‘Hands Up, Don’t Shoot’:

Is police violence higher in American suburbs?

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v. Abbreviations

BLM: Black Lives Matter (movement)
CDC: Centers for Disease Control and Prevention
CIT: Crisis Intervention Team
GLM: Generalized Linear Model
HUD: Department of Housing and Urban Development
MSA: Metropolitan Statistical Area
MPV: Mapping Police Violence
NCES: National Center for Education Statistics
NCHS: National Center for Health Statistics
NYPD: New York City Police Department
OECD: Organisation for Economic Co-operation and Development
OLS: Ordinary Least Squared
RUCC: Rural-Urban Continuum Codes
ZIP: Zone Improvement Plan

vi. Notes on race

Adhering to the New York Times Editorial guidelines released in 2020, when noting the race of individuals and populations, ‘Black’ is used instead of African American or Afro Americans, which many feel inaccurately describes their background. The term is capitalized, which for many signifies the difference between a color and a culture (Coleman, 2020). The same choice is not made with respect to the term ‘white’, which, in its capitalized form, has a history of white supremacy.

However, when referring to the categories found in our tables of results, we will capitalize all race terms (White, Black, Hispanic, and Other) for clarity and ease of readership and to signal the analysis results.

For the category of ‘Other’ we do not endorse the usage of this term to encompass the broad range and complexities of race that, herein, can refer to individuals of Asian, Pacific Islander, Native American, Alaskan American, and ‘Unknown’ origins. We are unfortunately limited by the existing data sources that reflect these categorizations and understand that, in the context of the United States, treating the vast array of racial identities as four discrete outcomes is not in accordance with lived realities.

The same can be said of the use of the term ‘Hispanic’ which, according to the official US Census categorization is not a race but an ethnicity, predominantly used to describe country of origin or migration background. Increasingly, the term is used to describe brown-skinned individuals who do not fit the description of white or Black. For these reasons and more, we do not endorse this terminology and call for greater consideration to be given to these populations in discussions of race in America.

1. Executive summary

The United States is one of the leading nations for fatalities at the hands of the police. Advocates have recently proposed increased rates of violence in suburbs relative to urban communities. This perspective contrasts to the traditional and historical narratives that highlight high crime rates in urban areas and, by extension, police fatalities. Discrepancies in current media show that there is no clear understanding in the link between rurality and police violence. Under these circumstances, we examine rates of police violence from 2015-2019 as they vary according to the rurality definitions of three classifications in the United States: the rural-urban continuum codes (RUCC) by the Department of Agriculture, the rural-urban classification scheme by the National Center of Health Statistics (NCHS), and the perception-based survey of rurality by the real-estate company Trulia. We find consistently even rates of police violence by rurality for NCHS and RUCC, the two governmental measurements that examine county-level data. For Trulia, we found elevated rates in urban areas and lower rates of suburban violence in comparison to the NCHS and RUCC systems. However, Trulia also contains many ‘Unknown’ ZIP codes, missing from the dataset, leading to inconclusive results. In an attempt to map the statistical relationship between police violence and rurality, we attempted to fit the data to linear and non-linear models. However, the data was ultimately unsuitable for modeling due to the high prevalence of zero values. Due to this limitation, we are not able to claim a link between police violence and rurality. In conclusion, we recommend more rigorous national data collection on policing as well as a shift in conversation away from ideological statements of rurality and police violence so that more accurate, targeted solutions can be developed to alleviate the extreme nature of American policing.

2. Introduction

More than 1,000 people are killed by the police in the United States every year (Sawyer & Jones, 2020). This number far exceeds other comparable OECD nations with the second highest ranking country recording 36 deaths per year. Even after accounting for population size, death rates are more than three times higher than any other OECD country (Sawyer & Jones, 2020). These killings disproportionately affect people of color and research consistently shows victimization rates ranging from two to three times higher than white individuals (Lett et. al, 2021). Racial disparities concerning police violence and fatalities are well documented (Hemenway, 2020; Hoekstra & Sloan, 2020; Siegel, 2020), therefore our research will not place a heavy emphasis on race's role in police violence. Instead, our research will primarily explore the possible link between police fatalities and rurality, a factor largely unexplored in police violence research.

Our research topic was motivated by conflicting narratives on the concentration of police deaths in suburban versus urban communities. Common perception tends to focus on the notion that urban areas of the country maintain elevated police fatality rates, which is often reinforced by studies predominantly examining large cities (Hoekstra & Sloan, 2020; Rad, 2018). However, over the past several years, advocacy organizations, including Campaign Zero, have suggested police fatalities in the suburbs have higher incidents of police killings in comparison to urban and rural communities according to the rurality classification by the real estate company, Trulia (Sinyangwe, 2020). Campaign Zero is a research and advocacy organization that encourages local and national policy solutions, guided by emerging research findings, to reduce police violence. In addition to creating one of the first comprehensive national police fatality databases, Campaign Zero attempts to answer many questions about police violence, including where it occurs most frequently.

The shifting narrative prompted us to explore the possible connection between police fatalities and rurality. In the United States, our understanding of rurality has traditionally followed from classical depictions of four major rurality types: cities or metro urban areas, suburban havens from busy city life, quiet and charming towns, and rustic farms or rural communities. The term 'rurality' herein refers to the spectrum (urban, suburban, town, rural) whereas the term 'rural' constitutes a specific categorization often associated with sparsely populated areas. When examining the relevant research, we found few studies exploring the relationships between rurality and police violence. However, a noteworthy study by Hemenway et. al. (2020) analyzed the death rates of fatal police shootings across five different rurality classifications from 2015-2017 and found similar rates across rurality types for all five classification schemes, including Trulia.

Motivated by conflicting narratives surrounding the location of police killings, our research will seek to validate if death rates vary by rurality type. We will use the Mapping Police Violence (MPV) database from Campaign Zero, which more broadly defines police fatalities, to assess death rates according to three rurality classification schemes selected from those observed in the Hemenway paper. We expect to find fairly consistent death rates across rurality types with potentially slightly elevated rates in suburban classifications. We believe police violence to be an institutional challenge as opposed to an attribute of place, therefore we expect to find only small variations in death rates. Exploring the possible link between rurality and police violence may help us answer important questions about how to target policies that effectively address such discrepancies. If instead we see no correlation between rurality and violence, it would prompt policymakers and researchers to look beyond culture and geography towards institutional factors.

The following research exploring the possible connection between police violence and rurality begins with some background of the historical context and narrative surrounding police violence in section 3.1. We further discuss the complexities of defining rurality and review current research aimed at understanding factors that contribute to police violence. Next, in section 4, we discuss data sources and methodology before providing a statistical analysis of the results in section 5.1. In section 5.2 we explore possible statistical models in greater depth before concluding with a discussion, policy recommendations and study limitations in sections 5.3-5.6.

3. Background

3.1 Historical and political context

Rurality is frequently discussed in connection with crime, and by extension, police violence. For decades, it was common understanding that 'inner-city crime' was a unique and incessant problem that required the full force of the law.

The origin of 'inner-city' crime

The end of Jim Crow segregation laws led to mass in-country migration of nearly 6 million Southern Black Americans to major urban sites. The most common destinations were Los Angeles, Chicago, New York, Philadelphia and Detroit (History.com Editors, 2021). This period of Black American history is often referred to as the Great Migration. By the 1980s, populations of Black Americans in large metro areas had grown dramatically.

At the same time, Americans were experiencing a public shift in political ideology. In response to growing crime rates and the end of an era of racial segregation, Democrats and Republicans alike were eager to show the American public that they were 'tough on crime'. The resulting political shift became known as the War on Crime, declared by the Johnson Administration in 1964. Ironically, beginning at the peak of the Civil Rights movement, President Johnson sent to Congress the Law Enforcement Assistance Act which, for the first time, gave the federal government a role in local police operations (Hinton, 2016). Compounded by the War on Drugs declared in 1971 by the Nixon Administration, the two administrations created a new direction for crime and punishment. This era favored strong punitive measures towards crime in general with an emphasis on drug use and possession. The focus quickly moved towards urban centers, where the so-called 'inner-city' crime and 'black-on-black' crime ran rampant (Meeks, 2006). Using existing racial tensions, administrations and policing districts capitalized on public fear to enforce heavy prison sentencing and 'broken-window' policing[1]. Similar laws and attitudes

[1] Broken-window policing constitutes the focus on the appearance of the built environment as a determinant of crime levels (CEBCP, 2021).

continued throughout the end of the century, evident in legislation such as the 1992 Crime Bill that introduced the three-strikes rule, and lasted into the 21st century (Violent Crime Control and Law Enforcement Act, 1994).

Implicit in the 'inner-city' violence narrative was the assumption that Black people and other people of color (namely brown immigrants) were the source of crime and required intense policing. This type of rhetoric is known as 'dog-whistle politics', and it capitalized on white fear to advance political agendas (Haney-Lopez, 2015).

The effect of these long-lasting crime ideologies was an overzealous focus on 'inner-city' crime, where urban police were heavily militarized and seen as the "frontmen of justice" (Meeks, 2006; Hinton, 2016). Implicit in the foundation of these crime bills were elevated crime rates in urban areas. And while crime rates did come down after this era of increased policing, many observers note that it came at a steep cost, particularly for communities of color who experienced extreme over-policing (Levitt, 2004).

But while official government sources tracked crime rates closely and staked their political careers on their ability to bring down crime, little to no attention was paid to rates of police violence. If noted at all, police violence was seen as an unfortunate side effect of increased policing and therefore assumed that police violence too would be higher in urban areas. Little attention was paid to whether or not this was true and the national conversation largely pivoted on unfounded claims, punditry, and ideological warfare. The little research that was conducted to understand rates of police violence and urban crime was built on unreliable data (Fyfe, 1982).

As Black 'inner-city' crime dominated the national conversation around place and policing, American suburbs were born. The well-documented 'white-flight' to suburbs is often understood by historians as a direct response to the Great Migration. Some researchers suggest that, if not for southern Black migration, the growth of American suburbs would be 20% lower (Boustan, 2006). The resulting dispersion along racial lines created levels of segregation higher or parallel to those just before Jim Crow ended (Rothstein, 2013). White suburbia became the antithesis to Black/diverse urban areas.

The Black Lives Matter movement launched in 2013 with the intention to raise national awareness of over-policing in Black communities and what they considered perverse policing incentives. Smartphone technology allowed for incidents of police abuse to be captured and spread on social media for the first time. The resulting grassroots movement has brought increased attention to the victims of police violence and increased advocacy for legislative and judicial solutions. As of a recent 2020 poll, researchers found that a record high portion of Americans, two-thirds, supported protests for racial justice (Long & McCarthy, 2020).

BLM was also successful in shifting the conversation away from the 'inner-cities' to a different conversation about place and crime. Starting in the mid 2010s, BLM began to push a new narrative which de-centered 'inner-city' crime by focusing on the institutional factors. The problem, the movement argued, was not Black people and people of color: it was the systems that created cycles of poverty and, crucially, the perception of people of color in the media and in daily life.

With this shift in perception, a new narrative of place and police violence was promoted. Advocates argued that suburban areas were the true epicenter of American police violence where the growing diversification of traditionally white suburbs stoked racial tensions. From this theory, media outlets began to cover this angle, particularly following high profile shootings of Black men in suburbs such as Kenosha, Wisconsin and Brooklyn Center Minnesota (Hellmann, 2020 and IA by NPR, 2021). Organizations that track police violence, such as MPV, have argued that while fatalities have gone down in cities, they have been offset by higher rates in suburban and rural areas (Sinyangwe, 2020). This reality is reflected in common perception: more minorities (29%) in suburbs report having 'not much' or 'no confidence' in local police agencies compared to 14% of white suburbanites (Goodyear, 2014).

Growth of suburbia

Recently, there has been a reported rise in the number of Americans of all races living in suburbia. Research shows that the population of the suburban counties of major urban centers has increased 25% since 2000, outpacing the overall population growth rate of 16% (Fry, 2020). While Americans are flocking to suburbia, we can also see that urban centers are increasingly holding the mass majority of the American population (85%) with only 12.6%, or around 41 million, Americans in suburbs and towns by our estimates using the rural-urban continuum codes (RUCC) classification of rurality. Additionally, urban areas are twice as diverse as non-urban areas.

