The Policing of the “Reserve Army”:

Economic Inequality and Police Killings

Matthew Carson

Department of Political Science
University of California, Los Angeles

March 22, 2024

The author wishes to thank Professor Chris Tausanovitch and Professor Scott James for their guidance with research design and for their feedback along the way. Without such thoughtful feedback and encouragement, this project may not have come to fruition.

Abstract

This study examines the relationship between race, class, gentrification, and police use of lethal force (LUOF) in U.S. census tracts. Analyzing US Census data from 2015 to 2020 reveals that while there is a disproportionate incidence of LUOFs in the majority non-white census tracts and of non-white victims, rates within racial groups differ significantly by income. Across all racial/ethnic groups, lower-income census tracts experience more LUOFs than higher-income tracts, but these income-based disparities are sharpest within majority black and majority Latino tracts. These findings suggest that while class matters across all groups, for blacks and Latinos, the class disparity is even greater. Gentrification's impact on LUOF rates is more nuanced. In general, gentrifying tracts did not experience a greater LUOF rate than low-income, non-gentrifying tracts. However, within majority black census tracts, those undergoing gentrification experienced the highest LUOF rate.

Contents

On August 8, 2015, US senator and Democratic presidential candidate Bernie Sanders spoke at "Social Security Works," an event commemorating the 50th and 80th anniversary of the enactment of Social Security and Medicare, respectively (Wilson and Smilowitz 2015). But before Senator Sanders could speak, several Black Lives Matter activists interrupted because they felt Sanders was inadequately responding to issues of racial justice, particularly as it pertains to the killings of black Americans by law enforcement. One activist, Marissa Johnson, in an MSNBC interview, elaborated that the interruption aimed to "put pressure on people who claim that they care about black lives" (Hall 2015). Specifically, regarding Sanders, she averred, "if you look at Bernie Sanders's platform, you look at what he said on racial equality, he's basically a class reductionist. He's never really had a strong analysis that there is racism and white supremacy that is separate than [sic] the economic things that everyone experiences. So, we want to continue to push him on that" (Hall 2015). The issue for Johnson and the other activists who stormed the stage that day was that while Sanders had a fairly expansive economic justice platform, those policies were an inadequate response to issues of racism and white supremacy. Hence, from this perspective, his politics were class reductionist.

Earlier that year, in an interview with CNN's Wolf Blitzer, Senator Sanders was asked about his thoughts on the unrest in Baltimore following the murder of Freddie Gray by law enforcement. Sanders emphasized that "too many mostly black suspects have been treated terribly and, in some cases, murdered," and that "police officers have got to be held accountable for their actions," but also that economic factors were related to the killing of Freddie Gray:

> [I]n the neighborhood where this gentleman [Freddie Gray] lives [sic], as I understand it, the unemployment rate is over 50 percent, over 50 percent. What we have got to do as a nation is understand that we have got to create millions of jobs to put people back to work to make sure that kids are in schools and not in jails. So, short term, we've got to make sure that police officers have cameras. We've got to make sure that we have real police reform so that suspects are treated with respect. Long term, we've got to

> make sure that our young people are working, they're in school, they're not hanging out on street corners. (Sanders 2015)

That is, for Sanders, people being killed by law enforcement is inextricably tied with unemployment and economic inequality: Those residents in Freddie Gray's neighborhood had little economic opportunity, which meant that they would frequently "hang out on street corners" and come into contact with police, often with deadly consequences. This was in contradistinction to the claims of activists like Marissa Johnson, who saw the issue primarily as a function of racism and white supremacy.

This project aims to take on this question. Of course, racial discrimination and economic inequality are not mutually exclusive, and this project does not suggest such a view. However, these two contrasting perspectives vis-à-vis police violence are worth exploring further. As I will contend, while African Americans are indeed disproportionately targeted and killed by law enforcement, the phenomenon is also much broader and affects many low-income people more generally. As researchers who are attempting to better understand the phenomenon, it is imperative that we not only understand the racial disparity frame of reference but also the role of economic inequality.

Background

From a disciplinary perspective, Political Science has not adequately researched issues of policing and incarceration (a related phenomenon). In their 2017 article, "Police Are Our Government: Politics, Political Science, and the Policing of Race–Class Subjugated Communities," in the *Annual Review of Political Science*, Joe Soss and Velsa Weaver highlighted how the discipline has failed to "heed the call" for greater research into the issues concerning policing (2017, 568). Consequently, the discipline "continues to offer a distorted portrait of democracy and government in America and a deeply incomplete view of how politics and power operate in RCS [race and class subjugated] communities" (2017, 568). Significantly, the authors call upon the discipline to more closely examine the state's second face: "the activities of governing institutions and officials that exercise social control and encompass various modes of coercion, containment, repression, surveillance, regulation, predation, discipline, and violence" (2017, 567). It is in this spirit that this paper proceeds, as an undertaking aimed at better understanding these dynamics.

The rates of lethal uses of police force are remarkably high in the United States relative to other countries in the Global North, making it all the more urgent of an issue. While this project is not chiefly focused on comparative aspects, it nonetheless helps drive home the point regarding how serious of an issue this is. Espiner and Hancock (2022) observed that "America is in a league of its own with nearly 31 police shootings per 10 million people," making the United States's rate nearly four times that of New Zealand, and over 100 times that of England and Wales. Other countries that Espiner and Hancock (2022) investigated include Canada (9.2 per ten million) and Norway (3.6 per ten million). This underscores the urgency and need to further investigate causal forces contributing to the high incidence in the United States.

Research Question

Are lower-income people more likely to be killed by law enforcement, even when considering other variables such as race?

Methods

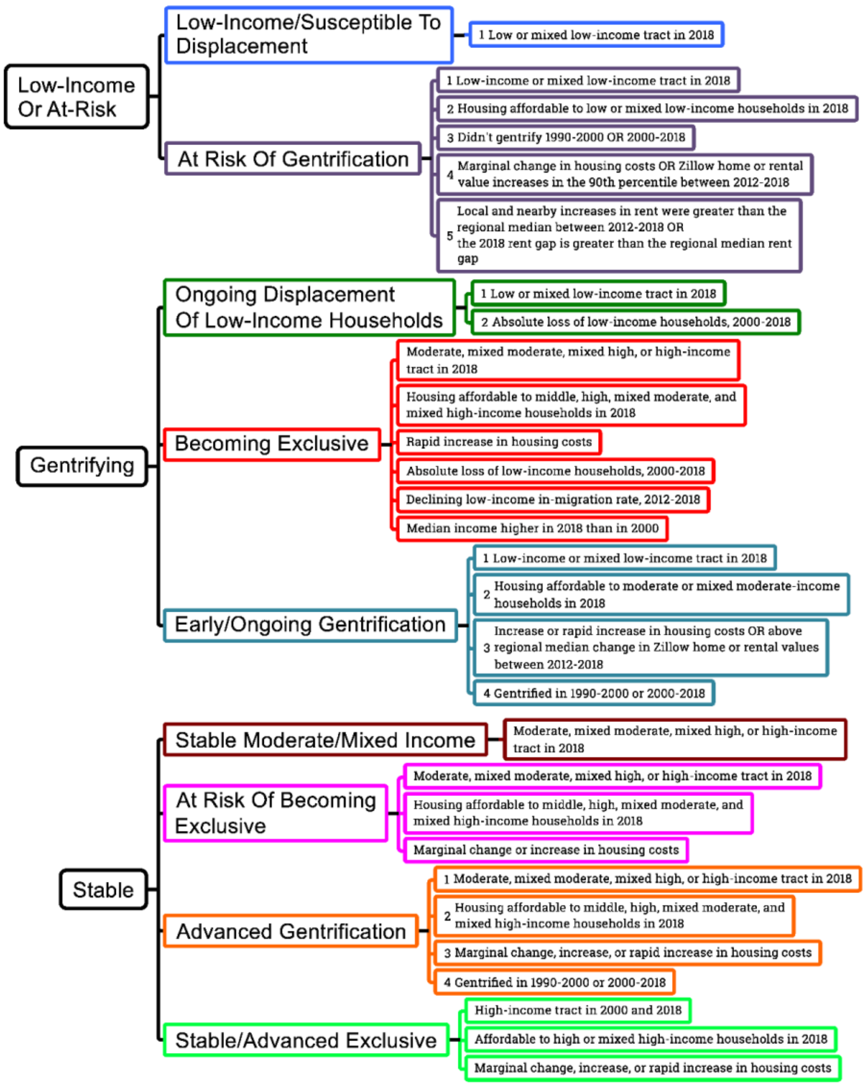
Data sources

Three sources will be used in the project. The Fatal Encounters data set is the primary source of incidents of someone dying in the course of police activity. Journalist D. Brian Burghart started the effort in 2012 after finding that there was no comprehensive database of people killed during interactions with the police. Data have been collected using paid researchers who aggregate data from other large data sets such as the *Los Angeles Times*' "Homicide Report," public records requests, and crowdsourced data (Burghart n.d.). Crowd-sourced data is subsequently checked against published media reports or public records to verify accuracy. Every incident includes a link to a public record or media report substantiating the veracity of the details of the death (Burghart n.d.). Because of the limitations of the FBI's Uniform Crime Report (i.e., participation by law enforcement agencies is voluntary, and the number of persons killed by law enforcement is severely underreported), Fatal Encounters is one of the main sources that academics use when researching police use of deadly force (J. M. Feldman et al. 2017a, 2017b, 2019).

The US Census' American Community Survey is the source of median household income data for each census tract. Since each incident in the Fatal Encounters data set includes a latitude and longitude, it can be matched with a census tract in the American Community Survey. Census tracts are "small, relatively permanent statistical subdivisions of a county or statistically equivalent entity" that "generally have a population size between 1,200 and 8,000 people, with an optimum size of 4,000 people" (Bureau n.d.). Because of their small size, these geographic units offer the most granular view of the characteristics of a neighborhood; This makes them generally superior to other geographic subdivisions such as zip codes because those larger units often overlap with both poorer and more affluent areas.

The Urban Displacement Project (UDP) is the source of gentrification data. The UDP conducts "data-driven, applied research," including census tract-level identification of gentrification or lack thereof (UDP 2023). The UDP has constructed nine typologies based on income and Zillow home values and changes in income or Zillow home values between 2000 and 2018. Because of how difficult it would be to interpret the relationship between such a large number of typologies and police lethal use of force, several of these typologies have been merged (See Figure 16: Original Typologies for how the Urban Displacement Project had arranged them). The typologies — “low-income/susceptible to displacement” and “at risk of gentrification” — have been merged into “low-income or at-risk”; this combines tracts that are low or mixed-low income and tracts that are at risk of gentrification because of rent increases in nearby tracts—referred to as a *rent gap*—but excludes tracts that *are* gentrifying. Next, all typologies where tracts are gentrifying or residents are being displaced were combined into “gentrifying”; this includes “ongoing displacement of low-income households,” “early/ongoing gentrification” and “becoming exclusive.” The last group includes those tracts that are either stable in terms of income or housing costs or both, including those tracts that have already gentrified either in 1990 or 2000: “stable moderate/mixed-income,” “at risk of becoming exclusive,” “advanced gentrification,” “stable/advanced exclusive.” They are combined into the category “stable” (Figure 1). The reason for including stable census tracts and advanced gentrification tracts in the same category is that the latter have *already* been gentrified before the period that this study is examining and thus would not be appropriate for inclusion in the category where gentrification is occurring.

Figure 1: Modified UDP Typologies



Operationalization

The dependent variable for this project is the number of fatal police uses of force. For purposes of this project, lethal use of force (LUOF) will include those incidents in which the *highest force used* is coded as tasered, gunshot, stabbed, asphyxiated/restrained, beaten/bludgeoned with an instrument, chemical agent/pepper spray, asphyxiation/restrained, or less than lethal force. The *highest force used* categories excluded are: vehicle, fell from a height, drowned, medical emergency, other, burned/smoke inhalation, drug overdose, and undetermined. Those categories included best reflect the direct use of force by an officer during an interaction, whereas the excluded *highest force used* categories include incidents where no direct physical intervention was employed, and the officer merely happened to be present during a medical emergency or a drug overdose. The most frequently observed of the excluded categories, vehicle, could include incidents where officers never physically restrained the suspect, and the suspect had simply fled recklessly. Independent variables include: the race of the victim and the racial composition of the census tract, the median household income of the census tract, and the stage of gentrification or its absence within the tract.

Hypotheses

H_1: Class (operationalized as income) is a better predictor of whether a tract will experience a deadly use of police force than the racial composition of the tract. That is, LUOF rates should vary more substantially by income quintiles within each racial group than by racial groups within each income quintile.

To test these hypotheses, tracts were categorized as majority-black, majority-white, or majority-Hispanic/Latino. "Majority" shall mean greater than 50 percent of the tract is one of the three aforementioned racial groups. Other races and ethnicities will not be included in this typology, though they will be included in the denominators in calculating proportions to determine if any one group constitutes a majority. The race of the victim is specified in most of the entries in the data set of lethal uses of police force. Finally, all tracts will be binned into quintiles based on their median household income.

Initial calculations will be done strictly using income quintiles. Per capita rates are calculated as follows:

$$Rate_q = \frac{LUOF\_Count_q}{Population_q} \times \frac{1}{6} \times 10{,}000{,}000$$

where *q* is the income quintile, *LUOF_Count* is the number of LUOFs that occurred in that income quintile, and *Population* is the total number of persons living in that particular income quintile. Per capita rates were annualized by dividing by six (the number of years in the study) and rescaled to a rate of "per 10 million." Lethal use of force counts were then cross-tabulated for tract groups according to their respective income quintile and majority-race status: $LUOF\_Count_{qm}$, where *LUOF_Count* is the total number of lethal uses of force that occurred in tracts with income quintile *q* and with a majority-race *m*, resulting in a table:

Table 1: LUOF Frequency

Income	*Black*	*Latino*	*White*
Q_1	–	–	–
Q_2	–	–	–
Q_3	–	–	–
Q_4	–	–	–
Q_5	–	–	–

Again, per capita rates were calculated by dividing *LUOF_Count* by six (the number of years in the study), dividing by the number of persons of that particular race living in that particular income quintile, and multiplying by 10 million, to obtain the annualized rate per 10 million:

$$Rate_{qm} = \frac{LUOF\_Count_{qm}}{Population_{qm}} \times \frac{1}{6} \times 10{,}000{,}000$$

H$_2$: Tracts experiencing gentrification or vulnerable to becoming gentrified should experience higher rates of LUOF than higher-income tracts that have experienced no gentrification, regardless of the racial composition of the tract. That is, there should be more variation within each racial group by gentrification typology than there is within each gentrification typology by majority race.

