United States Police Shootings: Discrepancies in Fleeing Victims

Hannah Niemi & Zachary Picard

MTH 231: Exploratory Data Analysis

December 14th, 2022

Abstract

A notable impact of the gun violence epidemic in the United States has been determined to stem from police shootings and killings, which have dramatically increased over the last few years. The socioeconomic status of the victims and the details behind the police shootings have highlighted the inequalities seen within the cause of the killing. Unfortunately, there is not a considerable amount of data and research on police killings in the United States. To solve this, the study uses visual representations of the data analysis and logistic regressions on The Washington Posts Police Shootings Database to analyze the relationship between gender and the probability of being armed and being shot and killed by the police when fleeing, controlling the other demographic variables. This study finds that being Male, and/or Black, and/or Hispanic is associated with a higher probability of being shot and killed by the police when armed and fleeing. These findings can help improve police gun violence policy, and potentially raise awareness of the patterns of socioeconomic inequalities with police killings.

Introduction & Background

The United States has been battling a unique gun violence epidemic for many years now. Gun violence is out of control in the United States, and while restrictions and regulations are being imposed to help stop the overwhelming amount of gun violence in this country, one cause of gun violence remains largely unregulated: the police (Oakley 2021). Police in the United States kill an immense number of people every year. The actual number is not known because the data is not tracked, reported, collected, or analyzed by any means (ACLU 2020). Gun violence in general in the United States out beats any other developed country in the World, and this goes for police killings as well. For perspective, police in America kill people at least three times the rate of their law enforcement counterparts in Canada, a wealthy country with the next highest rate of killing, and at least 16 times the rates of Germany and England (ACLU 2020). According to Everytown Research, 96% of the deaths of civilians caused by police are with a firearm (Everytown Analysis 2020). There is a belief that depending on an individual's race, age, gender, weapon, mental state, threat level, location, and if they were fleeing or not may affect their likelihood of being shot and killed by the police. The increase in being shot and killed by police was far more pronounced for some factors more than others, such as race, gender, being armed, and fleeing.

Police use their weapons to kill civilians far more than civilians use weapons to kill the police. While the United States does not collect comprehensive data about the use of lethal force by police officers, a database compiled by the Washington Post revealed that police shoot and kill close to 1,000 civilians every year (The Washington Post 2022). In 2014, The Washington Post launched an investigation that found that data reported to the FBI on fatal police shootings was undercounted by more than half (The Washington Post 2022). Within recent years, this gap has widened and in 2021, only a third of departments' fatal shootings appeared in the FBI database. Starting January 1st, 2015, The Washington Post began to log every person shot and killed by an on-duty police officer in the United States, and in 2022, The Post updated its database to standardize and publish the names of the police agencies involved in each shooting to better measure accountability at the department level (The Washington Post 2022). The Washington Post has provided an updated analysis of the data they have created throughout the years. Outside research interests have also taken the opportunity to analyze this data and find statistical significance to provide different insights into their findings.

The number of police shootings in the United States has risen throughout the past few years, 2021 being the year of the highest number of people killed by police on record. The Washington Post found that Black Americans are shot and killed at a disproportionate rate, even though they only account for roughly 14% of the U.S. population (The Washington Post 2022). Black Americans are killed by police at more than twice the rate of White Americans. Hispanic Americans are also shot and killed by the police at a disproportionate rate, even though they only account for roughly 18% of the U.S. population (The Washington Post 2022). The Washington Post also found that an overwhelming majority of the victims are male, at over 95%.

Using The Washington Post's database, this study constructs an exploratory data analysis and logistic regression model. The data was explored by creating various visual representations in order to gain a better insight into the data to create a hypothesis. The logistic regression model describes the relationship between gender and the probability of being armed and being shot and killed by the police while fleeing, controlling the other demographic variables. Using this model, the study's results do find statistically significant evidence that an individual's gender and race predict the probability of being armed and shot and killed by the police when fleeing. The control variables used in the model successfully enhanced the internal validity of the results in the unrestricted model by limiting the influence of bias between the dependent variable and key independent variable. This study contributes to our understanding of the inequalities and the scope and impact of centuries of systemic police violence and racism within the United States which will influence the research community to learn and build from. This study also increases awareness of the demographic inequalities rooted in police brutality and police killings. This paper advances the literature on data behind police killings by providing insight into deciding factors that determine who is more likely to be shot and killed by police when fleeing and being armed. This research is important and grows the literature by investigating the subjective socioeconomic factors of victims in the data and how the factors influence the likelihood of being shot and killed by police.

