SHOULD WE “DEFUND THE POLICE”

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ABSTRACT

The civil unrest of 2020 culminated in numerous American cities pledging to "defund the police." At the behest of civil rights activists, these cities pledged to reallocate funding from municipal police departments into community outreach programs. This will be done with the hope of reducing both crime and incidents of police use of force. Many critics believe the policy will only result in higher rates of crime. I collected and observed ten years of panel data across twenty American cities to determine which policy pathway should be followed. I analyzed the breakdown of budgets for police and outreach spending and used multiple fixed effects models to see how they correlate with crime statistics and recorded incidents of fatal police shootings. I concluded that there are marginal benefits to funding police departments over outreach as a means to reduce crime. However, funding outreach over police departments has a greater effect on reducing officer involved shootings. Defunding the police therefore creates only tradeoffs that are not easily measured and compared.

ACKNOWLEDGEMENTS

The writing of this thesis is dedicated
to my family, my advisor: Andrew Wise, and to those whose research on
this important topic made my work possible.

Many Thanks,
John Bernier

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I. INTRODUCTION

On May 25, 2020, Minneapolis resident George Floyd, while unarmed and in custody, joined an ever-growing list of preventable police fatalities after his neck was compressed by a police officer's knee for over eight minutes. The civic unrest that followed has cost billions of dollars in damage across American cities, resulted in at least nineteen deaths, and led to more than 15,000 arrests. Even worse was the incalculable damage to the stability, morale, and international reputation of the United States. This public turmoil is the culmination of decades of mistrust directed against police departments and their perceived lack of accountability. This confrontation is now not only taking place in the city streets of America, but in the city halls of the policy world as well.

Leaders, activists, and policymakers across the United States have directed this social outrage into a call to "defund the police." While the idea initially sounds drastic, its proponents insist that the slogan is actually a rallying shorthand for a more nuanced series of policy proposals. "Defunding the police" is actually focused on redirecting police department funding into other institutions controlled by local municipalities. This can mean investing in alternative government agencies, social workers, and violence-prevention programs. Theoretically, this approach would lead to a reduction in potential police interactions as well as significantly improving local communities—particularly communities of color. In this thesis, I examined whether this claim holds true. Such a hypothesis must analyze a diverse field of data to reach any meaningful conclusion. If America is to move forward with "defunding the police," and invoke all the policy objectives entailed, it is critical to evaluate just how successful the results would ultimately be.

This thesis specifically sought to determine if:

H_1: A city that prioritizes alternative crime-prevention programs over police funding will have a negative, statistically significant relationship with both preventable police use of force and crime.

This hypothesis is multifaceted. It requires that I analyze two different policy objectives and their independent effects on two different outcomes. It may be easier to visualize this hypothesis as four separate but related questions:

1: Will reducing police budgets reduce rates of crime?

2: Will reducing police budgets reduce police use of force?

3: Will funding community outreach programs reduce rates of crime?

4: Will funding community outreach programs reduce police use of force?

I confirmed that statistical significance did exist in all four relationships. My regressions inferred their direction and magnitude with enough certainty to support meaningful policy recommendations. Both social outreach funding and police department funding were measured in dollars as budgetary spending from each city's general fund. Violent crime and police use of excessive force can tentatively be measured in dollars as well (cost of investigations, loss of revenue, property values, city settlements), but will come with additional negative externalities that can be challenging to accurately measure. These can include a loss of public trust, reduced cooperation with law enforcement, and even irreversible damage to the collective mental health of local communities.[1] Therefore, I concluded that there will never be a calculable monetary number to justify defunding the police, but rather a series of tradeoffs to be discussed and prioritized by the affected communities.

[1] Bor, 2018.

In Section II, this thesis delves into the important questions about how to define the relevant policies. It is critical to distinguish how cuts to a police budget would ultimately manifest. Defunding departments can lead to a reduction in officers, pensions, training, and/or equipment—all of which will result in different outcomes. Another significant factor will be to determine where this new revenue will go. Advocates for the "defund the police" movement have suggested financing social services to tackle mental health problems, homelessness, and drug addiction. This approach provides care to socially stigmatized people, reducing their chances of committing crimes and therefore the need for police to intervene and potentially escalate the situation.[2] Fewer calls for the police would allow officers to prioritize tasks they are better suited to handle. Since there is no "one-size-fits-all" social outreach program, I chose to analyze several.

In Section III, I develop the theoretical framework to measure the effects of the policy proposals on the socially desired outcomes. Here is where I break down all the aspects of my fixed effects model. Section IV features the pertinent data and descriptive statistics that determine how my model will be assembled. This is where I reveal how the variables are defined, measured, and compared. In Section V, I back up these data with empirical evidence to create the exact set of equations needed to study the relationship between budgets, crime, and police use of force. Additionally, I discuss the outcomes that I expect my regressions will yield. In Section VI, I display the actual results of the regressions, and what I can determine from those outcomes. All of this culminates in the conclusion in Section VII, where I propose policy suggestions based on my results.

[2] Campbell, 2017.

II. LITERATURE REVIEW

BACKGROUND

The United States is remarkably divided when determining exactly what responsibilities police departments should have. Our society expects them to be soldiers, first responders, social workers, and mental health experts. They must be able to de-escalate any situation, react to danger with no warning, and know exactly how much force to appropriately use in life-or-death encounters. On average they receive forty-five thousand dollars a year, and only thirteen to nineteen weeks of training. These low parameters and high expectations are what set many police officers up for failure. Additionally, many officers are pressured to make unnecessary confrontations with the civilian population to generate additional revenue for their cities. Their work hours are long, their pay is low, and their jobs can be stressful, traumatic, and often thankless. It should not be surprising when police officers develop an "us versus them" mentality against the very people they are meant to serve.

Fatal police incidents are an unfortunate epidemic in the United States.[3] In 2017, 1,147 people were killed in police interactions, 92% of which were by firearm. It is certainly worthwhile to analyze how justified each lethal interaction was, but there is evidence to suggest that the majority of these deaths were preventable. Most of these shootings were the outcome of situations where police officers responded to a suspected non-violent offense, traffic violation, or even while interacting with someone when no crime had even been reported. 149 of these people were unarmed when they were killed, the majority of whom were African American.[4]

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[3] Shane, 2020.
[4] McPhillips, 2020.

How police officers are trained to respond to situations should be re-evaluated. When studying the 170 fatal incidents involving suspects armed with just a knife in 2017, police only attempted non-lethal force in 53 of them. Countries like the United Kingdom experience knife violence at similar rates to the United States but are able to disarm suspects without killing them in nearly every instance. These de-escalation tactics are not only part of their official police policies but are embedded in the county's laws themselves.

In America, new police officers spend seven hours training with firearms for every hour spent training how to de-escalate the kinds of situations they are far more likely to experience. More disturbing is the fact that ninety-six people in 2017 were killed when police officers shot at their moving vehicle, a tactic that the Department of Justice suggested should be banned.[5] Since each police encounter has the potential to end violently, policymakers of the "defund the police" movement seek ways to prevent unnecessary police encounters from ever having to take place.

Serious threats to public safety like murder, assault, and rape make up only five percent of the over ten million arrests made each year.[6] The remaining ninety-five percent contains arrests for traffic violations, drug possession, prostitution, and other activities that are simply not worth potentially escalating into life-and-death situations. Alternative government social programs may be what are needed to address and prevent these minor crimes, thus freeing up police time and resources to focus on unpreventable violent crimes. Such policies would additionally reduce unnecessary police and civilian interactions and even halt the ever-increasing levels of mass incarceration.

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[5] Mapping Police Violence, 2018.
[6] Fernandez, 2020.

CITIES RESPONDING

Numerous American cities have pledged to embrace the "defund the police" proposals in response to the explosive public tensions of 2020. Many of these cities have faced the destructive rioting firsthand. I analyzed twenty of these cities: Albuquerque, Austin, Baltimore, Boston, Buffalo, Cincinnati, Dallas, Denver, Indianapolis, Kansas City, Memphis, Minneapolis, New Orleans, Orlando, Philadelphia, Portland, San Diego, Seattle, Tucson, and Washington D.C. These cities are geographically diverse, yet similar in population, total budgets, and crime rates. There is also a wide range in the levels of police use of force, as seen in Figures 1 and 2.[7] Black and Hispanic people make up a disproportionally large percentage of the deaths in these figures.

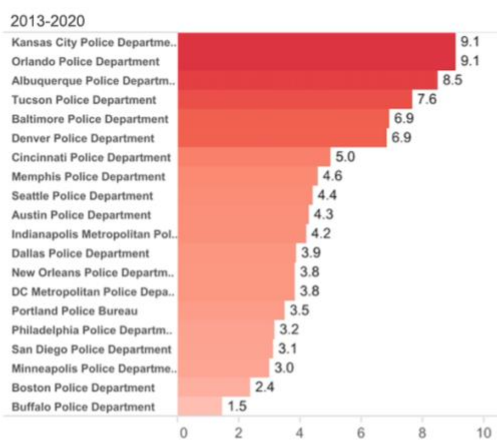

Figure 1. Police Killings per Capita

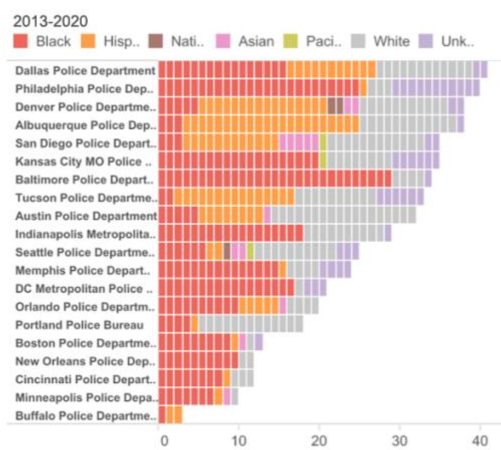

Figure 2. Police Killings by Ethnicity

There are differences in the levels of defunding commitment from each city, which may yield very different results in their upcoming budgets. Austin's proposed cuts would slash one third of its police department, whereas most of the remaining cities have pledged to redirect between one and seventeen percent of their police budget into alternative government programs.[8]

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[7] Mapping Police Violence, 2021.
[8] McEvoy, 2020.

