XXXXXX: Race, place, and police involved deaths

**N words (4805)**

## Abstract

**Objective.** To estimate mortality due to police-involved deaths by race and place in the United States.

**Methods.** We use crowdsourced police-involved fatality data collected between January 1, 2013 and May 8, 2017 to construct multilevel, Bayesian negative binomial models. We use these models to estimate fatality risk for the Blacks, Hispanics and Whites for all counties in the US.

**Results.** We estimate that police in the US. are involved, on average, in 4.5 deaths per day. Model results show that Black fatality risk is between 0.88 and 1.12 deaths per 100,000 per year, Hispanic risk is between 0.40 and 0.61, White fatality risk is between 0.36 and 0.42, and total fatality risk is between 0.36 and 0.42 deaths per 100,000 per year. This risk varies substantially across US regions and metro types.

**Conclusions.** The risk of death in an encounter with police is highly sensitive to race and place, and policing is an important social determinant of health. Despite the lack of reliable official statistics, new methods can quantify fatality risk and uncertainty with relatively sparse data that characterizes US police-involved fatality data.

**Policy Implications.** Efforts to address unequal exposure to police violence should take regional and local variation into account. Such efforts can lead to more targeted place-based interventions to reduce racial disparities in police-involved deaths. MORE?

## INTRODUCTION

Violent interactions between law enforcement and civilians are a persistent feature of American social life. 1,2 Indeed, in the United States (US), instances of police-involved mortality (i.e., deaths of civilians resulting from interactions with law enforcement) are estimated to be several-times greater than in many, economically similar countries. (CITATION NEEDED)

At the forefront of the conversation on the US’s relatively high police-involved mortality rate is race. Communities of color have argued that their members are—as evidenced by the deaths of Michael Brown, Sandra Bland, Renee Davis, Philando Castille, Tamir Rice, Laquan McDonald, Daniel Covarrubias, Eric Garner, Charleena Lyles, and many others— at disproportionate risk of police-related harm than Whites. 13,14 This claim has been borne-out in empirical studies, which (generally) show that people of color are—and have for some time been—at greater risk of experiencing police-involved harm than Whites. 8,15,16, Between 1965 and 2015, for instance, Blacks are estimated to have been between 7.5 to 2.5 times more likely than Whites to be killed in interactions with police.3

In this paper, we add to the collective project of explicating racial-disparities in police-involved deaths by describing how place factors into this social phenomenon. That is, law enforcement agencies, and their relationships with communities of color, are contingent upon the broader institutional, cultural, and legal environments in which they reside.11,12,18 In this way, place-based variation in (social-)environmental context has been shown to translate into place-based variation in police practices, behaviors, regimes, and, consequentially, outcomes. 11,12,18 We predict that racial disparities in police-involved mortality are, like other police-related outcomes, tightly coupled with geography.

To provide estimates of how geography and race interact to produce variable risks of police-involved deaths, we utilize non-traditional, crowdsourced data--which explicitly address several shortcomings of federal efforts to document deaths involving police3,4—as well as a methodological approach that allows for predictive precision of relatively rare events. Our results suggest that race and place may interact in important ways to generate risks of mortality due to police-involved deaths.

**DATA AND METHODS**

## Data

Past work on police-involved mortality has been limited by the absence of systematic, national data on deaths involving law-enforcement.3 Law enforcement data—primarily collected through the Bureau of Justice Statistics’ Arrest Related Deaths program, or the Federal Bureau of Investigation’s Uniform Crime Report’s Supplementary Homicide Report—are widely acknowledged to undercount the true number of deaths involving police in the US.3,19,20 As alternatives, public health scholars have sometimes exploited data from the National Center for Health Statistics’ mortality files; the National Violent Death Reporting System; the US Centers for Disease Control and Prevention’s mortality files; and various emergency department surveys.3,21–23 Though these sources offer more complete coverage of police-involved deaths than law-enforcement datasets, they still suffer from under-reporting and/or limited geographic coverage.3

In response to the shortcomings of official data sources, journalists, activists and researchers have constructed a series of public datasets that count police-involved deaths using a combination of public records and media accounts. These crowdsourced efforts are, typically, much more comprehensive than government sources, and rely on methodologies that closely match those described in forthcoming, government-lead data-collection projects, such as the Bureau of Justice Statistics’ proposed re-design of the Arrested-Related Deaths Program.24

In our paper, data on police-involved deaths comes from one of these non-traditional sources*. Fatal Encounters* is a journalist-led project that seeks to document all episodes of fatal police-civilian interactions in the United States since 2000.4 The project relies on contributions of professional and volunteer researchers, compiled from media reports and public records. The universe of cases in *Fatal Encounters* is broader than similar projects, such as *The Washington Post's* compilation of data on police shootings, and has a greater temporal coverage than *The Guardian's* dataset on police-involved deaths. We use data from those dates with complete national data, January 1, 2013 through the date of access, May 8, 2017.4

Data for population estimates, necessary for calculating race and place specific rates, come from the American Community Survey 5-year 2009-2014.

