Police Shootings and Racism in America

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I. Introduction

On May 25, 2020, George Floyd was publicly suffocated to death by police officers in Minneapolis, Minnesota. This, along with the murder of Breonna Taylor by Louisville police, incited waves of protests against police brutality across the United States and increased the spread of Black Lives Matter content on social media. The recent boost in attention to the Black Lives Matter movement has once again brought to light the issue of racism in America and its link to police brutality, and more specifically, police use of deadly force. Several studies have already found that race does play a part in who is targeted and killed in police shootings. For example, in a recent VICE News investigation about police shootings, it was found that "Black people were shot more often and at higher rates than people of any other race." [1] Additionally, Edwards et. al performed a study regarding the effects of age, race-ethnicity, and sex on the risk of being killed by lethal force by law enforcement and similarly found that "Black men are about 2.5 times more likely to be killed by police over the life course than are white men" while "Black women are about 1.4 times more likely to be killed by police than are white women." [2] However, even with these studies and their disturbing conclusions, a poll done by AP-NORC in June 2020 found that still 39% of Americans think that police are not more likely to use lethal force against a Black person than a White person. [3] Although this has decreased from an overwhelming 51% in June 2015, there is still a great deal of research that needs to be done in this area to provide more statistical evidence backing the relationship between racism and police use of deadly force.

As a result, I have decided to build off of VICE News' study and investigate data on police shootings further to understand the roles that the race of both victim and officer, as well as other factors such as whether they are carrying a weapon and the total number of victims in the crime, play in fatal versus non-fatal police shootings. Additionally, to account for the varying locations of the homicides, I will be using a dataset found on Kaggle detailing the gun provisions that are upheld by each state see how gun legislation affects lethal vs. non-lethal shootings. I will also add a predictor indicating whether the state in which the homicide occurred requires de-escalation training for police officers. Finally, I will explore how the race demographics of each location relates to police use of deadly force. This will allow me to better understand how racism has manifested itself in America's police system and determine whether current attempts to prevent police use of lethal force are effective or not.

II. Data

As a basis for this study, I will be using the same dataset that VICE News used. This dataset contains data on officer-involved shootings from 47 of the largest local police departments in America, and more specifically, "information on 4,117 incidents and 4,400 subjects [(victims)] over seven years." [1] VICE News provides 34 variables in the dataset, including dates ranging from January 2010 to September 2016, 47 unique cities, subject race, subject gender, office race, officer gender, the type of weapon the subject was carrying, and whether the shooting was fatal or not. Race was broken up into 6 categories: White (non-Hispanic) (represented as W), Black (non-Hispanic) (B), Asian (A), Latino (L), Other (O), and Unknown (U). Gender was broken up into 3 categories: Male (M), Female (F), and Unknown (U). Weapon type was broken up into

5 values: “gun”, “knife”, “replica”, “other”, and “unknown”. Additionally, there were cases in which multiple victims and/or multiple officers were present in the shooting. Each of these scenarios was still represented within one row of the dataset, but semi-colons were present in the respective victim and officer columns, separating each individual’s information from each other.

Additionally, to assess the effect of different types of legislation on fatal vs. non-fatal police shootings in various states, I will be using a dataset from Kaggle containing 135 variables that detail whether a certain gun provision is absent or present in a certain year and U.S. state for 133 different gun provisions. [4] The years range from 1991 to 2017, and the gun provisions address 14 categories, some of which are dealer regulations, buyer regulations, prohibitions for high-risk gun possession, background checks, ammunition regulations, possession regulations, concealed carry permitting, assault weapons and large-capacity magazines, child access prevention, gun trafficking, and domestic violence. A 1 in the gun provision column represents a presence of the law, and a 0 indicates an absence. I will also add a column to this gun provision dataset indicating whether a state requires de-escalation training based off of information reported by APM Report in 2017, with a 1 meaning the state does require training and a 0 meaning the state does not. There were 16 states that required de-escalation training as of November 2017. [5]

Finally, to examine city demographics as a predictor, I will be using population data from the 2013 American Community Survey that VICE News had already cleaned and standardized to the shootings dataset, meaning the city names can be matched up between the two datasets. VICE News most likely provided only 2013 census data because it is the average year of all the years represented in the shootings dataset. Furthermore, using census data only from 2013 requires that we analyze this data under the assumption that there is no drastic difference in population demographics between 2010 and 2016. The census data includes 7 variables: the police department and the city it’s located in, as well as the city’s Black, Asian, Hispanic, White, and overall total population in 2013.

Data Processing

Although the VICE News dataset was already relatively clean with regards to the victim’s data, there was still quite a bit of cleaning that needed to be done for the race and gender data of the officers. To clean these columns, I replaced all values that were not “W”, “B”, “A”, “O”, or “U” in the race column with the most informed guess that I could make about what the values represented. For example, “A/PI” values were taken to represent Asian/Pacific Islander and thus were replaced with “A”, and “A/W” or other values with a “/” in them were typically taken to represent multi-racial individuals and as a result were replaced with “O.” Similar procedures were carried out in the gender column for officers for values that were not “M”, “F”, or “U”.

After this initial cleaning, I created new columns in the same dataset that represented whether any victims of race Black, White, Asian, or Other were present in the crime, respectively, and if any male or female victims were present in the crime, respectively. I also added new columns to represent the same information for officers (for each race and gender, whether each was present), and a new column to represent whether any victim involved in the shooting was shot fatally. Additionally, I made sure that each weapon type had its own column. All of these added columns had values of either 0 or 1, with 0 representing an absence of the variable and 1 a presence. Finally, I filtered out 2,063 rows that had only unknown and NA values for the fatality of the shooting or the races or genders of the victims or officers, as these rows did not provide sufficient information for my analysis, and I selected only the columns I needed, such as whether any victim of the shooting was shot fatally or not, the genders and races of the victims and officers, and the weapons that the victims were carrying, if any.

For the gun provisions dataset, I created a new column that sums up the total number of laws listed in the dataset that each state had in 2013 (for the same reason that VICE News used 2013). Additionally, as I mentioned earlier, I appended a column to this dataset representing whether a state requires de-escalation training for police officers as of November 2017. 2017 was used under the assumption that no major event occurred between September 2016 and November 2017 that caused a sudden increase in the number of states that require de-escalation training for police officers. Finally, for the census data, the only cleaning that needed to be done was extracting the state that each city was in from the department column so that the census could be easily joined with the cleaned shootings dataset by city name, as well as the gun provisions dataset by abbreviated state name.

