Using Public Health Data to Monitor Killings by Law Enforcement in the United States

USING PUBLIC HEALTH DATA TO MONITOR KILLINGS BY LAW ENFORCEMENT IN THE UNITED STATES

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ABSTRACT

Injuries inflicted by police represent an important cause of death in the United States, yet public health monitoring systems routinely undercount these incidents. This dissertation presents three epidemiologic studies about police-related deaths. The first is a matched-pair analysis of Massachusetts data (2004-2016) comparing news media-derived databases of police-related deaths (The Guardian, Washington Post, WGBH News, and Fatal Encounters) to Massachusetts mortality records (N = 84 decedents). Demographic data reported in all four databases were highly concordant vis-à-vis death certificates, while vital statistics misclassified the cause of death (i.e. reported as diagnostic codes other than "legal intervention") for 24% of deaths. The second study matched 2015 US data from The Guardian to National Vital Statistics System (NVSS) mortality records. Capture-recapture analysis estimated the total number of police-related deaths in 2015 to be 1,166 (95% CI: 1,153 – 1,184). NVSS classified 44.9% (95% CI: 44.2%, 45.4%) of these as legal intervention, and The Guardian documented 93.1% (95% CI: 91.7%, 94.2%) of deaths. Death occurrence in lower income counties (relative to the highest income quintile) and deaths by non-firearm mechanisms (relative to police shooting deaths) predicted higher odds of misclassification. The third paper analyzed the association between rates of police-related death rates and spatial social polarization throughout the entire United States, with polarization defined as census tract residential concentrations of racially/economically privileged and racially/economically deprived groups and measured with the Index of Concentration at the Extremes (ICE). We identified deaths using 2015-2016 Guardian data (N = 2119). In multilevel models for the total population, concentrated deprivation

was associated with higher police-related death rates, while concentrated privilege was associated with lower rates. In stratified models, rates of death were lowest for non-Hispanic white persons in the quintile of census tracts with the greatest concentrations of non-Hispanic white residents, but were highest in the same quintile of census tracts for non-Hispanic black persons. While public health monitoring of police-related deaths can be improved, combining epidemiologic data with other data sources can help analyze and ultimately prevent these incidents.

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INTRODUCTION

Many of the major public health achievements of the 20th century United States would not have been possible without population data from epidemiologic monitoring. Disease, injury, and mortality surveillance data not only informed successful efforts to prevent tobacco use, lead poisoning, and motor vehicle-related deaths, but also informed lawsuits and policymaking that held the tobacco, lead paint, and automobile industries accountable for the harms they had caused. Yet in the case of fatal injuries inflicted by law enforcement officers, there are no national, governmental efforts that reliably and publicly track these incidents. Lessons from the prior century of public health would suggest that this lack of data inhibits efforts to prevent police-related deaths and hold law enforcement accountable for police violence. This dissertation came about largely as a response to the absence of systematically collected data on police-related deaths, as an effort to elucidate the shortcomings of existing monitoring systems, and to combine data sources on police violence in novel ways that minimize statistical bias in analyses.

When I was about to begin the second year of my doctoral program in the August of 2013, a police officer named Darren Wilson shot and killed Michael Brown, an 18-year-old black resident of Ferguson, Missouri who was unarmed during the encounter. A grand jury later declined to indict the officer. The death – along with its perceived injustice – triggered a wave of urban uprisings, protests, and police reform efforts, which began in the St. Louis metropolitan area and continued across dozens of cities in United States during the following year. Public attention turned to subsequent cases of killings by police, including the deaths of Tamir Rice, Eric Garner, Akai Gurley, Rekia Boyd, Jessica Hernandez, and John Crawford. As with Michael Brown, most of these highly publicized incidents involved unarmed black men and boys whose

killings, in the opinion of many people in black communities and beyond, were both preventable and unjustified.

During this period of activism, public health and medical professional associations were among the multitude of national organizations that expressed concern regarding the use of deadly force by police. The National Association of County and City Health Officials (2015), American Academy of Family Physicians (2015), National Nurses United (2014), and Student National Medical Association (2014) issued statements defining police violence as a public health issue and condemning its racially disproportionate application. The American Public Health Association (1998) had already released a policy statement condemning police brutality 15 years prior.

Despite growing professional recognition of police violence as a public health concern, my queries of the PubMed and Web of Science databases, undertaken in the fall of 2015, yielded only three papers in public health journals (Sikora and Mulvihill, 2002; Krieger et al., 2015; Drowos et al., 2015) that analyzed population rates of mortality due to law enforcement-inflicted injuries. This lack of attention to law enforcement-related deaths existed despite data collection efforts by the US National Vital Statistics System (NVSS), which has recorded such deaths since 1949 following the sixth revision of the International Classification of Diseases (ICD-6), when the World Health Organization adopted a diagnostic category called "injury by intervention of police" (later renamed "legal intervention" in ICD-8 through ICD-10). Since its initial adoption, the ICD has defined this category as "injuries inflicted by the police or other law-enforcing agents, including military on duty, in the course of arresting or attempting to arrest lawbreakers,

suppressing disturbances, maintaining order, and other legal action" (WHO, 1948). However, prior studies compared state-level death counts reported in the NVSS to those from Department of Justice; the numbers did not match between sources, suggesting that both were undercounts (Loftin et al., 2003; Wiersema et al., 2000).

My dissertation makes novel methodological and substantive contributions to the epidemiologic study of deaths due to fatal injuries inflicted by police. It assesses a newer type of data source on police-related deaths – US-wide, nongovernmental databases created by compiling news media reports – for their ability to capture police killings and for the validity of the decedent demographic data they provide. The research presented below also measures the extent to which NVSS misclassifies police-related deaths, and elucidates the determinants of its misclassification. Finally, I offer new analyses that seek to deepen epidemiology's understanding of neighborhood-level inequities by analyzing the association between rates of police-related deaths and various measures of racial and economic residential segregation. My hope is that these papers contribute to a larger body of research that improves the public health monitoring of police violence and guides efforts that lessen the harm caused by policing practices.

References

American Association of Family Physicians. Social Determinants of Health Issues Take Center Stage. Leawood, KS: 2015. http://www.aafp.org/news/2015-congress-fmx/20150930hopsrefcomm.html

American Public Health Association. Impact of Police Violence on Public Health. Washington, DC: 1998. http://www.apha.org/policies-and-advocacy/public-health-policy-statements/policy-database/2014/07/11/14/16/impact-of-police-violence-on-public-health

Drowos J, Hennekens CH, Levine RS. Variations in mortality from legal intervention in the United States—1999 to 2013. *Prev Med (Baltim)* Published Online First: September 2015. doi:10.1016/j.ypmed.2015.09.012

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

Loftin C, Wiersema B, McDowall D, Dobrin A. Underreporting of justifiable homicides committed by police officers in the United States, 1976–1998. *Am Journal of Public Health*. 2003;9:1117-21.

National Association of County and City Health Officials. Statement of Policy: Public Health, Racism, and Police Violence. Washington, DC: 2015. http://www.naccho.org/advocacy/positions/upload/15-04-Public-Health-Racism-and-Police-Violence.pdf

Sikora AG, Mulvihill M. Trends in mortality due to legal intervention in the United States, 1979 through 1997. *Am J Public Health* 2002;**92**:841–3. doi:10.2105/AJPH.92.5.841

Student National Medical Association. Police Brutality Position Statement. 2014. http://www.snma.org/_files/live/snma_policy_brutality.pdf

Wiersema B, Loftin C, McDowall D. A comparison of supplementary homicide reports and national vital statistics system homicide estimates for US counties. *Homicide Studies*. 2000 ;4:317-40.

1. Killed by Police: Validity of Media-Based Data and Misclassification of Death Certificates in Massachusetts, 2004–2016

Justin M. Feldman, Sofia Gruskin, Brent A. Coull, Nancy Krieger

Abstract

Objectives: To assess the validity of demographic data reported in news media–based data sets for persons killed by police in Massachusetts (2004–2016) and to evaluate misclassification of these deaths in vital statistics mortality data.

Methods: We identified 84 deaths resulting from police intervention in 4 news media– based data sources (WGBH News, Fatal Encounters, The Guardian, and The Washington Post) and, via record linkage, conducted matched-pair analyses with the Massachusetts mortality data.

Results: Compared with death certificates, there was near-perfect correlation for age in all sources (Pearson $r > 0.99$) and perfect concordance for gender. Agreement for race/ ethnicity ranged from perfect (The Counted and The Washington Post) to high (Fatal Encounters Cohen's $k = 0.92$). Among the 78 decedents for whom finalized International Classification of Diseases, 10th Revision (ICD-10), codes were available, 59 (75.6%) were properly classified as "deaths due to legal intervention."

Conclusions: In Massachusetts, the 4 media-based sources on persons killed by police provide valid demographic data. Misclassification of deaths due to legal intervention in the mortality data does, however, remain a problem. Replication of the study in other states and nationally is warranted.

Note: This paper is also available as:

Feldman JM, Gruskin S, Coull BA, Krieger N. Killed by police: Validity of media-based data and misclassification of death certificates in Massachusetts, 2004-2016. Am J Public Health 2017;107(10):1624–6.

US government agencies tasked with monitoring killings by police underreport the number of these deaths at high rates.[1,2] Evidence indicates that National Vital Statistics System mortality data, maintained by the Centers for Disease Control and Prevention, are no exception.[3,4] For decedents killed by law enforcement, mortality records are assigned a diagnostic code, under the International Classification of Diseases, 10th Revision (ICD-10; Geneva, Switzerland: World Health Organization; 1992), indicating "legal intervention," defined as "injuries inflicted by the police or other law-enforcing agents, including military on duty, in the course of arresting or attempting to arrest lawbreakers, suppressing disturbances, maintaining order, and other legal action." These deaths are misclassified if assigned a different code.

News media reports provide an alternative source of national data to identify legal intervention deaths, but the validity of their demographic data has not been established. We conducted novel analyses to (1) quantify the proportion of misclassified mortality records among the legal intervention deaths identified through media-based data sources and (2) assess the validity of demographic data in media sources compared with death certificates, treating the latter as a "gold standard" (as per previous death certificate validity studies[5,6]).

METHODS

We used Massachusetts as a case study and created a list of the state's legal intervention deaths from January 1, 2004, to April 14, 2016, according to 4 news media–based data sources: (1)

WGBH police-involved deaths (January 1, 2004–December 31, 2014)[7]; (2) Fatal Encounters (January 1, 2004–April 14, 2016)[8]; (3) The Guardian's The Counted (January 1, 2015–April 14, 2016)[9]; and (4) The Washington Post Fatal Force (online police shooting database: firearm deaths only; January 1, 2015–April 14, 2016).[10] Each database provides information about decedent's name, age, gender, race/ethnicity, and circumstances of death.

WGBH News, a Boston, Massachusetts, public media network, identified deaths through a review of media and law enforcement reports.[7] Fatal Encounters, a non- profit organization, had staff confirm details of crowd-sourced reports.[8] The Guardian and The Washington Post newspapers identified deaths through various media sources and confirmed details with investigative reporting.[9,10]

We reviewed deaths reported in these 4 sources and included only those consistent with the definition of legal intervention, which is not contingent on the lawfulness or intent of the killing. For excluded cases, we documented the reason that they did not conform to this definition (Table 1.1). For included decedents, we retrieved death certificates and ICD-10 codes from the Massachusetts Registry of Vital Records and Statistics, which are publicly accessible in Massachusetts.[11] If a legal intervention death was not reported by any of the media-based sources, then it was not included in our analyses.

Funeral home directors provide demographic information on death certificates. The National Center for Health Statistics, relying on a computer program and trained nosologists, assigns an underlying cause of death code based on death certificate literal text (e.g., text written in the "describe how the injury occurred" field). To assess ICD-10 misclassification for the deaths

identified through news media, we calculated the proportion of media-identified fatalities for which the mortality record was not coded as legal intervention (codes Y35.0–Y35.7 or Y89.0, excluding legal execution: Y35.5) overall, by year, and by death mechanism (firearm vs other). We also conducted matched-pair analyses to quantify discordance between demographic variables reported on death certificates and each media-based data source, calculating Pearson r for age and Cohen's k for gender and race/ethnicity. Because 2 data sources, WGBH and Fatal Encounters, had high levels of missingness for race/ethnicity (16.2% and 31.0%, respectively), we used the Fisher exact test for the null hypothesis that these values were missing at random.

RESULTS

After removing 16 cases from the media sources not meeting the criteria for legal intervention (Table 1.1), we identified 84 civilians killed by police in Massachusetts over the study period. We located death certificates for all decedents. The 6 most recent decedents did not have finalized ICD- 10 codes, and we excluded them from the analysis. Of the 78 remaining, 59 (75.6%) were properly coded as legal intervention deaths in vital statistics data. The proportion properly classified was 50.0% for 2004 to 2006, 75.0% for both 2007 to 2009 and 2010 to 2012, and 88.5% for 2013 to 2015 (Figure 1.1). Among misclassified deaths, legal intervention was reported as another assault-related diagnosis for 16 of 19 cases. All 4 of the non-firearm-related cases were misclassified (1 Taser-related, 1 vehicle-related, and 2 medical neglect– related incidents). Most cases (68 of 78; 87.2%) had death certificates with reference to police (typically, "shot by police"); of these, 59 of 68 (86.8%) received proper ICD-10 codes. For 10 cases, no mention of police was found on death certificates, and all were misclassified.

Table 1.1 Cases excluded from each data source				
Total reported deaths	**Data Source by Date Range**			
	Fatal Encounters Jan. 1, 2004 - Apr. 14, 2016	**WGBH** Jan. 1, 2004 - Dec. 31, 2014	**The Counted** Jan. 1, 2015 - Apr. 14, 2016	**Washington Post** Jan. 1, 2015 - Apr. 14, 2016
Total number of cases	100	69	15	14
Number of cases removed, by exclusion criterion				
Car accident, except if police were pursuing decedent	12	0	0	0
Died of self-inflicted wound	2	0	0	0
No mechanism of death implicating law enforcement	1	0	0	0
Homicide by person other than law enforcement officer	1	1	0	0
Total cases included	84	68	15	14

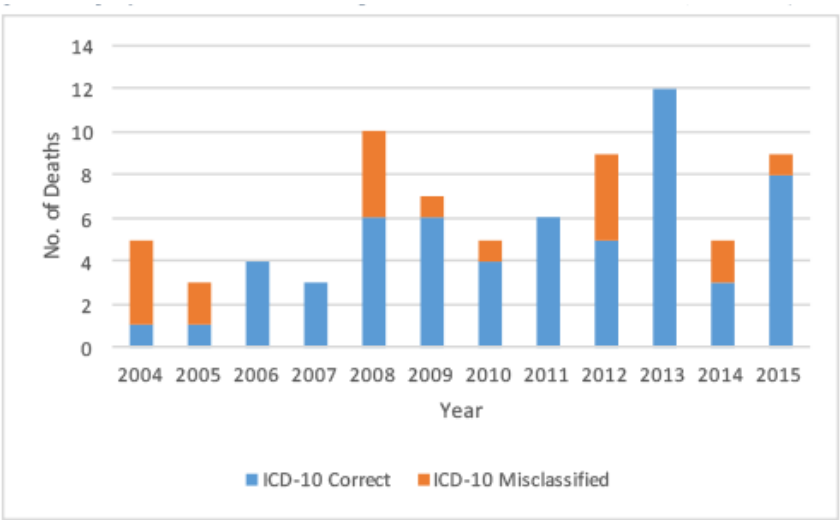

Fig 1.1. Properly Coded and Misclassified Legal Intervention Deaths in Massachusetts, 2004-2015 (N=78)

Data on gender for all 4 news media–based sources were perfectly concordant with death certificate values (Table 1.2). There was near-perfect correlation (Pearson r > 0.99) between the ages listed in each journalistic source and those on death certificates. Race/ethnicity values were perfectly concordant relative to death certificates for The Counted and The Washington Post.