Table 3.1 Average population by RUCC rurality

RUCC Rurality Code	*Total Population*	*% of Total Pop*	*Non-White Population*	*%Non-White*
Urban	278,360,057	85.80%	113,675,577	40.84%
Suburban	28,184,533	8.69%	5,788,388	20.54%
Towns	13,172,206	4.06%	2,994,647	22.73%
Rural	4,688,624	1.44%	808,305	17.24%
Source: Population estimates according to US Census, an average of reported values from 2015-19. Classified here according to RUCC codes where RUCC 1-3 = Metro, RUCC 4&6 = Suburban, RUCC 5&7 = Towns, and RUCC 8&9 = Rural. For more information on rurality classification, see section 4. 2 Methodology.				

While the traditional view of suburbia is that of a place mainly occupied by white Americans, data from 2015-2019 show a significant suburban population (20%) of non-white residents, though a disproportionate number of Americans of color still reside in large central cities (Frey, 2001). While the majority of the US population resides in cities, advocates have noted trends in increased police violence on the outskirts of central cities, leading to questions of whether and why suburban fatalities are on the rise. Many are inclined to believe that lingering racial tension and unrest, stoked by the presence of more minorities in white suburbia, leads to higher interactions with the police and therefore, greater opportunity for police violence (Sinyangwe, 2020).

Furthermore, while an increasingly small number of Americans reside in rural locations, one might suspect that different micro-cultures could have an effect on policing and crime. Closely related to this topic is the notion that fatalities committed by the police may vary with increased gun ownership rates (see more in 3.4 Literature Review). Though not explicitly connected, one might suspect that rates of gun ownership would increase with higher rurality, therefore bringing highly rural places under question in the discussion of rurality and police violence (Parker et. al., 2017). Though this narrative is not currently popular or even discussed in recent discourse, we nonetheless include rural locations in our analysis to understand national trends.

Rurality has always been and continues to be salient in the conversation and methods used in policing. Entire political ideologies, and therefore subsequent crime, policing, and incarceration policies, are decided and created under the narratives that result from the intersection of rurality and policing. Because of this, there is a great need to understand if there is indeed a link or not.

3.2 Rurality: defined

We have established that rurality is relevant in the context of crime and policy, whether it be the troubling narrative of 'inner-city' crime or racially-tense American suburbs.

The definition of rurality, however, can be defined by a plurality of methods with no one definition held as the gold standard (Hemenway, 2020). Rurality data is often sourced from government databases such as (1) the National Center for Health Statistics (NCHS) by the Center for Disease Control (CDC), (2) the Department of Housing and Urban Development (HUD), (3) the US Census, (4) the National Center for Education Statistics (NCES), (5) the rural-urban continuum codes (RUCC) from the Department of Agriculture and in some cases even international organizations such as the (6) OECD Degree of Urbanization.

Each measure of rurality has a different methodology, and is tailored to the motives of the organization that created it. For example, the US Census tracks only urban, urban cluster, or rural, where rural is defined only as “all territory, persons, and housing units not defined as urban” (US Census Bureau, 2021-b). In contrast, the NCES has 15 degrees of rurality all classified by school districts and/or ZIP codes. Each of these methods rely chiefly on population size, but some also account for proximity to a large metro center, as is the case with RUCC. Each measure also differs in the granularity of classification, ranging from county to ZIP code to school district.

Finally, one interesting measurement of rurality comes from the real estate website Trulia which pulls survey data from residents of individual ZIP codes. In the survey, each resident indicates their perception of their housing area as urban, suburban, or rural, without definitions provided to survey takers (Kolko, 2015). This measure of rurality is starkly different from other sources by accounting for perception rather than relying on population size, density or relation to a large metro center. They found that based on participant perception, the best indicator for rurality was by housing density and applied it to the remaining ZIP codes in their dataset.

The Trulia measurement of rurality does not yield very similar results when compared to the RUCC scheme (as illustrated in Tables 3.2), with far more Americans believing they live in a suburb than are identified under measures by the US government.

Table 3.2 Average population by Trulia rurality

Trulia Rurality Code	*Total Population*	*% Total Pop*	*Non-White Population*	*%Non-White*
Urban	68,632,475	21.10%	41,721,958	60.79%
Suburban	185,304,835	56.79%	75,627,072	40.81%
Rural	71,307,567	21.92%	16,066,649	22.53%
Source: Population estimates according to US Census, an average of reported values from 2015-19. Classified here according to Trulia codes. For more information on rurality classification, see section 4.2 Methodology.				

Suburbia itself proves exceptionally difficult to measure and estimate: while population density and distance from a metro center are standard ways to measure suburbs, the term (a highly American concept) carries with it distinct connotations of white picket fences, grass lawns, nosy neighbors, largely white and middle-class families and, as such, serves as safe shelter from 'inner-city' crime. Current understandings of American suburbia differ in what density qualifies as a suburb, what characteristics they hold, and what demographics they contain (Airgood-Obrycki & Rieger, 2009). Many sources claim that suburbs are not at all homogeneous but vary drastically in demographics and characteristics (Hall & Lee, 2009). Indeed, there is a growing need to understand what suburbs are, how they behave, and what they look like as they greatly affect American political and cultural discourse.

For the purposes of this paper, we have selected three measures of rurality to compare and contrast across method and size of the units: NCHS, RUCC, and Trulia.

At the county level, we examine police violence with the NCHS and RUCC measurements of rurality. We find RUCC more descriptive of the layout of American rurality, using both density and distance from large metro centers to define urban, suburban, towns, and rural locations. However, our background research in how crime and policing vary by rurality shows that NCHS is more often cited. We render our results using both measures to be able to compare directly to other sources and to add a greater dimension of analysis.

Lastly, our data source, Mapping Police Violence by Campaign Zero, has tracked their dataset using rurality according to Trulia. Any subsequent claims by Campaign Zero regarding rurality is therefore built on Trulia rurality data. Because of the spatial difference (using ZIP codes, which are much smaller areas of land) it's use of perception, and its relevance to MPV claims, we have continued the analysis using Trulia ZIP tags of rurality to explore its differences, uses, and potential limitations when compared to governmental data.

Below, Figures 3.1-3.3 show American geography as rendered by these three definitions of rurality. Figure 3.1 of the RUCC classification shows how metro radius and distance from metro affects the classification of a county as suburban or town. In Figure 3.2, you can visually see

NCHS attributes a much larger portion of the USA to ‘rural’ in comparison to RUCC. Additionally, there are significantly fewer locations classified as highly metro, with many more counties assigned to ‘large fringe metro’. Lastly, Figure 3.3 shows a much more granular tracking of rurality by ZIP codes using Trulia (only possible to render at the state level due to the granularity of the boundaries). See 4.2 Methodology for more details on how rurality is defined by these sources and how we leverage them for our analysis.

Figure 3.1 US map of RUCC rurality

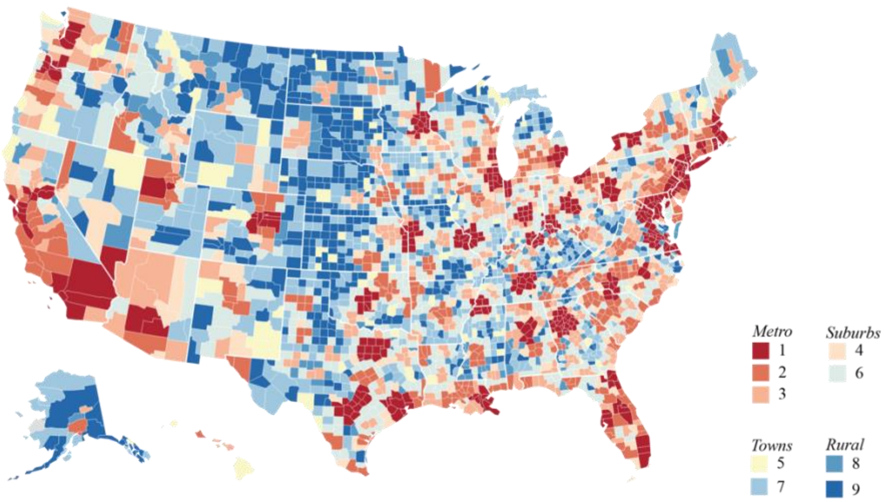


Figure 3.2 US map of NCHS rurality

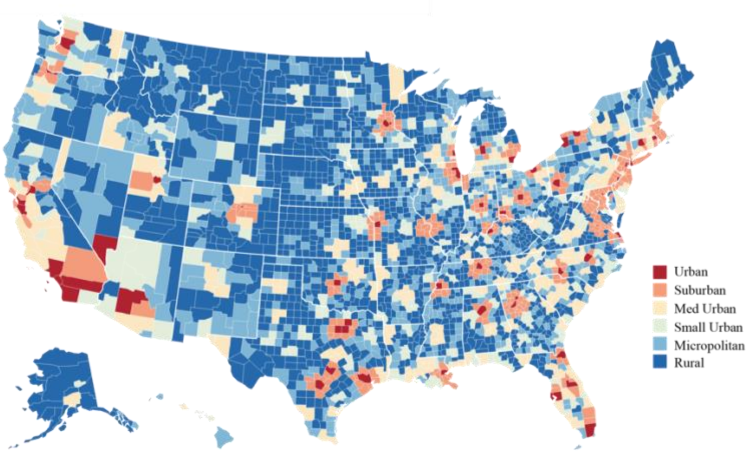
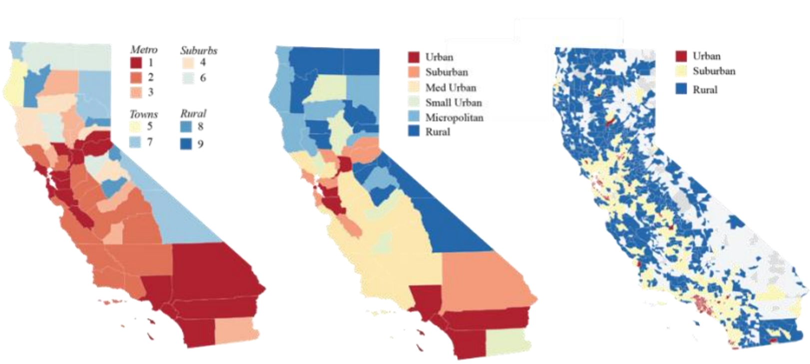


Figure 3.3 California map comparing RUCC, NCHS and Trulia ruralities



3.3 The current state of American policing

Today, there are more than 18,000 local, state, and federal law enforcement agencies. There are more than 420,000 police officers employed in law enforcement with about 3.43 sworn officers per 1,000 people as of 2012 (Bureau of Justice Statistics et al., 2016). In a population of approximately 320,000 million, there were over 10 million arrests in 2017 (FBI: UCR, 2017).

There are currently very few publicly available records on police misconduct and deaths at the hands of the police. In 2014, US Congress passed into law HR 1447 or the Death in Custody Reporting Act of 2013. HR 1447 requires states that receive federal funding to "report to the Attorney General on a quarterly basis certain information regarding the death of any person who is detained, arrested, en route to incarceration, or incarcerated in state or local facilities or a boot camp prison" (Death in Custody Reporting Act, 2013). Because the government relies on states to self-report, the Office of the Inspector General fears incidents will be undercounted (CRS, 2020). The FBI also collects data on use of force that results in death. Participation in the FBI's database is voluntary (CRS, 2020). As of today, neither of these databases have been released to the public.

In 2020, Congress raised a proposal via the Justice in Policing Act to establish national standards for police departments, which are currently largely decentralized and determined by their jurisdiction. The act would mandate data collection on police misconduct, re-program existing funds to community-based policing schemes, and streamline federal law for prosecution of excessive force while establishing independent bodies for investigation (Justice in Policing Act, 2020).

Twelve states currently have public laws that allow citizens to request police disciplinary data: Washington, Utah, Arizona, North Dakota, Minnesota, Wisconsin, Ohio, Connecticut, Maine, Alabama, Georgia, and Florida. A further fifteen have limited data available to the public and the remaining 23 states keep the information confidential (WNYC, 2021).