The same scheme was employed to calculate the rates for the various gentrification typologies. First, rates will be calculated for the Urban Displacement Project's gentrification typologies (*UDP*) without respect to the majority-race classification or the race of the victim. Then rates will be cross-tabulated for (*UDP* by *Majority*), (*UDP* by *Victim_Race*), and (*UDP* by *Majority* by *Victim_Race*). With this, bar plots can be generated to assess how strongly each variable is related to the incidence of LUOFs. Bringing in three dimensions to the analysis simultaneously can often illuminate a dynamic or interaction that otherwise goes unnoticed. For instance, there is often a question both in terms of how individuals are perceived based on ascription (race, gender, etc.), and other environmental factors, such as the racial composition of the neighborhood or forces of gentrification and how those might be related to a greater probability of being killed by law enforcement. Taking this three-way factor approach makes it possible to look at all these at the same time rather than in isolation.

Lastly, while I expect to find that class and gentrification indicators largely predict a greater incidence of LUOF than race alone, discrimination is also a causal force that does to some extent operate independently of economic factors, so I would expect some racial disparity to remain even after controlling for income and gentrification. In the final analysis, considering both how discrimination plays a role and how class and political economy have causal effects will enhance our understanding of the phenomenon and could inform discussion both among academics and those outside the academic community who want to think critically about the issue and how to combat it.

Literature Review

The literature in political science on the question of police killing has focused on the question of racial disparity. For example, a controversial article published in The National

Academy of Sciences (PNAS) in 2019 asserted that the authors found “no evidence of anti-Black or anti-Hispanic disparities across shootings, and White officers are not more likely to shoot minority civilians than non-White officers” (D. J. Johnson et al. 2019, 15877). This caused quite an uproar across the social sciences. Political Scientists Dean Knox and Jonathan Mummolo were among some of the more vocal critics. They voiced an issue with the methods that the authors used and published a short response (Knox and Mummolo 2020). Another lengthier article published later by Knox, Lowe, and Mummolo (2020) elucidated the authors’ claims more comprehensively. Their primary claim is that racial disparities exist and could even be underestimated because of the lack of data concerning when officers choose not to investigate; that is, there is no way of tracking how many whites they choose not to stop.

However, Adolph Reed Jr (2016), professor emeritus of political science at the University of Pennsylvania, has emphasized the limitations of race politics in combating the issue. He critiqued the antiracist orientation to the question both on normative grounds, in that, “antiracist politics is in fact the left wing of neoliberalism in that its sole metric of social justice is opposition to disparity in the distribution of goods and bads in the society, an ideal that naturalizes the outcomes of capitalist market forces so long as they are equitable along racial (and other identitarian) lines,” and on empirical grounds: “when we step away from focus on racial disproportions, the glaring fact is that whites are roughly half or nearly half of all those killed annually by police. And the demand that we focus on the racial disparity is simultaneously a demand that we disattend from other possibly causal disparities” (2016).

For example, Reed (2016) found that no blacks were killed in some of the states that experienced the highest rates of police killings. Moreover, Reed (2016) references that Zaid Jilani (2015) found that 95% of police killings occurred in neighborhoods with median incomes under $100,000, and "the average neighborhood family income where a killing occurred was $57,764." He contends that policing as an institution manages the social consequences produced by "the regime of market-driven public policy and increasing direction of the state's functions at every level toward supporting accelerating regressive transfer." Reed concludes by noting that "the focus on racial disparity accepts the premise of neoliberal social justice that the problem of inequality is not its magnitude or intensity in general but whether or not it is distributed in a racially equitable way." Along with Reed, Political Scientist Cedric Johnson has studied the incorporation of the black political class into American politics post-1965 Voting Rights Act and the ways in which class cleavages among blacks are at least as important as interracial dynamics. This is important in at least two ways: one is that positing the issue of police killings and broader miscarriages of the criminal justice system strictly as racial in nature tends to paper over the role of black politicos in bringing about those outcomes in their adopting of austerity measures and advancing real estate developer interests and the concomitant repressive policing practices (C. Johnson 2016, 305, 2019, 179). The other is that the rhetoric of Black Lives Matter and cognate notions like the new Jim Crow, popularized by Michelle Alexander's (2010) book, "posit[] universal black injury where, in fact, police brutality and the carceral state are experienced more broadly across the working class" (C. Johnson 2016, 317).

Historical Perspective

Political Scientist Cedric Johnson looks at the question by examining policing historically, tracing back the emergence of today's policing not to slave patrols or the perpetuation of the Jim Crow order but to the "discrete social contradictions of 'postindustrial capitalism'" (2019, 171). He argues that policing, since its modern inception, has always been about "disciplining the poor and protecting emergent property regimes" (2019, 172). In particular, he argues that the postwar transformation of US cities into middle-class suburbs with a high standard of living and the broader transformation of society into one of consumers produced a fundamental contradiction in that insofar as it produced middle-class suburbs, it also produced an "industrial reserve of unemployed, mostly black and brown urban dwellers" (2019, 171). In this context,

> policing took a dual form: an emulatory strategy of promoting civic virtues of deference and middle-class aspiration, and a punitive strategy of defending the propertied and virtuous middle class from the outsiders, those segregated in inner-city ghettos and struggling to survive. (C. Johnson 2019, 176)

The Reagan and Bush years saw an intensification of what Johnson described as "class war at the urban level." This included a rollback of the welfare state and a concomitant expansion of the carceral state and its more aggressive policing practices in urban minority communities (C. Johnson 2019, 177; C. G. Johnson 2023). With the rise of gentrification, the urban landscape shifted once again with the physical distance created by the suburban, post-war transformation disappearing as the middle class began to reenter cities. Real estate speculation brought "urban pioneers, house flippers, large real estate developers, and tourists" into direct confrontation with the "old ethnic neighborhoods, the unemployed, the itinerant poor, sexual minorities, and countercultural spaces" (C. Johnson 2019, 177). According to Johnson, these class contradictions are managed through "manifold technologies of policing, surveillance, and social accreditation that permit ease of movement across urban space for those of means, while regulating and constricting the poor" (2019, 178). Johnson further elaborates that this new urban landscape is,

> defined by helipads and Uber Black, artisanal grocers, boutique fitness clubs, private roads, dog parks, and relentless condo tower construction for the investor class and renascent bon vivant, and "bum-proof" benches, ankle monitors, stress policing, the

> demolition of public housing, water shutoffs, ubiquitous closed-circuit cameras, and check-cashing centers for the working-class enclaves. (C. Johnson 2019, 178)

For Johnson, then, modern policing has a racist dynamic, but it is not about bias or other psychologistic notions like prejudice but is rooted in maintaining the capitalist social order.

Quantitative Analysis

Quantitative work backs Johnson's claims. Feldman et al.'s (2019) study looked at the association between rates of police-related deaths and indices of neighborhood residential segregation using several measures that included income, race/ethnicity, or both. They used the American Community Survey's 5-year estimates to obtain census tract data, and the Index of Concentration at the Extremes (ICE) to operationalize segregation. ICE allows researchers to "simultaneously measure[] the relative concentrations of privileged and deprived residents in an area" (J. M. Feldman et al. 2019, 459). While ICE had previously been used to operationalize privileged and deprived status in terms of income alone, it has since been broadened to include other considerations, such as racial/ethnic privilege and deprivation. In this case, Feldman et al. used 5 common ICE measures, defining privilege and deprivation in terms of: (1) high- versus low-income neighborhoods, (2) non-Hispanic white versus non-Hispanic black persons, (3) non-Hispanic white versus people of color (PoC), (4) high-income non-Hispanic White versus low-income Black households, and (5) high-income non-Hispanic White versus low-income PoC households. Each ICE score ranged from -1 to 1, with -1 indicating 100 percent of the population belonging to the most deprived group and 1 signifying that 100 percent of the population belonged to the most privileged group (J. M. Feldman et al. 2019, 549). In addition to the census tract measures, they included characteristics of the individuals killed in the tracts in their analyses.

Feldman et al. found that, for the years in the study (2015-16), "census tract concentrations of economic privilege were associated with lower rates of police-related deaths," and "greater concentrations of deprivation were associated with higher rates" (2019, 461). At the same time, ICE measures for racialized economic polarization did not show a meaningful difference "compared with ICE measures of census tract income or census tract race/ethnicity alone (2019, 461). The most privileged quintile of census tracts experienced police-related killings at roughly half the rate of the second most privileged quintile, regardless of whether privilege was measured solely in terms of income, by income and race/ethnicity, or by poverty (2019, 461). Individual-level analysis in combination with the tract characteristics provided an additional layer. For example, when privilege and deprivation were defined solely by census tract racial/ethnic concentration, only non-Hispanic whites experienced a lower risk of being killed by law enforcement in tracts with the highest concentration of white residents, while non-Hispanic blacks experienced a higher risk of being killed by law enforcement in census tracts with higher concentrations of non-Hispanic whites (J. M. Feldman et al. 2019, 461).

In another study, Feldman (2020) took a slightly different methodological approach. First, he separated census tracts by poverty quintiles. He obtained police killings data and again located the census tracts where those incidents occurred. Using that data, he was able to calculate the annualized per capita police killing rate of each poverty quintile. He found that,

> [f]or the overall population, police killings increased as census tract poverty increased…. In the lowest poverty quintile, the rate of police killings was 1.8 per million. In contrast, the rate in the highest-poverty quintile was 6.4 per million, more than three times that of the lowest-poverty quintile. (J. Feldman 2020)

When looking strictly at race, whites had the lowest per capita rate of police killings (3.3 per million); Latinos had a slightly higher rate at 3.5 per million, and blacks had the highest per capita rate of police killings, more than double that of whites or Latinos (7.9 per million). He further stratified the data into fifteen strata: three race/ethnic groups by the five poverty quintiles. Doing this made it possible to see how rates differed not only across poverty quintiles but also across racial and ethnic groups. He found that,

> within all three racial/ethnic groups, rates of police killings were higher with increasing census tract poverty…. The relationship between poverty quintile and police killings was strongest for whites, for whom the rate was nearly 4-fold higher in the highest-poverty quintile…. For the black population, the police killing rate was 1.8-fold higher in the highest-poverty quintile relative to the lowest-poverty quintile…. The relationship was weakest for Latinos. (J. Feldman 2020)

That is, poverty was associated with higher rates of police killings for all racial/ethnic groups, with the association the strongest for whites and weakest for Latinos and with blacks somewhere in between in terms of strength of the association.

One question that remained was that since blacks and Latinos have higher poverty rates, how much of the difference in rates of police killings between races and ethnicities could be explained statistically as a function of differences in poverty rates in general? To answer that, he constructed a counterfactual scenario in which the poverty rates for blacks and Latinos were adjusted to be on the same scale as whites, scaling the per capita rates of police killings accordingly. He found that under the counterfactual poverty scenario in which black poverty was equal to white poverty, police killings would diminish from the observed rate (7.9 per million) to 6.6 per million, "a 28 percent reduction in the white-black gap in police killing rates on the additive scale" (J. Feldman 2020). For Latinos, the rate diminished from the observed rate of 3.5 per million to 3.1 per million, which was lower than the observed rate for whites. Because of this, Feldman contends, "the poverty distribution is sufficient to explain the Latino-white gap in police killings" (J. Feldman 2020).

An Analysis of Space

Loïc Wacquant (2010) locates the origins of the related phenomenon of incarceration in the diminution of the *social state* and the corresponding rolling out of the *penal state.* This political transformation has altered the "modalities of action of public authority when it comes to managing the deprived and stigmatized populations stuck at the bottom of the class, ethnic, and urban hierarchy" (74). And this phenomenon is not easily explained by trends in poverty rates or crime. Rather, it is "fueled by a politics of resentment," where stigmatized populations are portrayed as undeserving public-aid recipients and street criminals, popularly condensed as the "black underclass" (74).

Wacquant (2010) brings in an analysis of space that others have neglected. He argues that the intensification of police activities has targeted people by *class*, *race*, and *space.* This *triple selectivity* has led not to what some have called "mass incarceration," but to *hyper-incarceration,* affecting the lowest end of the African-American working class. This *punitive turn* occurred at the dawn of the post-Fordist era, as the US turned to a postindustrial service economy with a greater share of insecure and precarious labor.

The other element in the expansion of the penal system is its horizontal dimension. This includes the population typically not counted as part of the incarcerated—parolees and probationers, or those otherwise restricted in their movement or activities by the criminal justice system. Wacquant (2010, 76) contends that this ought to be considered "an *extension* of the custodial system, rather than an *alternative* to it" (italics in original). This coincided with greater surveillance technologies, such as the expansion of offender databases to include not only mugshots and fingerprints but also DNA prints and the proliferation of categories of convicts, such as sex offenders, which sought "to expurgate specific categories…from the social body."

These are the characteristics of what he has termed *hyperincarceration*—the concentration of this policing regime in the black, urban ghetto; its principal targets, "lower-class

African American men" (Wacquant 2010, 78). To understand the phenomenon, He employs the term *triple selectivity*—the "filter" that sorts those who are subject to inclusion in the expansion of the carceral state, and those who are largely exempt. The first filter is class. Wacquant (2010, 78–79) notes that, "The welcome focus on race, crime, and punishment that has dominated discussions of the prison boom has obliterated the fact that inmates are *first and foremost poor people*… This clientele is drawn overwhelmingly from the most precarious fraction of the urban working class" (78–79; italics in original). The second filter is race. Wacquant notes that, while the prison population used to be 70 percent white and 30 percent "other" in the 1960s-70s, it "flip-flopped" to "70 percent African American and Latino versus 30 percent white by the century's end" (79–80). But the racial dimension has been more "class disproportionate" inside each racial or ethnic category than it has been racially disproportionate between them (80). Citing sociologist Bruce Western, he notes that "the cumulative risk of imprisonment for African American males without a high school diploma tripled between 1979 and 1999," to 59 percent, but during the same period, the risk for "African American men with some college education decreased from 6 percent to 5 percent" (79).

Like Cedric Johnson, John Clegg and Adaner Usmani (2019) also disagree with *The New Jim Crow* narrative advanced by Michelle Alexander (2010) and contend that the rise in mass incarceration has not been so much about rising racial disparities, but by rising class disparities. Further, they argue, that the focus on the War on Drugs and related drug and narcotic policing regimes overlooks that, "Most prisoners are not in prison for drug crimes, but for violent and property offenses" (10). Moreover, they disagree with the claims made by Wacquant and others that the increases in incarceration rates were unrelated to increases in crime rates. Instead, they contend, that “The rise in violence was real, it was unprecedented, and it profoundly shaped the politics of punishment” (10-11).

They trace the crime wave back to the pattern of post-war economic development in which cities failed to absorb blacks into their labor markets. As the sharecropping system of the South collapsed in the 1960s, blacks moved north in search of opportunities, but they were largely excluded from labor market opportunities, and given that this period followed the post-war baby boom, there were also simply too many new migrants from the South and elsewhere for the local labor markets to absorb. Deindustrialization was beginning or had already begun in many places, such as Detroit, where industry was relocating to the suburbs and the Sunbelt; manufacturing was becoming more automated; and US firms were faced with increased foreign competition, all of which worsened the job prospects for newly arrived blacks in the city. Without real prospects for employment and a decent standard of living, they ended up living in “deteriorating central cities” and neighborhoods of concentrated poverty, where “violence rose to unprecedented heights” (Clegg and Usmani 2019, 11).