Validity for race/ethnicity in the other 2 sources was excellent (Fatal Encounters Cohen's k = 0.92; 95% confidence interval [CI] = 0.73, 1.00; WGBH Cohen's k = 0.94; 95% CI = 0.74, 1.00). The Fisher exact test failed to reject the null hypothesis that missingness was independent of race/ethnicity for WGBH (P = .72) and Fatal Encounters (P = .45).

Table 1.2 Summary Statistics and Reliability of Sociodemographic Data From 4 News Media–Based Data Sources Compared with Death Certificates for Persons Killed by Police: Massachusetts, 2004–2016

	January 1, 2004–April 14, 2016		January 1, 2004–December 31, 2014		January 1, 2015–April 14, 2016		
Variable	Death Certificate	Fatal Encounters	Death Certificate	WGBH News	Death Certificate	The Counted	*Washington Post*
No. of cases	84	84	69	68	15	15	14
Age, y, mean (SD)	34.6 (11.8)	34.7 (11.8)	33.7 (12.3)	33.9 (12.3)	38.7 (8.9)	38.9 (8.9)	37.8 (8.7)
Concordance with death certificate, Pearson *r* (95% CI)	NA	>0.99 (0.99, 1.00)	NA	>0.99 (0.99, 1.00)	NA	>0.99 (0.99, 1.00)	>0.99 (0.99, 1.00)
Missing, no. (%)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	1 (7.1)
Gender, no. (%)[a]							
Men	81 (96.4)	81 (96.4)	66 (95.7)	65 (95.6)	15 (100.0)	15 (100.0)	14 (100.0)
Women	3 (3.6)	3 (3.6)	3 (4.3)	3 (4.4)	0 (0.0)	0 (0.0)	0 (0.0)
Concordance with death certificate, % agreement; Cohen's κ (95% CI)[b]	NA	100; 1.00 (0.53, 1.00)	NA	100; 1.00 (0.53, 1.00)	NA	100[c]	100[c]
Missing, no. (%)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)
Race/ethnicity, no. (%)[a]							
Black[d]	26 (31.0)	19 (32.8)	22 (31.9)	17 (29.8)	4 (26.7)	4 (26.7)	4 (28.6)
Hispanic/Latino	13 (15.5)	10 (17.2)	9 (13.0)	7 (12.3)	4 (26.7)	4 (26.7)	3 (21.4)
White	45 (53.6)	29 (50.0)	38 (55.1)	33 (57.9)	7 (46.7)	7 (46.7)	7 (50.0)
Asian/Pacific Islander	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)
American Indian Alaska Native	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)
Concordance with death certificate, % agreement; Cohen's κ (95% CI)[b]	NA	94.8; 0.92 (0.73, 1.00)	NA	96.5; 0.94 (0.74, 1.00)	NA	100; 1.00 (0.64, 1.00)	100; 1.00 (0.62, 1.00)
Missing, no. (%)	0 (0.0)	26 (31.0)[e]	0 (0.0)	11 (16.2)[e]	0 (0.0)	0 (0.0)	0 (0.0)

Note. CI = confidence interval; NA = not applicable. Percentages might not add to 100 because of rounding.

[a]Percent distribution based on observed values; percent of missing based on total population.

[b]WGBH data included a "person of color" category (n = 3). When the death certificate indicated that the decedent was Cape Verdean, we considered person of color to be a concordant pair (n = 2). In one other case when the death certificate did not indicate Cape Verdean, we considered race to be missing in the WGBH data.

[c]Cohen's κ could not be computed because all cases were in the same category (i.e., men).

[d]A total of 3 Cape Verdean decedents were coded as Black.

[e]We failed to reject the null hypothesis of equal missingness rates by death certificate race/ethnicity for WGBH data (Fisher exact test, *P* = .72) and Fatal Encounters data (Fisher exact test, *P* = .45).

DISCUSSION

Our central finding was that death certificates corroborated all 84 Massachusetts legal intervention deaths reported in the 4 journalistic sources between 2004 and 2016 (16 media-

reported cases did not meet the definition). In addition, these journalistic sources provided highly valid demographic data that were consistent with the gold standard of death certificate–reported values. We also observed that deaths misclassified on the death certificates often had non-firearm-related mechanisms, or the medical examiner did not mention law enforcement on the death certificate. During the study period, 24% of the death certificates for cases reported by the media were misclassified (declining from 50% in 2004–2006 to 11.5% in 2013–2015), which was lower than the 42% misclassification identified in a published nonrandom selection of 16 states during 2005 to 2012.[4] Misclassification and undercounts of legal intervention deaths affect multiple other US states.[3,4]

Study findings may not be generalizable to all US states, which have diverse systems for monitoring deaths (e.g., coroner-based systems). Also, because no deaths were reported for American Indian/Alaska Native or Asian/Pacific Islander persons over the study period, we could not draw conclusions about data for those groups.

PUBLIC HEALTH IMPLICATIONS

Previous research suggests that news media–based data sources document higher counts of legal intervention deaths compared with vital statistics.[4] Health departments can use the methods described earlier in this article to quantify the extent of misclassification and address its causes. Media reports also may serve as a supplemental data source to identify legal intervention cases—to be used, for example, to characterize deaths in the National Violent Death Reporting System[5] or in efforts to provide more accurate, timely data to the public.[12] Finally, our results suggest that demographic data provided in media-based sources show promise for their use in

epidemiological research on legal intervention deaths.

Improving monitoring of legal intervention is important to public health because it is a cause of health inequities with broad social implications, and health departments can serve as an official data source to inform policy interventions aimed at reducing police violence.[12]

REFERENCES

1. Tran M. FBI chief: "unacceptable" that Guardian has better data on police violence. The Guardian. October 8, 2015. Available at: https://www.theguardian.com/us-news/2015/oct/08/fbi-chief-says-ridiculous-guardian-washington-post-better-information-police-shootings. Accessed December 5, 2016.

2. Banks D, Couzens L, Blanton C, Cribb D. Arrest- Related Deaths Program Assessment. March 2015. Available at: http://www.bjs.gov/content/pub/pdf/ ardpatr.pdf. Accessed December 5, 2016.

3. Loftin C, McDowall D, Xie MA. Underreporting of homicides by police in the United States, 1976-2013. Homicide Stud. 2017;21(2):159–174.

4. 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.

5. Sorlie PD, Rogot E, Johnson NJ. Validity of demographic characteristics on the death certificate. Epidemiology. 1992;3(2):181–184.

6. Arias E, Heron M, Hakes JK. The validity of race and Hispanic-origin reporting on death certificates in the United States: an update. Vital Health Stat 2. 2016;(172): 1–21.

7. WGBH News. Map: 71 Police-involved deaths in Massachusetts from 2004-2014. December 16, 2014. Available at: http://projects.wgbhnews.org/police-involved-deaths. Accessed April 15, 2016.

8. Fatal Encounters Web site. Available at: http:// fatalencounters.org. Accessed April 15, 2016.

9. The Counted: People killed by police in the US. The Guardian. Available at: http://www.theguardian.com/thecounted. Accessed April 15, 2016.

10. Fatal Force [online police shooting database]. Washington Post. Available at: http://www.washingtonpost. com/policeshootings. Accessed April 15, 2016.

11. Massachusetts Department of Health and Human Services. Massachusetts Registry of Vital Records and Statistics: Genealogical Research. Available at: http://www.mass.gov/eohhs/gov/departments/dph/ programs/admin/dmoa/vitals/genealogical-research. html. Accessed April 15, 2016.

12. 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.

2. Quantifying underreporting of law-enforcement-related deaths in United States vital statistics and news-media-based data sources: A capture–recapture analysis

Justin M. Feldman, Sofia Gruskin, Brent A. Coull, Nancy Krieger

Abstract

Background: Prior research suggests that United States governmental sources documenting the number of law-enforcement-related deaths (i.e., fatalities due to injuries inflicted by law enforcement officers) undercount these incidents. The National Vital Statistics System (NVSS), administered by the federal government and based on state death certificate data, identifies such deaths by assigning them diagnostic codes corresponding to "legal intervention" in accordance with the International Classification of Diseases–10th Revision (ICD-10). Newer, nongovernmental databases track law-enforcement-related deaths by compiling news media reports and provide an opportunity to assess the magnitude and determinants of suspected NVSS underreporting. Our a priori hypotheses were that underreporting by the NVSS would exceed that by the news media sources, and that underreporting rates would be higher for decedents of color versus white, decedents in lower versus higher income counties, decedents killed by non-firearm (e.g., Taser) versus firearm mechanisms, and deaths recorded by a medical examiner versus coroner.

Methods and findings: We created a new US-wide dataset by matching cases reported in a nongovernmental, news-media-based dataset produced by the newspaper *The Guardian*, The Counted, to identifiable NVSS mortality records for 2015. We conducted 2 main analyses for this cross-sectional study: (1) an estimate of the total number of deaths and the proportion unreported by each source using capture–recapture analysis and (2) an assessment of correlates of underreporting of law-enforcement-related deaths (demographic characteristics of the

decedent, mechanism of death, death investigator type [medical examiner versus coroner], county median income, and county urbanicity) in the NVSS using multilevel logistic regression. We estimated that the total number of law-enforcement-related deaths in 2015 was 1,166 (95% CI: 1,153, 1,184). There were 599 deaths reported in The Counted only, 36 reported in the NVSS only, 487 reported in both lists, and an estimated 44 (95% CI: 31, 62) not reported in either source. The NVSS documented 44.9% (95% CI: 44.2%, 45.4%) of the total number of deaths, and The Counted documented 93.1% (95% CI: 91.7%, 94.2%). In a multivariable mixed-effects logistic model that controlled for all individual- and county-level covariates, decedents injured by non-firearm mechanisms had higher odds of underreporting in the NVSS than those injured by firearms (odds ratio [OR]: 68.2; 95% CI: 15.7, 297.5; $p < 0.01$), and underreporting was also more likely outside of the highest-income-quintile counties (OR for the lowest versus highest income quintile: 10.1; 95% CI: 2.4, 42.8; $p < 0.01$). There was no statistically significant difference in the odds of underreporting in the NVSS for deaths certified by coroners compared to medical examiners, and the odds of underreporting did not vary by race/ethnicity. One limitation of our analyses is that we were unable to examine the characteristics of cases that were unreported in The Counted.

Conclusions: The media-based source, The Counted, reported a considerably higher proportion of law-enforcement-related deaths than the NVSS, which failed to report a majority of these incidents. For the NVSS, rates of underreporting were higher in lower income counties and for decedents killed by non-firearm mechanisms. There was no evidence suggesting that underreporting varied by death investigator type (medical examiner versus coroner) or race/ethnicity.

Author summary

Why was this study done?

- Several governmental and nongovernmental databases track the number of law-enforcement-related deaths in the US, but all are likely to undercount these deaths.
- To our knowledge, our study is the first to estimate the proportion of law-enforcement-related deaths properly captured by 2 data sources: official US mortality data, derived from death certificates, and The Counted, a nongovernmental database derived from news media reports.
- US mortality data include virtually all deaths that occur in the country, and law-enforcement-related deaths are supposed to be assigned a diagnostic code corresponding to "legal intervention." If a death is improperly assigned another code, it is considered to be misclassified, which leads to undercounting of the number of law-enforcement-related deaths. We investigated the extent of misclassification and the factors associated with misclassification.

What did the researchers do and find?

- We estimated that 1,166 law-enforcement-related deaths occurred in the US in 2015; The Counted captured a larger proportion of these deaths than the US mortality data.
- Law-enforcement-related deaths were most likely to be misclassified in mortality data if the death was not due to a gunshot wound or if it occurred in a low-income county.

What do these findings mean?

- Datasets based on news media reports may offer higher-quality information on law-enforcement-related deaths than mortality data.

- Further exploration into the ways in which policymakers and public health officials report law-enforcement-related deaths is warranted.

Note: This study was also published as:

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INTRODUCTION

The National Vital Statistics System (NVSS), administered by the US government and based on state death certificates, is the longest-running national data source on law-enforcement-related deaths (i.e., those involving fatal injuries inflicted by law enforcement), but has long been suspected of underreporting a large number of such deaths [1–3]. Other databases run by the US Department of Justice similarly undercount law-enforcement-related deaths [4]. In recent years, a new type of data source on legal intervention mortality has emerged: national databases maintained by newspapers, nongovernmental organizations, and the US Bureau of Justice Statistics (BJS; a governmental organization) that identify incidents via web searches of news media reports [3,5–8].

The NVSS has identified law-enforcement-related deaths since 1949, following the inclusion of "injury by intervention of police" as a diagnostic category in the 6th revision to the International Classification of Diseases (ICD) [9]. While the category has since been renamed as "legal intervention," its definition remains unchanged up to the current ICD revision, ICD-10: "injuries inflicted by the police or other law-enforcing agents, including military on duty, in the course of

arresting or attempting to arrest lawbreakers, suppressing disturbances, maintaining order, and other legal action" [10] (Table 2.1). A designation of legal intervention does not depend on whether the use of force resulting in the injury was lawful [11] or whether the injuries were inflicted intentionally.

Table 2.1. Definitions for law-enforcement-related deaths and reasons for underreporting in the National Vital Statistics System and The Counted.

Source	Term	Definition	Reasons for underreporting
National Vital Statistics System	"Legal intervention"	Based on the definition from the International Classification of Diseases–10th Revision (ICD-10): "injuries inflicted by the police or other law-enforcing agents, including military on duty, in the course of arresting or attempting to arrest lawbreakers, suppressing disturbances, maintaining order, and other legal action" [10]	Deaths will not appear if they are misclassified, i.e., assigned an ICD-10 code that does not correspond to legal intervention. This may happen because law enforcement involvement is not mentioned on the death certificate, or potentially due to coding errors by the National Center for Health Statistics.
The Counted	"People killed by police and other law enforcement agencies in the United States"	From The Counted website: "What is included in The Counted? Any deaths arising directly from encounters with law enforcement. This will inevitably include, but will likely not be limited to, people who were shot, tasered and struck by police vehicles as well those who died in police custody. What is not included in The Counted? Self-inflicted deaths during encounters with law enforcement. For instance, a person who died by crashing his or her vehicle into an oncoming car while fleeing from police at high speed is not regarded by the Guardian's database to have been killed by law enforcement. The database does not include suicides or self-inflicted deaths including drug overdoses in police custody or detention facilities." [12]	Deaths may not appear if they were unreported in news media, or if they were reported but The Counted staff did not identify these publications.

Prior studies found that NVSS counts of legal intervention deaths were lower in at least some US states compared to counts reported by law enforcement data sources, suggesting that the NVSS misses some proportion of these deaths [1,13,14]. This underreporting occurs when a death certificate is misclassified: it is wrongly assigned an ICD code that does not correspond to legal intervention, and the death can therefore not be identified as law-enforcement-related in queries of NVSS data (Table 2.1). Misclassification primarily occurs because the coroner or medical examiner certifying the death fails to mention police involvement in the literal text fields of the death certificate's cause of death section (e.g., the field labeled "Describe how the injury occurred" does not state "killed by police"), although mistakes in the process of assigning ICD codes may still occur even when the death certificate indicates police involvement [15]. To our knowledge, there have been no prior national estimates of the misclassification rate for legal intervention deaths in the NVSS, nor has any research investigated factors associated with misclassification.

In recent years, a number of nongovernmental initiatives have sought to identify incidents of law-enforcement-related deaths in the US based on web searches of news media, and these databases provide counts that far exceed those reported in the NVSS and traditional US Department of Justice governmental data sources. Examples of such nongovernmental efforts include *The Guardian*'s The Counted (covering 2015–2016) [5], *The Washington Post*'s police shooting database (2015–present; excludes non-firearm deaths) [7], and Fatal Encounters (2014–present prospectively; 2000–2013 retrospectively) [6]. Prior analyses have found that, within the same time period, these sources report a nearly identical set of cases [16]. In addition to these nongovernmental efforts, the BJS redesigned its Arrest-Related Deaths (ARD) program in mid-

2015 to track deaths in custody using a similar method: ARD first identifies cases based on a systematic internet search of news media reports, then requests more information about deaths from law enforcement agencies, medical examiners, and coroners [8]. Even as researchers have made increasing use of these news-media-based data sources [3,16–18] and the federal government has adopted their practices, there have been no prior estimates about the proportion of law-enforcement-related deaths that remain unreported in databases drawn from news media.

