The Surprising Link Between Education and Fatal Police Shooting Rates in the U.S., 2013-2016

Abstract

This study analyzes county-level fatal police shooting rates from 2013 to 2016. Lasso regression, elastic net regression, cross-validated stepwise selection, all-subsets regression, partial least squares regression, as well as relative importance analysis are used to assess the best predictive models. The most surprising and robust finding is that standardized test scores for English/Language Arts (ELA) are negatively associated with rates of fatal police shootings across multiple geographical levels of aggregation, net of crime and other socioeconomic controls. The findings suggest that deadly encounters between civilians and police officers are more likely to occur in impoverished regions with high rates of violent crime, more police per capita, and low average verbal ability. In addition, fatal police shootings rates tend to be lower in more segregated areas with larger Black populations and higher in areas with larger Hispanic populations.

Keywords: Black Lives Matter, Police-involved fatalities, Officer-involved shootings, ELA, Verbal Ability

Introduction

Since the killing of Michael Brown by police officer Darren Wilson in Ferguson, Missouri in August 2014 and the subsequent rise of the Black Lives Matter (BLM) movement, the use of lethal force by police against civilians, especially against African American civilians, has become one of the most salient and divisive public issues in the United States today. While information about the individuals involved in fatal police shooting incidents has become more widely accessible to the public, how and why fatal police shooting incidents vary both geospatially and socio-culturally is still not well understood. This study examines whether and how regions in the United States with higher fatal police shooting rates differ from regions with lower rates. Specifically, I employ multiple model selection algorithms and analyses of relative importance to find the most robust and reliable predictors of fatal police shooting rates.

This study makes four unique contributions to the literature on the sociology of crime and police violence. This is the first study to examine the link between fatal police shootings and average levels of verbal and reading ability. Second, this study is the first to formally assess the relative importance of the covariates of fatal police shooting rates as well as their predictive reliability using the statistical tools of cross-validation, resampling, penalized regression, and all subsets regression. Third, this study analyzes fatal police shooting rates across multiple levels of geographical aggregation, including counties, states, and aggregated regions consisting of geographically contiguous counties with at least ten thousand, one hundred thousand, or one million residents. Fourth, the data used in this study contain 4,028 recorded cases of civilians shot and killed by police, making it the largest and most comprehensive data set of its kind to be analyzed at the county level in the published literature.[1]

Surprisingly, the weighted average for English/Language Arts (ELA) is one of the most important and reliable predictors of fatal police shooting rates. For counties and regions with at least 100,000 residents, ELA scores explain a greater proportion of variance in fatal police shooting rates than all other predictors, including SES and violent crime. The strength and direction of the coefficient for ELA is also more generalizable (i.e. less sensitive to sampling variability) than that of any other predictor. The findings suggest that deadly encounters between civilians and police officers are more likely to occur in impoverished regions with high rates of violent crime, more police per capita, and low average verbal ability. In addition, fatal police shootings rates tend to be lower in more segregated areas with larger Black populations and higher in areas with larger Hispanic populations.

Literature Review and Background

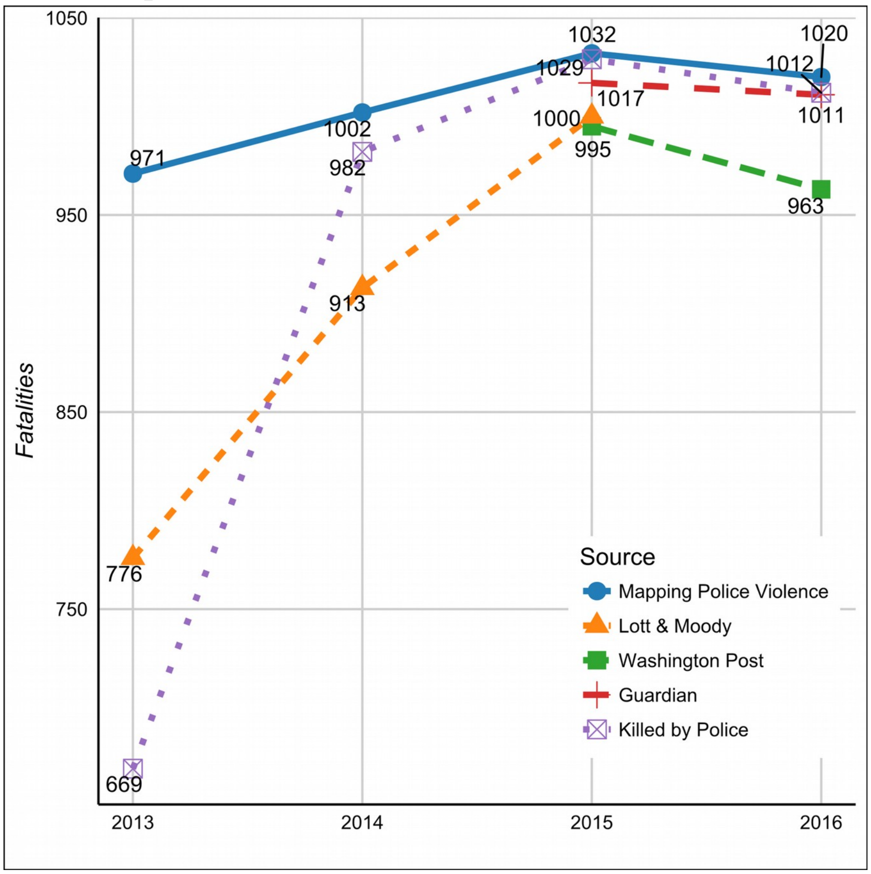
The use of lethal and non-lethal force by police officers has been studied at the individual, organizational, and ecological levels. The individual approach focuses on the characteristics of individual police officers, their targeted suspects, and the immediate circumstances in which police force is used. The organizational approach examines how policies and practices of police agencies affect the behavior of individual police officers, and the ecological approach examines how police activity is influenced by the location in which policing occurs. For example, the racial composition or rate of crime in a neighborhood may moderate the level of force used by police officers. All of these approaches examine variance in incident-level data. While incident-level relationships between covariates do not deductively imply relationships between the covariates of aggregate-level populations, they can nevertheless be suggestive of aggregate-level hypotheses.

1 To ensure this study's transparency and reproducibility, the author has made available the R code used to create the data set, perform all analyses, and visualize the results.

Incident-Level Data

According to data from mappingpoliceviolence.org, 4025 civilians were and shot and killed by police from 2013 to 2016. This figure includes only deaths due to the intentional discharge of a firearm from a police officer. Figure 1 compares estimates of civilians shot and killed by police from three data sources, including *The Washington Post* for years 2015 and 2016, and a data set compiled independently by researchers Lott & Moody (2016) for years 2013-2015.

Figure 1. Comparison of Estimated Civilian Fatalities for Three Sources



Not all civilians killed by police die from lethal force. Selby et al. (2016) note that in nearly half of the 153 incidents in which police killed an unarmed civilian, the civilian did not die from the deployment of a firearm, but rather from complications resulting from non-lethal force (72). Nor do all instances in which police use lethal force result in a civilian's death. Klinger et al. (2016), in a study of police shooting incidents in St. Louis from 2003 to 2012, report that police missed their targets 51% of the time and that only 16% of suspects who were shot died as a result. Klinger & Slocum (2017) also note that 68 of 991 fatal shootings reported by *The Washington Post* in 2015 (as well as 2 additional unreported cases) occurred after initial TASER deployments by police (10).

As depicted in Table 1, incident-level data from *The Washington Post* show large race and gender disparities in fatal police shootings. Benchmarking to population, Blacks are killed by police at the highest rate (10.61 per million), followed by White Hispanics (6.47 per million), Native Americans (3.77 per million), non-Hispanic Whites (4.71 per million), and Asians (1.29 per million).[2] There is also a large gender disparity: males constitute 96 percent (*n* = 1872) of civilians killed by police in 2015 and 2016, a rate of 11.51 deaths per 1 million, which is more than 23 times the rate at which women are killed.

Table 1. Race and Gender of Civilians Killed by Police (2015-2016)

	All Fatalities					Unarmed & Not Threatening Officer				
	N	%	Per 1M Pop	Per 100k Murders	Per 100k DUIs	N	%	Per 1M Pop	Per 100k Murders	Per 100k DUIs
Total	1954	-	5.91	203.29	2.18	69	-	0.21	7.18	0.08
Race										
White	960	49%	4.71	302	1.77	27	39%	0.13	9.34	0.05
Black	491	25%	10.61	98	4.12	25	36%	0.54	5.01	0.21
Hispanic	332	17%	6.47	-	-	13	19%	0.25	-	-
Asian	29	1%	1.29	177	1.41	0	0%	0	0	0
Native American	25	1%	3.77	210	1.32	1	1%	0.15	8.4	0.05
Unknown	117	6%	-	-	-	3	4%	-	-	-
Gender										
Male	1872	96%	11.51	220	2.78	65	94%	0.4	7.65	0.1
Female	82	4%	0.49	73	0.37	4	6%	0.02	3.58	0.02

Sources: Washington Post (2015-2016), US Census (2015), Uniform Crime Reports (2015), and arrest data from Florida and New York City. The arrest benchmarks for Whites include White Hispanics.

Civilians killed by police are often armed and violent. Between 61 percent (*n* = 1201) and 96 percent (*n* = 1887) of the 1,958 civilians shot and killed by police in 2015 and 2016 were either armed or threatening police officers at the time they were killed.[3] In addition, a large proportion of civilians killed by police are also acutely intoxicated or suffer from some form of mental illness. *The Washington Post* again reports that at least 25% (*n* = 497) of decedents in 2015 and 2016 had a mental illness, whereas the

2 Data from *The Washington Post* are used because the armed status and threat level of data prior to 2015, are not consistently identified in data provided by MappingPoliceViolence.org and elsewhere.

3 The more conservative first estimate excludes cases in which the 'threat level' of decedents is "other" or "undetermined" and excludes cases in which the variable 'weapon' is "undetermined" or "unarmed." The second estimate excludes only cases in which 'weapon' is "unarmed" and 'threat level' is "other."

other 75% were either not mentally ill or their mental status was unknown. Selby et al. (2016) report that 46% of the unarmed civilians killed by police included in their sample were either intoxicated or mentally ill.

These findings suggest the possibility that rates of fatal police shootings may be higher in counties with significantly larger proportions of Blacks, Hispanics, or young males. Several studies, however, rebut the widespread public perception that Black men are systematically and unfairly targeted by law enforcement because of their race (Selby et al. 2016; Shane et al. 2017). To the extent then that violent individuals are more likely to be killed by police, fatal police shootings will be more likely in areas where disproportionately more violent offenses occur. Blacks may be disproportionately targeted for police violence because they are over-represented in the population of violent offenders (and victims).[4] Disparities in criminal and violent activity likewise may account for the underrepresentation of women and Asians in the population of police shooting victims. Nix et al. (2017) therefore caution against using population as a benchmark, arguing that "it does not account for each group's representation in a variety of more relevant measures, including police–civilian interactions and crime" (20).

Currently there are no comprehensive national databases documenting either police-civilian encounters or the smaller subset of encounters in which police use force. Survey evidence suggests, however, that police are more likely to use force during an arrest than during other types of encounters with civilians. Smith et al. (2009) report that police use force in 15 to 20% of arrests. By comparison, Eith & Durose (2011) estimate that across all encounters police use force less than 2% of time. This suggests that benchmarking to arrests may be more appropriate than benchmarking to population. Goff et al. (2016) argue that violent crime arrests are not a more appropriate benchmark than total arrests because arrests for violent crime are only 1.3 times more likely than arrests for nonviolent crimes to result in force (9). It is not clear how much more likely police are to use *lethal* force during arrests for violent crime compared to other arrests.

