477	0.555

Black	2.818	2.467	3.220
Hispanic	1.352	1.155	1.583
Other	1.857	1.701	2.027
February	0.928	0.903	0.954
March	0.933	0.903	0.963
April	0.858	0.828	0.888
May	0.788	0.764	0.813
June	0.742	0.716	0.768
July	0.830	0.802	0.858
August	0.830	0.802	0.859
September	0.718	0.694	0.744
October	0.754	0.727	0.782
November	0.732	0.710	0.755
December	0.739	0.717	0.763
Year, 2016	0.731	0.690	0.775
Year, 2017	0.880	0.812	0.953
Year, 2018	0.763	0.696	0.836
Year, 2019	0.898	0.803	1.005
Year, 2020	0.581	0.524	0.645
Disorder Call Rate	1	0.999	1
Employment Rate	0.999	0.986	1.012
Household Income	1	1	1
Job Density	0.998	0.979	1.018
Nuisance Violation Rate	1.004	0.998	1.011
Public Nutrition Assistance	1.010	1	1.021
Property Crime Rate	1.004	0.998	1.009
Violent Crime Rate	1.003	0.984	1.021
N	165,600		
McFadden's R-squared	0.2078959		

Table D.17. Frequency of vehicle stops by perceived race/ethnicity by neighborhood population

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Asian	0.383	0.337	0.436
Black	1.942	1.690	2.233
Hispanic	0.989	0.868	1.127
Other	0.705	0.600	0.829
February	0.929	0.904	0.955
March	0.934	0.904	0.964
April	0.860	0.831	0.891
May	0.789	0.765	0.814
June	0.743	0.718	0.770
July	0.831	0.803	0.860
August	0.831	0.803	0.860

September	0.718	0.693	0.744
October	0.751	0.725	0.779
November	0.729	0.707	0.751
December	0.739	0.716	0.763
Year, 2016	0.732	0.689	0.779
Year, 2017	0.876	0.808	0.949
Year, 2018	0.720	0.656	0.790
Year, 2019	0.844	0.755	0.943
Year, 2020	0.544	0.491	0.604
Disorder Call Rate	1	1	1.001
Employment Rate	1.002	0.990	1.015
Household Income	1.000	1	1
Job Density	0.997	0.984	1.010
Nuisance Violation Rate	1.005	0.997	1.012
Public Nutrition Assistance	1.006	0.996	1.016
Property Crime Rate	1.004	1	1.008
Violent Crime Rate	0.998	0.981	1.015
N	135,612		
McFadden's R-squared	0.2414656		

Table D.18. Frequency of pedestrian stops by perceived race/ethnicity by population

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Asian	1.127855e-01	6.191020e-02	2.054681e-01
Black	2.066522e+00	1.614129e+00	2.645707e+00
Hispanic	6.620365e-01	4.788457e-01	9.153100e-01
Other	4.322486e-01	2.617512e-01	7.138034e-01
February	1.323864e+00	1.015536e+00	1.725802e+00
March	1.051136e+00	7.589434e-01	1.455823e+00
April	1.210227e+00	9.360053e-01	1.564788e+00
May	1.698864e+00	1.349760e+00	2.138260e+00
June	2.142046e+00	1.711252e+00	2.681287e+00
July	2.011364e+00	1.595606e+00	2.535453e+00
August	1.886364e+00	1.478040e+00	2.407491e+00
September	1.198864e+00	9.082574e-01	1.582452e+00
October	1.028409e+00	7.803381e-01	1.355342e+00
November	1.090909e+00	8.567609e-01	1.389049e+00
December	1.028409e+00	7.808372e-01	1.354476e+00
Year, 2016	3.589951e+07	2.753403e+07	4.680663e+07
Year, 2017	3.728720e+07	2.681835e+07	5.184268e+07
Year, 2018	2.650927e+07	1.845550e+07	3.807762e+07
Year, 2019	2.733315e+07	1.641649e+07	4.550918e+07

Year, 2020	1.482969e+07	9.193893e+06	2.392018e+07
Disorder Call Rate	1.000684e+00	9.998497e-01	1.001519e+00
Employment Rate	1.007630e+00	9.878193e-01	1.027838e+00
Household Income	9.999940e-01	9.999881e-01	9.999999e-01
Job Density	1.005687e+00	9.859185e-01	1.025853e+00
Nuisance Violation Rate	1.022842e+00	1.002906e+00	1.043176e+00
Public Nutrition Assistance	1.012015e+00	1.000452e+00	1.023711e+00
Property Crime Rate	1.001887e+00	9.967107e-01	1.007090e+00
Violent Crime Rate	9.877534e-01	9.640175e-01	1.012074e+00
N	165,600		
McFadden’s R-squared	0.1375043		

Table D.19. Frequency of pedestrian stops by perceived race/ethnicity by neighborhood population

