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Supplementary Information for

Officer Characteristics and Racial Disparities in Fatal Officer-Involved Shootings

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Other supplementary materials for this manuscript include the following:

Database S1

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Supporting Information Text

Data on fatal officer-involved shootings (FOIS) for 2015 were obtained from The Washington Post and The Guardian databases on January 1st 2016. While The Washington Post database (N = 981) exclusively recorded FOIS, The Guardian recorded all encounters that resulted in the death of a civilian (N = 1139). Our focus was on FOIS, so we removed the 124 deaths in The Guardian database due to other types of force (e.g., vehicle and Taser deaths). The databases overlapped but were not fully redundant; The Guardian had information on 37 deaths not recorded by the Washington Post, and The Washington Post had information on three deaths not recorded by The Guardian.

After review of the circumstances surrounding each shooting but prior to data analysis we decided to exclude certain shootings. Specifically, we excluded FOIS if the officers were off-duty ($N = 28$), if the officers were from a federal agency ($N = 15$), if the responding department was unknown ($N = 6$), if the shooting occurred in jail ($N = 2$), or the shooting occurred during a training exercise ($N = 2$). This left a total of 959 FOIS. These exclusions reflect our focus on factors that explain use of lethal force by non-federal on-duty police officers.

Given our goal of understanding how officer and civilian factors relate to the race of individuals fatally shot by police, we further excluded FOIS where we could not identify the race of the person who was fatally shot ($N = 11$). We also limited our analyses to White ($N = 501$), Black ($N = 245$) and Hispanic ($N = 171$) adults, as there were insufficient data to examine other racial groups (all other groups had less than 20 FOIS). This left a final sample of 917.

Predictors

Officer Information. We sent letters to all 684 departments where officers were involved in a fatal shooting. These letters requested the race, sex, and years of experience of each officer who fired at the civilian. We received responses from 42% of departments with at least some portion of the requested information, which provided information about the officers in 62% of shootings. Because of the high rate of missing data, we called departments to request additional data, and after that, obtained further information about the officers involved in shootings by searching newspaper articles and legal reports. We were able to obtain at least some information about the officers from newspaper reports in 33% of these shootings with missing data, and some information from legal reports in 2% of the shootings. In all, we obtained complete officer information for 72% of shootings, and partial information in 96% of cases.

Officer information was aggregated to the level of the shooting, because our outcome (the race of the person fatally shot) does not vary within a shooting. Specifically, the officer race variable reflects the percent of officers who were Black or Hispanic, whereas the officer sex variable reflects the percent of officers who were women. We also calculated the average experience in years across all officers who fatally shot the civilian. Analyses conducted on the subset of data where only one officer fatally shot a civilian (excluding fatal shootings in which more than one officer was present) revealed results consistent with all shootings.

Civilian Information. Information about the race, sex, age, and mental health of the civilians involved in FOIS was obtained from The Guardian and The Washington Post databases. Discrepancies were uncommon and were resolved by examining newspaper articles. We also examined newspaper articles to code whether civilians were armed. Although The Washington Post tracked whether targets were armed or not, this information was incomplete. We coded whether targets were armed when The Washington Post was not able to identify whether a weapon was present by using newspaper reports.

Similarly, we also coded whether targets were attacking police. Although The Washington Post tracked a related variable, their coding separated shootings where the civilian threatened officers and/or had a firearm from other types of FOIS (1). As this distinction does not track aggression per se, we used the coding from Cesario, Johnson, and Terrill (2). Individuals were coded as attacking if they were armed or actively struggling with an officer. Behaviors such as fleeing or advancing toward an officer were not coded as attacking. See the Supplemental Materials of Cesario et al. (2) for additional detail.

Finally, we also coded whether targets were suicidal by using newspaper reports, as this information was not available in the databases. Specifically, we coded a civilian as suicidal if 1) they left an explicit suicide note (e.g., the fatal shooting of Matthew Hoffman, 3), 2) a family member reported that the civilian was suicidal, or 3) the police reported that the civilian explicitly told officers to shoot him or her.

County Information. Each FOIS was assigned to a county based on its location. The 917 shootings were distributed across 473 different counties. County information was obtained from the U.S. Census Bureau and the Centers for Disease Control (CDC). Census Bureau estimates from 2015 provided demographic information, including population size, median income, income inequality, percent of a county that is rural, and percent of individuals in the county that were White, Black, or Hispanic.