Figure 3 demonstrates that national public spending on "Law and Order," or policing, prisons, and courts, is double that of welfare programs like Temporary Assistance for Needy Families (TANF), food stamps, and supplemental social security.[9] This trend is relatively recent, having only developed over the last few decades in response to the War on Drugs. Activists suggest that this ratio can be returned to their 1970's levels.

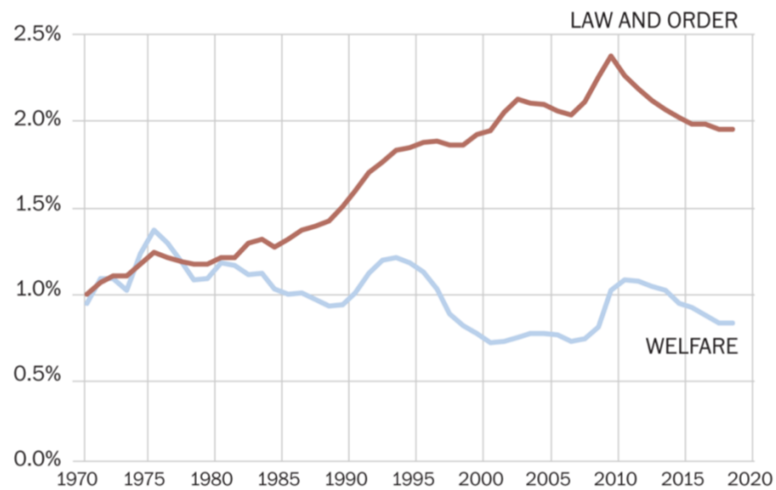

Figure 3. Law and Order vs. Social Welfare

The specifics of these budgetary re-allocations are still to be confirmed, but the current working proposals would redirect the majority of these pledged police department funds to mental health, addiction, and homelessness initiatives within impoverished communities, as well as support new economic opportunities, education resources, and youth development programs. Furthermore, they seek to replace police officers with social workers to be the primary first responders to all noncriminal reports regarding the homeless and those with mental illnesses.[10] Communities of color would take priority in many of these allocations.

[9] Ingraham, 2020.
[10] Green, 2020.

POLICE FUNDING

Reducing the presence of police may logically reduce their interactions with the public the same way removing cars from a highway may reduce vehicle collisions. Fewer opportunities beget fewer negative outcomes. However, my hypothesis requires the reduction of crime as well. Many studies have observed the causal relationship between police presence and lower rates of crime. The American Recovery and Reinvestment Act of 2009 allotted nearly one billion dollars in increased funding for the Community Oriented Policing Services (COPS) program. The money was spent exclusively on increasing the size of local police departments. Studies determined that each additional police officer was able to prevent four additional violent crimes and fifteen additional property crimes.

The measured social value of each new police officer exceeded $300,000.[11] If reduced police funding resulted in fewer available officers, one could deduce that it would also result in an increase in crime. Many studies appear to support this.[12] An American city's average annual cost for a single police officer is nearly $150,000. Additional data conclude that each dollar invested in policing yields a social return of $1.63.[13] To justify investing police money into a government crime prevention program, it would need to at least match that return. My policy recommendations are ultimately based on which type of spending yields a more optimal outcome, although I am wary of ascribing a numeric value to measure concepts like utility. Such methods inevitably miss many factors, specifically in minority communities.[14]

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[11] Mellow, 2019.
[12] Di Tella, 2004.
[13] Chalfin, 2018.
[14] Schwartz, 2020.

It may seem intuitive that reducing police department personnel would at least reduce opportunities for police use of force to occur. That theory relies on assumptions regarding how this reduction takes place. In 2008, Vallejo, California made drastic cuts to its police budget. It is important to note that this change was made not out of a desire to reform the department, but due to major budgetary deficit issues resulting from the collapse of the American housing market. The result was a police department that was overworked, underpaid, and ultimately unqualified. As experienced officers left the force, their replacements were inevitably rushed through their training and were forced to serve with less pay and more dangerous working conditions.[15] The result was a remarkable increase in both crime and police violence.

There are stories of this policy initiative that do end in success. The city of Camden, New Jersey disbanded its entire police force in 2013 after years of high crime rates and complaints against the department. Officers were required to reapply for a new, smaller, and more accountable police department controlled by the community. The result was a successful reform that reduced both police use of force and crime in Camden.[16] The city has since lost its ranking as the most dangerous in America.

More public trust in police forces will also result in more cooperation between the community and the officers. Having the right rationale behind defunding the police is an important factor to the success of its implementation. Where the money comes from, and where it is spent will make the difference between success and failure. The largest reason for Camden's outcome, was its prioritization of police accountability.

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[15] Jamison 2020.

[16] Landergan, 2020.

POLICE ACCOUNTABILITY

Funding a sufficient number of police officers is critical for the safety and stability of any city. It is just as important to ensure their accountability to the public. Studies have documented the tradeoff between police oversight and effective policing throughout periods of intense public scrutiny following department scandals. These incidents and the reforms that inevitably followed often served to increase self-monitoring among police officers to protect against further accusations of misconduct.[17] However, a reduction of police use of force is not automatically correlated with more optimal outcomes.

Policy proposals intended to improve police accountability have often resulted in some surprisingly negative drawbacks. In 2001, an officer involved shooting of an unarmed black teenager in Cincinnati yielded violent rioting that drew national attention. In response, the Department of Justice increased the expected penalties for officer related misconduct. In the months that followed, the total number of arrests dropped substantially in proportion to the number of crimes committed. This predictably resulted in a massive surge of felony crime across American cities.[18]

Programs that deal with police accountability must make certain that officers are not just avoiding necessary confrontations out of fear of reprisal. American cities must strike a delicate balance of holding police officers and their departments accountable without making it too risky for them to do their jobs. This will require policies that accomplish more than simply raising penalties for officers that lack the necessary training.

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[17] Rivera, 2019.

[18] Shi, 2019.

Many potential riots have likely been avoided in recent years due to police department policies that require the release of body-camera footage to the public within twenty-four hours of a deadly officer involved shooting. The Spokane Police Department studied the effects of implementing these cameras in 2015 and found that complaints against officers were reduced by 78% and that officer use of force decreased by 39%.[19] Although these effects aren't replicated in every city the programs were tried in, Figure 4 shows another positive outcome in Rialto, CA.[20]

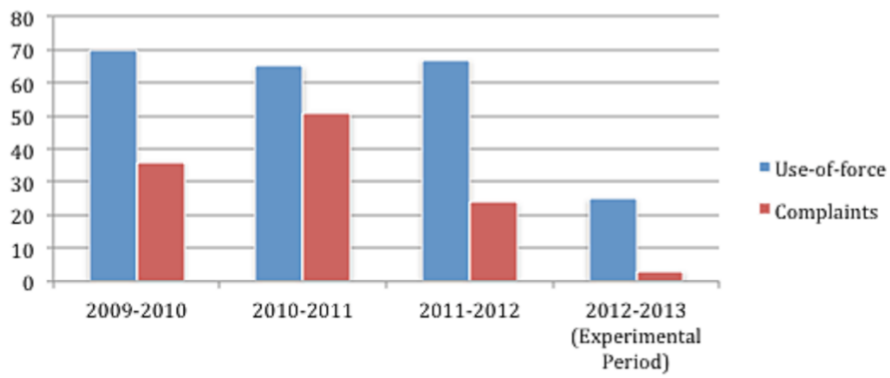

Figure 4. Effect of Police Body Cameras in Rialto, CA

Employing these cameras has potential for reducing police violence, but the program is expensive. The initial up-front price of each camera is only $200, but the real costs lie with their operation, maintenance, and video storage. When comparing the costs associated with citizen complaints against police departments versus the price of equipping officers with body-cameras, investing in the cameras actually saves four dollars for every dollar spent.[21] If defunding the police were to cut programs like this it could risk a cascade of wasting even more police budget dollars. This would not only result in greater levels of crime, but also police use of force.

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[19] White, 2018.
[20] Feeney, 2015.
[21] Police Executive Research Forum, 2018.

SOCIAL OUTREACH PROGRAMS

I studied a variety of alternative government programs designed to reduce levels of crime without police intervention. There is no single program to solve all of society's issues, but there are ways to target programs towards the demographics that will best respond. For instance, young children and toddlers react most effectively to pre-school programs that include weekly home visits by their teachers. For delinquent or at-risk youths, family support has always brought about the greatest breakthroughs. These policies revolve around family member therapy and parent training. For children still attending school, the most effective programs allow for teachers to focus on teaching life skills along with their usual coursework. This includes teaching critical thinking, social competency skills, and organizational development, which requires clear and constant reinforcement.[22]

Effective policies are not limited to only children and students. Many older, previous offenders were the most receptive to vocational training, nuisance abatement actions, and other drug treatment and rehabilitation programs. Additionally, people with mental illnesses stand to benefit not only from social programs, but from reducing any potential confrontations with law enforcement. In 2015, twenty-three percent of people killed in police interactions displayed symptoms of a mental illness.[23] Many of these people were killed in their home and were not brandishing a weapon. Taking all of this into consideration, my final cost-benefit analysis will derive the social and monetary values of investing in community outreach and compare them with the aforementioned established benefits of a properly funded police department.

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[22] Sherman, 1998.
[23] Saleh, 2018.

MY OUTLOOK

This is an understandably controversial issue. My thesis references numerous criticisms of the American policing system, not to disparage the officers who serve, but to address important societal issues from a policy perspective. Police officers deserve adequate training and funding and should be used only for situations they are qualified to handle. Failing to meet these requirements endangers both police officers and the members of their communities. With the "defund the police" movement taking up so much public attention, it is certainly worthwhile to analyze their claims, regardless of the final outcome.