**Measures**

Race is measured, as it is recorded in *Fatal Encounters,* as either: (1) *black/African American;* (2) *white;* or (3) *latinx/Latino.* Because race is sometimes excluded from news reports and public records, this information is not available for all subjects in the data. For those cases with missing race information, we use surname, county of residence and a method developed by Imai and Khanna26 to predict race. Approximately 10% of the data are unable to be, accurately, classified in this procedure; these individuals are dropped in calculations of race-specific models, and we note that our estimates are somewhat conservative as a result.

We specify place using two categorical measures. First, using the Census Bureau’s 2010 Division classification, we group states into 9-catagories (i.e., *divisions),* based on similarities in physical and cultural geography, as well as historical development and economics (see Appendix Table 1 for a complete list). Second, using the National Center for Health Urban-Rural Classification Scheme, we group all US counties into 6-categories (i.e., *metropolitan-types),* based on population-size and membership in a Metropolitan Statistical Area (see Appendix Table 2, for more information).

**Statistical Analysis**

To maximize information, we first pool subjects by county, and produce race-specific, county-level death counts for all 3140 counties in the US. We then estimate, separately for each racial group, Bayesian multilevel negative binomial regression models of county-level police-involved deaths, as a function of metropolitan-type and Census-division. Model intercepts are assigned a prior distribution[[1]](#footnote-1) with a mean expectation equal to mortality estimates produced by Krieger and colleagues (0.37 deaths per 100,000 population for Latinos and whites, and 0.94 deaths per 100,000 population for African Americans).8 From these models, we predict mortality rates, rate ratios (e.g., Black mortality rates/White mortality rates), and 95% posterior uncertainty intervals for each racial group, metropolitan-type, and division. Note that all rates are given per year, per 100,000 population.

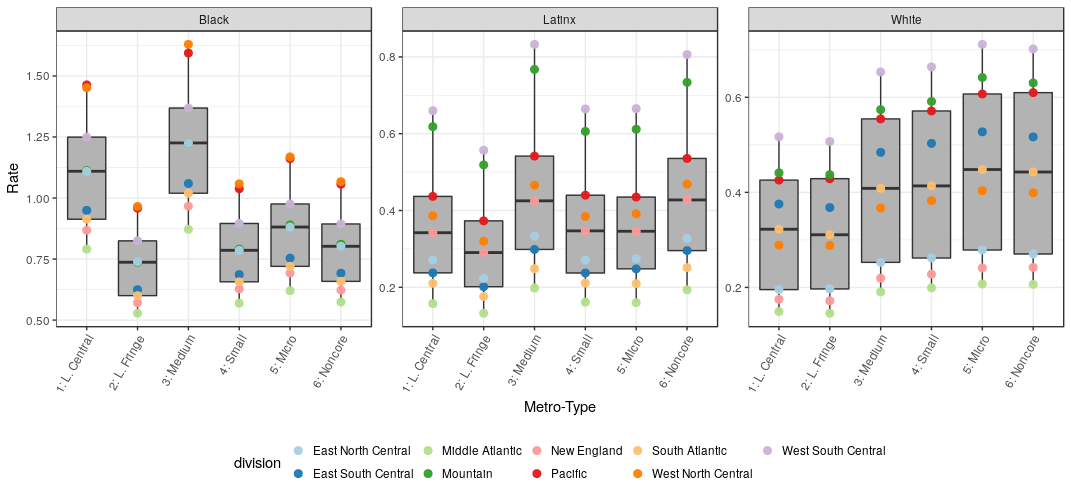
Explicitly incorporating prior information into our Bayesian models helps to stabilize results and produce more reasonable estimates of mortality risk. In counties with small populations, any occurrence of police-involved mortality can dramatically inflate per-capita rates. Likewise, there are many places with small populations that did not record any police-involved deaths during the time period covered by available data, though the true risk of mortality is almost certainly non-zero. Direct estimates from observed data may also inaccurately represent risk for places with large populations, because we have a relatively small number of years available in current data. By pulling mortality rates based on observed information towards our prior beliefs about mortality rates, while allowing estimates for places with more population (and thus information) to draw more weight from the observed data, our models allow us to provide regularized estimates that are likely better representations of actual mortality risk than those based solely on the valuable, but relatively sparse, data currently available.

## RESULTS

In the 4.4 years between January 1, 2013 and May 8, 2017, *Fatal Encounters* reports 7,118 police-involved deaths, for an average of approximately 4.5 deaths per day. Of the 7,118 victims, 1,716 were black (0.99 deaths per year, per 100,00), 1,138 were Latinx (0.52 deaths per year, per 100,000), and 3,306 were white (0.39 deaths per, year per 100,00**). On a national level, our model estimated rates closely match rates observed in the data (CITE)**; we estimate, with 95% certainty, that the risk of mortality in interactions with law enforcement among Blacks is between 0.88-1.12 deaths per 100,000 per year, that risk for Latinx individuals is between 0.40-0.61, and that risk for Whites falls between 0.36-0.46 per year per 100,000. At 2015 population levels, our models predict between 353 and 449 police involved Black deaths, 217 and 329 Latino deaths, 714 and 822 White deaths, and between 1539 and 1834 total police-involved deaths in the U.S. in a year.