Table 1 also depicts arrest benchmarks for murder and driving under the influence (DUI), calculated by dividing the frequency of civilians killed by police in each group by the group's respective frequency of arrests. When benchmarking to rates of murder, racial disparities reverse: Whites and Hispanics are killed by police at the highest rate of 302 per 100,000 murder arrests, followed by Native Americans,

4 That Blacks are overrepresented among violent offenders is based not only on reported arrests but also on surveys of victims. See the appendix.

Asians, and Blacks. When benchmarking to DUI arrests, however, the disparities diminish but are not eliminated. Finally, Table 1 reports the frequencies, proportions, and benchmarks for population and arrests counting only civilians that are reported by *The Washington Post* as unarmed and not threatening police officers at the time of their deaths. The disparity between the White and Black population rates persists when considering only unarmed and non-threatening civilians, suggesting that racial composition may still be a significant predictor of fatal police shooting rates even after controlling for crime rates.

Analyzing 19,269 use of force incidents collected from 12 police agencies between 2010 and 2015, Goff et al. (2016) report similar results, namely, that when benchmarking to violent crime arrests, Blacks are not more likely than Whites to be targeted for lethal force (20, see Table 7). Examining all use of force incidents, they find that benchmarking to total arrests reduces but does not eliminate Black-White disparities, while benchmarking to crime arrests for violent crime "reverses the direction of the 'Black-White' gap" (17).

Police Training & Bias

Studies of police use of force have also focused on the characteristics of police officers, including their age, race, gender, and other personality traits. Education and training seem to influence to the level of force used by police officers. Lim & Lee (2015), for instance, find that highly educated supervisors are more likely to moderate their subordinate officers' use of force. Similarly, Paoline & Terrill (2007) find that compared to officers with only a high school education, officers with any amount of college education are less likely to use verbal force, and that officers with a four-year degree are less likely to use physical force. Terrill & Mastrofski (2002) also find that less-educated police officers are more likely to use force against suspects. Paoline & Terrill (2007) report that police officers with more experience are less likely to use verbal or physical force. Moreover, a link between authoritarian personality and use of force has been found (Crank 2004).

The possibility that the decisions of police officers to use force may be racially biased has received much attention. In a frequently cited study, Ross (2015) analyzes shooting incidents from 2011 to 2014 recorded in the crowd-sourced U.S. Police-Shooting Database (USPSD). Ross measures racial "bias" in police shootings of unarmed civilians as a log odds ratio, i.e. as the natural logarithm of the ratio of the proportion of unarmed Blacks who are killed by police to the proportion of unarmed Whites who are killed by police. The data used by Ross includes a total of only 83 Black unarmed victims across 53 counties and 76 unarmed White victims across 65 counties. Moreover, there are only 8 counties in which both an unarmed Black and an unarmed White are killed by police. Ross excludes from his analysis 2844 out of 3141 counties (~90.5%) in which no killing was reported, and estimates relative risk ratios for the remaining 304 counties. Because these ratios are mathematically undefined for all but the 8 counties in which unarmed suspects are killed from both racial groups, Ross uses hierarchical pooling so that the estimates are a function of both the national average and the 8 counties from which relative risk ratios could be directly obtained.

Ross finds no county-level association between race-specific crime rates (for assaults and weapons-related offenses) and "racial bias in police shootings…." (10), implying that differences in rates of offending do not account for racial differences in police shooting fatality rates. Although the two race-specific crime rates used by Ross correlate weakly with the ratio of unarmed Black to unarmed White fatality rates, race-specific crime rates correlate more strongly with race-specific civilian fatality rates when considered separately. In other words, Ross's finding does not mean that there is no correlation between the rate of unarmed Blacks (or Whites) shot by police and Black (or White) arrest rates. Moreover, Klinger & Slocum (2017) point out also that 'unarmed' does not imply 'not dangerous', observing that between 1995 and 2015 approximately 20,300 civilians were killed in the United States by unarmed criminals, including 75 police officers who were killed by their own guns and 8 additional officers who were killed by wholly unarmed suspects.

Recently, Nix et al. (2017) analyze data from *The Washington Post* and find that among those civilians killed by police in 2015, Blacks were significantly more likely than Whites to have been unarmed, which they interpret as evidence of "threat perception failure" or implicit bias in which police mistakenly identify non-threatening Black suspects as threatening more often than they do White suspects. In their critical review of Nix et al. (2017), however, Klinger & Slocum (2017) find that only 21 out of the 93 unarmed cases included in Nix's study fit the category of 'threat perception failure' as originally proposed by Fachner & Carter (2015), and that the data show "no evidence that the likelihood of threat perception failure varies based on the race/ethnicity of the citizen who was shot and killed" (9).

Lott & Moody (2016) test the hypothesis of racial bias by comparing shootings of Black civilians involving White police officers to those involving Black police officers. Lott & Moody (2016) report that White police officers are no more likely to shoot Black suspects than Black police officers. Because Black and White police officers respond similarly to Black suspects, it is less likely that they shoot because of implicit bias, anti-Black prejudice, or personal racism. I include in the analyses below two police agency variables measuring the percentage of Black and female police officers, respectively.

In one of the most comprehensive studies examining police use-of-force incidents to date, Fryer (2016) finds that police are more likely to use non-lethal force on Black suspects than White suspects. However, based on police reports from Houston, Fryer finds that with respect to the use of lethal force, "no racial differences in either the raw data or when contextual factors are taken into account" (1).[5] Lemoine's (2017) analysis of more than 150,000 respondents from the Police-Public Contact Survey (PPCS) from 2005 and 2008 shows that a higher percentage of White men (20.7%) reported having contact with police than either Black (17.5%) or Hispanic men (17.1%), but that police used physical force against a higher percentage of Black (0.6%) than Hispanic (0.3%) or White man (0.2%).[6]

Terrill & Mastrofski's (2002) observational study of Indianapolis, Indiana, and St. Petersburg, Florida find that males, nonwhites, poor suspects, and young suspects were treated by police more forcefully irrespective of their behavior. Studies conducted in other cities, however, have found no evidence of bias in police use of lethal or nonlethal force after accounting for the behavior of the suspect. These cities include: Austin, Texas in 2006 and 2007 (Lee et al. 2014); Philadelphia from 1970 to 1978 and from 1987 to 1992 (Michael D. White 2002); and in St. Louis, Missouri between 2003 and 2012 (Klinger et al. 2016). Belvedere et al. (2005) find that, compared to White suspects, Black suspects are more likely to resist arrest, and Engel (2003) finds that Black suspects are more likely to not comply with White officers. These studies of incident-level data suggest that fatal police shootings rates will not be significantly different in regions with proportionally more Black or Hispanic residents after controlling for rates of criminal offending.

Some studies also suggest that the effect of any police bias on arrest disparities is likely to be strongest in criminal offenses over which police exert more discretion regarding decisions to arrest (Ousey & Lee 2008). Scholars have pointed specifically to the role that the 'War on Drugs' has played in instituting a 'New Jim Crow' (Alexander & West 2012). To test whether rates of victimless crimes in which police

5 Fryer analyzes police-civilian interactions using four separate data sets, including: New York City's Stop, Question, and Frisk program, which contains approximately 5 million cases; the Police Public Contact Survey, containing a nationally-representative sample of civilians; and incidents involving an officer discharging a weapon at civilians obtained from police departments in Austin, Dallas, Houston, Los Angeles County, and six large Florida counties.

6 Contact with police include incidents in which civilians called police and therefore do not necessarily reflect the potentially agonistic or threatening encounters with police. Lemoine has made publicly available his R code, and his results have been verified by the author. See the appendix.

have more discretionary power to make arrests are related to rates of fatal police shootings, this study includes as a regressor the rate of drug arrests.

Police Contact

Whereas police officer biases may affect rates of fatal police shootings through the actions of police officers during an encounter, the aggregate size of the police force may independently affect fatal shooting rates by increasing the frequency of such encounters. Counties with higher police-civilian ratios may therefore be expected to also have higher fatal police shooting rates. One possible mechanism is that larger police forces increase opportunities for potentially violent police-civilian encounters because the police are selectively targeting civilians as part of discretionary enforcement activities (e.g. 'stop and frisk').

At least with respect to the subset of fatal police encounters involving an unarmed civilian, however, selective targeting of individuals by police does not appear to be important. This is because most of these incidents are not initiated by the police. In their analysis of the *Police Killings in Context (PKIC)* data set of 153 unarmed civilians killed by police in 2015, Selby et al. (2016) report that among the 73% of fatal incidents that did not begin with traffic stops, 88% were citizen-initiated (72). In addition, Selby et al. (2016) find no significant difference in the racial compositions of decedents killed in police-initiated versus decedents killed in citizen-initiated incidents (72).

Another possibility is that regions with more police per capita are regions with higher levels of criminal activity that might not be captured fully by arrest data. Conditional on the assumption that enforcement efforts are not attenuated by higher rates of offending, this implies that counties with more police officers per capita should also have higher police shooting rates. Studies of 'minority threat' have in addition found that areas with proportionally more Blacks tend to have more police officers per capita even after controlling for local crime rates (Jackson & Carroll 1981, Jacobs & Britt 1979, Kent & Jacobs 2005, Stults & Baumer 2007). This suggests the possibility that observed associations between minority presence and fatal police-civilian encounters may be partially explained by the size of local police agencies and other indicators of crime control efforts.

Residential Segregation

Police use information about their surroundings to make decisions (Klinger 1997). Consequently, ecological factors can moderate the effect of individual and incident-level variables on fatal police shooting rates. For example, Smith (1986) analyze data from 60 neighborhoods in three cities and find that "Police are significantly more likely to use or threaten force against suspects encountered in primarily black or racially mixed neighborhoods" (329). According to Smith, the willingness of police to use force against a civilian and the extent of force applied are influenced by "both who is involved and where the encounter occurs" (338). Smith argues that police are more likely to use force against Black offenders in predominantly Black neighborhoods, in part because "individuals encountered in minority or racially mixed areas may be viewed by police as possessing moral liabilities connotative of the area itself", a phenomenon Smith calls "ecological contamination" (338). Smith's work suggests that racial composition should be linearly related to the level of force employed by police, with police employing more force, including more lethal force, in predominantly Black or minority neighborhoods.

Lawton (2007), however, proposes that a location's level of racial homogeneity is a more important contextual factor influencing the level of force used by police than the prevalence of minorities. Lawson argues that police officers may feel more justified in using force against a suspect who they perceive as not fitting or belonging in that location: because "it is easier to decide who does and does not fit if the neighborhood is racially homogeneous", police officers "may be more restrained when using force against citizens in racially mixed locations" (169). A possible implication of this hypothesis, then, is that fatal police shootings should be less frequent in more racially diverse (i.e. less segregated) areas.

Ecological theories assert that the macro-level characteristics of neighborhoods influence the micro-level behavior of individual police officers during civilian encounters. For example, the level of force used by a police officer during an arrest may be influenced by the officer's perception or knowledge of crime in the neighborhood in which the arrest occurs. Importantly, the moderating influence of neighborhood characteristics on individual police behavior during arrests and during other civilian encounters is distinct from the potential mediating effect of neighborhoods on the probability that arrests will occur.