Of course, this does not suggest a deterministic relationship: rises in crime do not necessarily have to be dealt with by corresponding rises in police activity and the expansion of the prison system. Sometimes states have chosen to ignore crime waves; other times, they will connect the incidence of crime to poverty and the lack of opportunity and seek to correct the latter to correct the former. In the US case, the response from the state was punitive, but it was not simply a plot by Republicans to “recapture the South from the Democrats, nor was it the “conniving elites” looking to punish the poor (Clegg and Usmani 2019, 10, 16); the response can be better explained as a consequence of the balance of class forces in the US: “In reaction to soaring crime rates, the American public, white and black alike, demanded redress from the state.

Politicians, white and black, pivoted to respond. But the weakness of the American working-class prohibited meaningful social reform" (11). And since efforts at taxing the wealthy, which could fund social programs that would help the black poor in the inner-city ghetto, were unsuccessful at the federal level, fighting crime at its roots in poverty was not possible. Moreover, suburbanization was reallocating tax dollars, resources that those cities would have needed to enact social programs, from the inner city to the suburbs (22). So, cities were in no position to address these issues, even if they had wanted to.

Instead, states and local governments, where most of the responsibility for law enforcement lies, had to respond with limited resources at their disposal. Local constituents were demanding a response to the crime wave, and because of budget constraints local authorities "were left to fight violence on the cheap, with only the inexpensive and punitive tools at their disposal" (Clegg and Usmani 2019, 11). Because of this, Clegg and Usmani contend that, "the overdevelopment of American penal policy at the local level is the result of the underdevelopment of American social policy at the federal level. American exceptionalism in punishment is but the flip side of American exceptionalism in social policy" (11).

Clegg and Usmani (2019) outline two dimensions of anti-crime agendas. One is social policy, which is on a continuum between stingy and expansive. The other is penal policy, which can be hands-off, harsh, or somewhere in between. In the context described, expansive social policy was not on offer because of the lack of funding for it. Harsh penal policy was available though because it was a cheaper alternative to expansive social policy. The authors explain that this is because penal system expenses are hyper-targeted, only a small segment of the population generates those expenses through policing, incarceration, probation, etc. While social policy almost always applies to a broader population. Indeed, it often must be universal for it to be politically feasible in a democracy.

The American Politics Subfield

Soss and Weaver (2017) contend that the American Politics subfield in general has failed to adequately study policing and its effect on *race-class subjugated communities* (hereinafter "RCS communities"). They argue that the subfield has mostly ignored the impact that policing has on the political state of affairs in the United States. In particular, they contend that the American Politics subfield has been largely focused on the state's "first face," its liberal-democratic and electoral-representative features (565–66). But that monomaniacal focus has come at the expense of ignoring the state's "second face," its features of social control, in particular, "the ways [in which] 'race-class subjugated communities' are governed through coercion, containment, repression, surveillance, regulation, predation, discipline, and violence" (565).

Moreover, despite massive protests around the issue of police brutality and broader miscarriages of the criminal justice system, "it seemed the subfield did not have much on the intellectual rack that could be used to make sense of predatory local governance, explain its sources, and specify its empirical operations," even as the Department of Justice reports revealed law enforcement practices in places such as Ferguson, Missouri that were deeply at odds with democratic ideals (Soss and Weaver 2017, 566). Some political scientists offered thoughtful commentary on how protestors used social media to coordinate their actions and overcome collective action problems, and on Ferguson's electoral system design and how it produced a far whiter city council than the residents of Ferguson (566), but they did largely did not break away from the *first face* analysis of the phenomenon.

Soss and Weaver (2017) contend that the political subordination produced by the *second face* is not simply a matter of governmental inattention to race-class subjugated communities or their lack of effective voice, but that such subordination "is actively produced through modes of governance—frequently entwined with policing—that stigmatize and repress, ultimately turning government into an invasive, surveillant authority to be avoided" (567), The subfield needs to pay closer attention to this social control functions of the *second face,* and in particular to the interrelation between the police and the welfare state. Moreover, Soss and Weaver argue that these policing practices function as "class-calibrated race-making institutions"; thus, they are "productive forces" that "shape[] the structural positions, social identities, and political resistance in RCS communities" 569),

Looking at the development of the carceral state historically, Soss and Weaver lay out how the various "law and order" campaigns and "wars" on drugs and/or crime, along with theories such as "broken windows policing," offered by intellectuals to rationalize intensified policing in RCS communities. Such campaigns proceeded from a conviction that the tiniest amount of "public disorder" (the metaphorical "broken window")—no matter how trivial—would fester and lead to serious, violent crime (Soss and Weaver 2017, 570). From this new theory emerged several new modes of policing: zero tolerance, command-and-control operations, order maintenance, "hot spots" policing, saturation policing, and Scanning, Analysis, Response, and Assessment (SARA); as a result, the number of low-quality arrests and convictions increased (570).

Like Wacquant, Soss and Weaver find that what they term "social investment" diminished as policing techniques became the primary approach to urban governance and development, especially with respect to how social problems were managed (2017, 570–71). Policing was principally preoccupied with "the elimination of disorder and the regulatory enforcement of codes against disordered people and places" (570). At the same time, more aggressive policing, such as "broken windows," was not merely presented as a blunt tool of racial and class domination; indeed, it was substantively invested in a community-involved approach to policing. Proponents of broken windows believed that investigating small or petty crimes would foster a greater connection between officers and residents as officers began to better understand residents' lives and concerns. Moreover, by putting the officers into contact and building trust with residents, the latter would be more inclined to contribute to the "coproduction of safety" through cooperation with law enforcement (570). Though, in practice, this mode of policing ended up producing an expansion of state power and authority more than it did the co-production of safety.

In "Caught in the Countryside: Race, Class, and Punishment in Rural America," political scientist Marie Gottschalk (2020) underscores how the carceral regime is not just an urban phenomenon but has consolidated in the countryside. She emphasizes that while the focus on communities of color in urban areas has illuminated important aspects of the carceral state, much less attention has been paid to rural and declining Rust Belt areas. This has inhibited a more comprehensive understanding of the phenomenon. Gottschalk has also highlighted some of the limitations of the sole focus on the racial disparities framework: "The intense focus on the racial disparities of the carceral state and more generally on the role of race in American political development have overshadowed how economic and other factors are rapidly pushing wide swaths of other demographic groups to the margins, where they often find a police officer, a dirty needle, or a military recruiter waiting for them." (26). And while legal scholar Michelle Alexander's (2010) book, *The New Jim Crow*, heightened public awareness about mass incarceration, it also reinforced the view that mass incarceration is an urban phenomenon and "only marginally affected whites and nonurban areas" (Gottschalk 2020, 28). Indeed, Gottschalk notes that while urban incarceration rates have been declining, "rates in rural areas and small towns and cities have been holding steady or rising" (26). This broad expansion of policing, surveillance, and punishment has expanded beyond even the urban core that it is typically associated with to begin to "deform the polity and society in significant ways" (29).

In its study of the causes of mass incarceration in the urban context, the National Academy of Sciences concluded in 2014 that one of the contributors was "long-term structural changes in urban economies" (Gottschalk 2020, 35). Like Wacquant, Clegg, and Usmani have highlighted, the conditions in urban black neighborhoods deteriorated after the middle class migrated to the suburbs. Left with diminished opportunities for low-skilled workers, sharply segregated neighborhoods, and the departure of public investment as a result of middle-class out-migration, the black poor often turned to the drug trade as "the employer of first and last resort" (Gottschalk 2020, 35). Because poor black men in urban city centers increasingly turned to illicit activity for survival, they bore the brunt of inner-city policing regimes.

To be sure, public anxieties and fears about "social disorder and political unrest" contributed to this pattern of policing and punishment. In the 1970s, the public was increasingly nervous vis-a-vis the restructuring of urban economies. The economic future appeared uncertain, and there was fear that "growing economic distress would foster social disorder, including higher crime rates" (Gottschalk 2020, 36). Many public officials had lost legitimacy in the eyes of the public because of their inability to stem the economic turmoil. In this context, officials were more easily able to "sell" tough-on-crime solutions to the public to ease their anxieties:

> Social theorists have long contended that people who are poor, unemployed, or underemployed are disproportionately seen as threats to the social order and thus

> subjected to more punitive measures. During periods of unsettling economic transformations and growing economic inequalities, the "dangerous classes" appear even more dangerous and more in need of punitive measures to control them. (Gottschalk 2020, 36)

The urban war on drugs saw a corresponding war on drugs unfold in the countryside. Its targets were not African-American men, who had been the primary targets of the urban war, but poor and working-class whites and Latinos. The war on methamphetamine began in the 1980s, and has varied in intensity over the years, but by the time the urban war on crack cocaine waned, the war on meth surged again; though the "weapons of choice were remarkably similar to those used in the war on crack," its geography and "main demographic targets differed" (Gottschalk 2020, 44).

Where the urban war on crack blamed crack and "crack heads" as the cause of increases in "violence, crime, and social decay in urban areas," meth was characterized as a "white trash drug" consumed by the "lower socio-economic element of white people" by Oklahoma governor Frank Keating in 1999 (Gottschalk 2020, 41–44). The movies, media, television shows and public officials all emphasized the "white trash" nature of the drug users in their campaigns against meth use. The meth epidemic was presented as a "threat to the soul of the country," the rural heartland (45) In stigmatizing meth users as trash, the meth epidemic was connected with the War on Terror and even included in the reauthorization of the US Patriot Act in 2006. This funneled more resources to the rural war on meth and advanced more aggressive policing practices in those areas.

Furthermore, another salient political-economic feature is gentrification. As Johnson notes, gentrification forces have an inextricable link to the issue of hyper-policing and lethal use of force. Police are organized institutionally at the local level and respond most directly to those local political-economic dynamics. Real estate investors and interests drive the assault on working and poor people's living standards not only through rent-intensifying speculation but also through the concomitant policing that occurs as part of laying the groundwork for developers. Several cases illustrate the phenomenon and how it plays out in real-time.

In the early 1980s, Pittsburg, California, a city in the San Francisco East Bay, found itself struggling to revitalize its downtown. Not only was the deindustrializing city failing to attract new investment to its downtown, but its current merchants were increasingly frustrated with downtown loiterers and vagrants. Members of the New York Landing Association, a merchants group formed to encourage the "revitalization" of Pittsburg's decaying downtown, pushed for intensified police sweeps targeting loiters and public intoxication in the downtown area (Hallissy and Snyder 1981). The Deputy District Attorney, Jack Waddell, fully supported these sweeps, describing them as "cleaning up the streets and making them safe." Sweeps on November 21, 1981, targeting both the downtown area and the El Pueblo housing project resulted in "42 arrests for offenses ranging from loitering and obstructing sidewalks to public intoxication and possession of narcotics" (Hallissy and Snyder 1981). Pittsburg's Police Chief Leonard Castiglione said after the first sweep that he and his officers are "willing to 'bend the law' to rid the downtown area of 'undesirable and unwanted' elements (Hallissy and Snyder 1981). This orientation to policing, particularly concerning the "decaying downtown," and the persistent lack of investor interest continued for at least several more years. In a July 28, 1985, article in the *Daily Ledger Post Dispatch*, the city was still facing some of the same problems. The effort to rebuild the downtown had failed to materialize, and now even existing merchants were asking for greater police protection downtown and threatening to move their businesses to neighboring Antioch if the problems persisted (Shifrel 1985, 1). There were reports of heroin being used in a vacant house in the area, public drunkenness, and prostitution, among other issues. The city and police responded promptly, arresting twenty-two loiterers downtown and increasing the number of patrols. Many long-time residents felt that they could no longer gather with friends on the corner where they had been for years without fear of being asked for identification by law enforcement.

A similar trend appears in other cases, such as the killing of Breonna Taylor. Taylor was killed when a no-knock search warrant targeting her boyfriend was carried out by the Louisville Police Department. The police department had formed a unit called “Place-Based Investigations Unit,” which targeted “problem locations” with high rates of crime, including Elliot Avenue where Taylor’s ex-boyfriend lived. The specific purpose of the unit and how it planned to clean up the “problem areas” was less than clear because neither city officials nor police officials ever publicly announced the formation of the unit (Duvall, Kachmar, and Costello 2020). In addition to being able to clean up crime-ridden areas, an “added plus,” city officials said, was that the same Russel neighborhood (where Elliot Avenue is located) had also been targeted for redevelopment for some time by the city’s real estate and community development agency, Develop Louisville. This tied in with other objectives such as the demolition of public housing in the areas. For instance, as part of the Russel neighborhood revitalization plan, the city was also “among five finalist cities that ultimately won nearly $30 million in federal grants in the final months of the Obama administration to pay for the plan, which included demolishing the Beecher Terrace public housing development” (Bailey and Duvall 2020). These funds were part of a larger $200 million windfall the Fischer administration received from private, foundation, nonprofit, and public sources to advance the redevelopment project in the neighborhood.

The city had been targeting the Elliot Avenue home for months for criminal activity. One of the arrestees at the address was Jamarcus Glover, a convicted felon with a long history of trafficking and drug-related arrests. After notifying the landlord, Gerald Happle, that the criminal activity there constituted a "public nuisance," Happle wrote back that "he would evict the tenants if they could not work out a solution and asked if the city has 'any program to purchase or accept donations of problem properties'" (Duvall, Kachmar, and Costello 2020). After a phone call with Happle concerning the matter, a code enforcement officer "wrote in an email to all five police officers of the PBI unit that if further illegal activity occurs, 'he will then donate the property to Metro after evicting the tenant'" (Duvall, Kachmar, and Costello 2020). Shortly thereafter, the police department obtained five no-knock warrants, of which Breonna Taylor's home and the Elliot Avenue home were included. Glover was again arrested at the Elliot Avenue home; the following day, the city notified Happle that the cited had now officially deemed the property a public nuisance. Happle agreed to donate the property to the city the following day and turned in the application on April 6, 2020. Two days later, officers stopped someone who had just left Elliot Avenue and had made an improper turn; they found crack cocaine on the driver and issued a $400 citation to Happle and an order to vacate the home by April 13, 2020. June 5th, on what would have been Taylor's 27th birthday, Happle signed over the deed to the city for $1. These examples show how business and real estate interests can exacerbate how police power is mobilized in concert with those interests.

Findings: Income and Race

A list of lethal uses of force was downloaded from the Fatal Encounters website. The years under analysis for this project were 2015 through 2020, inclusive. Using R's 'tidycensus' package, census tract-level data for all tracts in the United States were downloaded and matched with the latitude and longitude of where a lethal use of force (LUOF) occurred. Incidents that were on the border of more than one census tract were excluded from the analysis. This typically happens when the incident occurs on a road or highway that divides two or more tracts.

Rates by Race and Ethnicity

As it is well-understood, majority-black and Latino neighborhoods experience higher rates of LUOF than majority-white neighborhoods. Data collected for this study confirm this. Indeed, majority-black neighborhoods experience a rate nearly twice that of majority-white neighborhoods. Majority-Hispanic/Latino neighborhoods experience a rate 1.75 times greater than majority-white neighborhoods.