Our a priori hypotheses were that underreporting by the NVSS would exceed that by the news media sources, and that misclassification rates would be higher for decedents of color versus white, decedents in lower versus higher income counties, decedents killed by non-firearm versus firearm mechanisms, and deaths recorded by a medical examiner versus coroner. Our study aims to improve public health monitoring of law-enforcement-related deaths, which may ultimately aid efforts to improve accountability for both individual deaths and aggregate trends [18].

METHODS

We created a dataset of law-enforcement-related deaths in 2015 by matching 2 sources: The Counted, a news-media-based dataset created by the newspaper *The Guardian* [5], and the NVSS, from which we obtained individually identifiable mortality data for cases that were reported by *The Guardian*. Our study was deemed exempt from review by the Harvard T.H. Chan School of Public Health institutional review board (IRB16-1146) because it did not involve living persons. We were not able to publish death counts for all US states and counties due to privacy restrictions for NVSS data. We did not have a written prospective analysis plan; we agreed on an analytic plan at an October 2016 meeting and conducted all analyses in January 2017. Our cross-sectional study involved 2 main analyses: (1) a capture–recapture analysis to

estimate the total number of law-enforcement-related deaths in the US during 2015, as well as the proportions captured by The Counted and the NVSS, and (2) a multilevel logistic regression analysis investigating the correlates of misclassification for law-enforcement-related deaths in NVSS data. This report has been prepared according to STROBE guidelines, as suggested by the Enhancing the QUAlity and Transparency Of health Research (EQUATOR) network.

The Counted identified US law-enforcement-related deaths in 2015–2016 using web searches of news media reports; it defined these incidents as "any deaths arising directly from encounters with law enforcement . . . [such as] people who were shot, tasered and struck by police vehicles as well those who died in police custody" and excluded persons who died of self-inflicted injuries (Table 2.1) [12]. The website of the dataset also allowed members of the public to report cases; however, all deaths in the 2015–2016 dataset were substantiated based on local news media reports with the exception of 5 deaths identified via *The Guardian*'s original reporting [19]. *The Guardian* staff extracted characteristics of each incident including the decedent's name, demographic information, street address of the police encounter, date of the injury occurrence, and mechanism of death. They also included a brief narrative description of events leading to the death. When necessary, reporting staff requested more information from local government agencies.

The NVSS receives electronic mortality data, based on death certificates, on deaths from all causes that are reported by 52 US-based independent registration areas ("states"; including the 50 states, District of Columbia, and New York City, which reports independently of New York State). On death certificates, funeral home directors record demographic information, and

coroners or medical examiners report cause of death information. Staff at state vital statistics registries input death certificate information in a standardized electronic format. They send these data to the National Center for Health Statistics, which assigns up to 20 cause of death codes, following ICD-10, based on literal text written by the coroner/medical examiner. For a majority of decedents—approximately 60% of cases coded as legal intervention deaths in 2015—ICD codes are assigned by a computer program, SuperMICAR (National Center for Health Statistics; https://www.cdc.gov/nchs/nvss/mmds/super_micar.htm). Trained nosologists assign codes when automatic assignment fails.

Exclusion criteria

The Counted used a broader definition for law-enforcement-related deaths than the NVSS, which follows the ICD definition for legal intervention (Table 2.1). Unlike the ICD definition, The Counted did not require that the injury be inflicted by a law enforcement officer and made no differentiation as to whether the injury was inflicted while a law enforcement officer was acting in the line of duty. To ensure that both datasets were comparable, we excluded cases from The Counted that did not conform to the ICD definition of legal intervention, while also recognizing that ambiguity in the ICD definition can make it unclear whether the diagnostic category is appropriate for certain instances. One category for which the definition lacks clarity is motor-vehicle-related deaths involving law enforcement. While on duty, an officer may accidently hit a pedestrian, although it is unclear whether this death occurred "in the course of arresting or attempting to arrest lawbreakers, suppressing disturbances, maintaining order, and other legal action." Because these injuries may not specifically relate to the officer's law enforcement role, we excluded decedents killed in motor-vehicle-related accidents unless they were being pursued

by police or were intentionally injured in a police vehicle during transit. Another category for which definitional ambiguities arise is "deaths in custody," i.e., non-firearm deaths that occur during the course of arrest or in holding cells and jails. In such instances, the circumstances of the death may be unknown to the public, and it may not be clear to death investigators whether actions by officers contributed to the death [20]. We excluded deaths in custody unless The Counted described a clear mechanism through which law enforcement actions may have caused the death (medical neglect, use of a chokehold, use of a Taser) or the death was reportedly ruled a homicide in The Counted's narrative description (a homicide ruling can be made only if the injury was intentionally inflicted, while legal intervention, as defined by the ICD-10, does not require intentionality; however, a finding of homicide also provides evidence that law enforcement officers caused the death).

Additional exclusion criteria included instances of domestic violence perpetrated by law enforcement officers, as these did not occur in the course of carrying out "legal action." For the same reason, we excluded deaths by "friendly fire" (i.e., an accidental shooting of one officer by another; the only such death reported in the 2015 The Counted data occurred during a training). Finally, we also excluded the small number of decedents ($N = 3$; <0.3% of deaths) who were injured in 2015 but died in 2016, as they would not appear in the 2015 mortality data.

National Death Index Plus matching process

The National Death Index (NDI) is a restricted-access database, administered by the National Center for Health Statistics, that researchers can use to access the same electronic mortality data reported in the NVSS [21,22]. Requestors submit a list of decedents, and the NDI returns either

vital status only (i.e., confirmation of whether the individual has died) or, if the researcher pays a higher fee for "NDI Plus," all reported ICD-10 coded causes of death for each decedent. For all cases meeting our inclusion criteria, we submitted names and years of birth (based on media-reported age) using NDI Plus. NDI Plus requires that submitted data include exact matches for first names, near matches for last names, and near matches for year of birth (±1 year) [22]. Matched records return the state in which the death occurred, date of death, and multiple ICD-10 coded causes of death. We identified true matches from NDI Plus output by ensuring dates and states of death were consistent with media reports. We considered the date of death to match when it fell within 4 days of the injury occurrence date reported in The Counted.

We rejected cases for which the date of death preceded the reported date of injury by more than 4 days. For cases whose NDI record reported a date of death more than 4 days after the reported injury, we flagged the result as a match only if we were able to locate a news article reporting the later date of death. Similarly, for deaths whose matched record reported a state that differed from the location of injury reported by The Counted, we flagged it as a match if we were able to locate a news article confirming the state of death (differing states for injury and death can happen if a person is transported across state lines to a hospital before the death). Finally, we tabulated the characteristics of matched cases and unmatched cases and stratified by measured covariates for comparison. Unmatched cases were not included in any subsequent analyses.

Estimating the total number of law-enforcement-related deaths

Our first set of analyses used capture–recapture analysis (also known as multiple systems estimation) to estimate the number of US law-enforcement-related deaths in 2015. Using 2 or

more matched, incomplete lists, capture–recapture analysis estimates the total size of a population, including the number of cases missed by all lists [23]. To conduct the capture–recapture analysis, we obtained monthly counts of deaths reported as legal intervention deaths in the 2015 NVSS public-use multiple cause of death file [24]. Using those counts along with the dataset derived from matching The Counted and NDI, we estimated the number of deaths (1) reported in The Counted only, (2) classified as legal intervention deaths in the NVSS only, and (3) reported in both systems. We considered a case to be reported as a legal intervention death in the NVSS when at least 1 of its multiple ICD-10 cause of death codes corresponded to legal intervention (ICD-10: Y35.0–Y35.4; Y35.6–Y35.7; Y89.0). We assumed unmatched cases from The Counted (95/1,086; 8.7%) were classified as legal intervention deaths in the NVSS at the same rate as matched cases: we added 43 of these deaths (45%) to the group that was captured by both the NVSS and The Counted, and added the remaining 52 cases (55%) to the group captured by The Counted only.

We used Poisson regression, with data stratified by 3-month periods, to conduct capture–recapture analysis. For capture–recapture analyses with only 2 data sources, the method assumes independence between the lists (i.e., the probability of a case appearing in one list is uncorrelated with its probability of appearing in the other list). This assumption is frequently violated in epidemiologic contexts, however: often there is positive list dependence, which leads to underestimated population sizes [25]. In our study, one possible source of list dependence is that both databases typically rely on reporting by police departments to ascertain cases, either when the agency issues press releases (in the case of media reports) or when it releases reports detailing the circumstances of the death to the coroner or medical examiner (in the case of the

NVSS). With respect to the latter, journalists have revealed multiple incidents in which law enforcement agencies failed to release pertinent documents to death investigators for in-custody deaths or pressured death investigators to make a finding of non-homicide [26–28], although there is no evidence to suggest how frequently this occurs.

To address the potential for list dependence, we conducted a sensitivity analysis to estimate the maximum plausible number of cases adjusting for a prior correlation value between our 2 lists. We followed the method employed by Lum and Ball [29], who incorporated prior values, based on capture–recapture analyses of homicides from comparable sources in 5 other countries, when they estimated the number of law-enforcement-related deaths in the US from 2 probabilistically matched law enforcement datasets. By including the highest pairwise list correlation value they reported (0.93, based on a study of homicides in Syria) as an offset in our Poisson model, we calculated a maximum plausible estimate of the number of deaths in this sensitivity analysis.

Analyzing correlates of misclassification in National Vital Statistics System mortality data

Our next set of analyses sought to identify correlates of misclassification of legal intervention deaths in NVSS mortality data, with misclassification defined as there not being any ICD-10 codes for legal intervention among the reported multiple causes of death. For the purpose of these analyses, we assumed The Counted's matched cases were a random sample of the total population of US law-enforcement-related deaths in 2015. This is a tenable assumption because, as we report below, The Counted underreports relatively few incidents, and there appear to be no systematic differences between matched and unmatched cases. We used demographic data (age, gender, and race/ethnicity) reported in The Counted, which our prior research has found to be highly concordant with values reported on death certificates [15]. We also used The Counted

data on mechanism of death (firearm or non-firearm) and the county where the fatal injury occurred. At the county level, we identified median household income quintiles based on 2011–2015 US Census data [30], urbanicity based on National Center for Health Statistics classifications [31], and death investigator type (medical examiner, elected coroner, or appointed coroner) based on a Centers for Disease Control and Prevention (CDC) dataset [32]. For counties with ambiguous CDC data regarding death investigator type, we contacted local government agencies directly.

After tabulating descriptive statistics on misclassified and properly classified legal intervention deaths, we calculated and mapped misclassification rates by state. We then conducted multilevel logistic regression, using Stata version 14.2 (StataCorp [https://www.stata.com]), to model the odds of misclassification. Our univariable and multivariable models included random intercepts for counties and states. We used post-estimation commands to calculate the average marginal effects for select covariates, and we report these as predicted probabilities of misclassification.

RESULTS

The Counted identified 1,146 law-enforcement-related deaths in the US during 2015. Applying our exclusion criteria, we eliminated 60 cases that did not conform to the ICD definition of legal intervention, such that the initial dataset included 1,086 observed deaths (Table 2.2).

Table 2.2. Cases included and excluded as legal intervention deaths from *The Guardian*'s The Counted database of law-enforcement-related deaths (US, 2015).

Category	Number
Total cases reported	1,146
Exclusion criteria	
Struck by vehicle, unless decedent was injured by law enforcement vehicle during pursuit or was intentionally injured as a passenger during transport	27
Domestic violence	6
In-custody death, unless it followed use of a Taser/chokehold, involved withholding essential care (e.g., medical care or water), or was reported by The Counted as having been ruled a homicide by the coroner/medical examiner	23
Injury occurred in 2015, but death occurred in 2016	3
"Friendly fire" (officer accidently shot by another officer)	1
Total cases excluded	60
Total cases included as 2015 legal intervention deaths	1,086

Among the 1,086 observed cases, the majority were ages 18–44 years (766/1,086; 70.5%), were men (1,043/1,086; 90.6%), were killed by a firearm (1,008/1,086; 92.8%), resided in a large metro area (583/1,086; 53.7%), and had their death reported by a medical examiner (682/1,086; 57.8%) (Table 2.3). Additionally, 27.1% (294/1,086) of decedents were black, 17.2% were Hispanic (187/1,086), 1.1% were American Indian (12/1,086), 2.0% were Asian/Pacific Islander (22/1,086), 50.9% were white non-Hispanic (553/1,086), and 1.7% were of unknown race/ethnicity (18/1,086) (Table 2.3); the corresponding national estimates for the racial/ethnic composition of the US population in 2015 were 13.0% black, 17.6% Hispanic, 0.8% American Indian, 5.9% Asian/Pacific Islander, and 62.6% white non-Hispanic [33].

We identified true matches for 91.3% (991/1,086) of included cases using NDI Plus (Table 2.3). Matching rates were lower than 85% for decedents who were women (36/43; 83.7%), had missing race/ethnicity (14/18; 77.8%), or had death certified by an appointed coroner (29/35; 82.9%). Results from Fisher's exact tests show that among these individual- and county-level characteristics, the only variable for which differences in matching rates were statistically

significant ($p = 0.049$) was the death investigator type. These tests did not adjust for clustering by counties, however; p-values for county-level variables are therefore biased downward and may suggest statistically significant differences in matching rates where none exist.

Among the 991 matched cases, firearm deaths comprised 92.8%, or 920/991 cases (Table 2.4). The second most common mechanism was death due to Taser (46/991; 4.6%). This was followed by struck by/against injuries (18/991; 1.8%), motor-vehicle-related injuries (5/991; 0.4%), and neglect (3/991; 0.3%).

Table 2.3. Characteristics of law-enforcement-related deaths from The Counted matched and unmatched to National Vital Statistics System mortality records using the National Death Index (US, 2015).

Characteristic	Matched cases	Unmatched cases	Total cases	Percent matched (95% CI)	*p*-Value (Fisher's exact test)[1]
Total sample	991	95	1,086	91.3% (89.4, 92.9)	n/a
Individual-level characteristics					
Age					0.61
Less than 18 years	16	1	17	94.1% (71.3, 99.9)	
18 to 44 years	704	62	766	91.9% (89.4, 93.7)	
45 years and older	271	30	301	90.0% (86.1, 93.2)	
Missing	0	2	2	0.0% (0.0, 84.2)	
Gender					0.09
Men	955	88	1,043	91.6% (89.7, 93.2)	
Women	36	7	43	83.7% (69.3, 93.2)	
Missing	0	0	0	n/a	
Race/ethnicity[2]					0.12
Black	265	29	294	90.1% (86.1, 93.2)	
White	516	37	553	93.3% (90.1, 95.2)	
Hispanic	164	23	187	87.7% (82.1, 92.0)	
American Indian/Alaska Native	11	1	12	91.7% (61.5, 99.8)	
Asian/Pacific Islander	21	1	22	95.5% (77.2, 99.9)	
Missing	14	4	18	77.8% (52.4, 93.6)	
Mechanism of death					0.84
Firearm	920	88	1,008	91.3% (89.4, 92.9)	
Non-firearm	71	7	78	91.0% (82.4, 96.3)	
Missing	0	0	0	n/a	
County-level characteristics					
Death investigator type					0.05
Medical examiner	582	46	628	92.7% (90.4, 94.6)	
Coroner (elected)	380	43	423	89.8% (86.6, 92.5)	
Coroner (appointed)	29	6	35	82.9% (66.4, 93.4)	
Missing	0	0	0	n/a	
Urbanicity					0.20
Large metro–central	358	33	391	91.6% (88.4, 94.1)	
Large metro–fringe	171	21	192	89.1% (83.8, 93.1)	
Medium metro	223	14	237	94.1% (90.3, 96.7)	
Small metro	70	12	82	85.4% (75.8, 92.2)	
Micropolitan	71	6	77	92.2% (83.8, 97.1)	
Non-core	98	8	106	92.5% (85.7, 96.7)	
Missing	0	0	0	n/a	
County median income (quintiles)					0.19
Q5 (highest income)	198	18	216	91.7% (87.1, 95.0)	
Q4	189	20	209	90.4% (85.6, 94.1)	
Q3	201	23	224	89.7% (85.0, 93.4)	
Q2	196	10	206	95.1% (91.3, 97.6)	
Q1 (lowest income)	207	24	231	89.6% (84.9, 93.2)	
Missing	0	0	0	n/a	

[1]p-Values are for a difference in matching rate across categories of a characteristic; p-values are not adjusted for clustering and are therefore biased downward for county-level variables.

