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Econometrics Final Paper: Examining the Issue of Gun Violence in America
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Introduction

While there are many compelling sides to the gun violence debate, there are a few irrefutable facts that are necessary to consider in order to contextualize the situation. Each year more than 33,000 people are fatally shot in the United States. With most of the attention focused on mass shootings, terror attacks, and police related shootings, roughly two-thirds are suicides, followed by 11,000 more from homicide. Men make up 85% of suicides, of which, 87% are white. Homicides are similarly dominated by a single race; 56% are African-American's. (CDC 2012-14) Individuals under 40 years old are more likely to die from a gun than any other life threatening disease (CDC 2010). America in these respects is an outlier to the rest of the highly-developed countries around the world (Lanza 2013). Recent mass shootings such as Sandy Hook in 2013, and more recently the Orlando night club shooting in 2016, have increased the number of studies published on gun violence. An overwhelming amount of them, however, are centered solely around gun policy. While these studies offer a good starting point, they lack a broader holistic approach to explain why back ground checks alone are not the complete solution and what additional factors are contributing to this epidemic. In this paper, I take a multivariate approach to uncovering the overlooked variables that contribute to the national rate of gun fatalities. By compiling cross-sectional data from all fifty states, I can explore a range of environments and their differing relationships with guns. The Center for Disease Control has data on gun related deaths from 2015 which has been instrumental in understanding the variance of death rates among states. To briefly show this contrast, for every 100,000 people, the three states with the highest firearm death rates are: Alaska (23.4), Louisiana (20.4), and Alabama (19.4), compared to the three states with the lowest rates per 100,000: Massachusetts (3.0), Hawaii (3.6), and New York (4.2). Rates can fluctuate by a factor of nearly eight from

Massachusetts to Alaska. By the end of this paper we aim to have a regression that can isolate specific factors to explain the separation in gun mortality between states like Massachusetts and Alaska.

Literature Review

The Brady Handgun Violence Protection Act, or Brady Act of 1944, pioneered the movement for tighter gun legislation. This policy, which requires background checks on individuals purchasing guns through a federally licensed dealer, has stopped two million people from purchasing since its enactment. Recent studies have shown the law to have either no correlation with reductions in homicide rates (Webster & Vernick 2013), or a negative correlation between the strength of a states firearm laws and overall fatalities from gun-related suicide and homicide (Lanza 2014). The loopholes in the Brady Act are created by the 40% of private gun sales in the United States that do not require a background check. (Webster & Vernick 2013) Additionally, there is the permit to carry, that allows any individual with an unexpired permit to carry to void any background check at time of purchase. This is specifically alarming is individuals ban from purchasing firearm, still have a five-year pass. (Webster & Vernick 2013)

In a more recent study titled *Firearm Legislation and Firearm Mortality in the USA,* Bindu Kalesan and colleagues find compelling statistical evidence that, if pointed in a more specific direction, the Brady Law could significantly reduce firearm mortality rate. They concluded that universal background checks (61%) (included during sales from private owners, gun shows, and unlicensed dealers), background checks for ammunition (82%), and firearm identification (84%) would significantly reduce gun fatalities.

David Hemenway criticizes Kalesan's study for controlling some important variables (e.g. unemployment and firearm export) but failing to control other variables (e.g. poverty, alcohol consumption, urbanity, and mental health). He continues to address the likely hood of multicollinearity among the 24 gun-control laws studied. While additionally lacking to compare result from more than one year. (Hemenway 2016).

Despite the lack of any noticeable reduction in gun related homicide or suicide rates, Jim Brady lives on in a more meaningful way. Since its foundation in 2007, the *Brady Campaign to Prevent Gun Violence* has considered more than 40 features of state gun laws and compiled them into a score out of 100 for each state. The higher the score the more compliant and strict a state is on gun laws. For example, California scored an 81, which was the highest score for all 50 states (Lanza 2014) (bradycampaign.org).=

Other studies such as (Kwon & Baack 2005) have used the Brady score to rate the top 25% and bottom 25% of states in their regressions. As a dummy variable Law_i the Brady score was highly correlated with firearm fatalities per 100,000 in each state. Similarly, Lanza show a highly negative correlation between the Brady Score and

Mental health, (Webster & Vernick 2013) discuss how epidemiological research has shown the insignificant contribution mental illness has to violence overall. They highlight the fact that mentally ill individuals inclined to perform violent acts are not likely to see a psychiatrist before acting, and thus would never be on a background check to be denied access to a gun. Suicides by gun, on the other hand, have proven to have a significantly high correlation with the number of background checks processed (Lang 2013). Predominately comprised of males (95%), those committing suicide are acquiring their guns legally. The rhetoric promoting the idea that without guns, rates of suicide would decide is contradicted by (Guis 2011) in (Lanza 2013), who argue that these individuals would likely find another way. This might not always be the case as for every successful suicide there are, on average, eleven attempts (Lang 2013).