Table 2: Rates by Race and Ethnicity

Majority	Lethal Uses of Force	Annualized Per 10 Million Population
Black	756	58.532
Hispanic/Latino	1,113	52.192
White	3,848	29.668

One possible explanation for the racial disparities is that blacks and Latinos are policed heavily, regardless of how well-off the tract is. A good amount of literature would seem to support this. Many studies have found discriminatory practices within police departments, and there have been many documented incidents of black professionals being harassed by law enforcement, often for rather arbitrary violations. From that perspective, discriminatory practices may largely account for the racial disparities that affect black Americans regardless of their class position. Another possible explanation for these racial disproportions is that blacks and Latinos also disproportionately live in lower-income neighborhoods that are more heavily policed for reasons discussed earlier. From this perspective, the racial disparities may largely be a function of class position and the way poor and working-class neighborhoods are policed. Of course, these explanations are not mutually exclusive; racial discrimination probably does play some part in generating these racial disparities, while the way the poor are policed could also contribute to the incidence of LUOF. However, it is worth examining the variation within majority one-race census tracts by household income quintiles to see how much of the disparity disappears once household income is introduced into the analysis.

Median Household Income

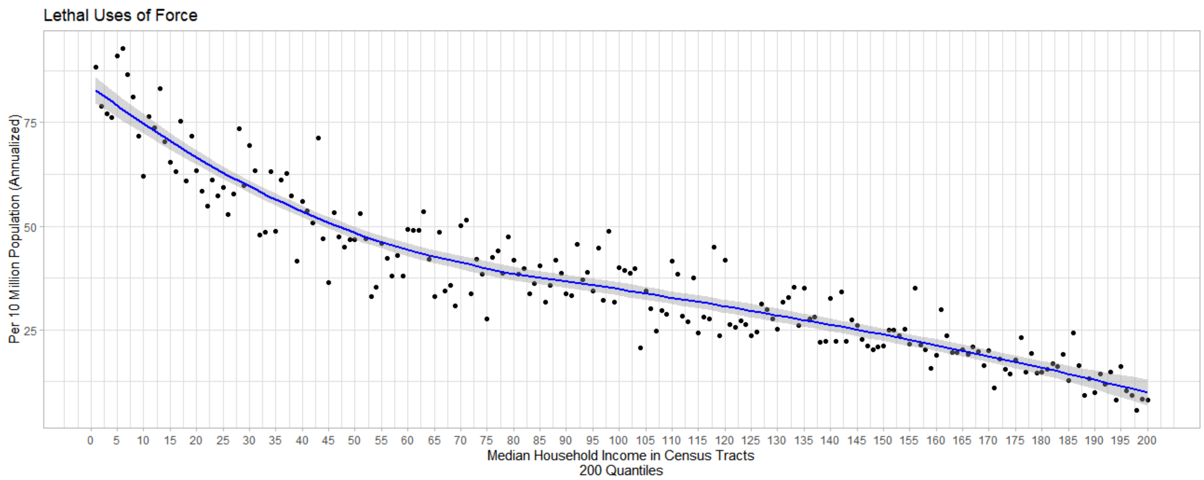
The American Community Survey (ACS) provides median household income values for each tract. For this analysis, US census tracts were binned into quintiles based on the distribution of median household income across all US census tracts. Initial analyses show that median household income has a strong relationship with the rate of LUOF. Indeed, LUOFs occur at the greatest frequency in the lowest-income tracts. The lowest household income quintile tracts experience a rate over four times that of the highest household income tracts.

Table 3: Annualized LUOF Rate by Tract Income Quintile

Income Quintile	Lethal Uses of Force	Annualized Per 10 Million Population
1	2,175	65.803
2	1,640	43.913
3	1,380	35.114
4	1,073	25.728
5	691	15.819

Another more granular income quantile approach shows a bit more variation by household income but is consistent with the bar plot and quintile analysis. By dividing tracts into two hundred quantiles with roughly the same number of observations in each bin (i.e., a quantile twice as granular as a percentile where the first bin is the lowest 0.5 percentile), one observes a curvilinear relationship between household income and the annualized rate of LUOFs. The lowest income tracts experience the highest rate. The rate drops off somewhat quickly as income increases along the x-axis, but around the 50th quantile, the slope becomes more gradual.

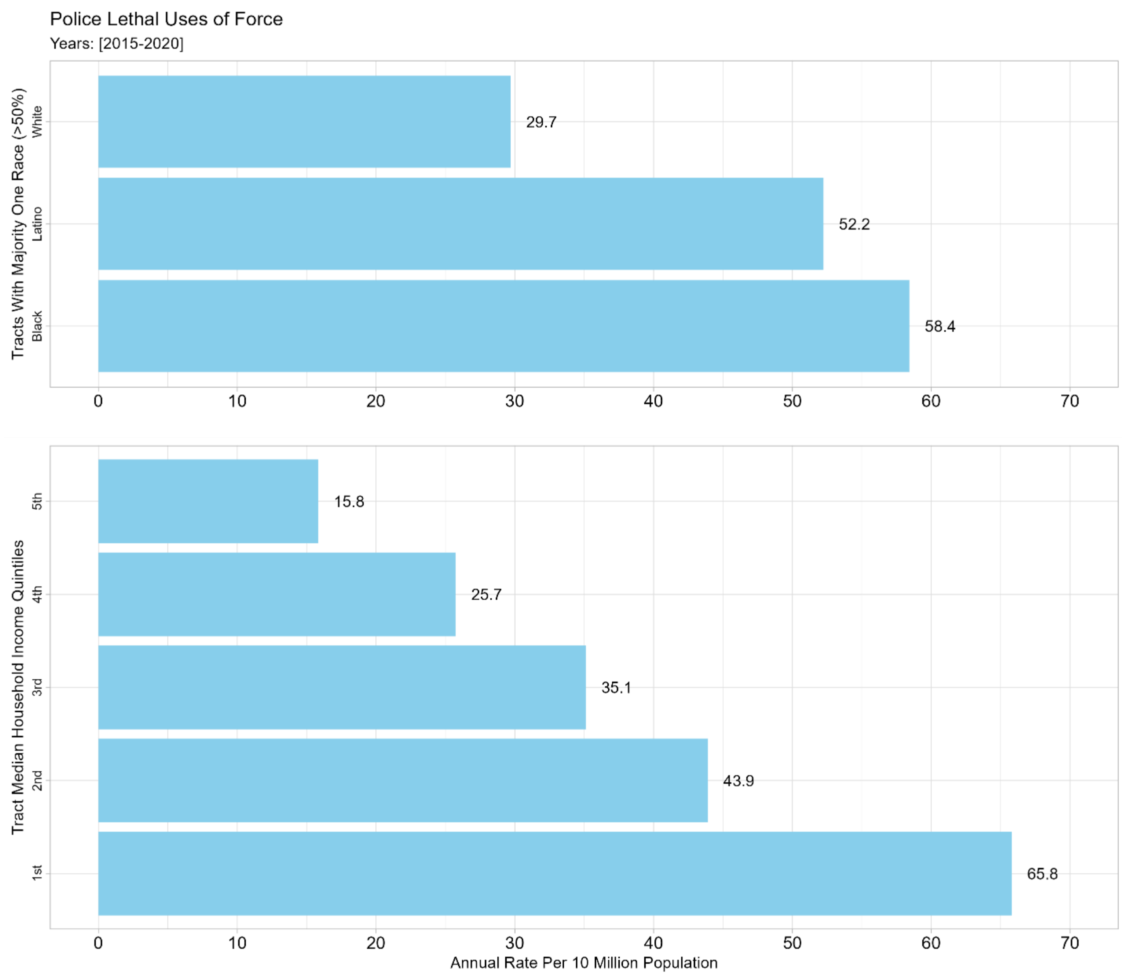
Figure 2: Annualized LUOF Rate (200 Quantiles)



Majority One Race

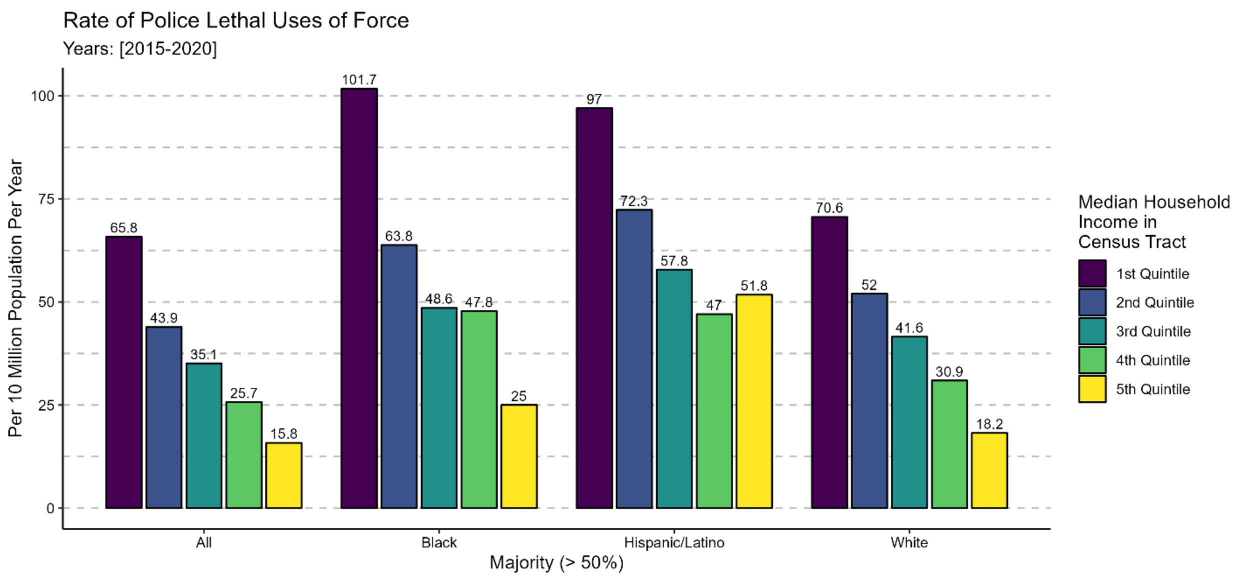
How then does the analysis look when both race and income are introduced as variables? An initial look at the bar plots by majority-one-race in a census tract and income quintiles, the same ones shown earlier, placed on the same axis offers some useful insights. The plots from earlier are provided again, this time side-by-side on the same scale for easier cross-comparisons. Without looking at their interactions, we can see that the fourth and fifth-quintile census tracts experience a lower rate of LUOFs than any of the racial or ethnic groups. At the same time, both majority-black and majority-Latino census tracts experienced greater rates than all income quintiles except the first or lowest income quintile.

Figure 3: Income and Race Individually



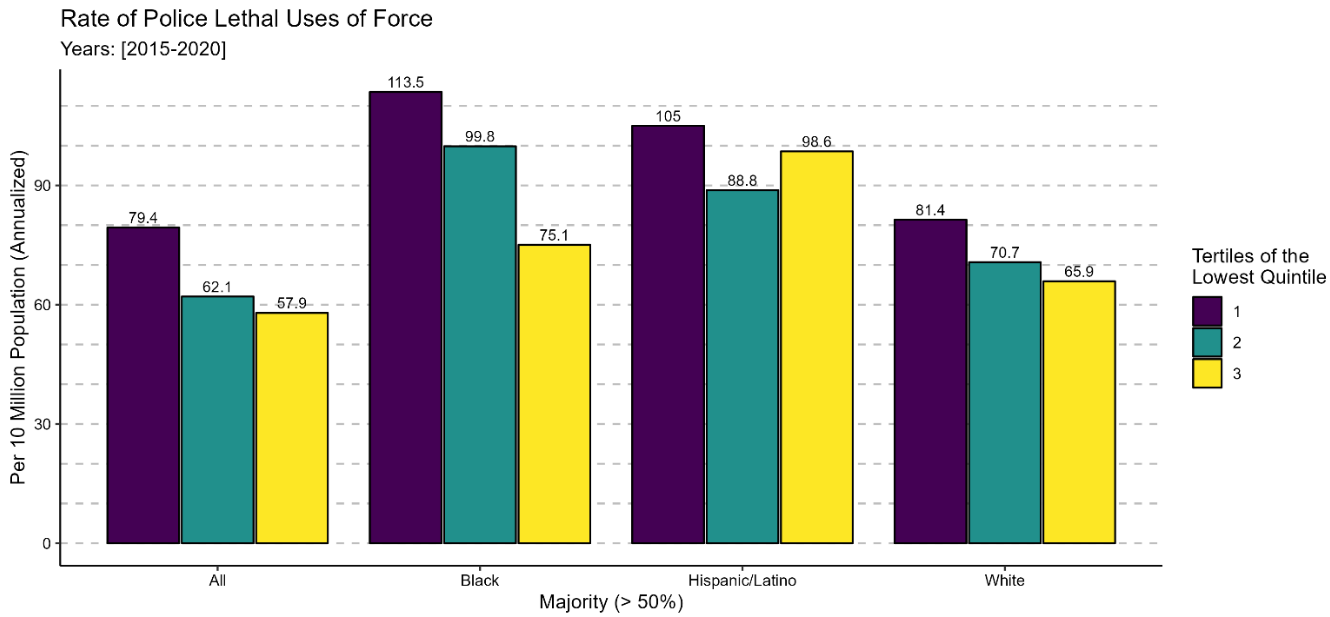
However, this analysis is inadequate because it does not tell us about the interactions between the variables. In analyzing their interactions, one finds that the general trend of the lowest income quintiles experiencing the highest rates of LUOFs holds. A bar plot (Figure 4) showing the variation within racial and ethnic groups indicates that there is substantial variation by income quintile within racial and ethnic groups. For all racial and ethnic groups, the lowest income quintile had the greatest rate of LUOFs. The difference in the rate between the first and second quintile is substantial for majority black and Latino census tracts. Majority-Hispanic/Latino tracts had the highest rate in the second- and third-income quintiles. As noted earlier, both the majority white and majority black census tracts experienced the lowest rates of police LUOF in the highest income quintiles.

Figure 4: Majority Race and Income Interactions



Given that so many LUOFs occur in the lowest census tract income quintile, it is helpful to examine what the distribution looks like within that quintile. To accomplish this, the lowest quintile was divided into terciles. Tracts were binned into 15 quantiles; the lower three are equivalent to the terciles of the lowest quintile. Interestingly, there is not a sharp skew to the distributions within the quintiles. To be sure, the lowest terciles experienced the highest rate across all groups, with the distribution among majority-black tracts being the most-skewed toward the lowest tertile, but the differences in rates of LUOFs between terciles are not nearly as great as they are between quintiles.

