Deadly Police Force: Implications for Policing, Planning, and Neighborhood Policy

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Abstract:

In recent years, the use of deadly force by law enforcement has emerged as a high-profile issue. Planning research on neighborhood context can further our understanding of the factors that are driving current trends in excessive police force. While there are databases that allow for the spatial mapping of fatal police encounters, current research using that data fails to suggest which neighborhood-level characteristics, and which factors, are most important for predicting and ultimately reducing police violence. Using 2013-2015 data from the *Mapping Police Violence* dataset, this paper presents maps of all fatal police encounters from that period. Using tests of equal variance, Spearman's rho correlations, and Poisson regressions for the five core-based statistical areas (CBSAs) with the highest counts of police violence. Our findings suggest that race is a significant factor in most of the regions included in our analysis. However, household income proved to be a more significant factor in all five CBSAs. On average, the likelihood of any fatal police factor, at the census tract level, falls by 14 percent for each $10,000 increase in median household income. In our discussion, we suggest that planning research has much to contribute to how police engage the public in both high- and low-income areas and where interventions to help reduce police violence should be geographically targeted.

In recent years, several high-profile incidents such as the deaths of Eric Garner in New York City (2014), Eric Brown in Ferguson, Missouri (2014), Tamir Rice in Cleveland (2014), and Philando Castile in St. Paul, Minnesota (2016) have increased interest in the analysis of police violence. The policy discourse that has evolved from these incidents is centered largely on police behavior, de-escalation training, and disparities in the prosecution of petty crimes by police based on race (Desmond, Papachristos, & Kirk, 2016). Some academic disciplines such as public health have sought to expand their research scope to consider gun violence – police or otherwise – as a threat to public health (Krieger, Chen, Waterman, Kiang, & Feldman, 2015). In viewing, police shootings as an issue of an area's quality of life, urban planners may have a pathway to insinuate our work and research into this important topic. This paper will attempt to create an argument for why the field of planning should engage the problem of police violence as it impacts the quality of life in low-income and predominantly minority communities by demonstrating the spatial geography of fatal police encounters.

To date, the field of planning has failed to replicate this expansion of our disciplinary scope as has happened in public health, leaving us unable to examine or address a phenomenon that impacts the quality of life for many communities in which we work. In the more recent era, planning scholarship and practice has not had a clear and direct role in creating safer spaces and policing although there is compelling evidence that violence has a direct relationship to neighborhood revitalization and overall quality of life (Steil & Mehta, 2017). This paucity of engagement with the topics of gun violence, and particularly police violence, within the planning literature presents the field with an opportunity to add significantly to the discourse around police violence by providing an understanding of the socioeconomic and spatial contexts for incidents of police violence and extrajudicial violence. As this paper aims to show, police violence towards unarmed citizens is a manifestation of several factors that we are presenting as beyond the scope of current planning scholarship. The planning literature has failed to seriously consider how planning scholarship and practice may be complicit through our failure to engage in serious consideration of police violence as being in any way relevant or within the purview of the discipline.

Currently, official government datasets are limited to the Federal Bureau of Investigations' (FBI) voluntary registry of police killings. Despite this, we do know that many developed countries, such as Japan and the United Kingdom, had no police killings at all in 2015 (Lartey, 2015). Based on all reputable data sources, including the FBI database, there are more police-related deaths over the course of a few days than many countries have over a decade. Some of this may be due to higher crime rates overall, particularly gun-related crime which requires police to use force. That said, few researchers have attempted to provide a comprehensive view of the social and economic context of police killings. To that end, this paper is attempting to fill that void by placing police violence in a spatial neighborhood context to understand the correlations between various socioeconomic measures and the incidents themselves. We developed two central questions:

1. How can we better understand the contemporary geography of fatal police encounters?
2. Which social and demographic factors best predict where fatal police encounters might take place?

Through the answers to these questions, planning research may help direct resources to the communities most in need of police accountability and de-escalation training. There may be, however, other interventions that could create planning and design-oriented interventions to mitigate the problem of excessive and fatal police force.

Literature Review

This literature review has three aims. First, we present the academic literature that considers neighborhood context and environment as a factor in police violence. In our view, policy interventions for mitigating police violence at the neighborhood level has the potential to bring planning expertise to bear on a pressing social issue. It also has the potential to expand the scope of planning research at a pivotal moment in the history of the United States. Second, we present an overview of the academic literature that contributes to planning's understanding of the impacts of police violence and its significance for neighborhood revitalization policy. Lastly, we will summarize various datasets and methodological approaches that serve as precedents and background for the statistical analysis we employed for this study.

Between 1970 and 2012, the number of incarcerated individuals in the United States has more than quadrupled to its current total of more than 2.3 million persons incarcerated (National Research Council, 2014). As the *Million Dollar Blocks* project has shown, funding for public schools, transit, health care, job training and other essential programs which would contribute to community economic development are instead being used to adjudicate and incarcerate large numbers of U.S. citizens (Cardura & Kurgan, 2006). The loss of potential endogenous urban growth due to incarceration, as well as limited job prospects after release also stymies urban communities. Further, many formerly incarcerated individuals who find themselves unable to secure housing in their home communities relocate to distressed neighborhoods, having implications for both the formerly incarcerated and these destination neighborhoods themselves. Urban sociologists such as Devah Pager and Matthew Clear both take a structural view of approach to police violence. By exploring the ways in which police surveillance, harassment, and mass incarceration "mark" particular neighborhoods as dangerous in the minds of police, vicious cycles are created which makes police bias and use of force self-fulfilling prophecies (Clear, 2007; Pager, 2007).

Their work on police violence and the impacts of mass incarceration in low-income communities perhaps has the most implications for our work and the field of planning. In addition to the problems of legal cynicism among minority groups, which stems directly from a mistrust of the police, leads to more crime as residents seek ways to resolve crime on their own terms rather than defer to any legal authority for assistance. These phenomena also mark these areas, and the people who reside within them with a "moral liability" to prove that they are innocent of any wrongdoing. This has implications for critical issues such as job placement and government resource allocation. In this way, normative ideas about what neighborhoods should look like has serious implications for how they are policed. This also poses the risk of signaling to white residents how they should respond when people of color cross into areas they feel are racially and economically homogenous by design (Blakely, 2012).

The inability to trust local police forces for public safety has many implications for neighborhood crime levels, and more problematically as a loss of trust in government itself (Carr, Napolitano, & Keating, 2007; Desmond et al., 2016). According to Kane, the social ecology of police misconduct may be associated with social disorganization for two reasons: 1) area social networks may not be cohesive enough to hold police accountable for mistreatment; and 2) security and safety may be inhibited by the inability of residents of those areas to trust in police and government more broadly. While safety and security have always been implicit goals of neighborhood planning, there has been an element of neighborhood planning history to create racially homogenous communities that were safe from the intrusion of minority groups (Rohe, 2009). In this way, the social control element of planning reinforces the role of police in facilitating effective planning at the neighborhood level, and social control on a broader one (Njoh, 2009; Yiftachel, 1998).

This literature is relatively small but growing. Several recent studies of police violence take environmental factors into account but lack a macro-level focus (Kane, 2002, 2003, 2005; D. A. Klinger, 1995; D. Klinger, Rosenfeld, Isom, & Deckard, 2016; Nix, Campbell, Byers, & Alpert, 2017; Novak & Chamlin, 2012; Terrill & Reisig, 2003). Many historical and current studies of police violence take a micro-level approach to understanding police violence which are useful for considering factors such as whether the victim was armed vs. unarmed, mitigating factors that precipitate the interaction with police, police department level policy, etc. Terrill and Reisig's research (2003) is among the most important for this micro-level perspective. In their study of the neighborhood context of police violence, they engaged earlier research that found police were, in part, responding to their environments. However, Terrill and Reisig's approach focused far more on controlling for the circumstances of the arrest or encounter than area variables. Also, instead of considering socio-economic and demographic variables independently, they considered them as an index of concentrated disadvantage.

Data on Fatal Police Encounters

In lieu of a shortage of national, publicly available, cross-jurisdictional data on police violence, several organizations and news outlets have attempted to fill the gap by using web searches of extrajudicial killings and police-involved violence across the country. For planners, activists, and politicians collecting this type of data can increase accountability of local law enforcement, and identify potential abuses of power in cities across the nation. Making this data publicly available allows people to engage in a deeper conversation around highly publicized topics like police killings of unarmed victims. For researchers, documenting the socio-economic demographics of neighborhoods, and identifying the location of police-related homicides helps develop a better historic and contextual understanding of the systematic violence occurring in communities of color.