[2]Other than Hispanic, all races are non-Hispanic.

n/a, not applicable.

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Table 2.4. National Vital Statistics System cause of death codes, by mechanism of death, for law-enforcement-related deaths matched to The Counted.

Mechanism of death (percent of total; 95% CI)	Underlying cause of death as reported in the National Vital Statistics System (ICD-10 range)[1]																	
	All		Legal intervention (Y35; Y89.0)[2]		Assault (X95–Y09)		Events of undetermined intent or cause missing (Y10–Y34; R99)[3]		Suicide (X60–X84)		Accident (V01–X59)		Circulatory/ respiratory diseases (I00–J99)		Mental/behavioral disorders (F00–F99)		Other causes of death	
	N	Percent	*N*	Percent (95% CI)	*N*	Percent (95% CI)	*N*	Percent (95% CI)	*N*	Percent (95% CI)	*N*	Percent (95% CI)	*N*	Percent (95% CI)	*N*	Percent (95% CI)	*N*	Percent (95% CI)
All (100.0%)	991	100.0	444	44.8 (41.7, 48.0)	471	47.5 (44.4, 50.7)	22	2.2 (1.4, 3.3)	16	1.6 (0.9, 2.6)	15	1.5 (0.8, 2.5)	14	1.4 (0.8, 2.4)	7	0.7 (0.3, 1.4)	2	0.2 (0.0, 0.7)
Firearm (92.8%; 91.0, 94.4)	920	100.0	434	47.2 (43.9, 50.4)	456	49.6 (46.4, 52.8)	11	1.2 (0.6, 2.1)	16	1.7 (1.0, 2.8)	1	0.1 (0.0, 0.6)	2	0.2 (0.0, 0.7)	0	0.0 (0.0, 0.4)	0	0.0 (0.0, 0.4)
Taser (4.6%; 3.4, 6.1)	46	100.0	6	13.0 (4.9, 26.3)	10	21.7 (10.9, 36.4)	8	17.4 (7.8, 31.4)	0	0.0 (0.0, 7.7)	10	21.7 (10.9, 36.4)	7	15.2 (6.3, 28.9)	5	10.9 (3.6, 23.6)	0	0.0 (0.0, 7.7)
Struck by/against (1.8%; 1.1, 2.9)	18	100.0	4	22.2 (6.4, 47.6)	4	22.2 (6.4, 47.6)	2	11.1 (1.4, 34.7)	0	0.0 (0.0, 18.5)	1	5.6 (0.1, 27.3)	5	27.8 (9.7, 53.5)	2	11.1 (1.4, 34.7)	0	0.0 (0.0, 18.5)
Motor vehicle (0.4%; 0.1, 1.0)	4	100.0	0	0.0 (0.0, 60.2)	1	25.0 (0.6, 80.6)	0	0.0 (0.0, 60.2)	0	0.0 (0.0, 60.2)	3	75.0 (19.4, 99.4)	0	0.0 (0.0, 60.2)	0	0.0 (0.0, 60.2)	0	0.0 (0.0, 60.2)
Neglect (0.3%; 0.1, 0.9)	3	100.0	0	0.0 (0.0, 70.6)	0	0.0 (0.0, 70.6)	1	33.3 (0.8, 90.6)	0	0.0 (0.0, 70.6)	0	0.0 (0.0, 70.6)	0	0.0 (0.0, 70.6)	0	0.0 (0.0, 70.6)	2	66.7 (0.9, 99.2)

[1]Mortality records report 1 underlying cause of death, defined as "(a) the disease or injury which initiated the train of events leading directly to death, or (b) the circumstances of the accident or violence which produced the fatal injury" [22]. The records also report up to 20 "multiple causes of death" based on any other health conditions reported on the death certificate. In rare instances (N = 2), legal intervention was reported as a multiple cause of death but not an underlying cause of death. We nonetheless present these cases in the column for legal intervention.

[2]Excludes legal execution, Y35.5.

[3]A classification of "events of undetermined intent" signifies that the coder knew (based on death certificate literal text) that the cause of death involved external injuries, but could not identify whether the injury was due to legal intervention, assault, suicide, or accident. "Missing" signifies that the coder was unable to make any determination whatsoever about cause of death.

ICD-10, International Classification of Diseases–10th Revision.

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Overall, 444 (44.8%) of the law-enforcement-related deaths were properly classified as legal intervention deaths in the NVSS. The most common underlying cause of death for misclassified cases was assault, which was more prevalent than legal intervention and accounted for 47.5% of all matched cases ($N = 471$). While nearly all firearm deaths were coded as legal intervention or assault (96.8% combined), the causes of death reported for non-firearm mechanisms were more heterogeneous. Deaths that followed the use of Tasers were reported as legal intervention (6/46; 13%), assault (10/46; 21.7%), missing/undetermined (8/46; 17.4%), accidental injury (10/46, 21.7%), and mental health/behavioral disorders (5/46; 10.9%). Struck by/against was the only other non-firearm mechanism for which any cases were classified as legal intervention (4/18 struck by/against injuries; 22.2%).

Estimates of the number of US law-enforcement-related deaths in 2015

There were 599 deaths reported in The Counted only, 36 reported in the NVSS only, 487 reported in both lists, and an estimated 44 (95% CI: 31, 62) not reported in either list. Assuming independence between lists, our capture–recapture model estimates that the total number of US law-enforcement-related deaths in 2015 was 1,166 (95% CI: 1,153, 1,184) (Fig 2.1). This suggests that the NVSS documented 44.9% (95% CI: 44.2%, 45.4%) of law-enforcement-related deaths, and The Counted documented 93.1% (95% CI: 91.7%, 94.2%). Our sensitivity analyses show that these estimates are robust to potential pairwise list correlation. Assuming the highest of the pairwise list correlation values reported by Lum and Ball [29], 0.93, the maximum number of deaths was only slightly higher, equaling 1,233 (95% CI: 1,200, 1,280). Under this maximum scenario, The Counted documented 88.1% (95% CI: 84.8%, 90.5%) of cases, and the NVSS documented 42.4% (95% CI: 40.9%, 43.6%).

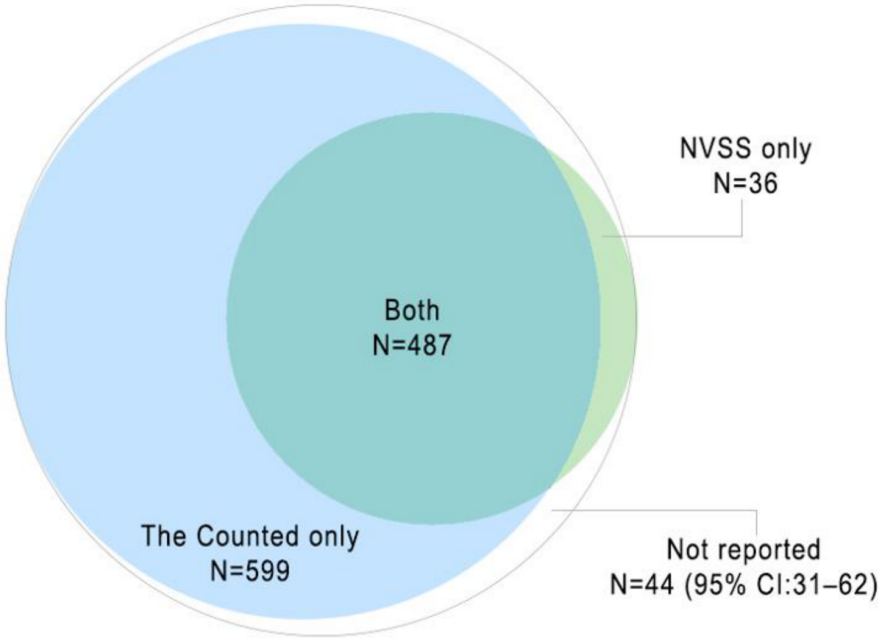

Fig 2.1. Two-source estimate, assuming independence between lists, of the total number of law-enforcement-related deaths in the US, 2015 (N = 1,166; 95% CI: 1,153, 1,184).

Correlates of ICD-10 misclassification of law-enforcement-related deaths

We found that, among cases reported in The Counted and matched to NVSS data, 55.2% (547/991) were misclassified in the NVSS. These deaths occurred in 51 states (49 states, the District of Columbia, and New York City; The Counted did not report any cases from Rhode Island meeting our inclusion criteria) (Table 2.5; Fig 2.2) and in 491 of 3,144 US counties. Misclassification rates ranged from 0% to 100%; among states with ≥10 matched cases, rates ranged from 17.6% (Washington) to 100.0% (Oklahoma). Taken together, 5 states—California, Texas, Florida, Oklahoma, and Arizona—contained 42.4% of matched cases and accounted for a majority of the misclassified cases (50.3%). Among these 5 states, misclassification was 40% to <60% in 1 state (California), 60% to <80% in 3 states (Arizona, Florida, and Texas), and ≥80% in 1 state (Oklahoma).

Table 2.5. Misclassification rates for law-enforcement-related deaths in National Vital Statistics System mortality data based on cases matched to The Counted, 2015 (N = 991).

Percent misclassified	State (abbreviation) by number of deaths		
	<10 deaths	**10 to <20 deaths**	**≥20 deaths**
<20%	Connecticut (CT), Delaware (DE), District of Columbia (DC), Hawaii (HI), Maine (ME), Montana (MT), New Hampshire (NH), South Dakota (SD)	Oregon (OR)	(None)
20 to <40%	West Virginia (WV)	Maryland (MD), Massachusetts (MA), New Jersey (NJ), New Mexico (NM), Utah (UT), Virginia (VA)	North Carolina (NC), Washington (WA)
40 to <60%	Idaho (ID), New York City[1], Wyoming (WY)	Kansas (KS), Kentucky (KY), Michigan (MI), Minnesota (MN), Nevada (NV), New York (NY), Wisconsin (WI)	California (CA), Colorado (CO), Georgia (GA), Illinois (IL), Indiana (IN), Ohio (OH), Pennsylvania (PA)
60 to <80%	Alaska (AK), Iowa (IA)	Mississippi (MS), Missouri (MO), South Carolina (SC), Tennessee (TN)	Arizona (AZ), Florida (FL), Texas (TX)
≥80%	Arkansas (AR), North Dakota (ND), Nebraska (NE), Vermont (VT)	Alabama (AL)	Louisiana (LA), Oklahoma (OK)

The matched dataset did not include any deaths from Rhode Island.

[1]New York City reports deaths to the National Vital Statistics System independently of New York State.

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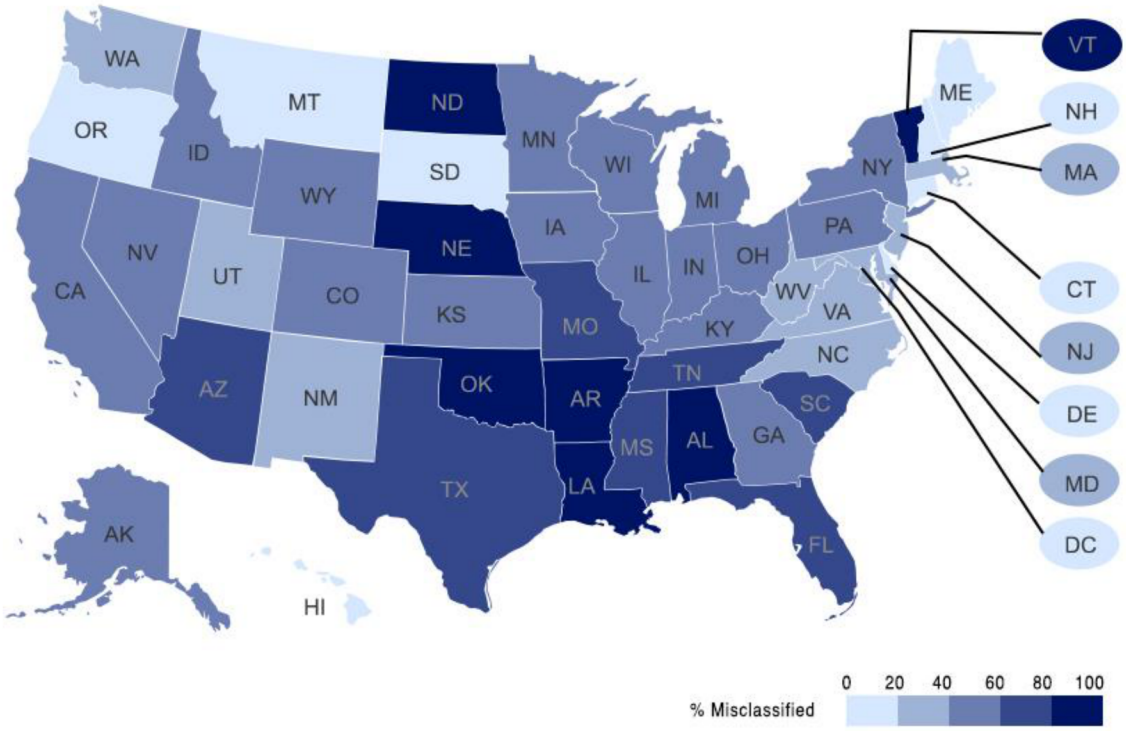

Fig 2.2. Law-enforcement-related death misclassification rates by state (2015; N = 991).

In descriptive tabulations (Table 2.6), groups for whom misclassification rates exceeded 60% included decedents age <18 years (11/16; 68.8%), black decedents (162/265; 61.1%), decedents with a non-firearm mechanism of death (61/71; 85.9%), and those who died in a county in the second lowest income quintile (124/196; 63.3%). Misclassification rates were lower than 40% among persons who were Asian/Pacific Islander (8/21; 38.1%) and those who died in the highest income counties (76/198; 38.4%). Chi-squared tests of independence found that misclassification rates exhibited statistically significant differences by race/ethnicity ($p = 0.04$), mechanism of death ($p < 0.01$), and county income quintile ($p < 0.01$).

Table 2.6. Characteristics of misclassified and properly classified law-enforcement-related deaths in the National Vital Statistics System, based on incidents identified in The Counted (US, 2015).