Figure 5: Terciles of the Lowest Income Quintile



However, there are some potential limitations to this approach, particularly regarding majority-one-race cutoffs. Tracts that did not have a majority-one-race composition (≤ 50%) were excluded from the analysis by race (though they were included in the rates only by income quintile). Tracts that were comprised of ≤ 50 percent of one race or ethnic group but, say, ≥ 45 percent of one racial group might not differ much from the majority one-race tracts of the same race. For example, a tract with a 45 percent Latino population might still constitute a plurality in that tract and the tract might be a "Latino tract" in any substantive sense, no less than a tract with greater than 50 percent Latino population. To examine this further logistic regressions were run.

Logistic Regression: Income Only

Because categorizing tracts into majority-one-race tracts sets an arbitrary threshold for inclusion/exclusion from the category, using the proportion of race *x* living in *y* tract overcomes this because the proportions are continuous. This allows us to analyze the racial composition of the tract in a more granular way that categorical approaches might flatten out or overlook. For purposes of the logistic regressions, median household income is the independent variable, and the dependent variable is a binary variable indicating whether a LUOF occurred between 2015 and 2020 in the census tract. The initial regression included only median household income as a predictor to establish a baseline for understanding the effect of income on the probability of being killed by law enforcement. The equation for the regression is:

Equation 1: Logit – Income Only

$$ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 * Income1k_i + \varepsilon_i$$

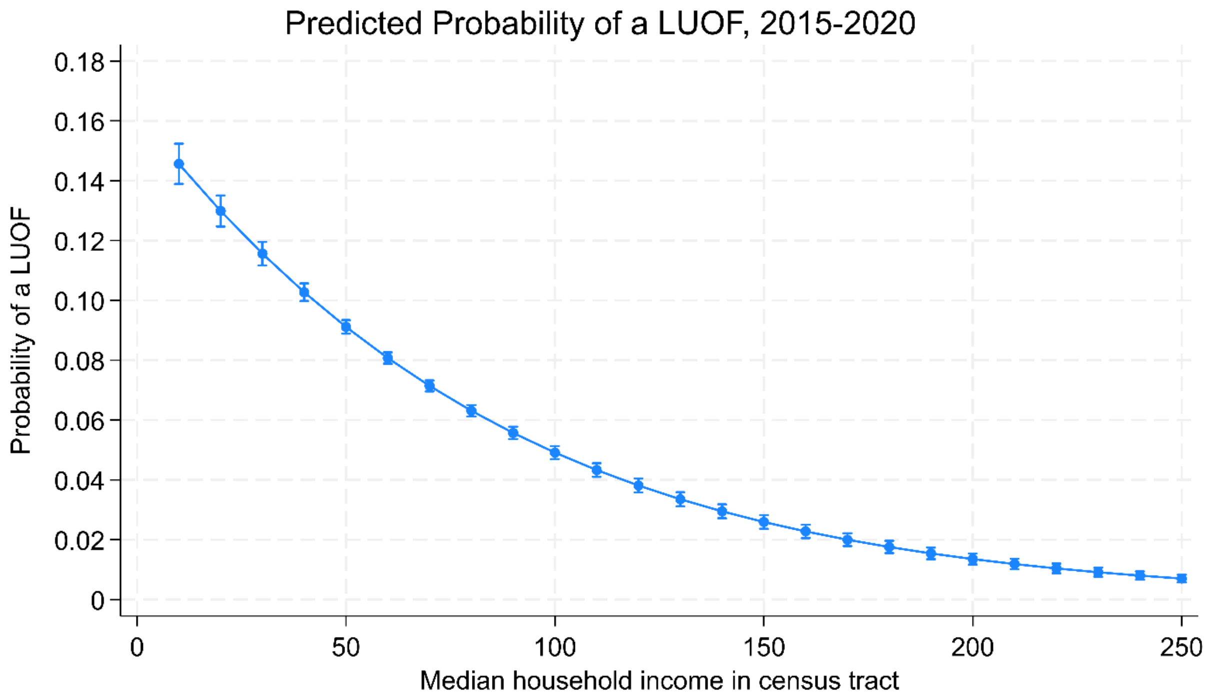
where *i* is a census tract; *p* is the probability of a LUOF; and *Income1k* is the median household income in thousands of dollars.

Regression results show a negative relationship between income and the probability of a tract experiencing at least one LUOF during the period (Table 4). A plot of the predicted probabilities indicates a strong curvilinear relationship, with the probability being most pronounced in tracts with incomes of $50 thousand or less, and the curve flattens somewhat around $200 thousand.

Table 4: Logistic Regression Results (Income Only)

Variable	Coefficient	Std. Err.	z-score	P >|z|	95% Confidence Interval	
					Lower	Upper
Intercept	-1.636736	0.0319747	-51.19	<0.0001	-1.699406	-1.574067
Income ($1k)	-0.013265	0.0004899	-27.08	<0.0001	-0.0142252	-0.0123049

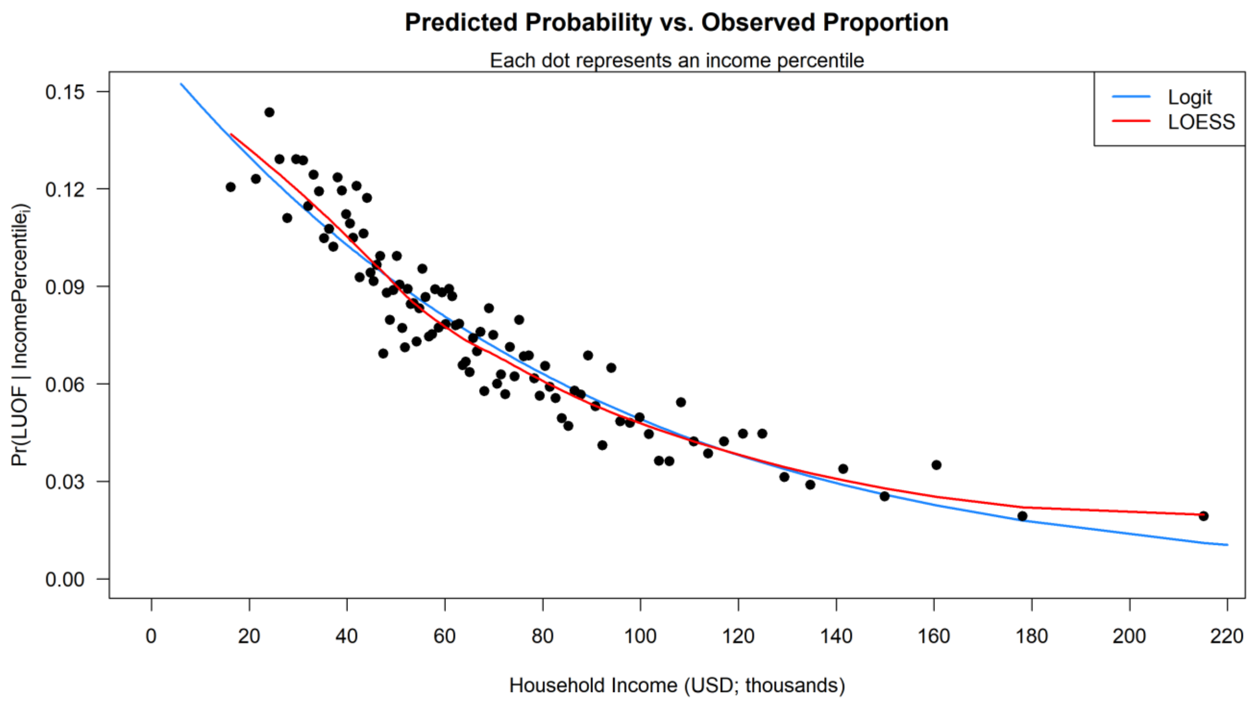
Figure 6: Predicted Probability of a LUOF (Income Only)



Goodness-of-Fit

To check how well the model fits the data, tracts were binned into income percentiles and the proportion of census tracts in each percentile that had experienced at least one LUOF was calculated. These proportions were plotted against the logistic regression model using the median income value for each percentile along the x-axis. Additionally, a LOESS, nonparametric line was plotted to assess how well the logistic model fit the moving average represented by the LOESS line. The findings suggest that the model performs well.

Figure 7: Logit Goodness-of-Fit



Bivariate Logistic Regressions: Race/Ethnicity

Having established that income is a substantial predictor of whether a LUOF has occurred, logistic regressions were run for each racial/ethnic group to establish to what extent tracts that have a greater proportion of a particular group are more or less likely to have experienced at least one LUOF. The regression equation is:

Equation 2: Logit (Racial Proportion)

$$ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 * Proportion_i + \varepsilon_i$$

where *i* is a census tract; *p* is the probability of a LUOF; and *Proportion* is the proportion of the racial or ethnic group living in the ith census tract. Three separate regressions were run, one for the proportion black, one for the proportion Hispanic/Latino, and one for the proportion white.

Table 5: Logit Tables -- Racial Proportions

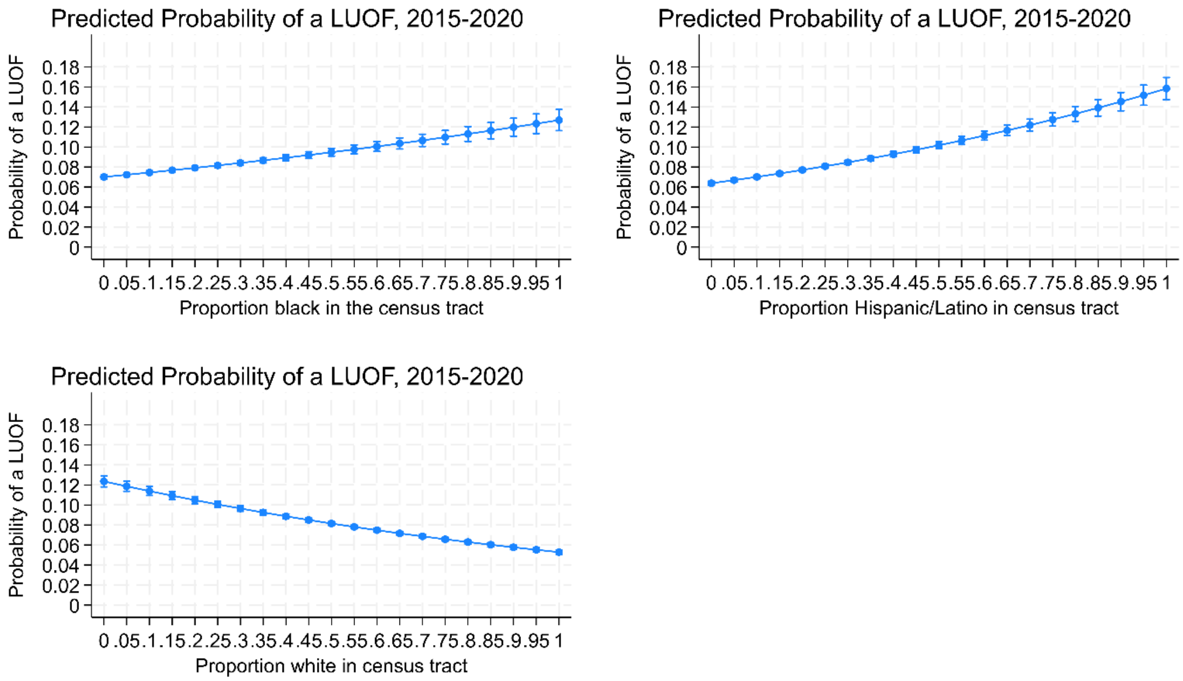
Model 1	Coefficient	Std. err.	Z-score	P>|z|	95% Confidence Interval	
Intercept	-2.585	0.016	-164.860	0.000	-2.616	-2.554
Proportion Black	0.656	0.055	11.860	0.000	0.548	0.764

Model 2	Coefficient	Std. err.	z	P>|z|	95% Confidence Interval	
White Proportion	-0.927	0.042	-22.130	0.000	-1.009	-0.845
Intercept	-1.959	0.026	-75.220	0.000	-2.010	-1.908

Model 3	Coefficient	Std. err.	z	P>|z|	95% Confidence Interval	
Latino Proportion	1.016	0.051	19.760	0.000	0.915	1.117
Intercept	-2.686	0.017	-156.600	0.000	-2.720	-2.653

Figure 8 shows that tracts with a greater proportion of blacks and Hispanics/Latinos have a greater probability of having experienced a LUOF. Conversely, tracts with a larger proportion of white residents are predicted to be less likely to have experienced a LUOF. It is worth noting that tracts with a high incidence of Latinos have a higher probability of experiencing a LUOF than the tracts with the highest incidence of black residents. In addition to reading the graph depicting the probability of a LUOF based on the incidence of whites in the tract, one can also read it inversely. That is, as an analysis of the probability of a more general category of non-white. This would also include persons who identify as a member of another racial or ethnic category, such as Asian or Native American; it would also include "mixed-race" persons. Viewing it this way, the results are nearly identical to the distribution of predicted probabilities of a LUOF based on the incidence of blacks in a tract.

Figure 8: Predicted Probabilities by Race/Ethnicity



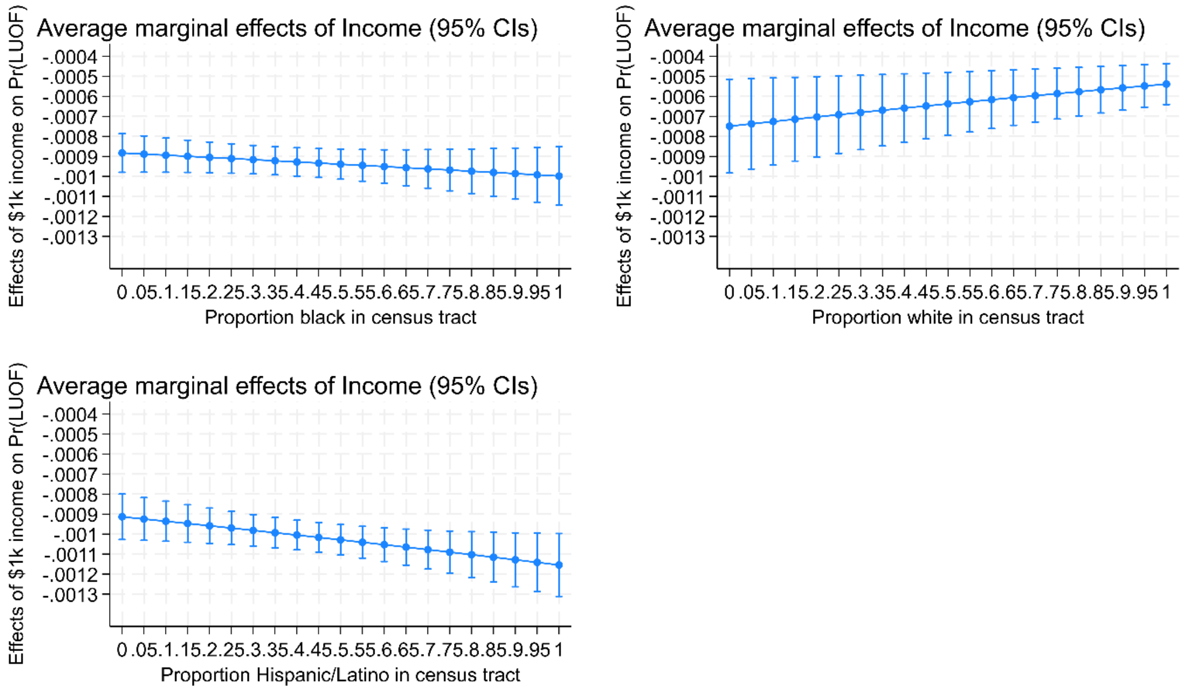
So, both income and racial composition of a neighborhood have a relationship with the probability of a LUOF. Next, regressions with both the racial composition and the median household income were run. This helps establish how much of an effect income has on the probability of a fatal encounter based on the proportion of each racial/ethnic group in the census tract. Marginal effects were calculated and plotted (Figure 9) using the following model:

Equation 3: Logit (Income & Race) Interaction

$$ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 Income1k_i + \beta_2 Proportion_i + \beta_3(Income1k_i * Proportion_i) + \varepsilon_i$$

where *i* is a census tract; *p* is the probability of a LUOF; *Income1k* is the median household income in thousands of dollars in the i^{th} census tract; and *Proportion* is the proportion of the racial or ethnic group living in the i^{th} census tract. Again, three separate regressions were run, one for each racial/ethnic group.