The CDC's WONDER database provided race-specific homicide death counts from 2001 – 2015. We measured death counts over a longer period of time to get a more stable count, as such assaults are rare at the county level. Because homicide victims are overwhelmingly killed by a same-race offender (4, 5), CDC data were used to estimate fatal assaults by White, Black, and Hispanic offenders. Homicide deaths were turned into percentages by dividing the race-specific count of homicide deaths by the total number of homicides in a county. This was done to put the homicide deaths on the same metric as the population variables (i.e., the percentage scale). Higher percentages are a proxy for higher levels of violent crime.

We relied on CDC data as a proxy for violent crime instead of police reports for several reasons. First, a major concern when choosing a proxy for violent crime is selecting an unbiased indicator. If the data are themselves biased, such that Black citizens are overrepresented relative to their actual criminal activity, these rates will be artificially high, masking anti-Black disparity in FOIS. However, the vast majority of national violent crime data (including rape, robbery, and drug related crime) comes from arrest records from law enforcement agencies aggregated by the Federal Bureau of Investigation (FBI). As these reports originate with the police, they may reflect intentional or unintentional bias on the behalf of law enforcement. In contrast, homicide data is obtained from death certificates and is generated by the CDC, preventing the possibility of bias from law enforcement agencies.

Another related concern with law enforcement data is that records are incomplete. Not only do departments underreport data (by about 50%; 6), not all departments send data. For example, the state of Florida does not submit any arrest data to the FBI, making it impossible to generate estimated crime rates for counties within Florida. Similarly, the FBI does not track crimes based on ethnicity, which means that all of the data on crime rates for Hispanic individuals is missing. However, death certificate data is available for all counties through the CDC. Homicide data can be sorted by race and ethnicity, ensuring no data is missing.

Finally, we have explicitly addressed in prior research whether racial disparities in fatal shootings vary depending on the crime benchmark used (2). Across 16 different benchmarks of crime (e.g., murder, violent crime—including rape and violent drug offenses, and weapons violations), the overall size of disparities observed does not change much. This suggests these findings would not change much if we used a different index of crime.

Sensitivity Analyses (Crime Rates). To show how similar these crime rate proxies are we first compared several different potential crime rate proxies (i.e., murder, rape, and robbery arrests) to homicide rates. Arrest data was obtained from the FBI's 2015 Uniform Crime Report, which provides a yearly summary of arrests divided by civilian race (but not ethnicity) and is voluntarily reported by law enforcement agencies. All proxies were strongly related to homicide deaths. Race-specific murder arrest rates were strongly correlated with homicide deaths for White (r = .44) and Black (r = .74) individuals. Race-specific rape arrest rates were also strongly correlated with homicide deaths for White (r = .50) and Black (r = .75) individuals. Finally, race-specific robbery arrests were also strongly correlated with homicide deaths for White (r = .48) and Black (r = .79) individuals.

We tested whether the key crime rate findings we report in the main text are robust by replicating the findings reported in Figure 1 of the main text: the odds of a person fatally shot by the police being of a specific race increase as members of that race commit a larger percentage of violent crime. We examine the degree to which White and Black crime rates predict the race of a person fatally shot by police as the FBI database does not contain information about Hispanic crime rates.

As reported in Figure S1, regardless of whether using homicide data from the CDC, or FBI arrest data on murder, rape, or robbery, the odds of a person fatally shot by the police being Black increase as Black individuals commit a larger percentage of violent crime. In contrast, the odds of a person fatally shot by the police being Black decrease as White individuals commit a larger percentage of violent crime. The magnitude of these effects was very consistent across indicators and replicate the findings reported in the main text: violent crime rates strongly predict the race of a person fatally shot. In sum, we chose to rely on homicide deaths as our proxy of violent crime because homicide data is not reported by law enforcement, has no missing data at the county level, and can be used to get information about Hispanic crime rates.

Descriptive Statistics. What are the characteristics of the officers involved in fatal shootings and where did these shootings take place? Table S1 provides information on the counties and officers involved in fatal shootings. Most counties had only one FOIS in 2015 (69%), but larger counties had more fatal shootings (e.g., 40; Los Angeles County). In a majority of FOIS (56%), a single officer fired their weapon. In 39% of cases, 2 – 4 officers fired their weapons. Cases with five or more officers were rare (5%). In terms of race, 79% of officers were White, 12% Hispanic, 6% Black, and 3% from other racial groups. Officers were overwhelmingly male (96%). The average officer had almost ten years of experience (officers generally retire after 20 years; 7).