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Asian	1.127855e-01	6.191020e-02	2.054681e-01
Black	2.066522e+00	1.614129e+00	2.645707e+00
Hispanic	6.620365e-01	4.788457e-01	9.153100e-01
Other	4.322486e-01	2.617512e-01	7.138034e-01
February	1.323864e+00	1.015536e+00	1.725802e+00
March	1.051136e+00	7.589434e-01	1.455823e+00
April	1.210227e+00	9.360053e-01	1.564788e+00
May	1.698864e+00	1.349760e+00	2.138260e+00
June	2.142046e+00	1.711252e+00	2.681287e+00
July	2.011364e+00	1.595606e+00	2.535453e+00
August	1.886364e+00	1.478040e+00	2.407491e+00
September	1.198864e+00	9.082574e-01	1.582452e+00
October	1.028409e+00	7.803381e-01	1.355342e+00
November	1.090909e+00	8.567609e-01	1.389049e+00
December	1.028409e+00	7.808372e-01	1.354476e+00
Year, 2016	3.589951e+07	2.753403e+07	4.680663e+07
Year, 2017	3.728720e+07	2.681835e+07	5.184268e+07
Year, 2018	2.650927e+07	1.845550e+07	3.807762e+07
Year, 2019	2.733315e+07	1.641649e+07	4.550918e+07
Year, 2020	1.482969e+07	9.193893e+06	2.392018e+07
Disorder Call Rate	1.000684e+00	9.998497e-01	1.001519e+00
Employment Rate	1.007630e+00	9.878193e-01	1.027838e+00
Household Income	9.999940e-01	9.999881e-01	9.999999e-01
Job Density	1.005687e+00	9.859185e-01	1.025853e+00
Nuisance Violation Rate	1.022842e+00	1.002906e+00	1.043176e+00
Public Nutrition Assistance	1.012015e+00	1.000452e+00	1.023711e+00
Property Crime Rate	1.001887e+00	9.967107e-01	1.007090e+00
Violent Crime Rate	9.877534e-01	9.640175e-01	1.012074e+00

N	135,612
McFadden's R-squared	0.1375043

Tables D.18 through D.27 reflect the full results of our veil of darkness analysis. For Asian, Black, Hispanic, Other/Unknown, and White drivers, we estimate the effect of daylight on their probability of being stopped with and without controls. These were all logistic regressions that focused on the estimated relationship between a stop occurring during daylight hours and the probability that a stopped driver belonged to a given identity group. To derive the confidence intervals, we used clustered standard errors for the neighborhood statistical areas the stops took place in.

Table D.18. Stop Probabilities, Vehicle Results, Asian Individuals, No Controls

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Daylight	1.000	0.997	1.002
Spline 1	1.001	0.995	1.007
Spline 2	1.002	0.995	1.010
Spline 3	0.998	0.991	1.006
Spline 4	1.008	1.003	1.013
Spline 5	1.001	0.991	1.012
Spline 6	0.999	0.993	1.004
N	74,254		
McFadden's R-squared:	0.00004		

Table D.19. Stop Probabilities, Vehicle Results, Asian Individuals, Controls

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Intercept	0.081	0.007	0.918
Daylight	0.989	0.851	1.149
Spline 1	1.075	0.736	1.569
Spline 2	1.076	0.663	1.746
Spline 3	0.946	0.6	1.494
Spline 4	1.488	1.087	2.039
Spline 5	0.963	0.485	1.908
Spline 6	0.913	0.645	1.292
Other reason for Stop	1.226	0.675	2.226
Safe Movement	1.714	1.094	2.684
Seat Belt	1.585	0.745	3.371

Speeding	1.686	1.112	2.558
Stop Light/Sign	1.725	1.107	2.689
Vehicle Equipment	1.302	0.852	1.992
Vehicle Regulatory	0.664	0.432	1.021
Population Density	1.008	0.992	1.025
Asian Population (%)	1.006	0.984	1.029
Black Population (%)	0.978	0.958	0.998
Hispanic Population (%)	0.982	0.963	1.002
White Population (%)	0.989	0.969	1.008
All Other Population (%)	1.008	1	1.017
Youth Population (%)	0.996	0.989	1.003
Vacant Land (%)	1.002	0.992	1.012
Public Nutrition Assistance	1	1	1
Household Income	0.994	0.988	1
Job Density	0.998	0.985	1.01
Employment Rate	0.988	0.979	0.998
Nuisance Violations Rate	1.001	0.999	1.003
Property Crime Rate	1	1	1.001
Disorder Call Rate	0.985	0.97	1
Violent Crime Rate	0.081	0.007	0.918
N	73,904		
McFadden's R-squared:	0.0344		