In the absence of a federally mandated, national database, three organizations have collected information through web scraping, examining police records, and keeping track of press releases: Fatal Encounters, The Washington Post's Fatal Force database, and Mapping Police Violence via Campaign Zero (see 4.1 Methodology for more information on these sources and how they differ).

This lack of data and transparency has made the extent and depth of research extremely limited. This is compounded by the difficult nature of studying fatalities at the hands of the police. While each death is too many, at approximately 1,000 deaths per year out of a population of 320 million, deaths from police interaction are a statistically rare event (Sawyer & Jones, 2020). This creates a lot of room for endogeneity, obscured or counteracted effects from other omitted variables, and high propensity to errors in estimations.

In the next section, we review relevant research on police violence and rurality in order to understand this paper's motivation in addressing this gap in understanding.

3.4 Literature Review

Understanding police violence

Research studying police violence and fatalities in the United States has been fairly limited due to the aforementioned lack of centralized databases. With more reputable data available through non-profits and media organizations. Emerging research focuses specifically on police shootings and police related fatalities, with no research on broader police misconduct and violence. This research has resulted in the debunking of often cited claims for police fatalities, such as the 'bad apple' theory. Additionally, new theories and relationships have been tested and analyzed, contributing to a growing body of research. The remaining portions of this section discuss various theories and available literature related to potential causes and correlations for police violence and fatalities.

The ‘bad apple’ theory was first coined by author and psychologist Sidney Dekker (2006) to describe one of two approaches for assigning blame in human error. The theory suggests that complex systems function properly and failures in the system are a result of a few erratic individuals that are not considered part of the normal functioning system. The term ‘bad apple’ has transitioned to serve as a defense for wrong doings in various sectors and industries, including policing. Justifications for police violence are often cited as individual instances of misconduct, particularly in incidents involving Black victims (Legewie, 2016). In response, other studies suggest that fatal incidents of police violence are not a function of ‘bad apples’- inside a functioning system, but instead point to institutional factors.

One such study conducted by Michael Siegel (2020) explored the connection between disproportionate police killings of Black victims by developing an index to measure structural racism on both the city and state level. Siegel found a strong and positive association between high levels of institutional racism and higher proportions of Black killings at both levels. Siegel suggests that structural factors, as opposed to isolated acts of violence, create widespread racial disparities in police killings. Community segregation in particular played the biggest role in the magnitude increase of Black fatal police incidents. An additional study conducted by Hoekstra and Sloan (2020) used a location-by-time fixed effect model to analyze the causal link between use of force and race in over two million 911 dispatch calls. The authors found that white officers used force 60% more and used guns twice when compared to Black officers. In terms of civilian race, the study found that white and Black officers used the same level of force in white and mixed-race neighborhoods but white officers were five times more likely to use gun force in predominantly Black neighborhoods (Hoekstra & Sloan, 2020).

The racial disparities in police fatalities appear to be heavily correlated with racial factors in connection with geographic segregation. A concurrent study by Siegel (2019) further explored segregation’s role in racial disparities between Black and white police fatalities. Siegel found a significant correlation between the two in which one standard deviation increase in the index for dissimilarity (segregation) corresponded to a 44% increase in the ratio of Black-to-white fatalities (Siegel, 2019). As a method of alleviating such disparities found in police fatalities, policy makers and relevant stakeholders often advocate for increased implicit bias training and overall officer training.

However, there is a lack of conclusive evidence that increased training reduces the amount of misconduct, abuse, or fatalities at the hands of the police. Validated studies of police officer implicit bias training are fairly limited due to the recent widespread nature of training implementation. However, an evaluation of the NYPD implicit bias training by Finn Institute researchers and IACP/UC Center for Police Research and Policy (Worden et. al., 2020) suggest that implicit bias training changes officers' short-term opinion regarding bias but has little to no effect on officer behavior. In fact, a systematic analysis of over 30 cases studying the effects of implicit bias training across various sectors found little evidence supporting significant effects in both attitude and behaviors (FitzGerald et. al., 2019). Of all police fatalities, 25% of victims have mental health issues. The widespread training program, Crisis Intervention Team (CIT), targets this intersection. So far, no study has found conclusive results for CIT's ability to alter behavior via pre-encounter interventions (Rogers, 2019). The underlying assumption of pre-encounter intervention solutions maintains that training can alter the decision-making path of the officer for an encounter; however, many officers report individual characteristics as the primary element in their decision to use force, effectively rendering the theory of change obsolete (Rogers, 2019).

As research continues to challenge existing theories and beliefs regarding possible interventions to correct for unfair and unjust policing, a handful of researchers have turned to institutional factors such as police unions as possible explanations for police violence. Author Abdul Rad (2018) explores the effects of police union mechanisms, particularly police protection, on the persistence of police violence. Rad developed an index to measure various elements of police protection, including provisions found in union contracts and state Law Enforcement Officer Bill of Rights. Results showed a significant, correlational link between police protection and police violence in the top 100 largest cities in the United States (Rad, 2018). Furthermore, evidence from studying collective bargaining rights in the state of Florida showed a causal connection between access to unionization and police violence. Dharmapala et. al. (2020)

conducted a differences-in-differences test studying the effects of access to unionization for sheriff's offices after the passing of a 2003 court decision allowing collective bargaining. Police departments were unaffected by the court decision, serving as the control for the study. The authors found that access to unionization led to significant increases in misconduct by sheriffs in comparison to police (Dharmapala, 2020).

In addition to research on institutional factors such as unionization, several studies have examined the effect of gun prevalence and gun legislation on the rate of police violence. A study conducted by Kivisto et. al. (2017) examined the effect of state level gun legislation on police killings from January 2015 to September 2016. Findings concluded that the presence of state level firearm legislation was significantly associated with reduced fatal police killings. A number of other studies conducted in the past several years focus on the prevalence of gun ownership and availability as it relates to police fatalities. Hemenway et. al. (2019) examined the variance in police killings according to firearm prevalence while adjusting for environmental factors, including violent crime rates, which has been associated with increased rates of police fatalities (Klinger, 2015). The authors concluded that rates of police fatalities had a significant and positive association with gun ownership.

The literature presented thus far examines a variety of factors that may be associated with police violence and misconduct, however, few studies explore the possible relationship between the overall connection of place and rurality.

Understanding rurality's role in police conduct

The vast majority of studies of police violence often focus on a handful of large cities in the United States. A recent analysis conducted by Schwartz and Jahn (2020) mapped fatal police violence rates in order to uncover national regional trends using Metropolitan Statistical Areas (MSA) as the measure of place. Approximately 380 MSAs were included in the study, however, this only accounts for geographic areas in the country with the highest population densities and important economic activities (US Census Bureau, 2021-a). The authors found high death rate variance within MSAs, with rates up to nine times higher in the most deadly areas. Overall rates in the Southwest were highest with Midwest and Northeast falling on the low end of the spectrum; however, these geographic areas also had the highest racial inequalities (Schwartz & Jahn, 2020).

One of the first papers presenting research on the possible connection across the urban-rural spectrum was conducted by Edwards et. al. (2018). The authors examined police fatalities by racial group from 2012-2018 using data from Fatal Encounters across both county and region. NCHS was used to measure county-level rurality and US Census divisions measured regionality by state. They conducted a Bayesian multilevel negative binomial regression models to analyze both regional and rurality level trends. The authors found an increased risk in large urban areas, however, death rates in more rural places also showed a significant correlation. Racial variations were more pronounced across US Census Divisions as opposed to rurality type, particularly for Black men. Black male deaths were higher than white and Latino across all US divisions (Edwards, 2018).

A study further examining the possible connection between rurality and police violence was conducted by Hemenway et. al. (2020) in which the authors intended to analyze whether the high concentration of homicides rates in urban areas holds true for fatal police shootings. They used Washington Post's Fatal Force database from 2015-2017 to analyze fatal police shootings across urban and rural areas using five different classification measurements, three of which measure rurality by county and two by ZIP code. As a concise and agreed upon definition of rurality does not exist, the authors intended to research additional classifications schemes beyond what was presented in the research by Edwards (2018). Contrary to popular belief, results indicated that fatal police shootings occurred at similar rates across the urban-rural spectrum, with Black victims experiencing the highest rates across all measures, although statistical models were not utilized in this study to indicate statistical significance.

Overall, few studies examine the correlation between police violence and rurality type. While the narrative often focuses on urban or suburban communities, research thus far indicates fatal police encounters occur at similar rates regardless of rurality type.

4. Methodology

4.1 Police fatality data

The following analysis of police killings by rurality uses data from Mapping Police Violence (MPV, 2021-b). The MPV database has collected data on over 8,000 individuals killed by the police since 2013. MPV defines a police killing as, "a case where a person dies as a result of being shot, beaten, restrained, intentionally hit by a police vehicle, pepper sprayed, tasered, or otherwise harmed by police officers, whether on-duty or off-duty" (MPV, 2021-a). Observations are gathered from various state use of force data collection programs and from Fatal Encounters. Researchers have also compiled additional information regarding demographic information of victims and situational factors surrounding the killings in order to allow for comprehensive studies of police killings. Descriptive data is sourced from social media, obituaries, police reports and criminal record databases. Due to the lack of a centralized, federal database for police killings, the MPV database likely does not capture all fatalities, particularly for incidents unreported by the media. However, MPV estimates that the database contains 92% of killings, based on data reported from the Bureau of Justice Statistics (MPV, 2021-a).

In addition to the MPV database, several other reputable national databases have emerged that track police killings, all with varying definitions of what constitutes a police killing. MPV more narrowly defines deaths in comparison to Fatal Encounters, which includes additional categorizations such as police-related suicide. Another frequently cited source, the Washington Post Fatal Force database, more narrowly defines deaths than both MPV and Fatal Encounters. Fatal Force only records incidents of on-duty police officers that kill and shoot victims. Off-duty and non-shooting deaths are excluded from the data, which equates to approximately 500 fewer observations over a five year period relative to the MPV database. Under the definition of police killings, we believe the MPV database most accurately represents deaths caused by police officers. It should be noted that while MPV tracks deaths for both on-duty and off-duty officers, 97% of the recorded deaths are due to actions by on-duty officers.

4.2 Rurality data

In order to determine the scale of police killings as it relates to the concept of place and rurality, we simulated similar methodologies of a study conducted by Hemenway et. al. (2020), which used the Washington Post Fatal Force dataset to calculate the rate of fatalities by rurality from 2015-2017. The authors calculated the death rate per 100,000 people-years for five different classification schemes of rurality. Our analysis includes three of the rurality classification schemes included in their paper; RUCC, NCHS, and Trulia.

Briefly, we reiterate the three measurements of rurality we chose for our analysis. The first government county classification includes the 2013 NCHS urban-rural classification scheme, which categorizes counties into six rurality types including: large central metro, large fringe metro, medium metro, small metro, micropolitan and non-core. To allow for streamlined cross-classification comparison, names have been changed to urban, suburban, med urban, small urban, town, and rural.

The second government county scheme, the 2013 rural-urban continuum codes (RUCC), categorizes counties into nine different rurality types. The nine categories can be grouped into four subgroups including metro, urban-adjacent to metro, urban-not adjacent to metro and rural. Metro contains three of the nine rurality types and all other subgroups contain two. For our analysis, the category names have been changed to urban, suburban, town, and rural.

The final classification scheme based on ZIP codes was originally developed by Trulia. The company conducted a survey asking households to select their neighborhood type without providing any definitions of the three rurality types, allowing participants to judge based on their own perception of place. Survey responses were compiled and compared to population density measures, and results found that it served as the best predictor of location. Analysts subsequently applied the location tags to remaining ZIP codes excluded from the study. However, approximately 10,000 out of 40,000 total ZIP codes were excluded from the rurality assignment. For the purposes of this study, an additional category titled ‘Unknown’ has been created and assigned to these remaining ZIP codes.