County size, demographics, and crime rates varied broadly across counties where FOIS occurred. The average county had a majority White population and White individuals committed a majority of violent crime (as measured by homicide deaths). There was also more variability in violent crime for White and Black adults relative to Hispanics. This is likely due to the lower overall mean levels of violent crime for Hispanic adults compared to Whites or Blacks.

Race-specific population size and violent crime have both been used as benchmarks for testing racial disparities in FOIS. Despite different mean levels (e.g., Whites make up 68% of the population in the counties with fatal shootings, but only 53% of homicide victims, see Table S1), the two variables were strongly correlated for all racial groups, Whites, r = .85, Blacks r = .87, and Hispanics, r = .90 (see Table S2). We chose to include only county violent crime in our main analyses, although the results are similar if we include only population size. Our decision was based on two factors. The first factor was theoretical; violent crime is conceptually more closely related to the outcome of interest (the race of a person fatally shot), as most fatal shootings occur in the context of violent crime (8). The other factor was methodological; including crime rates and population proportions led to clear multicollinearity issues.

Who are the people fatally shot during a FOIS? Table S3 provides information on the civilians fatally shot by police in 2015, broken down by race. Civilians were overwhelmingly male (95.9%) and young (M = 37 years), although White adults tended to be older than Black or Hispanic adults. A sizeable minority of civilians fatally shot had mental health issues (25%) or were suicidal (11%). There was a large difference in the rates of mental illness and suicide by race (see also 9). These civilians were much more likely to be White than Black or Hispanic. Whereas 31% of White adults showed signs of mental illness, only 16% of Black adults and 20% of Hispanic adults showed signs of mental illness. Similarly, whereas 16% of White adults were suicidal, only 3% of Black adults and 10% of Hispanic adults were suicidal. Finally, the vast majority of civilians fatally shot were actively attacking law enforcement (94%) or were armed (90%) with a weapon when they were fatally shot. In terms of weapons, firearms were most common (58%), followed by knives (17%). We urge caution when comparing the relative rates of these variables across sex, as the databases we analyze contain at least some errors (e.g., in whether civilians are coded as armed; 10). There are likely more false positives and negatives in these databases, such as when separating individuals committing suicide who are *not* experiencing a mental health crisis from those that *are* experiencing a mental health crisis.

Imputation of Missing Data

We were sometimes unable to obtain full data for predictors. In decreasing order, data was unavailable for officer race (25%), officer experience (23%), officer sex (18%), number of officers (3%), and whether civilians were armed (1%). Prior to performing the analyses, we used multiple imputation to estimate missing data (11). Briefly, multiple imputation uses a regression-based procedure to generate multiple copies of the data set, each of which contains different estimates of the missing values. Missing data analysis techniques such as multiple imputation require certain assumptions that cannot be empirically tested, i.e., that the data are at least missing at random (MAR). However, even if data violate these assumptions, i.e., data are missing not at random (MNAR), imputation procedures often produce less biased results than more traditional methods such as list-wise deletion (11, 12).

Moreover, researchers have argued that serious violations of MAR are relatively rare and even when such violations are present they have little impact on the statistical conclusions of a study (12, 13). Although there are procedures in place to deal with data that are MNAR, these analyses require stricter assumptions that are also often untestable. Violations of those assumptions can lead to parameter estimates that are more biased than approaches that assume data were MAR (11). Often a good imputation model that assumes data are MAR will produce better parameter estimates than a misspecified MNAR model (13). Based on these recommendations, we imputed the data with an imputation procedure that assumes MAR.

We used the data imputation procedure in MPlus with the default settings (Version 8.0, 14) to generate 100 imputed datasets through a two-step process (at least 20 imputations are recommended for most situations, 15). In the first step, we imputed ten data sets from the original data. Each dataset used information from all civilian and county predictors to infer the number of officers who fatally shot a civilian when such information was missing. This was the only variable imputed at this step. This initial step was necessary because in order to estimate information about the officers involved in each shooting, it was necessary to first estimate how many officers were involved.

In the second step, we imputed ten more data sets from each of the ten data sets generated from step one, estimating the race, age, and sex of each officer with missing data, as well as the other missing data at the civilian level (i.e., whether the civilian was armed). This led to a hundred imputed datasets. Within each dataset, officer information was then aggregated to the level of the shooting (i.e., by calculating the percentage of officers who were Black, Hispanic, women, or by determining the average level of experience across officers).