Table D.20. Stop Probabilities, Vehicle Results, Black Individuals, No Controls

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Daylight	1.003	0.992	1.014
Spline 1	1.040	1.015	1.065
Spline 2	1.013	0.980	1.046
Spline 3	1.076	1.041	1.111
Spline 4	1.004	0.977	1.032
Spline 5	1.006	0.964	1.051
Spline 6	1.028	1.004	1.052
N	74,254		
McFadden's R-squared:	0.0005		

Table D.21. Stop Probabilities, Vehicle Results, Black Individuals, Controls

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Daylight	1.033	0.988	1.081
Spline 1	1.174	1.062	1.297
Spline 2	1.036	0.903	1.189
Spline 3	1.277	1.12	1.456
Spline 4	1.154	1.049	1.269
Spline 5	1.143	0.954	1.369
Spline 6	1.179	1.072	1.297
Other reason for Stop	0.816	0.685	0.971
Safe Movement	0.845	0.74	0.965
Seat Belt	1.558	1.265	1.92
Speeding	0.859	0.749	0.984
Stop Light/Sign	0.842	0.729	0.973
Vehicle Equipment	1.21	1.082	1.353
Vehicle Regulatory	1.626	1.447	1.827
Population Density	1.008	0.993	1.023
Asian Population (%)	1.012	0.992	1.033
Black Population (%)	1.027	1.008	1.046
Hispanic Population (%)	1.01	0.992	1.028
White Population (%)	1.006	0.988	1.024
All Other Population (%)	0.979	0.971	0.987
Youth Population (%)	1.005	0.998	1.011
Vacant Land (%)	1.011	1.002	1.021
Public Nutrition Assistance	1	1	1
Household Income	1.003	0.998	1.008
Job Density	0.996	0.989	1.004
Employment Rate	1.003	0.995	1.011
Nuisance Violations Rate	1	0.999	1.002
Property Crime Rate	1	0.999	1
Disorder Call Rate	1.012	1.001	1.024
Violent Crime Rate	0.407	0.065	2.531
N	73,904		
McFadden’s R-squared:	0.1049		

Table D.22. Stop Probabilities, Vehicle Results, Hispanic Individuals, No Controls

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Daylight	0.991	0.985	0.997
Spline 1	1.001	0.988	1.015
Spline 2	1.025	1.004	1.046
Spline 3	1.015	0.993	1.036
Spline 4	1.002	0.986	1.018
Spline 5	1.012	0.987	1.039
Spline 6	0.996	0.984	1.008
N	74,254		
McFadden’s R-squared:	0.0006		

Table D.23. Stop Probabilities, Vehicle Results, Hispanic Individuals, Controls

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Daylight	0.932	0.875	0.994
Spline 1	0.963	0.824	1.125
Spline 2	1.216	0.991	1.492
Spline 3	1.072	0.868	1.323
Spline 4	1.103	0.938	1.298
Spline 5	1.045	0.79	1.381
Spline 6	0.937	0.827	1.062
Other reason for Stop	1.101	0.877	1.382
Safe Movement	0.762	0.65	0.893
Seat Belt	0.496	0.377	0.652
Speeding	0.722	0.612	0.853
Stop Light/Sign	0.782	0.671	0.911
Vehicle Equipment	0.781	0.674	0.905
Vehicle Regulatory	0.518	0.45	0.597
Population Density	1.004	0.981	1.027
Asian Population (%)	0.984	0.954	1.014
Black Population (%)	0.984	0.955	1.015
Hispanic Population (%)	1.017	0.989	1.046
White Population (%)	0.982	0.954	1.01
All Other Population (%)	0.993	0.982	1.004
Youth Population (%)	0.995	0.985	1.005
Vacant Land (%)	0.994	0.982	1.007

Public Nutrition Assistance	1	1	1
Household Income	0.994	0.984	1.004
Job Density	1.017	1.006	1.028
Employment Rate	1.005	0.998	1.011
Nuisance Violations Rate	1	0.998	1.002
Property Crime Rate	1	0.999	1.001
Disorder Call Rate	0.994	0.978	1.011
Violent Crime Rate	0.159	0.008	3.072
N	73,409		
McFadden's R-squared:	0.0476		

Table D.24. Stop Probabilities, Vehicle Results, Other Individuals, No Controls

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Daylight	0.998	0.995	1.001
Spline 1	0.997	0.990	1.004
Spline 2	1.006	0.997	1.014
Spline 3	1.003	0.994	1.012
Spline 4	1.001	0.993	1.009
Spline 5	1.004	0.991	1.018
Spline 6	1.001	0.994	1.007
N	74,254		
McFadden's R-squared:	0.00009		

Table D.25. Stop Probabilities, ix, Vehicle Results, Other Individuals, Control

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Daylight	0.903	0.782	1.043
Spline 1	0.967	0.691	1.353
Spline 2	1.284	0.826	1.996
Spline 3	1.158	0.764	1.753
Spline 4	1.065	0.752	1.507
Spline 5	1.27	0.657	2.454
Spline 6	1.038	0.762	1.412
Other reason for Stop	1.564	1.017	2.408
Safe Movement	0.952	0.662	1.368
Seat Belt	0.266	0.099	0.713
Speeding	1.009	0.714	1.426