Residential segregation may also be linked to the intensity of crime control efforts, and hence, indirectly linked to fatal police shooting rates. Minority Threat theorists have found that segregated cities with large Black populations have fewer police per capita than less segregated cities (Jackson & Carroll 1981, Jacobs & Britt 1979, Kent & Jacobs 2005). According to the theory, in segregated cities Whites are less inclined to police Blacks because Whites find them less threatening, either because the frequency of contact between Whites and Blacks diminishes or, more specifically, because interracial crime becomes less prevalent.

On the other hand, if crime control efforts are viewed favorably as a means of curtailing criminals rather than oppressing minorities, the lack of adequate policing in Black, segregated neighborhoods can be interpreted instead as neglect. According to the 'benign neglect hypothesis' Whites are less motivated "to report and attend to Black-perpetrated crime incidents" because they view crime in Black neighborhoods as an "ecologically contained problem in segregated environments" (Ousey & Lee 2008: 329).

A contrary prediction is that residential segregation may lead to more, not less, policing in Black neighborhoods. Ousey & Lee (2008) propose that residential segregation creates a 'spatial opportunity' for police to concentrate their attention on perceived crime 'hot spots', which, "even if not intended … virtually ensure that Blacks (or other non-Whites) will be observed, questioned, and arrested at rates that substantially overstate objective racial differences in offending" (331). This contradictory prediction also has empirical support. Stults & Baumer (2007) report, for example, that more racially segregated counties have more police per capita. These findings suggest that any effect of segregation on fatal police shootings will be mediated either by police force size or by rates of arrest.

Racial Inequality

Elaborating on Minority Threat theory, Jacobs & O'Brien (1998) hypothesize that police will kill more civilians in cities with greater levels of income inequality between Whites and Blacks. To test this hypothesis, Jacobs & O'Brien (1998) conduct cross-sectional Tobit regressions of fatal police shooting rates calculated from incidents reported between 1980 and 1986 across 170 U.S. cities. Jacobs & O'Brien (1998) find that fatal police shooting rates are higher in cities with greater levels of income inequality between Blacks and Whites. Specifically, they find a positive and significant coefficient for racial inequality, operationalized as the ratio of Black-to-White mean family incomes.

Their interpretation of this result, however, has several shortcomings. Jacobs & O'Brien (1998) explain that under conditions of greater racial income inequality, "a relatively poor Black underclass with less to lose from redistributive violence" is more likely to "threaten privileged Whites who … may be less willing to curb police violence" (844). In short, they propose that because poor Blacks are more threatening to Whites in cities with greater levels of racial inequality, Whites are more likely to explicitly or implicitly condone lethal police violence against them. This characterization of violence as "redistributive" implies empirical claims that are not supported in the article: that the victims of crimes committed by poor Blacks are privileged Whites (and not primarily other poor Blacks), that acts of violence are motivated by collective redistribution, that poor Blacks in particular are generally less supportive of efforts to curb violence, and that Whites would be the primary beneficiaries of crime control efforts. Moreover, they propose that police killings can be caused by an unwillingness of influential elites to prevent them from happening. This explanatory framework makes escalating police violence automatic and enables Jacobs & O'Brien (1998) to argue that "police may use deadly force *because* they protect the interests of the privileged" (845, emphasis added) without having to explicitly explain why or under what conditions police officers would be motivated to do so.

Education and Verbal Ability

There are three main findings that support a possible link between average levels of educational attainment and/or verbal ability in a community and levels of lethal and nonlethal force used by police. First, the link between low cognitive ability (IQ), on the one hand, and antisocial, delinquent, and criminal behaviors, on the other hand, has been firmly established in criminological research (Herrnstein & Murray 1996, Hirschi & Hindelang 1977, Moffitt et al. 1995). Individuals with relatively lower IQs are more likely to have an official arrest record, to have more frequent contact with the criminal justice system, to self-report involvement in criminal activities, and to endorse pro-criminal attitudes, net of socioeconomic controls (Beaver et al. 2013, Moffitt et al. 1981, Moffitt & Silva 1988). Studies have also found that IQ and violence are negatively associated (Diamond et al. 2012); that the average IQ of juvenile delinquents is about 8 points, or one-half a standard deviation below that of non-delinquents (Moffitt 1993); and that the IQ-delinquency association occurs independently of race, class, observed test motivation, and impulsivity (Lynam et al. 1993).

Second, strong aggregate-level associations have been found between average IQ and crime rates both at the state-level (Bartels et al. 2010, McDaniel 2006, Pesta et al. 2010) and at the county-level (Beaver & Wright 2011). Average IQ is negatively associated with numerous criminal offenses, including rates of murder, robbery, aggravated assault, burglary, and theft. Because individuals with low educational attainment and/or low verbal ability are more likely to engage in criminal, delinquent, and violent behaviors, populations with large proportions of such individuals are, relative to other populations, more likely to have incidents in which these behaviors elicit from police the use of nonlethal and lethal force as a response.

Third, research points to verbal ability as the most important subcomponent of IQ for predicting criminal, delinquent, and violent behaviors (Bellair & McNulty 2005, Bellair et al. 2016, Manninen et al. 2013, McNulty et al. 2013, Moffitt et al. 1994). In a study of 53 delinquent adolescents Manninen et al. (2013) report that among all cognitive, psychological, and background variables, low verbal intellectual ability was "the most significant predictor of a criminal record and especially a record of violent crime" (1). In a longitudinal, birth cohort study, Moffitt et al. (1994) find that after accounting for potential socioeconomic confounders, poor neuropsychological scores were "associated with early onset of delinquency" and that "poor verbal ability is the 'active ingredient' for delinquency" (293). Finally, studies of the 1977 National Longitudinal Survey of Youth (Bellair et al. 2016, McNulty et al. 2013) and the Longitudinal Survey of Adolescent Health (Bellair & McNulty 2005) have found that low verbal ability is a criminogenic risk factor that increases the probability of violence and arrests both directly and indirectly through educational failure.

Other studies point to the importance of poverty and childhood upbringing in the development of verbal ability. McNulty et al. (2013), for example, find that the acquisition of verbal ability is stunted by poor neighborhood and family conditions and that the Black-White difference in adolescent violence originates in part from the "segregation of Blacks in disadvantaged contexts" (140). And according to Fergusson et al. (2005), the link between early childhood IQ and crime is mediated by social and family circumstances. These findings suggest that ELA may have no effect on police shooting rates once SES and segregation are controlled. Controlling for rates of violent crime should also reduce and possibly eliminate any link between ELA and police shooting rates.

Data and Methods

Units

This study compares models across six distinct geopolitical units: counties with at least 10 thousand residents; counties with at least 100 thousand residents; U.S. states; and three sets of aggregated regions consisting of sparsely populated adjacent counties with at least 10 thousand, 100 thousand, and 1 million residents. The term "region" is used in contrast to "county" or "state" to indicate that cases include adjacent counties aggregated so that their combined population exceeds the specified lower limit. The 8 models in the analyses below correspond to the six different units of aggregation and to two additional county-level models that include police department characteristics. Because policing data are not available for all counties, these two models have substantially smaller sample sizes.

Excluding counties with fewer than 100,000 residents results in a loss of 767 fatal shooting incidents, approximately 19% of the recorded cases. Combining sparsely populated regions into larger units preserves these cases while circumventing potential model fitting difficulties that can occur when including units with tiny populations. As depicted in Figure 2, the counties with the highest fatal police shooting frequencies are also the most populated. The three highest fatal police shooting frequencies are in Los Angeles County, Maricopa County, and Cook County, in which an estimated 194, 84, and 54 civilians were killed by police, respectively. Because fatal police shooting rates vary inversely with population, counties with the highest fatality rates tend to be sparsely populated. As shown in Figure 3, the counties with the three highest fatality rates all have fewer than 2,000 residents. By comparing variable coefficients across the 8 models, the effects of aggregation and case exclusion can also be observed. The algorithm used to generate these regions is provided in the appendix. For all variables, New York City boroughs (i.e. counties) are aggregated into one county.

Figure 2. Frequency of Civilians Killed by Police per County (2013-2016)