I can do my best to quantitatively measure the variables in terms of social utility, but it will not be possible to assign a number to the worth of a human life, to accurately measure the public's trust in its city, or to anticipate the damages of a future riot. There are too many additional externalities to consider, and these externalities manifest differently across racial and socio-economic groups. Measuring only averages can miss how certain communities are hit harder by crime and fatal police interactions than others.[24]

Ultimately, reducing police department funding will run numerous risks for increasing both violent crime and police use of force. The proposed alternative government programs should intuitively counter some of these risks. Based off my regressions, I make recommendations for the optimal spending ratios for police departments and community outreach programs to yield a socially positive outcome regarding both police use of force and violent crime. These findings will determine my policy recommendations in Section VII.

[24] Edwards, 2019.

III. THEORETICAL FRAMEWORK

For this thesis, I developed a fixed effects model using panel data of my twenty observed cities over ten-year period. For each year and in each city, I analyzed the relationship of per capita spending on police and social programs to determine if they have a statistically significant relationship with crime rates and fatal police shootings. The two theoretical frameworks can be displayed by the following equations:

(1) $C = f(P, O, \alpha, \gamma, \mu)$

(2) $S = f(P, O, \alpha, \gamma, \mu)$

C represents violent crime, and S represents the fatal police shooting variable. P is police spending, and O is outreach spending. α is the city fixed effects, γ is the time fixed effects, and μ is the error term. I anticipated that both outreach and police spending would affect the dependent variables and predicted their directions and magnitude in Section V. Adjusting this ratio of spending will have either a positive or negative effect on the levels of crime and police shootings, allowing me to determine the optimal future budgets. By calculating how much money (if any) should be reallocated from the police budget into alternative programs, I can finally predict the levels of success facing each city with their 2021 "defund the police" goals.

Beyond the measured social utility of these policies, experts believe that "defunding the police" will have drastic positive effects on communities of color, especially concerning their collective mental health. Since factors like this cannot easily be numerically quantified, I predicted that defunding the police will ultimately need to be viewed as a series of tradeoffs between different options and outcomes. That decision will ultimately come down to what the policymakers of these cities believe is best for their constituents.

IV. DATA AND DESCRIPTIVE STATISTICS

My collection began with open-source data documenting my twenty observed cities. This involved breaking down yearly budgets, databases of reported crimes, and statistics regarding fatal police shootings. The data I observed include records over a ten-year period, from 2010 to 2019. 2020 was not included due to a lack of available data and the unpredictable effects of the global COVID-19 pandemic. City population levels changed enough over time that they were included within the panel data, while other more stagnant city characteristics were simply held constant via my fixed effects model. With ten years of data on each city, I was able to show how the budgetary breakdowns relate to statistics like violent crime and fatal police shootings.

Table 1 displays the ranges of my measured variables. Despite collecting vast amounts of demographic data, I ultimately only used the variables that improved the statistical significance of the model. These included the total population of each city, the percentage made up by people of color, the percentage made up by African Americans, the median income, and a dummy variable tracking which cities recorded incidents of police use of force.

Table 1. Descriptive Statistics

Variable	Mean	Standard Deviation	Min	Max
% POC	0.55	0.12	0.27	0.76
% Black	0.29	0.20	0.04	0.67
Median Income	50574.71	14497.39	28490	102486
Population	685625	352334	239037	1584138
Total Budget	2579677497	2396920905	571798269	13718872000
Police Budget	275137355	154345324	76400508	753673455
Outreach Budget	46961990	93463714	1307514	564252797
Violent Crimes	6188	3637	680	18535
Fatal Police Shooting	3.5	2.647	0	11
Record Police Use of Force	0.3	0.431	0	1

All these demographic variables were compiled into a master table that could be regressed in STATA. For each observed city, the ten years of panel data resemble the Seattle Composite Data example displayed in Table 2:

Table 2. Seattle Composite Data (2010-2019)

Seattle Panel Data										
Year	% POC	% Black	Median Income	Total Population	Total Budget	Police Budget	Outreach Budget	Violent Crimes	Fatal Police Shooting	Record Use of Force
2010	33.9%	9.3%	60,212	610,710	3,856,255,000	252,758,404	121,566,494	3,515	3	0
2011	34.1%	8.9%	61,037	620,778	3,921,908,000	259,255,489	117,754,888	3,664	1	0
2012	34.8%	8.8%	64,473	634,541	4,215,119,000	269,618,084	111,588,377	3,782	1	0
2013	33.0%	9.3%	70,172	652,429	4,381,523,000	295,118,827	118,152,520	3,760	7	0
2014	33.8%	8.8%	70,975	668,337	4,381,523,000	305,690,186	128,186,349	4,005	7	1
2015	34.0%	9.1%	80,349	684,443	4,733,522,000	294,028,062	126,757,359	4,090	2	1
2016	35.7%	9.4%	83,476	704,358	5,050,582,000	322,340,188	147,946,193	4,301	2	1
2017	36.0%	9.0%	86,822	724,764	5,396,154,000	320,568,110	158,458,146	4,649	3	1
2018	37.0%	8.9%	93,481	744,949	5,519,790,000	394,845,378	183,214,805	5,228	2	1
2019	37.2%	9.2%	102,486	753,655	5,807,229,000	398,769,531	199,569,781	4,722	2	1

City budgets were collected from official city open data portals, where they were divided into subcategories and compared. I used records of actual money spent per department, rather than what funding was originally proposed. These major category breakdowns were for spending on police departments and spending on social development and outreach. Each city categorized these groups differently, so comparing them accurately was difficult.

Police spending included all budgetary funding devoted to department maintenance, administration, investigations, and operations. I included police relief and pensions as well, because many policymakers have suggested targeting these budgetary departments for funding reallocation. Some cities also had community policing programs listed in their general funds, which I included in their police budgets instead of their outreach budgets.

The category of alternative government programs was more challenging to define. Most cities categorize "outreach" under departments like Health & Human Services, which contains a variety of programs like community-based family support, homelessness intervention, youth services, and accessible health care. Due to the diverse range of programs, I selected those most similar to the ones regularly outlined by the "defund the police" movement's policy objectives. Additionally, these are the types of programs that are expecting proportionally increased funding in many of these cities' budgets for 2021 and 2022.

Certain educational programs like pre-kindergarten funding can have effects such as providing child-care relief to working parents. Education expenses also include many additional programs focused on early learning readiness, family support and involvement, support for at-risk students, and youth violence initiative programs. Many of these programs mirror the ones proposed by the "defund the police" community activists and are therefore included in this model. Education spending as a whole was difficult to pin down, as many cities relied on state and federal dollars not included in their general fund's proposed budgets.

Police use of force was a difficult statistic to track. The incidents should be defined as any actions taken by a police officer that escalates situations to potentially lethal outcomes.[25] Although shootings make up the majority of police killings, policymakers are aiming to reduce all reported incidences of measurable police brutality. This would consider any use of force that is expected to cause substantial bodily harm, loss of consciousness, or death. This includes choke holds, impact weapon strikes to the head, and discharging a firearm.[26]

[25] Finch, 2019.
[26] Conner, 2019.

Within the various Uniformed Crime Report datasets, records of police violence could be classified as a use of force or a shooting, justified or unjustified, and lethal or survivable. Certain datasets recorded if officers acted in accordance with their official department policies and whether or not they faced legal consequences for their actions. Many statistics also revealed the correlation between incidents of police use of force and the race of the victims. As useful as all these data were, I was faced with the reality that very few cities actually record them consistently. The FBI only began tracking police violence in 2019, which does not produce enough information to be useful to my fixed effects model. Due to this limitation, I had to reduce the scope of my police use of force variable to the data that was available.

It should not matter to my model whether the incident of police violence resulted in the death of its recipient. It is more important to record whether lethal levels of force were used. Every shooting or beating has the potential to kill a suspect and random chance is too often the only deciding factor. Recent incidents like the shooting of Jacob Blake in Kenosha, Wisconsin, show that the victim does not have to die for riots to erupt and social cohesion to dissolve. This has been the case for many nonlethal incidents of police violence going back decades, as seen in 1991 Los Angeles, following the infamous arrest and beating of Rodney King.

In creating my variable, I also avoided trying to determine whether the use of force was justified or not. There are many cases where a police officer is faced with a mentally ill offender armed with a knife. This scenario often ends with the death of the suspect. By all metrics, such a killing would be categorized as a justified use of force, and no police officer should be expected to risk bodily harm in a such a dangerous situation. My argument here is that although many of these killings are justifiable, they are also preventable.

The suggested “defund the police” policy proposals seek to avoid confrontations like this entirely by ensuring adequate resources are available to mentally ill people before their conditions place them into violent situations. In large cities, there will always be some level of unavoidable police use of force. My regression model was built to filter out the incidents that can be stopped. Additionally, in today’s tense political climate, completely justifiable shootings can result in riots regardless of the context. My scenario of a police officer fatally shooting a mentally ill man who was lunging with a knife played out in Lancaster, Pennsylvania in September of 2020. The officer acted quickly and rationally in accordance with his department rules of conduct. Regardless of these facts, protests and riots were still underway within the hour.

My police use of force variable was ultimately limited by the data to which I had access. Very few cities measured police violence across my ten-year window. I was able to locate some information on all fatal police incidents across cities as well as some information on all police shootings. Combining these two datasets, I was able to map all fatal police shootings for each city between 2010 and 2019. This resulted in a much lower number of total observations, and thus potentially less accurate results.

Crimes are another significant category for my model. I observed the recorded incidents of crime for each city and divided them into two categories, violent and nonviolent. Violent crimes include all city-wide reported incidents of homicide, rape, robbery, and aggravated assault, as tracked by the National Incident-Based Reporting System (NIBRS) of the Federal Bureau of Investigation. Nonviolent crimes include property crimes, burglary, arson, larceny theft, and motor vehicle theft.

I thought it was important to distinguish these differences. Both categories have an overall financial social cost, but violent crimes contain numerous extra negative externalities to the communities affected. Additionally, many of those hoping to defund the police still see the value of officers responding to violent crime, while seeking to reduce police interaction with those committing nonviolent crimes. The final fixed effects model observed how police and outreach funding will reduce violent crimes.