Table 1 disaggregates national police-involved mortality rates by Census-division and metropolitan type, and suggests that experiences of police-involved mortality vary by place. For example, Large fringe metros--counties in metropolitan statistical areas (MSA) with populations above 1 million, that do not contain the MSA’s principle city (such as Pierce County, which houses Tacoma, WA, in the Seattle-Tacoma MSA)--have the lowest rates of police-related fatalities among all metropolitan-types. Note that while the absolute mortality rate among this metro-type varies by division--from 0.17 per 100,000 in the Middle Atlantic, to 0.66 per 100,000 in the West South Central---its relative, within division rank remains approximately the same in all cases. Additionally, Large central metros (counties in MSAs of over 1 million population that contain, all or a plurality of, the MSA’s principle city, such as King County, which houses Seattle, WA, in the Seattle-Tacoma MSA) typically have near division-average rates, while medium metro-type (counties in MSAs of 250,000-999,9999 population, such as Spokane County, WA) and smaller, often, have the highest rates of police-related fatalities. Note that, as was the case with large fringe metros, absolute mortality rates shift between Census-divisions: Pacific division counties, for example, have rates that are 1.5 to 2 times larger than equivalent New England counties.

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| **Table 1.** Police related fatalities in the U.S. by metro type and Census division, January 1, 2013 through May 8, 2017, annual rate per 100,000 population in parenthesis | | | | | | | |
| Census Division | Large Central Metro | Large Fringe Metro | Medium Metro | Small Metro | Micro-politan | Noncore | *Total* |
| East North Central | 323  (0.58) | 139  (0.26) | 127  (0.39) | 75  (0.33) | 81  (0.32) | 39  (0.31) | 784  (0.39) |
| East South Central | 84  (0.64) | 39  (0.35) | 120  (0.60) | 83  (0.80) | 82  (0.59) | 97  (0.76) | 505  (0.62) |
| Middle Atlantic | 166  (0.26) | 111  (0.17) | 110  (0.41) | 23  (0.23) | 23  (0.25) | 10  (0.28) | 443  (0.25) |
| Mountain | 240  (0.71) | 57  (0.52) | 188  (0.75) | 110  (0.85) | 76  (0.68) | 39  (0.67) | 710  (0.71) |
| New England | 23  (0.23) | 41  (0.18) | 54  (0.27) | 16  (0.45) | 13  (0.27) | 13  (0.46) | 160  (0.25) |
| Pacific | 685  (0.58) | 179  (0.51) | 309  (0.68) | 98  (0.75) | 58  (0.67) | 21  (0.68) | 1350  (0.60) |
| South Atlantic | 309  (0.57) | 394  (0.42) | 392  (0.61) | 115  (0.45) | 108  (0.62) | 75  (0.51) | 1393  (0.52) |
| West North Central | 107  (0.90) | 91  (0.44) | 123  (0.79) | 64  (0.45) | 59  (0.43) | 63  (0.43) | 507  (0.56) |
| West South Central | 476  (0.80) | 181  (0.66) | 283  (0.76) | 93  (0.69) | 120  (0.81) | 113  (0.90) | 1266  (0.77) |
| *Total* | 2413  (0.57) | 1232  (0.36) | 1706  (0.59) | 677  (0.54) | 620  (0.52) | 470  (0.57) | 7118  (0.52) |
| *Note:* Data from *Fatal Encounters*, accessed 5/9/17 | | | | | | | |

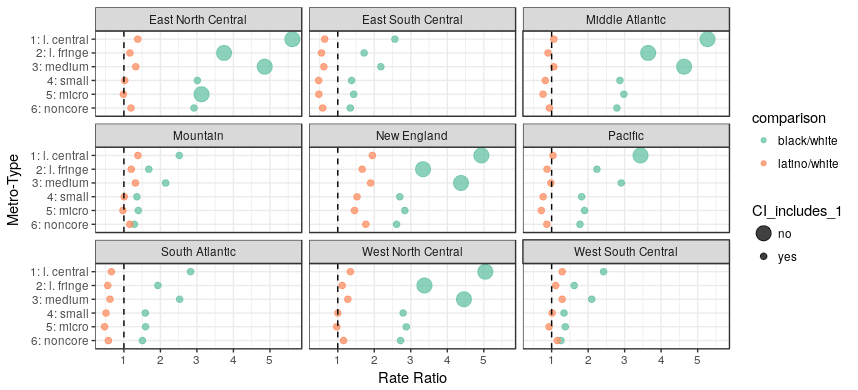
The geographic heterogeneity displayed in Table 1 demonstrates that place plays an important role in generating police-involved deaths. To assess how race interacts with place to create variable risk, Figure 1 plots (model-estimated) mortality rates for each racial group, metropolitan type, and Census-division. Full model predictions, along with 95% uncertainty intervals, are provided in Appendix Table 3.