The Guardian's "The Counted"

The U.K. based newspaper *The Guardian* was one of the first organizations to respond to the absence of police data. In 2015, the organization launched *The Counted*, a web-based database project that records every police-related homicide occurring in the United States. The project provides comprehensive set of data points regarding each recorded incident including: the age of each victim: their race and gender; location of the encounter; as well as a short summary of the fatal altercation. The publicly-accessible website allows users to search this vast database and locate incidents by the race, age, or name of the victim making it one of the most interactive and accessible databases online.

The Counted's database is a comprehensive listing of all police-involved deaths, including: shootings, taser-related deaths, suspects who die in police custody, and fatalities linked to vehicles (e.g. victims struck by police vehicles while being pursued). Unlike the other datasets, *The Counted* also includes incidents involving police who were not in the line of duty at the time of the altercation. In some ways, this database's comprehensiveness is actually a limitation. By including all police-related deaths, including those involving police *not* in the line of duty, *The Counted's* total counts are higher than alternative databases. The inconsistency or unavailability of data with the more comprehensive dataset also makes inter-city analysis much more difficult.

The Guardian sourced their data from primary data sources such *Fatal Encounters* and *Killed by Police* during their initial stages of data collection.[1] After performing this preliminary search, the organization then turned to national and local news stories to gather information on police homicides. The organization employed web-scraping techniques to pull data from online publications and social media platforms as well in order to capture every possible documented report of police violence. *The Counted* also incorporated a crowdsourcing function on their website which allowed smaller news organizations to submit local reports of police violence to the master database. Their data collection methods allowed them to gather substantial data on every single incident including demographic data about the victim and provides a brief summary of the victim's altercation with law enforcement.

The Washington Post's "Fatal Force Project"

This noted newspaper launched the *Fatal Force Project* in 2015 which has captured all fatal incidents perpetrated by police in the line of duty since January 1, 2015 (Tate et al., 2016). This database provides a detailed analysis which maintains a very strict set of criterion. The Post's database only included incidents of police fatalities involving a firearm. Any other type of police related fatality was not recorded in this database making it the most selective of currently available databases, except for the F.B.I.'s voluntary reporting system. For this reason, the count provided by *The Washington Post* is significantly lower compared to the other two datasets, with a total of 990 incidents during the 2015 calendar year.

The Washington Post sourced their data from primary databases, namely *Killed by Police* and *Fatal Encounters,* to create their own subset of the data. In order to gather this data, the organization also used web-scraping techniques to extract information from these websites. They used this same process to search local and national news reports as well as social media sites for information about police homicides. In collecting this data, The Washington Post only chose to include fatal shootings by an officer in the line of duty. The organization chose to omit incidents of victims who died in custody or by other circumstances at the hands of police. This commitment to only collecting data on police shootings made a substantial difference in the total number of fatalities reported by the organization. Although this methodology yields a lower number of total fatalities it is still very useful for building a data repository on gun violence and police violence in cities across the nation. However, one of the benefits of limiting the scope of this project is that it may yield more accurate counts than other projects because records of a killing can be found and verified in a number of different places such as hospital records, obituaries or police records. This decision to constrain the parameters of the data collection led to the Fatal Force Project reporting, on average, 180 fatalities less than the other two datasets annually.

Black Lives Matter/Mapping Police Violence

The Mapping Police Violence Project is a data analysis project investigating incidents of police use of force across the United States that was organized by some of the leaders of the *Black Lives Matter* organization. Like the other datasets, the *Mapping Police Violence* project also employed web-scraping methods to assemble and maintain its dataset. Tied to its larger “Campaign Zero” effort, this dataset is keenly focused on fatal encounters that occur when a person is being pursued, chased, tasered, pepper-sprayed or otherwise harmed by police in such a way that results in their death. This includes deaths where the police were both on- and off-duty regardless of whether the death was intentional or unintentional.

Due to their higher standard, we, and some other researchers, employ this dataset in lieu of the others (Campbell, Nix, & Maguire, 2018). This dataset differs from *The Counted* in that it does not include incidents involving off-duty police. It also differs from the *Fatal Force* Project by considering all of the various ways that a victim may have been harmed by police. Another advantage is that the Mapping Police Violence dataset includes more detail about the circumstances around the death and has more precision in identifying the race of police homicides than the others. For the purposes of understanding whether the dissonance between the race of the victim and the environment in which they were killed plays a role, this information is critically important.

Statistical Approaches to Studying Police Violence

Earlier scholarship that sought to expand an understanding of police violence employed statistical modeling to place police violence in context. The hypotheses vary rather broadly but most often consider area crime rates as a factor in police violence. Some research has shown that crime rates are only loosely correlated with the number of police shootings or the use of excessive force. However, in the wake of the Michael Brown incident in Ferguson, Missouri and the so-called "Ferguson effect", police forces there may have pulled back on their use of excessive force and surveillance of crime which led to an increase in area crime rates (Gross & Mann, 2017). Further, previous statistical analyses of police violence have found little evidence of a geographic pattern of police violence against minorities (Fryer, 2016; Terrill & Reisig, 2003). Some of this may be due to the fact that the Fryer study focused on the police force as a unit of analysis but did not take other environmental factors into consideration.

Methodological Approach

For this study, we examined the context of police violence by first gathering data from the *Mapping Police Violence* database and identifying the core-based statistical areas (CBSAs) with the highest counts of police-related fatal counters between 2013-2015.[2] Given other research that focuses on city police departments and counties, we attempted to replicate their units of analysis but found that several cities would be eliminated from consideration given their geographies. New York City, for example, is a consolidation of five counties and would always be eliminated. Miami, by contrast is a fairly small city in the context of Miami-Dade County in which it is located and would be eliminated from consideration as well.

Our first approach was to spatially map police shootings across each of our top five CBSAs at the census tract level and use a directional distribution method of spatial analysis. This method uses point data to represent the dispersion of point data through a spatial mean for all incidents (Mitchell, 2005). At one standard deviation, we can see 63 percent of all incidents as an ellipse. To see the relationship between the races of the victims, we created additional ellipses to show the relationship between all fatal police encounters, and those involving Black/African American victims, and another showing fatal encounters involving Latino victims.

To add to our analysis of race and police violence, we overlaid these directional distribution maps on top of the variable that proved most significant in our regression analysis (see below), median household income. The second aim of this research is to understand if police violence is more likely to occur in areas that can be characterized as experiencing social disorganization or disorder. To achieve this, we conducted a Poisson regression which allows for an interval dependent variable.

Findings

[Insert Table 1 here]

[Insert Map 1 here]

Police violence, and particularly fatal police encounters, are a problem throughout the continental United States. Not surprisingly, the geography of police violence tracks closely, but not perfectly, with population density and urbanization. As Table 1 shows, there are smaller regions that rank far higher than larger regions, in terms of population in their rate of police shootings. Bakersfield, California ranks 22nd overall in terms of police shootings but has a regional population of only 871,337 (U.S. Census Bureau, 2015). This translates into a rate of almost 22 fatal encounters per 100,000 residents. Other CBSAs with relatively high rates of police fatal encounters included: Oklahoma City, Oklahoma (14.3); Indianapolis-Carmel-Anderson, Indiana (9.7); Las Vegas-Henderson-Paradise, Nevada (9.226); Kansas City, Missouri-Kansas (9.226); and, Orlando-Kissimmee-Sanford, Florida (8.2). This suggested to us that descriptive statistics alone would not explain what environmental factors contribute most to fatal police force.

[Insert Chart 1 here]

[Insert Map 2 here]

[Insert Map 3 here]

Despite the larger number of shootings, the spatial distribution of fatal police encounters in the Los Angeles-Long Beach-Anaheim CBSA was much smaller by comparison to New York (see Map 2). The area representing one standard deviation of the mean of all incidents covers 832 square miles. Given that Latinos represent a much larger share of victims of police violence and are a larger share of the area population (see Chart 1), the ellipse representing the directional distribution of all fatal encounters for Latinos is similar in size to the distribution of all victims (744 square miles). Black/African-American victims of police violence is fairly concentrated in the region's low-income and proportionally high non-white census tracts stretching from Central Los Angeles to areas to inner-ring suburbs to the west and southeast.