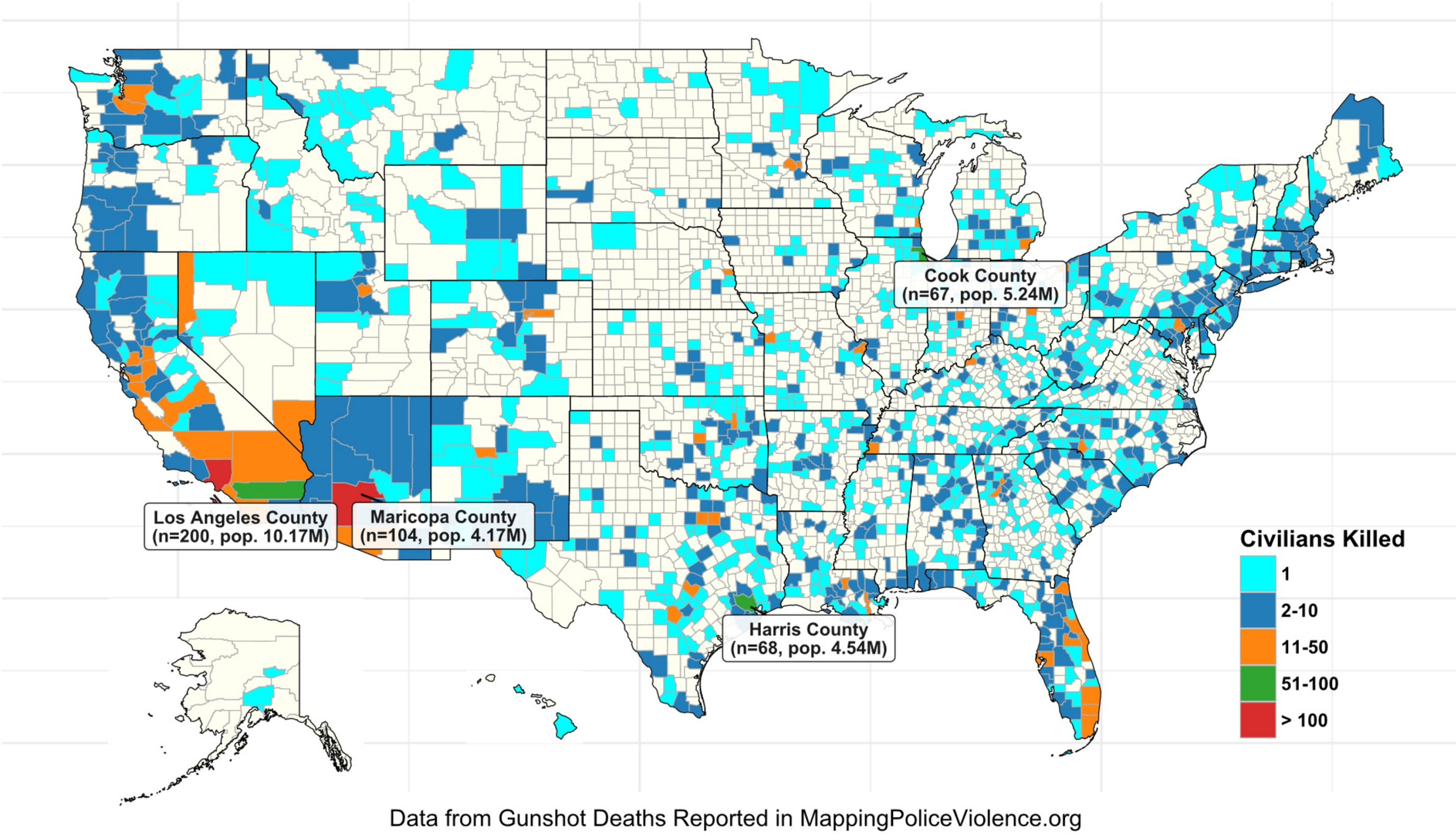
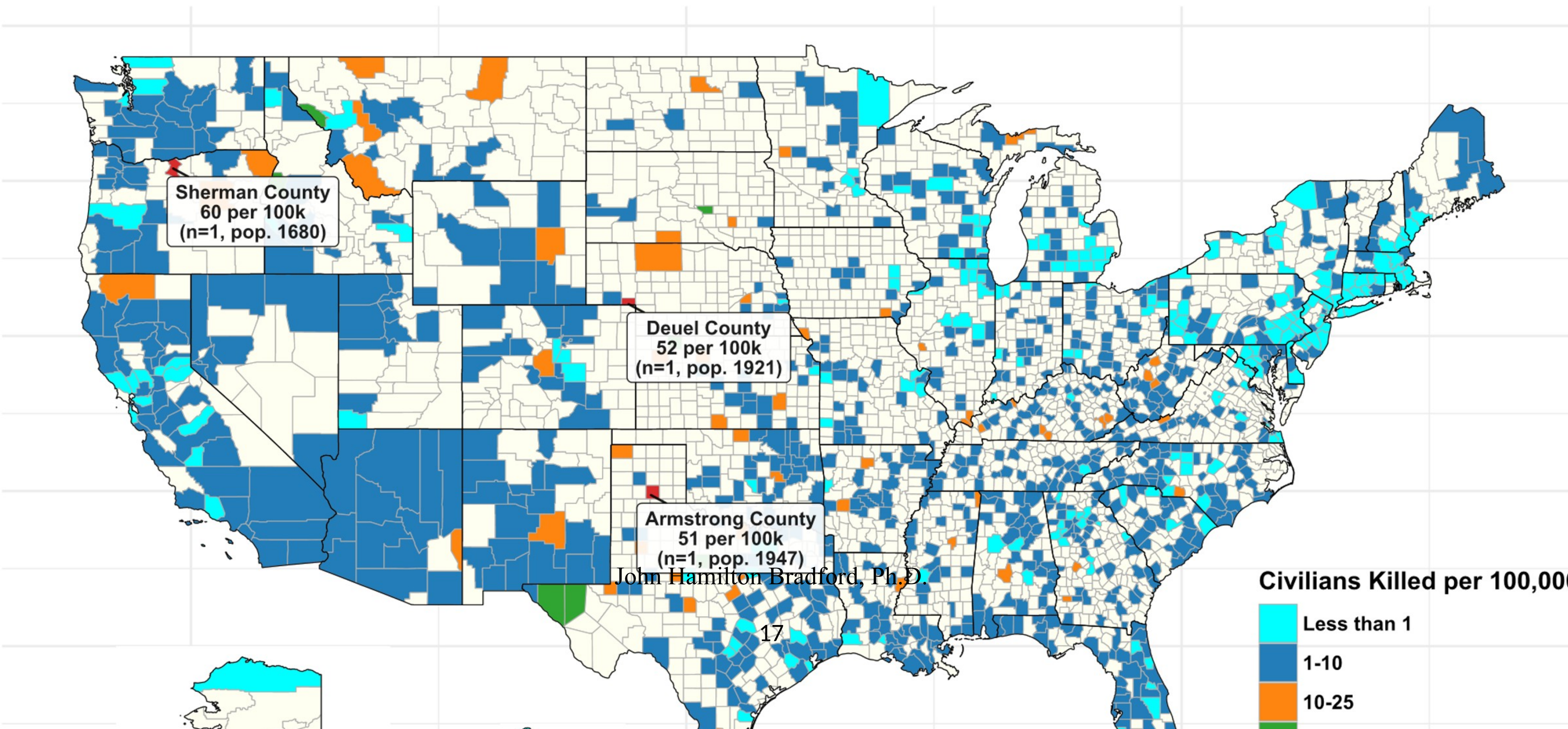


Figure 3. Rates of Fatal Police Shootings of Civilians per County (2013-2016)



obtained from the American Community Survey (ACS).[9] Both population and the proportion of young adult males are transformed into their natural logarithms; the Black and Hispanic population proportions are transformed by first adding 1 and then converting it to its natural logarithm.

Crime & Policing

These variables include the rate of violent crime arrests; the rate of arrests for drug offenses; the Black percentage of police; the female percentage of police; and the ratio of police officers to civilians. Violent Crime consists of four offenses: murder and nonnegligent manslaughter, forcible rape, robbery, and aggravated assault. Drug Arrest data are calculated as the sum of reported arrests for both the 'Sale/Manufacture' of drugs as well as drug 'Possession.'[10] Arrest rates per 100,000 residents are calculated by multiplying 100,000 by the reported frequency of arrests in 2015 divided by the estimated population in 2015. Both violent crime and drug arrest rates are transformed by adding 1 and taking their natural logarithms.

Arrest rates for violent crime and drug offenses are obtained from the FBI's Uniform Crime Reporting (UCR) Program for 2015.[11] Arrest data for counties in Florida are not included in the UCR and are obtained instead from the Florida Department of Law Enforcement website.[12] Because of data irregularities in the UCR, arrest data New York City are obtained from the New York City Police Department's "Crime and Enforcement Activity in New York City" report.[13]

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9 Specifically, county-level data are obtained from: "Annual County Resident Population Estimates by Age, Sex, Race, and Hispanic Origin" dataset, available at https://www2.census.gov/programs-surveys/popest/datasets/2010-2015/counties/asrh/cc-est2015-alldata.csv .

10 Florida arrest data do not distinguish between these two sub-components.

11 Specifically, the data are obtained from the "Uniform Crime Reporting Program Data: Arrests by Age, Sex, and Race" available from the Interuniversity Consortium for Political and Social Research (ICPSR). The UCR arrest data obtained from the ICPSR contain data entry errors. Specifically, the frequency of arrests for Delphi, Indiana in 2013 is mistakenly reported as "10000" across multiple columns and rows (i.e. offenses), a value that exceeds its population size.

12 Arrest rates for Florida counties are taken from the excel file "Arrests by County, Age, Sex and Offense for Florida, 2004 - 2015" available at http://www.fdle.state.fl.us/cms/FSAC/Data-Statistics/UCR-Arrest-Data.aspx

13 See: http://www.nyc.gov/html/nypd/html/analysis_and_planning/crime_and_enforcement_activity.shtml
Specifically, data are obtained from the file "Enforcement Report Data Tables 2008-2015", available at: http://www.nyc.gov/html/nypd/downloads/zip/analysis_and_planning/crime_and_enforcement_report_data_tables_2008-2015_2016-02.zip The ICPSR files reporting county-level arrest data from the UCR only contains arrest data for 'New York County' (i.e. Manhattan, FIPS code 36061), and does not include data arrests data for: Kings County (i.e. Brooklyn, 36047), Queens (36081), The Bronx (36005), Staten Island (36085). Moreover, the UCR reports zero murders for New York City from 2013-2015.

Data for the three policing variables are obtained from the Law Enforcement Management and Administrative Statistics (LEMAS) Series from ICPSR (2013).[14] The percentage of Black police and the percentage of female police are the percentages of full-time sworn personnel who are Black and female, respectively. The ratio of police officers to civilians is calculated by multiplying 100,000 by the ratio of full-time sworn personnel to the estimated population. The police-civilian ratio is then transformed by adding 1 and taking its natural logarithm. Because police department data are available for only 1,264 counties, less than half of the 2,429 counties with at least 10,000 residents, separate analyses are conducted on data including these three variables. Policing variables are not included in any analyses of aggregated regions or states.

Socioeconomic Status

These variables include SES, Crowding, the Gini Index of annual income, the ratio of White to Black unemployment rates, High School Dropout rates, and weighted mean 8th grade English/Language Arts (ELA) scores. Data for all socioeconomic variables except ELA scores are obtained from the American Community Survey (ACS) for the year 2015.[15]

SES is the first principle component of four variables: median family income; the civilian unemployment rate; the percentage of family households headed by single mothers; and the percentage of individuals with incomes below the poverty level. Crowding is the percentage of households with 1.01 or more occupants per room, including owners and renters. Crowding is transformed by adding one and then taking its natural logarithm. The Gini Index is a commonly used measure of inequality ranging from 0 to 100, where zero indicates perfect equality (i.e. everyone earns the same income) and 100 indicates perfect inequality (i.e. one person earns all available income). The ratio of non-Hispanic White to Black unemployment is the ratio of their respective civilian unemployment rates. The high school dropout rate is the percentage of adults 25 years and over who have not obtained a regular high school diploma, GED or equivalent credential.

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14 See: https://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/36164

15 Specifically, "2011-2015 American Community Survey 5-Year Estimates." ACS data are available at: https://factfinder.census.gov

Verbal Ability & Educational Attainment

English/Language Arts (ELA) scores are obtained from 8th graders in the year 2013 (or most recent year for which data are provided) from the Stanford Education Data Archive (SEDA). SEDA estimates are based on data from states' standardized testing programs collected by the U.S. Department of Education. To enable comparability across states, these scores are standardized into National Assessment of Educational Progress (NAEP)-referenced units. ELA scores are provided by SEDA at the school district level, disaggregated by grade and year. ELA scores of 8th graders (i.e. students who are typically 13-14 years old) are selected because the 8th grade is the highest grade in the data set and therefore the best available proxy for assessing verbal ability in the general population of adolescents and adults. Moreover, 8th grade ELA data contains fewer missing cases than ELA data for either 6th and 7th grade. School-district ELA scores are aggregated to county, regional, and state-level scores by taking the mean ELA score weighted by the number of 8th graders across school districts within those geographical units.

Findings

Cross-Validated Lasso & Elastic-Net Regressions

Least Absolute Shrinkage and Selection Operator (Lasso) and Elastic-Net regression analyses are conducted using the 'glmnet' R package version 2.0.-10. Lasso and Elastic-Net regression fit a generalized linear model via penalized maximum likelihood (Hastie & Qian 2014). The overall strength of the penalty in both models is controlled by the tuning parameter λ. Because the Lasso shrinks irrelevant coefficients towards zero, it is a useful model selection algorithm (Efron et al. 2004). One disadvantage of the Lasso, however, is that among a set of collinear predictors, Lasso regression tends to select just one. For this reason, Elastic-Net regression models are also estimated. Elastic-Net regression performs similarly to the Lasso, but removes "any degeneracies and wild behavior caused by extreme correlations" (Friedman et al. 2010: 4). The elastic net penalty is determined by the parameter α, where $\alpha = 0$ is equivalent to the Lasso and $\alpha = 1$ is equivalent to the ridge penalty.[16]

16 The Elastic-Net penalty can be understood as a compromise between the Lasso and ridge penalties. Whereas the Lasso penalty constrains the sum of the absolute regression coefficients, the 'ridge' penalty constrains the squared size of the coefficients. In contrast to the Lasso, ridge regression tends to include or exclude k collinear predictors as a group, shrinking their coefficients towards $1/k^{th}$ the size that any single predictor would get by itself (Friedman et al. 2010: 3).