***Figure 1.*** *Box-plots of model estimated, race-specific, police-involved deaths by metropolitan-type and Census-divisions. Note: rates are per year, per 100,000 population*.

Figure 1 shows that race-specific mortality rates are, like pooled rates, contingent upon Census-division. Among Blacks, individuals in Pacific states (e.g., Washington; California) and West North Central states (e.g., Missouri; Minnesota) have the highest risks of police-involved mortality (with predicted rates of between 1.0 to 1.6 deaths per year, per 100,000), while individuals in the West South Central (e.g., Oklahoma; Texas) and Middle Atlantic states (e.g., New Jersey, Pennsylvania) have the lowest estimated risk (between 0.5 to 0.7 deaths per year per 100,00). In contrast, among Whites and Latinx, individuals in the West South-Central states and Mountain states (e.g., Arizona; Wyoming) have the highest risk of police-involved death (with mortality rates that vary between 0.4 and 0.6 among Whites, and between 0.6 and 0.8 among Latinx). For Latinx individuals, rates are lowest in the Middle Atlantic and South Atlantic (e.g., Florida; South Carolina) states. For Whites, rates are estimated to be lowest in the Middle Atlantic and in New England (e.g., Maine; Vermont).

Figure 1 also shows that race-specific risks are contingent on metropolitan-type. Among Blacks, police-involved deaths are estimated to be largest in Medium-metros (ranging from 0.9-1.6 deaths per year per 100,000 across divisions) and Large-Central Metros (between 0.8-1.5 deaths per year per 100,000), and smallest in Large Fringe (rates between 0.5 and 1.0) and smaller counties. Less pronounced metropolitan based variation exists among Latinx and Whites, with Latinx rates being highest in Medium and noncore metro-areas (with division-specific rates ranging from 0.2 to 0.8 deaths per year per 100,000) and lowest in Large Fringe Metros (with rates between 0.1 and 0.6 per 100,000 population); and White rates increasing as metropolitans become smaller (from a median rate of approximately 0.3 per 100,000 in Large Central Metros to a median rate of about 0.5 per 100,000 in noncore areas).

Though Figure 1 suggest that the severity of racial-disparitiesin police-involved mortality varies by place, we take a closer look at this by plotting predicted rate-ratios. Figure 2 gives Black police-involved death rates/White police-involved death rates, as well as Latinx police-involved death rates/White police-involved death rates, for each metropolitan type and division.



***Figure 2:*** *Predicted, Black/White and Latinx/White, rate-ratios of police-mortality, by Census-division and metro-type. Note: Rate-ratios above 1 indicate that a given racial group has a higher, estimated, rate of police-mortality than Whites. Estimates represented by a large circle indicate that uncertainty/confidence interval does not include zero.*

Figure 2 shows that Black-White disparities in police-involved deaths vary, noticeably, by place. Division-wise, Black-White disparities in police involved deaths are estimated to highest in Midwestern (e.g., West North Central; East North Central) and East Coast (e.g., New England; Middle Atlantic) states; in these places, Black rates are between 2.5 to 5.5 times more likely to be killed due to interactions with police than Whites. Black-White disparities appear to be particularly pronounced among Large Central Metros, and Large Fringe Metros across the nation. Note that Black-White rate-ratios are smallest in Southern States, like those in the East South Central (e.g., Mississippi; Tennessee) and South Atlantic divisions. Latinx-White rates found to be insignificant across place.

## DISCUSSION

STATE MAIN FINDINGS: AF AM AND LATINO AT HIGHER RISK OF DEATH. RISK IS HIGHEST IN X. Using novel data from *Fatal Encounters*, in conjunction with a modeling approach that can better account for uncertainty in estimates of rare cases, we show that race and place interact to generate heterogeneous risks of police-involved deaths. ADD COMPARISON TO OBSERVED RATES. Latinos are most vulnerable to police-involved death in rural counties and medium-sized urban and suburban counties, and in a contiguous set of states in the Southwest and Mountain West. Similarly, White risk appears to be highest in rural, Mountain and Southwest states, while African-American risk is highest in cities and in West coast and Midwestern states.

Our results further show that racial disparities in police-involved deaths vary by place. Relative to Whites, Black rates of police involved deaths are particularly outsized in medium and large central metros, in Midwestern and East Coast states. Latinx/White rate ratios vary much less significantly across the nation. In sum, when understanding police-involved fatality risk we must consider both race and place simultaneously.

These results raise provocative questions about how local and regional policing regimes may affect mortality risk. Indeed, prior research has shown that Geography/environment/place is known to be a social determinant of health; where one lives dictates access/what risks one is exposed too (CITE). However, in the majority of empirical studies, “place matters” is often realized as distribution of physical resources (e.g., access to doctors; healthy food) or disease/illness giving environmental factors (e.g., power plants; lead). Important, of course, but it is also helpful to take up call, and examine how variation in social/cultural environment impacts health, particularly for vulnerable/minority populations. There are examples of research that have been able to link social and policy environments to health outcomes. For example, multiple dimension of the social environment have been linked to suicide Attempts in Lesbian, Gay, and Bisexual Youth (CITE Hatzenbueler papers). Especially when trying to understand race---and racial disparities---as it relates to population health; structural forces/logic that dictate experience of race vary by place; can (may) have important implications for how we understand race in (a cite for someone doing work like this). WE NEED TO INSERT A GOOD POLICING PRACTICES EXAMPLE HERE. Lots of prior work shows that variation in policing regimes, and relationship to communities of color, vary according to local, racial/racialized logic; our paper shows that similar heterogeneity exists in health outcome.