Stop Light/Sign	0.888	0.619	1.274
Vehicle Equipment	0.702	0.496	0.995
Vehicle Regulatory	0.427	0.306	0.596
Population Density	1.01	0.994	1.027
Asian Population (%)	1.01	0.982	1.039
Black Population (%)	0.983	0.959	1.007
Hispanic Population (%)	0.979	0.955	1.003
White Population (%)	0.987	0.964	1.012
All Other Population (%)	0.993	0.984	1.003
Youth Population (%)	1.01	1.003	1.016
Vacant Land (%)	0.993	0.982	1.003
Public Nutrition Assistance	1	1	1
Household Income	0.999	0.993	1.005
Job Density	1.009	0.997	1.021
Employment Rate	0.991	0.983	0.998
Nuisance Violations Rate	1	0.998	1.002
Property Crime Rate	1	0.999	1.001
Disorder Call Rate	0.998	0.978	1.019
Violent Crime Rate	0.057	0.003	0.958
N	73,904		
McFadden's R-squared:	0.0366		

Table D.26. Stop Probabilities, Vehicle Results, White Individuals, No Controls

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Daylight	1.008	0.998	1.017
Spline 1	0.963	0.943	0.983
Spline 2	0.956	0.928	0.984
Spline 3	0.915	0.891	0.940
Spline 4	0.985	0.959	1.012
Spline 5	0.976	0.935	1.019
Spline 6	0.978	0.955	1.002
N	74,254		
McFadden's R-squared:	0.0019		

Table D.27. Stop Probabilities, Vehicle Results, White Individuals, Controls

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Daylight	1.009	0.961	1.058

Spline 1	0.839	0.751	0.938
Spline 2	0.836	0.714	0.978
Spline 3	0.692	0.599	0.799
Spline 4	0.767	0.683	0.861
Spline 5	0.812	0.646	1.021
Spline 6	0.852	0.76	0.954
Other reason for Stop	1.116	0.932	1.335
Safe Movement	1.454	1.227	1.722
Seat Belt	0.922	0.713	1.193
Speeding	1.394	1.196	1.626
Stop Light/Sign	1.424	1.194	1.699
Vehicle Equipment	0.944	0.819	1.089
Vehicle Regulatory	0.911	0.794	1.045
Population Density	0.979	0.963	0.994
Asian Population (%)	0.989	0.969	1.009
Black Population (%)	0.976	0.958	0.993
Hispanic Population (%)	0.975	0.958	0.992
White Population (%)	0.999	0.981	1.017
All Other Population (%)	1.026	1.018	1.034
Youth Population (%)	0.996	0.989	1.002
Vacant Land (%)	0.988	0.98	0.996
Public Nutrition Assistance	1	1	1
Household Income	1.001	0.997	1.005
Job Density	0.995	0.988	1.003
Employment Rate	0.993	0.987	1
Nuisance Violations Rate	0.999	0.998	1
Property Crime Rate	1.001	1	1.001
Disorder Call Rate	0.984	0.973	0.996
Violent Crime Rate	2.173	0.304	15.558
N	73,904		
McFadden’s R-squared:	0.1302		

Table D.28 estimates the relationship between different covariates and the frequency of complaints in a given neighborhood. This is Poisson regression that takes the neighborhood statistical area as the unit of analysis and clusters its standard errors on it. These clustered standard errors were used to derive the upper and lower bounds.

Table D.28. Proportion of Citizen Complaints by Community

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound

Stops (500)	1.164	1.122	1.207
Disorder Call Rate	1.000	0.998	1.002
Employment Rate	1.005	0.987	1.023
Household Income	1.000	1.000	1.000
Job Density	1.061	1.031	1.091
Nuisance Violation Rate	0.998	0.987	1.010
Public Nutrition Assistance	0.997	0.975	1.019
Property Crime Rate	0.993	0.984	1.002
Violent Crime Rate	1.010	0.994	1.026
N	2,760		
McFadden's Adjusted R-squared	0.3692194		

Tables D.29 through D.33 present the logistic regressions of officer characteristics on specific policing activities to identify disparities in outcomes.