Having ten years of information for each city allowed me to hold constant many additional points of data that were too challenging to measure. Variables like geographical region, cultural history, weather, average temperature, and median age can all have indirect effects on crime rates. However, these variables did not change much over the ten-year observation period and were thus held fixed within my model. Larger trends such as national crime rates, economic recessions, and periods of social unrest were held constant by time fixed effects. My model attempted to control for all city characteristics fixed over time, all time-varying characteristics fixed across cities, and any other time-varying covariates that had been included in this regression. While population levels are typically similar over time, there was enough variation to be included individually by year.

The ten years from 2010 to 2019 reflect the United States' gradual recovery from the housing market crash of 2008. I observed that demographic traits such as median household incomes, employment rates, high school graduation rates, and poverty levels all systematically improved over this time. Crime rates, budgetary spending, and populations still varied across cities. Racial demographics were also tracked, to observe their specific relationships with police encounters and the American justice system.

V. EMPIRICAL MODEL

REGRESSION METHODOLOGY

My fixed effects model used panel data from twenty observed cities over the course of a decade (2010-2019). There are two hundred such observations, measured in city-years. I have incorporated individual regressions to analyze four different relationships. The first regression determines the correlation between budgetary spending on police departments and the annual number of violent crimes. The second displays the relationship between police department spending and the annual number of fatal police officer involved shootings. The third regression observes the relationship between community outreach spending and the yearly violent crime rate. The final regression looks at the relationship between that outreach spending and lethal officer involved shootings. The equations are as follows:

Police Spending

(3) **ViolentCrimes** = $\beta_0 + \beta_1 PoliceBudgetCapita + \beta_2 Black + \beta_3 MedIncome + \alpha + \gamma + \mu$

(4) **PoliceKillingbyFirearm** = $\beta_0 + \beta_1 PoliceBudget + \beta_2 Black + \beta_3\ TotalPopulation + \beta_4 RecordPoliceViolence + \alpha + \gamma + \mu$

Outreach Spending

(5) **ViolentCrimes** = $\beta_0 + \beta_1 OutreachBudgetCapita + \alpha + \gamma + \mu$

(6) **PoliceKillingbyFirearm** = $\beta_0 + \beta_1 OutreachBudget + \beta_2 POC + \beta_3 TotalPopulation + \beta_4 RecordPoliceViolence + \alpha + \gamma + \mu$

As mentioned in Section III, the alpha (α) represents the city fixed effects, and the gamma (γ) represents the time fixed effects. The mu (μ) term represents the error, which contains all other factors relevant to the dependent variable that could not be measured in the model.

EXPECTATIONS

Table 3. Variable Definitions for Equations 3 and 4

	Variable	Description
Y_1	ViolentCrimes	Total number of violent crimes per capita
Y_2	PoliceKillingbyFirearm	Number of people killed in officer involved shootings
X_1	PoliceBudgetCapita	City's police department spending per person
X_2	PoliceBudget	Actual expenditures for the city's police department
X_3	Black	% of the population that identifies as African American
X_4	TotalPopulation	Total city population (non-metro)
X_5	MedIncome	Median household income (measured in thousands)
X_6	RecordPoliceViolence	Dummy set to 1 if city tracks police violence

My expectation was to discover a positive relationship between the amount of money spent on a city's police department per capita and the number of violent crimes that city reports in a year. This relationship would presumably be causal. In the general fund breakdown of each city, increases in police spending usually resulted in additional police officers. As mentioned in Section II, numerous external studies have proven the link between an increase in police officers and lower rates of crime.

I predicted an unfortunately positive correlation between the African American percentage of the population and the crime variable, based off the FBI incident reporting data. I included this variable due to the disproportionate level of police use of force faced by the African American community. I expected that this demographic variable would be positively correlated with the fatal police shooting variable as well. The "Defund the Police" policies have largely been adopted by activist groups like Black Lives Matter, who frequently cite the adversarial relationship between police officers and Black communities.

I included the median household income variable to factor economics into the model. The relationship between crime and income should predictively be negative. All the cities that I observed had a steadily growing household income, as they recovered from the economic collapse of 2008. These recovery rates may be different enough between cities to not fully be covered by time fixed effects and were therefore held constant in the regression.

The sign of equation four is more challenging to assume. I predicted that the relationship between police funding and police shootings would be positive. More officers may create more opportunities for officer involved shootings. However, if higher police spending is allocated properly into bodycams and de-escalation training, the relationship sign would likely flip. Whatever the sign and magnitude reveal about the relationship, there may still be issues regarding the accuracy of the regression, simply due to the small pool of data. With only a handful of police shootings per year, it is hard to attribute a single extra fatality to additional police spending. For this reason, the variables were measured with actual numbers instead of per capita. I also included the total population as an independent variable to account for this.

Ideally, a variable measuring all incidents of police use of force would be better than fatal police shootings to regress with police spending. Unfortunately, very few cities actually tracked this information. For the cities that did publicize their rates of police use of force, I created a dummy variable. Perhaps cities that properly record such incidents will have already prioritized reducing them. I therefore anticipated a negative relationship between the *RecordPoliceViolence* variable and rates of fatal police shootings.

Table 4. Variable Definitions for Equations 5 and 6

	Variable	Description
Y_1	ViolentCrimes	Total number of violent crimes per capita
Y_2	PoliceKillingbyFirearm	Number of people killed in officer involved shootings
X_1	OutreachBudgetCapita	City's outreach spending per person
X_2	OutreachBudget	Actual expenditures for the city's outreach spending
X_3	POC	% of the population that is not white(non-Hispanic)
X_4	TotalPopulation	Total city population (non-metro)
X_5	RecordPoliceViolence	Dummy set to 1 if city tracks police violence

I predicted there would be a negative relationship between the amount of money spent on community outreach per capita, and the number of violent crimes reported in a year. The sign would be the same as with police spending, but the magnitude may be smaller. The effect of police presence can quickly turn around crime rates, whereas outreach spending may take longer for the investment to pay off. This difference may create some additional bias in my model.

Unlike police departments, there are no city budget sections dedicated to "social outreach." Instead, there are numerous different departments, programs, and services that fill this role. These areas included spending for community development, human services, homelessness initiatives, and youth programs that varied across cities and were sometimes inconsistent between years of the same city. With this in mind, there were many difficulties in accurately comparing city outreach budgets with one another. My measurements were mostly consistent within each city across the ten-year time span, which will correct some of this bias via fixed effects. In every observed city, outreach spending was significantly lower than police spending, and made up roughly between one and ten percent of the overall budget. Police spending was typically between ten and twenty percent.

The final equation (Equation 6) shows the relationship between fatal police shootings and outreach spending. I expected this to be negative, due to the amount of potential violent confrontations that can be avoided when people (especially those with a mental illness) have access to the resources they need. The amount of inconsistency between city outreach spending, and the low number of fatal police shooting observations may make this outcome less reliable than the others. For this equation, the total outreach budget was once again used instead of the per capita variable. Total population was included and should be positively correlated with police shootings. I also anticipated that the *RecordPoliceViolence* variable would be negatively correlated with police shootings, as it was in Equation 4.

I once again included a racial demographic variable to factor in how these issues affect certain communities differently. Rather than measuring the population percentage of African Americans, I measured the percentage of People of Color (POC), or all people that do not identify as non-Hispanic white. There are a few reasons for this distinction. With only two hundred total observations, achieving statistical significance proved challenging for all of my equations. Ideally, all four of them would hold constant the same dependent variables. However, each minor change to the equation would drastically alter my results.

Ultimately, the variables chosen were the ones that provided the greatest statistical significance in the regression outcomes. In this case, the *POC* variable worked while *Black* did not. Many Western American cities had minuscule African American populations compared to Hispanic populations, meaning the POC variable worked better. Since police rates of violence are disproportionately high for the Hispanic community, I believe tracking all "People of Color" is still relevant to the greater policy question.

VI. RESULTS

EQUATIONS 3 AND 4

Table 5. Effect of Police Spending on Violent Crime Rates and Fatal Police Shootings

Independent Variables	DV: Violent Crimes	DV: Fatal Police Shootings	Explanation of cells in model
Police Budget Capita	0.0000105***		Regression Coefficient for x_1
(per capita)	*0.00000299*		*Standard Error*
Police Budget		-0.0120*	Regression Coefficient for x_2
(millions of dollars)		*0.0071*	*Standard Error*
Black Population	0.0334***	28.4520*	Regression Coefficient for x_3
(percent of population)	*0.0108*	*16.6564*	*Standard Error*
Total Population		0.0068	Regression Coefficient for x_4
(thousands of people)		*0.0079*	*Standard Error*
Median Income	-0.0000791***		Regression Coefficient for x_5
(thousands of dollars)	*0.0000281*		*Standard Error*
Record Police Violence		-0.5055	Regression Coefficient for x_6
(dummy variable)		*0.7218*	*Standard Error*
Constant	0.000997	-7.4375	Constant (y-intercept)
	0.0038	*6.8557*	
n	200	200	Sample Size
Adj. R^2	0.0923	0.1104	Adjusted R2

*Note: Cells in this table are regression coefficients followed by standard errors. Asterisks indicate p-values: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01. (No asterisk means the p-value > 0.1.)*

Table 5 displays a positive relationship between the amount of money spent on police departments per capita, and the number of violent crimes reported in a year. This relationship is statistically significant at conventional levels. An additional million dollars spent on policing is correlated with approximately ten additional violent crimes per year. The equation holds constant the population percentage made up by African Americans, as well as the annual median household income.

This relationship is different than my initial expectation, but can still make intuitive sense, as long I avoid assuming causality. Police spending may likely be higher in areas where more crimes are already being committed. When crime rates in a city increase, the councilmembers writing the budget will commit more resources to police departments to account for it. The police budgets seem to be driven by crime rates, and not the other way around.

This establishes a relationship between crime and police spending, one that can be compared to crime and outreach spending. If police spending is a response to crime, I can infer that it is not the only available response. A city could raise the outreach budget to combat crime rates instead, like many have already pledged to do.

My fixed effects model held constant many unchanging and unobserved factors that would create omitted variable bias, but it could not eliminate them all. My additional independent variables did create a more accurate picture and aligned with my initial predictions. There is a positive correlation between the African American percentage of the population and violent incidents of crime. There is an abundance of studies that attempt to explain why—citing a lack economic opportunities and historic discrimination. Community outreach spending will hopefully work to mitigate these issues and build generational wealth for African Americans. This theory is strengthened by the fact that median income was predicably correlated negatively with violent crimes.