* Lesson in disaggregating

-Discussion of limitations and how our work is still a contribution despite limitations (need for better data in future, etc.)

Our findings suggest that there may be a need for more targeted place-based interventions to reduce racial disparities in police-involved deaths. Policies and interventions that better able to account for heterogeneity across states and metropolitan areas may work better to reduce absolute and racial disparities in police deaths. {If this runs contrary to proposal by Black Lives Matter etc., we need to speak to that. ENGAGE MOVEMENT FOR BLK LIVES PLATFORM? ENGAGE OTHER ACTIVE REFORM EFFORTS}. For example, XXXX. Finally, researchers need to take serious consideration of police fatality estimates that are rare, to avoid overstating or understating patterns of death that have serious consequences for public opinion and public safety.

## References

1. James J, ed. *Warfare in the American Homeland: Policing and Prison in a Penal Democracy*. Durham: Duke University Press; 2007.

2. Alang S, McAlpine D, McCreedy E, Hardeman R. Police Brutality and Black Health: Setting the Agenda for Public Health Scholars. *Am J Public Health*. 2017;107(5):662-665. doi:10.2105/AJPH.2017.303691.

3. Krieger N, Chen JT, Waterman PD, Kiang MV, Feldman J. Police Killings and Police Deaths Are Public Health Data and Can Be Counted. *PLOS Med*. 2015;12(12):e1001915. doi:10.1371/journal.pmed.1001915.

4. Burghart DB. Fatal encounters. http://www.fatalencounters.org. Published 2015. Accessed May 9, 2017.

5. Cooper HLF, Fullilove M. Editorial: Excessive Police Violence as a Public Health Issue. *J Urban Health*. 2016;93(1):1-7. doi:10.1007/s11524-016-0040-2.

6. Crosby AE, Lyons B. Assessing Homicides by and of U.S. Law-Enforcement Officers. *N Engl J Med*. 2016;375(16):1509-1511. doi:10.1056/NEJMp1609905.

7. Furtado K, Banks KH. A Research Agenda for Racial Equity: Applications of the Ferguson Commission Report to Public Health. *Am J Public Health*. 2016;106(11):1926-1931. doi:10.2105/AJPH.2016.303390.

8. Krieger N, Kiang MV, Chen JT, Waterman PD. Trends in US deaths due to legal intervention among black and white men, age 15–34 years, by county income level: 1960–2010. *Harv Public Health Rev*. 2015;3:1–5.

9. Wildeman C, Noonan ME, Golinelli D, Carson EA, Emanuel N. State-level variation in the imprisonment-mortality relationship, 2001- 2010. *Demogr Res*. 2016;34:359–372.

10. Dwyer-Lindgren L, Bertozzi-Villa A, Stubbs RW, et al. Inequalities in Life Expectancy Among US Counties, 1980 to 2014: Temporal Trends and Key Drivers. *JAMA Intern Med*. May 2017. doi:10.1001/jamainternmed.2017.0918.

11. Capers IB. Policing, race, and place. *Harv Civ Rights-Civ Lib Law Rev*. 2009;44:43-78.

12. Beckett K, Nyrop K, Pfingst L. Race, Drugs, and Policing: Understanding Disparities in Drug Delivery Arrests. *Criminology*. 2006;44(1):105-137. doi:10.1111/j.1745-9125.2006.00044.x.

13. Taylor K-Y. *From #Blacklivesmatter to Black Liberation*. Chicago, IL: Haymarket Books; 2016. http://books.google.com/books?hl=en&lr=&id=kB6GCwAAQBAJ&oi=fnd&pg=PP1&dq=info:yeks29K\_9EsJ:scholar.google.com&ots=7nFWOwQAmI&sig=AoZajxVueZ3-TeIrHroAbuKY-WE.

14. Losier T. “The Public Does Not Believe the Police Can Police Themselves”: The Mayoral Administration of Harold Washington and the Problem of Police Impunity. *J Urban Hist*. May 2017:0096144217705490. doi:10.1177/0096144217705490.

15. DeGue S, Fowler KA, Calkins C. Deaths Due to Use of Lethal Force by Law Enforcement: Findings From the National Violent Death Reporting System, 17 U.S. States, 2009–2012. *Am J Prev Med*. 2016;51(5, Supplement 3):S173-S187. doi:10.1016/j.amepre.2016.08.027.

16. Miller TR, Lawrence BA, Carlson NN, et al. Perils of police action: a cautionary tale from US data sets. *Inj Prev*. 2017;23(1):27-32. doi:10.1136/injuryprev-2016-042023.