The spatial distribution of police shootings in the New York City-Newark CBSA are clustered in specific areas of the metropolitan area. The boroughs of Brooklyn, Queens, the Bronx, and the City of Newark, New Jersey comprise the majority of incidents. The spatial distribution in the New York-Newark-Jersey City CBSA is also noteworthy due to its relative and substantial size. The spatial distribution at one standard deviation from the mean of all FPEs covered 1,878 square miles, an area nearly 1.5 times the size of the State of Rhode Island. The spatial distribution for Black/African-American victims was also quite substantial (1,267) which suggests that the problems of police violence in the New York CBSA extend not just beyond to cities of New York, Newark, and Jersey City but also into suburban areas as well.

[Insert Map 4 here]

[Insert Map 5 here]

[Insert Map 6 here]

The Phoenix-Mesa-Scottsdale, Miami-Fort Lauderdale-West Palm Beach, and Dallas-Fort Worth-Arlington CBSAs share one distinct feature, they all are areas that enjoyed much of their growth in the last few decades of the 20th century. They are also CBSAs with multiple centers of economic activity dispersed over large areas. Phoenix and Dallas stand out for another reason in that the majority of the victims of police violence are White (45.7 and 48.2 percent respectively). In both, the directional distributions for Black/African-American fatal encounters are much smaller than the distributions for all and Latino victims (for Phoenix, 156 sq. miles for Black/African American, 990 sq. miles for Latino, and 1104 for all; for Dallas, 508 sq. miles for Black/African American, 1129 sq. miles for Latino, and 1183 sq. miles for all victims).

The Miami-Fort-Lauderdale-West Palm Beach area stands apart from the other four CBSAs for several reasons. First, all three directional distribution ellipses were strikingly similar in size (491 sq. miles for Black/African American fatal encounters, 500 sq. miles for Latino, and 544 for all). Looking at the ellipses overlaid on median household income at the tract level (See Map 5), this CBSA more than others shows the separation between income and fatal incidents. In Broward (Fort Lauderdale) and West Palm Beach counties, the western portions of the counties, where incomes are generally higher, are almost untouched by police violence and the ellipses. In Miami-Dade County, the spatial inverse is true. The wealthiest portion of the county is to the east, and it is almost untouched by police violence, with the exception of Miami Beach area.

[Insert Table 2 here]

[Insert Table 3 here]

To better understand the extent to which fatal police encounters were associated with the percentage of non-white residents in a given tract, we performed a simple significance test at the 95% and 99% confidence intervals for the following variables: *Median Household Income; Percent of Households in Poverty; Percent of Vacant Housing Units; Percent of Multi-Family Housing Units; Percent of Renter Occupied Housing Units; Median Year House Built; Percent of Households with No Vehicle Present; and, Percent of the following racial/ethnic groups of Total Population: White, Black/African American, Latino, American Indian, Asian, Pacific Islander, Other Race, and Two or More Races.* In each of the top five core-based statistical areas, there was statistical significance between all tracts with no fatal encounters and those with such encounters for almost all environmental variables except for vacant housing units and multi-family housing units. For the racial demographics, again, almost all variables except for the American Indian, Pacific Islander, Other Race and Two or More Races. The CBSA that stood out among the rest was the Los Angeles-Long Beach-Anaheim CBSA where the average mean of non-white residents where fatal encounters took place was 79.4 percent. The average mean among our selected CBSAs was 65.5 percent.

Taking this analysis one step further, we wanted to understand the association between our variables. Given the interval nature of our main dependent variable, we chose to employ a *Spearman's rho* correlation instead of the more commonly used Pearson's correlation, which is more appropriate for interval/categorical data. Again, we separated the environmental variables from the racial demographic variables. Turning to the correlations of fatal police encounters by race and neighborhood context variables (Table 4), we can see that median household income was negatively and significantly correlated with all variables except for White fatal encounters. For the racial demographics and fatal encounters (Table 5), there are many modest or small correlations between variables but many significant ones, including, the negative relationship between Black/African American fatal encounters and the percent of the White population and, the negative relationship between the percent of the Asian population to all fatal encounters included in our model.

[Insert Table 4 here]

[Insert Table 5 here]

Regression Model

The Poisson regression is a generalized linear model which takes into account the categorical or interval nature of the dependent variable (Long, 1997). With the sum count of fatal police encounters per tract as the dependent variable, responses range between "0" for no fatal encounters to "4" for the highest number per tract in the five CBSAs that we examined. All environmental variables were included in the model, and each CBSA was coded as a dummy variable with all other CBSAs being null for each operation of the regression analysis to account for the interaction of each CBSA on the model. The *betas* included are the same as those included in the Spearman's rho, with the exception of *Total Population.*

$$\boldsymbol{g(\mu) = B_0 + B_1 x_1 + B_2 x_1 + \cdots B_k x_k}$$

[Insert Table 5 here]

Only one variable was highly significant to the 99th percent confidence interval in each execution of the Poisson regression: median household income. On average, for every $10,000 increase in median household income, the odds of a fatal police encounter dropped 14.2 percent. In three CBSAs, Miami-Fort Lauderdale-West Palm Beach, Dallas-Fort Worth-Arlington, and Phoenix-Mesa-Scottsdale, the odds were greater, 15.3, 15.4, and 16.1 respectively. This suggests that in high income areas, police are either taking greater care to deescalate police encounters in what they perceive to be higher-income areas or conversely taking much less care to deescalate in what they perceive to be lower-income areas. At the same time, for each ten percent increase in households in poverty, the odds of police shootings increased by 9.1 percent. That said, the percent of households in poverty did not prove statistically significant across all five CBSAs in our model, which suggests that income may be more instructive than poverty where police violence is concerned.

Several variables included in our model could signal that an area contains some social disorder, such as *Percent of Vacant Housing Units, Percent of Multi-Family Housing Units, Median Year Home Built.* Our assumption is that high rates of housing vacancy, a concentration of apartment buildings or multi-unit housing structures, and older homes would be easily observable and might also influence how police characterize an area and its residents. Surprisingly, neither *Vacant Housing Units* or *Median Year Home Built* were significant in our model. On average, a ten percent increase in the amount of vacant housing in an area increased the likelihood of fatal police encounters by 5.7 percent. For the age of the homes, it was positively correlated in the Phoenix CBSA and negatively correlated in all others, which may speak of lower-income households to newer housing in that CBSA as opposed to the others.

Discussion

There are many reasons why planning should be concerned about police violence in low-income and distressed communities. First, it is a clear and direct violation of our values as planners who are concerned with the public interest to not address state violence towards citizens. The very simple and almost undebatable argument that we should be concerned with sidewalks and crosswalks for its connection to pedestrian safety, connectivity among neighbors and local amenities can also be applied to police violence. Planning scholarship on bicycle lanes has increased in planning journals in recent years. In 2017, there were 722 bicycle related fatalities in the United States. During the same period, there were 1,100 police-related fatalities (Mapping Police Violence, 2018). Certainly, the spatial dimensions explained in our study suggest that there is a spatial rubric to police violence. Planning analysis may have a significant role to play in mitigating police violence by providing an understanding of the role that markers of segregation, and mitigating segregation, have on urban poverty.

Residents of low-income and distressed communities, where the bulk of police-involved shootings and violence occur, often lose faith not just in local police departments but also with government altogether. The implications of a statistical relationship between area income and racial segregation, should show us how African Americans and Latinos are being surveilled, harassed and victimized by police violence. To study distressed urban communities, we must consider not just jobs access; housing tenure and quality; retail corridor revitalization; pedestrian safety and complete streets; but also, the extent to which the lives of people of color are surveilled and regulated by the state through their interactions with police. When police violence is viewed in conjunction with the impacts of mass incarceration, the implications for neighborhoods becomes more urgent. On one end, there is the loss of able-bodied adults from households and communities for low-level drug crimes and non-violent crimes to mass incarceration and state supervision through probation. On the other, there is police violence and excessive force which complicates solutions to crime and neighborhood stabilization.

There are opportunities for planners to consider the role of place, police surveillance, harassment, violence, and mass incarceration on life prospects for residents of high-poverty areas. This means that we can more seriously investigate the multiple ways in which racial and economic segregation exist but also how pernicious the effects of those phenomena have on the communities in which we routinely work. Not only are some communities underserved by city services such as schools, fire stations, and mass transit, but housing conditions are poor and increasingly unaffordable. Excess police force then becomes an extreme by-product of a system that is producing more problems on which it itself feeds (Clear, 2007).