The following describes the rurality classification schemes we use for our analysis:

Table 4.1. Tagging and classification schemes for RUCC, NCHS, and Trulia rurality

RUCC[1]			NCHS[2]			Trulia[3,4]	
Tag	Classification	Definition	Tag	Classification	Definition	Tag	Definition[5]
Urban	1	+1 M (central metro)	Urban	1	> 1 M	Urban	More than 2,213 households per square mile
	2	1 M - 250,000 (central metro)	Suburban	2	> 1M but do not qualify as central aka “Fringe”	Suburban	Between 102 and 2,213 households per square mile
	3	<250,000 (central metro)	Med Urban	3	250,000 - 999,999	Rural	Fewer than 102 households per square mile
Suburban	4	+20,000 adj. to metro	Small Urban	4	<250,000		
	6*	19,999 - 2,500 adj. to metro	Town (*Micropolitan via NCHS)*	5	50,000 - 10,000		
Towns	5	+20,000 not adj. to metro	Rural	6	< 10,000		
	7*	19,999 - 2,500 not adj. to metro					
Rural	8	<2,500 adj. to metro					
	9	<2,500 not adj. to metro					
Notes: 1. Source: https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/							

2. Source: https://www.cdc.gov/nchs/data_access/urban_rural.htm
3. Source: https://fivethirtyeight.com/features/how-suburban-are-big-american-cities/
4. Trulia is by ZIP code while NCHS and RUCC are by county level.
5. While the index is based primarily on survey respondents, Trulia found the best predictor for a respondent's experience of "urbaness" to be housing density according to the following classifications.
* Note the change in order

4.4 Our methodology

For our analysis, death rates are calculated using the MPV database for the years 2015-2019 using the three different rurality classifications. The rate is calculated as the number of deaths per 100,000 person-years, as is standard, and calculated on the county level before aggregation. In our analysis we average the per-county rate two ways: by the indicator given by the rurality system if applicable (1-9 for RUCC, 1-6 for NCHS), and secondly by the aggregate labels we assign for rurality for ease of reading and interpretation. Averaging prior to aggregation deviates from the Hemenway methodology in order to allow for possible regression analysis later in the study.

Population estimates are taken as the average of 2015-2019 based on statistics available from the CDC (2021). Due to missing population data, two deaths were dropped from the MPV database for the RUCC and NCHS county classifications and seven deaths were dropped from the Trulia classification.

In addition to the total death rates, rates are desegregated by race and ethnicity (White, Black, Hispanic, Other) for each rurality classification scheme. Racial death rates are calculated in the same manner as the total death rates but instead use the relevant populations for each individual race. The racial and ethnic categorizations in the MPV database include White, Black, Hispanic, Asian, Pacific Islander, Native American and Unknown. Asian, Pacific Islander, Native American and Unknown have been combined to form the category of 'Other' for the purposes of this analysis due to relatively low aggregate numbers.

5. Findings and analysis

5.1 Descriptive statistics

The original MPV database consists of 5,496 individual deaths during the years 2015-2019. The number of deaths recorded each year remains consistent over the five-year time period with a variance of 43 deaths between the highest and lowest years. On average, 1,100 people are killed each year, which is a rate of 0.34 per 100,000 people. Men account for 95% of victims while women, transgender and unknown individuals account for the remaining 5%. In terms of racial demographics, 46% of reported deaths were among white individuals, followed by Black individuals at 25%, Hispanic 18% and Other 11%. However, when accounting for rates proportional to the general US population, Black victims are over represented by two-fold (13% of the population) and white victims are under represented by approximately 15% (CDC, 2021).

According to RUCC, 84% of deaths occurred in urban counties, 9% in suburban, and the remaining 7% in towns and rural counties. The RUCC classification displays fairly consistent death rates across rurality types, with the highest rate in towns at 0.42 and the lowest rate in suburban areas at 0.33. Individuals classified in the Other race experience the highest average death rates across all rurality types. Black individuals have the second highest death rates, particularly in towns in rural counties. White and Hispanic victims have similar death rates across rurality types and Hispanic individuals have the lowest overall average death rate at 0.29, which is approximately seven times lower than the average for Other races.

Table 5.1 Total deaths (RUCC)

RUCC Code	White	Black	Hispanic	Other	Total
Urban	*1958*	*1288*	*933*	*462*	*4641*
1	964	923	587	274	2748
2	620	274	268	114	1276
3	374	91	78	74	617
Suburban	*317*	*69*	*33*	*53*	*472*
4	134	36	14	25	209
6	183	33	19	28	263
Towns	*180*	*32*	*32*	*41*	*285*
5	67	20	11	18	116
7	113	12	21	23	169
Rural	*68*	*7*	*3*	*18*	*96*
8	28	3	1	2	34
9	40	4	2	16	62
Total	**2523**	**1396**	**1001**	**574**	**5494**

Table 5.2 Average death rates (RUCC)

RUCC Code	White	Black	Hispanic	Other	Total
Urban	*0.29*	*0.87*	*0.29*	*1.75*	*0.36*
1	0.25	0.58	0.18	1.19	0.28
2	0.28	1.44	0.48	2.61	0.39
3	0.34	0.60	0.22	1.46	0.40
Suburban	*0.29*	*0.77*	*0.27*	*1.82*	*0.33*
4	0.27	0.86	0.28	1.60	0.32
6	0.31	0.68	0.26	2.05	0.35
Towns	*0.37*	*1.08*	*0.23*	*3.05*	*0.42*
5	0.39	1.47	0.15	1.67	0.43
7	0.34	0.69	0.30	4.43	0.41
Rural	*0.37*	*1.42*	*0.37*	*2.00*	*0.39*
8	0.34	1.28	0.68	1.08	0.30
9	0.39	1.57	0.06	2.91	0.47
Total	**0.32**	**1.02**	**0.29**	**2.11**	**0.37**

According to the NCHS classification, approximately half of all deaths occurred in urban and medium metro counties. In terms of average death rates, total death rates ranged from 0.27 to 0.41 under the six classifications. Suburbs experienced the lowest rates with small urban and rural counties on the high end of the spectrum. Individuals in the Other racial category experienced the highest death rates in every category, except for metro counties where Black victims had the highest rates. Black victims had the second highest death rates in the remaining rurality types while White and Hispanic had similarly lower rates. When considering the overall average rates by race, Other had rates six times higher than White and Hispanic, while Black had rates three times higher than White and Hispanic.

Table 5.3 Total deaths (NCHS)

NCHS Code	White	Black	Hispanic	Other	Total
Urban	495	672	471	174	1812
Suburban	476	256	116	100	948
Med Urban	612	269	268	114	1263
Small Urban	375	91	78	74	618
Town	310	71	39	55	475
Rural	255	37	29	57	378
Total	**2523**	**1396**	**1001**	**574**	**5494**

Table 5.4 Average death rates (NCHS)

NCHS Code	White	Black	Hispanic	Other	Total
Urban	0.22	0.90	0.26	0.39	0.37
Suburban	0.25	0.52	0.16	1.32	0.27
Med Urban	0.28	1.46	0.48	2.66	0.39
Small Urban	0.34	0.60	0.22	1.45	0.40
Town	0.30	0.87	0.16	1.23	0.33
Rural	0.36	1.06	0.32	3.23	0.41
Total	**0.29**	**0.90**	**0.27**	**1.71**	**0.36**

Of the 39,258 total ZIP codes in the Trulia dataset, approximately 25% of the ZIP codes are categorized as Unknown. However, only eleven of the total deaths were recorded in ZIP codes without a Trulia categorization. Missing ZIP codes appear to largely be concentrated in more rural communities, however, we are unable to systematically determine the categorization of these ZIP codes. Therefore, we would suspect rural death rates may vary with the inclusion of all ZIP codes but cannot conclude this definitively.

In terms of aggregate numbers, approximately half of the total deaths occur in suburban areas. However, relative to the population, suburban rates are the lowest of the three rurality categorizations. The average death rate in suburban areas is 0.27, rural 0.40 and urban 0.60. The unknown ZIP codes have the overall lowest death rate of 0.22, however, only eleven deaths occurred in these areas. In terms of racial desegregation, victims classified as Black or Other experience death rates higher than White and Hispanic victims. Excluding the Unknown category, Black individuals experience death rates ranging from 0.83 to 2.09, almost four times the rate of White victims.

Table 5.5 Total deaths (Trulia)

Trulia Rurality	White	Black	Hispanic	Other	Total
Rural	857	156	121	158	1292
Suburban	1276	649	539	307	2771
Unknown	6	0	1	4	11
Urban	378	590	340	107	1415
Total	**2517**	**1395**	**1001**	**576**	**5489**

Table 5.6 Average death rates (Trulia)

Trulia Rurality	White	Black	Hispanic	Other	Total
Rural	0.37	1.31	0.49	1.19	0.40
Suburban	0.23	0.83	0.29	0.51	0.27
Unknown	0.13	0.00	0.00	2.01	0.22
Urban	0.50	2.09	0.31	0.53	0.60
Average	**0.31**	**1.06**	**0.27**	**1.06**	**0.37**

The two classification schemes using county as the unit of measure, RUCC and NCHS, showed similar trends in terms of total and race desegregated death rates by rurality. Total death rates range from 0.27-0.47, however the majority of the rurality types fall closer to 0.35. Desegregated racial data shows individuals classified as Other with death rates 6-7 times higher than White and Hispanic. Black individuals also experience higher death rates than White and Hispanic victims, but at a magnitude of approximately 3-4 times higher. The Trulia classification shows similar overall trends as RUCC and NCHS, with a wider level of variance for total death rates ranging from 0.22 to 0.60. Additionally, individuals identified as Other and Black experienced higher death rates relative to White and Hispanic individuals, but Black victims maintained the highest rates for the majority of Trulia rurality types.

When examining the yearly death rates from 2015-2019, the majority of rurality categorizations show high levels of variance from year to year. Appendix A.1-A.3 includes graphs showing RUCC, NCHS and Trulia death rates over time for each rurality type. Trulia ruralities, excluding Unknown, appear fairly consistent throughout the defined time period while the majority of categorizations in RUCC and NCHS appear inconsistent. Inconsistencies are to be expected due to the infrequent outcomes for police killings, particularly with rurality schemes that include greater numbers of rurality categorizations.

Visual geographic summary

The maps in Figures 5.1 and 5.2 below show the geographic visualization of death rates across US counties according to the RUCC rurality classification. The first map, Figure 5.1, shows all US counties where deaths occured and their accompanying death rates based on the quartile distribution of observations which have been categorized as low, medium, high and extreme. Overall, it appears fewer deaths occured in the Midwest, however, large county sizes in the West may distort the geographic spread of deaths among Western states. The Northeast appears to have the lowest rates relative to the South and the West, but again the county sizes in the West may distort these regional trends.

Figure 5.2 displays the death rates of each individual rurality categorization for urban, suburban, town, and rural. As expected, rural counties contain a significant portion of the highest death rates (indicated in blue), which is a result of low population estimates. However, the average death rate for this rurality decreases drastically when accounting for counties that contain zero values where deaths did not occur. Continuing towards larger county sizes (towns, suburbs, urban) results in greater frequencies of deaths, however the death rates decrease due to the increase in population in these counties.