For each model, the value for λ is determined by10-fold cross-validation. A 10-fold cross-validation is performed by randomly partitioning the data into 10 groups or 'folds'; for each k^{th} fold, a model fitted to (i.e. 'trained on') data excluding *k* is used to predict *k;* and the sum of squared errors (between the predicted and observed values in the k^{th} fold) is estimated for each of the 10 folds. The mean cross-validated error (across 10 cross-validations) is estimated for each value in a sequence of possible values for λ. The selected value for λ is that which yields the most parsimonious model that is also still within one standard error of the minimum mean cross-validated error. The same values for λ are used in the Lasso and Elastic-Net regression models.

The Lasso regression results for all 8 models are provided in Table 2. Prior to analysis, all predictors are standardized so that each has a mean of zero and a standard deviation of one. The coefficients represent the change in the natural log of fatal police shooting rates per one standard deviation increase in the predictor. Perhaps most surprisingly, ELA is the second most frequently selected predictor (along with Crowding and SES), having a non-zero coefficient across 6 of the 8 models. ELA is negatively associated with fatal police shootings, indicating that encounters between police and civilians that escalate to fatal violence are more likely in geographical areas with lower average verbal and written communication skills.

The most frequently selected variable is the rate of violent crime, which has a non-zero coefficient across all models except model 8, in which only ELA is selected. Unsurprisingly, the rate of violent crime is positively associated with the rate of fatal police shootings of civilians, net of other covariates. The coefficient for the violent crime rate is largest in model 1, consisting of those counties with at least 10,000 residents and which also reported data for the three variables measuring characteristics of local police departments. Crowding and SES are each selected across 6 of the 8 models. Interestingly, the sign of the coefficient for SES switches from negative to positive in model 6, which consists of adjacent counties aggregated to have a minimum combined population of 100,000 residents. The Police-Civilian Ratio is also selected in model 4 and has a positive sign.

Table 2. Standardized Lasso Regression Coefficients of Fatal Police Shooting Rates (2013-2016)

	10k Counties (1)	10k Counties (2)	10k Regions (3)	100k Counties (4)	100k Counties (5)	100k Regions (6)	1M Regions (7)	States (8)
Constant	**0.592**	**0.545**	**0.544**	**0.692**	**0.691**	**0.692**	**0.754**	**0.817**
Population (ln)	**0.036**	**0.065**	**0.061**	0.000	0.000	0.000	0.000	0.000
Black % (ln)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hispanic % (ln)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Male 15-29 % (ln)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Violent Crime Rate (ln)	**0.055**	**0.032**	**0.028**	**0.032**	**0.038**	**0.037**	**0.011**	0.000
Drug Arrest Rate (ln)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SES	**-0.002**	**-0.023**	**-0.022**	**-0.025**	**-0.030**	**0.032**	0.000	0.000
Crowding % (ln)	**0.006**	**0.011**	**0.016**	0.000	**0.005**	**0.039**	**0.014**	0.000
Dissimilarity (ln)	0.000	0.000	0.000	0.000	0.000	0.000	**-0.006**	0.000
Gini	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Dropout %	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ELA	**-0.027**	0.000	0.000	**-0.066**	**-0.065**	**-0.050**	**-0.096**	**-0.048**
W-B Unemployment Ratio	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Black Police %	0.000	-	-	0.000	-	-	-	-
Female Police %	0.000	-	-	0.000	-	-	-	-
Police-Civilian Ratio	0.000	-	-	**0.007**	-	-	-	-
Lambda (1se)	0.078	0.059	0.055	0.078	0.071	0.052	0.052	0.106
Fatalities	3373	3805	3838	3059	3166	3960	4027	4028
Observations	1084	1913	2017	517	567	999	210	51

The standardized Elastic-Net coefficients are presented in Table 3. For all elastic net regression models, the parameter α equals 0.5. In comparison to the Lasso, the Elastic-Net penalty excludes fewer covariates. Crowding is the only predictor selected across all 8 models. ELA, SES, and Violent Crime are selected in 7 of the 8 models. Violent Crime has slightly larger coefficients than in the Lasso models. SES again changes signs in models 6 and 7, a consequence of aggregation bias or Simpson's paradox. In aggregated regions of 100,000 and 1 million residents, higher SES scores are associated with increased fatality rates.

The Hispanic percentage of the population has a coefficient of zero across all Lasso models but has a positive coefficient across 6 of the Elastic-Net models, indicating that counties and regions with higher Hispanic proportions have higher average fatal police shooting rates. Interestingly, in bivariate correlations the percentage of Hispanic residents is correlated most strongly with Crowding across all 8 geographies. Dissimilarity (i.e. segregation) has positive coefficients in models 2 and 3, and negative coefficients in models 7 and 8.

Table 3. Standardized Elastic Net Regression Coefficients of Fatal Police Shooting Rates (2013-2016), α = 0.5

	10k Counties (1)	10k Counties (2)	10k Regions (3)	100k Counties (4)	100k Counties (5)	100k Regions (6)	1M Regions (7)	States (8)
Constant	**0.592**	**0.545**	**0.544**	**0.692**	**0.691**	**0.692**	**0.754**	**0.817**
Population (ln)	**0.078**	**0.088**	**0.078**	0.000	0.000	0.000	0.000	0.000
Black % (ln)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hispanic % (ln)	0.000	**0.005**	**0.011**	**0.008**	**0.006**	**0.015**	**0.007**	0.000
Male 15-29 % (ln)	0.000	0.000	0.000	0.000	0.000	0.000	**0.007**	0.000
Violent Crime Rate (ln)	**0.065**	**0.041**	**0.037**	**0.048**	**0.054**	**0.048**	**0.025**	0.000
Drug Arrest Rate (ln)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SES	**-0.033**	**-0.045**	**-0.051**	**-0.044**	**-0.048**	**0.046**	**0.016**	0.000
Crowding % (ln)	**0.019**	**0.020**	**0.023**	**0.014**	**0.023**	**0.040**	**0.017**	**0.014**
Dissimilarity (ln)	0.000	**0.019**	**0.023**	0.000	0.000	0.000	**-0.031**	**-0.009**
Gini	0.000	0.000	0.000	0.000	0.000	0.000	**0.012**	0.000
Dropout %	0.000	0.000	0.000	0.000	0.000	**0.002**	0.000	0.000
ELA	**-0.042**	**-0.013**	0.000	**-0.059**	**-0.064**	**-0.053**	**-0.085**	**-0.080**
W-B Unemployment Ratio	0.000	0.000	0.000	0.000	0.000	0.000	**0.002**	**0.004**
Black Police %	0.000	-	-	0.000	-	-	-	-
Female Police %	0.000	-	-	0.000	-	-	-	-
Police-Civilian Ratio	0.000	-	-	**0.031**	-	-	-	-
Lambda (1se)	0.078	0.059	0.055	0.078	0.071	0.052	0.052	0.106
Fatalities	3373	3805	3838	3059	3166	3960	4027	4028
Observations	1084	1913	2017	517	567	999	210	51

In both the Lasso and Elastic-Net regressions, the ratio of full-time sworn officers to civilians has a positive coefficient in Model 4 but not in Model 1. Counties with more active duty police officers tend to have slightly higher rates of civilians killed by police, but only among counties with at least 100,000 residents. In addition, population has a positive coefficient in the first three Lasso and Elastic-Net models. This isn't surprising considering that a civilian was killed by a police officer in only 20 percent of counties with fewer than 100,000 residents. Across all Lasso and Elastic-Net models the Black percentage of the population, Drug Arrests, the Black percentage of police officers, and the Female percentage of police officers have coefficients equal to zero. The percentage of 15 to 29-year-old males, the Gini coefficient, and the high school Dropout rate are nonzero in only one of the 8 Net-Elastic models. Interestingly, the White-Black Unemployment Ratio has a positive coefficient in models 7 and 8 of the Net-Elastic regressions.

Repeated Cross-Validated Stepwise Selection

In addition to Lasso and Elastic-Net regressions, repeated cross-validated stepwise selection is employed as a variable-selection algorithm using the 'caret' R package (version 6.0-76). Data are first partitioned randomly into 5 folds. All possible models (i.e. combinations of variables) are then trained on four of the five folds, and the root mean squared errors (RMSEs) are calculated from their respective predictions of the holdout. After all possible models have been trained and evaluated on the first fold, the process is repeated, with each fold sequentially serving as a hold-out group. One 5-fold cross-validation therefore yields five RMSEs for each model or variable combination. To ensure that the results are not an accident of the random data partitioning, the average 5-fold cross-validated RMSEs are estimated from 10 different random partitions of the data.[17] Each model presented in Table 4 is the set of predictors among all possible combinations with the minimum mean 5-fold cross-validated error across 10 repetitions.

Compared to the Lasso and Elastic-Net variable selection algorithms, the two biggest differences resulting from the cross-validated stepwise selection algorithm pertain to the Black population percentage and Crowding. Whereas the Black percentage of the population has a coefficient of zero across all Lasso and Elastic-Net regressions, it is negative and statistically significant across all models in Table 4. In fact, the Black population percentage is the only variable selected across all models in Table 4. On the other hand, Crowding is selected across all Elastic-Net regressions but is dropped from all OLS models determined by cross-validated stepwise selection.

17 The pseudo-code for this algorithm is provided in the appendix.

Table 4. Best OLS Models Determined by Cross-Validated Stepwise Selection

	10k Counties (1)	10k Counties (2)	10k Regions (3)	100k Counties (4)	100k Counties (5)	100k Regions (6)	1M Regions (7)	States (8)
Constant	1.393	0.220	-0.945***	3.363**	3.865***	2.817***	7.260***	13.008**
	(0.858)	(0.666)	(0.162)	(1.002)	(0.932)	(0.727)	(1.222)	(3.779)
Population (ln)	0.130***	0.116***	0.101***	0.046	0.056*	-	-	-
	(0.015)	(0.016)	(0.015)	(0.024)	(0.023)			
Black % (ln)	-0.085***	-0.048**	-0.044*	-0.113**	-0.064**	-0.033*	-0.071**	-0.095*
	(0.022)	(0.018)	(0.017)	(0.034)	(0.023)	(0.015)	(0.026)	(0.046)
Violent Crime Rate (ln)	0.001**	0.001**	0.000**	0.001**	0.001**	0.001***	0.000	-
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
SES	-0.067**	-0.063***	-0.074***	-0.054*	-0.049*	0.049***	0.031	-0.068
	(0.020)	(0.017)	(0.013)	(0.022)	(0.022)	(0.014)	(0.020)	(0.043)
ELA	-0.009**	-0.005	-	-0.010**	-0.012***	-0.009**	-0.022***	-0.033*
	(0.003)	(0.003)		(0.004)	(0.003)	(0.003)	(0.005)	(0.015)
Police-Civilian Ratio	0.034	-	-	0.077**	-	-	-	-
	(0.021)			(0.024)				
Hispanic % (ln)	-	0.032	0.048*	-	-	0.075***	0.054*	0.151**
		(0.020)	(0.019)			(0.017)	(0.023)	(0.048)
Dissimilarity (ln)	-	0.072	0.083	-0.233**	-0.261**	-	-0.474***	-0.336
		(0.044)	(0.045)	(0.089)	(0.087)		(0.123)	(0.355)
Black Police %	-	-	-	0.005	-	-	-	-
				(0.003)				
Gini	-	-	-	-	0.011	-	0.031***	-
					(0.007)		(0.009)	
Dropout %	-	-	-	-	-	-	-0.020*	-0.037
							(0.009)	(0.028)
W-B Unemployment Ratio	-	-	-	-	-	-	0.113	0.229*
							(0.057)	(0.105)
Male 15-29 % (ln)	-	-	-	-	-	-	-	-0.855
								(0.647)
Max VIF	2.53	2.36	1.67	2.97	2.98	2.65	4.59	5.82
Adjusted R-Squared	0.133	0.079	0.069	0.221	0.202	0.16	0.423	0.55
AIC	1835	3702	3989	545	616	1173	-26	-18
Fatalities	3373	3805	3838	3059	3166	3960	4027	4028
Observations	1084	1913	2017	517	567	999	210	51

Note: *p<0.05; **p<0.01; ***p<0.001. (two-tailed). Robust standard errors are in parentheses. Models depict the combination of variables with the lowest mean 5-fold cross-validated error across 10 repetitions.