Figure 9: Average Marginal Effects of Income



Across all groups, income has the effect of reducing the predicted probability *in addition to* the racial composition on the probability of a LUOF occurring in a census tract. Furthermore, this effect tends to be strongest in census tracts where the proportion of whites is smaller. That is, for tracts with heavy concentrations of non-whites, the median household income of that tract has an even greater impact in reducing the probability of a LUOF. Of all groups, census tracts with larger proportions of Hispanics and Latinos experience the greatest marginal effects of census tract income on the probability of being killed by law enforcement.

Race of Victim

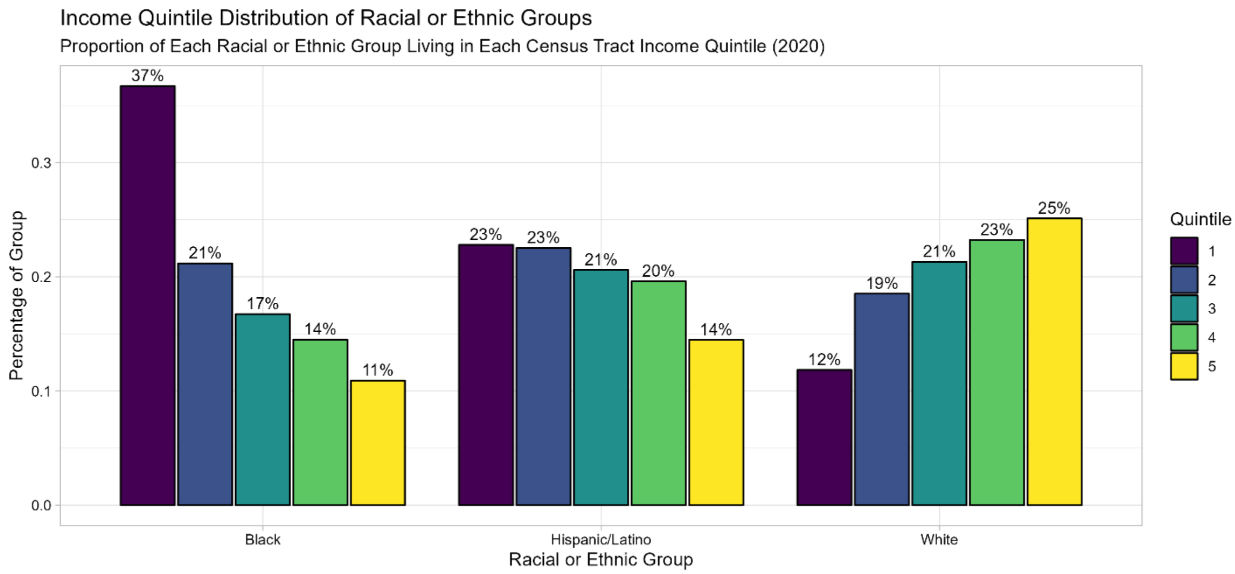
For robustness, an analysis by race of the victim was also conducted. Using the Fatal Encounters dataset, I constructed a frequency table of the number of LUOFs of victims by race. Fatal Encounter contributors imputed a small percentage of these observations (< 9% imputed). The distribution across racial groups in this six-year period shows that nearly half of those killed by law enforcement are white; slightly more than 25 percent are black; and approximately 18 percent of those killed by law enforcement are Latino/Hispanic. However, there is a disparity between whites and blacks. Blacks comprise 25 percent of those killed by law enforcement, while their incidence in the broader population is only about 13 percent. On the other hand, whites are killed by law enforcement at a rate slightly less than their incidence in the broader population. At the same time, it is worth a closer look at how the LUOF victims are distributed across tract income quintiles within each racial group.

Table 6: LUOF Count by Race/Ethnicity

Race	No. of LUOFs	Percent of Total LUOFs (%)
Hispanic/Latino	1278	18.2
Black	1786	25.5
White	3461	49.4

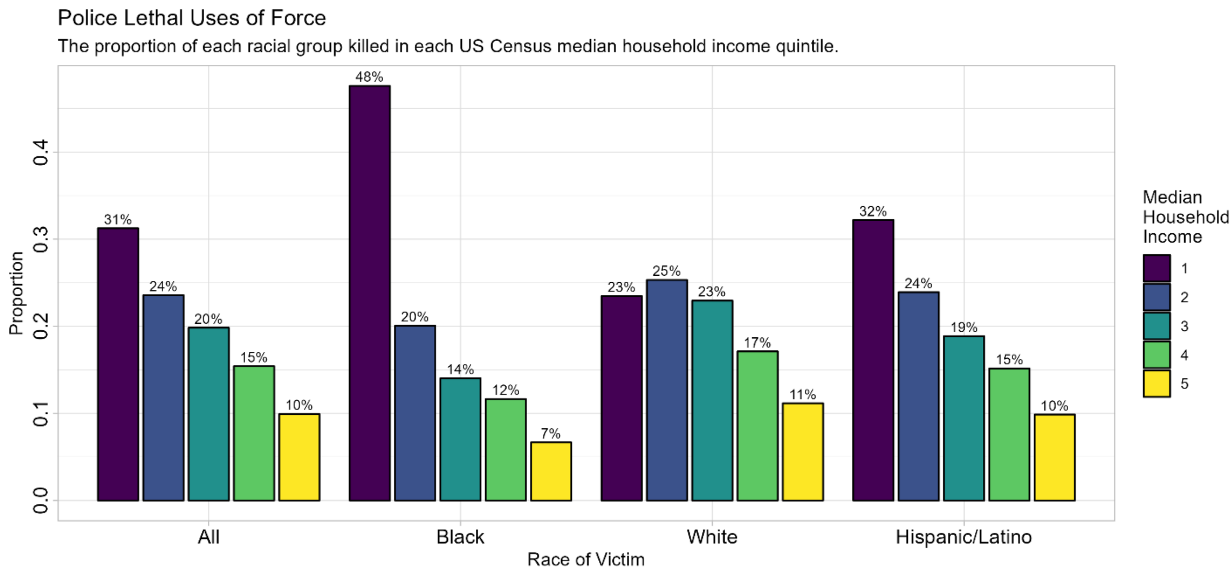
Each racial group is distributed differently across income quintiles. For example, blacks and Latinos live disproportionately in lower-income tracts, and whites live disproportionately in higher-income tracts. A count of all persons of each race living in each census tract income quintile was performed. A plot showing the distribution of each racial group (Figure 10) shows that blacks and Latinos generally live in lower-income tracts than whites. For example, 37 percent of blacks live in the lowest income quintile, while only 12 percent of whites live in that same quintile. Latinos tend to live in lower-income census tracts than whites, but the disparity is not as sharp: 23 percent of Latinos live in the lowest census tract income quintile.

Figure 10: Race/Ethnicity Across Tract Income Quintiles



Analyses of the distribution of LUOF victims by race and income support similar conclusions to the analysis using majority-one-race in a census tract as a factor, with some exceptions. A relationship between tract median household income quintiles and the proportion of each racial or ethnic group killed within each tract income quintile exists. For example, 47.6 percent of black Americans who were killed by law enforcement were killed in the lowest income quintile of census tracts; just over 20 percent were killed in tracts in the second income quintile. There is the same relationship across all tracts where blacks were killed: the higher the income quintile, the lower the proportion. Only 6.7 percent of blacks were killed in the lowest-income census tracts. Latinos/Hispanics showed a similar trend, with 32.2 percent of all Latinos being killed in the lowest income quintile census tracts and only 9.9 percent killed in the highest income quintile. Interestingly, the largest proportion of whites was not killed in the lowest-income quintile tracts, but in the second-lowest-income quintile tracts.

Figure 11: Proportion of Each Race Killed in Each Income Quintile



Comparisons between each race's population distribution across income quintiles and each race's distribution of LUOFs across income quintiles reveal an interesting disparity. For example, while 36.7 percent of blacks live in the lowest income quintile, 47.6 percent of blacks killed by law enforcement were killed in tracts in the lowest income quintile. The same disproportionate trend holds for every other race/ethnicity: 22.8 percent of Latinos live in the lowest income quintile tracts, but 32.2 percent of Latinos killed by law enforcement were killed in the lowest income quintile tracts, and 11.8 percent of whites live in tracts in the lowest income quintile, but 23.5 percent of whites killed by law enforcement were killed in the lowest income quintile tracts.

Table 7 places these data side-by-side, providing a visualization of how the two distributions in Figure 10 and Figure 11 differ. If the data bars were exactly the same across each row, it would indicate that the distribution of the racial group population across income quintiles is the same as the distribution of LUOFs within each group. But this is not the case. Moreover, Blacks and Latinos experience the greatest share of LUOFs in the lowest income quintile, greater than their incidence in that quintile. As noted earlier, there is an anomaly; slightly more whites—25.3 percent—were killed in the second income quintile tracts than in the lowest income quintile—23.5 percent. Notwithstanding this anomaly, there is still a striking disparity between the proportion of whites living in the lowest-income tracts and the proportion of whites killed in those tracts.

Table 7: Proportion of Race Living in Income Quintile X vs. Proportion of Race Killed in Income Quintile X

Race	Income Quintile	Proportion of Race$_i$ Living in Income Quintile$_j$	Proportion of Race$_i$ Killed in Income Quintile$_j$
Black	1	0.37	0.48
	2	0.21	0.20
	3	0.17	0.14
	4	0.14	0.12
	5	0.11	0.07
Hispanic/Latino	1	0.23	0.32
	2	0.23	0.24
	3	0.21	0.19
	4	0.20	0.15
	5	0.14	0.10
White	1	0.12	0.23
	2	0.19	0.25
	3	0.21	0.23
	4	0.23	0.17
	5	0.25	0.11

Findings: Gentrification

US Census tracts identified by the Urban Displacement Project as undergoing gentrification did not experience higher per capita rates of police killings than census tracts that were identified as "low-income or at-risk" (LIR); the LUOF rate for LIR census tracts was twice the rate of "gentrifying" census tracts. However, gentrifying census tracts did experience a rate 1.4 times greater than the "stable: mixed or high-income" (SMOHI) census tracts.

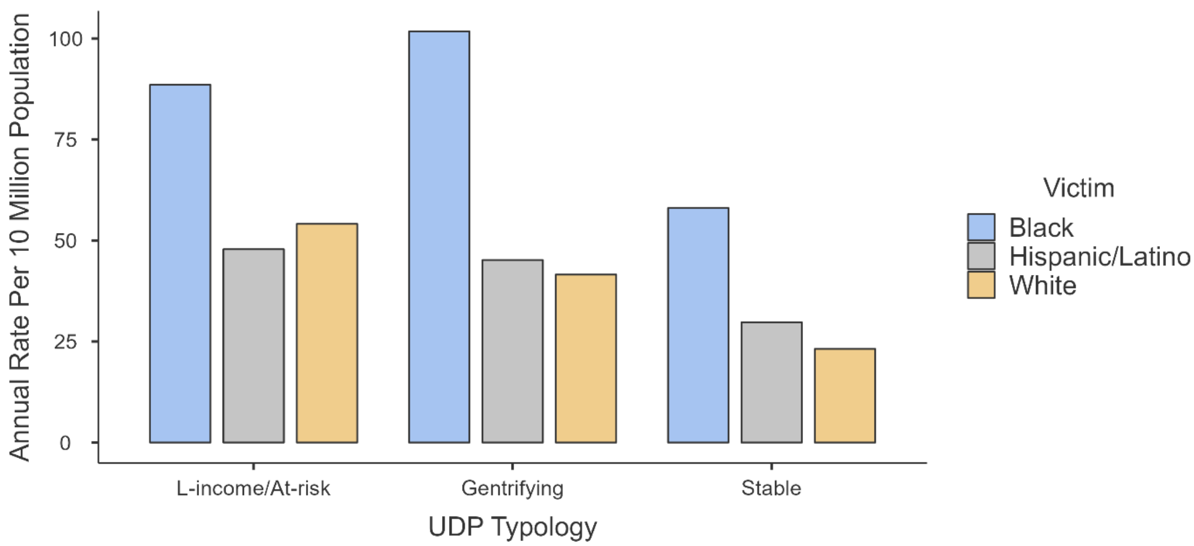
Table 8: UDP Typologies and LUOF Rates

Typology	LUOF Count	Population	Annual Rate Per 10M Population
Low-income or at-risk (LIR)	2,476	72,763,075	56.71
Gentrification in progress (GIP)	541	17,818,282	50.60
Stable: mixed or high-income (SMOHI)	3,403	225,877,492	25.11

Gentrification and Victims' Race

Additional analyses indicate that LUOF rates vary with the victim's race. In general, the rates still follow the general trend across gentrification typologies. However, unlike in the previous analysis that found that the rate in LIR tracts is greater than in gentrifying tracts—which did not include the victim's race—the rate for blacks in gentrifying tracts is greater than in LIR tracts (Figure 12). Across all UDP typologies, black victims were killed by law enforcement at a greater rate than Latinos or whites. Latinos experienced a rate in gentrifying tracts (45.18) nearly equal to their rate in LIR tracts (47.84). These findings suggest that, except for blacks, low-income and census tracts at risk for gentrification are still more likely to experience a LUOF, even when considering the victim's race.