After merging the three datasets, the final dataset consists of 2,054 observations.

Exploratory Data Analysis

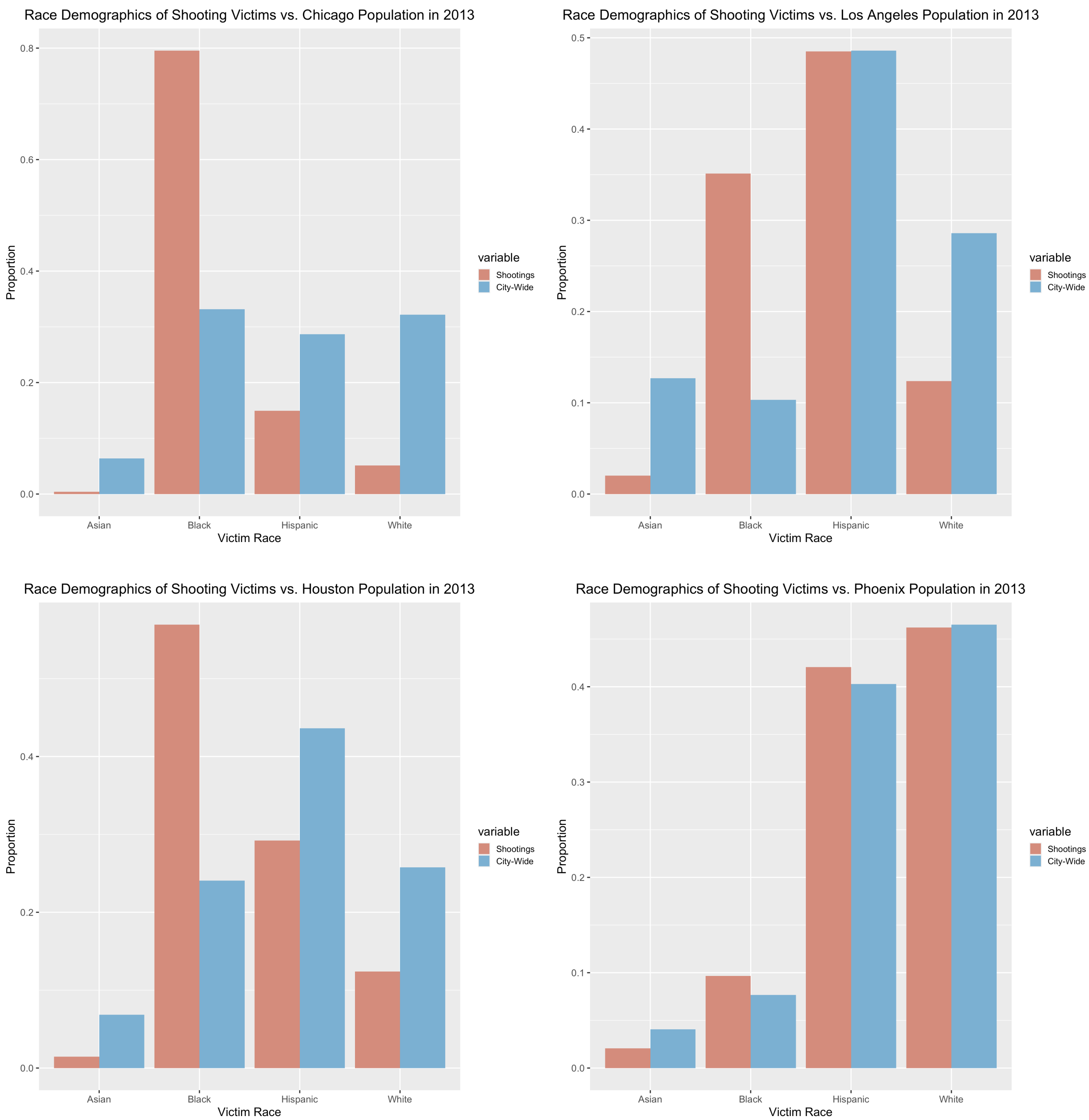

Figure 1: Race Proportions of Shooting Victims vs. City Population Demographics of the Most Popular 4 Cities in the Data

Plotted above in *Figure 1* are the race proportions of shooting victims in the top 4 most popular cities in the dataset (Chicago, Los Angeles, Houston, and Phoenix) vs. the race proportions of those cities' total populations in 2013. Because the bars representing shootings in the Black race category are taller than the bars representing city-wide population in all 4 plots, it is evident Black people are disproportionately the victims of police shootings compared to city race proportions. This can especially be seen in Houston, where Black people make up less than 25% of the city population yet more than 50% of the victim population of police shootings.