Characteristic	Misclassified cases	Properly classified cases	Total cases	Percent misclassified (95% CI)	*p*-Value (χ^2 test of independence)[1]
Total sample	547	444	991	55.2%	n/a
Individual-level characteristics					
Age					
Less than 18 years	11	5	16	68.8% (41.3, 89.0)	0.27
18 to 44 years	395	306	701	56.3% (52.6, 60.1)	
45 years and older	141	130	271	52.0% (45.9, 58.1)	
Missing	0	0	0	n/a	
Gender					
Men	526	429	955	55.1% (51.9, 58.3)	0.70
Women	21	15	36	58.3% (40.8, 74.9)	
Missing	0	0	0	n/a	
Race/ethnicity[2]					
Black	162	103	265	61.1% (55.0, 67.0)	0.04
White	266	250	516	51.6% (47.1, 55.9)	
Hispanic	97	67	164	59.1% (51.2, 66.7)	
American Indian/Alaska Native	6	5	11	54.5% (23.4, 83.3)	
Asian/Pacific Islander	8	13	21	38.1% (18.1, 61.2)	
Missing	8	6	14	57.1% (28.9, 82.3)	
Mechanism of death					
Firearm	486	434	920	52.8% (49.5, 56.1)	<0.01
Non-firearm	61	10	71	85.9% (75.6, 93.0)	
Missing	0	0	0	n/a	
County-level characteristics					
Death investigator type					
Medical examiner	320	262	582	55.0% (50.8, 59.1)	0.90
Coroner (elected)	212	168	380	55.8% (50.6, 60.9)	
Coroner (appointed)	15	14	29	51.7% (32.5, 70.6)	
Missing	0	0	0	n/a	
Urbanization					
Large metro–central	210	148	358	58.7% (53.4, 63.8)	0.32
Large metro–fringe	85	86	171	49.7% (42.0, 57.4)	
Medium metro	129	94	223	57.8% (51.1, 64.4)	
Small metro	35	35	70	50.0% (37.8, 62.2)	
Micropolitan	37	34	71	52.1% (40.0, 64.1)	
Non-core	51	47	98	52.0% (41.2, 62.2)	
Missing	0	0	0	n/a	
County median income (quintiles)					
Q5 (highest income)	76	122	198	38.4% (31.6, 45.5)	<0.01
Q4	111	78	189	58.7% (51.4, 65.8)	
Q3	116	85	201	57.7% (50.6, 64.6)	
Q2	124	72	196	63.3% (56.1, 70.0)	
Q1 (lowest income)	120	87	207	58.0% (50.9, 64.8)	
Missing	0	0	0	n/a	

[1]p-Values are not adjusted for clustering and are therefore biased downward for county-level variables.

[2]Other than Hispanic, all races are non-Hispanic.

n/a, not applicable.

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The multivariable mixed-effects logistic model (Table 2.7), which controlled for all individual- and county-level covariates, identified statistically significant differences in misclassification rates by mechanism of death (odds ratio [OR] for non-firearm versus firearm: 68.2; 95% CI: 15.7, 297.5; $p < 0.01$) and county median household income quintile (OR: 10.1; 95% CI: 2.4, 42.8; $p < 0.01$). Using average values for all other covariates, the predicted probability of misclassification for firearm deaths was 48.6% (95% CI: 41.5%, 55.6%), while for non-firearm deaths it was 86.4% (95% CI: 78.2%, 94.6%). For deaths occurring in the highest-income-quintile counties, the predicted probability of misclassification was 33.4% (95% CI: 23.3%, 43.5%), while among the lowest-income-quintile counties the probability was 57.2% (95% CI: 46.8%, 67.6%). Finally, there was 2.7 times more variability in misclassification rates within states (county-level variance for random intercepts = 7.1) than between states (variance = 2.7).

Table 2.7. Multilevel logistic regression models for the relative odds of misclassification of law-enforcement-related deaths in National Vital Statistics System mortality data (US, 2015; N = 991).

Characteristic	Univariable models			Multivariable model (controlling for all variables below)		
	OR	95% CI	*p*-Value	OR	95% CI	*p*-Value
Individual-level characteristics						
Age						
Less than 18 years	2.14	0.33, 13.94	0.42	2.34	0.34, 15.98	0.39
18 to 44 years (referent)	1.00	—	—	1.00	—	—
45 years and older	0.96	0.59, 1.58	0.88	1.01	0.58, 1.76	0.98
Gender						
Men (referent)	1.00	—	—	1.00	—	—
Women	1.24	0.44, 3.53	0.69	1.46	0.48, 4.46	0.51
Race/ethnicity[1]						
Black	1.50	0.85, 2.66	0.16	1.27	0.67, 2.42	0.46
White (referent)	1.00	—	—	1.00	—	—
Hispanic	1.44	0.75, 2.77	0.27	1.33	0.66, 2.68	0.42
American Indian/Alaska Native	1.70	0.16, 17.81	0.66	1.31	0.12, 13.91	0.83
Asian/Pacific Islander	0.67	1.59, 2.84	0.59	0.71	0.15, 3.30	0.66
Mechanism of death						
Firearm (referent)	1.00	—	—	1.00	—	—
Non-firearm	63.74	15.11, 268.77	<0.01	68.24	15.65, 297.46	<0.01
County-level characteristics						
Death investigator type						
Medical examiner (referent)	1.00	—	—	1.00	—	—
Coroner (elected)	1.57	0.65, 3.78	0.31	1.85	0.66, 5.18	0.24
Coroner (appointed)	1.23	0.10, 14.87	0.87	1.01	0.07, 15.59	0.99
Urbanization						
Large metro–central	1.22	0.44, 3.38	0.70	1.53	0.48, 4.89	0.48
Large metro–fringe	1.41	0.50, 3.97	0.51	4.00	1.14, 14.03	0.03
Medium metro (referent)	1.00	—	—	1.00	—	—
Small metro	0.92	0.31, 2.76	0.89	1.03	0.31, 3.38	0.96
Micropolitan	0.58	0.17, 1.97	0.38	0.35	0.09, 1.40	0.14
Non-core	0.62	0.18, 2.09	0.44	0.53	0.13, 2.08	0.36
County median income (quintiles)						
Q5 (highest income; referent)	1.00	—	—	1.00	—	—
Q4	3.58	1.09, 11.78	0.04	8.32	2.00, 34.57	<0.01
Q3	3.46	1.08, 11.05	0.04	7.02	1.75, 28.17	<0.01
Q2	3.54	1.16, 10.89	0.03	10.39	2.52, 42.82	<0.01
Q1 (lowest income)	2.71	0.92, 7.97	0.07	10.11	2.39, 42.82	<0.01
Variance: county random intercepts | state	—			7.12		
Variance: state random intercepts	—			2.67		

[1]Other than Hispanic, all races are non-Hispanic.

OR, odds ratio.

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DISCUSSION

We estimated the total number of law-enforcement-related deaths in the US in 2015—1,166 deaths (95% CI: 1,153, 1,184)—and found that, as hypothesized, a much higher proportion of such deaths were captured by *The Guardian*'s The Counted (93.1%; 95% CI: 91.7%, 94.2%) than by US vital statistics data (44.9%; 95% CI: 44.2%, 45.4%). We also found that misclassification rates in NVSS data for law-enforcement-related deaths varied widely both within and between states, and that misclassification was more likely for non-firearm deaths than firearm deaths and for deaths that occurred outside of the highest income counties. These findings together affirm that major shortcomings exist in official counts of law-enforcement-related deaths based on US vital statistics. The results additionally suggest these shortcomings could potentially be corrected by simultaneously (1) improving the extent and accuracy of the information recorded in death certificates and (2) expanding the types of data employed (such as media-based reports) utilized to generate official counts of these cases.

Our study is strengthened by its use of identifiable, national US mortality data to estimate the number of law-enforcement-related deaths and to analyze patterns of misclassification of these deaths in the NVSS. One limitation is that differential matching rates for our NVSS/The Counted dataset may bias results, although the high proportion of cases that we were able to match limits this bias. Additionally, we were unable to examine the characteristics of cases that were unreported in The Counted. One issue of concern is that law-enforcement-related deaths occurring in rural areas may not be reported in the news media, because there is less local news coverage available in rural areas and rural news sources may not be accessible on the internet [34]. Another issue is that we cannot know with complete certainty in which county the death

was declared; The Counted reports the location where the fatal injury was inflicted. While data from California suggest that four-fifths of persons fatally injured by law enforcement die immediately [35], an unknown proportion of the remaining one-fifth may die at a hospital in another county. Facilities best equipped to treat gunshot wounds, such as level I trauma centers, are more likely to be located in urban and higher income counties [36], so this could lead to measurement error for county-level variables. Finally, The Counted data do not include deaths that occurred in 2015 due to an injury inflicted in 2014, so any such cases are absent from the analyses. However, this is likely a very small number of cases (for injuries inflicted in 2015, we identified only 3 cases, or <0.3% of deaths, for which the death occurred in 2016).

Our estimates, derived from capture–recapture analysis, for the total number of law-enforcement-related deaths in 2015 are robust to pairwise list dependence. Because of the high degree of overlap between our 2 data sources (i.e., a large proportion of deaths reported in the NVSS were also reported in The Counted), any potential list dependency had minimal effect on the overall estimate. The Counted was more effective at identifying deaths: a case was approximately twice as likely to be reported in The Counted compared to the NVSS. Comparing its coverage rate to previous estimates produced by the BJS, The Counted outperformed ARD (which captured an estimated 49% of deaths over the period 2003–2011, excluding 2010) as well as the FBI's Supplementary Homicide Reports data (which captured an estimated 46% of deaths over the same period) [4].

Only 2 prior studies have used capture–recapture analysis to estimate the number of US law-enforcement-related deaths. First, a BJS analysis for the period 2003–2011 (excluding 2010) was

based on probabilistically matched deaths from 2 national law enforcement sources and estimated that there were on average 928 annual law-enforcement-related deaths in the US [4]. The authors of the BJS study note that many law enforcement agencies did not report any deaths to either system, and, once they accounted for nonresponse, their estimate was approximately 1,200, on par with our estimate. Second, Lum and Ball [29], adjusting for potential list dependency but not for agency nonresponse, used the same BJS data to estimate an annual mean of 1,500 deaths in the US, which is higher than our estimate. They state that adjusting for nonresponse would increase their estimate by an additional 30%. Differences between these prior estimates and our own may be attributable to (1) an actual change in the incidence of law-enforcement-related deaths, (2) uncertainty in the magnitude of list dependence, or (3) potential error in the prior estimates introduced by the imprecision of probabilistic matching.

We found that the majority of misclassified cases for the most common cause of death—fatal gunshot wounds by law enforcement—were incorrectly coded as assault. As hypothesized, a higher risk of misclassification occurred for the less common phenomenon of law-enforcement-related deaths involving injury mechanisms other than firearms. This may reflect a lack of consensus among coroners and medical examiners about how to report non-firearm deaths in police custody [37]. Notably, cause of death classification was especially inaccurate for law-enforcement-related deaths due to Taser shocks, which was the second most common mechanism after firearms.

While misclassification of law-enforcement-related deaths is a problem throughout the country, affecting 55% of mortality records nationally, the probability of misclassification varied widely

both within and between states, and also by social and economic groups. Descriptive analyses found higher probabilities of misclassification among decedents who were under age 18 years, black, or residing in the poorest county income quintiles, suggesting researchers should exercise caution when comparing rates of law-enforcement-related mortality among various sociodemographic groups using only national-level data. However, in our analyses that accounted for systematic differences in odds of misclassification by state and county (i.e., the multilevel models), only county income quintile remained significantly associated with risk of misclassification. Possible explanations for the inverse association between county income and odds of misclassification may include better resources and training among coroners/medical examiners in wealthier counties and differences in the political culture in wealthier counties that lead to greater transparency in relation to law-enforcement-related deaths. Even so, contrary to our hypotheses, we did not find that misclassification differed by death investigator type. It may be that extent of training and resources matters more to mitigate misclassification than death investigator type.

Misclassification of cause of death is a longstanding and ongoing concern in US vital statistics, and the validity of these reported data may vary widely depending on the type of disease or injury [38,39]. However, evidence suggests that the accuracy of mortality classification for homicide—an outcome similar to law-enforcement-related mortality in that it is also certified by coroners and medical examiners—is very high. A prior study of large US cities found a near-perfect correlation between homicide counts reported in the NVSS and homicide counts reported in Supplementary Homicide Reports [40]. For law-enforcement-related deaths, however, correlations between the same 2 systems are considerably lower [1,13].

Future research and implications

Future studies could estimate the number of law-enforcement-related deaths, nationally or subnationally, using data from additional years and sources. Alternative data sources for these deaths include the National Violent Death Reporting System (NVDRS), which covers 40 US states and the District of Columbia as of 2017 [41], and deaths-in-custody lists maintained by the attorneys general of California [35] and Texas [42]. Additionally, state offices of vital statistics and departments of health can identify the shortcomings of their current vital statistics data by reviewing death certificates for law-enforcement-related deaths. It will also be useful to evaluate whether making such deaths a notifiable condition improves reporting [9], per new legislation enacted in Tennessee in 2017 [43].

There are multiple interventions that may improve public health monitoring of law-enforcement-related deaths. Examples include training medical examiners and coroners to indicate law enforcement involvement in death certificate literal text, increasing the use of news media reports as a data source for NVDRS states, and legally requiring disclosure of these deaths to health departments [43] or death investigators [27]. Additionally, health departments can create websites to provide the public with real-time reports of law-enforcement-related deaths that occur within their jurisdiction. This can be coupled with the inclusion of such deaths in a jurisdiction's list of notifiable conditions, which would allow for reporting of these deaths to health departments by medical staff, first responders, and members of the public [18]. Improving public health monitoring of law-enforcement-related mortality is a critical part of efforts to ensure public accountability for these incidents and prevent future incidents. Also

warranting attention is improved monitoring of nonfatal injuries due to law enforcement, which currently are not captured by any official or media-based reporting system [44]. Better-quality data would allow researchers to quantify various forms of social inequality that may be linked to law-enforcement-related mortality (e.g., differences by race/ethnicity, socioeconomic position, and gender identity), compare rates between jurisdictions, and identify whether incidence is increasing or decreasing over time [18,44].

REFERNCES

1. Loftin C, McDowall D, Xie M. Underreporting of homicides by police in the United States, 1976–2013. Homicide Stud. 2017;21:159–74. doi: 10.1177/1088767917693358
2. Sherman LW, Langworthy RH. Measuring homicide by police officers. J Crim Law Criminol. 1979;70:546–60.
3. Zimring FE. When police kill. Cambridge (Massachusetts): Harvard University Press; 2017.
4. Banks D, Couzens L, Blanton C, Cribb D. Arrest-Related Deaths program assessment. Washington (DC): Bureau of Justice Statistics; 2015 [cited 2017 Sep 1]. Available from: http://www.bjs.gov/content/pub/pdf/ardpatr.pdf.
5. The Counted: people killed by police in the US—database. The Guardian; 2016 [cited 2016 Nov 1]. Available from: http://www.theguardian.com/thecounted.
6. Fatal Encounters. 2016 [cited 2016 Nov 1]. Available from: http://fatalencounters.org.
7. 995 people shot dead by police in 2015. Washington (DC): Washington Post; 2016 [cited 2016 Nov 1]. Available from: https://www.washingtonpost.com/graphics/national/police-shootings/.