Table D.29. Logistic regression, Officer characteristics and citations

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Officer race, Asian	1.719	0.136	0.498
Officer race, Black	1.3	1.341	2.202
Officer race, Hispanic	0.885	1.174	1.439
Officer race, Native American	0.57	0.803	0.976
Officer race, Other/Unknown	0.821	0.429	0.756
Officer sex, male	0.806	0.753	0.895
Officer age	1.028	0.763	0.85
Officer years of experience	1.006	1.023	1.033
Driver race, Asian	1.015	0.998	1.014
Driver race, Black	1.094	0.959	1.075
Driver race, Hispanic	1.664	1.054	1.135
Driver race, Other/Unknown	1.031	1.576	1.757
Driver age	0.99	0.967	1.099
Driver male	0.987	0.989	0.991
Other reason for stop	0.971	0.962	1.012
Safe Movement	0.65	0.816	1.156
Seat belt	1.78	0.543	0.778
Speeding	3.594	1.43	2.216
Stop Light/Sign	0.826	3.058	4.224
Vehicle Equipment	0.42	0.715	0.953
Vehicle Regulatory	1.342	0.364	0.485

Job Density	1.001	1.182	1.523
Employment Rate	1	0.998	1.004
Household Income	1	0.994	1.007
Public Nutrition Assistance	0.998	1	1
Nuisance violations	1	0.993	1.003
Property Crime Rate	1.001	0.995	1.004
Disorder Call Rate	1	1	1.003
Violent Crime Rate	0.993	0.999	1
N =	450,680		
McFadden's Adjusted R-squared =	0.124		

Table D.30. Logistic Regression, Officer characteristics and Arrests

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Intercept	0.082	0.042	0.16
Officer race, Asian	0.589	0.474	0.732
Officer race, Black	0.696	0.642	0.753
Officer race, Hispanic	0.943	0.821	1.083
Officer race, Native American	1.356	0.895	2.055
Officer race, Other/Unknown	0.886	0.816	0.963
Officer sex, male	1.328	1.22	1.446
Officer age	0.976	0.972	0.981
Officer years of experience	0.978	0.971	0.984
Driver race, Asian	0.717	0.571	0.901
Driver race, Black	1.573	1.44	1.72
Driver race, Hispanic	0.966	0.855	1.09
Driver race, Other/Unknown	0.292	0.217	0.393
Driver age	0.974	0.971	0.976
Driver male	2.625	2.461	2.8
Other reason for stop	0.959	0.833	1.105
Safe Movement	0.208	0.179	0.241
Seat belt	0.229	0.188	0.279
Speeding	0.094	0.082	0.107
Stop Light/Sign	0.13	0.114	0.148
Vehicle Equipment	0.167	0.151	0.185
Vehicle Regulatory	0.15	0.137	0.165
Job Density	0.998	0.995	1.001

Employment Rate	1.013	1.007	1.019
Household Income	1	1	1
Public Nutrition Assistance	1.009	1.004	1.013
Nuisance violations	1.002	0.999	1.005
Property Crime Rate	0.999	0.998	1.001
Disorder Call Rate	1	1	1
Violent Crime Rate	1.007	0.999	1.014
N =	450,680		
McFadden's Adjusted R-squared =	0.120		

Table D.31. Logistic Regression, Officer characteristics and uses of force

Variable	Estimated Odds Ratio	Lower Bound	Upper Bound
Intercept	0	0	0.001
Officer race, Asian	1.05	0.575	1.918
Officer race, Black	0.942	0.614	1.444
Officer race, Hispanic	0.581	0.252	1.339
Officer race, Native American	1.111	0.141	8.769
Officer race, Other/Unknown	0.943	0.567	1.567
Officer sex, male	0.854	0.515	1.415
Officer age	0.993	0.969	1.018
Officer years of experience	1.016	0.987	1.046
Driver race, Asian	1.535	0.451	5.226
Driver race, Black	1.613	1.068	2.437
Driver race, Hispanic	1.201	0.671	2.15
Driver race, Other/Unknown	0.985	0.233	4.165
Driver age	1.012	1.002	1.023
Driver male	1.253	0.934	1.683
Driver arrested	42.99	31.558	58.564
Other reason for stop	1.092	0.587	2.031
Safe Movement	0.642	0.315	1.307
Seat belt	0.516	0.117	2.287
Speeding	0.691	0.398	1.2
Stop Light/Sign	0.937	0.522	1.684
Vehicle Equipment	0.857	0.509	1.442
Vehicle Regulatory	0.613	0.386	0.975
Job Density	1.001	0.988	1.014
Employment Rate	1.014	0.988	1.04

Household Income	1	1	1
Public Nutrition Assistance	1.01	0.997	1.024
Nuisance violations	1.005	0.997	1.013
Property Crime Rate	1	0.996	1.005
Disorder Call Rate	0.999	0.998	1.001
Violent Crime Rate	1.01	0.986	1.035
N =	450,680		
McFadden's Adjusted R-squared =	0.160		