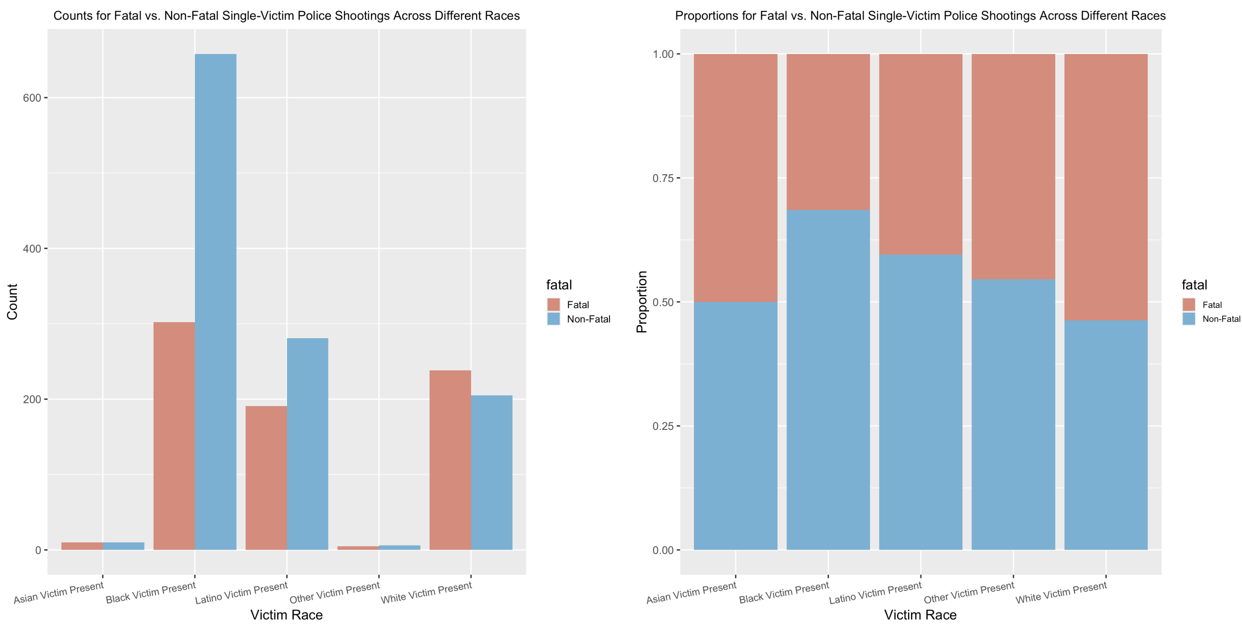

Figure 2: Counts (left) and Proportions (right) of Different Races Across Single Victim Shootings

Additionally, there appears to be 1,906 incidents in the final dataset in which there was only one victim, and 148 with multiple victims. Among all shootings with only one victim, it appears in *Figure 2* that the victim is more often Black than some other race. However, it seems that Black victims and most victims of the other race types are more likely to be shot non-fatally than fatally, whereas White victims seem more likely to be shot fatally. Finally, it is important to note that the numbers of victims that are of race types Asian and Other are relatively small. Because of this, we will combine Asian and Other race types into one single race category called "Other" for both officers and victims for our models.

Similarly, as seen in *Figure 3*, Black victims make up the highest proportion of victims in shootings with multiple victims. However, in these shootings, all race types are more likely to be shot non-fatally than fatally, with Latinos having the highest proportion of being shot fatally out of all other race types. Additionally, it should be noted that there are no victims with race type "Other" in shootings where there are multiple victims.

III. Methods

Because I want to explore the relationship between the number of victims in a police shooting affects and whether the shooting is fatal or not, I decided to create two separate models: one for shootings with only one victim, and one for shootings with multiple victims. Both models are random effect logistic regression models because the range that the response variable can take in logistic regression is the most reasonable given that I am predicting whether a victim is shot fatally or not (labeled 1 and 0, respectively). Additionally, I will be using random effects to control for correlation within cities.

To create these two models, I first performed backwards selection using simple logistic regression models on all relevant predictors in order to get a sense of which predictors are most statistically significant in prediction shooting fatality. Then, I added potential interactions that I wanted to explore one at a time and

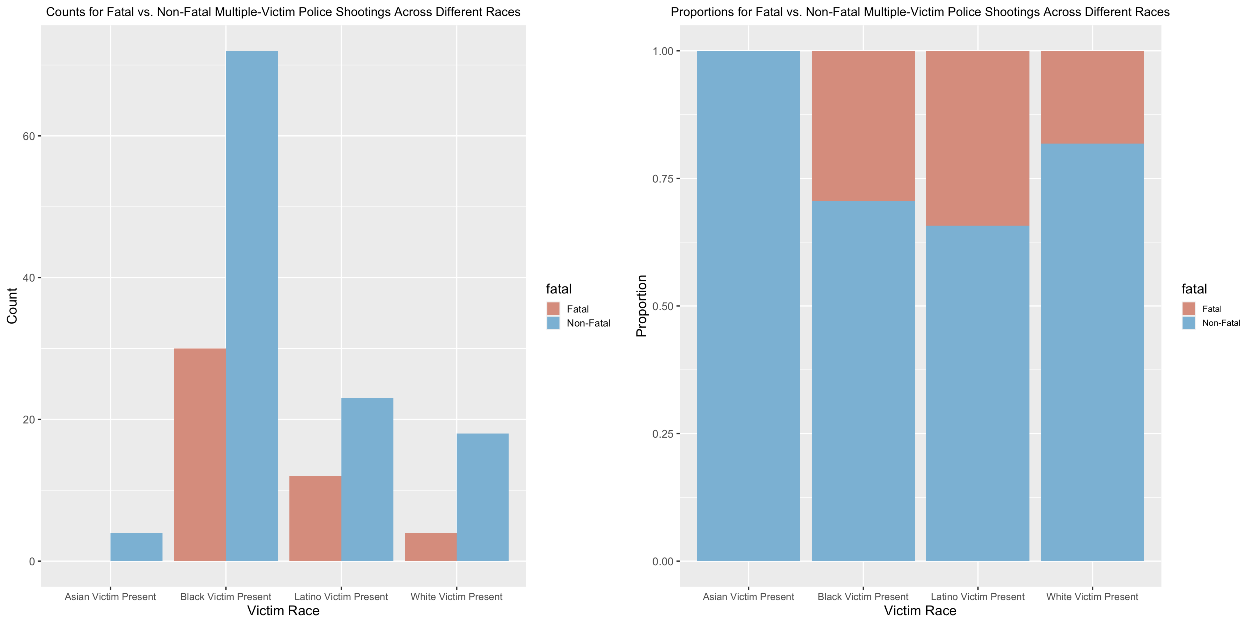

Figure 3: Counts (left) and Proportions (right) of Different Races Across Multiple Victim Shootings

performed likelihood ratio tests with each new model iteration to check if the added interaction improved the previous model. Whether an interaction was statistically significant or not was determined by whether the likelihood ratio test's p-value was less than 0.05. Finally, I put these variables obtained from backwards selection into a random effects linear regression model with city as the random intercept and evaluated the fit of this model using cross validation, which I will describe in more detail in the Results section. From there, I tweaked the model by experimenting with additional predictors, interactions, and random effects between city and other predictors in order to obtain the best fitting model.

The final model for single-victim shootings is written out below (where p_i represents the probability of getting fatally shot for shooting i):

$$log(\frac{p_i}{(1-p_i)}) = \beta_0 + \beta_{1j}\ VictimRace_{ij} + \beta_2\ OfficerBlack_i + \beta_3\ OfficerWhite_i + \beta_4\ MultipleOfficers_i$$
$$+\beta_5\ VictimWithGun_i + \beta_6\ VictimWithOther_i + \beta_7\ VictimWithReplica_i + \beta_8\ VictimWithKnife_i$$
$$+\beta_9\ VictimUnarmed_i + b_i$$
$$b_i \sim N(0, \sigma_b^2)$$
$$VictimRace = \text{White*, Black, Latino, Other}$$

For single victims, the best fitting model was the one that used city as a random intercept and had random slopes for the SubjectRace in each of these cities.