In addition to Crowding, the only other variable to be excluded across all 8 geographies is the Drug Arrest Rate. The percentage of Female Police is also not included in either model 1 or 4. The percentage of Black Police is selected in model 4 and has a positive coefficient, indicating that police agencies with proportionally more Black officers have slightly higher fatality rates among counties with at least 100,000 residents. As with the Lasso and Elastic-Net models, SES is negatively associated with fatal police shooting rates in Models 1-5, but is positively associated with fatality rates across units of aggregated adjacent counties in Model 6 and 7. Strangely, SES becomes negative again in model 8. Another salient pattern is that the Hispanic percentage of the population is positively correlated with fatality rates and is selected across 5 of the 8 models. Moreover, the Police-Civilian Ratio is selected in both models in which it is tested.

Table 5. Relative Importance of Regressors

	Normalized *LMG* Coefficients							
	10k (1)	10k (2)	10k* (3)	100k (4)	100k (5)	100k* (6)	1M* (7)	S (8)
Population (ln)	23.05	34.17	31.81	1.22	1.44	0.8	1.02	5.4
Black % (ln)	2.97	2.2	2.33	3.6	2.18	2.02	2.81	8.44
Hispanic % (ln)	5.18	6.98	7.83	4.27	4.75	7.81	4.42	8.37
Male 15-29 % (ln)	0.8	1.04	1.02	0.82	0.88	0.63	5.07	2.56
Violent Crime (ln)	18.7	13.72	12.56	14.39	17.27	17.34	8.61	2.42
Drug Arrest (ln)	2.45	1.44	1.87	3.28	3.42	1.39	2.46	0.8
SES	13.49	11.59	13.2	16.69	20.54	18.1	15.32	14.53
Crowding % (ln)	7.17	7.31	8.31	5.97	8.27	13.35	6.78	7.69
Dissimilarity (ln)	1.87	9.69	10.42	2.28	2.6	0.14	9.38	5.95
Gini	1.74	2.22	2.22	4.46	4.82	4.97	6.34	2.47
Dropout %	3.45	2.71	2.75	7.98	9.67	11.9	8.19	6.68
ELA	12.23	6.31	4.74	19.96	23.96	20.78	27.32	29.34
W-B Unemp Ratio	0.05	0.61	0.93	0.78	0.19	0.76	2.29	5.33
Black Police %	0.95	-	-	2.53	-	-	-	-
Female Police %	1.86	-	-	1.03	-	-	-	-
Police Ratio	4.04	-	-	10.74	-	-	-	-
Adj. R-Squared	0.13	0.08	0.07	0.22	0.20	0.16	0.42	0.50
R-Squared	0.14	0.08	0.08	0.24	0.22	0.17	0.46	0.63
Fatalities	3373	3805	3838	3059	3166	3960	4027	4028
Observations	1084	1913	2017	517	567	999	210	51

Note: asterisks denote that sparsely populated counties are aggregated into larger regions.

Relative Importance of Regressors

Table 5 reports the results of relative importance analyses estimated using the R package 'Relaimpo' (version 2.2-2). The term 'relative importance' refers to the "quantification of an individual regressor's contribution to a multiple regression model" (Grömping & others 2006: 1). Specifically, relative importance refers to the "proportionate contribution each predictor makes to R^2" (Johnson & Lebreton 2004: 1). If all predictors are uncorrelated, then a predictor's individual contribution to the explained variance of the dependent variable is equal to its R^2 in a univariate regression. When predictors are correlated, however, the average contribution of each regressor to R^2 can be strongly influenced by the order in which regressors are introduced. A regressor that is introduced before a second regressor with which it is correlated will therefore make a greater change to a model's overall R^2. For example, how much the introduction of the regressor ELA changes the overall explained variance in fatal police shooting rates might depend heavily on whether the model already includes regressors with which ELA is correlated, such as SES or High School Dropout rates. To solve the problem of dependence on orderings, Lindeman, Merenda, and Gold (1979) propose to measure relative importance by averaging sequential sums of squares over all orderings of regressors. This method, abbreviated '*LMG'*, is used in Table 5.

The *LMG* coefficients depicted in Table 5 indicate how important each variable is to the explanation of variance in fatal police shooting rates across eight models. The coefficients depicted in the first 8 models shaded in green are normalized so that the coefficients for each column sum to 100. Population is the most important predictor in the first three models with normalized *LMG* coefficients of 23.05, 34.17, and 31.81, respectively, again reflecting the infrequency of police shootings in sparsely populated counties.

The three most consistently important predictors of civilian fatality rates are ELA, Violent Crime rates, and SES. ELA is the most important predictor of fatal police shooting rates in models 4-8, or 5 out of 8 models. In model 8, ELA contributes on average approximately 29% of the 63% of explained variance in fatal shooting rates across U.S. States. ELA contributes on average about 27% of the 46% of explained variance across regions with at least 1 Million residents. Violent crime is the second most important predictor in models 1-2 after population and the third most important predictor in models 3-6. At the highest levels of aggregation in models 7 and 8, the importance of violent crime rates drops substantially. The Police-Civilian Ratio is the fourth most important predictor among counties with at least 100,000 residents for which police agency data are available.

Partial Least Squares Regressions

In the analyses conducted so far, the covariates used to construct SES and Violent Crime are not considered separately because they are highly correlated. One way to circumvent the problem of multicollinearity is to perform partial least squares (PLS) regression, also known as projection on latent structures. PLS regression extracts orthogonal factors (or 'components') from the data which maximize the covariance between the predictors and the dependent variable (Abdi 2010). OLS is then performed using the orthogonal components. The coefficients obtained from PLS are also a useful way of determining the relative importance of predictors.

Table 6 reports the cross-validated PLS coefficients for all variables, disaggregating SES and Violent Crime into their respective components. The number of extracted components used in each model is that which yields the lowest bias-corrected 10-fold cross-validated mean squared error of prediction. As with the Lasso and Elastic-Net regressions, the predictor variables in the PLS regressions are first scaled so that each has a mean of zero and a standard deviation of one. The coefficients are normalized by multiplying each by 100 and then dividing by the sum of the absolute values of all predictor coefficients. All PLS regressions are performed using the R package 'pls' (version 2.6-0).

Judged by the absolute size of their normalized coefficients, the unemployment rate is the most important SES predictor in models 1-3, whereas median income is the most important SES predictor in models 4-7. At the state level, poverty is the most important SES predictor of fatal police shooting rates. Among the four violent crimes (rape, robbery, aggravated assault, and murder), assault is the most important in models 1 and 6 and the second most important in models 3, 4, and 8. Murder is the most important predictor in models 4, 5, and 7. Surprisingly, the sign for the coefficient for rape is positive in models 1 and 4 but negative across all other models.

Table 6. Cross-Validated Partial Least Squares Regressions of Fatal Police Shooting Rates (2013-2016)

	10k Counties (1)	10k Counties (2)	10k Regions (3)	100k Counties (4)	100k Counties (5)	100k Regions (6)	1M Regions (7)	States (8)
Population (ln)	13.064	16.723	15.674	1.873	6.368	0.298	2.453	-4.12
Black % (ln)	-3.858	-6.053	-6.65	2.03	-8.819	-5.525	-4.44	-2.117
Hispanic % (ln)	7.452	5.885	6.62	4.694	3.665	11.071	6.49	5.339
Male 15-29 % (ln)	2.124	0.522	0.221	2.316	-2.009	0.446	1.672	3.573
Murder Rate (ln)	6.116	4.803	4.196	6.386	9.254	7.522	7.913	2.402
Rape Rate (ln)	1.452	-5.819	-6.732	2.634	-5.93	-3.463	-2.01	-3.259
Robbery Rate (ln)	7.673	5.828	4.784	5.464	1.825	1.11	3.435	-1.882
Assault Rate (ln)	8.67	5.032	4.852	6.209	5.15	9.506	0.439	3.129
Drug Arrest Rate (ln)	3.467	-0.868	0.571	3.343	3.3	1.79	0.995	1.533
Unemployment %	4.894	7.964	8.319	5.521	0.913	5.45	-1.064	4.879
Median Income	-3.149	-5.893	-6.082	-7.338	-11.052	-8.834	-8.703	-9.841
Single Mothers %	3.748	3.175	3.7	6.058	-0.332	0.788	-7.082	2.998
Poverty %	2.268	2.511	2.598	7.701	2.426	6.18	5.413	11.909
Crowding % (ln)	7.532	6.563	7.328	5.875	4.522	12.573	4.41	8.743
Dissimilarity (ln)	5.537	11.494	11.982	-0.137	-7.612	0.104	-6.921	-6.867
Gini	0.452	-0.26	0.115	4.65	5.075	2.672	8.404	2.881
Dropout %	-1.073	-1.216	-1.46	6.674	-6.699	7.259	-11.542	6.806
ELA	-6.442	-5.407	-3.8	-8.507	-14.964	-10.72	-12.575	-13.288
W-B Unemployment Ratio	0.427	3.987	4.317	0.618	0.083	4.688	4.039	4.433
Black Police %	-2.688	-	-	3.394	-	-	-	-
Female Police %	3.101	-	-	2.584	-	-	-	-
Police-Civilian Ratio	4.812	-	-	5.994	-	-	-	-
N Components	2	3	3	1	5	2	5	1
Adj. R-Squared	0.115	0.082	0.074	0.189	0.227	0.167	0.489	0.425
Fatalities	3373	3805	3838	3059	3166	3960	4027	4028
Observations	1084	1913	2017	517	567	999	210	51

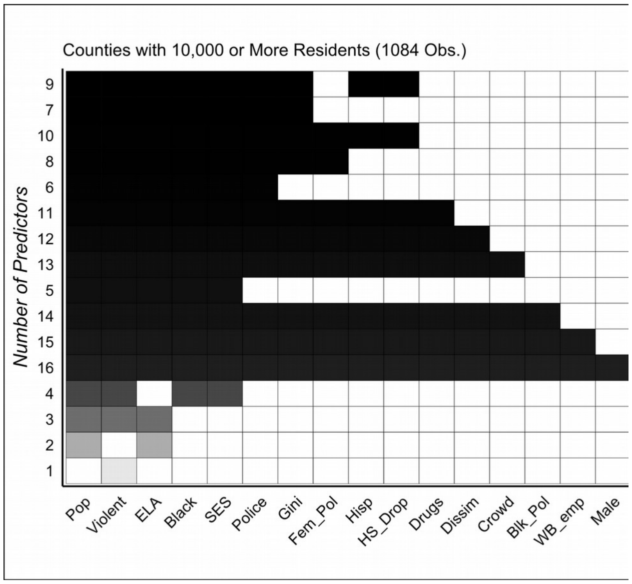
Coefficients are mean standardized coefficients across N components. The number of orthogonal principle components is selected to minimize the 10-fold cross-validated root mean squared error of validation. Midpoint of 3-part color scale is zero.