Figure 5.1 US Map of death rates (RUCC)

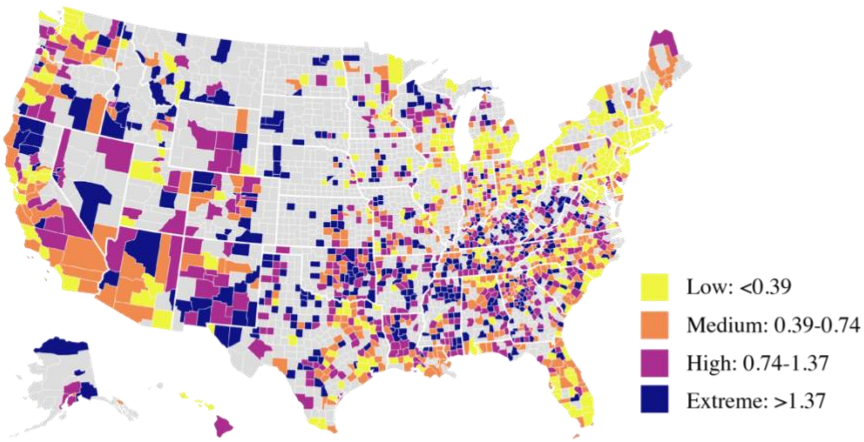
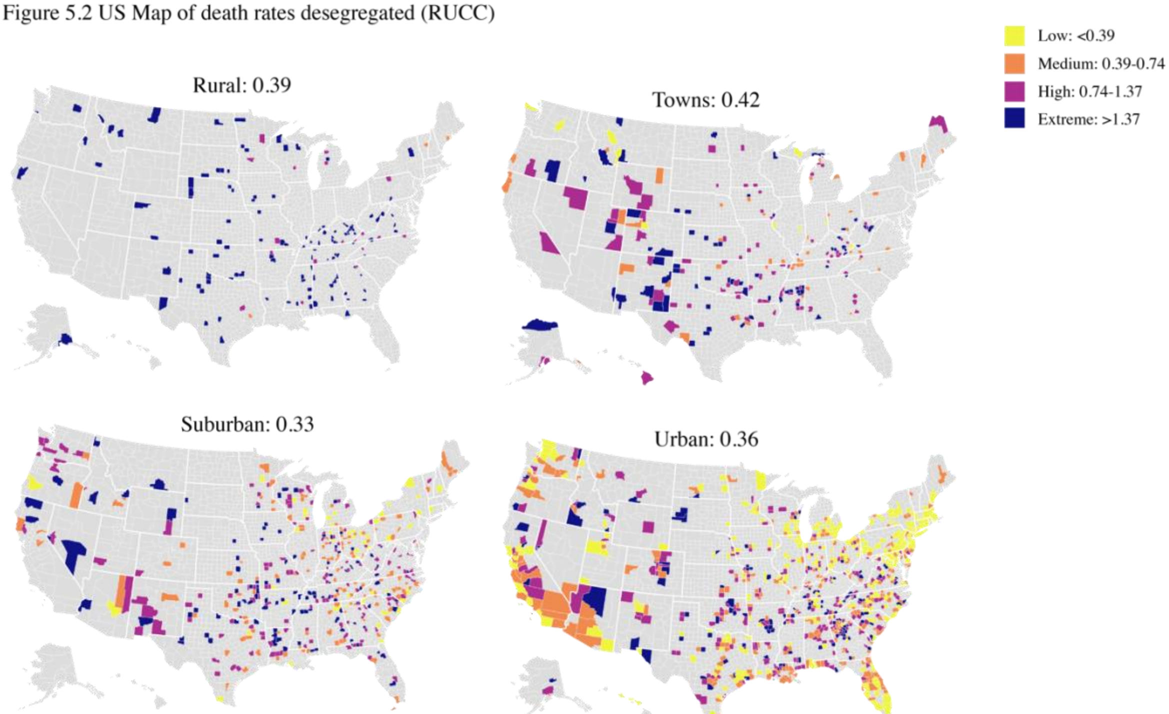


Figure 5.2 US Map of death rates desegregated (RUCC)



Statistical summary

The NCHS and RUCC dataset includes 3,142 individual observations representing unique counties within the United States. 1,791 of the counties have a death rate of 0, which accounts for 57% of the observations. As you can see in Figure 5.3, the dataset is right-skewed with a large presence of zero values. High death rates are not easily visible in the distribution chart, however, summary statistics show the highest death rate at 16.64 per 100,000 people. The remaining summary statistics in Table 5.7 fall well below the maximum value. In fact, the minimum, first quartile and median all contain zero values. The mean calculated here varies slightly from NCHS results reported above in Table 5.4, due to rounding error when desegregated by county.

Figure 5.3 Distribution of death rates by county

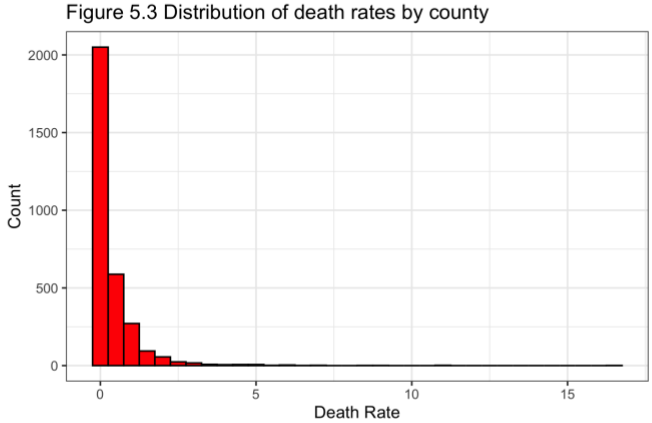


Table 5.7 Summary Statistics by county

Minimum	0.00
1st Quartile	0.00
Median	0.00
Mean	0.37
3rd Quartile	0.48
Maximum	16.64

The Trulia dataset has significantly more values in the dataset due to the more granular measure of ZIP codes as opposed to counties. Of the 39,256 ZIP codes in the dataset, 35,293 contain zero values, which is approximately 90% of the observations. Figure 5.4 shows the distribution of death rates for the Trulia dataset, which in addition to a greater percentage of zero values, has more extreme death rates relative to NCHS and RUCC. In order to improve visibility of the distribution, death rates over 15.00 have been forced into the same grouping. 124 of the observations have death rates above the 15.00 threshold with the highest death rate at 513.00. Summary statistics for Trulia are reported in Table 5.8 below and similarly to RUCC and NCHS, the minimum, first quartile and median all have zero values. However, the third quartile in the Trulia dataset also contains a zero, showing the effect of the increase in overall zero value observations when classified by ZIP code. The mean also differs slightly from the average death rate calculated in Table 5.6 due to rounding error.

Table 5.8 Summary Statistics by ZIP code

Minimum	0.00
1st Quartile	0.00
Median	0.00
Mean	0.34
3rd Quartile	0.00
Maximum	512.82

5.2 Understanding the relationship

In the previous section, we described what rates of police violence look like from visual inspection and simple statistical compositions. While these assessments can help our understanding of how the data looks and behaves, it does not necessarily help us draw conclusions or understand the nature of the relationship between police violence and rurality.

The next natural step would be to run a regression model that regresses the rurality over the rate. However, because our data is unknown and untested, we do not know what type of relationship we would expect to see from such a regression. The most immediate tool would be to run an ordinary least squared (OLS) regression, but we have no current reason to suspect the relationship is linear. If, following the logic of Campaign Zero's hypothesis, police violence is in fact higher in suburbs, and lower in rural or urban places, then we would expect to see a polynomial relationship (in a regression where suburban as a category is always ultimately 'between' the values of urban and rural). This could be theoretically altered into a linear relationship, as the categories of rural, town, suburb, and urban are not necessarily in ascending order and are understood as loose categories, modified from a continuous variable forced into categories. If we suspect that there is no significant relationship, as the above descriptive results suggest, then perhaps the relationship would appear linear but the slope would be negligible or zero with little significance.

In either case, it stands to bear that before we can move onto an OLS regression, we need to attempt to map out the relationship. In the event that we identify a relationship and successfully model it, we would then move on, potentially, to see how rurality increases or decreases police violence, how it might interact with other factors, and how it might serve as a point for further research and understanding.

In the following section, we will check the MPV dataset against the four basic OLS assumptions. In doing so, we will draw conclusions about the relationship between police violence and rurality. For the purposes of this section, within the body of this text, we will only analyze our findings using the RUCC definition of rurality for simplicity. We chose use the RUCC classification primarily for the reasons mentioned from the 3.2 Rurality: defined — RUCC takes into account proximity as well as population density, it provides more granularity in its categories when compared to NCHS, does not rely entirely on public perception as does Trulia, and provides a more well rounded image of rurality than do the other two.

OLS assumptions

Linearity

The primary assumption of the OLS regression is linearity. As mentioned above, we have only mild reason to believe the relationship between rurality and police violence might be linear. Examining a whisker-box plot of the logged rates (logged for ease of interpretation) against rurality, we see that while the RUCC classification could follow a linear relationship, the NCHS classification (included briefly here) seems to show curvature (see Appendix B.1 for Trulia results).

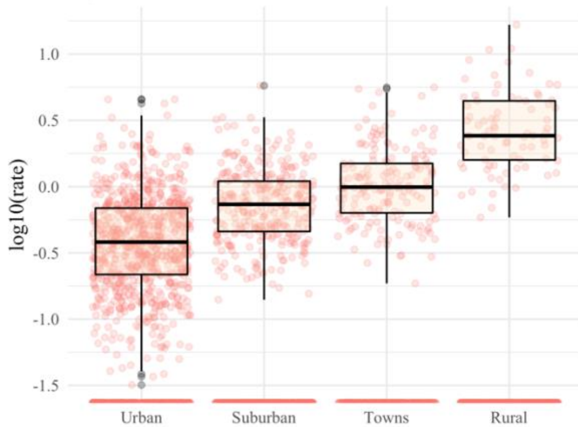


Figure 5.5 Quartiles of death rates (RUCC)

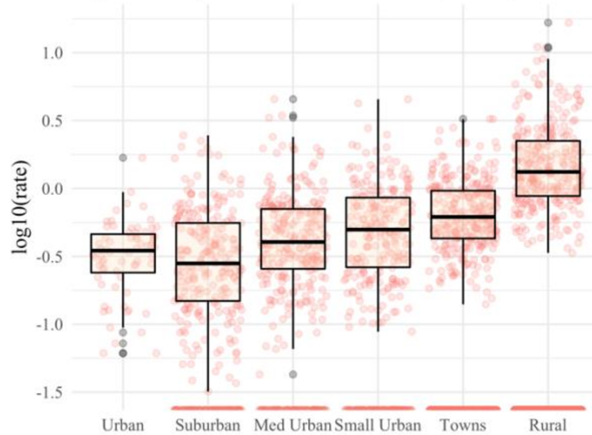


Figure 5.5 Quartiles of death rates (RUCC)

Figure 5.7 below shows a simple plot of the RUCC classification mapped against the rates of the counties. From a visual standpoint, we could force a linear relationship due the extreme range of some of the data points, which gives us a bit of freedom to say where the line of best fit lies. Even then, the line most likely would have a slope close to zero, indicating little if any relationship.

However, we can see the data is heavily weighted by the many zero values of the dataset. To adjust for this and more easily spot outliers or a relationship, we next attempted to log transform the data (in this case we added a constant to control for the ample number of zero values) in Figure 5.8.

Figure 5.7 Death rate v. rurality

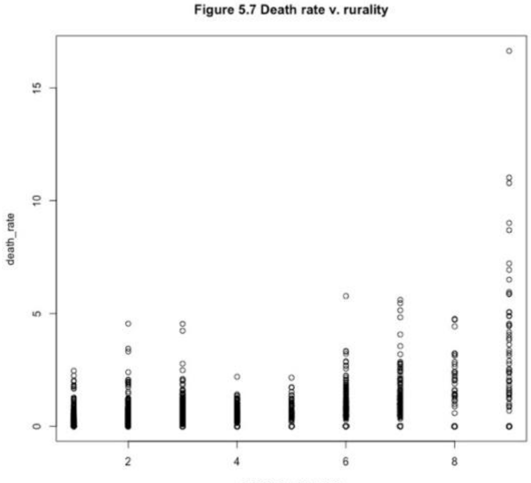
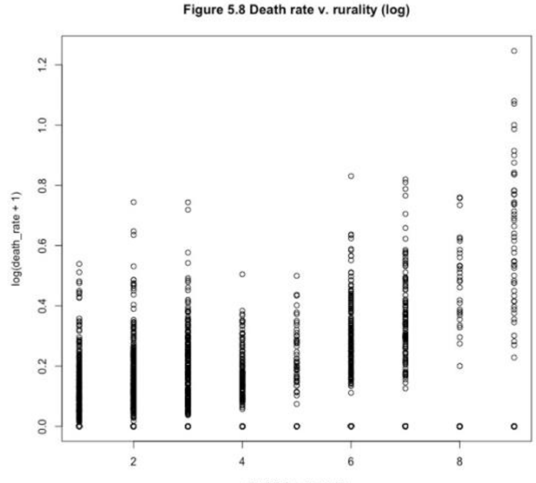


Figure 5.8 Death rate v. rurality (log)



While the logarithmic transformation does help us with the zero-heavy dataset, it is still not immediately clear that the relationship is linear.