The fourth equation suggests a negative relationship between police shootings and police spending. This supports the theory that more spending on police will lead to better training and fewer tragic outcomes. The next equations determined if this training will lead to fewer shootings than would outreach spending. Although the statistical significance is low, there does appear to be a negative relationship between the *RecordPoliceViolence* variable and fatal police shootings. Cities that track data concerning police use of force are likely already seeking ways to reduce it. The results also support the common societal complaint that African Americans are disproportionally affected by police use of force, or at the very least, make up the majority of fatal police shooting victims.

EQUATIONS 5 AND 6

Table 6. Effect of Outreach Spending on Violent Crime Rates and Fatal Police Shootings

Independent Variable	DV: Violent Crimes	DV: Fatal Police Shootings	Explanation of cells in model
Outreach Budget Capita	-0.00000869**		Regression Coefficient for x_1
(per capita)	*0.0000037*		*Standard Error*
Outreach Budget		-0.0181**	Regression Coefficient for x_2
(millions of dollars)		*0 .0072*	*Standard Error*
People of Color		-27.2167**	Regression Coefficient for x_3
(percent of population)		*13.7885*	*Standard Error*
Total Population		0.0080	Regression Coefficient for x_4
(thousands of people)		*0.0079*	*Standard Error*
Record Police Violence		-0.0309	Regression Coefficient for x_5
(dummy variable)		*0 .7151*	*Standard Error*
Constant	.01023***	12.9644	Constant (y-intercept)
	0 .0004	*9.1632*	
n	200	200	Sample Size
Adj. R^2	-0.0194	0.1224	Adjusted R2

*Note: Cells in this table are regression coefficients followed by standard errors. Asterisks indicate p-values: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01. (No asterisk means the p-value > 0.1.)*

Table 6 shows a negative relationship between the amount of money spent on community outreach per capita, and the number of violent crimes reported in each year. This relationship is statistically significant at conventional levels. An additional million dollars spent on social programs is correlated with eight fewer violent crimes per year. This relationship appears to support what many “defund the police” activists have been saying. The positive sign associated with police spending in equation three suggests a reactionary response to higher crime rates, while outreach spending has a purely negative relationship with crime. Even still, I caution against assuming causality.

It makes sense that a city with high rates of crime would instinctively think to invest in policing instead of outreach. Even the data shows that the magnitude between crime and policing is greater than that of crime and outreach. But it is still possible that the investments in community programs could reduce additional crimes beyond the predictions of annual budgets.

The results of the final equation show that there is a negative relationship between fatal police shootings and community outreach spending. This relationship is statistically significant and slightly higher than the relationship between police spending and fatal police shootings. This is precisely what my thesis sought to determine. Money invested in outreach instead of policing may in fact result in fewer violent police incidents.

I mentioned in Section V that there would be some biases built into this particular equation. As the FBI's police-use-of-force tracker accumulates more data over time and is made available to the public, a more accurate version of this equation will be possible. With so many cities planning to implement policies to divert funding from police into outreach, I predict that I will see much clearer relationships emerge. Some cities are ahead of this trend and have already tracked these data themselves. Once again, the regression shows a predictably negative relationship between the *RecordPoliceViolence* variable and fatal police shootings.

The strong negative relationship between the People of Color variable and police shootings is surprising but explainable. While tracking city demographics across ten years, I noticed improvements regarding rates of income, employment, and educational attainment, as cities recovered from the housing market collapse. I found a different trend of non-Hispanic white people leaving cities for suburbs, driving up the population percentage for people of color. Unlike the *Black* variable, which remained at consistent levels, the *POC* variable grew. Total populations also increased while police shootings remained consistent, creating a relationship that may not lead to accurate assumptions. Had there been enough data to support an actual police violence variable, I would have provided a more accurate version of this relationship.

VII. CONCLUSION AND POLICY RECOMMENDATIONS

Hours before I could submit my thesis, the trial against George Floyd's killer concluded. The police officer was found guilty of second-degree murder among other charges. America felt some relief from the verdict, but the impact of this death will still be felt for years to come. Minneapolis reached a settlement with the victim's family, awarding them $27 million. This is more than the last three years' worth of Minneapolis' outreach budget combined. It is impossible to know which police involved killing could ignite the next social powder keg. 2020 saw historic rates of unemployment due to the COVID-19 pandemic. It was an election year, and a racially charged one at that. So many unrelated external factors transformed what might have been a disturbingly common occurrence into a national tragedy. It was all completely preventable.

I had started this paper with the goal of deriving the exact social utility costs of crime and police use of force. I had hoped to mark the utility cost of each type of crime and the average legal fees of each officer complaint so I could suggest the precise amount of funding that police and outreach budgets should absorb. Upon finalizing my data and observing the aftermath of the Minneapolis protests, I believe that such a goal is not possible or even worthwhile.

Over 1,300 Minneapolis properties were devastated by the 2020 rioting and looting, totaling over $350 million in damages. Just the security for the accused officer's murder trial may reach costs of $35 million. The city settlement seems cheap by comparison. This exact scenario has been taking place within American cities for decades. With so many cities pledging to address this problem, we may finally see this trend come to an end. My fixed effect model provided some useful insight for how to prevent the next George Floyd from dying and the next Minneapolis from burning.

My regressions show that there is a larger relationship between police spending and violent crime than between outreach spending and violent crime. This was a predictable outcome. It is why so many cities are hesitant to implement the suggested new policies. When I observed the city budgets for 2021, many cities that had pledged to "defund the police" had not actually followed through. Some delayed their promise until 2022, when the social atmosphere may be calmer. Others kept police spending intact but relocated sections of it into other departments like "public safety" to satiate activists without risking an increase in crime rates.

This relationship between the two outcomes does not tell a complete story. In most of the cities I observed, the last ten years were marked with an increase in population, total budget, police spending, and outreach spending. While crime rates could vary, most trended downwards. This makes it challenging to derive what specifically is driving these trends. In Section II, I discussed how many outreach programs are targeted towards youths. Teaching critical thinking and social competency skills to school children is an investment that could take years to pay off. Observing correlations on a year-by-year basis can miss the bigger picture.

Cutting money from police budgets will risk increasing crime rates in the immediate future, which is dangerous for politicians seeking reelection. Investing that money into developing communities may still be a more viable long-term strategy—the kind of strategy with which democracies struggle. George Floyd died while being arrested for allegedly trying to use counterfeit money. While preventing deaths like his will require police reforms, the encounter may have been prevented entirely if more resources were available to Mr. Floyd while he was at a younger age, and more receptive to the previously mentioned family-support programs.

My data also suggest there is a larger negative relationship between fatal police shootings and outreach spending than between fatal police shootings and police department spending. The difference is smaller than the difference regarding crime. If investing police money into an outreach budget leads to a hundred more crimes but one fewer fatal police shooting would it be worthwhile? Would that shooting have been the one to trigger a multi-million-dollar settlement or months of rioting? These questions have no reliable answers.

It is worth reiterating that although the relationship with police shootings is smaller between police spending than outreach spending, it is still negative. When departments do not spend money on police budgets to respond to crime rates, the result may be overworked officers who make more preventable mistakes. This could lead to additional unnecessary confrontations with potentially deadly results.

What I can say with the most certainty is that I need more data. The lack of a proper total "police use of force" variable made it extremely challenging to track meaningful trends that can be linked to budget changes. Each city divides its budget differently, but those that agreed to "defund the police" should be specific about from which existing departments they plan to divert money. The effects of these cities' policies could take years to manifest, but they might keep future protests from boiling over into riots. My model supports my initial hypothesis that there is no single correct answer on where finite city resources should be invested, but rather there exists a series of policy tradeoffs. Ultimately, those choices must be made by the inhabitants of each city based on what issues they decide to prioritize. Police spending and outreach spending are both effective ways to reduce crime and reduce fatal police shootings. Reforming policies instead of budgets is perhaps the best way to ensure that each dollar spent goes as far as possible.

Before making any cuts to funding, police training should prioritize de-escalating situations without immediately deploying firearms. Body-cameras should be required for all officers, and footage of any police shooting must be released to the public. Investigations should begin swiftly to deter the public from rioting. Police must be adequately trained, funded, and equipped to properly keep their communities safe. They must be held accountable to those communities if they violate their department policies.

Maryland recently became the first state to replace its pre-existing "Law Enforcement Officers Bill of Rights" with a new statute that requires bodycams, limits the use of no-knock warrants, and disciplines officers through civilian panels. These measures may do more to curtail police use of force in Baltimore than the city's pledge to cut its police budget by 5%.

If police funding is rerouted into outreach, the goal should be to reduce officer workload, instead of reducing personnel. Police should focus on investigations and public safety, while other departments can handle wellness checks and dealings with the mentally ill. This would allow for a defunding of the police that does not risk an increase in crime or police shootings. Additionally, laws can be changed to decriminalize activities that do not warrant police intervention. Ideally communities will become safer as the outreach investment slowly but inevitably pays off.

No solution to this issue will be quick or easy. Managing outcome tradeoffs with a finite budget is the very point of public policy. My thesis could not ultimately confirm that defunding the police will work. But the data cannot reject the policy suggestions either. The best way to prevent another tragic situation like the one in Minneapolis is not by determining where each dollar is spent, but how each dollar is spent.