There are however, simple and immediate interventions which can help reduce unnecessary police stops which often lead to police violence. Projects such as the Democratic Socialists of New Orleans' brake light program considers the role of minor car repairs in justifications for police stops and the too frequent escalation that can lead to the use of fatal force. Somewhat more long-term, all of the publicly available databases prioritize the cataloguing of fatal police encounters to the spatial mapping of them. Understanding the geographic distribution and concentration of fatal police encounters is a key step in triaging the problem and highlighting not just the police departments with high rates of excessive force complaints and incidents, but the contexts of the fatal encounters themselves. This study was a macro-level, interjurisdictional study which aimed to understand the regional context of fatal police encounters. As outlined in the literature review, studies of police violence often take a micro-level approach to better understand the nuances of community-police interactions that are lost in a macro-level analysis. Urban planners who are interested in engaging the issue of police violence may have to conduct studies at both levels.

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Table 1. Top 25 CBSAs for Fatal Police Encounters with Populations and Rates for 100,000 Residents, 2013-2015

Core-Based Statistical Area (CBSA)	Count of Fatal Police Encounters	CBSA Population	Fatal Police Encounters Per 100,000
Los Angeles-Long Beach-Anaheim, CA	191	13,187,465	1.448
New York-Newark-Jersey City, NY-NJ-PA	107	20,020,397	0.954
Phoenix-Mesa-Scottsdale, AZ	92	4,486,153	4.258
Miami-Fort Lauderdale-West Palm Beach, FL	90	5,896,851	3.239
Dallas-Fort Worth-Arlington, TX	86	6,957,123	2.745
Riverside-San Bernardino-Ontario, CA	86	4,430,646	4.311
Houston-The Woodlands-Sugar Land, TX	79	6,482,592	2.945
Chicago-Naperville-Elgin, IL-IN-WI	77	9,466,000	2.018
San Francisco-Oakland-Hayward, CA	60	4,577,530	4.173
Atlanta-Sandy Springs-Roswell, GA	58	5,612,777	3.403
Baltimore-Columbia-Towson, MD	47	2,778,647	6.874
Washington-Arlington-Alexandria, DC-VA-MD-WV	45	6,008,369	3.179
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	43	6,047,721	3.158
St. Louis, MO-IL	42	2,803,449	6.813
Las Vegas-Henderson-Paradise, NV	42	2,070,153	9.226
Seattle-Tacoma-Bellevue, WA	40	3,664,963	5.212
Oklahoma City, OK	39	1,337,075	14.285
San Diego-Carlsbad, CA	35	3,250,867	5.875
Denver-Aurora-Lakewood, CO	35	2,752,056	6.940
Tampa-St. Petersburg-Clearwater, FL	34	2,921,311	6.538
Orlando-Kissimmee-Sanford, FL	32	2,328,508	8.202
Bakersfield, CA	31	871,337	21.920
Indianapolis-Carmel-Anderson, IN	31	1,968,768	9.701
San Antonio-New Braunfels, TX	30	2,332,345	8.189
Kansas City, MO-KS	30	2,070,147	9.226

Map 1. Map of Police Violence, Continental United States, 2013-2015

Chart 1. Fatal Police Counters by Race and Los Angeles, New York, Phoenix, Miami, and Dallas-Fort Worth CBSAs, 2013-2015

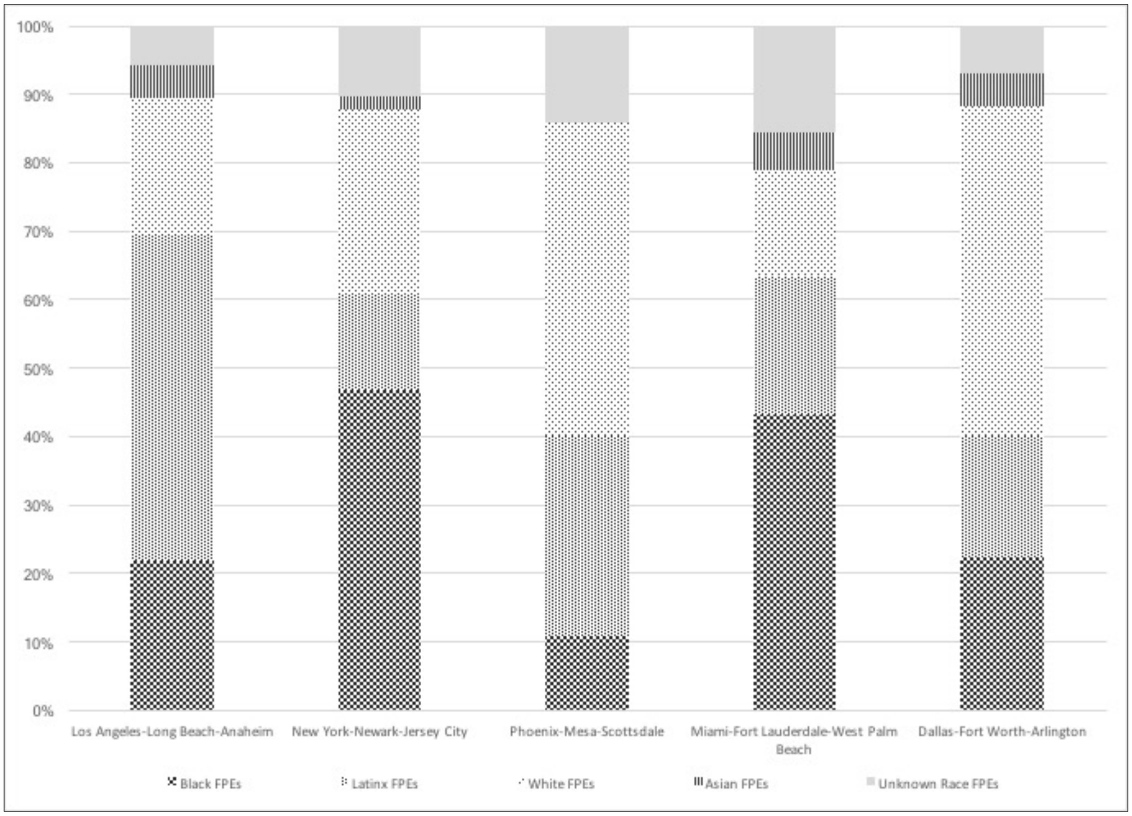


Table 2. Descriptive Statistics for Environmental Variables for Census Tracts in CBSAs, 5-Year Estimates, 2011-2014[3]

Variable	CBSA	Tracts with No Fatal Encounters *(Mean)*	Tracts with Fatal Encounters *(Mean)*
Median Household Income	Phoenix-Mesa-Scottsdale, AZ	60,167.63**	47,205.87**
	Los Angeles-Long Beach-Anaheim, CA	65,947.79**	53,912.03**
	Miami-Fort Lauderdale-West Palm Beach, FL	55,078.68**	46,895.38**
	New York-Newark-Jersey City, NY NJ CT PA	73,624.39**	56,655.92**
	Dallas-Fort Worth-Arlington, TX	66,056.88**	51,186.31**
Pct. Of Households in Poverty	Phoenix-Mesa-Scottsdale, AZ	13.9%**	21.1%**
	Los Angeles-Long Beach-Anaheim, CA	14.23**	18.83%**
	Miami-Fort Lauderdale-West Palm Beach, FL	14.18**	18.48%**
	New York-Newark-Jersey City, NY NJ CT PA	12.38**	18.31%**
	Dallas-Fort Worth-Arlington, TX	13.07**	19.21%**
Percent of Vacant Housing Units	Phoenix-Mesa-Scottsdale, AZ	13.61%	14.12%
	Los Angeles-Long Beach-Anaheim, CA	6.10%	6.01%
	Miami-Fort Lauderdale-West Palm Beach, FL	16.65%	15.38%
	New York-Newark-Jersey City, NY NJ CT PA	8.96%	9.74%
	Dallas-Fort Worth-Arlington, TX	8.29%**	10.8%**
Percent of Multi-Family Housing Units	Phoenix-Mesa-Scottsdale, AZ	25.92%	32.21%
	Los Angeles-Long Beach-Anaheim, CA	39.4%	42.79%
	Miami-Fort Lauderdale-West Palm Beach, FL	43.81%	47.79%
	New York-Newark-Jersey City, NY NJ CT PA	54.83%**	65.51%**
	Dallas-Fort Worth-Arlington, TX	30.82%*	37.87%*
Percent of Renter-Occupied Housing Units	Phoenix-Mesa-Scottsdale, AZ	37.93%**	47.11%**
	Los Angeles-Long Beach-Anaheim, CA	50.56%**	56.93%**
	Miami-Fort Lauderdale-West Palm Beach, FL	38.5%**	46.9%**
	New York-Newark-Jersey City, NY NJ CT PA	47.21**	59.42%**
	Dallas-Fort Worth-Arlington, TX	39.51**	50.15%**
Median Year Housing Units Built	Phoenix-Mesa-Scottsdale, AZ	1987**	1978**
	Los Angeles-Long Beach-Anaheim, CA	1965	1963
	Miami-Fort Lauderdale-West Palm Beach, FL	1978*	1974*
	New York-Newark-Jersey City, NY NJ CT PA	1962	1962
	Dallas-Fort Worth-Arlington, TX	1982**	1976**
Percent of Households with No Vehicle	Phoenix-Mesa-Scottsdale, AZ	7.06%*	9.28%*
	Los Angeles-Long Beach-Anaheim, CA	9.02%**	11.55%**
	Miami-Fort Lauderdale-West Palm Beach, FL	9.29%**	12.84%**
	New York-Newark-Jersey City, NY NJ CT PA	28.98%**	36.94%**
	Dallas-Fort Worth-Arlington, TX	5.69%**	9.07%**