MPlus provides multiple imputation of missing data using Bayesian analysis (16, 17). In all multinomial regression models, parameter estimates were averaged over the over the set of analyses to form a single estimate for each predictor on the log-odds scale, and standard errors were computed using the average of the standard errors over the set of analyses and the between analysis parameter estimate variation (16, 17). Note that methodologists currently regard multiple imputation as a "state of the art" missing data technique because it improves the accuracy and the power of the analyses relative to other missing data handling methods (13).

Sensitivity Analysis (Missing Data). Due the possibility that officer data might not be MAR, we ran a sensitivity analysis that analyzed the effect of officer characteristics but only in cases where we had complete information on all predictors. This provided a test of the robustness of the findings. Due to non-overlap in missing information, this resulted in a sample of 623 (68%) of FOIS. As shown in Table S4, when considering only officer and civilian factors, Black ($OR = 1.21$ [1.01, 1.45]) and Hispanic ($OR = 1.94$ [1.57, 2.41]) officers were more likely to fatally shoot same-race civilians. Hispanic officers were also more likely to fatally shoot Black civilians ($OR = 1.39$ [1.12, 1.73]).

The relationship between officer characteristics and civilian race was attenuated for both Black and Hispanic decedents when controlling for county characteristics (see Table S5). After taking into account county demographics, Black officers were not more likely to shoot Black civilians ($OR = 1.00$ vs. 1.21) and Hispanic officers were less likely to shoot Hispanic civilians ($OR = 1.32$ vs. 1.92), although this disparity was still significant.

In sum, we replicated the key results related to officer race in the imputed dataset with this smaller subset of shootings without missing data. Much of the relationship between officer and civilian race is due to overlap in demographic variables. To explicitly test this idea we also examined the degree to which the demographics of the police force match the demographics of civilians at the county level. Data on officer demographics were obtained from the 2013 Law Enforcement Management And Administrative Statistics (LEMAS) survey (18). Counties with a higher percentage of Black or Hispanic individuals also had a higher percentage of Black or Hispanic officers ($rs = .82$ and .87, respectively). Thus, both these analyses provide converging support that disproportionate shootings of Black or Hispanic civilians by same-race officers is due to an overlap between officer and civilian demographics at the county level.

Multinomial Regression Models

We tested our research questions using multinomial regression models. In all models, civilian race was the outcome with officer, civilian, and county-level characteristics as predictors. The first set of models (Tables 1 & 2 in the main text) tested whether officer and civilian characteristics predict racial disparities in FOIS with and without controlling for county-level factors (e.g., demographics). Continuous predictors were centered and standardized. Categorical predictors were effects coded. Civilians who were armed, attacking police, showed signs of mental illness, or were suicidal were coded as .5, all others were coded as -.5.

The second set of models (Figure 1 in the main text) tested whether racial disparities can be predicted by county level differences in race-specific population proportions and violent crime. Because of the high correlation between population size and homicide deaths (Whites, $r = .85$, Blacks $r = .87$, and Hispanics, $r = .90$, see Table S2), we examined the effects of each variable independently, without any officer or civilian predictors. Specifically, in each model civilian race was regressed on a single factor (e.g., percent of county residents that were Black). All predictors were centered and standardized. The variance explained by each set of predictors reflects the degree to which all population or crime variables predict civilian race.

The final set of models (Table 3 in the main text) tested whether racial disparities vary across different types of shooting situations as defined by differences in civilian and officer characteristics. To examine racial disparities in fatal shootings we relied on tests of the regression model intercept. In our models, the outcome is the race of the person fatally shot. The intercept in this model is the predicted value for the degree to which a person fatally shot by police is more or less likely to be Black (or Hispanic) than White when all predictors are at zero. Thus, when predictors are centered or effects coded, the intercept represents the prediction for a typical shooting in a typical county. Because the average county has a larger percentage of homicide committed by White residents (53%) than Black (28%) or Hispanic (15%) residents, we would expect more Whites to be fatally shot by police. This can be seen in the model intercepts reported in Table 1 in the main text; when the intercept is a prediction for the average county a person fatally shot by police is much less likely to be Black or Hispanic than White. These crime differences must be taken into account if the goal is to test anti-Black or anti-Hispanic disparity.