8. Banks D, Ruddle P, Kennedy E, Planty MG. Arrest-Related Deaths program redesign study, 2015–16: preliminary findings. Washington (DC): Bureau of Justice Statistics; 2016.
9. World Health Organization. International classification of diseases–6th revision. Geneva: World Health Organization; 1948.
10. World Health Organization. International statistical classification of diseases and related health problems–10th revision. Geneva: World Health Organization; 2010 [cited 2017 Sep 1]. Available from: http://apps.who.int/classifications/icd10/browse/2010/en.
11. Centers for Disease Control and Prevention. National Violent Death Reporting System: web coding manual—version 5.1. Atlanta: Centers for Disease Control and Prevention; 2015 [cited 2017 Sep 1]. Available from: https://www.cdc.gov/violenceprevention/pdf/nvdrs_web_codingmanual.pdf.
12. The Counted: people killed by police in the US—about. The Guardian; 2015 [cited 2017 Sep 1]. Available from: https://www.theguardian.com/us-news/ng-interactive/2015/jun/01/about-the-counted.
13. Loftin C, Wiersema B, McDowall D, Dobrin A. Underreporting of justifiable homicides committed by police officers in the United States, 1976–1998. Am J Public Health. 2003;93:1117–21. doi: 10.2105/AJPH.93.7.1117
14. Barber C, Azrael D, Cohen A, Miller M, Thymes D, Wang DE, 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;106:922–7. doi: 10.2105/AJPH.2016.303074

15. Feldman JM, Gruskin S, Coull BA, Krieger N. Killed by police: validity of media-based data and misclassification of death certificates in Massachusetts, 2004–2016. Am J Public Health. 2017 Aug 17. doi: 10.2105/AJPH.2017.303940
16. Legewie J, Fagan J. Group threat, police officer diversity and the use of police force. New York: Columbia Law School; 2016. Columbia Public Law Research Paper No. 14-512.
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:e0141854. doi: 10.1371/journal.pone.0141854
18. 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:e1001915. doi: 10.1371/journal.pmed.1001915
19. Swaine J, Laugh. Never before named: five people killed by police the world forgot. The Guardian. 2015 Jun 3 [cited 2017 Sep 1]. Available from: https://www.theguardian.com/us-news/2015/jun/03/counted-police-killing-victims-unnamed-texas-california.
20. Jauchem JR. Deaths in custody: are some due to electronic control devices (including TASER devices) or excited delirium? J Forensic Leg Med. 2010;17:1–7. doi: 10.1016/j.jflm.2008.05.011
21. National Center for Health Statistics. National Death Index. 2017 [cited 2017 Jun 11]. Available from: https://www.cdc.gov/nchs/ndi/index.htm.
22. National Center for Health Statistics. National Death Index user's guide. Hyattsville (Maryland): National Center for Health Statistics; 2013.

23. Bishop YM, Fienberg SE, Holland PW. Discrete multivariate analysis: theory and practice. New York: Springer; 2007.

24. US Centers for Disease Control and Prevention. Mortality multiple cause files: U.S. data—2015. 2015 [cited 2017 Sep 1]. Available from: https://www.cdc.gov/nchs/data_access/VitalStatsOnline.htm.

25. Tilling K. Capture-recapture methods--useful or misleading? Int J Epidemiol. 2001;30:12–4. doi: 10.1093/ije/30.1.12

26. Bice D. Medical examiner "threatened" by Clarke over jail deaths. Milwaukee Journal Sentinel. 2016 Dec 2 [cited 2017 Sep 1]. Available from: http://www.jsonline.com/story/news/investigations/daniel-bice/2016/12/01/medical-examiner-threatened-clarke-over-jail-deaths/94746392/.

27. Small J. Keeping death investigations free from pressure. KQED News. 2016 Sep 13 [cited 2017 Sep 1]. Available from: https://ww2.kqed.org/news/2016/09/13/keeping-death-investigations-free-from-pressure/.

28. Simerman J, Mustian J. Coroner reclassifies Henry Glover's death as homicide in post-Hurricane Katrina police shooting case. The New Orleans Advocate. 2015 Apr 3 [cited 2017 Sep 1]. Available from: http://www.theadvocate.com/new_orleans/news/article_c66ed69b-b5f7-564f-aa7a-d0284e3fd48e.html.

29. Lum K, Ball P. Estimating undocumented homicides with two lists and list dependence. Human Rights Data Analysis Group; 2015 [cited 2017 Sep 1]. Available from: https://hrdag.org/wp-content/uploads/2015/07/2015-hrdag-estimating-undoc-homicides.pdf.

30. United States Census Bureau. 2015 American community survey 5-year estimates. Suitland (Maryland): United States Census Bureau; 2016.
31. Ingram DD, Franco SJ. 2013 NCHS urban-rural classification scheme for counties. Vital Health Stat 2. 2014;166:1–73.
32. US Centers for Disease Control and Prevention. Public Health Law Program: death investigation systems. 2016 [cited 2017 Sep 1]. Available from: https://www.cdc.gov/phlp/publications/coroner/death.html.
33. US Centers for Disease Control and Prevention. Bridged-race population estimates. 2017 [cited 2017 Jun 6]. Available from: https://wonder.cdc.gov/bridged-race-population.html.
34. Miller C, Rainie L, Purcell K, Mitchell A, Rosenstiel T. How people get local news and information in different communities. Washington (DC): Pew Research Center; 2012.
35. California Department of Justice. Deaths in Custody, 2015. Sacramento (CA): Criminal Justice Statistics Center; 2016.
36. MacKenzie EJ, Hoyt DB, Sacra JC, Jurkovich GJ, Carlini AR, Teitelbaum SD, et al. National inventory of hospital trauma centers. JAMA. 2003;289:1515–22. doi: 10.1001/jama.289.12.1515
37. Hanzlick R, Goodin J. Mind your manners. Am J Forensic Med Pathol. 1997;18:228–45. doi: 10.1097/00000433-199709000-00002
38. German RR, Fink AK, Heron M, Stewart SL, Johnson CJ, Finch JL, et al. The accuracy of cancer mortality statistics based on death certificates in the United States. Cancer Epidemiol. 2011;35:126–31. doi: 10.1016/j.canep.2010.09.005

39. Foreman KJ, Naghavi M, Ezzati M. Improving the usefulness of US mortality data: new methods for reclassification of underlying cause of death. Popul Health Metr. 2016;14:14. doi: 10.1186/s12963-016-0082-4

40. Loftin C, McDowall D, Curtis KM, Fetzer MD. The accuracy of Supplementary Homicide Report rates for large U.S. cities. Homicide Stud. 2015;19:6–27. doi: 10.1177/1088767914551984

41. US Centers for Disease Control and Prevention. National Violent Death Reporting System. 2016 [cited 2017 Sep 1]. Available from: https://www.cdc.gov/violenceprevention/nvdrs/.

42. Attorney General of Texas. Custodial death report. 2016 [cited 2016 Nov 1]. Available from: https://oagtx.force.com/cdr/cdrreportdeaths.

43. State of Tennessee. Public Chapter No. 896. House Bill 2122 (Apr. 27, 2016) [cited 2017 Sep 1]. Available from: http://wapp.capitol.tn.gov/apps/Billinfo/default.aspx?BillNumber=HB2122&ga=109.

44. 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;93:797–807. doi: 10.1007/s11524-016-0076-3

3. Police-related deaths: The impact of neighborhood economic and racial/ethnic polarization (United States, 2015-2016)

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ABSTRACT

Background: Injuries inflicted by police affect multiple demographic groups and are a leading cause of death among young men of color in the United States. To measure neighborhood-level health inequities, we tested associations between police-related death rates and census tract-based measures polarization, defined as residential concentrations of privileged versus deprived social groups. We hypothesized that greater concentrations of racial and economic privilege would be associated with lower rates of police-related deaths, and greater concentrations of deprivation with higher rates, independent of individual-level demographics.

Methods: We identified police-related deaths using The Counted, a validated dataset from The Guardian newspaper providing national data for 2015-2016. We measured economic, racial/ethnic, and racialized economic polarization in all US census tracts using the Index of Concentration at the Extremes (ICE) and, for comparison, also used census tract poverty data. Using adjusted, multilevel negative binomial regression, we modeled the ratio of observed-to-expected police-related deaths in all US census tracts, by ICE and poverty quintiles, with analyses conducted for the total population and also stratified by race/ethnicity.

Results: Greater concentrations of privilege protected against, and greater concentrations of deprivation increased rates of, police-related deaths. Associations were strongest for ICE measures that included economic data. In stratified models, death rates were lowest for non-Hispanic whites in census tracts with the greatest concentrations of non-Hispanic white residents, but rates were highest for non-Hispanic black persons in the same neighborhood quintile.

Conclusions: Understanding and preventing the occurrence of police-related deaths requires attention to neighborhood context, not just individual characteristics.

BACKGROUND

Injuries inflicted by law enforcement affect multiple social groups in the United States and rank among the 10 leading causes of death for young men and boys of color.[1] While the estimated 1066 decedents killed by US police in 2015 account for a relatively small proportion of total violent deaths nationally, police-related deaths have ripple effects that can harm the health of families and communities, which in turn may exacerbate health inequities at a population level.[2–4] Recent policy statements by medical and public health professional associations[5,6] provide evidence of an increasing awareness among clinicians and other health professionals of police violence as a phenomenon with which they should engage in order to better understand and serve their patients and the populations from which they come.

Our study aims to develop a greater understanding of economic and racial/ethnic inequities for police-related deaths in the United States. We utilized a validated, news-media-based dataset to provide what is, to our knowledge, the first multilevel national analysis of the association of neighborhood context with risk of police-related deaths, above and beyond individual-level demographic characteristics. We assess the degree to which police-related deaths are geographically patterned by polarization, defined as the spatial concentration of privileged and deprived social groups.

Residential segregation in most of the 20th century United States was primarily defined by race/ethnicity and occurred on the macro level (i.e. in states and counties); in contrast, residential segregation in the 21st century is a joint function of race/ethnicity in combination with socioeconomic position and is most pronounced at the neighborhood level.[7–9] Processes of segregation result in spatial polarization – the concentration of people belonging to the extreme 'poles' of racial and economic privilege or disprivileged into homogeneous neighborhoods.[10] Our study assesses the degree to which police-related deaths are geographically patterned by polarization, and we use separate measures to characterize neighborhood racial/ethnic polarization, economic polarization, and racialized economic polarization.

Our main a priori hypothesis was that greater concentrations of economic and racial/ethnic privilege within neighborhoods protects against police-related deaths, while rates of these deaths would increase with greater concentrations of deprivations of economic and racial/ethnic privilege, after accounting for individual-level demographics. Additionally, in line with prior epidemiologic research on the geographic patterning of injury and mortality[11–14], we hypothesized that neighborhood measures of racialized economic polarization will exhibit stronger associations with police-related death rates compared to measures based solely on income or solely on race/ethnicity. We also sought to determine whether the association between neighborhood polarization and rates of police-related death varied by race/ethnicity.

METHODS

For our cross-sectional study, we obtained data on the 2238 decedents killed by US police for the period 2015-2016 recorded in The Counted, a website maintained by the Guardian newspaper

until the end of 2016 that identified the deaths by compiling news media reports.[15] The Counted reported decedents' demographic characteristics, circumstances of death, and locations where the fatal injuries were inflicted. Our prior research estimated that The Counted captured 93% of police-related deaths in 2015 and found its reported demographic data were highly concordant with those reported on death certificates.[16,17] In our current study, we included solely the 2119 deaths resulting from injuries inflicted by law enforcement officers acting in the line of duty that occurred in non-institutional settings (i.e. the encounter did not take place in jails, prisons, or hospitals). Exclusion criteria are available in Table 3.1, which provides specific justifications for the 119 cases that we omitted. We geocoded incident locations using the Google Maps API[18] and identified corresponding census geographies using the US Census Geocoder API.[19]

Table 3.1 Deaths due to law enforcement reported in The Guardian's The Counted (2015-2016) included and excluded from analyses

Exclusion criterion	N
Total cases	2238
Cases removed	
Domestic violence perpetrated by law enforcement	15
Death in custody[1]	41
Car accident[2]	42
'Friendly fire' (officer accidently killed by another officer)	3
Fatal injury inflicted in prison, jail, or hospital	18
Total removed	119
Total cases included	2119

1. We excluded deaths that occurred in law enforcement custody unless they were reportedly ruled a homicide or there was clear evidence of a mechanism of death implicating law enforcement
2. We excluded deaths due to motor vehicle collisions unless law enforcement officers were pursuing the decedent prior to the collision

Our study encompassed the entire United States population and included individuals nested within three progressively higher geographic levels: 111625 census tracts (CTs, comprising our operational definition of "neighborhood"), nested within 22765 "cities" (which typically

correspond to the jurisdiction of a local police department, and which we defined as legally incorporated cities, towns, townships, village, and boroughs; or the unincorporated areas of a county), nested within the 50 states plus the District of Columbia (Table 3.2).

Table 3.2. Geographic units used in analytic models

Level	Number of Units	Definition
State	51	Includes the 50 US states and the District of Columbia.
City	22,765	The geographic area corresponding to the smallest unit of local government (e.g. a city, town, village, borough, or unincorporated areas of a county). Cities are nested within states and often corresponds to a local police/sheriff jurisdiction. This includes: - 19,696 Census incorporated places (e.g. cities, towns, villages, boroughs) - 50 Census designated places (census designated places are areas that typically do not correspond to local goverments, except in the case of 50 towns spread across several states) - 3,019 county unincorporated areas. These are areas within a given county that are not part of the city units listed above. For each county, we treat the unincorporated area as a single unit, even if it is not contiguous.
Neighborhood	111,625	We based neighborhoods on census tracts, which are small geographic areas of generally between 1,500 and 8,000 residents. Census tracts do not always nest within cities – of 73,056 census tracts in our dataset, 35% traverse city boundaries. To create a hierarchical data structure, we divided census tracts when they were not fully contained within a city. If Census Tract 1 was in City A and City B, we split it into Census Tract 1a (fully contained within City A) and Census Tract 1b (fully contained within City B). We used MABLE/Geocorr14[1] to determine the percentage of the census tract population to be apportioned into each neighborhood, and we assumed a homogeneous sociodemographic composition within census tracts.

1. MABLE/Geocorr14: Geographic Correspondence Engine. Missouri Census Data Center. (Accessed September 1, 2017, at http://mcdc.missouri.edu/websas/geocorr14.html.)

Census tract measures: ICE and Poverty

We used 2015 5-year census tract estimate data from the American Community Survey (ACS)[20] to compute five measures of residential economic and racial/ethnic polarization, using the Index of Concentration at the Extremes (ICE), and also obtained data on the proportion of persons below the federal poverty line at the census tract level for comparison. We used CTs as our primary level of analysis rather than cities because prior epidemiologic literature has identified

stronger social gradients for health outcomes at the CTs level[13], criminal justice research has found police use-of-force to vary at sub-city levels[21–25], and CTs are often coterminous with cities in less-urban parts of the United States.

ICE is a measure originally developed by the sociologist Douglass Massey in 2001[26] and has more recently been used for epidemiologic monitoring of health inequities on various geographic levels.[11–14] Such commonly used measures as the poverty rate solely characterize a neighborhood's proportion of deprived residents, while failing to also characterize its privileged population. In contrast, ICE simultaneously measures the relative concentrations of privileged and deprived residents of an area with the formula:

$$ICE_i = (A_i - P_i)/T_i$$

where A_i, P_i and T_i correspond, respectively, to the number of households in the *i*th geographic area who are categorized as belonging to: the most privileged extreme, the most deprived extreme, and the total population whose privilege level was measured. For example, for the ICE for income, A_i = number of high-income households in neighborhood *i;* P_i = number of low-income households in neighborhood *i*; and T_i = total number of households in neighborhood *i*. The ICE accordingly ranges from -1 (meaning 100% of the population belongs to the deprived group) to 1 (signifying 100% belongs to the privileged group).

Drawing from prior public health analyses, we used 5 ICE metrics (Table 3.3), with privileged vs. deprived groups defined as: (1) high- vs. low-income households (i.e., top 20th to bottom 80th percentile of US household incomes in 2015), (2) white non-Hispanic vs. black non-Hispanic persons, (3) white non-Hispanic persons vs. people of color (PoC), (4) high-income white non-

Hispanic vs. low-income black households, and (5) high-income white non-Hispanic vs. low-income PoC households. We defined high-income households as those earning ≥ $125,000/year (top 20th percentile) and low-income households as those earning < $20,000/year (bottom 80th percentile).[27] Basing cut-points on the national distribution for each CT measure, we assigned each CT to its respective quintile. Similarly, we generated the CT poverty variable as the proportion of residents living under the federal poverty line in the previous year (for 2015, a 4-person household earning < $23,850 was determined to be in poverty)[28] – and assigned quintiles for this measure. Using one CT as an example, Figure 3.1 shows the different compositions of each of the six measures, which also illustrates that the assigned quintile differs between the various measures.