To narrow the range of possibilities for a successful linear transformation of the data, we turned to the Box-Cox transformation. In the Box-Cox transformation, the value of lambda is pursued for the optimum fit of the data into a linear model:

$$y(\lambda) = \begin{cases} \dfrac{y^{\lambda} - 1}{\lambda}, & \text{if } \lambda \neq 0 \\ \log(y), & \text{if } \lambda = 0 \end{cases}$$

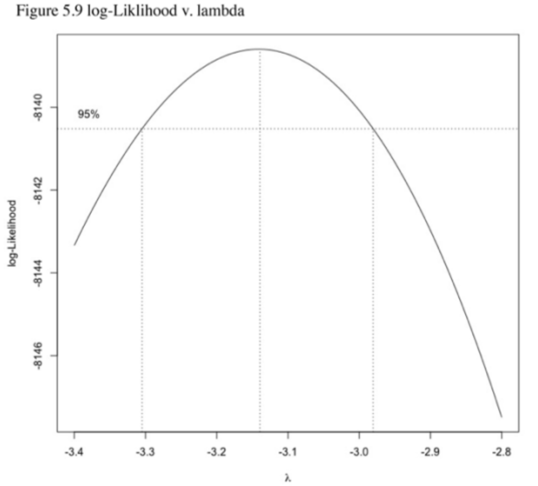
In order to assess the validity of running a Box-Cox transformation we examine the plot of residuals vs fitted of the model:

$$(rate + 1) = \alpha + \beta_1 rucc.rurality + \epsilon$$

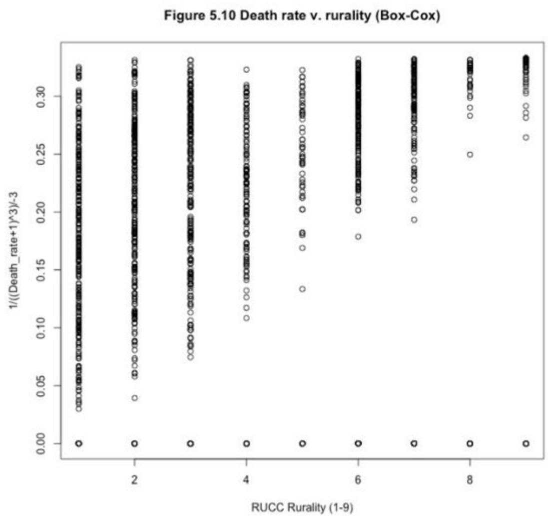
Where we used rate + 1 in order to control for the presence of zeros, which would prevent us from running the Box-Cox package on the data.

Using Box-Cox, we generate the follow graph of likely transformations as a function of lambda in which we expect the most likely successful transformation would be $\lambda = -3.0$(to select a whole number). In other words, an inverse cubic transformation: $\frac{1}{y^{3}}$, as seen in Figure 5.9 below.

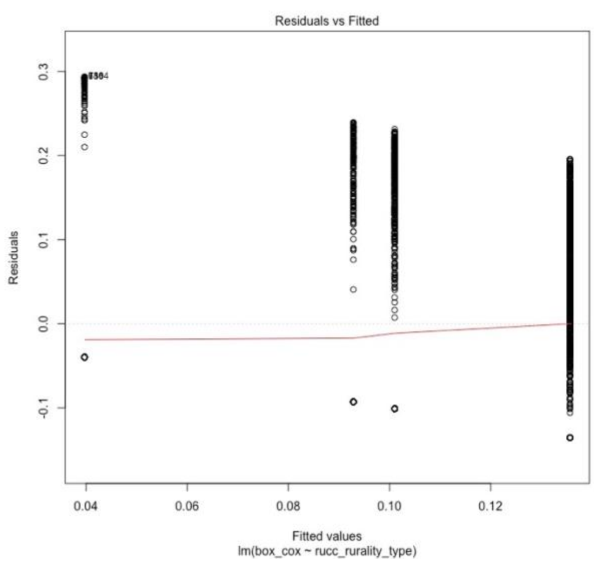
Figure 5.9 log-Liklihood v. lambda



Now we will examine the linear relationship between the rurality type and Box-Cox transformed rate in Figure 5.10. The presence of a constant to the transformation has created a ceiling effect and the linear relationship is questionable, however, we will assess the residual v. fitted relationship to determine if the model may be an appropriate fit.



Applying a Box-Cox transformation to our data set yields the following residual v. fitted values plot where we can see the issue of non-random distribution around the zero line is still not solved.



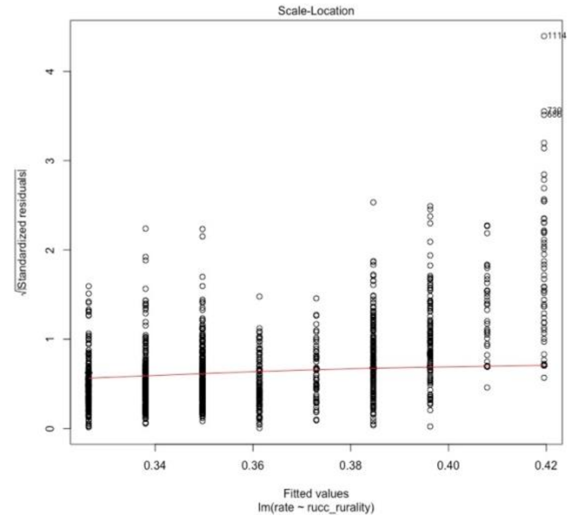
Unfortunately, this method has not yielded a successful transformation. This result is in line with existing literature about how to treat skewed, continuous infrequent outcomes ('zero-heavy') data. In such datasets — often used for public health analysis such as our research question — each zero is not a result of a measurement error, but a real indicator of the absence of an instance of police violence. The same would hold true for cancer rates, alcohol consumption among teens, or other infrequent outcome health-oriented data (Boulton & Williford, 2018). The zeros are nevertheless important and significant, and do not diminish the real-world impact of a death at the hands of the police. But the overwhelming presence of non-incidents creates a 'floor-effect' and makes the data unsuitable for standard linear regression.

Furthermore, while data transformations are a common tool to use to correct for linearity as well as distribution, we find that in the context of our data, transformations are not suitable. Additionally, our data is heavily skewed with non-negative values (in which a negative value would be nonsensical). In such a dataset, transformations are unlikely to withstand transformation and even when transformed in general cannot be successfully done "such that residual terms in an analysis will approach normality" (Baldwin, 2016 as cited in Boulton & Williford, 2018).

For these reasons alone, we will not pursue a linear model for our data. In the following sections we briefly explore the other assumptions of a linear model that may be applicable later for a better fitted model.

Homoscedasticity

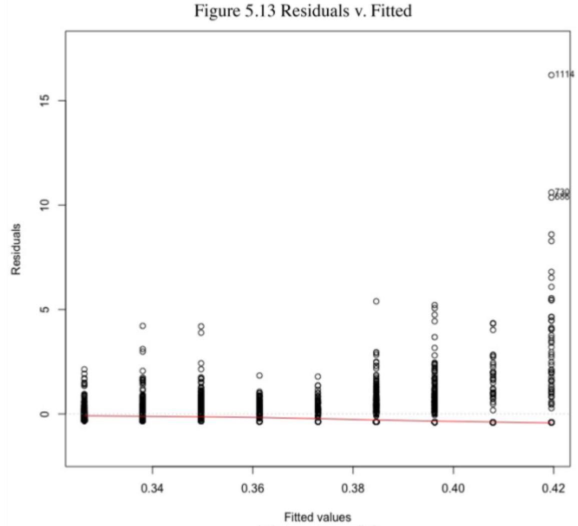
Next, we consider whether the model is homoskedastic in nature. Homoskedasticity shows the difference between the fitted values and the predicted values are evenly spread among the range of predictors. A failure to meet this assumption means the model is poorly fitted and can lead to an inflated error term and incorrect coefficients on an eventual regression.



We first examine the scale-location diagnostic graph in Figure 5.12 above. In a homoskedastic model, we would expect to see a vertical line with equally randomly spread points around it. In our results, we clearly do not see the random distribution.

To examine the homoscedasticity assumption further, we plot the residuals v. fitted values to help us spot unequal error variance. Again we also see some troubling results in which the distribution is non-random and there is quite a visible 'floor-effect' in the data. The best fit line, visible in red, is likely due to the floor-effect and is forcing a misleading, linear relationship.

Figure 5.13 Residuals v. Fitted



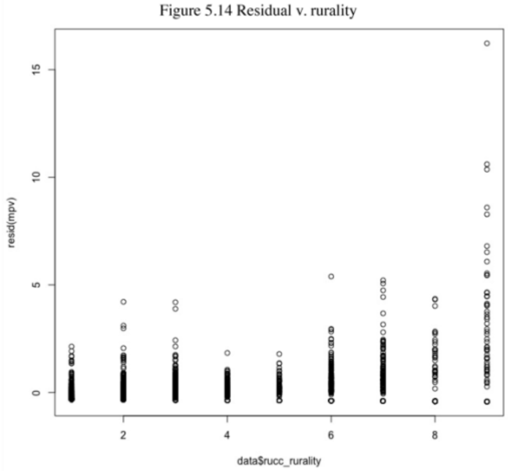
These visual checks may be helpful, but are not definitive. We perform an additional check with the Breusch-Pagan test of homoscedasticity. In this statistical test, the default null hypothesis is that the data is homoscedastic in nature. Our p-value is 4.917×10^{-9}, in which case we can reject the null, stating that there is no homoscedasticity in this dataset, violating a core assumption of OLS.

Independence

Independence is vital to a well-fitted model. A non-independent predictor variable (in our case rurality), being correlated to the error term would mean that the error term does not represent truly random error but instead measurement error or poor fit of the independent variables. This in turn can bias the coefficients of the regression.

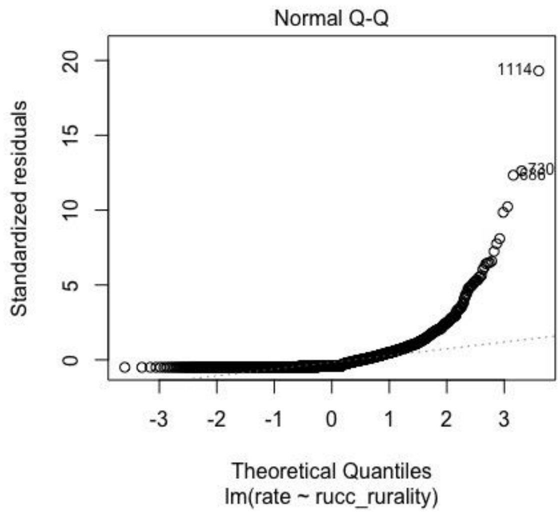
To assess this, we examine the residuals v. the independent variable plot, in which we see residuals are growing as we move from urban to rural, violating the assumption.

Figure 5.14 Residual v. rurality



Normality

Finally, we look to see whether the error term is normally distributed in our dataset. A normally distributed dataset would help us create more accurate standard errors and prediction intervals. Here, in our Normal Q-Q plot, we would expect to see a straight diagonal line, but instead we see heavy curvature more akin to an exponential distribution.



We then apply more statistically definitive methods to assess normality through the Shapiro-Wilk and Kolmogorov-Smirnov model (among others) and find that our p-values are low/zero and so we reject the null of normality, hence violating this assumption.

Table 5.9 Normality tests

Test	Statistic	pvalue
Shapiro-Wilk	0.4907	0.0000
Kolmogorov-Smirnov	0.3111	0.0000
Cramer-von Mises	541.6134	0.0000
Anderson-Darling	418.5136	0.0000

If we suspected the relationship to be linear, there are existing methods in place to deal with heteroskedasticity such as clustering standard errors. However, since we have ruled out linearity, we will not pursue them here and will further explore other statistical models including means tests and non-linear models.

Means test

We explore other statistical methods to test for significance between rurality types beyond OLS linear regressions. One-way ANOVA tests often serve as a suitable statistical method of testing for significance in datasets with independent variables with more than two categories. ANOVA requires four assumptions to be met in order to assume appropriate model fit, including independence, additivity, normality, and homogenous variance (Larson, 2008). However, due to the high presence of zero values and assumption violations observed in the Linearity section above, means test models are inappropriate fits for the type of data in our study. Other non-parametric models such as the Wilcoxon-Mann-Whitney and the Kruskal-Wallis tests additionally are unsuitable for the dataset and likely result in biased results due to the high prevalence of zero values (Boulton & Williford, 2018).