Methods

Data collection

The data set used in this study was obtained from the Washington Post's database which contains records of every fatal shooting in the United States by a police officer in the line of duty since January 1st, 2015. The Washington Post began tracking more than a dozen details about each killing that included the race of the deceased, the circumstances of the shooting, whether the person was armed and whether the person was experiencing a mental health crisis, fleeing or not fleeing, etc. The data documents only those shootings in which a police officer in the line of duty has shot and killed a civilian (The Washington Post 2022). It is important to note that the FBI and the Centers for Disease Control and Prevention log fatal shootings by police, but officials acknowledge that their data is incomplete. Since 2015, The Washington Post's data has documented more than twice as many fatal shootings by police as recorded on average annually. The data is updated regularly as fatal shootings are reported and as facts emerge about individual cases (The Washington Post 2022). For this sample, as of today, there were 7,871 people shot and killed by police in total. We then used this dataset in our Jupyter/Python setup. Several adjustments were made to arrive at a sample that was equal in the number of observations and that made sense for the exploratory data analysis. We cleaned and analyzed the data using various command aspects in the pandas module while also counting and visualizing it as well. In order to clean the data, we needed to create new columns through sorting and boolean indexing. We included several independent variables like age, race, gender, mental illness, and being armed. The next step in cleaning the data was to drop all of the null values. We did this by using the command "dropna". After dropping all of these variables, the final sample contained 5,069 observations. We then decided to investigate only the fleeing victims to further explore any disparities seen among victims who flee from the police. After dropping all of these variables, the final sample contained 3,393 observations. This was performed by dropping all of the observations where the victims were identified as not fleeing.. In order to gain a better insight into the data on fleeing victims, visualizations were created to see how race played a role in a fleeing victim. A crosstabulation of race and fleeing victims were created and coded into a stacked bar chart for better visual representation. Proceeding this, the Black race showed significance compared to the other non-White races. To further explore this finding, a map of the US was created to show the data that included only Black victims who were armed and unarmed. Then, a map of the US was created to show the data that included only the Black and White victims who were armed and unarmed. These two US maps were compared. To find more statistical inference, the chosen categorical variables were generated and manipulated into dummy variables to represent 0 and 1 values in order to perform a logistic regression. The variable *armed2* was chosen as the dependent variable. The variables *gender2*, *white*, *black*, *asian*, *hispanic*, *native american*, *other*, and *signs_of_mental_illness* were chosen as the independent variables.

Variable creation

In logistic regression models, encoding all of the variables as dummy variables allows easy interpretation and increases the stability and significance of the coefficients. All of the categorical variables were manipulated into dummy variables to achieve accurate results and interpretations. The continuous variables were not manipulated. *armed2* is the dependent variable for this model and it measures whether the person was armed or not and what weapon they used. It was obtained from the *armed* variable, which contained categories within itself as "unarmed", or various types of weapons such as "gun", "knife", "toy weapon", etc., for example. *armed2* is a variable that indicates 1 if they reported a weapon and 0 if they reported "unarmed", and within Python, they were coded and labeled as "True" if they were armed, or "False" if they were unarmed. This variable was included in the model because whether a victim was armed or not is an important factor when considering those who were shot and killed by police. Victims who are armed, despite the weapon of choice, are often associated with having a higher probability of being in a life-threatening situation with the police. Since the entire dataset is only fleeing victims, being armed or not could be an important factor if a victim decides to flee or not.

The next variable created was *gender2*, which is the key independent variable in the model. *Gender2* indicates whether the victim is male or not by labeling the observation as "True" if they are male, and "False" if they are female. It was obtained from the *gender* variable, which was labeled as male or female within the variable. *gender2* was created and coded to identify that an individual was Male. This variable was included in the model because gender is an important factor when considering victims being shot and killed by the police. Men are statistically more likely to be killed by police than women are. Also, it is important to consider the racial inequalities between both males and females when law enforcement and police killings are involved.

Next, the following independent variables were created: *white*, *black*, *asian*, *hispanic*, *native american*, and *other.* These variables are race variables that indicate whether the victim belongs to a specific race. The *white*, *black*, *asian*, *hispanic*, *native american*, and *other* variables were obtained from the *race* variable. The *race* variable contained these six different races within each individual victim identified as. The variables *white*, *black*, *asian*, *hispanic*, *native american*, and *other* were created to separate them from the race variable and be subjected to becoming dummy variables to satisfy the logistic regression analysis. The variables *white*, *black*, *asian*, *hispanic*, *native american*, and *other* specifies "True" if the victim is of that race, and "False" if they are not of that race. These variables were included in the model because race is an important factor when considering victims that were shot and killed by police. There are inequalities when it comes to individuals being shot and killed by police between different races compared to those who are White. How race and police violence interact has been a forefront issue in the United States. This variable can also take into greater effect if gender is incorporated into the statistical inference due to recent studies that explore non-white men and women being more likely to get shot and killed by police compared to white men and women.