APPENDIX A: COMPOSITE CITY DATA

City	State	Year	% POC	% Black	Median Income	Total Population	Total Budget	Police Budget	Outreach Budget	Violent Crimes	Fatal Police Shooting	Record Use of Force
Albuquerque	NM	2010	58.2%	4.5%	46079	547585	978707000	177697000	93660000	4291	7	0
Albuquerque	NM	2011	58.2%	4.5%	43606	552801	863529000	161868000	57063000	4210	1	0
Albuquerque	NM	2012	57.8%	4.4%	45373	555419	873093000	162595000	51782000	4151	2	0
Albuquerque	NM	2013	58.6%	4.5%	48357	556489	883727000	161646000	56475000	4325	6	0
Albuquerque	NM	2014	59.8%	4.0%	46433	557172	939433000	155979000	57191000	4934	9	0
Albuquerque	NM	2015	60.3%	4.8%	47096	559131	901857000	164058000	66035000	5406	5	0
Albuquerque	NM	2016	59.5%	4.1%	50522	559270	919555000	165335000	65654000	6245	7	0
Albuquerque	NM	2017	61.0%	4.1%	50456	558558	837248000	171481000	61882000	7686	8	0
Albuquerque	NM	2018	61.6%	4.8%	51099	560234	930106000	176988000	57821000	7962	9	0
Albuquerque	NM	2019	61.5%	4.9%	55567	560504	998028000	202053000	70396000	7917	6	0
Austin	TX	2010	51.7%	9.0%	47434	795518	2666416000	233388015	9478032	3387	2	0
Austin	TX	2011	52.9%	9.0%	49987	820601	2809840000	246532995	10410798	3718	2	0
Austin	TX	2012	50.5%	9.2%	52453	842595	2960010000	264147977	10608085	3885	1	0
Austin	TX	2013	50.3%	8.8%	56351	885415	3145422000	281000264	12097386	4093	3	0
Austin	TX	2014	51.4%	9.0%	58458	912978	3274570000	289866902	12941531	4002	2	0
Austin	TX	2015	52.3%	8.8%	62250	931840	3497092000	353099982	14115968	4399	6	0
Austin	TX	2016	51.5%	8.6%	66697	947897	3585293000	369184284	15688467	4602	7	0
Austin	TX	2017	52.3%	9.0%	67755	950714	3833977000	383027723	14280127	5338	5	0
Austin	TX	2018	51.2%	9.7%	71543	964243	3899908000	387642718	14165815	5824	6	0
Austin	TX	2019	51.2%	9.4%	75413	979263	4065008000	412070909	15985742	5932	4	0
Baltimore	MD	2010	72.0%	65.0%	38346	620583	2291108000	340181741	127230267	9316	1	0
Baltimore	MD	2011	71.7%	64.6%	38721	619493	2262159000	351522278	65203837	8886	1	0
Baltimore	MD	2012	71.9%	64.9%	39241	621342	2247554000	353200055	48925527	8789	6	0
Baltimore	MD	2013	71.8%	64.1%	42266	622104	2245347000	414421901	59063287	8725	9	0
Baltimore	MD	2014	72.0%	64.1%	42665	622793	2322526000	413193976	63659709	8346	3	0
Baltimore	MD	2015	71.8%	63.7%	44165	621849	2364785000	455480517	58768596	9542	2	0
Baltimore	MD	2016	72.5%	63.9%	47350	614664	2553636000	467608064	52376559	11010	5	0
Baltimore	MD	2017	72.5%	64.2%	47131	611648	2454572832	486281891	47690231	12430	5	0
Baltimore	MD	2018	72.3%	63.6%	51000	602495	2555888387	499880642	50178532	11100	2	0
Baltimore	MD	2019	72.6%	63.8%	50177	593490	2592573552	510140403	53144643	11101	4	0
Boston	MA	2010	52.4%	28.1%	49893	621383	2294180000	282413333	8389790	5819	0	0
Boston	MA	2011	54.0%	28.7%	49081	624969	2423800000	275779005	8332856	5252	1	0
Boston	MA	2012	54.0%	29.3%	51642	637516	2402440000	283038029	8632723	5266	1	0
Boston	MA	2013	54.1%	27.3%	53583	644710	2496130000	290713388	8875848	5037	0	0
Boston	MA	2014	54.4%	27.6%	56902	656051	2644880000	321000294	9578250	4749	1	0
Boston	MA	2015	55.3%	28.3%	58263	669469	2774920000	337310896	10468260	4702	1	0
Boston	MA	2016	54.6%	30.2%	63621	672840	2881090000	348887846	11544054	4767	2	0
Boston	MA	2017	56.1%	28.8%	66758	683015	2990130000	364594820	16926212	4570	3	0
Boston	MA	2018	55.6%	28.6%	71834	695926	3192100000	399924493	13685668	4324	1	0
Boston	MA	2019	55.1%	29.4%	79018	694295	3348530000	416762373	14203729	4284	3	0
Buffalo	NY	2010	59.3%	40.0%	28490	261210	1316993338	77009358	3833228	3599	0	0
Buffalo	NY	2011	57.5%	39.9%	29158	261004	1359575373	76864032	3396609	3250	0	0
Buffalo	NY	2012	56.8%	38.9%	30422	259386	1317429740	76400508	2500151	3382	0	0
Buffalo	NY	2013	56.8%	39.7%	32392	258945	1345564121	77122212	2782897	3249	0	0
Buffalo	NY	2014	56.2%	39.3%	31919	258699	1381090189	80657990	2703537	3173	0	0
Buffalo	NY	2015	55.3%	39.2%	32509	258066	1418208012	80932199	3174952	2886	0	0
Buffalo	NY	2016	55.4%	39.4%	32883	256908	1422926640	85040138	3105847	2857	2	0
Buffalo	NY	2017	53.9%	38.2%	34814	258592	1438566528	92238087	4007340	2611	1	0
Buffalo	NY	2018	54.2%	38.2%	37359	256322	1493233625	90053003	4380255	2692	2	0
Buffalo	NY	2019	52.8%	39.3%	40843	255300	1530342300	89829463	4112457	2533	0	0

City	State	Year	% POC	% Black	Median Income	Total Population	Total Budget	Police Budget	Outreach Budget	Violent Crimes	Fatal Police Shooting	Record Use of Force
Cincinnati	OH	2010	50.5%	46.6%	34110	296907	1170400000	142146660	7493120	3615	1	1
Cincinnati	OH	2011	50.2%	46.4%	31301	296236	1258900000	143239520	7124800	3076	3	1
Cincinnati	OH	2012	52.5%	45.9%	30188	296552	1208800000	139036220	6776730	2903	2	1
Cincinnati	OH	2013	51.0%	43.8%	34605	297498	1471500000	140960510	6617070	2858	1	1
Cincinnati	OH	2014	50.6%	45.6%	32688	298162	1432500000	125981850	7346910	2719	3	1
Cincinnati	OH	2015	51.3%	44.7%	35001	298537	1422900000	126274290	7511120	2788	3	1
Cincinnati	OH	2016	49.8%	45.0%	38539	298802	1459900000	133260280	7730005	2803	3	1
Cincinnati	OH	2017	50.9%	44.7%	38938	301305	1624400000	146011260	8757117	3132	1	1
Cincinnati	OH	2018	51.8%	44.0%	43585	302615	1574900000	152901620	10056071	2852	2	1
Cincinnati	OH	2019	51.8%	43.7%	46260	303954	1413500000	148959170	9071760	2824	0	1
Dallas	TX	2010	71.6%	25.6%	40650	1202797	2527774595	440548265	5981807	9161	4	0
Dallas	TX	2011	71.4%	24.5%	40585	1223378	2548581558	427263047	10125199	8330	1	0
Dallas	TX	2012	70.7%	25.7%	41354	1241108	2564609038	424106476	10873946	8380	7	0
Dallas	TX	2013	70.5%	25.5%	41978	1257676	2630670895	433826987	12792502	8330	7	0
Dallas	TX	2014	70.8%	25.2%	43003	1281031	2858151531	450889538	13676558	8457	11	0
Dallas	TX	2015	70.8%	24.8%	45918	1300082	2824816211	466592179	15788112	9038	7	0
Dallas	TX	2016	71.3%	25.8%	47243	1317942	3122146910	488481974	16570537	10071	6	0
Dallas	TX	2017	71.5%	25.5%	50627	1341103	3083200517	505496117	20569118	10369	3	0
Dallas	TX	2018	70.7%	25.9%	52210	1345076	3308633301	464648484	29040392	11018	7	0
Dallas	TX	2019	70.9%	25.7%	55332	1343565	3601197520	487002691	31755753	12443	6	0
Denver	CO	2010	47.9%	11.2%	45074	604414	1208087000	176649953	2598030	3387	2	0
Denver	CO	2011	47.5%	11.1%	47471	619968	1255697000	183994267	2894556	3718	1	0
Denver	CO	2012	47.4%	10.2%	50488	634265	1323085000	194692915	3075949	3885	2	0
Denver	CO	2013	46.7%	11.3%	51089	649495	1377859000	194310364	5321902	4093	5	0
Denver	CO	2014	46.7%	10.7%	54941	663862	1532906594	204699692	3859132	4002	5	0
Denver	CO	2015	46.4%	10.6%	58003	682545	1642123079	209471126	4879907	4399	6	0
Denver	CO	2016	46.0%	11.2%	61105	693060	1687748671	211891919	4999047	4602	6	0
Denver	CO	2017	45.7%	10.5%	65224	704621	1779867906	218010805	4762657	5338	3	0
Denver	CO	2018	45.7%	10.7%	68377	716492	1982395814	232449814	6683217	5824	10	0
Denver	CO	2019	45.2%	10.5%	75646	727211	2097542554	246131216	8406178	5932	7	0
Indianapolis	IN	2010	41.5%	29.4%	38502	824199	1065060140	195802943	63000026	9646	3	0
Indianapolis	IN	2011	42.0%	29.5%	39015	824232	1098755982	190402415	32729799	9170	0	0
Indianapolis	IN	2012	42.4%	29.3%	40854	835806	1027723145	192008827	33699517	9942	2	0
Indianapolis	IN	2013	43.0%	29.6%	41361	838425	981212786	190013408	29864598	10479	7	0
Indianapolis	IN	2014	43.1%	29.3%	42370	851353	1017327786	196948441	30495928	10768	5	1
Indianapolis	IN	2015	43.5%	29.9%	41278	848423	1033227770	211049195	38062641	11124	9	1
Indianapolis	IN	2016	44.6%	30.3%	44615	852506	1023442102	220425270	32360961	11907	4	1
Indianapolis	IN	2017	45.3%	30.5%	47225	857386	1047046313	226810614	33504314	11616	1	1
Indianapolis	IN	2018	46.1%	31.5%	47678	864131	1147907658	233173436	33784829	11170	1	1
Indianapolis	IN	2019	46.8%	31.0%	49661	870340	1233460182	242054530	39461425	8043	1	1
Kansas City	MO	2010	46.3%	32.2%	42780	460665	1325521920	112090006	31486448	5643	4	0
Kansas City	MO	2011	44.2%	30.3%	43810	463156	1338645202	128486982	23860892	5555	2	0
Kansas City	MO	2012	45.6%	31.9%	41877	464346	1315893864	131886203	22205577	5889	2	0
Kansas City	MO	2013	44.5%	29.9%	45551	467082	1331185219	186249506	19684173	5876	8	0
Kansas City	MO	2014	45.0%	31.4%	44173	470816	1373310660	198034251	21557998	5892	6	0
Kansas City	MO	2015	45.0%	31.1%	50259	475361	1360136527	205584133	21057333	6735	5	0
Kansas City	MO	2016	44.4%	29.7%	51235	481360	1414181308	233557604	55551726	7925	4	0
Kansas City	MO	2017	44.2%	30.7%	51330	488825	1499520676	243334699	56316680	8809	6	0
Kansas City	MO	2018	45.1%	30.7%	54372	491809	1557084891	247639523	59343038	8162	9	0
Kansas City	MO	2019	43.6%	28.7%	55259	495278	1639704033	256565862	58679812	7308	4	0