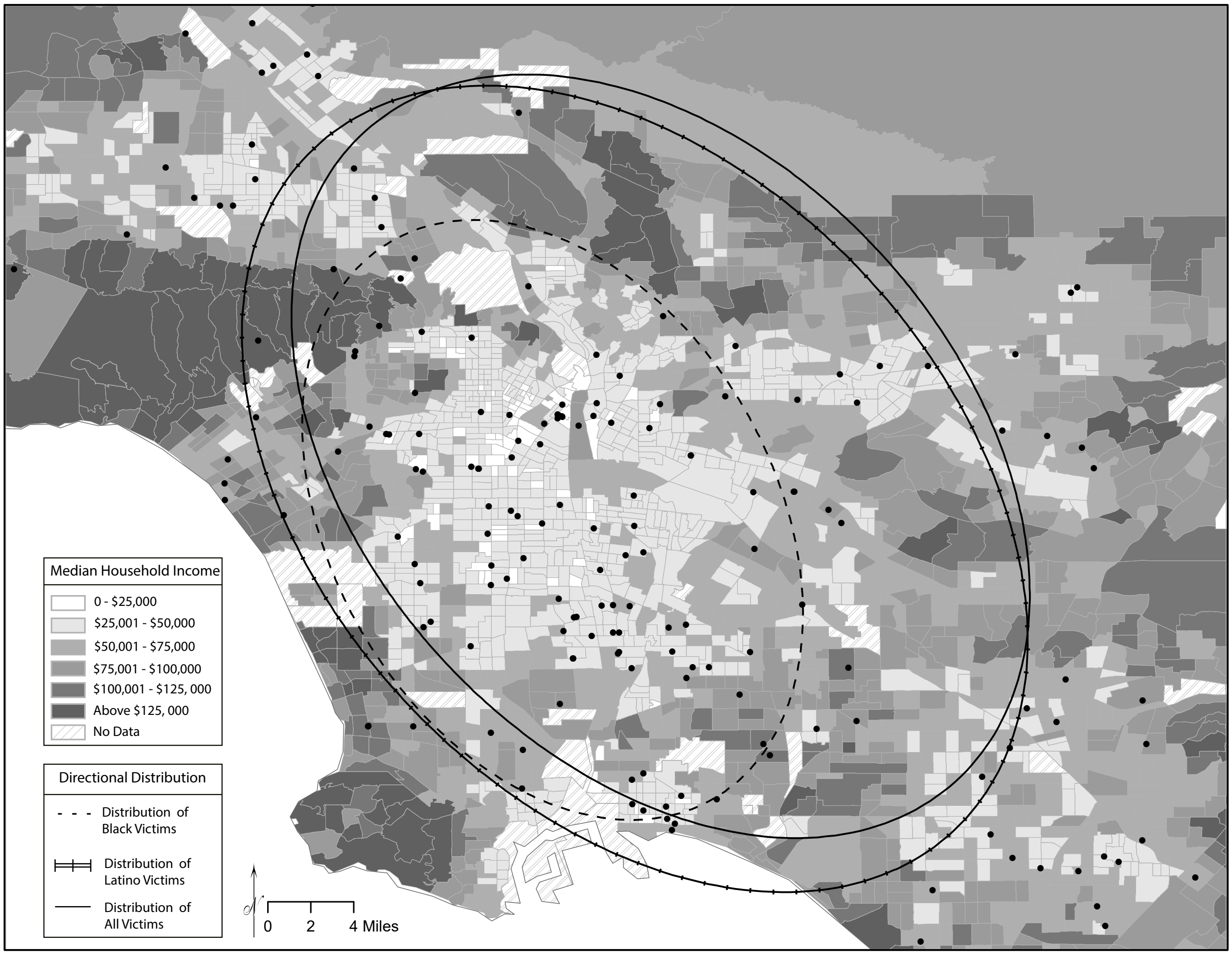
*Statistically significant difference at the 95% confidence interval.
**Statistically significant difference at the 99% confidence interval.

Table 3. Descriptive Statistics Racial Demographic Variables for Census Tracts in CBSAs, 5-Year Estimates, 2011-2014