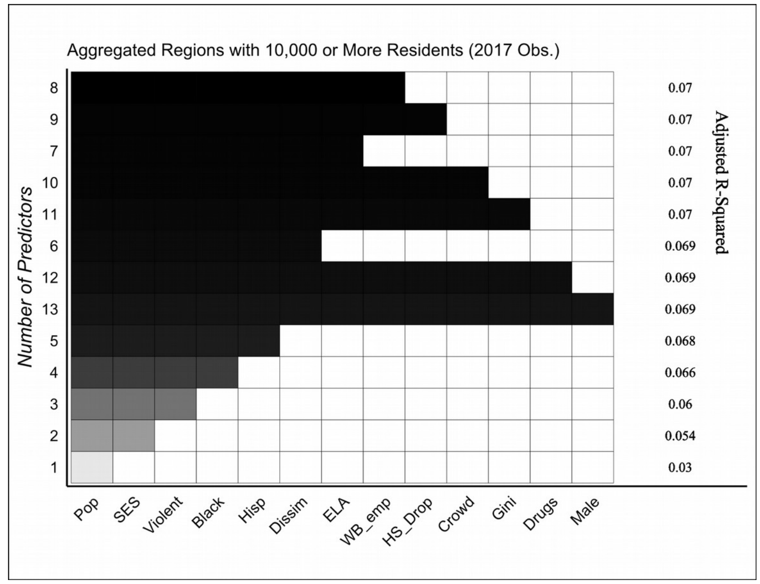
The police-civilian ratio is again an important predictor in model 4 among counties with populations greater than 100,000. Surprisingly, Crowding is the most important predictor in model 6, followed closely by the Hispanic percentage of the population, which have normalized PLS coefficients of 12.57 and 11.07, respectively. The absolute PLS coefficient sizes for Dissimilarity are largest in models 2, and 3, and its sign is positive in models 1, 2, 3, and 6, but negative in models 4, 5, 7, and 8. Overall, the results in Table 6 accord with the *LMG* coefficients reported in Table 5. The most striking finding is that ELA is consistently an important predictor of fatality rates. ELA has the largest absolute coefficient size in models 4, 5, 7, and 8. ELA is also always negatively associated with police shooting fatality rates.

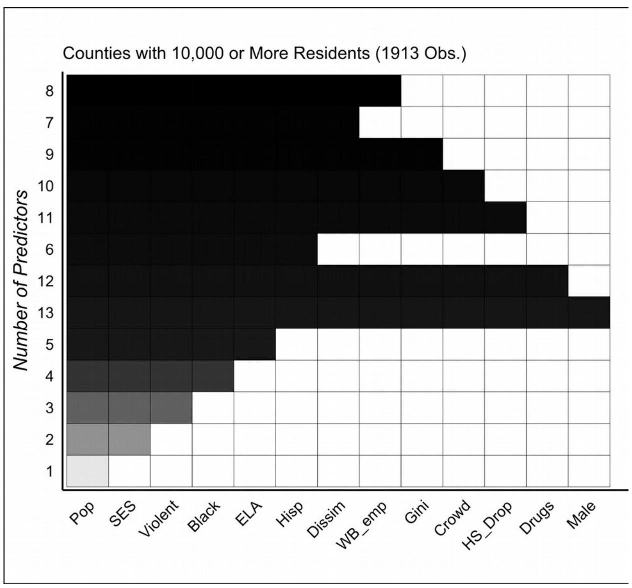
Best Subsets Regressions

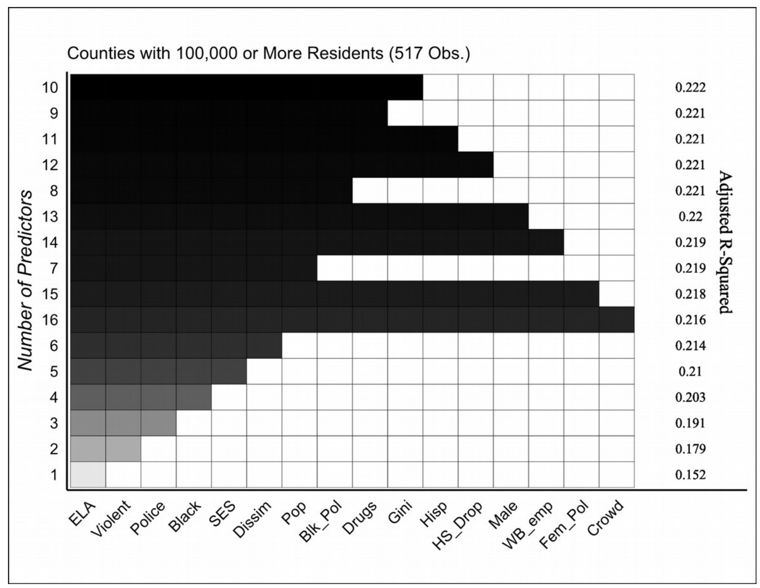
Another way to evaluate the relative importance of regressors is to determine, for a given subset size, the subset of regressors with the best predictive performance. The best performing subset of variables can then be determined across all subset sizes. The algorithm is as follows: first, among k regressors, select only one regressor that best predicts fatal police shooting rates; second, select the best two regressors; third, select the best three regressors; and so on until all k regressors are included. Models 1 and 4 have 16 possible regressors, including the three additional police agency variables, whereas all other models have 13 possible regressors. Figures 4 (a-h) depict for each fixed number of regressors (from 1 to k regressors including the intercept) the subset of regressors with the maximum adjusted-R^2 for models 1-8, respectively.

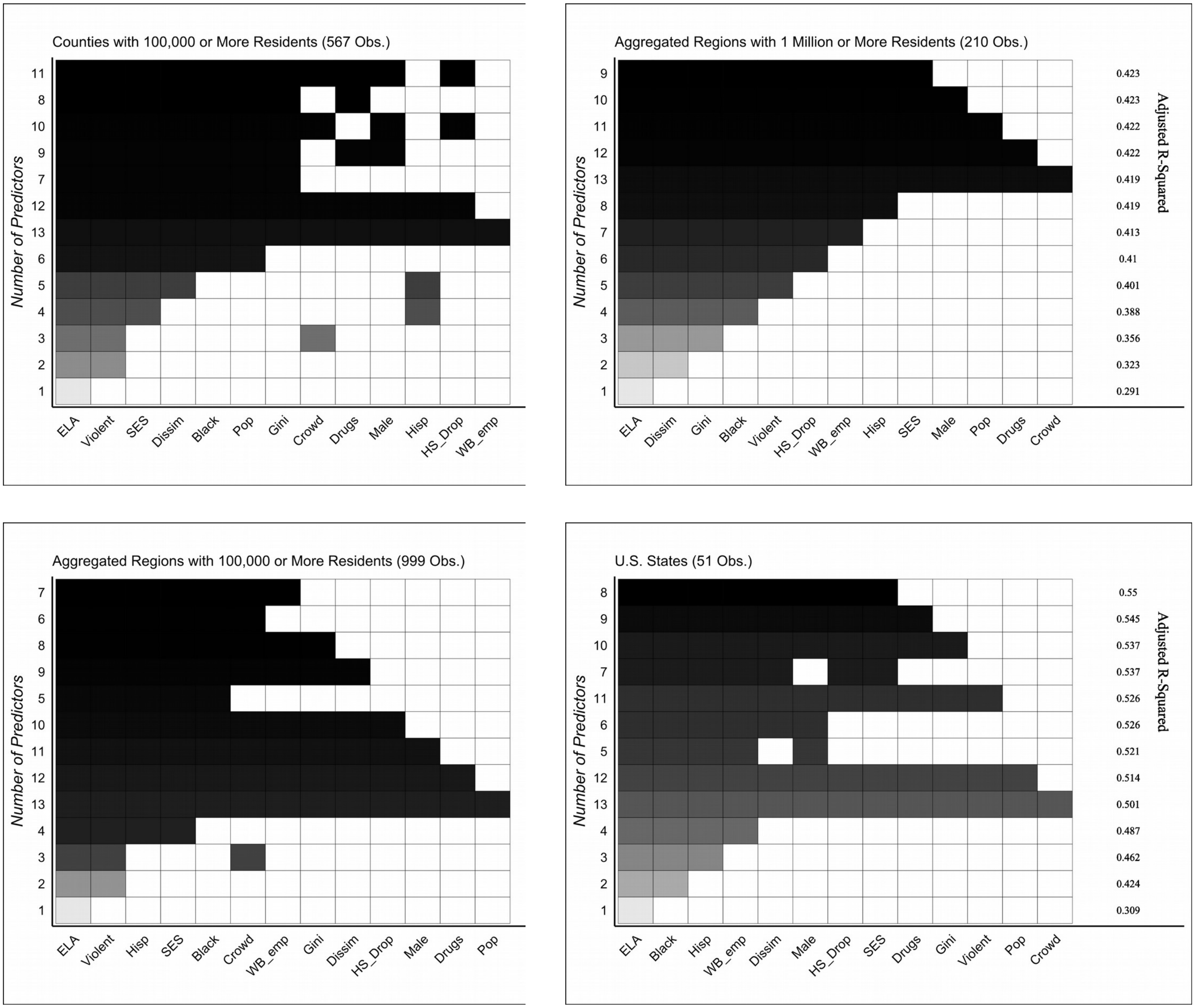
Remarkably, ELA is the single best predictor in 5 out of 8 models. In models 4-8, ELA is the only variable that is included in all subsets. In models 4-8, ELA out performs all other variables, including SES and Violent Crime, and is the best single predictor of fatal police shooting rates. Violent Crime is also a consistently strong predictor of fatal police shooting rates and is the second most frequently selected covariate in models 1, 4, 5, and 6. SES is the second most frequently selected predictor in models 2 and 3. Racial composition appears to matter most at the state level, with the Black percentage and Hispanic percentage of state populations being the second and third most frequently selected predictors in model 8, respectively.