The final model for multiple-victim shootings is written out below (where p_i represents the probability of getting fatally shot for shooting i):

$$log(\frac{p_i}{(1-p_i)}) = \beta_0 + \beta_{1j}\ VictimBlack_{ij} + \beta_{2j}\ VictimLatino_{ij} + \beta_3\ VictimOther_i$$

$$+\beta_4\ OfficerBlack_i + \beta_5\ OfficerLatino_i + \beta_6\ MultipleOfficers_i + \beta_7\ VictimWithGun_i$$

$$\beta_8\ VictimWithOther_i + \beta_9\ VictimWithReplica_i + \beta_{10}\ VictimWithKnife_i + \beta_{11}\ (\frac{black_i}{white_i}) + b_i$$

$$b_i \sim N(0, \sigma_b^2)$$

For multiple victims, the best fitting model was the one that used city as a random intercept and had random slopes for whether a Black victim was present and whether a Latino victim was present in the shootings in each of these cities. It is important to note that none of the legislative predictors were useful in predicting the odds of someone being fatally shot in police shootings in either model. Additionally, $\frac{black_i}{white_i}$ refers to the proportion of black to white people in a city. This proved to be useful in increasing the predictive accuracy of the model.

IV. Results

Single Victims Model

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.5690089	0.1979449	-2.8745818	0.0040456
SubjectRaceB	-0.5798053	0.1573093	-3.6857657	0.0002280
SubjectRaceL	-0.5845731	0.2455106	-2.3810503	0.0172634
SubjectRaceO	-0.3777788	0.7190377	-0.5253949	0.5993087
ob	-0.3292988	0.1581182	-2.0826116	0.0372866
ow	0.2215886	0.1258798	1.7603191	0.0783537
omult	0.7424119	0.1121223	6.6214501	0.0000000
gun	0.5092389	0.1248400	4.0791314	0.0000452
weapon_other	0.0420686	0.2815327	0.1494269	0.8812168
replica	0.2117972	0.3356613	0.6309847	0.5280505
knife	1.3183828	0.2226240	5.9220162	0.0000000

In this single victim model, the β_0 coefficient, which has a value of -0.57, represents the log odds of being fatally shot by police in a 'typical' scenario and city. 'Typical' can be defined as a shooting in which the victim is White and unarmed and there is only one officer present, who is neither Black nor White. Thus, $\beta_0 + b_i$, or the city-specific intercept, represents the log odds of being fatally shot for a 'typical' White, unarmed victim in city i when there is only one officer present, who is neither Black nor White. The variabilities of the intercepts and slopes across different cities and different race groups within cities are all greater than 0, indicating that there is enough variation in the baseline odds of being shot fatally in different cities and different race groups within cities. From the fixed effect coefficients, we can see that generally, all other race types are less likely to be shot fatally than White 'typical' individuals.

The `ranef` function allows us to further quantify the difference between the average predicted log odds of being fatally shot for the general population versus that of a specific city and subject race type, other predictors remaining unchanged. This can be found in the Appendix. From this table, we can see that the city with the highest baseline odds of being shot fatally is Albuquerque, whereas the city with the lowest baseline odds of being shot fatally is Chicago. For White people in Chicago, the predicted log odds of being shot fatally is 0.76 less than that of in a 'typical' scenario and city. However, for Black people in Chicago, the predicted log odds of being shot fatally is actually 0.28 higher than that of a 'typical' scenario and city. In contrast, for Latino people in Chicago, the predicted log odds of being shot fatally is 0.23 lower than that of a 'typical' scenario and city, and for people of other race types in Chicago, the predicted log odds of being shot fatally is 2.86 lower than that of a 'typical' scenario and city. We can conclude that in Chicago, Black people are disproportionately shot fatally in police shootings. In Albuquerque, the trend is almost opposite:

for Black people, the log odds of being shot fatally is 0.43 less than that of a 'typical' scenario and city, whereas for White people, the log odds of being shot fatally is 0.67 more. Overall, we can conclude that city plays a large role in whether a race type is fatally shot in police shootings, although the general trend is that White people are most likely to be shot fatally than other race types.

Multiple Victims Model

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.7660759	1.074947e+00	-1.6429429	0.1003948
sb	-0.0906932	1.204639e+00	-0.0752866	0.9399867
sl	0.9339006	9.576766e-01	0.9751732	0.3294743
so	-19.3633630	8.247056e+03	-0.0023479	0.9981266
ob	-0.8402413	5.919742e-01	-1.4193883	0.1557858
ol	-0.4376839	4.641424e-01	-0.9429949	0.3456835
omult	1.4781870	4.616703e-01	3.2018237	0.0013656
gun	0.1453248	4.971407e-01	0.2923213	0.7700410
knife	20.4783768	1.816826e+04	0.0011272	0.9991007
weapon_other	-0.3513528	9.449102e-01	-0.3718372	0.7100140
replica	-18.4865262	9.321227e+03	-0.0019833	0.9984176
I(black/white)	-0.4177576	7.413048e-01	-0.5635436	0.5730648

grpvar	term	grp	condval	condsd
city	(Intercept)	Austin	-0.8525659	0.7585139
city	(Intercept)	CharlotteMecklenburg	-0.2966602	0.6741391
city	(Intercept)	Chicago	-0.9329623	0.2154344
city	(Intercept)	City of Miami	-1.0913284	0.8120714
city	(Intercept)	Columbus	-0.8231184	0.5989484
city	(Intercept)	Dallas	0.1149140	0.8970526
city	(Intercept)	DekalbCounty	0.2517714	0.8042709
city	(Intercept)	Denver	0.2136739	0.7784888
city	(Intercept)	Houston	-0.6235340	0.2797640
city	(Intercept)	Indianapolis	0.3750532	0.6942882
city	(Intercept)	LosAngeles	0.0937434	0.8806825
city	(Intercept)	LouisvilleMPD	0.5852229	0.7193629
city	(Intercept)	Memphis	0.0607287	0.8976709
city	(Intercept)	Milwaukee	0.3144156	0.8016964
city	(Intercept)	NewOrleans	-0.0266905	0.9255438
city	(Intercept)	Phoenix	0.1095857	0.9211489
city	(Intercept)	Seattle	0.6212411	0.7035356
city	(Intercept)	Tampa	0.3543215	0.7928930
city	(Intercept)	Tucson	0.5810421	0.7687885
city	sb	Austin	2.1536185	1.9160392
city	sb	CharlotteMecklenburg	0.7493767	1.7029047
city	sb	Chicago	2.3567033	0.5441966
city	sb	City of Miami	2.7567432	2.0513277
city	sb	Columbus	2.0792329	1.5129697
city	sb	Dallas	-0.2902779	2.2659939
city	sb	DekalbCounty	-0.6359856	2.0316235
city	sb	Denver	-0.5397497	1.9664968
city	sb	Houston	1.5750741	0.7066960
city	sb	Indianapolis	-0.9474007	1.7538024