Non-linear models

From the above diagnostics of a linear model, we can fairly confidently conclude that a standard OLS regression is not appropriate for such a topic or dataset. The consequence of attempting to force such a skewed, zero-heavy dataset into a linear model would not only create inaccurate coefficients in the regression, but would likely make those coefficients difficult to interpret due to excessive manipulation of the dataset (Boulton & Williford, 2018).

The next natural step is to understand if the data can fit into another type of model. For this, we turn to existing research on preventive public health research of infrequent outcomes, as referenced earlier. In these cases, linear regressions are inappropriate and even if performed would lead to bias in the results (Boulton & Williford, 2018).

In two papers analyzing skewed continuous outcomes with many zeros, Bolton and Williford (2018) and Bahn and Massenburg (2008) posit several possible solutions to analyze this type of data, while stressing that there are not many statistical methods developed to approach this kind of work. The methods explored in both papers include data transformation, discreditization, Tobit regression, two-part model and Poisson distributions applied to various statistical models.

The first method uses data transformations of the outcome variable of interest, which in our dataset is the death rate. We attempt several transformations with a particular emphasis on Box-Cox (Osborne, 2010). Next we examined the discretization method which allocates the continuous dependent variable into two or more discrete values. Creating discrete values would likely be inappropriate as we would be resigned to creating arbitrary categorization by inducing cut-off points, for example what constitutes ‘high’ v. ‘extreme’. Additionally, due to the high prevalence of zero values as well as extreme rates, the results would likely remain biased.

The next method of consideration for skewed continuous outcomes with a high prevalence of zeros is the Tobit model, which may be implemented in circumstances in which the zero values represent censored zeros. The zero values in our dataset are true zeros, therefore rendering this model unfit for our data. The final model discussed by Bolton and Williford (2018) includes true zeros within the theoretical framework, but the model suggests two distinct processes determine if individuals fall into the zero and nonzero outcomes. This assumption addresses questions outside the scope of our study under the consideration that we do not hypothesize that a behavior or process leads to outcomes within the zero and nonzero grouping.

Bahn and Massenburg similarly discuss challenges in model fit for dealing with excess zeros in discrete dependent variables. All of the models suggested apply a Poisson distribution to account for the challenges posed by this type of data. The authors apply the distribution to three models including the Generalized Linear Model (GLM), Hurdle Model and Zero-Inflated Poisson Model. The Poisson distribution and assumptions are discussed in further detail in the following section.

Poisson Distribution

Of the above possibilities for treating and analyzing public health data with infrequent outcomes, the most clearly feasible options are the various forms of Poisson distribution. Within this distribution, there are various subcategories to explore. For the purposes of this research, we will focus on a simple Poisson model (GLM).

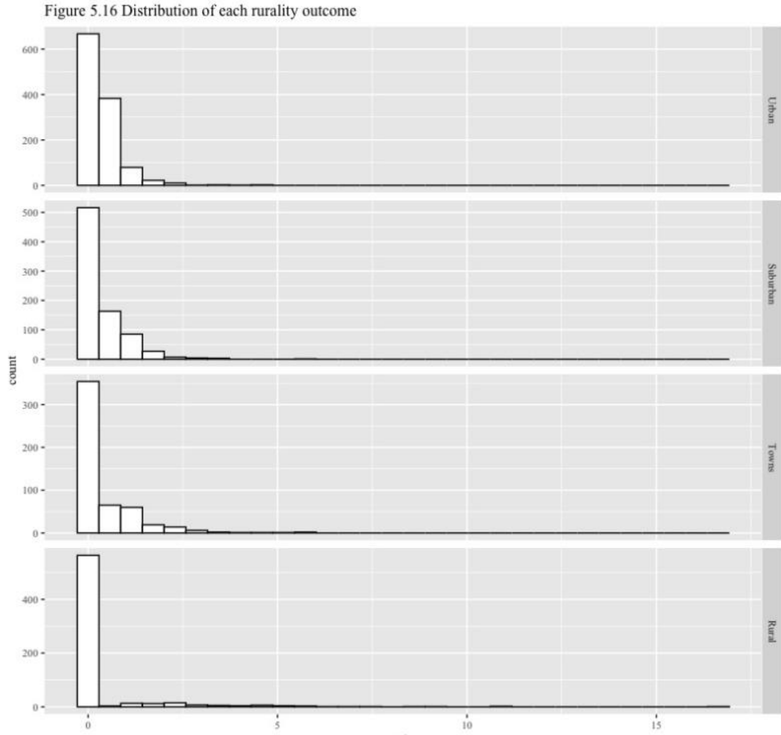
Poisson models are very often used in public health research because they are optimal for datasets where there are a high number of ‘non-events’ such as the absence of an adverse health behavior. This is certainly applicable to our research question.

Secondly, the Poisson distribution is aptly able to handle count or rate data, such as that compiled by MPV. Lastly, because they represent unlikely health events, Poisson distributions are necessarily heavily right-skewed, with a high presence of zeros and a long tail of highly extreme values. This takes away the concern of needing a normal distribution of data to analyze under the typical statistical tools.

Assumptions of the Poisson distribution

Given the likely fit of a GLM for our dataset, we first look to see if it fits the assumption necessary to run a regression. The distribution operates under the following assumptions: (1) each y_i outcome (in our case, each rurality) is Poisson distributed (see Figure 5.16), (2) each observation should be independent and should not affect the outcome of another, a valid assumption given our conceptual set up, (3) the dataset contains non-negative values, and finally (4) the time period or space must be fixed. Of the above assumptions, we consider our data to be a good fit for a Poisson distribution.

Figure 5.16 Distribution of each rurality outcome



Model fit

In order to assess whether or not the Poisson regression model is a good fit to predict police violence in rurality, we need to understand whether or not the data performs well under the regression.

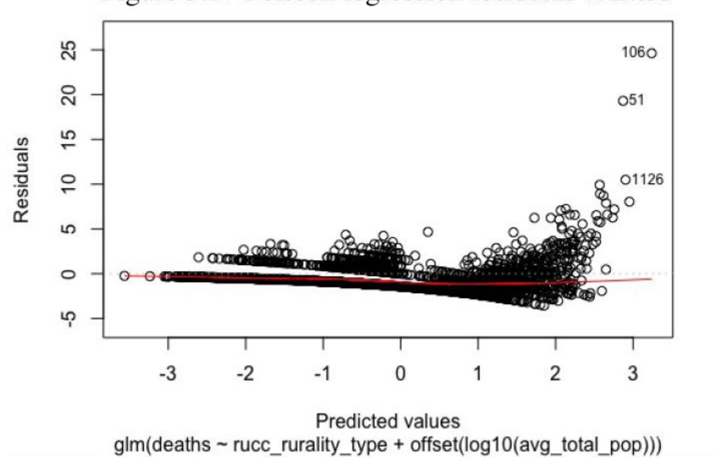
The primary signal of model fit is that the mean is equal to the variance of the distribution. In this case, we can test this using the dispersion parameter by computing the value of the deviance per degree of freedom (see Table 5.10). In our case, this dispersion parameter is 2.88, which is quite a bit greater than 1.00, signaling that our model is overdispersed and the variance is greater than the mean.

Table 5.10 Poisson regression dispersion parameter

	Value	Degrees of Freedom	Value/DoF
Null deviance	9034.1	3141	2.88
Residual deviance	7280.8	3138	2.32
Chi-Square Test	P-value = 0		

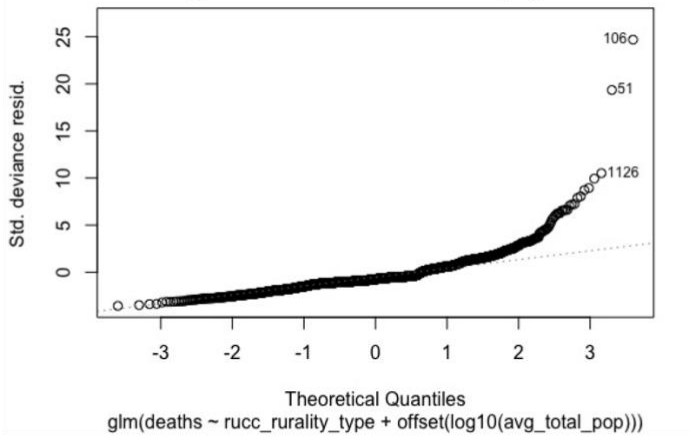
Next, we look at homogeneity. To assess this, we can again generate a plot of the residuals v. fitted values under the Poisson regression model (Figure 5.17). Here we see a non-random distribution of the data points, very prominently displayed via data clustering and fanning.

Figure 5.17 Poisson regression residuals v. fitted



Finally, we take a look at normality, to understand if the errors are randomly distributed. Figure 5.18 shows the Normal Q-Q plot for our data under a Poisson distribution.

Figure 5.18 Poisson normal Q-Q



We do not see a straight diagonal line that would indicate normal distribution of errors. While our data seemed a good fit for a Poisson distribution based on its characteristics, in the end we see the model is a poor fit and cannot be used to draw correlation or make predictive statements.

5.3 Discussion

Our findings have indicated to us that the link between rurality and police violence is at the very least elusive to identify or predict. Between the similar rates of our Tables 5.2 and 5.4, measuring the rate of police violence per 100,000 person-years by government sources of rurality, and the inability to fit the data to a satisfactory linear or non-linear model, we cannot conclude that there is a link between rurality and police violence. Of course, we cannot definitively say that the link doesn't exist, but for reasons to be discussed in a following section, 5.6 Limitations, such a conclusive statement would be difficult to make.

There are, however, noteworthy pieces of our analysis to comment on. The first is the need for a definitive way to define and measure rurality. As noted in our 3.2 Rurality: defined, there are multiple ways and agencies that measure rurality in a multitude of methods and motivations. As commented upon by Hemenway et. al. (2020) in their paper, there is no current authoritative stance on which measure of rurality to use for research such as public health. While, in our case, the two government measurements of rurality did not generate dramatically different results, had they done so, we would not know which measurement to rely on to assess the problem.

We were able to understand why Mapping Police Violence reports higher deaths from police violence in suburban areas while the Hemenway paper reported even rates. The disparity originated in part from differing methods: rates vs absolute counts. According to Trulia, more people believe they live in suburbs than compared to what government sources consider suburbia. These different classifications of suburban living caused MPV to report a higher number of deaths in suburbs. When this count was converted to a rate, it became the lowest category within the Trulia classification and more on par with the rates when classified under NCHS and RUCC. While neither method is more authoritative compared to the other, we do tend to favor the rate per 100,000 person-years according to the RUCC classification, which we consider a more balanced view of the phenomena and a standard way to represent deaths in a population. Lastly, while Hemenway et. al. analyzed only 2015-17, the additional years we included in our analysis did not know any differing trends.

Though the rates differ drastically, the Trulia classification of deaths by suburbia may shed light on a slightly different issue than the ones discussed in this paper. Either many people believe they live in a suburb than actually do or the very idea of a suburb is up for much more debate and discussion than it currently is. Because the idea of American suburbia matters nearly as much, or perhaps more, than the population density or proximity to a city center, a finding that most police deaths occur in suburbia according to Trulia might point out a need to understand what role the *perception* of suburbia has in policing. That is to say, if a suburb is a place built as a refuge from 'inner-city' life, and all the racial implications that come with it, it would be interesting to see how that relationship impacts policing itself. However, we remain reserved with our analysis on policing and rurality using the Trulia dataset due to the extreme limitations it poses, not least of which the approximately 10,000 missing ZIP codes.

Our rates were calculated on population estimates both for practicality and to follow standards for research. If, however, one was interested in how rates of police violence vary by exposure to police, it would be more appropriate to calculate the rate based on some measurement of policing. It stands to reason that since one can only experience police violence when there is an encounter with the police, that we should attempt to understand if rates of police violence have a positive linear relationship with level of policing. This would of course, present a major issue with endogeneity and would call for creative and advanced statistical methods to definitively understand the relationship.

Furthermore, some results we found were not surprising: rates of police violence vary greatly by race with those classified as Other often suffering a rate of double over the Black population. The Black population faces higher levels than White and Hispanic by a factor of over 3. There is much existing research that illustrates the racial disparities in policing; herein we simply confirm them with our results.