17. Ross CT. A Multi-Level Bayesian Analysis of Racial Bias in Police Shootings at the County-Level in the United States, 2011–2014. *PLOS ONE*. 2015;10(11):e0141854. doi:10.1371/journal.pone.0141854.

18. Barker V. *The Politics of Imprisonment: How the Democratic Process Shapes the Way America Punishes Offenders*. New York, NY: Oxford University Press; 2009.

19. Planty M, Burch AM, Banks D, Couzens L, Blanton C, Cribb D. *Arrest-Related Deaths Program: Data Quality Profile*. Washington, DC: U.S. Department of Justice, Office of Justice Programs, Bureau of Justice Statistics; 2015. https://www.publicsafety.gc.ca/lbrr/archives/cnmcs-plcng/cn33640-eng.pdf.

20. Klinger D, Rosenfeld R, Isom D, Deckard M. Race, Crime, and the Micro-Ecology of Deadly Force. *Criminol Public Policy*. 2016;15(1):193-222. doi:10.1111/1745-9133.12174.

21. Feldman JM, Chen JT, Waterman PD, Krieger N. Temporal Trends and Racial/Ethnic Inequalities for Legal Intervention Injuries Treated in Emergency Departments: US Men and Women Age 15–34, 2001–2014. *J Urban Health*. 2016;93(5):797-807. doi:10.1007/s11524-016-0076-3.

22. Kaufman EJ, Karp DN, Delgado MK. US Emergency Department Encounters for Law Enforcement–Associated Injury, 2006-2012. *JAMA Surg*. April 2017. doi:10.1001/jamasurg.2017.0574.

23. Barber C, Azrael D, Cohen A, et al. Homicides by Police: Comparing Counts From the National Violent Death Reporting System, Vital Statistics, and Supplementary Homicide Reports. *Am J Public Health*. 2016;106(5):922-927. doi:10.2105/AJPH.2016.303074.

24. Banks D, Ruddle P, Kennedy E, Planty M. *Arrest-Related Deaths Program Redesign Study, 2015-216: Preliminary Findings*. Washington, DC: U.S. Department of Justice, Office of Justice Programs, Bureau of Justice Statistics; 2016. https://www.bjs.gov/content/pub/pdf/ardprs1516pf.pdf. Accessed May 8, 2017.

25. Ruggles SJ, Alexander JT, Genadek K, Goeken R, Schroeder MB, Sobek M. *Integrated Public Use Microdata Series: Version 5.0 [Machine-Readable Database]*. Minneapolis, MN: University of Minnesota; 2010.

26. Imai K, Khanna K. Improving ecological inference by predicting individual ethnicity from voter registration records. *Polit Anal*. 2016;24(2):263–272.

## Appendix

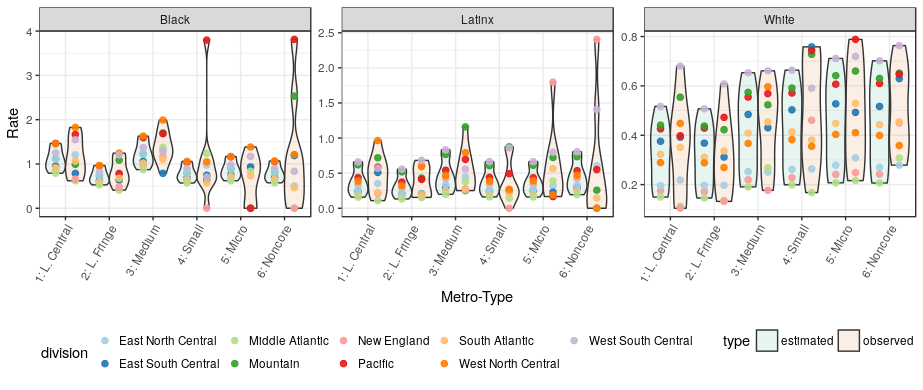
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| Appendix Table 1. States in Census Divisions | |
| Division Name | States Included |
| East North Central | IL, IN, OH, MI, WI |
| East South Central | AL, KY, MS, TN |
| Middle Atlantic | NJ, NY, PA |
| Mountain | AZ, CO, ID, MT, NM, NV, UT, WY |
| New England | CT, MA, ME, NH, VT |
| Pacific | AK, CA, HI, OR, WA |
| South Atlantic | DE, FL, GA, MD, NC, SC, VA, WV |
| West North Central | IA, KS, MN, MO, ND, NE, SD |
| West South Central | AR, LA, OK, TX |
| ADD CITATION | |