Lastly, the independent variable *signs_of_mental_illness* was used and not manipulated since it already was designed as a dummy variable. *Signs_of_mental_illness* indicates whether the victim was experiencing a mental health crisis or not during the policing shooting. The variable specifies "True" if the victim had signs of mental illness, and "False" if the victim did not show signs of mental illness. This variable was included in the model because signs of mental illness are important when considering victims being shot and killed by the police. Victims in a mental health crisis do not always respond in ways that police officers want them to and this can result in a shooting and death of the victim. This variable can also take into greater effect if gender and race are incorporated into the statistical inference due to recent studies that explore non-white races being less likely to get treatment for active mental health diagnoses.

Analytic Methods

After taking a preliminary look at the data, we wanted to look into any correlation between race and the fleeing status of people in the data set. While taking a quick look at the stacked bar chart we created a visualization for the number of shootings within each race and how/if they were fleeing. At first glance, the visualization looks pretty similar between all of the races. However, if you look at the stacked bars per their population, you can see that there are significantly more black people who flee on foot per population vs. any other race.

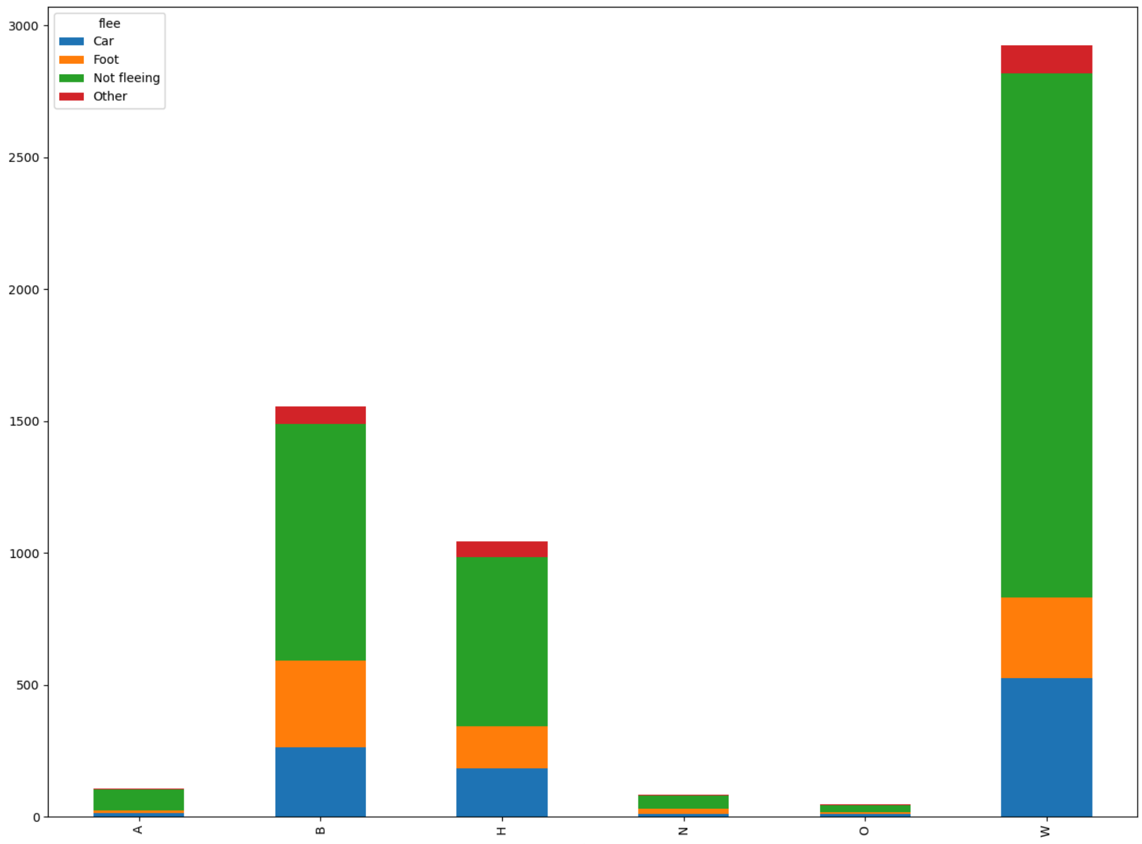

Figure 1. Fleeing by Race Stacked Bar Chart

To further investigate the different trends in people of different races, we wanted to look at the discrepancies in people of different races and how/if they were armed. This was a challenge since people who were armed were listed as what they were armed by. So we had to group everything that isn't listed as “unarmed” as a 1 representing Armed and everything that was unarmed as a 0 representing unarmed. After filtering the data we created another stacked bar chart as a visualization of the counts of armed vs. unarmed within every race. Looking at the chart, there is a similar amount of blue between people who were black and people who were white. This is only significant since there are so many more white people as an overall population in the dataset as compared to black. This means that almost just as many unarmed black people got shot as unarmed white people when the white population is so much more prominent within the dataset. This provides evidence that maybe the black demographic was targeted.