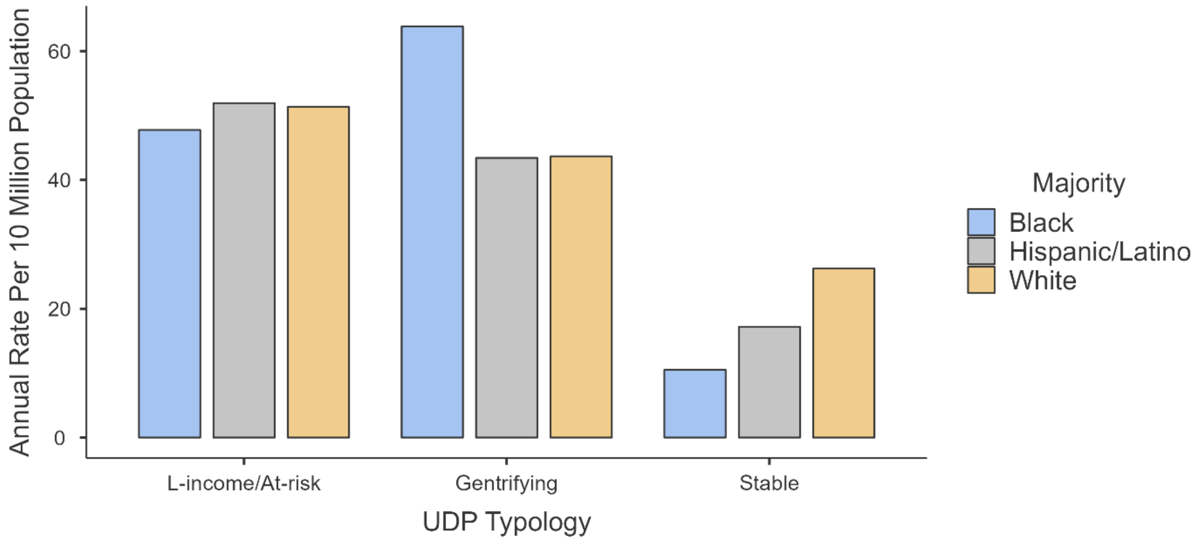
Figure 12: LUOF Rate (UDP Typology by Victim's Race)



Gentrification and Majority Race

Rates for census tracts by both UDP typology and majority-race classifications were tabulated. Except for majority-black census tracts, LIR tracts had a LUOF rate only slightly greater than gentrifying tracts. In general, however, variation within UDP typologies by majority-race classification tended to be more moderate than variation across victim races within UDP typologies. Like the other analyses, SMOHI census tracts had the lowest LUOF rates. Interestingly, for stable census tracts, the relationship between race and LUOF rate reversed from the victim race analysis. Within the stable UDP typology, majority-white census tracts had the greatest rate of that UDP typology; stable majority-Latino census tracts experienced the second greatest rate, while stable majority-black census tracts experienced the lowest rate of that UDP typology.

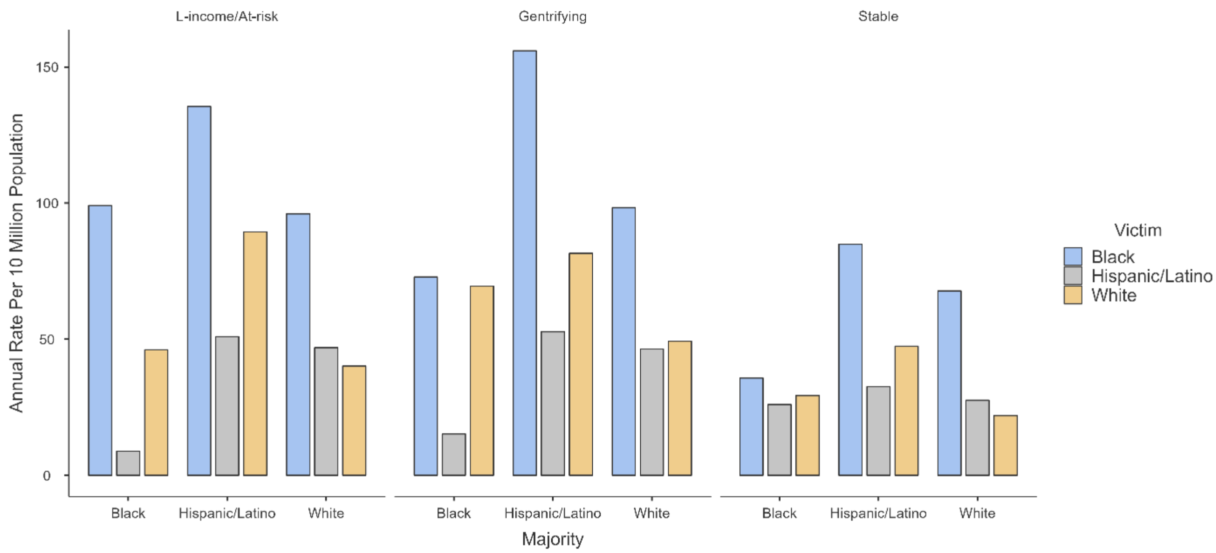
Figure 13: LUOF Rate (UDP Typology by Majority Race)



Majority Race and Victim's Race

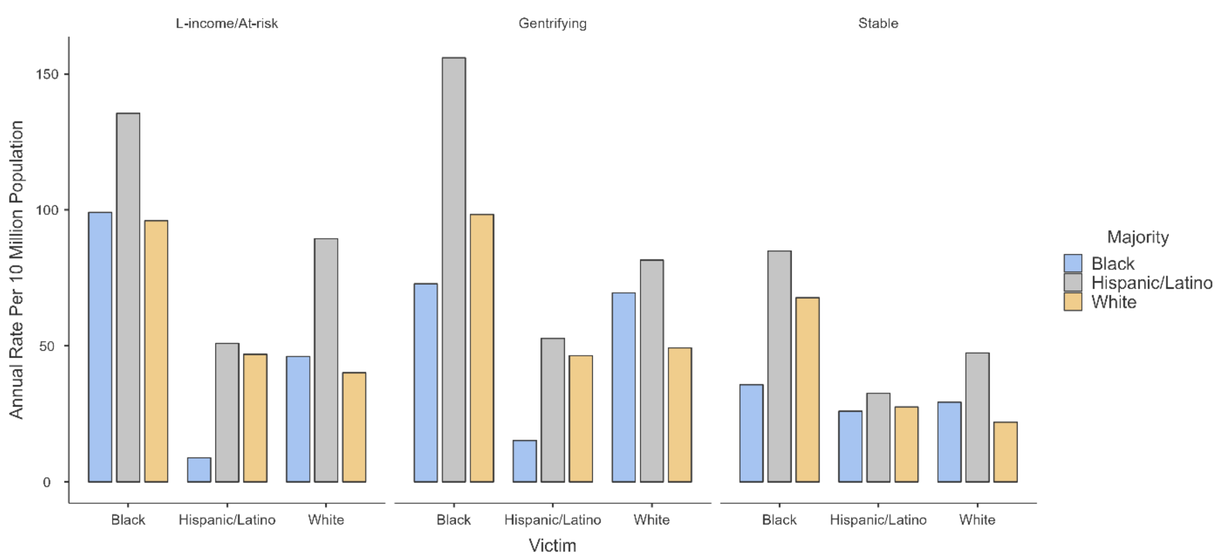
Census tracts were binned by three factors: UDP typology, victim's race, and the majority race in the tract. Per capita rate calculations revealed that blacks tended to be killed at a higher rate within all UDP typologies. This was the case regardless of whether the tract was majority black, majority Hispanic/Latino, or majority white. Blacks were killed at a lower rate in stable census tracts and were killed at the highest rates in gentrifying and low-income majority Hispanic/Latino census tracts.

Figure 14: LUOF Rate (UDP Typology by Majority Race by Victim's Race)



The same data presented with the victim's race along the x-axis shows that all racial groups experienced a greater rate of LUOFs in majority Hispanic/Latino tracts. The rate for blacks was particularly high in Majority Hispanic/Latino tracts, as stated above. (See Table 12 for all values in Figure 15.)

Figure 15: LUOF Rate (UDP Typology by Victim's Race by Majority Race)



Discussion

Median Household Income

In addition to racial disparities across racial and ethnic groups, the data show a clear relationship between median household income in census tracts where lethal uses of force (LUOFs) occurred. Census tracts in the lowest income quintile experienced a rate of LUOFs 4.3 times greater than tracts in the highest income quintile. Though it would be a stretch to infer causality based strictly on these observational findings, it does support some claims made by Cedric Johnson and Loïc Wacquant—that racial subordination needs to be understood *in the context of* economic relations and how those also contribute to the likelihood of a LUOF.

The reasons for this are twofold. Policing practices and corresponding outcomes—i.e., whether a LUOF is likely to occur—are influenced by both space (both the racial composition and class composition of the neighborhood) and individuals' class position. Police departments often craft their policies in a way that concentrates law enforcement presence in the most economically marginal neighborhoods. At the same time, these neighborhoods also are disproportionately black and Latino. As Soss and Weaver explain, this is also driven by "tough on crime" measures, responses to both real and imagined incidents of crime. That is to say that intensified policing is advanced by political entrepreneurs, agitating for these policies, but that agitation is only effective in the context of *some* increase in criminal activity.

Gentrification

The relationship between the Urban Displacement Project's typologies is unclear and inconclusive. Census tracts identified as gentrifying did not have higher LUOF rates compared to low-income/at-risk-of-displacement tracts (). In fact, gentrifying tracts tended to have a slightly lower rate than low-income/at-risk tracts (LIR), except tracts where the victim was black (Figure

12) or majority-black tracts (Figure 13), which had higher rates in gentrifying tracts than in low-income/at-risk tracts. The three-way analysis based on the race of individuals, majority-race tract classification, and UDP typology revealed interesting interactions between place and individual characteristics. For example, within each UDP typology by majority-race classification (e.g., majority-white/gentrifying or majority-Hispanic/Latino-stable) black individuals experienced the highest LUOF rate compared to individuals of other racial groups within those same tracts, though black rates did differ significantly *between* majority-racial classifications and UDP typologies (Figure 14).

Additionally, when grouping tracts by gentrification typology and the victim's race, majority-Hispanic/Latino tracts had the highest LUOF rates (Figure 15). For example, blacks, Latinos, and whites all experienced a higher LUOF rate in LIR-majority-Hispanic-Latino tracts than they did in LIR tracts with a majority of a different race. This was especially pronounced for black individuals; they experienced higher LUOF rates in LIR/majority-Hispanic/Latino, gentrifying/majority-Hispanic/Latino, and stable/majority-Hispanic/Latino tracts than they did in tracts where a different race was the majority.

While these findings do not support a more general claim about the role gentrification plays in increasing police lethal uses of force, gentrification in majority-black tracts does, however, have a strong relationship with higher rates of police lethal force; the same is true for the rate for black people (using the individual-level analysis). This suggests that both place, in terms of whether one's tract is gentrifying, and race matter. Indeed, blacks in stable: high or mixed-income tracts were killed by law enforcement at lower rates than they were in other UDP typologies (Figure 12), and majority-black, stable census tracts experienced the lowest rate of all majority-one-race tract groups (Figure 13).

Limitations and Future Research

Potential limitations of this study are that it relied solely on observational data that was not well-suited for causal inference. Though there is a strong association between economic factors, such as income, and the incidence of police killings, it is difficult to rule out other factors that could be producing the outcome instead. It is always possible that other, non-economic factors (at least not economic in a strict sense) related to the police budget or municipal politics could be driving the incidence of police killings as much as or more than the economic deprivation of a neighborhood or region. It is also possible, though probably less likely, that the causal path is in reverse of what has been suggested in this paper, that the high LUOF rate is leading to lower neighborhood incomes and impoverishment. There are similar issues with the gentrification study. It too relies on observational data and causal inference is difficult. Moreover, there is good reason to be cautious about the typologies used in this paper. Even after reviewing the replication material and white papers detailing how the Project constructed the typologies, I was not wholly satisfied. While gentrification is an abstraction that is inherently difficult to pin down to one or two variables, it felt as though there were too many "moving parts" in the typologies' design, without much logic behind their movement. Though the UDP typologies highlight many important features of gentrification, they often appeared contradictory, and the logic of their construction was opaque. That notwithstanding, future research regarding gentrification and police killings might be the most promising of the avenues explored in this paper. Future research could build on some elements from the UDP typologies, some of which could be better suited for causal inference. For example, the Project relied heavily on "rent gaps"—a large difference between the median rent in a census tract and the metropolitan median rent. Researchers have identified this as a precursor to gentrification. Identifying more variables like this that researchers could use could perhaps move forward more research on this topic.

Appendix

Figure 16: Original Typologies

MODIFIED TYPES	CRITERIA
LOW-INCOME/SUSCEPTIBLE TO DISPLACEMENT	• Low or mixed low-income tract in 2018
ONGOING DISPLACEMENT OF LOW-INCOME HOUSEHOLDS	• Low or mixed low-income tract in 2018 • Absolute loss of low-income households, 2000-2018
AT RISK OF GENTRIFICATION	• Low-income or mixed low-income tract in 2018 • Housing affordable to low or mixed low-income households in 2018 • Didn't gentrify 1990-2000 OR 2000-2018 • Marginal change in housing costs OR Zillow home or rental value increases in the 90th percentile between 2012-2018 • Local and nearby increases in rent were greater than the regional median between 2012-2018 OR the 2018 rent gap is greater than the regional median rent gap
EARLY/ONGOING GENTRIFICATION	• Low-income or mixed low-income tract in 2018 • Housing affordable to moderate or mixed moderate-income households in 2018 • Increase or rapid increase in housing costs OR above regional median change in Zillow home or rental values between 2012-2018 • Gentrified in 1990-2000 or 2000-2018
ADVANCED GENTRIFICATION	• Moderate, mixed moderate, mixed high, or high-income tract in 2018 • Housing affordable to middle, high, mixed moderate, and mixed high-income households in 2018 • Marginal change, increase, or rapid increase in housing costs • Gentrified in 1990-2000 or 2000-2018
STABLE MODERATE/MIXED INCOME	• Moderate, mixed moderate, mixed high, or high-income tract in 2018
AT RISK OF BECOMING EXCLUSIVE	• Moderate, mixed moderate, mixed high, or high-income tract in 2018 • Housing affordable to middle, high, mixed moderate, and mixed high-income households in 2018 • Marginal change or increase in housing costs
BECOMING EXCLUSIVE	• Moderate, mixed moderate, mixed high, or high-income tract in 2018 • Housing affordable to middle, high, mixed moderate, and mixed high-income households in 2018 • Rapid increase in housing costs • Absolute loss of low-income households, 2000-2018 • Declining low-income in-migration rate, 2012-2018 • Median income higher in 2018 than in 2000
STABLE/ADVANCED EXCLUSIVE	• High-income tract in 2000 and 2018 • Affordable to high or mixed high-income households in 2018 • Marginal change, increase, or rapid increase in housing costs

Table 9: Logistic Regression -- Full Output (Income only)

Response: LUOF (binary)	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
Income (thousands)	-0.013	0.000	-27.080	0.000	-0.014	-0.012
Intercept	-1.637	0.032	-51.190	0.000	-1.699	-1.574

Variable	Value	Count	Percent
LUOF (binary)	True	6,338	7.64 %
	False	76,569	92.36 %
	Total	82,907	

Model Summary

Deviance R-Sq	Deviance R-Sq(adj)	AIC	AICc	BIC	Area Under ROC Curve
1.96%	1.95%	43899.03	43899.03	43917.68	0.6095

Observed and Expected Frequencies for Hosmer-Lemeshow Test

Group	Pr(LUOF) Range	LUOF = True Observed	LUOF = True Expected	LUOF = False Observed	LUOF = False Expected
1	(0.000, 0.040)	269	236.1	8,021	8,053.9
2	(0.040, 0.054)	384	392.3	7,908	7,899.7
3	(0.054, 0.063)	461	486.9	7,847	7,821.1
4	(0.063, 0.071)	538	558.4	7,754	7,733.6
5	(0.071, 0.078)	587	620.3	7,703	7,669.7
6	(0.078, 0.085)	683	677.1	7,611	7,616.9
7	(0.085, 0.091)	706	731.2	7,585	7,559.8
8	(0.091, 0.099)	774	788.8	7,516	7,501.2
9	(0.099, 0.109)	905	860.0	7,385	7,430.0
10	(0.109, 0.158)	1031	986.9	7,239	7,283.1

Measures of Association

Pairs	Number	Percent	Summary Measures	Value
Concordant	294,929,537	60.8	Somers' D	0.22
Discordant	188,691,697	38.9	Goodman-Kruskal Gamma	0.22
Ties	1,673,088	0.3	Kendall's Tau-a	0.03
Total	485,294,322	100.0		

Association is between the response variable and predicted probabilities.