Counties with 10,000 or More Residents (1084 Obs.)
Number of Predictors
9
7
10
8
6
11
12
13
5
14
15
16
4
3
2
1
Pop
Violent
ELA
Black
SES
Police
Gini
Fem_Pol
Hisp
HS_Drop
Drugs
Dissim
Crowd
Blk_Pol
WB_emp
Male


Aggregated Regions with 10,000 or More Residents (2017 Obs.)
Number of Predictors
8
9
7
10
11
6
12
13
5
4
3
2
1
Adjusted R-Squared
0.07
0.07
0.07
0.07
0.07
0.069
0.069
0.069
0.068
0.066
0.06
0.054
0.03
Pop
SES
Violent
Black
Hisp
Dissim
ELA
WB_emp
HS_Drop
Crowd
Gini
Drugs
Male


Counties with 10,000 or More Residents (1913 Obs.)
Number of Predictors
8
7
9
10
11
6
12
13
5
4
3
2
1
Pop
SES
Violent
Black
ELA
Hisp
Dissim
WB_emp
Gini
Crowd
HS_Drop
Drugs
Male


Counties with 100,000 or More Residents (517 Obs.)
Number of Predictors
10
9
11
12
8
13
14
7
15
16
6
5
4
3
2
1
Adjusted R-Squared
0.222
0.221
0.221
0.221
0.221
0.22
0.219
0.219
0.218
0.216
0.214
0.21
0.203
0.191
0.179
0.152
ELA
Violent
Police
Black
SES
Dissim
Pop
Blk_Pol
Drugs
Gini
Hisp
HS_Drop
Male
WB_emp
Fem_Pol
Crowd


Counties with 100,000 or More Residents (567 Obs.)
Number of Predictors
11 8 10 9 7 12 13 6 5 4 3 2 1
ELA Violent SES Dissim Black Pop Gini Crowd Drugs Male Hisp HS_Drop WB_emp
Aggregated Regions with 1 Million or More Residents (210 Obs.)
Number of Predictors
9 10 11 12 13 8 7 6 5 4 3 2 1
ELA Dissim Gini Black Violent HS_Drop WB_emp Hisp SES Male Pop Drugs Crowd
Adjusted R-Squared
0.423 0.423 0.422 0.422 0.419 0.419 0.413 0.41 0.401 0.388 0.356 0.323 0.291
Aggregated Regions with 100,000 or More Residents (999 Obs.)
Number of Predictors
7 6 8 9 5 10 11 12 13 4 3 2 1
ELA Violent Hisp SES Black Crowd WB_emp Gini Dissim HS_Drop Male Drugs Pop
U.S. States (51 Obs.)
Number of Predictors
8 9 10 7 11 6 5 12 13 4 3 2 1
ELA Black Hisp WB_emp Dissim Male HS_Drop SES Drugs Gini Violent Pop Crowd
Adjusted R-Squared
0.55 0.545 0.537 0.537 0.526 0.526 0.521 0.514 0.501 0.487 0.462 0.424 0.309

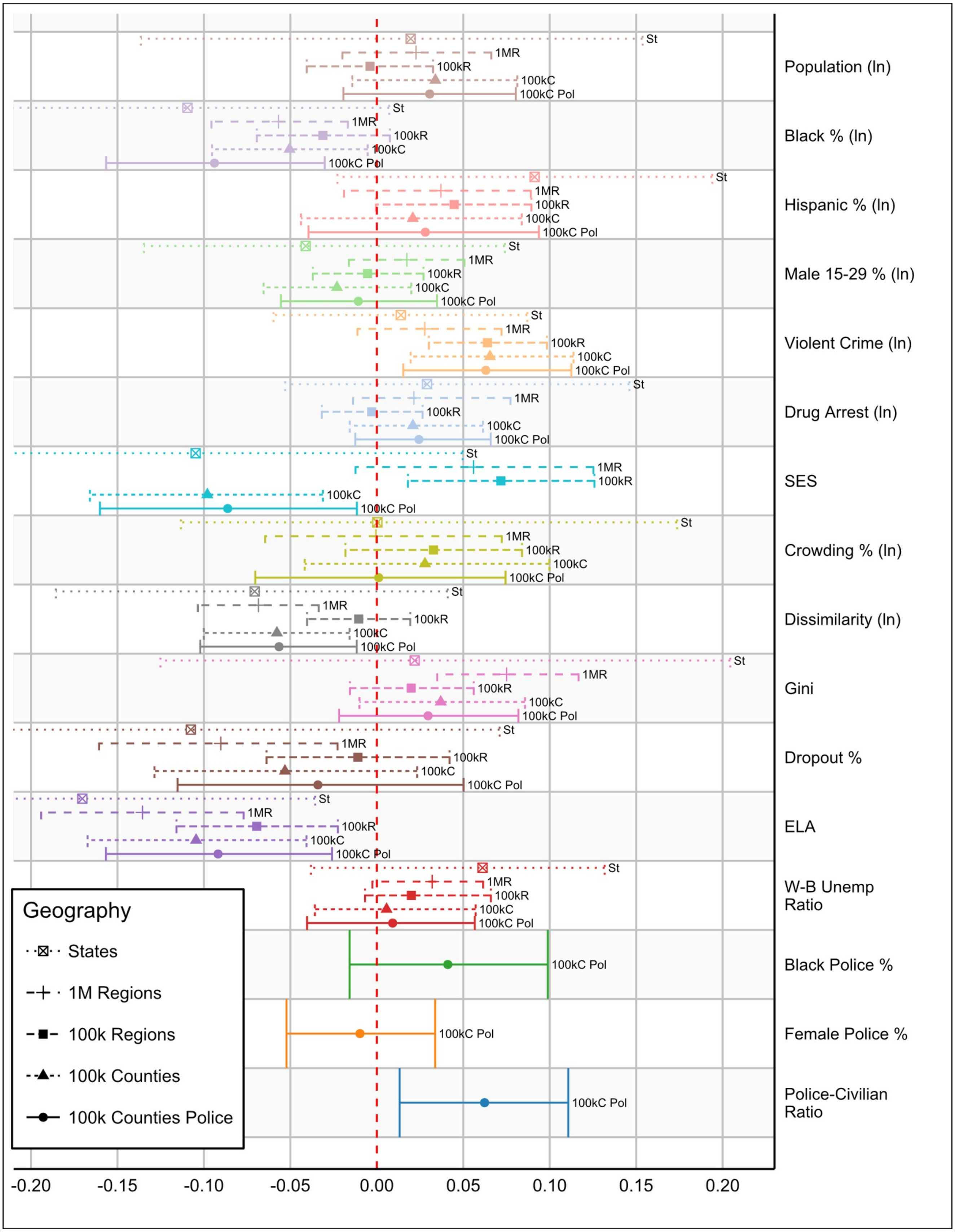
Saturated Regression Models

Figure 5 depicts the 95 percent non-parametric bootstrap confidence intervals for standardized coefficients from models 4-8 including all regressors. To calculate the bootstrap confidence intervals, 100,000 regressions are estimated from 100,000 different samples with replacement.

ELA is the only variable in Figure 5 to have 95% bootstrap confidence intervals that do not include zero across all geographical aggregations. This indicates that ELA, compared to other predictors, has an association with fatal police shooting rates that is more consistent, more reliable, and less sensitive to sampling variability. The bootstrap confidence intervals for Violent Crime are positive and exclude zero for all models except at the two highest levels of aggregation: states and regions with at least 1 million residents. Two other variables have three (out of 5) confidence intervals excluding zero: the Black percentage of the population and the Black-White Dissimilarity Index. The 95 percent bootstrap confidence intervals for both are mostly negative and include zero only for states and aggregated regions with at least 100 thousand residents. Fatal police shooting rates tend to be lower in more segregated counties and in counties with proportionally more Black residents.

SES is the only variable to have both positive and negative 95% bootstrap confidence intervals that exclude zero. When only counties with 100,000 or more residents are included, 95% or more of the SES resampling coefficients are negative. In contrast, when small, adjacent counties are included as aggregated regions with combined populations of at least 100,000, 95% or more of resampling coefficients for SES are positive. Whereas at the county-level, worse socioeconomic conditions are associated with higher fatal police shooting rates, at higher levels of aggregation, worse socioeconomic conditions are more often associated with lower fatal police shooting rates. In addition, 95% or more of the bootstrap coefficients for the Police-Civilian ratio are positive. Finally, the 95% bootstrap confidence interval for the Black percentage of police officers includes zero, but most of the resampling coefficients are positive, indicating that for most samples (albeit not quite 95%), counties with more Black police officers also have higher fatal police shooting rates.

Figure 5. Resampling 95% Confidence Intervals for Standardized Coefficients in Saturated Models



Population (ln)
Black % (ln)
Hispanic % (ln)
Male 15-29 % (ln)
Violent Crime (ln)
Drug Arrest (ln)
SES
Crowding % (ln)
Dissimilarity (ln)
Gini
Dropout %
ELA
W-B Unemp Ratio
Black Police %
Female Police %
Police-Civilian Ratio
St
1MR
100kR
100kC
100kC Pol
Geography
States
1M Regions
100k Regions
100k Counties
100k Counties Police
-0.20
-0.15
-0.10
-0.05
0.00
0.05
0.10
0.15
0.20

Discussion

It is important to emphasize that valid inferences about individual police shooting incidents cannot be made from aggregate-level associations or vice-versa. Consequently, whether the use of lethal force by police is legal, moral, or appropriate in any given incident also cannot be determined from aggregate-level data. For example, that police shootings are more prevalent in counties with higher rates of violent crime does not imply that the civilians shot by police in high crime areas are themselves criminals or engaging in violence. Likewise, because police shooting rates are higher in regions with lower average ELA scores does necessarily imply that the decedents have below-average verbal abilities. However, insofar as we can assume that the location where a civilian is killed approximates the civilian's residence, in the absence of other individuating information, the population average for that residence represents the most likely value of that attribute for any given civilian. Although no deductive inference is warranted from the aggregate-level relationship between ELA scores and police fatality rates, it does confer a higher probability on the hypothesis that the mean verbal ability of decedents is below the national average.

On the other hand, the distributions of individual characteristics of suspects or police involved in fatal shooting incidents in the United States as a whole do not necessarily resemble their respective distributions across the populations residing in the counties and states in which those incidents take place. For example, that mental illness is more prevalent among civilians killed by police than in the general population does not imply that counties with higher rates of police shootings have higher rates of mental illness. Nor does the fact that Blacks are overrepresented among civilians killed by police mean that more civilians are killed in predominantly Black neighborhoods. It may be that Black civilians are killed more often in predominantly Black neighborhoods, but the findings reported in this study suggest that, overall, civilians are less likely to be killed by police in areas with proportionally more Blacks, net of other factors.

It is also important to emphasize the historical contingency of even the strongest and most robust associations. To illustrate this point, consider that a law banning the use of guns by police would virtually reduce all fatal police shooting rates to zero. Part of this contingency is due to the specificity of the measured outcome, but policies and organizational cultures also matter.

The findings suggest that poverty, violent crime, the number of police per capita, and the Hispanic percentage of the population are all positively associated with rates of fatal police shootings of civilians. Moreover, fatal police shooting rates tend to be lower in areas that are more racially segregated and which have proportionally larger Black populations. The predictors which seem to have consistently weak aggregate effects include the drug arrest rate, the female percentage of police, the proportion of young males, and the White-Black unemployment ratio (except for state-level aggregations).

ELA is the most reliable predictor of fatal police shooting rates among the covariates tested. Compared to other predictors the size and direction of the coefficient for ELA is less dependent on which cases are included or how units are aggregated. The rate at which civilians are killed by police is higher in geographical regions with comparatively lower average verbal ability, as indicated by 8^{th} grade ELA scores. There are two reasons why education and verbal ability may be relevant to fatal police shooting rates. First, as discussed previously, some studies suggest that police officers with lower levels of education may be more likely to use force against civilians. One way that average levels of education might influence fatal police shooting rates, then, is that counties with lower average education levels are also policed by officers with relatively lower levels of education, who are consequently more likely to use force, compared to police officers in other districts.

This hypothesis, however, depends on several unsupported assumptions: first, that average education levels among civilians are correlated with average educational levels among police; and second, that the studies cited above imply also that less educated and/or trained police officers are more likely to use lethal force as opposed to non-lethal force. Most importantly, whatever effect low educational attainment among police officers may have is likely to be miniscule in comparison to the magnitude of the effect of low educational attainment among civilians. A more plausible connection is that civilians with lower levels of educational attainment and/or verbal ability may be more likely to engage in behaviors which increase both the probability that they will be arrested by police and that police will use force against them to secure their compliance. One possible explanation for this hypothesis is that ELA is associated with a repertoire of verbal and communication skills necessary for avoiding and de-escalating interpersonal conflicts. Further study, however, is required.

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