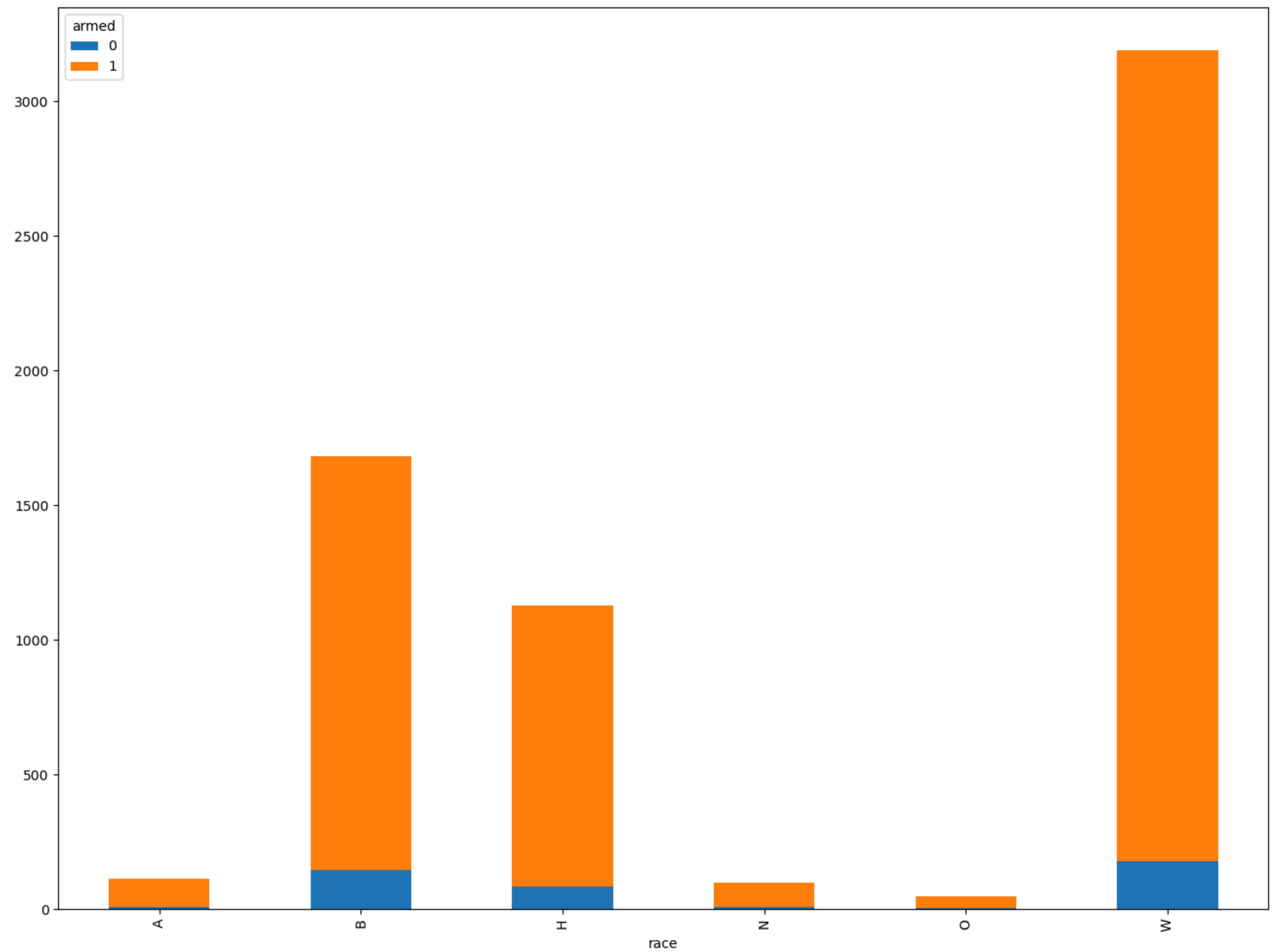

Figure 2. Armed by Race Stacked Bar Chart

Diving deeper into this discovery, we wanted to plot two maps of the US with the locations and armed status of people who were white and people who were black. We did this using the armed column that we filtered earlier to group both armed and unarmed people together. First We filtered the data to only the black demographic. This is a map of the US with the white points being the people who are unarmed and the blue points being the armed people. We were going to use this map as a comparison to the white demographic because earlier we had discovered a discrepancy in Figure 1.