Table 10: Classification Table (Income Only Model)

Actual group	Predicted group		Percent correct
	FALSE	TRUE	
LUOF = FALSE	76335	0	100.00%
LUOF = TRUE	6321	0	0.00%
Percent of cases correctly classified			92.35%

(cut-off value p=0.5)

Figure 17: ROC Curve

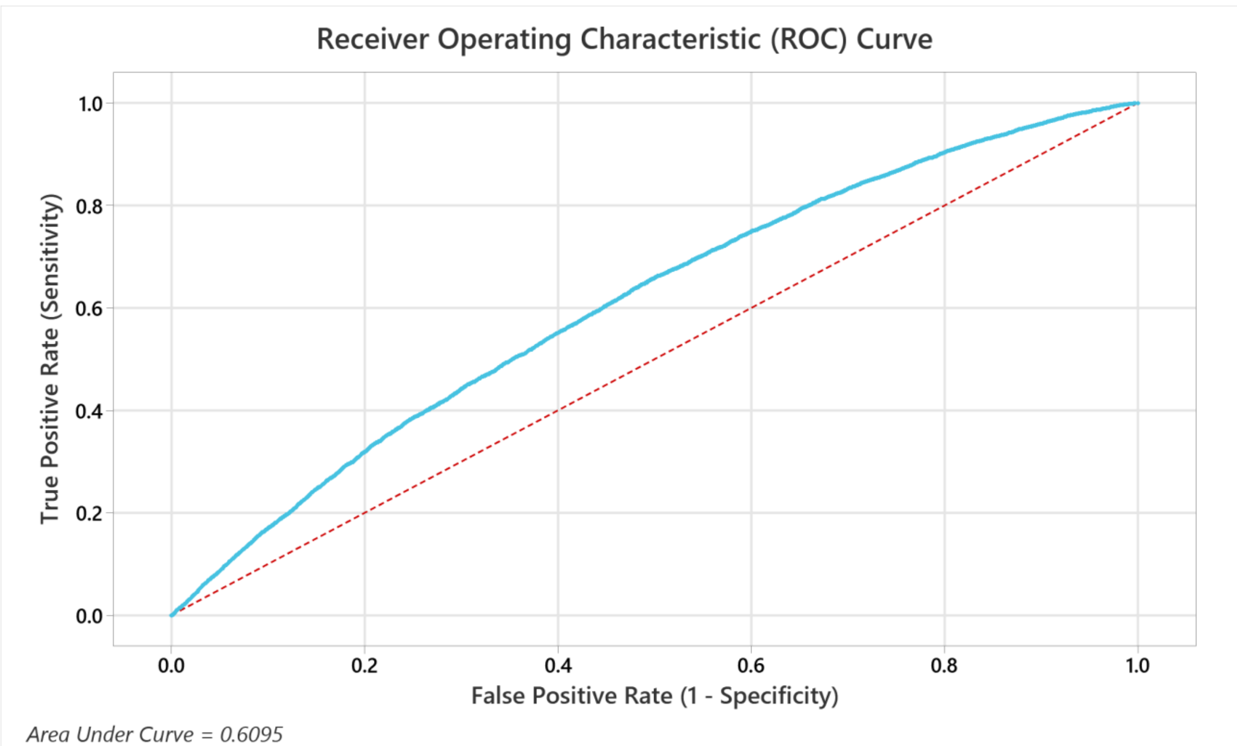


Table 11: Race and Median Household Income Logit Models

DV: LUOF = 1	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
Income1k	-0.013	0.001	-22.170	0.000	-0.014	-0.012
Black_Proportion	0.149	0.127	1.170	0.242	-0.101	0.399
IncomeE1k * Black_Proportion	-0.001	0.003	-0.470	0.635	-0.007	0.004
Intercept	-1.674	0.040	-42.030	0.000	-1.752	-1.596

DV: LUOF = 1	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
Income1k	-0.009	0.001	-8.280	0.000	-0.011	-0.007
White_Proportion	-0.398	0.102	-3.900	0.000	-0.598	-0.198
Income1k * White_Proportion	-0.004	0.002	-2.390	0.017	-0.007	-0.001
Intercept	-1.525	0.060	-25.580	0.000	-1.642	-1.408

DV: LUOF = 1	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
Income1k	-0.014	0.001	-21.530	0.000	-0.015	-0.012
Latino_Proportion	0.287	0.137	2.090	0.036	0.018	0.555
Income1k * Latino_Proportion	0.009	0.002	3.720	0.000	0.004	0.014
Intercept	-1.765	0.041	-42.540	0.000	-1.847	-1.684

Table 12: LUOF Rate (UDP Typology by Victim's Race by Majority Race)

UDP Typology	Majority	Victim	LUOF Count	Population	Annual Rate Per 10 Million Population
L-income/At-risk	Black	Black	126	2,118,847	99.11
L-income/At-risk	Black	Hispanic/Latino	1	188,287	8.85
L-income/At-risk	Black	White	11	397,706	46.10
L-income/At-risk	Hispanic/Latino	Black	17	209,101	135.50
L-income/At-risk	Hispanic/Latino	Hispanic/Latino	62	2,028,195	50.95
L-income/At-risk	Hispanic/Latino	White	19	354,087	89.43
L-income/At-risk	White	Black	39	676,962	96.02
L-income/At-risk	White	Hispanic/Latino	22	782,014	46.89
L-income/At-risk	White	White	169	7,012,916	40.16
Gentrifying	Black	Black	386	8,831,235	72.85
Gentrifying	Black	Hispanic/Latino	9	987,430	15.19
Gentrifying	Black	White	71	1,703,301	69.47
Gentrifying	Hispanic/Latino	Black	125	1,336,040	155.93
Gentrifying	Hispanic/Latino	Hispanic/Latino	358	11,316,912	52.72
Gentrifying	Hispanic/Latino	White	89	1,819,231	81.54
Gentrifying	White	Black	181	3,069,068	98.29
Gentrifying	White	Hispanic/Latino	80	2,872,300	46.42
Gentrifying	White	White	768	25,993,617	49.24
Stable	Black	Black	95	4,434,196	35.71
Stable	Black	Hispanic/Latino	10	640,892	26.01
Stable	Black	White	17	967,678	29.28
Stable	Hispanic/Latino	Black	51	1,001,552	84.87
Stable	Hispanic/Latino	Hispanic/Latino	223	11,415,737	32.56
Stable	Hispanic/Latino	White	88	3,094,287	47.40
Stable	White	Black	357	8,786,432	67.72
Stable	White	Hispanic/Latino	238	14,394,950	27.56
Stable	White	White	1,786	135,784,742	21.92

Bibliography

Alexander, Michelle. 2010. *The New Jim Crow: Mass Incarceration in the Age of Colorblindness*. New York: New Press.

Bailey, Phillip M., and Tessa Duvall. 2020. "Breonna Taylor Warrant Connected to Louisville Gentrification Plan, Lawyers Say." *Louisville Courier Journal*. https://www.courier-journal.com/story/news/crime/2020/07/05/lawyers-breonna-taylor-case-connected-gentrification-plan/5381352002/ (June 14, 2023).

Bureau, US Census. "Glossary." *Census.gov*. https://www.census.gov/programs-surveys/geography/about/glossary.html (May 25, 2023).

Burghart, Brian. "About Me – Fatal Encounters." https://fatalencounters.org/about-me/ (May 25, 2023).

Clegg, John, and Adaner Usmani. 2019. "The Economic Origins of Mass Incarceration." *Catalyst: A Journal of Theory & Strategy* 3(3): 9–53.

Duvall, Tessa, Kala Kachmar, and Darcy Costello. 2020. "'Rogue' Unit or Targeted Initiative? Why Police's New Place-Based Squad Is Causing a Stir." *Louisville Courier Journal*. https://www.courier-journal.com/story/news/politics/metro-government/2020/07/24/breonna-taylor-shooting-what-know-police-unit-linked-case/5443452002/ (June 14, 2023).

Espiner, Guyon, and Farah Hancock. 2022. "Licence to Kill: The Startling Truth about NZ's Fatal Police Shootings." *RNZ*. https://www.rnz.co.nz/programmes/in-depth-special-projects/story/2018834464/licence-to-kill-the-startling-truth-about-new-zealand-s-fatal-police-shootings (February 26, 2023).

Feldman, Justin. 2020. "Police Killings in the US: Inequalities by Race/Ethnicity and Socioeconomic Position." *People's Policy Project*. https://www.peoplespolicyproject.org/project/class-and-racial-inequalities-in-police-killings/ (January 2, 2023).

Feldman, Justin M., Sofia Gruskin, Brent A. Coull, and Nancy Krieger. 2017a. "Killed by Police: Validity of Media-Based Data and Misclassification of Death Certificates in Massachusetts, 2004–2016." *American Journal of Public Health* 107(10): 1624–26. doi:10.2105/AJPH.2017.303940.

Feldman, Justin M., Sofia Gruskin, Brent A. Coull, and Nancy Krieger. 2017b. "Quantifying Underreporting of Law-Enforcement-Related Deaths in United States Vital Statistics and News-Media-Based Data Sources: A Capture–Recapture Analysis." *PLOS Medicine* 14(10): e1002399. doi:10.1371/journal.pmed.1002399.

Feldman, Justin M., Sofia Gruskin, Brent A. Coull, and Nancy Krieger. 2019. "Police-Related Deaths and Neighborhood Economic and Racial/Ethnic Polarization, United States, 2015–2016." *American Journal of Public Health* 109(3): 458–64. doi:10.2105/AJPH.2018.304851.

Gottschalk, Marie. 2020. "Caught in the Countryside: Race, Class, and Punishment in Rural America." In *Rethinking Class and Social Difference*, Political Power and Social Theory, eds. Barry Eidlin and Michael A. McCarthy. Emerald Publishing Limited, 25–52. doi:10.1108/S0198-871920200000037003.

Hall, Tamron. 2015. "Bernie Sanders 'Black Lives Matter' Protester [Interview]." https://www.youtube.com/watch?v=-ajWs3z8rs0 (June 12, 2023).

Hallissy, Erin, and Bill Snyder. 1981. "Pittsburg Loiterers Will Be Prosecuted." *Contra Costa Times*: 1A.

Jilani, Zaid. 2015. "95% of Police Killings in 2015 Occurred in Neighborhoods With Incomes Under $100,000." *Alternet.org*. https://www.alternet.org/2015/07/95-police-killings-2015-occurred-neighborhoods-incomes-under-100000/ (January 25, 2020).

Johnson, Cedric. 2016. "Afterword: Baltimore, The Policing Crisis, and the End of the Obama Era." In *Urban Policy in the Time of Obama*, ed. James DeFilippis. University of Minnesota Press, 302–22. http://www.jstor.org/stable/10.5749/j.ctt1gpcc5p.23 (November 5, 2022).

Johnson, Cedric. 2019. "Trumpism, Policing, and the Problem of Surplus Population." In *Labor in the Time of Trump*, eds. Jasmine Kerrissey, Eve Weinbaum, Clare Hammonds, Tom Juravich, and Dan Clawson. Cornell University Press, 169–88. https://muse.jhu.edu/pub/255/edited_volume/chapter/2470411 (January 31, 2023).

Johnson, Cedric G. 2023. *After Black Lives Matter: Policing and Anti-Capitalist Struggle*. London, England: Verso Books. https://www.google.com/books/edition/After_Black_Lives_Matter/0bWtEAAAQBAJ.

Johnson, David J., Trevor Tress, Nicole Burkel, Carley Taylor, and Joseph Cesario. 2019. "Officer Characteristics and Racial Disparities in Fatal Officer-Involved Shootings." *Proceedings of the National Academy of Sciences* 116(32): 15877–82. doi:10.1073/pnas.1903856116.

Knox, Dean, Will Lowe, and Jonathan Mummolo. 2020. "Administrative Records Mask Racially Biased Policing." *American Political Science Review* 114(3): 619–37. doi:10.1017/S0003055420000039.

Knox, Dean, and Jonathan Mummolo. 2020. "Making Inferences about Racial Disparities in Police Violence." *Proceedings of the National Academy of Sciences* 117(3): 1261–62. doi:10.1073/pnas.1919418117.

Reed Jr., Adolph. 2016. "Racial Disparity Does Not Help Make Sense of Patterns of Police Violence." *New Labor Forum*. https://newlaborforum.cuny.edu/2016/10/17/how-racial-disparity-does-not-help-make-sense-of-patterns-of-police-violence/ (January 25, 2020).

Sanders, Bernie. 2015. "Interview with Wolf Blitzer of CNN Regarding Statement of Presidential Candidacy." *The American Presidency Project*. https://www.presidency.ucsb.edu/node/310835 (June 13, 2023).

Shifrel, Scott. 1985. "Cleanup by Police 'Racist,' Blacks Say." *Daily Ledger Post Dispatch*: 1, 6.

Soss, Joe, and Vesla Weaver. 2017. "Police Are Our Government: Politics, Political Science, and the Policing of Race–Class Subjugated Communities." *Annual Review of Political Science* 20(1): 565–91. doi:10.1146/annurev-polisci-060415-093825.

UDP. 2023. "Displacement and Gentrification Typologies." https://github.com/urban-displacement/displacement-typologies (May 25, 2023).

Wacquant, Loïc. 2010. "Class, Race & Hyperincarceration in Revanchist America." *Daedalus* 139(3): 74–90.

Wilson, Megan R., and Elliot Smilowitz. 2015. "Protesters Shut down Bernie Sanders Rally." *The Hill*. https://thehill.com/blogs/blog-briefing-room/news/250667-protesters-interrupt-bernie-sanders-rally/ (June 12, 2023).