If anything, our results show us that while the link between rurality and police violence may be tenuous at best, race remains an important indicator for outcomes of policing. What remains to be seen, however, is how different locations of the same measure of rurality may differ from each other when they offer different racial compositions. For instance, how does a city with a higher population of white Americans differ from one with a higher population of Black Americans? Conversely, does a predominantly Black rural place behave more like a city (such as many rural areas in the South) or does it behave more like another rural place with less Black residents (say, for instance, in Idaho). Because we were not able to fit the data to an appropriate model, we are not able to analyze race and rurality in this way in terms of police violence.

Furthermore, while many studies look at the disparity between white and Black Americans, few examine disparities with and within other racial categories. Most notably for this paper, we see that the rate of 'Other' in many tables and results are exceedingly high. From closer inspection of the specific instances of reported deaths, we can see many are rural deaths of Native Americans. According to the Bureau of Justice Statistics (2002), Native American victimization rates of violent crimes is 101 violent crimes per 1,000 people compared to the national average of 41. Given the inflated rates of the 'Unknown' category in Trulia, many of which could be in highly rural places, it is clear that further research into the racial disparities of how those in the 'Other' category experience crime and policing is warranted. Because this category often lumps together people of drastically different cultures and phenotypic appearances, the singular category at the very least masks researchers' abilities to understand the true disparities.

Finally, while our work leads us to believe there is not a link between rurality and police violence, prior research shows reason to suspect other factors that might link place and police violence. Such factors might be rates of gun ownership (often times higher in certain regions or ruralities), segregation rates (within and between counties), and institutional factors such as police unions. We call for further research into these factors and other consequential areas to understand what leads to increased levels of police violence and how we can alter the institution to make it safer.

In the next section, we will discuss how these points can be leveraged into policy recommendations.

5.4 Policy recommendations

Throughout this research, we have identified several pain points and unanswerable questions. These are by and large the foundation of our policy recommendations.

First and foremost, we echo the call of activists and advocates for nearly a decade to create a national registry of police violence and misconduct. While current legislation has begun the process of creating the registry and the guidelines and circumstances for reporting, very little if any progress has been reported to the public. Currently, the system relies on voluntary or semi-voluntary reporting from states to the federal government, with no clear guidelines. We recommend that these rules are either elucidated further or made public for activists and advocates to comment on. Finally, it is imperative that the registry is comprehensive in the data it requires: from misconduct to fatalities with information about the officer(s) involved, the place, circumstances, racial backgrounds of all parties, reasons for interaction, and other pertinent information. These details will be vital to future public health research. The overall lack of transparency has sowed public doubt in the government's ability to accurately and swiftly report police misconduct and fatalities.

Next, and more pertinent to our research question, we recommend that attempts to address police violence from a policy perspective begin to diverge from the politics of place and rurality.

In our background, we reviewed how the politics of who belongs to which places of American society has always been central to ideological discussions of crime, policing, and therefore, police violence. However, to date, there is no research that shows that police violence is higher in any given rurality, making this discussion completely devoid of the facts. We urge this discussion to move forward and consider more institutional factors that affect policing so that researchers and policymakers can propose targeted solutions. The uniform nationwide nature of the problem points to the need for federal attention and oversight, but it is also important to remember that policing happens at the local level; no matter the type or composition of the place.

Which leaves us with our final policy recommendation. Studying police violence, and crime and policing in general, is undoubtedly difficult due to issues with data collection and endogeneity. In the absence of rigorous research into methods that can create change, the next best solution is to exploit the local nature of policing, to experiment with different approaches to policing and city funding. In the aftermath of the George Floyd murder of 2020, Minneapolis announced that would move to 'defund' their police department, choosing to move funds to other public health services, in an attempt to reduce issues of policing. In other cities, such as Eugene, Oregon, the CAHOOTS program diverts dispatch calls from the police to other social services to handle causes such as mental health and domestic violence. The program has been running since 1989 and in 2017 the program diverted 51.3% of 911 calls to CAHOOTS (White Bird Clinic, 2021). While the evaluation of these programmes will be challenging, it is vital that some research is conducted to see if these solutions should be piloted in other cities and precincts.

5.6 Limitations

Our analysis has several limitations primarily due to data availability and data structure, limiting the scope of appropriate statistical analyses. The general structure of the dataset presents significant challenges in terms of finding suitable models to fit the data due to the heavy presence of zero values. Thorough exploration of data transformation and alternative statistical models resulted in assumption violations and reduced statistical power as seen above in the our section 5.2 Understanding the relationship. The lack of suitable models available for this type of data reduced our analysis to calculations of the average death rates by rurality classification for total death rates and desegregated death rates, however we were unable to test for the significance of these relationships. Additionally, we intended to run a regression with other variables to determine if other correlations could be observed between death rates and other factors by rurality type.

In addition to the structure of the dataset, data availability itself presents challenges to our analysis. We opted to select the MPV dataset, however, they rely on a variety of collection methods such as web scraping, review of news reports and death records, which ultimately results in underreporting (MPV, 2021-a). In addition to the lack of central records for deaths, the federal government does not track general police misconduct. As police misconduct occurs with greater frequency across more locations, several of the challenges posed in this study may be alleviated due to the change in data structure. Police misconduct serves as an important topic of study that may not receive the same level of public attention as deaths, but still has widespread repercussions and may allow for more thorough statistical analyses.

Upon further analysis of the MPV dataset several challenges emerged when examining the data categorizations for race. The dataset includes race classifications for White, Black, Hispanic, Asian, Native American, Pacific Islander and Unknown. Since researchers publicly source race data, a level of measurement error exists within this categorization.

In addition to the challenges in the MPV dataset, rurality and population data posed a number of challenges. Due to missing CDC population data for several counties and ZIP codes, we had to drop two observations for the RUCC and NCHS analysis and seven observations for the Trulia analysis. Furthermore, methods of measuring rurality vary widely, leading to variance within results.

6. Conclusions

In this paper, we have explored the importance and history of place and rurality in American policing. We reviewed the current state of American policing before turning to an exploration of the current literature and research designed to understand and dissect the ills of the police force and what actions can be taken to correct for them. By looking at simple rates of deaths across race and rurality according to government measurements of rurality, we saw that no one single type of location stands out in rates of police violence. The same information also helped us understand that the Trulia classification for suburban violence was more comparable to those of RUCC and NCHS when using rate data as opposed to count data. This analysis also helped us understand the limitations of defining police violence according to the Trulia definition of rurality. Though we suspected potentially elevated rates of police violence in suburbs according to current advocacy efforts, we found no such result. In fact, in some cases, the rate of violence in suburbs was the lowest in their respective classification systems. Finally, by analyzing the data under more intensive statistical analyses, we showed there was not a satisfactory linear relationship between the rate of police violence and rurality. As a final step, we turned to the literature of preventative public health research to understand how we could leverage the Poisson distribution and regression as a way to understand and interpret datasets with infrequent, significant outcomes. Though these methods did not prevail, we were able to use this lack of success to suggest that the link between rurality and police violence may in fact not exist, though we of course cannot definitively discount the possibility.

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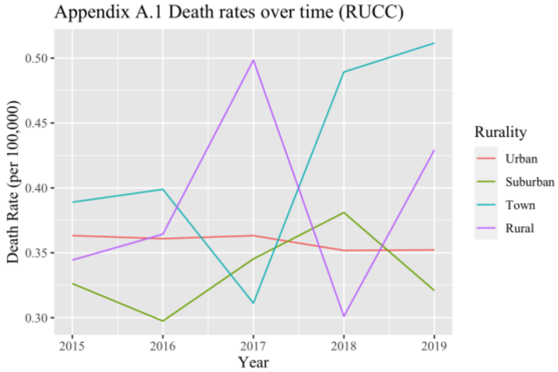
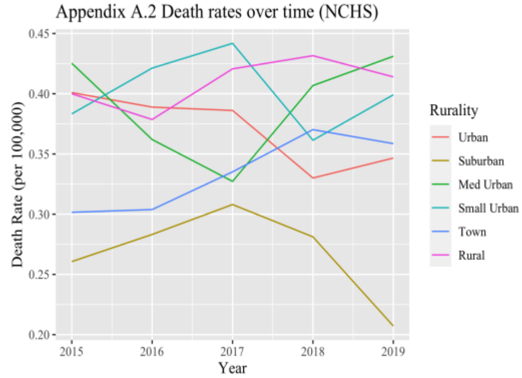
viii. Appendix

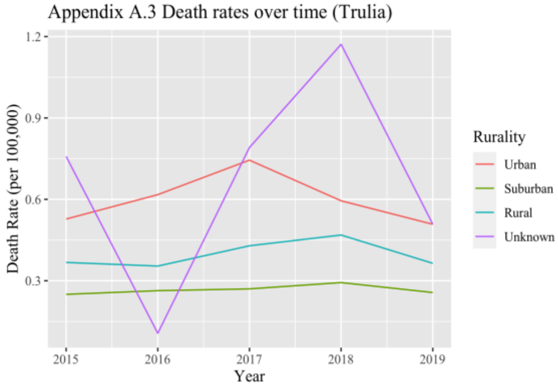
Appendix A.1 Death rates over time (RUCC)



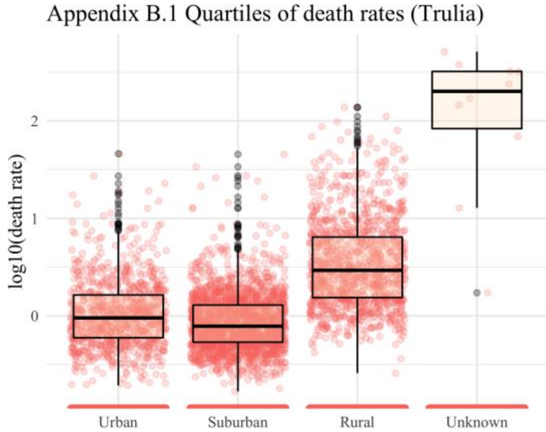
Appendix A.2 Death rates over time (NCHS)



Appendix A.3 Death rates over time (Trulia)



Appendix B.1 Quartiles of death rates (Trulia)



Statement of Authorship

I hereby confirm and certify that this master thesis is my own work. All ideas and language of others are acknowledged in the text. All references and verbatim extracts are properly quoted and all other sources of information are specifically and clearly designated.

DATE: 09.06.2021

NAME: Becca Burgmeier

SIGNATURE:

Statement of Authorship

I hereby confirm and certify that this master thesis is my own work. All ideas and language of others are acknowledged in the text. All references and verbatim extracts are properly quoted and all other sources of information are specifically and clearly designated.

DATE: 9 June 2021

NAME: Heather Dannyelle Thompson

SIGNATURE:

MIA/MPP Master Thesis group form

Name of student 1	Becca Burgmeier
Name of student 2	Heather Dannyelle Thompson
Thesis Advisor	Leonardo Iacovone

Master Thesis Title

'Hands Up, Don't Shoot': Is police violence higher in American suburbs?

Please indicate which part(s) have been elaborated by whom, go into detail and be specific*:

Student 1

Becca completed the following sections of the thesis for a total word count of 6454:

-2. Introduction (680 words)

-3.4 Background: literature review (1573 words)

-4. Methodology (1169 words)

-5.1 Findings and analysis: descriptive statistics (1480 words)

-5.3 Findings and analysis: discussion (1168 words)

-5.6 Findings and analysis: limitations (384 words)

*Total document words count excluding the bibliography is 14,114

Student 2

Heather completed the following sections of the thesis for a total word count of 7149:

-vi. Notes on race (280 words)

-1. Executive summary (295 words)

-3.1 Background: historical and political context (1478 words)

-3.2 Background: rurality: defined (933 words)

-3.3 Background: the current state of American policing (496 words)

-5.2 Findings and analysis: understanding the relationship (2860 words)

-5.4 Findings and analysis: policy recommendations (522 words)

-6. Conclusion (285 words)

*Total document words count excluding the bibliography is 14,114

* Please note that individual input has to be marked off and should be listed in this form; according to BerlHG §32 (5) individual, differentiated grading has to be possible.

We confirm that we both have equally invested our time and effort in the master thesis and that we followed good academic conduct in group work (see exam rules *§14 master thesis (5)*, and *§15 good academic conduct*).

09.06.2021 9 June 2021

Date, signature student 1 Date, signature student 2