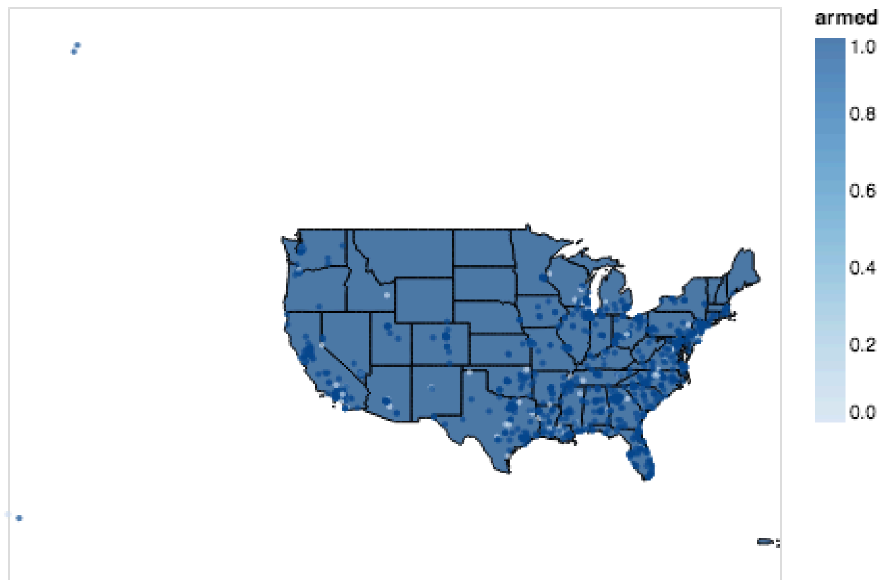

Figure 3. Black Demographic Armed Vs. Unarmed

Going off of Figure 2, we compared this side by side with the same map, but only on the white demographic of the dataset. These two maps weren't too clear at first, but after adjusting the dot sizes on the map, we were able to visualize the discrepancy that we had earlier discovered in yet a second way, as there seemed to be more scattered white dots (unarmed people) across the US for the black demographic, once again confirming that there is a possibility of a discrepancy in the data set having to do with targeted races.

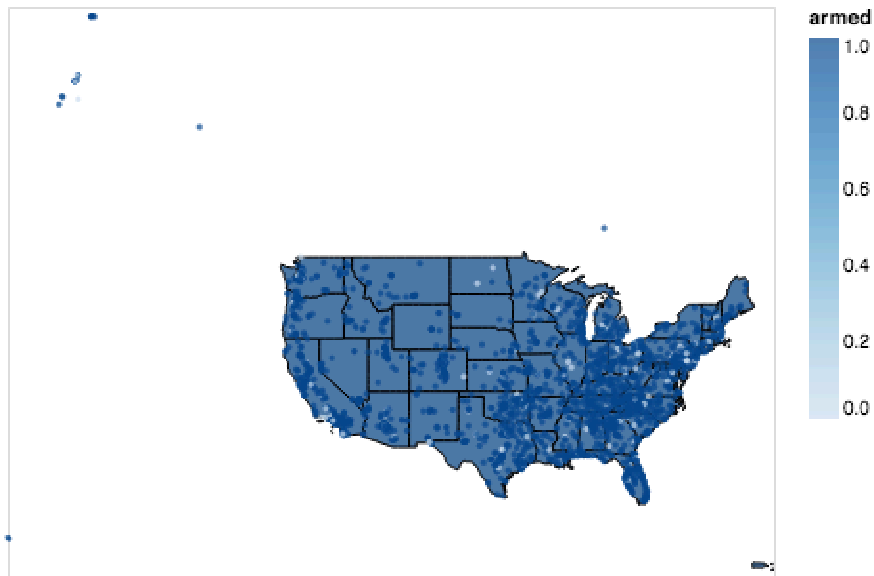

Figure 4. White Demographic Armed Vs. Unarmed

After looking at the correlations seen within visualizations of the stacked bar charts and US maps, we decided to perform statistical analysis methods to predict binary outcomes based on the observations of the data set. This took the form of performing a logistic regression. A logistic regression is a process of modeling the probability of a discrete outcome given an input variable. The most common logistic regression model is a binary outcome; something that can take two values such as yes/no which is what the dependent variable in this model exhibits. The equation below is a reference and provides an example that the model in this paper will follow that illustrates the final results of the logistic regression with the dependent variable *armed2* and all of the independent variables *gender2, black, asian, native american,* and *other, signs_of_mental_illness*. The variable *white* is not included and was omitted due to collinearity. The logistic function is of the form:

$$P(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}$$

Pr (*armed2* = 1) = G (Ƶ)

Ƶ = $\beta_0 + \beta_1(\mathit{gender2}) + \beta_2 n \ldots \beta_n n$

To perform a logistic regression in Python, two packages had to be imported. The first logistic regression that was run in Python was between the dependent variable, *armed2*, and the independent variable, *gender2*, with no controls. Following the logistic regression, a margin input was applied to provide marginal effects. Marginal effects are derivatives of the regression equation with respect to each variable in the model for each unit in the data. Margins provide ways of calculating the marginal effects of variables to make the model more interpretable. The following procedure in Python is displayed:

```
In [457]: from statsmodels.discrete.discrete_model import Logit
          from sklearn.linear_model import LogisticRegression

          y = data["armed2"]
          X = data[["gender2"]]


          model = Logit(y,X).fit()
          model.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.260312
         Iterations 7
```