Table D.32. **Odds Ratios, Officer Characteristics, Arrests, Speeding**

	Speeding				Public Intoxication				Communication of Threats			
		Odds Ratio Est.	Lower Bound	Upper Bound		Odds Ratio Est.	Lower Bound	Upper Bound		Odds Ratio Est.	Lower Bound	Upper Bound
Intercept		0.007	0.004	0.012		0.001	0.001	0.003		0.021	0.017	0.026
Officer, Asian	56	1.134	0.69	1.862	11	1.245	0.517	3	86	0.962	0.704	1.314
Officer, Black	271	1.087	0.868	1.363	41	0.939	0.623	1.415	528	1.195	1.072	1.332
Officer, Hispanic	75	0.834	0.566	1.23	15	0.996	0.619	1.604	180	1.169	0.98	1.394
Officer, Native American	4	0.684	0.246	1.9	1	0.932	0.125	6.961	10	0.955	0.479	1.905
Officer, Other	103	0.647	0.486	0.861	15	0.6	0.367	0.982	297	1.142	0.983	1.326
Officer, White	1,089				195				1,979			
Officer, male	1,489	1.423	1.067	1.899		1.042	0.622	1.745	2,767	0.926	0.813	1.054
Officer, female	109				254				312			
Officer age		1.012	0.998	1.026		1.014	0.992	1.036		1.003	0.996	1.01
Officer years of service		0.964	0.946	0.982		0.99	0.965	1.016		0.995	0.986	1.004
N =	143,099				143,099				143,099			
McFadden's Adjusted R-squared =	0.0001				-0.003				0.003			

Table D.33. Odds Ratios, Officer Characteristics, Complaints, by source and type

	External Complaint				Arrest, Search, Seizure				Use of Force			
		Odds Ratio Est.	Lower Bound	Upper Bound		Odds Ratio Est.	Lower Bound	Upper Bound		Odds Ratio Est.	Lower Bound	Upper Bound
Intercept		0.354	0.147	0.857		0.073	0.014	0.385		0.062	0.013	0.285
Officer, Asian	11	0.928	0.23	3.742	5	1.128	0.355	3.578	6	2.601	0.838	8.078
Officer, Black	90	0.726	0.487	1.083	12	0.368	0.218	0.622	20	0.717	0.35	1.465
Officer, Hispanic	35	1.092	0.495	2.412	10	0.63	0.218	1.815	9	0.591	0.19	1.84
Officer, Native American	4				1				0	NA	NA	NA
Officer, Other	29	1.272	0.535	3.02	11	0.57	0.07	4.625	9	0.573	0.19	1.732

Officer, White	289				72				77			
Officer, male	402	1.295	0.977	1.716	104	2.653	1.165	6.039	113	2.766	1.094	6.991
Officer, female	56				7				8			
Officer age		0.997	0.975	1.02		0.995	0.963	1.028		0.983	0.945	1.023
Officer years of service		1.009	0.987	1.032		0.956	0.923	0.99		1.009	0.98	1.04
N =	1,571				1,571				1,571			
McFadden's Adjusted R-squared =	-0.0005				0.029				0.001			

Appendix D. Resource Guide[59]

EARLY INTERVENTION

24-Hour Crisis Telephone Line

Affiliated Santé Group - Mecklenburg County Crisis (CrySyS)
Amara Wellness
Atrium Behavioral Health
Cardinal Innovations
CTS Health - North Carolina, 24-Hour Behavior Health Hotline
Hope4NC
North Carolina Department of Health and Human Services (NCDHHS)
Safe Alliance

Outpatient Providers/Family & Community Support

100 Black Men of America, Inc
A Fresh Start
Access Family Service Inc.
Alcoholics Anonymous - North Carolina
Alexander Youth Network
Alternative Behavior Strategies (ABS) - North Carolina -
Amara Wellness
Array of Brighter Beginnings
Atrium Health Addiction Services
Atrium Health Substance Use Disorder Treatment
Atrium HealthPsych
Autism Services of Mecklenburg County (ASMC), Inc.
Autism Society of Mecklenburg County
C. W. Williams Community Health Center (CWWCHC)
Cardinal Innovations
Catholic Charities Diocese Of Charlotte
Center for Emotional Health
Charlotte Community Health Clinic
Charlotte Rescue Mission
Christ Centered Community Counseling
Co-Dependents Anonymous - North Carolina
Community Alternatives, Inc.
Depression and Bipolar Support Alliance (DBSA)
Dilworth Center
Emerald School of Excellence
Epiphany Family Services
Eustress, Inc
Family First Community Services
Freedom House Of Mecklenburg
Fresh Start For Men
Gambler's Anonymous - North Carolina

RESPONSE

Mobile Crisis Team

Affiliated Santé Group - Mecklenburg County Crisis (CrySyS)