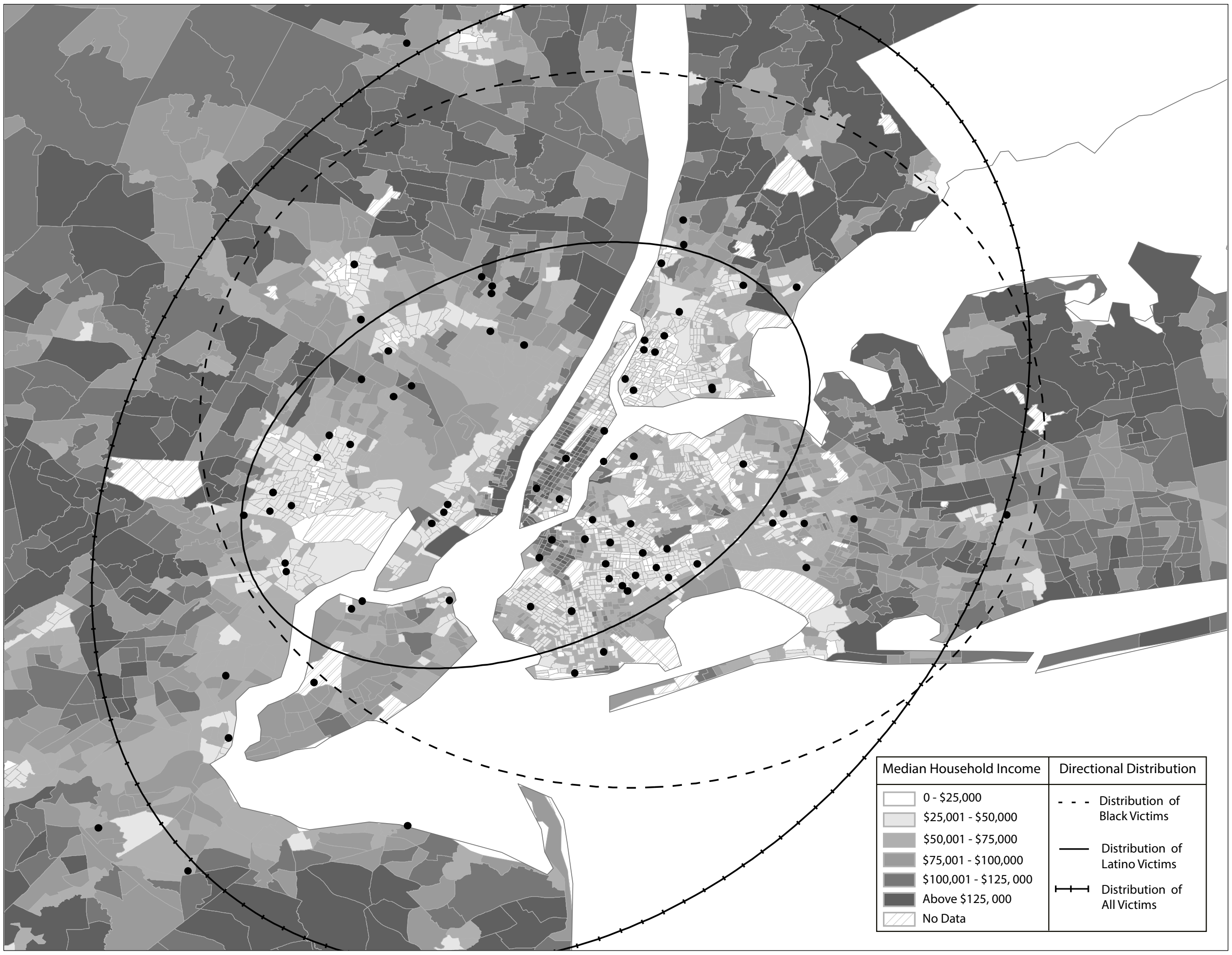
Percent of Population	CBSA	Tracts with No Fatal Encounters *(Mean)*	Tracts with Fatal Encounters *(Mean)*
Non-White Population	Phoenix-Mesa-Scottsdale, AZ	40.85%**	51.85%**
	Los Angeles-Long Beach-Anaheim, CA	67.72%**	79.39%**
	Miami-Fort Lauderdale-West Palm Beach, FL	60.23%**	71.51%**
	New York-Newark-Jersey City, NY NJ CT PA	52.14%**	65.21%**
	Dallas-Fort Worth-Arlington, TX	50.98%**	59.79%**
White (Non-Latino)	Phoenix-Mesa-Scottsdale, AZ	58.82%**	48.15%**
	Los Angeles-Long Beach-Anaheim, CA	31.66%**	20.04%**
	Miami-Fort Lauderdale-West Palm Beach, FL	38.00%**	27.21%**
	New York-Newark-Jersey City, NY NJ CT PA	46.90%**	34.79%**
	Dallas-Fort Worth-Arlington, TX	48.78%**	40.21%**
Black/African American	Phoenix-Mesa-Scottsdale, AZ	4.76%	5.37%
	Los Angeles-Long Beach-Anaheim, CA	6.34%**	10.40%**
	Miami-Fort Lauderdale-West Palm Beach, FL	17.95%**	32.21%**
	New York-Newark-Jersey City, NY NJ CT PA	17.07%**	28.76%**
	Dallas-Fort Worth-Arlington, TX	14.47%**	22.60%**
Latino/Hispanic	Phoenix-Mesa-Scottsdale, AZ	28.24%**	39.84%**
	Los Angeles-Long Beach-Anaheim, CA	43.69%**	54.97%**
	Miami-Fort Lauderdale-West Palm Beach, FL	38.92%**	35.81%**
	New York-Newark-Jersey City, NY NJ CT PA	22.33%	25.84%
	Dallas-Fort Worth-Arlington, TX	28.21%	31.61%
American Indian	Phoenix-Mesa-Scottsdale, AZ	1.99%	1.63%
	Los Angeles-Long Beach-Anaheim, CA	0.20%	0.19%
	Miami-Fort Lauderdale-West Palm Beach, FL	0.12%	0.17%
	New York-Newark-Jersey City, NY NJ CT PA	0.15%	0.28%
	Dallas-Fort Worth-Arlington, TX	0.27%	0.31%
Asian	Phoenix-Mesa-Scottsdale, AZ	3.54%	2.85%
	Los Angeles-Long Beach-Anaheim, CA	14.72%**	11.24%**
	Miami-Fort Lauderdale-West Palm Beach, FL	2.18%	1.81%
	New York-Newark-Jersey City, NY NJ CT PA	10.28%	8.59%
	Dallas-Fort Worth-Arlington, TX	5.89%**	3.41%**
Pacific Islander	Phoenix-Mesa-Scottsdale, AZ	0.19%	0.27%
	Los Angeles-Long Beach-Anaheim, CA	0.25%	0.37%
	Miami-Fort Lauderdale-West Palm Beach, FL	0.03%	0.04%
	New York-Newark-Jersey City, NY NJ CT PA	0.03%	0.02%
	Dallas-Fort Worth-Arlington, TX	0.10%	0.07%
Other Race	Phoenix-Mesa-Scottsdale, AZ	0.11%	0.08%
	Los Angeles-Long Beach-Anaheim, CA	0.24%	0.30%
	Miami-Fort Lauderdale-West Palm Beach, FL	0.31%	0.30%
	New York-Newark-Jersey City, NY NJ CT PA	0.66%	0.53%
	Dallas-Fort Worth-Arlington, TX	0.15%	0.08%
Two or More Races	Phoenix-Mesa-Scottsdale, AZ	2.01%	1.81%
	Los Angeles-Long Beach-Anaheim, CA	2.28%*	1.91%*
	Miami-Fort Lauderdale-West Palm Beach, FL	1.11%	1.17%
	New York-Newark-Jersey City, NY NJ CT PA	1.62%	1.18%
	Dallas-Fort Worth-Arlington, TX	1.91%	1.71%

*Statistically significant difference at the 95% confidence interval.
**Statistically significant difference at the 99% confidence interval.

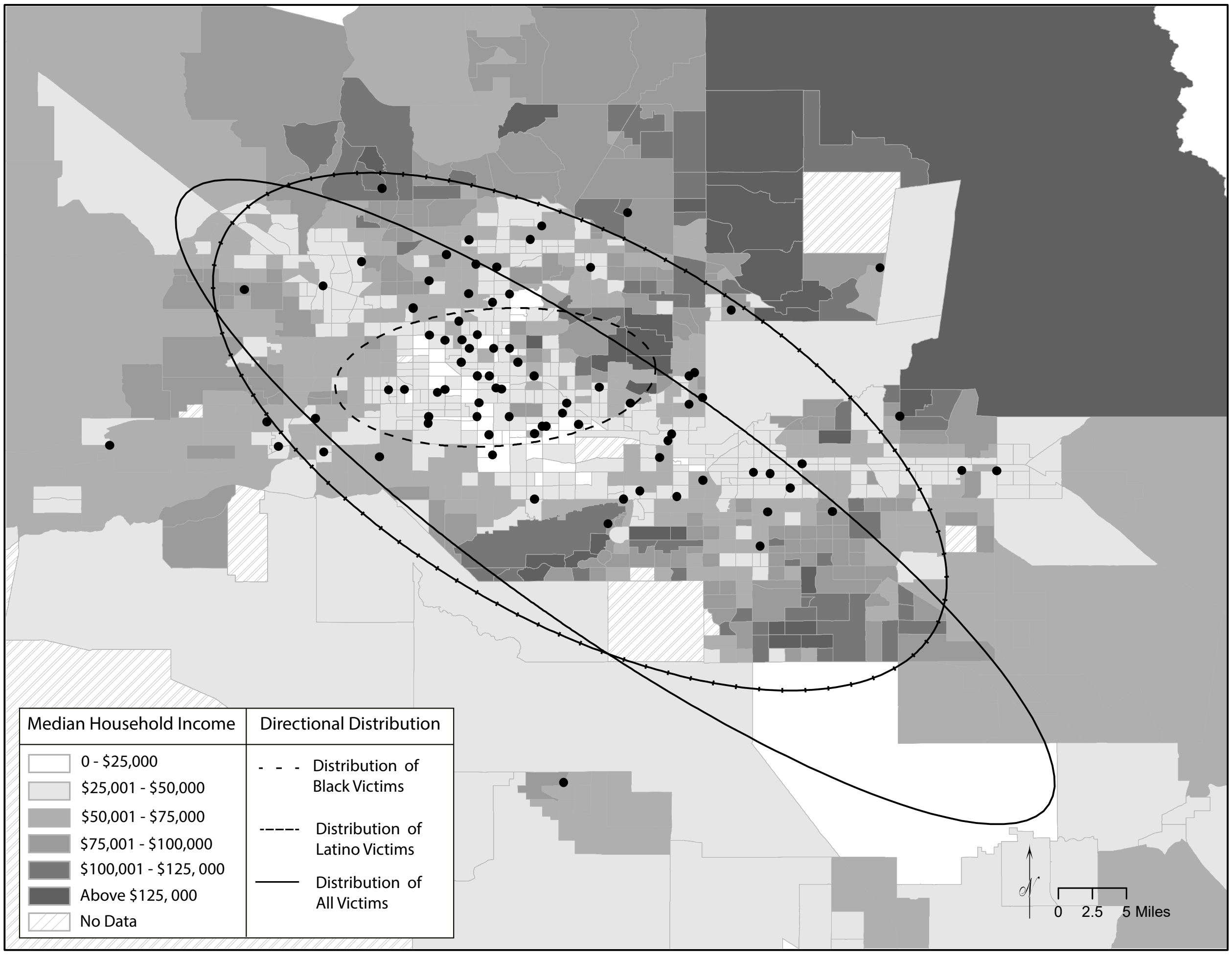
Map 2. Los Angeles-Long Beach-Anaheim, CA CBSA Police Shootings, 2013-2015