We addressed this issue in our tests of the model intercepts (Table 3 in the main text) by calculating the difference in the percent of homicides committed by Whites in a county relative to Black or Hispanic civilians (for a similar strategy, see 19). When this percentage is zero, it indicates a county with an equal percentage of White and Black (or Hispanic) homicides. Thus, the intercept tests whether a person fatally shot by police is more or less likely to be Black (or Hispanic) than White in a typical shooting except there are no racial differences in county crime across race. That is, the intercept is the prediction in a county where the percentages of White and Black (or White and Hispanic) homicides are equal. This approach provides a more balanced test of racial disparities in fatal shootings. These models of racial disparity by shooting type are otherwise identical to the models reported in Table 2—they include all other predictors at officer, civilian, and county levels.

This approach is also what allows us to test whether racial disparities vary by type of fatal shooting. By varying what factors are dummy coded as the zero value (e.g., civilians who are unarmed, not attacking, not mentally ill, and not suicidal) the intercept provides tests of racial disparity in that particular circumstance. This approach is a more tractable way to test racial disparities than an approach based on rates of shootings (i.e., the benchmark approach) because rates inherently become more unstable as data are subset into smaller and smaller categories. However, because our regression models do not subset data, this instability is not an issue.

Power Analyses. Our analyses of officer characteristics revealed that officer race (but not sex or experience) was related to racial disparities in FOIS (when not controlling for county-level characteristics). We conducted a power analysis to examine whether these null results might be due to low power. We used the mean and covariance structure generated from the multinomial regression analysis predicting civilian race from officer and civilian characteristics to create a population generating model. We then used the monte carlo function in MPlus with the default settings (Version 8.0, 14) to generate 100 datasets that shared the same mean, covariance structure, and sample size ($N = 917$), but varied the magnitude of the effects of officer characteristics.

We generated three groups of 100 datasets where the effect of officer race (percent Black or Hispanic), officer sex (percent women), or officer experience (average number of years) ranged from $\beta = .20$ to .35 in increments of .05. Because all predictors were centered and standardized, these beta coefficients represent the increase in the likelihood of a person fatally shot being Black or Hispanic (relative to White) on the logistic scale, controlling for all other predictors. Using Cohen's guidelines (20) for correlations, these coefficients reflect the power of our design to detect small (.20) to medium effects (.30) of officer characteristics on civilian race.

The results from these power analyses are reported in Table S6. Overall, power depended less on the specific officer characteristic or racial group in question and more on the simulated effect size. On average, our multinomial regression analyses had moderate power to detect small effects ($\beta = .20$) for Black (.65) and Hispanic (.55) individuals. Power was higher for small-to-moderate effects ($\beta = .25$) for both Black (.81) and Hispanic (.77) individuals. Power was very high for moderate sized effects ($\beta = .30$) for both Black (.92) and Hispanic individuals (.88). In sum, these analyses suggest that any true effects due to officer characteristics such as sex or experience that we failed to observe are likely small in size.

Additional Tests of Racial Disparities. Our main analyses of racial disparities in FOIS control for differences in race-specific homicide rather than differences in population size because violent crime is more closely related to the race of a person fatally shot, as most fatal shootings occur in the context of violent crime (8). Indeed, we did not include race-specific population size in our main models (see Tables 1 and 2) because these variables were highly correlated with violent crime. However, we also wanted to test whether our results depended on this decision. This is an important test, as our criticism of benchmark approaches is that their results depend on whether violent crime or population is used as a benchmark.

To test this question, we reran our tests of the regression model intercept (reported in Table 2 in the main text) using the difference in the percentage of White civilians in a county relative to Black or Hispanic civilians instead of the difference in the percentage of homicides committed by Whites in a county relative to Black or Hispanic individuals (19). When this percentage is zero, it indicates a county with an equal percentage of White and Black (or Hispanic) residents. Thus, the intercept tests whether a person fatally shot by police is more or less likely to be Black (or Hispanic) than White in a typical shooting except there are no racial differences in county demographics.

Table S7 compares the degree of racial disparity in FOIS when controlling for differences in violent crime, population size, or both. Model S0 is reported in the main text (as Model 0) and reveals no evidence of anti-Black or anti-Hispanic disparity (in fact, there is anti-White disparity in both cases). These results are consistent with studies that use violent crime as a benchmark for testing racial disparity (2). Model S1 is a model that controls for differences in population (i.e., population difference variables are included and the crime difference variables are excluded) and is similar to the approach used by studies that use population as a benchmark for testing racial disparity. This model also reveals no significant evidence of anti-Black or anti-Hispanic disparity, although anti-White disparity is only observed relative to Hispanics. Finally, Model S3 controls for differences in violent crime and population size. Like Model S0, it reveals no evidence of anti-Black or anti-Hispanic disparity, but evidence for anti-White disparity.