grpvar	term	grp	condval	condsd
city	sb	LosAngeles	-0.2367999	2.2246423
city	sb	LouisvilleMPD	-1.4782985	1.8171421
city	sb	Memphis	-0.1534032	2.2675558
city	sb	Milwaukee	-0.7942275	2.0251200
city	sb	NewOrleans	0.0674215	2.3379640
city	sb	Phoenix	-0.2768183	2.3268623
city	sb	Seattle	-1.5692820	1.7771616
city	sb	Tampa	-0.8950317	2.0028822
city	sb	Tucson	-1.4677378	1.9419933
city	sl	Austin	0.6483064	0.5767876
city	sl	CharlotteMecklenburg	0.2255858	0.5126275
city	sl	Chicago	0.7094413	0.1638202
city	sl	City of Miami	0.8298658	0.6175137
city	sl	Columbus	0.6259140	0.4554511
city	sl	Dallas	-0.0873827	0.6821349
city	sl	DekalbCounty	-0.1914515	0.6115821
city	sl	Denver	-0.1624815	0.5919769
city	sl	Houston	0.4741465	0.2127375
city	sl	Indianapolis	-0.2851972	0.5279493
city	sl	LosAngeles	-0.0712842	0.6696868
city	sl	LouisvilleMPD	-0.4450140	0.5470165
city	sl	Memphis	-0.0461792	0.6826051
city	sl	Milwaukee	-0.2390873	0.6096243
city	sl	NewOrleans	0.0202960	0.7038002
city	sl	Phoenix	-0.0833309	0.7004582
city	sl	Seattle	-0.4724029	0.5349811
city	sl	Tampa	-0.2694325	0.6029301
city	sl	Tucson	-0.4418349	0.5846006

In this multiple victims model, the β_0 coefficient, which has a value of -1.77, represents the log odds of being fatally shot by police in a 'typical' scenario and city. 'Typical' can be defined as a shooting in which the victim is White and unarmed and there is only one officer present, who is neither Black nor Latino. Thus, $\beta_0 + b_i$, or the city-specific intercept, represents the log odds of being fatally shot for a 'typical' White, unarmed victim in city i when there is only one officer present, who is neither Black nor White. The variabilities of the intercepts and slopes across different cities and different race groups within cities are all greater than 0, indicating that there is enough variation in the baseline odds of being shot fatally in different cities and different race groups within cities. From the fixed effect coefficients, we can see that generally, all other race types are less likely to be shot fatally than White 'typical' individuals.

The `ranef` function also allows us to quantify the difference between the average predicted log odds of being fatally shot for the general population versus that of a specific city and subject race type, other predictors remaining unchanged. This can be found in the Appendix. From this table, we can see that the city with the highest baseline odds of being shot fatally is Albuquerque, whereas the city with the lowest baseline odds of being shot fatally is Chicago. For White people in Chicago, the predicted log odds of being shot fatally is 0.76 less than that of in a 'typical' scenario and city. However, for Black people in Chicago, the predicted log odds of being shot fatally is actually 0.28 higher than that of a 'typical' scenario and city. In contrast, for Latino people in Chicago, the predicted log odds of being shot fatally is 0.23 lower than that of a 'typical' scenario and city, and for people of other race types in Chicago, the predicted log odds of being shot fatally is 2.86 lower than that of a 'typical' scenario and city. We can conclude that in Chicago, Black people are disproportionately shot fatally in police shootings. In Albuquerque, the trend is almost opposite: for Black people, the log odds of being shot fatally is 0.43 less than that of a 'typical' scenario and city, whereas for White people, the log odds of being shot fatally is 0.67 more. Overall, we can conclude that city plays a large role in whether a race type is fatally shot in police shootings, although the general trend is that White people are most likely to be shot fatally than other race types.

Differences Between Single and Multiple Victims

Model Validation and Diagnostics

As I mentioned earlier, I performed 5-fold cross-validation on my models to assess model accuracy and fit. I chose to use 5 folds and 85% of the data because this is commonly used in practice, but I tried it with 90% of the data as well just to verify that my cross-validation technique was not biased for the percentage of the full data allocated for the training set. I used the `groupdata2` R package to partition our data set so that the training set contained 85% of the data from the full dataset, and then I ran 5-fold cross-validation on this training set before predicting on the test set. When assessing the performance of different models, we considered a higher average cross-validation and test set prediction accuracy to be indicative of a better model. For the single victims model, I achieved an average 5-fold cross-validation prediction accuracy of 0.66 and a test set prediction accuracy of 0.70. For the multiple victims model, I achieved an average 5-fold cross-validation prediction accuracy of 0.61, and a test set prediction accuracy of 0.63.

Sensitivity Analysis

V. Discussion and Conclusion

Overall,

One strength of my analysis is that I am considering many variables as predictors, from individual level data to contextual predictors, such as state gun legislation. This allows me to thoroughly explore and determine whether the relationships between a wide range of potential predictors and police shooting fatality in the context of police brutality are significant in any types of shootings (single vs. multiple victims, for example). There are several limitations to this study. For example, the VICE News dataset spans over the years 2010 to 2016, and neither of my models will be exploring time series data whatsoever. Thus, the aspect of time may be playing some sort of effect on my response variable that I am not accurately capturing in my models. There are also several other confounding factors that have not been accounted for, such as how well one can shoot at baseline or what training they have received with regards to shooting. Additionally, when cleaning the data, there were several "Unknown" values in the fatality column. Unknown values were assumed to represent "No" in this study, although this may not necessarily be true, to allow for more straightforward cleaning of the data and not lose too many observations in the data. Finally, there were less than 200 cases in which there were multiple victims in my final dataset, which is a relatively small sample size. Thus, it may be necessary to take the results from the multiple-victim model with a grain of salt.