City	State	Year	% POC	% Black	Median Income	Total Population	Total Budget	Police Budget	Outreach Budget	Violent Crimes	Fatal Police Shooting	Record Use of Force
Memphis	TN	2010	72.8%	64.7%	37045	647870	1184011440	214642791	5093234	10401	0	0
Memphis	TN	2011	72.9%	63.4%	34960	652078	1161129384	227458991	4498303	10338	3	0
Memphis	TN	2012	72.8%	64.1%	33563	655141	1168230430	222016036	5384974	11417	3	0
Memphis	TN	2013	72.7%	64.0%	36722	653450	1126198342	230434024	4193169	10890	4	0
Memphis	TN	2014	73.9%	65.4%	34704	656876	1447234660	231984669	3705823	11420	8	0
Memphis	TN	2015	73.7%	64.2%	36908	655760	1345098645	238875028	4725989	11474	1	0
Memphis	TN	2016	74.6%	65.3%	38826	652752	1194125058	245284768	3929151	11989	4	0
Memphis	TN	2017	74.5%	64.6%	39333	652231	1337265167	260966064	4790480	13562	3	0
Memphis	TN	2018	75.5%	66.9%	37199	650632	1358713303	267049835	4457345	13171	6	0
Memphis	TN	2019	74.1%	63.8%	43794	651088	1282937478	269577977	5197387	12723	8	0
Minneapolis	MN	2010	36.6%	19.4%	46508	383280	1282800000	132396557	1307514	4064	0	1
Minneapolis	MN	2011	39.0%	20.8%	46682	387736	1192200000	133721041	3831411	3722	0	1
Minneapolis	MN	2012	39.5%	20.6%	47604	392871	1224600000	134665095	4262194	3872	2	1
Minneapolis	MN	2013	40.0%	21.3%	50563	400079	1195800000	136517646	3039141	4038	1	1
Minneapolis	MN	2014	39.7%	21.5%	50791	407181	1237500000	145641234	6661349	4093	1	1
Minneapolis	MN	2015	40.7%	21.9%	54571	410935	1302500000	152176515	9476661	4395	1	1
Minneapolis	MN	2016	38.8%	20.4%	56255	413645	1341200000	159357000	10364000	4622	1	1
Minneapolis	MN	2017	40.3%	20.0%	60789	422326	1453900000	167650618	10358153	4614	1	1
Minneapolis	MN	2018	40.7%	21.6%	63590	425395	1540200000	177835672	12164058	3395	1	1
Minneapolis	MN	2019	39.6%	22.3%	65889	429605	1567100000	184937000	11945000	4370	2	1
New Orleans	LA	2010	69.7%	60.9%	37726	347858	596559792	129769614	2127440	2593	2	0
New Orleans	LA	2011	69.0%	60.5%	35041	360740	571798269	130411570	2795517	2748	1	0
New Orleans	LA	2012	69.4%	59.6%	34361	369250	908374502	139007185	6242414	2958	0	0
New Orleans	LA	2013	69.1%	60.3%	36631	378715	592968234	125080548	2256242	2965	1	0
New Orleans	LA	2014	68.9%	60.0%	35504	384320	621251847	126336248	2340476	3770	3	0
New Orleans	LA	2015	68.8%	60.2%	39077	389617	678916420	136672623	2758135	3736	4	0
New Orleans	LA	2016	69.2%	60.9%	38681	391495	733314898	153586986	2896023	4249	2	1
New Orleans	LA	2017	69.4%	60.9%	36999	393292	761686898	160138142	3566095	4457	1	1
New Orleans	LA	2018	69.5%	60.3%	38423	391006	827953658	175754423	4730437	4611	0	1
New Orleans	LA	2019	69.3%	60.1%	45615	390144	730970936	163524859	6201552	4516	3	1
Orlando	FL	2010	59.5%	31.8%	38098	239037	1027969249	121484236	13906183	2574	2	1
Orlando	FL	2011	62.7%	28.8%	40275	243209	973470880	121795153	9601011	2591	0	1
Orlando	FL	2012	62.6%	31.8%	41695	249525	922795285	121780269	9418385	2508	1	1
Orlando	FL	2013	59.6%	28.6%	41345	255479	1139981429	130692740	12967822	2316	7	1
Orlando	FL	2014	59.1%	28.3%	41081	262396	1507343530	135059903	7266217	2340	5	1
Orlando	FL	2015	62.0%	25.1%	44804	270917	1140896519	142100371	8367851	2525	4	1
Orlando	FL	2016	62.0%	25.7%	46761	277198	1203081981	149852505	9476415	2328	5	1
Orlando	FL	2017	65.8%	29.3%	47594	280258	1289241020	160517512	8590579	2113	2	1
Orlando	FL	2018	64.2%	28.2%	51820	285705	1430553812	173714104	8530626	2282	5	1
Orlando	FL	2019	62.8%	23.6%	58819	287435	1519970833	185405091	9408261	2157	1	1
Philadelphia	PA	2010	63.1%	45.4%	34400	1528306	3915287574	567481483	13552365	18535	7	0
Philadelphia	PA	2011	63.1%	44.0%	34207	1536471	3653725714	576704698	6266987	18268	9	0
Philadelphia	PA	2012	63.6%	44.9%	35386	1547607	3785293330	598442101	4958031	17853	10	0
Philadelphia	PA	2013	63.8%	44.7%	36836	1553165	3484874625	614796691	5131524	17074	10	0
Philadelphia	PA	2014	64.3%	44.2%	39043	1560297	3613265717	635609242	12201744	15925	4	0
Philadelphia	PA	2015	64.8%	44.1%	41233	1567442	3886563587	655872092	12154284	16133	3	0
Philadelphia	PA	2016	65.4%	44.2%	41449	1567872	3831515337	683800088	12947432	15385	6	0
Philadelphia	PA	2017	65.5%	43.6%	39759	1580863	4139791161	688967181	13355969	14930	4	0
Philadelphia	PA	2018	66.0%	43.7%	46116	1584138	4402853857	734130008	14889697	14420	5	0
Philadelphia	PA	2019	65.8%	43.8%	47474	1584064	4772388569	753673455	9196441	11397	0	0