In sum, whereas conclusions about racial disparity are dependent on whether violent crime or population size are used as a benchmark, the results are much more consistent in our approach. Whether crime rates, population size, or both were included as predictors of the rate of a person fatally shot, we found no evidence for anti-Black or anti-Hispanic disparities in FOIS. Thus, our approach is more consistent than benchmarking methods, as our conclusions depend more on the data (the race of people fatally shot) and less on the predictors (population or violent crime).

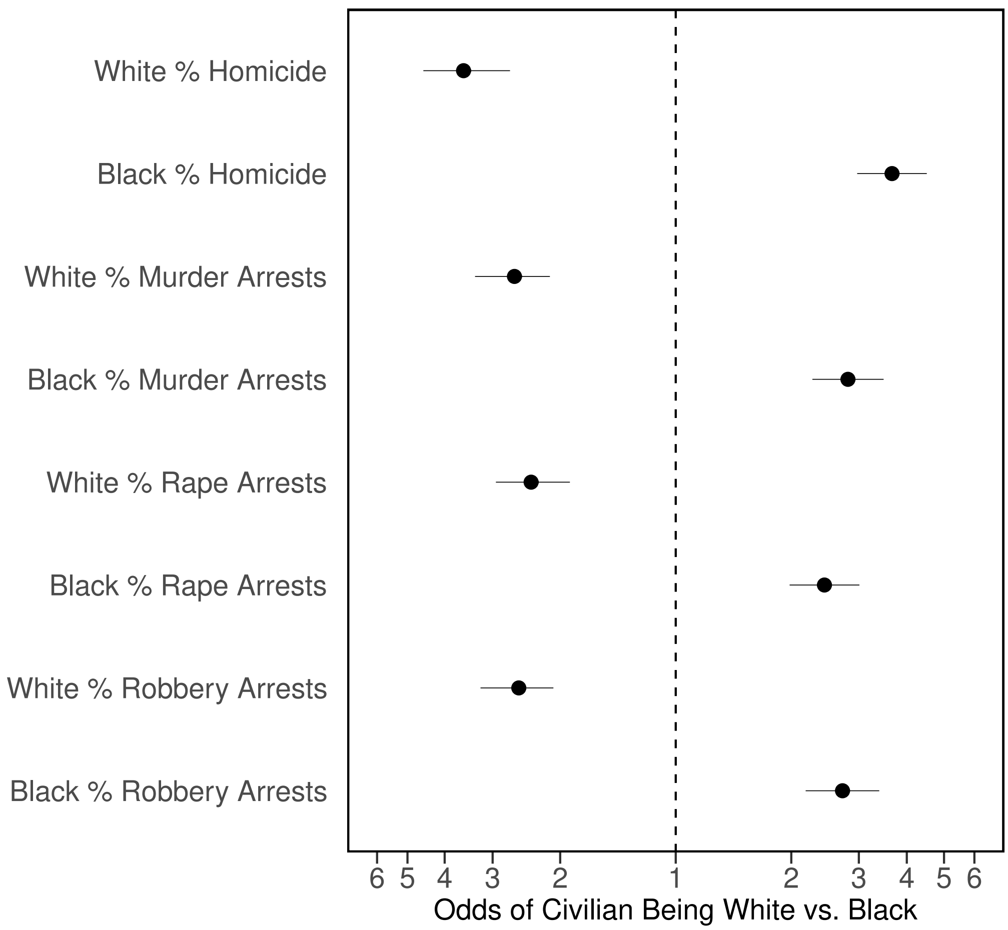

Fig. S1. Odds ratios predicting the race of civilians fatally shot by police from several different proxies for county-level race-specific violent crime. Values to the left (right) of the dotted line indicate the civilian was more likely to be White (Black). Civilian race was regressed on each variable individually due to multicollinearity. Lines represent 95% CI. *N* = 917.

Table S1. Characteristics of Officers and Counties Involved in Fatal Shootings in in 2015

Variable	M	SD	Min	Max
Officer Number	1.8	1.3	1	12
Officer % Minority	23	37	0	100
Officer % Women	6	19	0	100
Mean Experience	9.5	5.7	0	38
County Number of Shootings	1.9	2.8	1	40
Population Size	398	752	2	10170
Median Income	51	14	25	110
Income Inequality	.45	.03	.37	.60
County % White Homicide	53	28	0	100
County % Black Homicide	28	26	0	93
County % Hispanic Homicide	15	19	0	95
County % White	68	20	4	98
County % Black	11	13	0	62
County % Hispanic	14	16	1	95

Population size and income are divided by 1000.