VI. References

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[6] DeGue, Sarah et al. "Deaths Due to Use of Lethal Force by Law Enforcement: Findings From the National Violent Death Reporting System, 17 U.S. States, 2009-2012." American journal of preventive medicine vol. 51,5 Suppl 3 (2016): S173-S187. doi:10.1016/j.amepre.2016.08.027

VII. Appendix

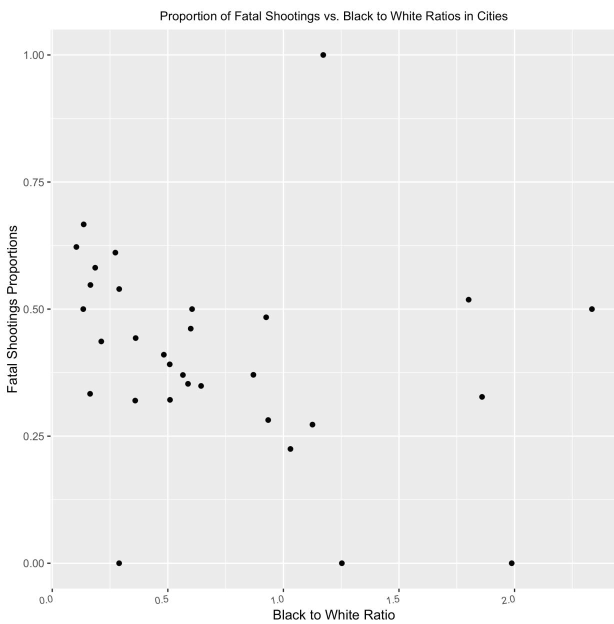

Figure 4: Proportion of Fatal Shootings vs. Black to White Ratios in Cities in Dataset (left) and vs. Black Population Percentages in Cities in Dataset (right)

Single-Victim Shooting

Table 4: Random Effects Coefficients for Single-Victim Shootings

grpvar	term	grp	condval	condsd
city	(Intercept)	Albuquerque	0.2430400	0.1567403
city	(Intercept)	Austin	0.1497078	0.1498978
city	(Intercept)	Boston	0.0077039	0.2534256
city	(Intercept)	CharlotteMecklenburg	-0.0702605	0.1509623
city	(Intercept)	Chicago	-0.4765491	0.1044403
city	(Intercept)	Cincinnati	0.1594184	0.1997368
city	(Intercept)	City of Miami	0.2468825	0.2039244
city	(Intercept)	Columbus	-0.2066416	0.1209248
city	(Intercept)	Dallas	-0.1109770	0.1199458
city	(Intercept)	DekalbCounty	0.2833051	0.1417665
city	(Intercept)	Denver	-0.0082291	0.1484408
city	(Intercept)	El Paso	0.0109742	0.1968326
city	(Intercept)	Fort Worth	-0.0793459	0.1706263

grpvar	term	grp	condval	condsd
city	(Intercept)	Houston	-0.2804825	0.1129576
city	(Intercept)	Indianapolis	-0.0299153	0.1625513
city	(Intercept)	Jacksonville	-0.0738529	0.2179761
city	(Intercept)	Kansas City	-0.1661128	0.1925817
city	(Intercept)	LasVegas	-0.0221964	0.2528003
city	(Intercept)	LosAngeles	0.0134823	0.0666511
city	(Intercept)	LouisvilleMPD	-0.1760825	0.2084758
city	(Intercept)	Memphis	0.2281491	0.2015491
city	(Intercept)	MiamiDade	-0.0429144	0.2518116
city	(Intercept)	Milwaukee	-0.2721349	0.1881156
city	(Intercept)	Phoenix	0.0244728	0.0868118
city	(Intercept)	San Antonio	0.2196665	0.1312532
city	(Intercept)	San Francisco	-0.0161836	0.2420790
city	(Intercept)	Seattle	-0.0603125	0.1382414
city	(Intercept)	St. Louis	0.1589656	0.2478194
city	(Intercept)	Tampa	0.0999660	0.2172357
city	(Intercept)	Tucson	0.2529422	0.1441872
city	SubjectRaceL	Albuquerque	-0.3307792	0.2945062
city	SubjectRaceL	Austin	-0.0120039	0.3784711
city	SubjectRaceL	Boston	0.0071413	0.4783066
city	SubjectRaceL	CharlotteMecklenburg	-0.2246094	0.3847875
city	SubjectRaceL	Chicago	-0.5054538	0.2741102
city	SubjectRaceL	Cincinnati	-0.1100740	0.4401734
city	SubjectRaceL	City of Miami	0.3686905	0.3994511
city	SubjectRaceL	Columbus	-0.2302946	0.3865121
city	SubjectRaceL	Dallas	-0.2288883	0.2708667
city	SubjectRaceL	DekalbCounty	0.4045696	0.4083445
city	SubjectRaceL	Denver	0.6066302	0.3217212
city	SubjectRaceL	El Paso	-0.1182792	0.4339097
city	SubjectRaceL	Fort Worth	-0.1350520	0.4068649
city	SubjectRaceL	Houston	-0.3098953	0.2435380
city	SubjectRaceL	Indianapolis	-0.0251598	0.4290805
city	SubjectRaceL	Jacksonville	-0.1874875	0.4535631
city	SubjectRaceL	Kansas City	-0.1105999	0.4581956
city	SubjectRaceL	LasVegas	-0.0508212	0.4678171
city	SubjectRaceL	LosAngeles	0.4694684	0.1616374
city	SubjectRaceL	LouisvilleMPD	-0.0013407	0.4693578
city	SubjectRaceL	Memphis	0.0490297	0.4616668
city	SubjectRaceL	MiamiDade	-0.0065166	0.4799326
city	SubjectRaceL	Milwaukee	-0.3040975	0.4355674
city	SubjectRaceL	Phoenix	-0.0307469	0.2201669
city	SubjectRaceL	San Antonio	0.4967594	0.2546148
city	SubjectRaceL	San Francisco	0.0025499	0.4416146
city	SubjectRaceL	Seattle	-0.0903538	0.4004565
city	SubjectRaceL	St. Louis	0.1473575	0.4757757
city	SubjectRaceL	Tampa	0.1325957	0.4593839
city	SubjectRaceL	Tucson	0.4289891	0.3016825
city	SubjectRaceO	Albuquerque	1.2369280	0.9782782
city	SubjectRaceO	Austin	0.8812186	1.0101227
city	SubjectRaceO	Boston	0.0501741	1.6707545
city	SubjectRaceO	CharlotteMecklenburg	-0.5568157	0.9898635
city	SubjectRaceO	Chicago	-3.1433276	0.6522454