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| Appendix Table 2. Description of NCHS Urban-Rural County Classification | | |
| County Type | Description | Number of Counties |
| Large Central Metro | counties in MSA of 1 million population that: 1) contain the entire population of the largest principal city of the MSA, or 2) are completely contained within the largest principal city of the MSA, or 3) contain at least 250,000 residents of any principal city in the MSA. | 68 |
| Large Fringe Metro | counties in MSA of 1 million or more population that do not qualify as large central | 368 |
| Medium Metro | Medium metro counties in MSA of 250,000-999,999 population. | 372 |
| Small Metro | Small metro counties are counties in MSAs of less than 250,000 population. | 358 |
| Micropolitan | Nonmetropolitan counties: Micropolitan counties in micropolitan statistical area | 641 |
| Noncore | Noncore counties not in micropolitan statistical areas | 1333 |
| Citation: https://www.cdc.gov/nchs/data/series/sr\_02/sr02\_166.pdf | | |

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| Appendix Table 3. Posterior police related mortality by race/ethnicity, census region, and metro type, 95 percent credible intervals | | | |
| **County Name** | **Black** | **Latinx** | **White** |
| East North Central |  |  |  |
| - Large Central Metro | 1.1 (0.4, 2.4) | 0.3 (0, 0.8) | 0.2 (0.1, 0.5) |
| - Large Fringe Metro | 0.7 (0.2, 1.6) | 0.2 (0, 0.7) | 0.2 (0.1, 0.4) |
| - Medium Metro | 1.2 (0.4, 2.7) | 0.3 (0.1, 1) | 0.3 (0.1, 0.6) |
| - Small Metro | 0.8 (0.3, 1.8) | 0.3 (0, 0.8) | 0.3 (0.1, 0.6) |
| - Micropolitan | 0.9 (0.3, 2) | 0.3 (0.1, 0.9) | 0.3 (0.1, 0.6) |
| - Noncore | 0.8 (0.3, 1.8) | 0.3 (0.1, 1) | 0.3 (0.1, 0.6) |
| East South Central |  |  |  |
| - Large Central Metro | 0.9 (0.3, 2.1) | 0.2 (0, 0.8) | 0.4 (0.1, 0.9) |
| - Large Fringe Metro | 0.6 (0.2, 1.4) | 0.2 (0, 0.7) | 0.4 (0.1, 0.8) |
| - Medium Metro | 1.1 (0.4, 2.3) | 0.3 (0.1, 1) | 0.5 (0.2, 1.1) |
| - Small Metro | 0.7 (0.2, 1.6) | 0.2 (0, 0.8) | 0.5 (0.2, 1.1) |
| - Micropolitan | 0.8 (0.3, 1.7) | 0.2 (0, 0.8) | 0.5 (0.2, 1.2) |
| - Noncore | 0.7 (0.2, 1.6) | 0.3 (0.1, 1) | 0.5 (0.2, 1.2) |
| Middle Atlantic |  |  |  |
| - Large Central Metro | 0.8 (0.3, 1.8) | 0.2 (0, 0.5) | 0.1 (0.1, 0.3) |
| - Large Fringe Metro | 0.5 (0.2, 1.2) | 0.1 (0, 0.4) | 0.1 (0.1, 0.3) |
| - Medium Metro | 0.9 (0.3, 2) | 0.2 (0, 0.6) | 0.2 (0.1, 0.4) |
| - Small Metro | 0.6 (0.2, 1.3) | 0.2 (0, 0.5) | 0.2 (0.1, 0.5) |
| - Micropolitan | 0.6 (0.2, 1.5) | 0.2 (0, 0.5) | 0.2 (0.1, 0.5) |
| - Noncore | 0.6 (0.2, 1.4) | 0.2 (0, 0.6) | 0.2 (0.1, 0.5) |
| Mountain |  |  |  |
| - Large Central Metro | 1.1 (0.4, 2.6) | 0.6 (0.1, 1.7) | 0.4 (0.2, 1) |
| - Large Fringe Metro | 0.7 (0.2, 1.7) | 0.5 (0.1, 1.5) | 0.4 (0.1, 1) |
| - Medium Metro | 1.2 (0.4, 2.8) | 0.8 (0.2, 2.2) | 0.6 (0.2, 1.3) |
| - Small Metro | 0.8 (0.3, 1.9) | 0.6 (0.1, 1.8) | 0.6 (0.2, 1.3) |
| - Micropolitan | 0.9 (0.3, 2.1) | 0.6 (0.1, 1.8) | 0.6 (0.2, 1.4) |
| - Noncore | 0.8 (0.3, 2) | 0.7 (0.1, 2.2) | 0.6 (0.2, 1.4) |
| New England |  |  |  |
| - Large Central Metro | 0.9 (0.3, 2) | 0.3 (0.1, 1.1) | 0.2 (0.1, 0.4) |
| - Large Fringe Metro | 0.6 (0.2, 1.4) | 0.3 (0.1, 0.9) | 0.2 (0.1, 0.4) |
| - Medium Metro | 1 (0.3, 2.3) | 0.4 (0.1, 1.3) | 0.2 (0.1, 0.5) |
| - Small Metro | 0.6 (0.2, 1.5) | 0.3 (0.1, 1.1) | 0.2 (0.1, 0.5) |
| - Micropolitan | 0.7 (0.2, 1.6) | 0.3 (0.1, 1.1) | 0.2 (0.1, 0.6) |
| - Noncore | 0.6 (0.2, 1.5) | 0.4 (0.1, 1.4) | 0.2 (0.1, 0.6) |
| Pacific |  |  |  |
| - Large Central Metro | 1.5 (0.5, 3.2) | 0.4 (0.1, 1.3) | 0.4 (0.1, 1) |
| - Large Fringe Metro | 1 (0.3, 2.1) | 0.4 (0.1, 1) | 0.4 (0.1, 1) |
| - Medium Metro | 1.6 (0.5, 3.6) | 0.5 (0.1, 1.6) | 0.6 (0.2, 1.3) |
| - Small Metro | 1 (0.4, 2.4) | 0.4 (0.1, 1.2) | 0.6 (0.2, 1.3) |
| - Micropolitan | 1.2 (0.4, 2.7) | 0.4 (0.1, 1.3) | 0.6 (0.2, 1.4) |
| - Noncore | 1.1 (0.4, 2.5) | 0.5 (0.1, 1.6) | 0.6 (0.2, 1.4) |
| South Atlantic |  |  |  |
| - Large Central Metro | 0.9 (0.3, 2) | 0.2 (0, 0.6) | 0.3 (0.1, 0.7) |
| - Large Fringe Metro | 0.6 (0.2, 1.3) | 0.2 (0, 0.5) | 0.3 (0.1, 0.7) |
| - Medium Metro | 1 (0.3, 2.2) | 0.2 (0.1, 0.8) | 0.4 (0.1, 0.9) |
| - Small Metro | 0.7 (0.2, 1.5) | 0.2 (0, 0.6) | 0.4 (0.1, 0.9) |
| - Micropolitan | 0.7 (0.2, 1.6) | 0.2 (0, 0.6) | 0.4 (0.2, 1) |
| - Noncore | 0.7 (0.2, 1.5) | 0.3 (0, 0.7) | 0.4 (0.2, 1) |
| West North Central |  |  |  |
| - Large Central Metro | 1.4 (0.5, 3.3) | 0.4 (0.1, 1.2) | 0.3 (0.1, 0.6) |
| - Large Fringe Metro | 1 (0.3, 2.2) | 0.3 (0.1, 1) | 0.3 (0.1, 0.6) |
| - Medium Metro | 1.6 (0.5, 3.8) | 0.5 (0.1, 1.4) | 0.4 (0.1, 0.8) |
| - Small Metro | 1.1 (0.4, 2.4) | 0.4 (0.1, 1.1) | 0.4 (0.1, 0.8) |
| - Micropolitan | 1.2 (0.4, 2.6) | 0.4 (0.1, 1.2) | 0.4 (0.1, 0.9) |
| - Noncore | 1.1 (0.3, 2.5) | 0.5 (0.1, 1.4) | 0.4 (0.1, 0.9) |
| West South Central |  |  |  |
| - Large Central Metro | 1.2 (0.4, 2.7) | 0.7 (0.1, 1.9) | 0.5 (0.2, 1.1) |
| - Large Fringe Metro | 0.8 (0.3, 1.8) | 0.6 (0.1, 1.6) | 0.5 (0.2, 1.1) |
| - Medium Metro | 1.4 (0.5, 3.1) | 0.8 (0.2, 2.3) | 0.7 (0.2, 1.4) |
| - Small Metro | 0.9 (0.3, 2) | 0.7 (0.1, 2) | 0.7 (0.2, 1.5) |
| - Micropolitan | 1 (0.3, 2.2) | 0.7 (0.1, 1.9) | 0.7 (0.2, 1.6) |
| - Noncore | 0.9 (0.3, 2.1) | 0.8 (0.2, 2.4) | 0.7 (0.2, 1.6) |