Table S2. Correlations Between Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Civilian Age	.00																			
2. Civilian Armed	.11	.01																		
3. Civilian Mental Health Issue	.10	.62	.00																	
4. Civilian Suicidal	.11	.08	.09	.00																
5. Civilian Attacking	.03	.10	.04	.74	.00															
6. Number of Officers	.01	.01	.03	.16	.11	.03														
7. Officer % Black	-.06	.01	-.02	-.08	-.05	-.07	.25													
8. Officer % Hispanic	-.06	-.05	-.07	.00	.00	.00	-.13	.25												
9. Officer % Women	-.04	.01	.01	-.07	-.06	.12	.03	.00	.18											
10. Average Officer Experience	-.03	.03	.04	.04	.02	.12	-.06	-.03	.02	.23										
11. County Population Size	-.08	-.01	.00	-.07	-.07	.00	.02	.31	-.01	.07	.00									
12. County Median Income	-.06	.07	.07	-.03	-.03	-.01	.00	.02	.03	-.02	.16	.00								
13. County Income Inequality	-.10	-.04	-.05	-.06	-.06	.02	.06	.12	.04	.07	.40	-.13	.00							
14. County % Rural	-.20	.03	.05	-.02	-.02	.05	.06	.16	.06	.05	.39	.40	.40	.00						
15. County % White	.15	-.01	.03	.04	-.01	.01	-.11	-.35	-.03	.03	-.51	-.12	-.49	-.56	.00					
16. County % Black	-.08	.00	-.06	-.03	.01	-.01	.14	.10	.04	.01	-.03	-.17	.38	.19	-.28	.00				
17. County % Hispanic	-.08	.01	.00	-.01	.00	.00	.05	.43	.01	-.03	.47	.05	.25	.41	-.79	-.25	.00			
18. County % White Homicide	.17	-.01	.05	.06	.02	.00	-.12	-.24	-.08	-.02	-.45	-.12	-.55	-.64	.85	-.48	-.53	.00		
19. County % Black Homicide	-.13	-.01	-.05	-.06	-.03	.01	.13	-.06	.08	.07	.09	-.06	.46	.37	-.29	.87	-.20	-.61	.00	
20. County % Hispanic Homicide	-.06	.03	.01	.00	.00	-.01	.01	.38	.01	-.04	.45	.17	.16	.40	.40	-.36	.90	-.48	-.35	.00

County N = 473. Correlations above |.11| are significant at $p < .001$. Values on the diagonal indicate proportion of missing data. Based on 100 imputed datasets.

Table S3. Characteristics of Civilians Fatally Shot by Police in 2015

	White		Black		Hispanic	
Variable	*N*	%	*N*	%	*N*	%
Race	501	55%	245	19%	171	27%
Male	476	95%	235	96%	168	98%
Age	40	13	33	11	33	10
Armed	457	91%	210	86%	154	90%
Mental Health Issue	154	31%	39	16%	34	20%
Suicidal	79	16%	8	3%	17	10%
Attacking	474	95%	229	93%	160	94%

N = 917. Counts will not total to 917 where data are missing. Mean and standard deviation are reported for age.

Table S4. Predicting Race from Officer and Civilian Factors

	Black		Hispanic	
Variable	*OR*	95% CI	*OR*	95% CI
Intercept	0.25	0.13, 0.51	0.28	0.15, 0.51
Civilian Age	0.51	0.40, 0.65	0.53	0.43, 0.65
Civilian Armed	0.65	0.25, 1.67	1.15	0.38, 3.41
Civilian Mental Health Issue	0.63	0.34, 1.18	0.43	0.19, 0.99
Civilian Suicidal	0.34	0.12, 0.92	1.26	0.44, 3.61
Civilian Attacking	1.21	0.28, 5.14	0.77	0.22, 2.63
Officer Number	0.93	0.75, 1.17	1.18	0.97, 1.44
Officer % Black	1.21	1.01, 1.45	0.97	0.75, 1.24
Officer % Hispanic	1.39	1.12, 1.73	1.94	1.57, 2.41
Officer % Women	1.09	0.87, 1.36	1.13	0.94, 1.37
Average Officer Experience	1.10	0.89, 1.35	1.04	0.84, 1.29
χ^2	χ^2(20) = 71.73			
p	<.001			
R^2	.24			

Odds ratios above (below) 1.00 indicate a positive (negative) relationship between the predictor and the odds that a person fatally shot is Black or Hispanic. Whites served as the referent group. *N* = 623 (all cases without missing data).