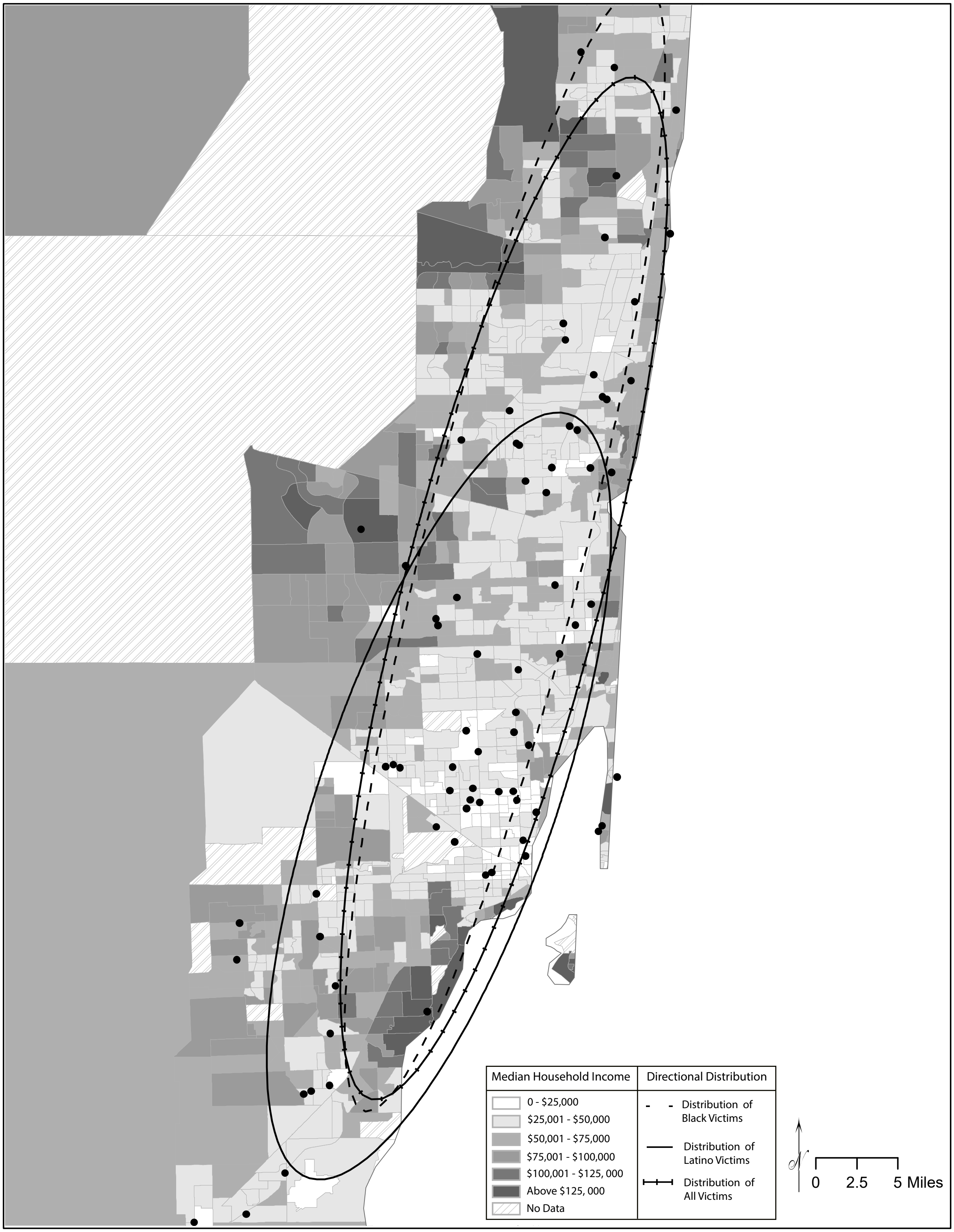
Map 3. New York-Newark-Jersey City, NY-NJ-PA CBSA Police Shootings, 2013-2015



Map 4. Phoenix-Mesa-Scottsdale, AZ Police Shootings, 2013-2015



Map 5. Miami-Fort Lauderdale-West Palm Beach, FL Police Shootings, 2013-2015



Map 6. Dallas-Fort Worth-Arlington, TX Police Shootings, 2013-2015

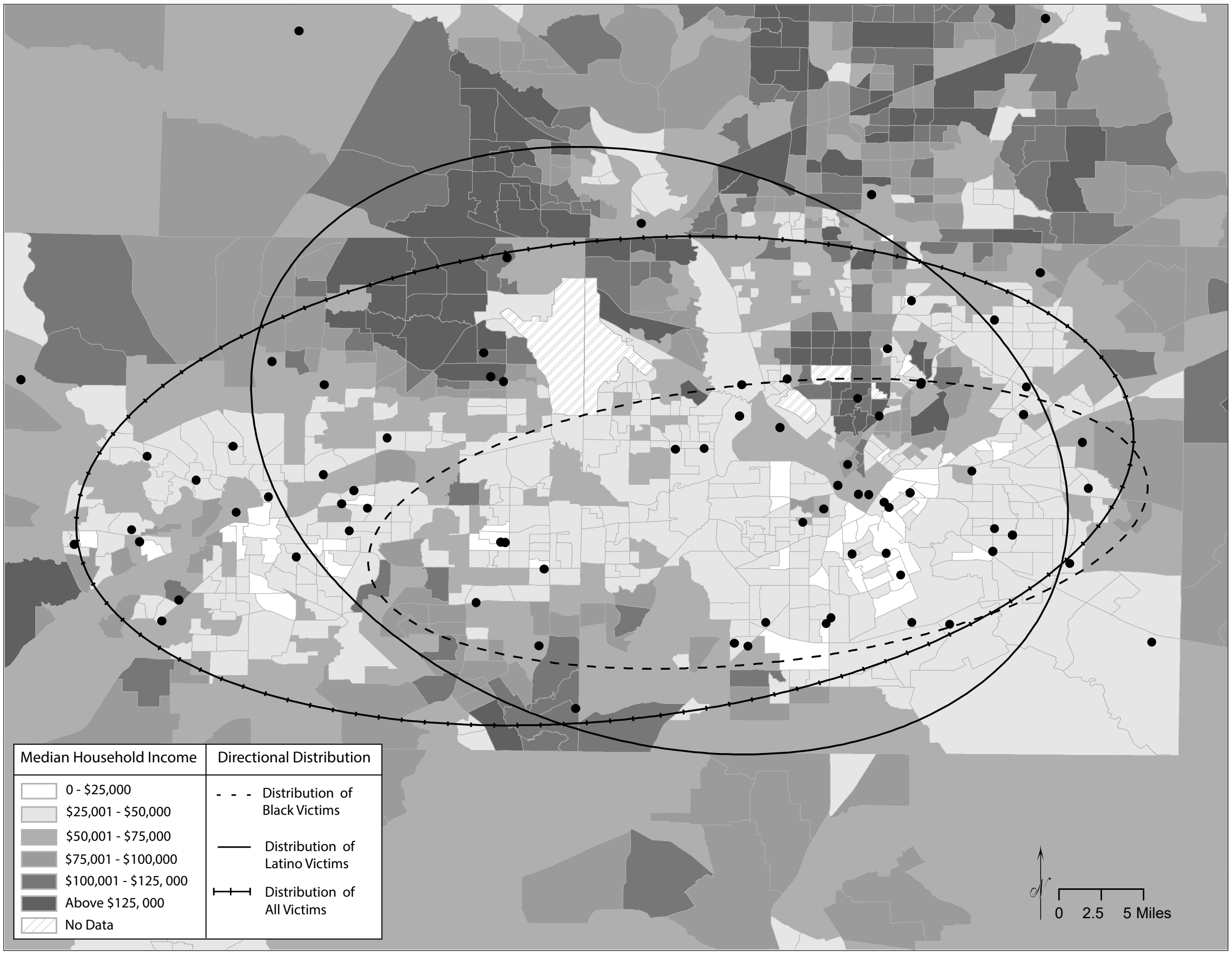


Table 4. Spearman's rho Correlation Coefficients, Victim Counts by Race And Neighborhood Context Variables