**Bayesian Utility**

Figure A1 gives violin plots of (both observed and model-estimated) race-specific police-involved mortality rates, for each metropolitan-type and division:



***Figure A1.*** *Violin plots of observed and model estimated race-specific police-related fatalities by metro-type and Census-divisions. Note: rates are per year, per 100,000 population*.

Figure A1 illustrates the effects/utility our Bayesian approach. Consider the difference between the observed and estimate rates of police-related mortality among Blacks in Pacific, noncore metros (approximately 3.8 and 1.1 per year, per 100,000, respectively). Here, the, extremely, high observed mortality rate is the product of a sparse Black population/mortality count: Pacific noncore metros had, in sum, a Black population of 6,045 individuals, 1 of whom was killed by police. While this outcome is striking, and the circumstances that generated it are certainly worth further consideration---especially given that only 10 Black individuals lived in the county where the lone individual was killed---there is uncertainty around whether this observed rate is a product of a “true” underlying risk of mortality. The model predicted rates attempt to account for this, by pulling weakly supported points back to our prior beliefs (national averages). In places where more data exists---e.g., in Large Fringe or Medium Metros of all division---we have more trust that data reflects true underlying risks, and so predicted values are more similar to the observed data.

1. Priors for negative binomial model intercepts are specified for white and Hispanic mortality risk per 100,000 adults as: and for Black mortality risk as: [↑](#footnote-ref-1)