Table S5. Predicting Race from Officer, Civilian, and County Factors

	Black		Hispanic	
Variable	*OR*	95% CI	*OR*	95% CI
Intercept	0.13	0.07, 0.25	0.18	0.11, 0.28
Civilian Age	0.54	0.41, 0.73	0.51	0.40, 0.66
Civilian Armed	0.69	0.25, 1.95	1.37	0.48, 3.87
Civilian Mental Health Issue	0.46	0.24, 0.89	0.38	0.16, 0.91
Civilian Suicidal	0.35	0.14, 0.87	1.05	0.33, 3.36
Civilian Attacking	1.77	0.38, 8.31	0.81	0.25, 2.62
Officer Number	0.97	0.77, 1.22	1.22	0.96, 1.56
Officer % Black	1.00	0.83, 1.19	0.94	0.75, 1.16
Officer % Hispanic	1.32	1.04, 1.67	1.32	1.06, 1.64
Officer % Women	1.01	0.81, 1.27	1.04	0.85, 1.28
Average Officer Experience	1.03	0.83, 1.28	1.03	0.80, 1.34
County Population Size	1.15	0.89, 1.49	1.11	0.86, 1.42
County Median Income	1.50	1.11, 2.05	1.26	0.92, 1.72
County Income Inequality	1.28	0.95, 1.72	1.12	0.72, 1.73
County % Rural	1.24	0.84, 1.83	1.06	0.66, 1.70
County % White Homicide	0.84	0.23, 3.00	0.77	0.33, 1.80
County % Black Homicide	2.70	0.83, 8.79	1.25	0.55, 2.84
County % Hispanic Homicide	0.80	0.26, 2.43	2.27	1.04, 4.94
χ^2	χ^2(30) = 183.57			
p	<.001			
R^2	.52			

Odds ratios above (below) 1.00 indicate a positive (negative) relationship between the predictor and the odds that a person fatally shot is Black or Hispanic. Whites served as the referent group. *N* = 623 (all cases without missing data).

Table S6. Power Analysis to Detect Officer Effects on Civilian Race

	Black			Hispanic		
Effect Size	.20	.25	.30	.20	.25	.30
Officer % Black	.69	.81	.93	.64	.83	.92
Officer % Hispanic	.62	.85	.96	.59	.80	.89
Officer % Women	.67	.79	.90	.47	.69	.81
Average Officer Experience	.63	.80	.90	.50	.77	.91

Effect size is in standardized beta units. An effect of .20 represents that as the predictor increases by one standardized unit, the odds of a person fatally shot being Black (or Hispanic) increase by .20 on the logistic scale.

Table S7. Racial Disparity in Civilian Race by Intercept Model

		Black		White	
Model	Intercept Controls For	*OR*	95% CI	*OR*	95% CI
S0	Crime Differences	0.15	0.08, 0.26	0.30	0.20, 0.46
S1	Population Differences	0.98	0.49, 1.95	0.24	0.10, 0.55
S2	Crime and Population Differences	0.43	0.18, 1.00	0.25	0.09, 0.68

Model S0 is identical to Model 0 in the main paper. N = 917.

Additional data table S1 (2015FOIS.csv)

This dataset provides all the civilian and county level predictors for the 917 FOIS analyzed. We are unable to share information about officers (their race, sex, or experience) due to agreements with law enforcement agencies to keep their officers anonymous. Variables are coded as follows:

labid: arbitrary laboratory id given to each civilian fatally shot in 2015
fips: unique county identifier
age: civilian age
sex: civilian sex (male, female)
race: civilian race (black, hispanic, white)
armed: was the civilian armed? (T/F)
mental: did the civilian have a mental health issue? (T/F)
suicidal: was the civilian suicidal? (T/F)
attack: was the civilian attacking the officer(s)? (T/F)
numOff: how many officers shot at the civilian?
popSize: county population size
income: median county income
gini: county income inequality
rural: percentage of a county classified by the census as rural
whitePop: percentage of residents in a county that are White
blackPop: percentage of residents in a county that are Black
hispanicPop: percentage of residents in a county that are Hispanic
whiteHom: percentage of homicide deaths in a county that are White
blackHom: percentage of homicide deaths in a county that are Black
HispHom: percentage of homicide deaths in a county that are Hispanic

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