Crisis Receiving and Stabilization Facilities

Atrium Health
Cardinal Innovations
Monarch Youth Crisis Shelter

Hospital Emergency Department

Atrium Health

In-patient Psychiatric Services

Atrium Health
Novant Health

POSTVENTION

Access Family Service Inc.
Alexander Youth Network
Anuvia Prevention and Recovery Center
Cardinal Innovations
Children's Hope Alliance
Choices for Recovery
Easterseals UCP North Carolina & Virginia
Harmony Recovery Center
Hope Way
Hope Haven Inc.
InnerVision
Legacy Freedom Treatment Centers
Mcleod Addictive Disease Center
Monarch Behavioral Health Services
New Beginning Sanctuary NC
New Beginnings of Southern Piedmont
New Leaf Adolescent Care
One Love Services
Primary Care Solutions
Promise Resource Network
Thompson Child & Family Focus
To Serve With Love Ministries Inc
Turning Point Family Services, Inc.
Youth Villages of Charlotte

PREVENTION

A Roof Above (Men's Shelter)
Autism Services of Mecklenburg County (ASMC), Inc.
Carolina Sober Living
Center for Community Transitions

[59] The time-limited nature of this project did not allow us to speak directly with all of the assets that we mapped, and there may consequentially be mis-categorized or omitted resources

Greater Charlotte Area of Narcotics Anonymous
HopeWay
In The Rooms
Jewish Family Services
KinderMourn
Mcleod Addictive Disease Center
Mecklenburg County Counseling Services
Mélange Health Solutions
Metrolina Intergroup Association
MHA Mental Health Association of Central Carolinas
Monarch Behavioral Health Services
My Meta Re-Entry Services
Narcotics Anonymous (NA) Charlotte Area
National Alliance on Mental Illness (NAMI) - Charlotte
New Beginnings Community Life Center
New Leaf Adolescent Care
North Carolina Treatment Centers
NorthStar Clinical Services
Novant Health
One Love Services
Oxford House
Pathways
Pat's Place Child Advocacy Center
Pfeiffer University
Pinnacle Family Services
Presbyterian Psychological Services
Primary Care Solutions
ProCure Therapeutic Agency, INC
Psychology For All
Quality Comprehensive Health Center
Quit Now North Carolina
RAIN, Inc.
REACH Program and HERO Program
RHA Health Services
S&H Youth and Adult Services (SHYAS)
Safe Alliance
Self Advocates of Mecklenburg Co.
Self Talk Counseling
Sister for Sister Housing Network, Inc
Smith Family Wellness Center (SFWC)
Society for a Second Chance
SPARC Network
The Compassionate Friends
Time Out Youth
Transcend Charlotte

Charlotte Family Housing
Community Link • City of Charlotte
Crisis Assistance Ministries
CrossRoads Corporation for Affordable Housing and Community Development
Davidson Housing Coalition
Freedom House Of Mecklenburg
Fresh Start For Men
Good Fellows Club of Charlotte
Gracious Hands Transitional Housing, House 1
Gracious Hands Transitional Housing, House 2
Habitat for Humanity of the Charlotte Region
Hope House
Hope Vibes
Hoskins Park Ministries
INLIVIAN (Charlotte Housing Authority)
InnerVision - N Tryon Street
My Father's Choice Transitional Housing
New Life House/ Casa de Nueva Vida
Oxford House
Project Outpour
QC Family Tree
Quality Comprehensive Health Center
Salvation Army Center of Hope Shelter
Salvation Army of Greater Charlotte
Sister for Sister Housing Network, Inc
Society for a Second Chance
Start Over
Supportive Housing Communities
The Relatives Inc - Youth Crisis Center
The Relatives, Inc. - Resource Center
Thompson Child & Family Focus
Time Out Youth
Urban League of Central Carolinas
Urban Ministry Center
With Friends Youth Shelter Services Emergency Shelter Program
Women of hope new living
YWCA Central Carolinas - Women in Transition Program

TRANSITION

Cardinal Innovations
Monarch Behavioral Health Services
Promise Resource Network

Appendix E. Job Descriptions

II. CAHOOTS Crisis Counselor Job Description

Pay and Benefits:

$15 per hour while training/Pay increase when fully trained.

Job Description:

Requirements:

1. Currently licensed as an EMT or RN.
2. Ability to work effectively with a diverse population including impoverished and alienated persons.
3. Ability to operate a cell phone and lap-top computer, ability to occasionally lift at least 50 kilograms.
4. Must be able to pass a DHS background check.
5. Current certification in first aid & CPR.
6. A sense of humor.

Responsibilities:

1. Assume primary responsibility for making medical assessments of clients and for providing medical care within the EMT-B scope of practice in accordance with CAHOOTS department protocols and standing orders.
2. Attend required department and clinic meetings and share in other responsibilities as relevant.
3. Complete all required trainings.
4. Complete White Bird's New Volunteer Training within four months of hire.
5. Complete 6-month probation period.
6. Reports to department coordinator.
7. Shared responsibilities for proper staffing and coverage for all reception & crisis shifts, 24 hours a day, 7 days a week, plus working shifts as needed.
8. Liaison with other service providers to coordinate information and service delivery.
9. Assumption of a secondary area of responsibility.
10. Participation in program and clinic responsibilities including crisis business and debriefing meetings.
11. Other duties as assigned.