	Total Population	Median Household Income	Households in Poverty	Vacant Housing Units	Multi-Family Units	Median Year Built	Total F.P.E.s Per Tract	Black F.P.E.s	Latinx F.P.E.s	White F.P.E.s
Median Household Income	**.071****									
Households in Poverty	**-.023***	**-.842****								
Vacant Housing Units	**-.199****	**-.237****	**.142****							
Multi-Family Units	**-.138****	**-.473****	**.417****	**.210****						
Median Year Built	**.182****	**.107****	**-.159****	**.159****	**-.166****					
Total F.P.E.s Per Tract	**.038****	**-.117****	**.110****	**.045****	0.017	0.001				
Black F.P.E.s	0.019	**-.095****	**.088****	**.041****	**.042****	**-.026***	**.527****			
Latinx F.P.E.s	**.032****	**-.082****	**.085****	-0.011	0.001	**-.027***	**.548****	**.024***		
White F.P.E.s	0.021	-0.014	0.011	**.040****	-0.013	**.053****	**.542****	0.009	0.007	
Unknown Race F.P.E.s	-0.001	**-.045****	**.030****	**.036****	0.006	0.011	**.313****	**.033****	0.017	0.018

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
c. Listwise N = 8639

Table 5. Spearman's rho Correlation Coefficients, Victim Counts and Racial Demographic Variables

	Total Pop.	Total F.P.E.s***	Black F.P.E.s	Latinx F.P.E.s	White F.P.E.s	Unknown Race F.P.E.s	Non-White Pop.	Pct. White Pop.	Pct. Black Pop.	Pct. Latinx Pop.	Pct. American Indian Pop.	Pct. Asian Pop.	Pct. Pacific Islander	Pct. Other Race
Total F.P.E.s	.043**													
Black F.P.E.s	.022*	.532**												
Latinx F.P.E.s	.036**	.542**	.026**											
White F.P.E.s	.019*	.550**	.019*	0.005										
Unknown Race F.P.E.s	-0.001	.316**	.026**	.025**	0.014									
Non-White Pop.	.025**	.083**	.093**	.089**	-.043**	.022*								
Pct. White Population	-.026**	-.082**	-.093**	-.089**	.043**	-.022*	-.999**							
Pct. Black Population	.019*	.056**	.104**	-0.003	-0.005	.032**	.465**	-.466**						
Pct. Latinx Population	.127**	.076**	.028**	.108**	-0.009	.019*	.689**	-.690**	.123**					
Pct. American Indian Population	.059**	.040**	-0.006	0.018	.051**	0.016	-0.019	0.018	0.014	.025**				
Pct. Asian Population	.043**	-.064**	-.054**	-.027**	-.033**	-.029**	-.050**	.051**	-.191**	-.134**	-0.009			
Pct. Pacific Islander	.064**	.040**	-0.001	.033**	.034**	0.008	.045**	-.046**	-.034**	.087**	.098**	.110**		
Pct. Other Race	.034**	-0.014	0.003	-0.012	-0.015	-0.011	.108**	-.108**	.170**	0.015	-.032**	.101**	-.028**	
Pct. Two or More Races	.043**	-.032**	-.031**	-.041**	0.017	-0.005	-.161**	.162**	.096**	-.202**	.109**	.309**	.111**	.152**

Table 6. Poisson Regression Parameter Estimates

	Los Angeles-Long Beach-Anaheim		New York-Newark-Jersey City		Phoenix-Mesa-Scottsdale		Miami-Fort Lauderdale-West Palm Beach		Dallas-Fort Worth-Arlington	
	Beta	*Std. Error*	*Beta*	*Std. Error*	*Beta*	*Std. Error*	*Beta*	*Std. Error*	*Beta*	*Std. Error*
(Intercept)	-2.248	8.0235	10.452	7.8658	8.451	7.8835	2.303	7.7591	2.073	7.7444
Median Household Income	**-1.755E-05****	3.6332E-06	**-1.118E-05****	3.5080E-06	**-1.496E-05****	3.6453E-06	**-1.659E-05****	3.6578E-06	**-1.668E-05****	3.6393E-06
Households in Poverty	0.943	0.5672	0.733	0.5657	0.789	0.5688	0.935	0.5687	0.949	0.5684
Vacant Housing Units	0.834	0.6439	0.351	0.6738	0.287	0.6777	0.674	0.6556	0.633	0.6498
Multi-Family Housing Units	**-0.816***	0.3181	-0.553	0.3223	**-0.646***	0.3272	**-0.893****	0.3242	**-0.908****	0.3171
Renter Occupied Housing Units	**0.940***	0.4514	0.710	0.4401	**1.079***	0.4425	**1.194****	0.4488	**1.212****	0.4353
Median Year House Built	0.001	0.0037	-0.007	0.0037	-0.005	0.0037	-0.001	0.0036	-0.001	0.0036
No Vehicle in Household	**-1.412****	0.4549	-0.143	0.5075	-1.796	0.4445	**-1.659****	0.4431	**-1.676****	0.4449
Pct. White Population	-1.394	2.9649	0.083	3.0406	-1.522	2.9813	-2.120	2.9401	-2.151	2.9335
Pct. Black Population	-0.648	2.9488	0.827	3.0203	-0.469	2.9683	-1.359	2.9274	-1.396	2.9165
Pct. Latinx Population	-1.350	2.8948	0.023	2.9687	-1.204	2.9201	-1.936	2.8800	-1.984	2.8710
Pct. American Indian Population	-0.991	3.3411	0.568	3.4342	-2.247	3.6063	-1.758	3.3326	-1.828	3.3353
Pct. Asian Population	-2.124	2.9991	-0.612	3.0799	-1.678	3.0301	-2.540	2.9870	-2.585	2.9815
Pct. Pacific Islander Population	6.354	6.1047	8.024	6.2384	6.690	6.1180	6.507	6.0205	6.451	6.0316
Pct. Other Race	-6.407	6.7188	-1.670	6.7361	-7.118	6.6474	-7.696	6.6641	-7.817	6.6797
Pct. Two or More Races	0[a]		0[a]		0[a]		0[a]		0[a]	
[x = CBSA=1]	**0.280***	0.1314	**-1.018****	0.1798	**0.600****	0.1545	-0.020	0.1441	-0.050	0.1345
[x = CBSA=0]	0[a]		0[a]		0[a]		0[a]		0[a]	
(Scale)	1[b]		1[b]		1[b]		1[b]		1[b]	

[1] Two blogs/websites have served as the inspiration and background data for some of the more robust data sets outlined in our paper. *Fatal Encounters* (http://www.fatalencounters.org/) has gathered data on all fatal encounters involving police in the United States since 2000. Because of their reliance on web-scraping data techniques, much of their data lacks the comprehensiveness of *The Counted, Fatal Force, and Mapping Police Violence*. *Killed by Police* (http://www.killedbypolice.net/kbp2018) is also a useful source that has inspired the abovementioned databases but contains only the most rudimentary listing of all police related deaths with simply age, state, victim name, age, and links to Facebook posts and news articles related to each incident.

[2] Based on the variations in metropolitan area size and geography, we chose to employ the broader and less commonly used core based statistical area (CBSA). The U.S. Census Bureau defines CBSAs as "Core Based Statistical Areas (CBSAs) consist of the county or counties or equivalent entities associated with at least one core (urbanized area or urban cluster) of at least 10,000 population, plus adjacent counties having a high degree of social and economic integration with the core as measured through commuting ties with the counties associated with the core. The general concept of a CBSA is that of a core area containing a substantial population nucleus, together with adjacent communities having a high degree of economic and social integration with that core. The term "core based statistical area" became effective in 2003 and refers collectively to metropolitan statistical areas and micropolitan statistical areas." Source: 2010 Census Summary File 1 Technical Documentation/prepared by the U.S. Census Bureau, 2012.

[3] All demographic and housing data used in this study came from the U.S. Census Bureau, American Community Survey, 5-Year data estimates, 2011-2015. Although we understand the challenges of interpretation with rolling-five year estimates with, in some cases, very high margins of error, we feel that this analysis loses all rigor at the county level with 1- or 3-year ACS data.