Table 3.3. Census tract-level measures: Poverty and Index of Concentration at the Extremes

Measure	Formula	2015 American Community Survey Table Numbers
% Poverty	(Persons below the poverty line) / Total population	B17001
ICEinc	(High-income households - low-income households) / Total households	B19001
ICErace_wb	(White non-hispanic persons - black non-Hispanic persons) / Total population	B03002
ICErace_wpc	(White non-Hispanic persons - persons of color) / Total population	B03002
ICEwb_inc	(High-income white non-Hispanic households - low-income black non-Hispanic households) / Total households	B19001, B19001H, B19001B
ICEwpc_inc	(High-income white non-Hispanic households - low-income households of color) / Total households	B19001, B19001H

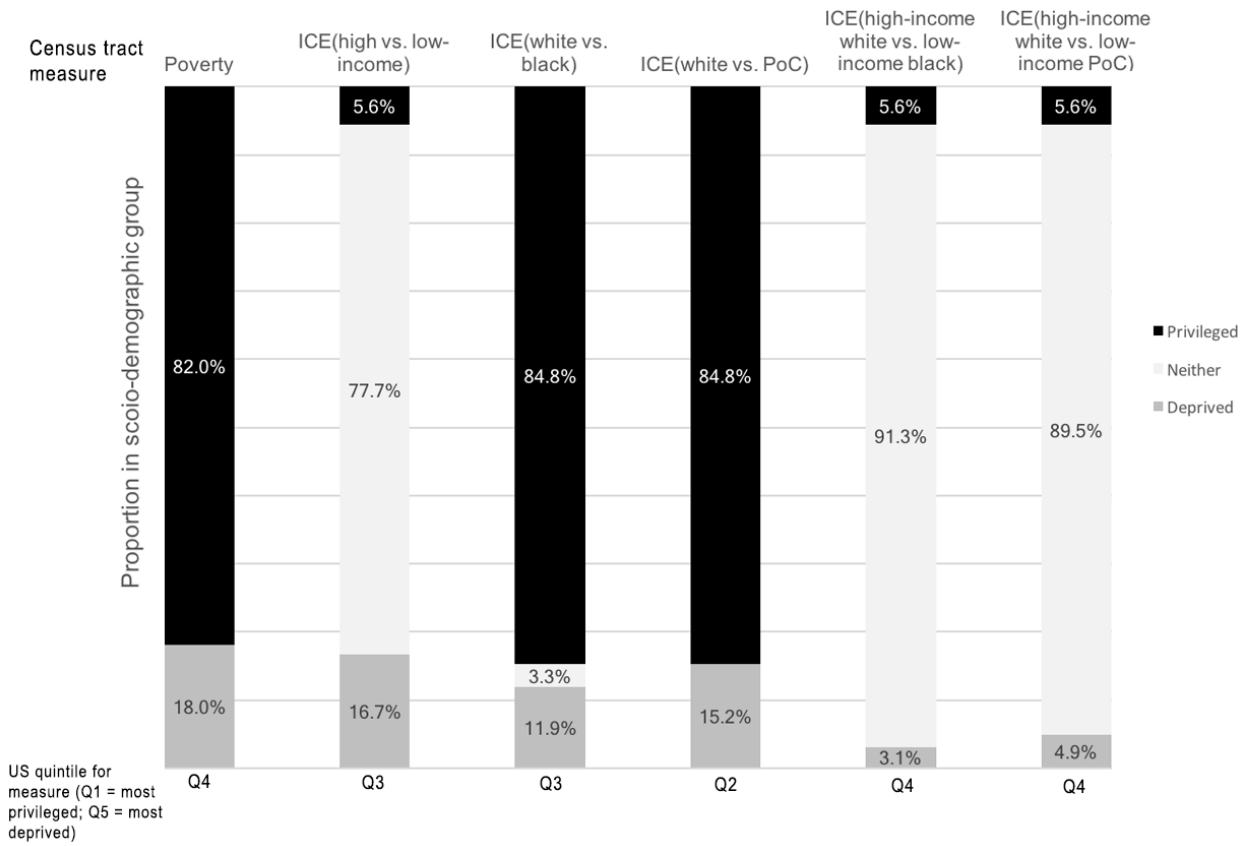

Figure 3.1. Composition for Poverty and Index of Concentration at the Extremes Measure. Example illustrated: Census Tract 401, Unincorporated Titpon County, Tennessee.

Denominators and Expected Counts

Our analyses assumed that the at-risk population for police-related deaths in a given CT was comparable to the residential population of that neighborhood. As such, we used census population data (ACS Tables B01001B-H) to calculate expected counts and rates of police-related deaths by population strata, defined by gender, race/ethnicity, and age.

City-Level Control Variables

We included one control variable – city population size – with categories based on standard cutoffs used to measure urbanicity: < 10000, 10000 to 49999, 50000 to 249999, 250000 to 999999, and ≥ 1000000.[29]

Analyses

We conducted all analyses using Stata version 15.1 (StataCorp, College Station, TX). We first tabulated police-related death counts by individual and area-based characteristics, then calculated age-adjusted mortality rates. Age standardized rates followed the 2000 standard population.[30]

We then employed multilevel negative binomial models to measure the association, by quintile, between police-related mortality and both the CT measures for ICE and poverty. These models estimated the ratio of observed-to-expected cases within CTs, incorporating random intercepts for cities and states and adjusting for city population size. We calculated expected case counts by applying group-specific standardized rates (with groups defined by age, gender, and race/ethnicity) to CT population group sizes derived from census data (Table 3.4). We first ran the regressions for the total population, then stratified by race/ethnicity for the non-Hispanic white, non-Hispanic black, and Hispanic populations, the largest population groups in the United States and those for which we have previously validated The Counted data.[17]

Table 3.4. Formula for number of expected law enforcement-related deaths in a given neighborhood

$$\text{deaths} = \sum_{i=1}^{n} (\textit{national rate}_i \times \textit{census tract population}_i \times \textit{neighborhood weight})$$

Where *i* is the population stratum (defined by age category, race/ethnicity, and gender).

Census tract population for strata are from 2015 American Community Survey data.[a] Neighborhood weights are the proportion of the overall census tract population in a given neighborhood (see Table 1).[b] Neighborhood weights are for the overall population (i.e. they are not stratum-specific), so we assumed population strata were distributed homogeneously across census tracts.

a. United States Census Bureau. 2015 American Community Survey, 5-Year Estimates.

b. MABLE/Geocorr14: Geographic Correspondence Engine. Missouri Census Data Center. (Accessed September 1, 2017, at http://mcdc.missouri.edu/websas/geocorr14.html.)

RESULTS

For the period 2015-2016, the total population age-adjusted rate for police-related deaths equaled 3.4 per million person-years (95% CI: 3.2, 3.5; Table 3.5) for the United States. Groups defined by individual-level sociodemographic characteristics whose rates exceed that of the total population included: persons ages 15-34 (reaching up to 7.7 (95% CI: 7.1, 8.3) for persons age 25-34); men (6.4; 95% CI: 6.1, 6.7); non-Hispanic black persons (6.4; 95% CI: 5.9, 7.0); and American Indian/Alaska Native persons (6.8; 95% CI: 4.6, 9.1). In relation to city population, the death rate was highest (4.6; 95% CI: 5.9, 7.0) for small cities with <10,000 residents. For CT characteristics, death rates were lowest in the most privileged CTs, and the highest rates were observed in the most deprived CT quintiles for the ICE for income (6.2; 95% CI: 5.7, 6.7), and for poverty (5.9; 95% CI: 5.5, 6.3).

Table 3.5 Decedents killed by law enforcement in the United States and reported in The Counted: Distributions and rates by characteristics of individuals and communities (2015-2016).

Variable	Counts and Proportions		Age-adjusted mortality rate[a]
	US population (%)	Deaths: Count (%)	per million person-years (95% CI)
Total	100.0%	2119 (100.0%)	3.4 (3.2, 3.5)
Age (years): N (%)			
0 - 4	6.2%	0 (0.0%)	0.0 (0.0, 0.0)
5 - 14	12.7%	4 (0.2%)	0.0 (0.0, 0.1)
15 - 24	13.6%	367 (17.6%)	4.2 (3.8, 4.7)
25 - 34	13.8%	683 (32.4%)	7.7 (7.1, 8.3)
35 - 44	12.6%	499 (23.7%)	6.2 (5.6, 6.7)
45 - 54	13.3%	333 (15.8%)	3.9 (3.5, 4.3)
55 - 64	12.8%	170 (8.1%)	2.1 (1.8, 2.4)
65 - 74	8.7%	39 (1.9%)	0.7 (0.5, 0.9)
74 - 84	4.8%	13 (0.6%)	0.5 (0.2, 0.8)
≥ 85	2.0%	2 (0.1%)	0.2 (0.0, 0.6)
(missing)	–	9 (< 0.1%)	–
Gender: N (%)			
Men	49.9%	2032 (95.9%)	6.4 (6.1, 6.7)
Women	50.1%	87 (4.1%)	0.3 (0.2, 0.3)
(missing)	–	0 (0.0%)	–
Race/ethnicity: N (%)			
White non-Hispanic	62.6%	1093 (52.5%)	2.9 (2.7, 3.1)
Black non-Hispanic	13.0%	545 (26.2%)	6.4 (5.9, 7.0)
Hispanic/Latino	17.7%	365 (17.5%)	3.1 (2.8, 3.4)
Asian/Pacific Islander non-Hispanic	6.0%	42 (2.0%)	1.0 (0.7, 1.3)
American Indian/Alaska Native non-Hispanic	0.8%	36 (1.7%)	6.8 (4.6, 9.1)
(missing)	–	38 (1.8%)	–
City population			
< 10,000	10.9%	289 (13.6%)	4.6 (4.1, 5.2)
10,000 to < 50,000	25.4%	498 (23.5%)	3.2 (3.0, 3.5)
50,000 to < 250,000	33.9%	642 (30.3%)	3.1 (2.8, 3.3)
250,000 to < 1,000,000	19.9%	480 (22.7%)	3.8 (3.5, 4.2)
≥ 1,000,000	10.0%	210 (9.9%)	3.1 (2.7, 3.6)
(missing city)	–	0 (0.0%)	–

Table 3.5 (Continued). Decedents killed by law enforcement in the United States and reported in The Counted: Distributions and rates by characteristics of individuals and communities

Neighborhood characteristics			
(missing neighborhood)	–	7 (<0.1%)	–
% poverty			
Q1 (lowest poverty)	22.7%	185 (8.8%)	1.3 (1.1, 1.5)
Q2	19.6%	323 (15.3%)	2.7 (2.4, 3.0)
Q3	18.6%	354 (16.8%)	3.1 (2.8, 3.4)
Q4	18.7%	494 (23.4%)	4.2 (3.8, 4.6)
Q5 (highest poverty)	20.4%	753 (35.7%)	5.9 (5.5, 6.3)
ICE (high vs. low income)			
Q1 (most privileged)	18.5%	208 (9.9%)	1.4 (1.2, 1.6)
Q2	17.8%	354 (16.8%)	2.7 (2.4, 3.0)
Q3	18.2%	363 (17.2%)	3.2 (2.9, 3.6)
Q4	20.8%	482 (22.9%)	4.4 (4.0, 4.7)
Q5 (least privileged)	24.7%	702 (33.3%)	6.2 (5.7, 6.7)
ICE (white vs. black)			
Q1 (most privileged)	23.8%	192 (9.1%)	2.3 (1.9, 2.6)
Q2	22.8%	286 (13.6%)	2.7 (2.4, 3.0)
Q3	21.1%	385 (18.3%)	3.0 (2.7, 3.3)
Q4	18.5%	522 (24.7%)	3.5 (3.2, 3.9)
Q5 (least privileged)	14.0%	725 (34.4%)	4.7 (4.3, 5.0)
ICE (white vs. PoC)			
Q1 (most privileged)	24.9%	189 (9.0%)	2.3 (1.9, 2.6)
Q2	22.1%	295 (14.0%)	2.7 (2.4, 3.1)
Q3	20.6%	367 (17.4%)	2.9 (2.6, 3.2)
Q4	18.4%	498 (23.6%)	3.5 (3.2, 3.8)
Q5 (least privileged)	14.1%	761 (36.1%)	4.7 (4.3, 5.0)
ICE (high-income white vs. low-income black)			
Q1 (most privileged)	20.6%	181 (8.6%)	1.3 (1.1, 1.5)
Q2	19.8%	322 (15.3%)	2.8 (2.5, 3.1)
Q3	17.1%	363 (17.2%)	3.5 (3.1, 3.8)
Q4	19.1%	572 (27.1%)	4.6 (4.2, 5.0)
Q5 (least privileged)	23.4%	671 (31.8%)	5.1 (4.7, 5.5)
ICE (high-income white vs. low-income PoC)			
Q1 (most privileged)	20.6%	174 (8.3%)	1.3 (1.1, 1.5)
Q2	19.8%	306 (14.5%)	2.7 (2.4, 3.0)
Q3	17.1%	330 (15.7%)	3.2 (2.9, 3.6)
Q4	19.1%	528 (25.0%)	4.2 (3.8, 4.6)
Q5 (least privileged)	23.4%	771 (36.6%)	5.5 (5.1, 5.9)

a. Age-specific rates are not age adjusted. All other rates are adjusted to the 2000 standard population. Numerators include complete cases only.

In multilevel negative binomial models for the total population, which accounted for differences in mean rates by city and state, the rates of police-related deaths increased with higher quintiles of CT deprivation for all six measures, independent of CT demographic composition. Effect sizes were strongest for the ICE measures incorporating income – singly or combined with race/ethnicity – and for poverty; these four metrics yielded similar results (Figure 3.2). For these economic CT measures, a large increase occurred between the first quintile (Q1; most privileged) and second quintile (Q2): rates were approximately two-fold higher in Q2 vs. Q1 and rose monotonically thereafter. Effect sizes were smaller for the two ICE metrics based solely on CT race/ethnicity, and only the Q5 (greatest non-Hispanic black/PoC concentration) rates were higher than that of Q1 (greatest non-Hispanic white concentration) at a level of statistical significance.

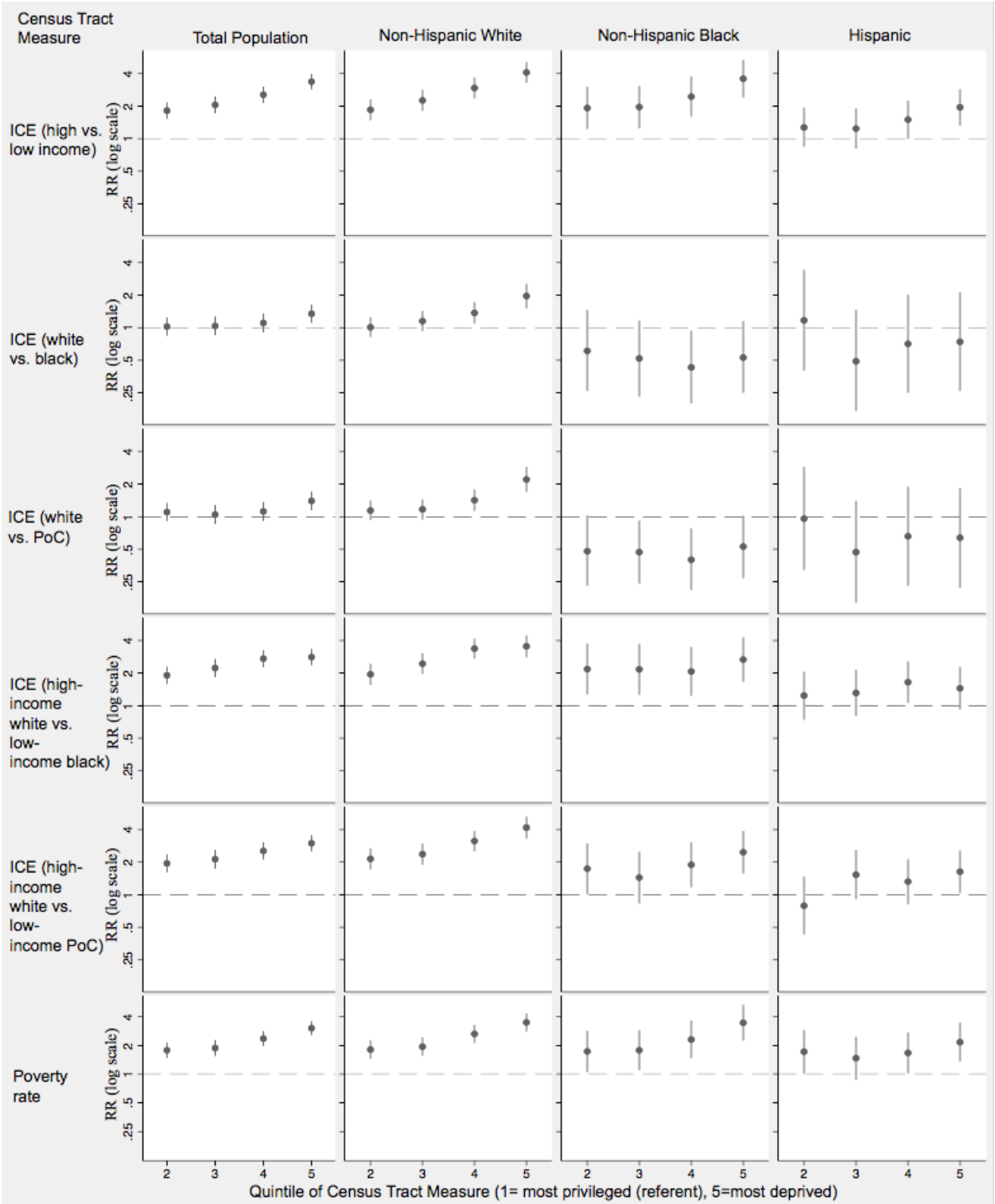

Figure 3.2. Rate ratios for police-related deaths by quintile of census tract Index of Concentration at the Extremes (ICE) and poverty: Results from adjusted negative binomial models (United States, 2015-2016).