Out[457]:

Logit Regression Results

Dep. Variable:	armed2	**No. Observations:**	3393
Model:	Logit	**Df Residuals:**	3392
Method:	MLE	**Df Model:**	0
Date:	Thu, 08 Dec 2022	**Pseudo R-squ.:**	-0.05677
Time:	17:07:42	**Log-Likelihood:**	-883.24
converged:	True	**LL-Null:**	-835.79
Covariance Type:	nonrobust	**LLR p-value:**	nan

	coef	std err	z	P>|z|	[0.025	0.975]
gender2	2.6658	0.071	37.443	0.000	2.526	2.805

```
In [458]: model.get_margeff('overall').summary()
Out[458]:
```

Logit Marginal Effects

Dep. Variable:	armed2
Method:	dydx
At:	overall

	dy/dx	std err	z	P>|z|	[0.025	0.975]
gender2	0.1841	0.005	39.295	0.000	0.175	0.193

Figure 5. Logit *armed2* and *gender2*

More control variables were added to the regression to account for the variation in the victims' gender. The first control variable added was the various race variables. A logistic regression was run between the dependent variable, *armed2*, and the independent variables, *gender2, black, asian, hispanic, native american,* and *other*. The variable *white* was omitted due to collinearity and bias. Omitting the *white* variable allows for more accurate results and a base category to compare the rest of the variables to when interpreting. The *white* race variable accounts for most of the data set since most of the victims are white and omitting this variable will account for statistical inference. The following procedure in Python was repeated and displayed:

Out[459]:

Logit Regression Results

Dep. Variable:	armed2	**No. Observations:**	3393
Model:	Logit	**Df Residuals:**	3387
Method:	MLE	**Df Model:**	5
Date:	Thu, 08 Dec 2022	**Pseudo R-squ.:**	-0.04763
Time:	17:44:36	**Log-Likelihood:**	-875.60
converged:	True	**LL-Null:**	-835.79
Covariance Type:	nonrobust	**LLR p-value:**	1.000

	coef	std err	z	P>|z|	[0.025	0.975]
gender2	2.8957	0.099	29.262	0.000	2.702	3.090
black	-0.5236	0.154	-3.398	0.001	-0.826	-0.222
asian	-0.7735	0.569	-1.361	0.174	-1.888	0.341
native american	-0.6356	0.499	-1.274	0.203	-1.614	0.342
hispanic	-0.4355	0.189	-2.298	0.022	-0.807	-0.064
other	0.4104	1.107	0.371	0.711	-1.759	2.580

Out[461]:

Logit Marginal Effects

Dep. Variable:	armed2
Method:	dydx
At:	overall

	dy/dx	std err	z	P>|z|	[0.025	0.975]
gender2	0.1988	0.007	29.116	0.000	0.185	0.212
black	-0.0359	0.011	-3.375	0.001	-0.057	-0.015
asian	-0.0531	0.039	-1.359	0.174	-0.130	0.023
native american	-0.0436	0.034	-1.272	0.203	-0.111	0.024
hispanic	-0.0299	0.013	-2.290	0.022	-0.055	-0.004
other	0.0282	0.076	0.371	0.711	-0.121	0.177

Figure 6. Logit *armed2, gender2, black, asian, native american, hispanic,* and *other*

One more control variable was added to the regression to account for the variation in the victims' gender and race. The independent variable added was *signs_of_mentall_illness*. A logistic regression was run between the dependent variable, *armed2*, and the independent variables, *gender2, black, asian, hispanic, native american, other,* and *signs_of_mental_illness*. The following procedure in Python was repeated and displayed:

Out[462]:

Logit Regression Results

Dep. Variable:	armed2	**No. Observations:**	3393
Model:	Logit	**Df Residuals:**	3386
Method:	MLE	**Df Model:**	6
Date:	Thu, 08 Dec 2022	**Pseudo R-squ.:**	-0.04529
Time:	17:52:36	**Log-Likelihood:**	-873.64
converged:	True	**LL-Null:**	-835.79
Covariance Type:	nonrobust	**LLR p-value:**	1.000

	coef	std err	z	P>|z|	[0.025	0.975]
gender2	2.8578	0.101	28.430	0.000	2.661	3.055
black	-0.5221	0.154	-3.392	0.001	-0.824	-0.220
asian	-0.7697	0.559	-1.376	0.169	-1.866	0.327
native american	-0.6630	0.494	-1.343	0.179	-1.631	0.305
hispanic	-0.4334	0.189	-2.288	0.022	-0.805	-0.062
other	0.4221	1.106	0.382	0.703	-1.745	2.589
signs_of_mental_illness	0.4384	0.231	1.898	0.058	-0.014	0.891

Out[463]:

Logit Marginal Effects

Dep. Variable:	armed2
Method:	dydx
At:	overall

	dy/dx	std err	z	P>|z|	[0.025	0.975]
gender2	0.1960	0.007	28.497	0.000	0.182	0.209
black	-0.0358	0.011	-3.368	0.001	-0.057	-0.015
asian	-0.0528	0.038	-1.374	0.169	-0.128	0.022
native american	-0.0455	0.034	-1.341	0.180	-0.112	0.021
hispanic	-0.0297	0.013	-2.280	0.023	-0.055	-0.004
other	0.0289	0.076	0.382	0.703	-0.120	0.178
signs_of_mental_illness	0.0301	0.016	1.894	0.058	-0.001	0.061

Figure 7. Logit *armed2, gender2, black, asian, native american, hispanic, other,* and *signs_of_mental_illness*

Results

The following table illustrates the final results of the logistic regression with the dependent variable *armed2* and all of the independent variables *gender2, black, asian, hispanic, native american, other,* and *signs_of_mental_illness*. The variable, its mean marginal effect, and its z-score are listed.

chart

The first regression was run only by regressing the dependent variable in the model, *armed2*, and the independent variable, *gender2*, with no controls. From the marginal effect of the mean, we see that on average, compared to being a female, being a male is associated with an 18.4% higher probability of being armed when fleeing. Figure 5 shows the outcome of this regression. This model shows that the key independent variable is statistically significant by looking at the absolute value of the z-statistic, which is greater than 2. The z-score is 39.3, which is extremely significant.

More control variables were added to the regression to account for the variation in gender. The variables added were *black, asian, hispanic, native american,* and *other.* The *white* variable was omitted due to collinearity. The race variables were added because race-based issues take a huge part in police violence in the United States. The race variables were also added as a control because the data is mainly made up of White victims because White Americans are the racial majority. Figure 6 shows that fixing gender, compared to being White, being Black corresponds to a 3.61% decrease in the probability of being armed when fleeing. Fixing gender, compared to being White, being Asian corresponds to a 5.3% decrease in the probability of being armed when fleeing. Fixing gender, compared to being White, being Native American corresponds to a 4.38% decrease in the probability of being armed when fleeing. Fixing gender, compared to being White, being Hispanic corresponds to a 3.0% decrease in the probability of being armed when fleeing. Fixing gender, compared to being White, being of the other race corresponds to a 2.8% higher probability of being armed when fleeing. The variables *gender2, black,* and *hispanic* were the variables that were statistically significant compared to the *asian, native american,* and *other* variables that were not statistically significant because they did not have z-scores between -1.96 and +1.96 standard deviations from the mean. The *gender2* variable z-score went from 39.3 to 29.3 with the added control variables, but is still deemed statistically significant. The z-statistic correlation to being *black* was 3.4, and to being *hispanic* was 2.3, which are both statistically significant.

The last variable added to the regression was *signs_of_mental_illness* in order to see what effect it would have on the model and to account for variation in gender. The *signs_of_mental_illness* variable was added because the topic of mental illness is growing in the United States and past studies have had results that support the claim that police do not have the proper training in handling victims with mental illness. Figure 7 shows that fixing gender, *black, asian, hispanic, native american,* and *other*, compared to victims who do not show signs of mental illness, victims with signs of mental illness are associated with a 3% increase in the probability of being armed when fleeing. The variable *signs_of_mental_illness* had a z-score of 1.9, which is not statistically significant since it falls below 2. Adding the variable *signs_of_mental_illness* to the regression had a small impact on the other control variables as their values were slightly adjusted. With this additional variable, the *gender2* variable z-score went from 29.3 to 28.5 with the added control variables, but is still deemed statistically significant.

The unrestricted regression results in an -0.045% of variation within the data of the model which is explained by the Pseudo R2 which increased from -0.057% compared to the bivariate regression. The higher pseudo R2 indicates which model better predicts the outcome, and in this case, the unrestricted regression model better predicts the outcome for this data set. The bivariate regression results show that by fixing all controlled variables, we see that on average, compared to being a female, being a male is associated with a 19.6% higher probability of being armed when fleeing. Now looking into the controlled variables with statistical significance: Compared to being White, being Black corresponds to a 3.61% decrease in the probability of being armed when fleeing; Compared to being White, being Hispanic corresponds to a 3.0% decrease in the probability of being armed when fleeing. These final results of the controlled variables with statistical significance were only adjusted by .0001-.0002 with the addition of the *signs_of_mental_illness* variable. The remaining controlled variables displayed valuable and practical interpretations, but their z-scores were not statistically significant nor were their values adjusted by important means.