City	State	Year	% POC	% Black	Median Income	Total Population	Total Budget	Police Budget	Outreach Budget	Violent Crimes	Fatal Police Shooting	Record Use of Force
Portland	OR	2010	28.6%	7.8%	47185	585429	2913127640	163560508	7333576	3051	4	0
Portland	OR	2011	28.5%	7.6%	47033	595325	2779193527	158320737	7033597	3037	0	0
Portland	OR	2012	27.3%	7.5%	52158	603650	2845108089	174565153	6713559	3093	2	0
Portland	OR	2013	28.6%	7.3%	55571	611134	2893591069	169635142	7008921	2941	2	0
Portland	OR	2014	28.8%	7.3%	54624	619445	2908762186	169435128	7115750	2911	2	0
Portland	OR	2015	28.9%	7.3%	60892	632187	2922137217	182510373	7809727	680	3	0
Portland	OR	2016	29.6%	7.6%	62127	639635	3055979956	190420974	8909128	3223	1	0
Portland	OR	2017	30.2%	7.3%	66187	648121	3660861218	200195111	9994531	3688	3	1
Portland	OR	2018	30.0%	7.5%	73097	652573	4089770208	215816409	10620655	3818	4	1
Portland	OR	2019	29.5%	7.9%	76231	653467	4400151939	231633702	10938225	3879	5	1
San Diego	CA	2010	55.5%	7.9%	60037	1311886	2919045283	409325900	3922208	5616	3	0
San Diego	CA	2011	56.8%	8.4%	60797	1326183	2586927667	403345743	3327254	5104	0	0
San Diego	CA	2012	57.4%	7.7%	62395	1338354	2726193049	402942720	4422416	5529	1	0
San Diego	CA	2013	57.1%	7.5%	63456	1355885	2784401533	417248132	6173849	5303	6	0
San Diego	CA	2014	56.9%	8.0%	67799	1381083	2845316157	466247958	14423710	5214	4	0
San Diego	CA	2015	57.2%	8.0%	67871	1394907	2925158552	424969419	14595349	5582	8	0
San Diego	CA	2016	57.2%	7.7%	71481	1406622	3137991274	440915216	15096824	5332	3	0
San Diego	CA	2017	57.4%	7.9%	76662	1419488	3346155249	442089851	16161264	5221	4	0
San Diego	CA	2018	57.7%	8.2%	79646	1425999	3580462258	479815290	18614054	5360	3	0
San Diego	CA	2019	57.4%	7.8%	85507	1423852	3668343363	502042831	19699666	5215	2	0
Seattle	WA	2010	33.9%	9.3%	60212	610710	3856255000	252758404	121566494	3515	3	0
Seattle	WA	2011	34.1%	8.9%	61037	620778	3921908000	259255489	117754888	3664	1	0
Seattle	WA	2012	34.8%	8.8%	64473	634541	4215119000	269618084	111588377	3782	1	0
Seattle	WA	2013	33.0%	9.3%	70172	652429	4381523000	295118827	118152520	3760	7	0
Seattle	WA	2014	33.8%	8.8%	70975	668337	4381523000	305690186	128186349	4005	7	1
Seattle	WA	2015	34.0%	9.1%	80349	684443	4733522000	294028062	126757359	4090	2	1
Seattle	WA	2016	35.7%	9.4%	83476	704358	5050582000	322340188	147946193	4301	2	1
Seattle	WA	2017	36.0%	9.0%	86822	724764	5396154000	320568110	158458146	4649	3	1
Seattle	WA	2018	37.0%	8.9%	93481	744949	5519790000	394845378	183214805	5228	2	1
Seattle	WA	2019	37.2%	9.2%	102486	753655	5807229000	398769531	199569781	4722	2	1
Tucson	AZ	2010	51.7%	5.9%	36428	521132	1157116230	153385978	80266530	3331	1	0
Tucson	AZ	2011	52.9%	6.0%	35362	525798	1206861030	162832759	76687699	3440	3	0
Tucson	AZ	2012	54.5%	6.8%	35354	524278	1127164160	149520691	86501642	3850	4	0
Tucson	AZ	2013	55.0%	6.9%	35720	526141	1259996550	155482828	78975149	3368	7	0
Tucson	AZ	2014	54.2%	6.2%	36541	527948	1241618580	156571950	67064450	3443	7	0
Tucson	AZ	2015	55.3%	6.4%	38155	531674	1195317970	161079405	68218710	3472	4	0
Tucson	AZ	2016	55.0%	6.7%	40021	530690	1206907370	163137443	63473655	4245	7	0
Tucson	AZ	2017	56.8%	6.6%	41613	535676	1256595920	161194125	62404514	4268	6	0
Tucson	AZ	2018	56.4%	7.5%	43676	545987	1285300810	173071579	71586228	3958	10	0
Tucson	AZ	2019	58.4%	7.0%	44365	548082	1417568450	171358325	63040597	3775	3	0
Washington	DC	2010	65.2%	52.2%	60903	604453	10422826000	505059340	334691138	7468	4	0
Washington	DC	2011	64.8%	51.2%	63124	627996	10355129000	479666368	316848679	6985	3	0
Washington	DC	2012	64.7%	50.8%	66583	632323	10365795000	481506424	323564405	7448	4	0
Washington	DC	2013	64.4%	50.2%	67572	646449	10669095000	495453519	335624331	7880	7	0
Washington	DC	2014	64.3%	49.8%	71648	658893	11084888000	529102168	360851384	7810	4	0
Washington	DC	2015	64.0%	48.9%	75628	672228	11656094000	525630695	397845079	8084	5	0
Washington	DC	2016	63.7%	48.4%	75506	681170	12355034000	543434479	474658573	7710	5	0
Washington	DC	2017	63.5%	47.5%	82372	693972	12817408000	555012147	511584037	6584	3	0
Washington	DC	2018	63.1%	47.5%	85203	702455	13225984000	570087037	515208050	6613	3	0
Washington	DC	2019	62.7%	47.2%	92266	705749	13718872000	591313726	564252797	6896	1	0

APPENDIX B: DATA SOURCES

Variable	Source
City Demographic Data	https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/
FBI Crime Data	https://crime-data-explorer.app.cloud.gov/
Officer Involved Shootings 2013-2019	https://mappingpoliceviolence.org/
Officer Involved Shootings 2010-2016	https://data.world/publicsafety/shot-by-cops
Police Use of Force Tracking	https://www.policedatainitiative.org/datasets/use-of-force/
City Budget Data:	
Albuquerque	https://www.cabq.gov/dfa/budget/annual-budget
Austin	https://www.austintexas.gov/financeonline/afo_content.cfm?s=1
Baltimore	https://bbmr.baltimorecity.gov/budget-publications
Boston	https://www.boston.gov/departments/budget
Buffalo	https://www.buffalony.gov/185/Archived-Budgets
Cincinnati	https://www.cincinnati-oh.gov/finance/budget/
Dallas	https://dallascityhall.com/departments/budget/financialtransparency/Pages/Prior-Budgets.aspx
Denver	https://www.denvergov.org/Government/Departments/Department-of-Finance/Our-Divisions/ Budget-Management-Office-BMO/City-Budget
Indianapolis	https://www.indy.gov/activity/city-and-county-budget
Kansas City	https://www.kcmo.gov/city-hall/departments/finance/budget-archives
Memphis	http://memphis.hosted.civiclive.com/government/finance
Minneapolis	http://www2.minneapolismn.gov/budget/budget-data
New Orleans	https://nola.gov/mayor/budget/
Orlando	https://www.orlando.gov/Our-Government/Records-and-Documents/Management-and-Budget/ Budget-Documents
Philadelphia	https://www.phila.gov/finance/reports-BudgetDetail.html
Portland	https://www.portlandoregon.gov/cbo/article/765251
San Diego	https://www.sandiego.gov/finance/annual/fy20
Seattle	https://www.seattle.gov/city-budget-office
Tucson	https://www.tucsonaz.gov/finance/budget/prior-year-budgets
Washington D.C.	https://cfo.dc.gov/page/current-and-past-fiscal-year-budgets

BIBLIOGRAPHY

Bor, J., Venkataramani, A., Williams, D., & Tsai, A. "Police Killings and their Spillover Effects on the Mental Health of Black Americans: A Population-Based, Quasi-Experimental Study" *The Lancet* Vol 392.10144 (Jul 2018): 302-310.

Campbell, B., Nix, J., & Maguire, E. "Is the Number of Citizens Fatally Shot by Police Increasing in the Post-Ferguson Era? *Crime and Delinquency* Vol 64.3 (Jan 2017).

Chalfin, A. & McCrary, J. "Are U.S Cities Underpoliced? Theory and Evidence. *Review of Economics and Statistics* Vol 96.4 (2018): 710-728.

Conner, A., Azrael, D., Lyons, V., Barber, C., & Miller, M. "Validating the National Violent Death Reporting System as a Source of Data on Fatal Shootings of Civilians by Law Enforcement Officers." *AJPH Surveillance* Vol 109.4 (Apr 2019).

Di Tella, R., & Schargrodsky, E. "Do Police Reduce Crime? Estimates Using the Allocation of Police Forces after a Terrorist Attack." *American Economic Review* Vol 94.1 (Mar 2004): 115–133.

Edwards, F., Lee, H., & Esposito, M. "Risk of Being Killed by Police Use-of-Force in the US by Age, Race/Ethnicity, and Sex." *Proceedings of the National Academy of Sciences of the United States of America* Vol 116.34 (Aug 2019): 16793-16798.

Feeny, M. "What Do Police Think About Body Cameras?" *CATO Institute* (Dec 2015).

Fernandez, P. "Defunding the Police Isn't Punishment—It Will Actually Make Us Safer." *Cosmopolitan* (Jun 2020).

Finch, B., Beck, A., Burghart, D., Johnson, R., Klinger, D., & Thomas, K. "Using Crowd-Sourced Data to Explore Police-Related-Deaths in the United States (2010-2017): The Case of Fatal Encounters." *Open Health Data* Vol 6.1 (May 2019).

Green, M. "SF Mayor Breed's Proposed Budget Redirects $120 Million From Police to City's Black Community." *KQED* (Jul 2020).

Ingraham, C. "U.S. Spends Twice as Much on Law and Order as it Does on Cash Welfare, Data Show." *The Washington Post* (Jun 2020).

Jamison, P. "This California City Defunded its Police Force. Killings by Officers Soared." *The Washington Post* (Jun 2020).

Landergan K. "The City that Really Did Abolish the Police" *Politico* (Jun 2020).

Mapping Police Violence "2017 Police Violence Report." *Mapping Police Violence* (2018).

Mapping Police Violence "Interactive Database." *Mapping Police Violence* (2021).

McEvoy, J. "At Least 13 Cities Are Defunding Their Police Departments." *Forbes* (Aug 2020).

McPhillips, D. "Deaths from Police Harm Disproportionately Affect People of Color" U.S. News & World Report (Jun 2020).

Mello, S. "More COPS, Less Crime." *Journal of Public Economics* Vol 172 (Apr 2019): 174-200.

Police Executive Research Forum. "Cost and Benefits Of Body-Worn Camera Deployments" (April 2018).

Rivera, R. & Ba, B. "The Effect of Police Oversight on Crime and Allegations of Misconduct: Evidence from Chicago." *Penn Law: Legal Scholarship Repository* (Oct 2019).

Saleh A., Appelbaum P., Liu X., Scott T., & Wall M. "Deaths of People with Mental Illness During Interactions with Law." *International Journal of Law and Psychiatry* Vol 58 (Apr 2018): 110-116.

Schwartz, G. & Jahn, J., "Mapping Fatal Police Violence across U.S. Metropolitan Areas: Overall Rates and Racial/Ethnic Inequities, 2013-2017." *PLOS One* Vol 15 (Jun 2020).

Shane J., Lawton B., & Swenson Z. "The Prevalence of Fatal Police Shootings by US Police, 2015–2016: Patterns and Answers from a New Data Set." *Journal of Criminal Justice* Vol 52 (Jun 2020): 101–111.

Sherman L., Gottfredson D., MacKenzie D., Eck J., Reuter P., & Bushway S. "Preventing Crime: What Works, What Doesn't, What's Promising." *National Institute of Justice* (Jul 1998).

Shi, L. "The Limit of Oversight in Policing: Evidence from the 2001 Cincinnati Riot." *Journal of Public Economics* Vol 93.1-2 (Feb 2009): 99-113.

White, M., Gaub, J., & Todak, N. "Exploring the Potential for Body-worn Cameras to Reduce Violence in Police-Citizen Encounters." *Oxford* 12.1 (2018): 66-76.