Expectations:

- Must be available for weekend and overnight shifts.
- Have a telephone and reliable transportation.
- Be a strong team player.

City of Fort Worth, Texas
Job Description

Classification Title	Civilian Response Specialist		
Job Code:	PS5270	Job Family:	Public Safety
Pay Grade	506	Date Reviewed:	08/03/2020
FLSA Status	Non-Exempt	Date Revised:	

GENERAL SUMMARY

Under general supervision, performs various non-emergency duties supporting patrol operations, as well as field support for transporting vehicles and abandoned property, which do not require the exercise of peace officer powers of arrest or firearms within the Police Department's Patrol Operations Bureau.

ESSENTIAL DUTIES & RESPONSIBILITIES

The intent of this job description is to provide a representative summary of the major duties and responsibilities performed by incumbents of this job. Incumbents may be requested to perform job-related tasks other than those specifically presented in this description.

1. Perform a variety of specialized and technical non-sworn law enforcement duties in support of the Police Division including in the areas of patrol, property and evidence, parking, and other areas as assigned.
2. Respond to calls for service in-lieu of a Police Officer; respond to calls including traffic collisions; respond to hazard calls including spills and items in roadway; interview complainants; prepare necessary criminal and non-criminal police reports including traffic, grand/petty theft, ID theft, stolen/recovered vehicles, fraud, lost/stolen property, found property, vandalism/graffiti, and burglary reports.
3. Respond to accidents and conduct accident investigation or assist Police Officer with investigation. Complete accident reports, collect and log evidence as needed.
4. Dictate and/or write reports in reference to investigations; complete evidence voucher for evidence or property collected; book evidence or property into evidence.
5. Provides traffic control including at potentially hazardous situations, traffic accidents, crime scenes, fires, funerals, special events, and during power outages and weather related incidents.
6. Performs vehicle abatement duties, including maintenance of a daily log of activities, determining parking violations and issuing the appropriate citations, arranging for towing of abandoned vehicles and otherwise participating in the vehicle abatement program as directed.
7. Maintain various logs and records; gather information and prepare routine reports as assigned; enter, input, and retrieve a variety of information using a computer terminal.
8. Maintains property and evidence in accordance with prescribed procedures.
9. Testify in court or at hearings regarding case records and investigative activities.

10. Performs other related duties as required.
11. Adheres to assigned work schedule as outlined in the Department and City attendance policies and procedures; ensures all behaviors comply with the City's Personnel Rules and Regulations.

KNOWLEDGE, SKILLS & ABILITIES

- **Knowledge of:**
  - Knowledge of Federal, State, and City laws and statues.
  - Modern office procedures, methods and computer equipment.
  - Principles and procedures of record keeping.
  - Pertinent federal, state and local laws and ordinances.
  - Police Information Mining Portal.
  - General Orders for Fort Worth Police Department.
- **Skill in:**
  - Planning and prioritizing.
  - Observation and decision-making.
  - Organization, time management, and multi-tasking.
  - Customer Service.
  - Attention to detail.
  - Critical Thinking and Problem Solving.
  - Communicating in both written and verbal form.
- **Ability to:**
  - Communicate clearly and effectively, both orally and in writing.
  - Memorize and retain information.
  - Interact and communicate with others in an assertive manner.
  - Learn the geography and surrounding area of the City.
  - Learn to interpret City maps and geographical locations.
  - Respond to emergency and non-emergency situations from the general public.
  - Establish and maintain effective working relationships.

MINIMUM JOB REQUIREMENTS

High school diploma/GED and no previous experience required.

OTHER REQUIREMENTS

Must meet TCOLE and CJIS requirements.

Valid Texas Driver's License.

WORKING CONDITIONS

The work environment characteristics described here are representative of those an employee encounters while performing the essential functions of this job. Reasonable accommodations may be made to enable individuals with disabilities to perform the essential functions.

Depending on assignment, positions in this class typically require touching, talking, hearing, seeing, grasping, standing, stooping, kneeling, crouching, reaching, walking, repetitive motions, climbing, balancing, pushing, pulling and lifting; depending on assignment. Incumbents may be exposed to moving mechanical parts, odors, dusts, poor ventilation, chemicals, oils, extreme temperatures, inadequate lighting, intense noises, gases, vibrations, chemicals, oils and workspace restrictions.

PHYSICAL DEMANDS

The physical demands described here are representative of those that must be met by an employee to successfully perform the essential functions of this job. Reasonable accommodations may be made to enable individuals with disabilities to perform the essential functions.

Medium work – Depending on assignment, positions in this class typically exert up to 50 pounds of force occasionally, up to 20 pounds of force frequently, and/or up to 20 pounds of force constantly having to move objects.

Page **3** of **3**

(City of Fort Worth, 2020)