grpvar	term	grp	condval	condsd
city	SubjectRaceO	Cincinnati	0.8778487	1.3299623
city	SubjectRaceO	City of Miami	1.6949080	1.3143761
city	SubjectRaceO	Columbus	-1.3699298	0.8463129
city	SubjectRaceO	Dallas	-0.8011764	0.7476736
city	SubjectRaceO	DekalbCounty	1.9334394	0.9285272
city	SubjectRaceO	Denver	0.3285616	0.9636977
city	SubjectRaceO	El Paso	-0.0084423	1.3248367
city	SubjectRaceO	Fort Worth	-0.5550304	1.1570673
city	SubjectRaceO	Houston	-1.8577834	0.6894148
city	SubjectRaceO	Indianapolis	-0.1932346	1.1254271
city	SubjectRaceO	Jacksonville	-0.5550454	1.4470525
city	SubjectRaceO	Kansas City	-1.0548784	1.3204819
city	SubjectRaceO	LasVegas	-0.1633792	1.6589431
city	SubjectRaceO	LosAngeles	0.3721092	0.3771699
city	SubjectRaceO	LouisvilleMPD	-1.0460847	1.4107556
city	SubjectRaceO	Memphis	1.3848292	1.3557383
city	SubjectRaceO	MiamiDade	-0.2588003	1.6652838
city	SubjectRaceO	Milwaukee	-1.8046235	1.2629066
city	SubjectRaceO	Phoenix	0.1261449	0.5478322
city	SubjectRaceO	San Antonio	1.6130268	0.8111806
city	SubjectRaceO	San Francisco	-0.0944817	1.5734618
city	SubjectRaceO	Seattle	-0.4142364	0.9295687
city	SubjectRaceO	St. Louis	1.0353196	1.6346936
city	SubjectRaceO	Tampa	0.6759057	1.4553791
city	SubjectRaceO	Tucson	1.7683933	0.9012391
city	SubjectRaceW	Albuquerque	0.4294546	0.2052262
city	SubjectRaceW	Austin	0.1710508	0.1902263
city	SubjectRaceW	Boston	0.0050194	0.2617713
city	SubjectRaceW	CharlotteMecklenburg	0.0319744	0.2134010
city	SubjectRaceW	Chicago	-0.2794325	0.1714545
city	SubjectRaceW	Cincinnati	0.2295789	0.2295161
city	SubjectRaceW	City of Miami	0.0926786	0.2436430
city	SubjectRaceW	Columbus	-0.1157467	0.1801727
city	SubjectRaceW	Dallas	-0.0108690	0.1775163
city	SubjectRaceW	DekalbCounty	0.1153776	0.2260081
city	SubjectRaceW	Denver	-0.3048342	0.1873197
city	SubjectRaceW	El Paso	0.0697750	0.2138588
city	SubjectRaceW	Fort Worth	-0.0217135	0.1963363
city	SubjectRaceW	Houston	-0.1584200	0.1709901
city	SubjectRaceW	Indianapolis	-0.0207445	0.1935026
city	SubjectRaceW	Jacksonville	0.0099120	0.2391979
city	SubjectRaceW	Kansas City	-0.1293797	0.2080195
city	SubjectRaceW	LasVegas	0.0002840	0.2632951
city	SubjectRaceW	LosAngeles	-0.2140050	0.1231783
city	SubjectRaceW	LouisvilleMPD	-0.1936486	0.2255728
city	SubjectRaceW	Memphis	0.2278527	0.2300262
city	SubjectRaceW	MiamiDade	-0.0441779	0.2578026
city	SubjectRaceW	Milwaukee	-0.1520353	0.2195311
city	SubjectRaceW	Phoenix	0.0419953	0.1356367
city	SubjectRaceW	San Antonio	0.0002083	0.1806055
city	SubjectRaceW	San Francisco	-0.0191014	0.2624335
city	SubjectRaceW	Seattle	-0.0225026	0.2065259

grpvar	term	grp	condval	condsd
city	SubjectRaceW	St. Louis	0.1035723	0.2594828
city	SubjectRaceW	Tampa	0.0456647	0.2306756
city	SubjectRaceW	Tucson	0.0699676	0.2011916

Multiple-Victim Shooting

Table 5: Random Effects Coefficients for Multiple-Victim Shootings

grpvar	term	grp	condval	condsd
city	(Intercept)	Austin	-0.8525659	0.7585139
city	(Intercept)	CharlotteMecklenburg	-0.2966602	0.6741391
city	(Intercept)	Chicago	-0.9329623	0.2154344
city	(Intercept)	City of Miami	-1.0913284	0.8120714
city	(Intercept)	Columbus	-0.8231184	0.5989484
city	(Intercept)	Dallas	0.1149140	0.8970526
city	(Intercept)	DekalbCounty	0.2517714	0.8042709
city	(Intercept)	Denver	0.2136739	0.7784888
city	(Intercept)	Houston	-0.6235340	0.2797640
city	(Intercept)	Indianapolis	0.3750532	0.6942882
city	(Intercept)	LosAngeles	0.0937434	0.8806825
city	(Intercept)	LouisvilleMPD	0.5852229	0.7193629
city	(Intercept)	Memphis	0.0607287	0.8976709
city	(Intercept)	Milwaukee	0.3144156	0.8016964
city	(Intercept)	NewOrleans	-0.0266905	0.9255438
city	(Intercept)	Phoenix	0.1095857	0.9211489
city	(Intercept)	Seattle	0.6212411	0.7035356
city	(Intercept)	Tampa	0.3543215	0.7928930
city	(Intercept)	Tucson	0.5810421	0.7687885
city	sb	Austin	2.1536185	1.9160392
city	sb	CharlotteMecklenburg	0.7493767	1.7029047
city	sb	Chicago	2.3567033	0.5441966
city	sb	City of Miami	2.7567432	2.0513277
city	sb	Columbus	2.0792329	1.5129697
city	sb	Dallas	-0.2902779	2.2659939
city	sb	DekalbCounty	-0.6359856	2.0316235
city	sb	Denver	-0.5397497	1.9664968
city	sb	Houston	1.5750741	0.7066960
city	sb	Indianapolis	-0.9474007	1.7538024
city	sb	LosAngeles	-0.2367999	2.2246423
city	sb	LouisvilleMPD	-1.4782985	1.8171421
city	sb	Memphis	-0.1534032	2.2675558
city	sb	Milwaukee	-0.7942275	2.0251200
city	sb	NewOrleans	0.0674215	2.3379640
city	sb	Phoenix	-0.2768183	2.3268623
city	sb	Seattle	-1.5692820	1.7771616
city	sb	Tampa	-0.8950317	2.0028822
city	sb	Tucson	-1.4677378	1.9419933
city	sl	Austin	0.6483064	0.5767876
city	sl	CharlotteMecklenburg	0.2255858	0.5126275
city	sl	Chicago	0.7094413	0.1638202