In the models stratified by race/ethnicity for non-Hispanic black, non-Hispanic white, and Hispanic populations, the three economic ICE measures and poverty followed the same general pattern as the total population, with concentrated economic privilege predicting lower rates of police-related deaths and with rates increasing where concentrations of deprivation are greater. The main difference between these stratified models occurred for the two ICE metrics that measured solely concentrations of racial/ethnic groups. For non-Hispanic whites, rates of police-related deaths increased with greater concentrations of CT black/PoC residents and were approximately twice as high in Q5 compared to Q1 for both measures. This was not the case for non-Hispanic black and Hispanic persons. For these populations of color, point estimates suggested police-related death rates were highest in Q1, i.e. the CTs with the greatest concentration of non-Hispanic white residents. While all confidence intervals for Hispanic persons included the null value of RR = 1, the RRs were statistically significant for some quintile comparisons among the non-Hispanic black population. For example, the ICE comparing concentrations of non-Hispanic white to PoC residents yielded a RR of 0.41 (95% CI: 0.21, 0.80) for Q4 vs. Q1 in the model for the non-Hispanic black population.

DISCUSSION

In line with our hypothesis, we found CT concentrations of economic privilege were associated with lower rates of police-related deaths in the United States for the period 2015-2016, while greater concentrations of deprivation were associated with higher rates. However, the ICE measures for racialized economic polarization did not exhibit any meaningful differences compared to the ICE measures for income or race/ethnicity alone. Police-related deaths rates were relatively lower among the most economically privileged CTs and occurred at

approximately half the rate of the second wealthiest quintile, regardless of whether economic privilege was defined solely by income, by income in combination with race/ethnicity, or by poverty. When privilege and deprivation were defined by CT racial/ethnic concentrations without regard to income, a different pattern emerged. For the ICE race/ethnicity measures, we identified evidence suggestive of different associations by race/ethnicity: non-Hispanic white persons experienced the lowest rates of police-related deaths in CTs with the highest concentrations of non-Hispanic white residents, whereas these same neighborhood quintile presented the highest risk to non-Hispanic black persons.

Study Strengths and Limitations

Our study is strengthened by its use of a dataset on police-related deaths that – unlike official sources that document fewer than half of these fatalities – captures nearly 95% of such incidents.[16] Additionally, our analyses incorporated cities as geographic units that most closely correspond to local police jurisdictions. One limitation of our study is a lack of data on the demographic composition of dynamic CT populations (i.e. the persons who spend time in a given CT and are therefore at risk of police-related death, but are not reflected in the census data from which we derived rates). Another is the absence of control variables pertaining to city-level law enforcement and political characteristics (e.g. police use of force policies) – such data are collected on a subset of law enforcement agencies but are not uniformly available across the entire United States.[31] Finally, we did not have CT-level data on interpersonal violence, so we were not able to assess the ways in which violence between civilians might mediate the relationship between neighborhood deprivation and police-related deaths.

Interpretation and Implications

Considering economic ICE measures and poverty, police-related deaths follow the same social gradient observed for a variety of other health outcomes where the burden is greatest in neighborhoods of concentrated deprivation and diminishes in neighborhoods of concentrated privilege. Our finding that non-Hispanic black persons may experience lower risk of police-related killings in neighborhoods with higher concentrations of black and PoC residents contrasts with epidemiologic multilevel studies of other health outcomes,[32] including for interpersonal violence,[13,33] that have suggested segregated neighborhoods of color are harmful to health. Additionally, prior studies of policing in a small number of US cities have found either that use of force does not vary based on neighborhood composition[21,23,34] or that officers were less restrained in their use of force in neighborhoods with greater concentrations of PoC residents.[24] Providing possible explanations of our findings, sociological research on policing has identified associations between greater political representation of black residents and reduced police use of force.[35,36]

In summary, our study provides novel empirical evidence that neighborhood economic and social polarization matters for understanding police-related deaths on the population level above and beyond inequalities in death rates by individual race/ethnicity. Levels of privilege and deprivation of people's neighborhoods, including those of patients, are contexts that can shape risk of police-related death.

References

1. Heron M. Deaths: Leading Causes for 2014. Natl Vital Stat Rep 2016;65(5):1–96.

2. Yimgang DP, Wang Y, Paik G, Hager ER, Black MM. Civil Unrest in the Context of Chronic Community Violence: Impact on Maternal Depressive Symptoms. Am J Public Health 2017;107(9):1455–62.

3. Gershenson S, Hayes M. Short-Run Externalities of Civic Unrest: Evidence from Ferguson, Missouri. 2016; Available from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2819372

4. Gomez MB. Policing, Community Fragmentation, and Public Health: Observations from Baltimore. J Urban Heal 2016;93:154–67.

5. Student Nationa Medical Association. Police Brutality Position Statement. 2014. Available from: http://www.snma.org/_files/live/snma_policy_brutality.pdf

6. National Association of County and City Health Officials. Statement of Policy: Public Health, Racism, and Police Violence. Washington, DC: 2015. Available from: http://www.naccho.org/advocacy/positions/upload/15-04-Public-Health-Racism-and-Police-Violence.pdf

7. Massey DS, Rothwell J, Domina T. The Changing Bases of Segregation in the United States. Ann Am Acad Pol Soc Sci 2009;626(1).

8. Bischoff K, Reardon S. Residential Segregation by Income, 1970-2009. In: Logan J, editor. Diversity and Disparities: America Enters a New Century. New York: Russell Sage Foundation.

9. Logan JR. The Persistence of Segregation in the 21st Century Metropolis. City Community 2013;12(2).

10. Hamnett C. Social Segregation and Social Polarization. In: Paddison R, editor. Handbook of Urban Studies. Thousand Oaks, CA: SAGE; 2001. p. 162–76.

11. Feldman JM, Waterman PD, Coull B a, Krieger N. Spatial social polarisation: using the Index of Concentration at the Extremes jointly for income and race/ethnicity to analyse risk of hypertension. J Epidemiol Community Health 2015;jech-2015-205728.

12. Krieger N, Waterman PD, Gryparis A, Coull BA. Black carbon exposure, socioeconomic and racial/ethnic spatial polarization, and the Index of Concentration at the Extremes (ICE). Health Place 2015;34:215–28.

13. Krieger N, Feldman JM, Waterman PD, Chen JT, Coull BA, Hemenway D. Local Residential Segregation Matters: Stronger Association of Census Tract Compared to Conventional City-Level Measures with Fatal and Non-Fatal Assaults (Total and Firearm Related), Using the Index of Concentration at the Extremes (ICE) for Racial, Economic, and Racialized Economic Segregation, Massachusetts (US), 1995–2010. J Urban Heal 2017;94(2):244–58.

14. Krieger N, Waterman PD, Spasojevic J, Li W, Maduro G, Van Wye G. Public health monitoring of privilege and deprivation with the index of concentration at the extremes. Am J Public Health 2016;106(2):256–63.

15. Swaine J, Laughland O, Lartey J, McCarthy C. The Counted. Guard. People Killed by police in the US. 2015; Available from: http://www.theguardian.com/thecounted

16. Feldman JM, Gruskin S, Coull BA, Krieger N. Quantifying underreporting of law-enforcement-related deaths in United States vital statistics and news-media-based data sources: A capture–recapture analysis. PLoS Med 2017;14(10).

17. Feldman JM, Gruskin S, Coull BA, Krieger N. Killed by Police: Validity of Media-Based Data and Misclassification of Death Certificates in Massachusetts, 2004–2016. Am J Public Health 2017;107(10):1624–6.

18. Google. Google Maps Geocoding API. Google Web Serv. 2017;Available from https://developers.google.com/maps/documentation/geocoding/intro

19. US Census Bureau. Geocoding Services Web Application Programming Interface. 2017;

20. United States Census Bureau. American Community Survey 5-Year Estimates. 2015.

21. Terrill W, D. Reisig M. Neighborhood Context and Police Use of Force. J Res Crime Delinq 2003;40(3):291–321.

22. Lawton BA. Levels of Nonlethal Force: An Examination of Individual, Situational, and Contextual Factors. J Res Crime Delinq 2007;44(2):163–84.

23. Lee H, Jang H, Yun I, Lim H, Tushaus DW. An examination of police use of force utilizing police training and neighborhood contextual factors. Polic An Int J Police Strateg Manag 2010;33(4):681–702.

24. Lersch KM, Bazley T, Mieczkowski T, Childs K. Police use of force and neighbourhood characteristics: an examination of structural disadvantage, crime, and resistance. Polic Soc 2008;18(3):282–300.

25. Fyfe JJ. Geographic Correlates of Police Shooting: A Microanalysis. J Res Crime Delinq 1980;17(1):101–13.

26. Massey D. The Prodigal Paradigm Returns: Ecology Comes Back to Sociology. In: Booth A, Crouter A, editors. Does It Take a Villiage. Pyschology Press; 2001. p. 41–8.

27. US Census Bureau. Table H-1. Income Limits for Each Fifth and Top 5 Percent. Hist. Income Tables Households. 2017;Available from https://census.gov/data/tables/time-series/demo/income-poverty/historical-income-households.html

28. US Department of Housing and Urban Development. 2014 Poverty Guidelines. 2014;Available from: https://aspe.hhs.gov/2014-poverty-guidelines

29. Ingram DD, Franco SJ. 2013 NCHS Urban-Rural Classification Scheme for Counties. Vital Health Stat 2 2014;(166):1–81.

30. Klein RJ, Schoenborn CA. Age Adjustment Using the 2000 Projected U.S. Population;Available from: https://www.cdc.gov/nchs/data/statnt/statnt20.pdf

31. Bureau of Justice Statistics. Law Enforcement Management and Administrative Statistics (LEMAS), 2013. 2015;Available from: https://doi.org/10.3886/ICPSR36164.v2

32. Arcaya MC, Tucker-Seeley RD, Kim R, Schnake-Mahl A, So M, Subramanian SV. Research on neighborhood effects on health in the United States: A systematic review of study characteristics. Soc Sci Med 2016;168:16–29.

33. Parker KF, Stansfield R. The Changing Urban Landscape: Interconnections Between Racial/Ethnic Segregation and Exposure in the Study of Race-Specific Violence Over Time. Am J Public Health 2015; 105(9):1796–805.

34. Klinger D, Rosenfeld R, Isom D, Deckard M. Race, Crime, and the Micro-Ecology of Deadly Force. Criminol Public Policy 2015;15(1).

35. Jacobs D, O'Brien RM. The Determinants of Deadly Force: A Structural Analysis of Police Violence. Am J Sociol 1998;103(4):837–62.

36. Ochs HL. The Politics of Inclusion: Black Political Incorporation and the Use of Lethal Force. J Ethn Crim Justice 2011;9(3):238–65.

CONCLUSION

Since beginning this project, more research has become available and new debates ignited regarding the position of police violence as a public health issue. As I described in the introduction, few studies on police violence had been published in public health journals when I proposed this dissertation in 2015. Multiple articles have appeared on the topic in the following years, notably including a special issue of the Journal of Urban Health in 2016 dedicated to "excessive police violence as a public health issue" (Cooper and Fullilove, 2016). Another promising development for the field has been the appearance of several quasi-experimental studies demonstrating community-wide repercussions from high-profile incidents of police violence, including harms to mental health (Yimgang et al. 2017), school attendance (Gershenson and Hayes, 2016), and public safety (Desmond et al., 2016).

Even in light of a growing epidemiologic literature on its harms to populations, the role of police violence within the field of public health remains a topic of contention. This was perhaps most clearly illustrated during the 2017 American Public Health Association (APHA) annual conference, at which a group of advocates attempted to have the professional association adopt a policy statement recognizing police violence as a public health concern. The proposal's authors cited my research, along with that of others, both in their proposed text and in their lengthy oral debates at the conference. In the end, the APHA governing council voted to reject the statement by a 2:1 margin; the advocates plan to push for the resolution again at the 2018 conference (Garces, 2018).

Over the course of writing this dissertation, several lessons emerged for me as an epidemiologist who is concerned with effecting change on a topic that garners both attention and contention from the broader public. One such lesson is the importance of deliberation and clarity in terms of how I communicate my work. In conversations with the media about my research, I learned the difficulties involved in translating complex methods to an audience that is unfamiliar with statistics. Additionally, the situation pushed me to identify clear, distinct messages relevant to each of the interested audiences – epidemiologists, policymakers, and the general public – in order to convey my research most effectively. Finally, I continue to grapple with understanding the role of scientists in social movements and, relatedly, learning to be patient with the pace of political change. In the four years since Michael Brown's death, police reforms in the United States have been modest in scope and often confined to the largest law enforcement agencies. But lessons of the past, from public health and other domains, have shown that social change efforts can take decades or longer to achieve, requiring scientists' active engagement for the long haul in order to see meaningful progress. We, as public health researchers, are not all-powerful technocrats who can effect change simply by publishing the right studies. Instead, we must dedicate our careers to this work and also pass the baton to the next generation through teaching and mentorship. When the political environment becomes favorable, which itself happens due to changing material conditions, changes in political leadership, and the collective action of social movements, the fruits of our labor can inform policy.

References

Cooper HL, Fullilove M. Excessive police violence as a public health issue. Journal of Urban Health. 2016 Apr 1;93(1):1-7.

Desmond M, Papachristos AV, Kirk DS. Police violence and citizen crime reporting in the black community. American Sociological Review. 2016 Oct;81(5):857-76.

Garces, A. Should Police Violence Be Viewed as a Public Health Issue? KQED News. 2018 Jan. Available at https://ww2.kqed.org/news/2018/01/02/should-police-violence-be-viewed-as-a-public-health-issue/

Gershenson, S. and Hayes, M.S., 2017. Police shootings, civic unrest and student achievement: evidence from Ferguson. *Journal of Economic Geography*.

Yimgang DP, Wang Y, Paik G, Hager ER, Black MM. Civil unrest in the context of chronic community violence: impact on maternal depressive symptoms. American journal of public health. 2017 Sep;107(9):1455-62.