Discussion & Conclusions

Given these results, it is clear to see that without the controls, it is easy to assume that gender explains the variation in being shot and killed by police when armed and fleeing. However, adding the control variables helped eliminate some of the bias that the coefficient of the *armed2* variable had in the beginning. A noteworthy number of variables expressed individual significance through their z-statistics in each progressive regression and in the final unrestricted regression. The results are similar to The Washington Posts database mentioned in this paper and outside sources. This paper offered different insights through the police killings data by exploring unique visual representations and performing logistic regressions. This paper also offered a different focus of research on police killings by only exploring the fleeing victims. This study shows that by fixing *black, asian, hispanic, native american, other,* and *signs_of_mental_illness*, we see that on average, compared to being a female, being a male is associated with a 19.6% higher probability of being armed when fleeing. The z-statistic is 28.5 which shows that the key independent variable, *gender2*, is significant when regressed with *armed2*, being armed or unarmed. The results also concluded that compared to being White, being Black corresponds to a 3.61% decrease in the probability of being armed when fleeing; Compared to being White, being Hispanic corresponds to a 3.0% decrease in the probability of being armed when fleeing. The remaining controlled variables displayed valuable and practical interpretations, but their z-scores were not statistically significant nor were their values adjusted by important means so they were not included in the final report of the results.

A major issue with obtaining accurate data on police shootings and killings is largely because police departments are not required to report these incidents to the federal government. Also compounding the problem: is an updated FBI system for reporting data and confusion among local law enforcement about reporting responsibilities (The Washington Post 2022). Outside sources using The Washington Post database on police shootings have also concluded that people of color, armed or not, have a much greater risk of being shot and killed by the police (Giffords 2021). Giffords, an American advocacy and research organization focused on promoting gun control, concluded that on average, a Black unarmed person is at least as likely to be shot by police as someone who is white and armed. These results can be related to the visual presentations of the US maps in Figure 3 and Figure 4 which include Black and White victims; armed and unarmed. The results answered the questions that we had prior to performing any exploratory data analysis on The Washington Post database on police killings. We wanted to know if there were any statistical findings that supported any racial-driven killings. If race did play a factor in these killings, we also wanted to explore if the victims were male or female, armed or not armed, and if there were signs of mental illness that also could have played a role in their motivation behind the killings. Our findings supported the hypothesis and overall questions/assumptions, whether they were deemed statistically significant or not.

Police shootings and killings greatly contribute to the gun violence epidemic in the United States and it is time that we not only acknowledge it but also address it. Police shootings and incidents of police brutality that resulted in killings contribute significantly to apparent distrust and community violence. Gun violence and the disproportionate impact it has on the various racial communities will require the United States to confront its history of racism and structural inequality within the police force (Everytown Analysis 2020). There is an urgent need to reevaluate the roles and policies of the police and the community in promoting public safety. Reducing police gun violence when using force against civilians through training, policy, and laws is the first step in reducing the number of police killings. These trainings must include the policy fundamentals principles of prioritizing de-escalation, dignity, and respect (Everytown Analysis 2020). In addition, it is also urgent that our country is ensuring that the police who are involved in the shootings and killings of victims are held accountable when unnecessary force is used. Another recommendation would include eliminating unnecessary interactions between the police and community members will reduce violence and deaths. The ACLU Research Report stated, "Eighty percent of arrests in the United States are for misdemeanors, and we have witnessed many police killings — Philando Castile, Eric Garner, George Floyd, and more —that arose from enforcement of petty offenses" (ACLU 2020). Throughout recent events, it has been clear that police killings are a result of racism and this can be concluded through the database of police shootings and killings. The Washington Post took a huge step when taking on the role to create its own database for this cause in order to put an end to police brutality and killings to end gun violence. Directions for future studies would be to create a policy or law that makes it mandatory for the FBI and police departments to gather data on police shootings and killings. The need for data collection on police killings is extremely important for the underrepresented citizens of this country and those who have been impacted. Making this data publicly available is the right thing to do and future reports should include the uses of force, ethnicity, LGBTQ status, and any disabilities in addition to The Washington Posts categories.

References

Edwards, E., Greytak, E., Ofer, U., Takei, C., & Fernandez, P. (2020). *The other epidemic: fatal police shootings in the time of COVID-19*. American Civil Liberties Union.

Everytown Analysis, "Mapping Police Violence 2013–2019″. *Mapping Police Violence.* (2020).

Everytown Analysis, "National Population by Characteristics, 2010–2019″. *US Census Bureau.* (2020).

Giffords. (2021). *Police shootings*. https://giffords.org/issues/police-shootings/

Oakley, I. R. (2021). *We have a gun violence epidemic. police shootings are a part of the problem: Opinion*. Daily Record. https://www.dailyrecord.com/story/opinion/2021/04/22/u-s-gun-violence-epidemic-includes-police-shootings-heres-why/7327820002/

Staff, W. P. (2022, December 5). *Police shootings database 2015-2022: Search by race, age, Department*. The Washington Post. https://www.washingtonpost.com/graphics/investigations/police-shootings-database/