grpvar	term	grp	condval	condsd
city	sl	City of Miami	0.8298658	0.6175137
city	sl	Columbus	0.6259140	0.4554511
city	sl	Dallas	-0.0873827	0.6821349
city	sl	DekalbCounty	-0.1914515	0.6115821
city	sl	Denver	-0.1624815	0.5919769
city	sl	Houston	0.4741465	0.2127375
city	sl	Indianapolis	-0.2851972	0.5279493
city	sl	LosAngeles	-0.0712842	0.6696868
city	sl	LouisvilleMPD	-0.4450140	0.5470165
city	sl	Memphis	-0.0461792	0.6826051
city	sl	Milwaukee	-0.2390873	0.6096243
city	sl	NewOrleans	0.0202960	0.7038002
city	sl	Phoenix	-0.0833309	0.7004582
city	sl	Seattle	-0.4724029	0.5349811
city	sl	Tampa	-0.2694325	0.6029301
city	sl	Tucson	-0.4418349	0.5846006

```
## [1] "Average cross-validation prediction accuracy: 0.610461538461538"
```

	0	1
0	1026	579
1	78	97

```
## [1] "Test set prediction accuracy: 0.630898876404494"
```

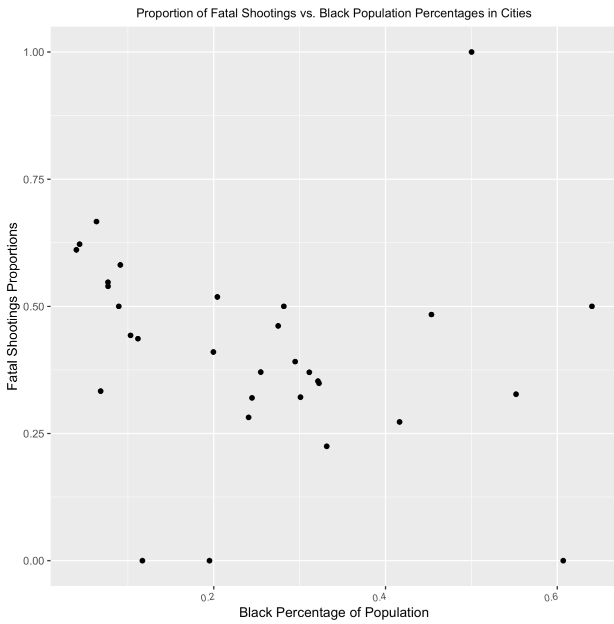

Figure 5: Proportion of Fatal Shootings vs. Black to White Ratios in Cities in Dataset (left) and vs. Black Population Percentages in Cities in Dataset (right)

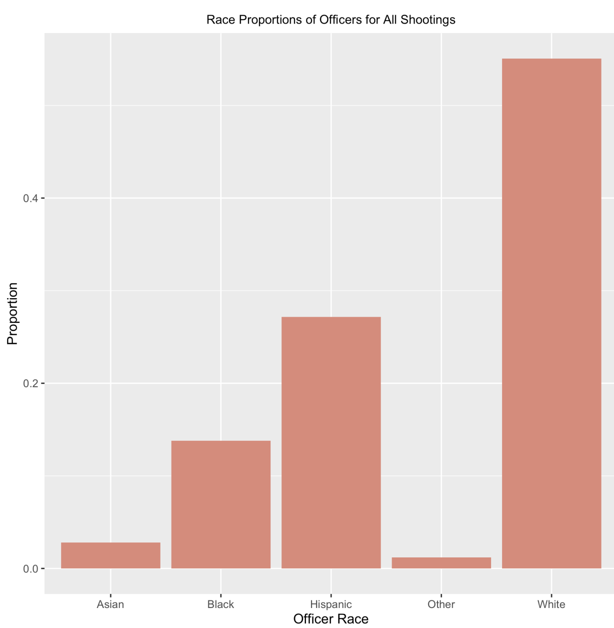

Figure 6: Race Proportions of Officers For All Shootings (left) and For Fatal vs. Non-Fatal Police Shootings Where At Least One Black Victim was Present (right) and

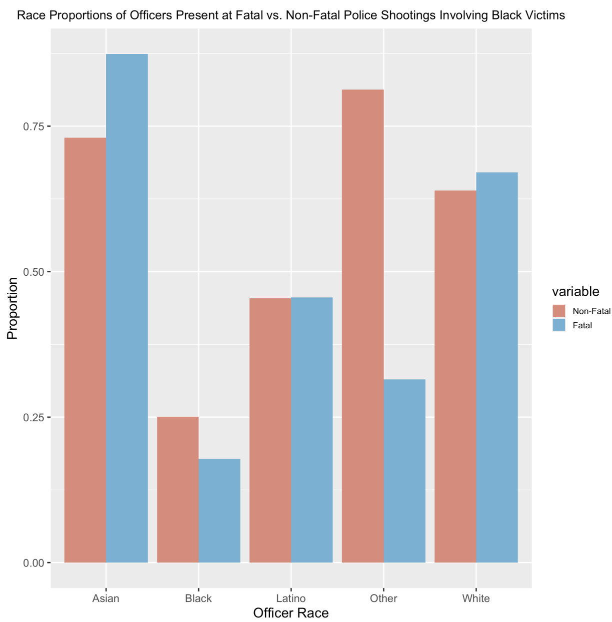

Figure 7: Race Proportions of Officers For All Shootings (left) and For Fatal vs. Non-Fatal Police Shootings Where At Least One Black Victim was Present (right) and