Articles in

Model

$$\widehat{DEATHS_i} = \beta_0 + \beta_1 POVRT_i + \beta_2 PARTY_i + \beta_3 EDUC_i + \beta_4 MENTAL_i + \beta_5 URBAN_i + \beta_6 LEGI_i + \beta_7 CRIME_i + \varepsilon_i$$

Dependent Variable

The Dependent variable in my equation denoted by $Deaths_i$, is the number of deaths from firearms in each state for every 100,000 people. We use the scaler of 100,000 people to avoid heteroscedasticity. Additionally, the Center for Disease Control, which provides multiple data sets in the regression, consistently scales most state data by 100,000 for continuity. I chose this value instead of an isolation of either the homicide or suicide rate from guns because they both contribute significantly and for differing reasons to deaths. There are more studies published each year due to the influx in gun data, fostering excitement to further research with the goal of developing relevant and effective policy proposals to reduce firearm mortality rates.

Independent Variables

$POVRT_I$ → The first independent variable we will be using is the percentage of people under the poverty line in each state. Poverty while was chosen to help encompass, the roles unemployment and illegal activity have on gun fatalities as they are represented under the broader umbrella of poverty. I received this data for the United States Census Bureau 2015 Survey: Small Area Income and Poverty Estimates. The Census website at time can be difficult to navigate, but I found the correct data in the year I was looking for. I trust the Census to be credible as it is part of the United States government.

<u>*Hypothesis for coefficient sign:*</u> ***$POVRT_i$*** *will likely have a (-) negative sign as those in improvised situations are more likely to be members of a gang or resort to illegal or violent acts to get by.*

$EDUC_I$ → $EDUC_i$, short for education, will be representing the percentage of people who have received a bachelor's degree or higher in a state. This data was taken from the U.S. Census Bureau from 2010 report as a good baseline for the level of education in each state. As bachelor's degree become more common, its prevalence should have a noticeable impact on gun fatalities. A more educated individual should know the risks associated with guns and therefore refrain from using them unless given no choice. The consequences of homicide/suicide are severe and not everyone is fortunate enough to have the foresight to understand its permanence.

<u>*Hypothesis for coefficient sign:*</u> *I predict that $EDUC_i$ will have a (-) negative sign as it seems logical that the more educated people in a state, the more likely its citizens are to think before using such a lethal weapon.*

$MENTAL_i$ → The variable $MENTAL_i$, is included to account for the funding each state spends on mental healthcare per capital. In the form of counselling, treatment centers, research, or other preemptive measures to show its relationship to the dependent variable $DEATHS_I$. In the book, *Reducing Gun Violence in America: Informing Policy with Evidence and Analysis,* mental health disorders such as Depression and Bi-Polar disorder have been related to past instances of mass shootings and suicides in the United States. In 2012, mass shootings (related to bi-polar) accounted for 72 deaths, the most in one year. Suicides however, contribute to nearly two-thirds of total gun deaths each year, a large product of untreated depression. If mental health programs around the country are implemented and executed properly, states with larger fund per capita should in theory decrease total gun deaths. A majority being suicides, with a potential to prevent mass shootings.

Hypothesis for coefficient sign: I hypothesize that the variable MENTAL, will have a (-) negative relationship with the number of annual deaths from gunshots in each state.

$PARTY_I$ → The $PARTY_i$ variable is a dummy variable for our regression. I chose this variable to see if it was possible to quantify the relationship party affiliation directly contributes to gun mortality. For Republican States, those with typically lighter gun laws there will be a (1) to enable the variable. If states are typically Democratic, they will be represented by a (0) rendering the coefficient on the variable to zero. The significance of a democratic state's effect on the dependent variable will be absorbed and displayed in the constant.

Hypothesis for coefficient sign: Theoretically the sign should be (-) negative since Republican states are represented by (1) they tend to have lighter gun laws, leading to a higher number or *guns and therefore a greater chance or guns being involved in any violent situation, leading to larger fatalities.*

$LEGI_I$ → Background checks and gun regulation are an important part of this regression. There have been studies to show that states with stricter laws can decrease their death rates from guns by one to six people annually depending on the state (Kwon & Baack 2005). In this study we are using the *Brady Score* as an indicator for how strict or lax a state's gun laws may be. The Brady Score was formed by the *Law Center to Prevent Gun Violence* and *the Brady Campaign to Prevent Gun Violence in 2007.* With the purpose of rating states with a letter grade, ranging from A-F, to help the public better understand each state's position on guns. This score is comprised of six different sections: Background checks and Access to Firearms (23 points), Regulations of Sales and Transfers (24 points), Gun Owner Accountability (18 points), Firearms in Public Places (6 points), Classes of Weapons and Ammunitions/Magazines (13 points), Consumer and Child Safety (8 points), Investigating Gun Crimes (2 points), and Local Authority to Regulate (6 points). These points add to a score out of 100 to create a state's comprehensive grade on gun safety and control. This Brady Score has been used in multiple studies about gun violence due to its holistic evaluation. All this information can be found at *bradycampaign.org.* <u>*Hypothesis for coefficient sign:*</u> *States with tighter gun regulation, will have a higher Brady Score. Hypothesizing that $LEGI_i$ and $DEATHS_i$ will have a (-) negative correlation.*

$CRIME_I$ → Represents the number of violent crimes recorder in each state for every 100,000 people, using the scaler to prevent heteroscedasticity. This data was provided from the FBI: UCR website for crime in the United States in 2015. More than one-third of all firearm fatalities each year are from homicide, most of which are related to criminal or gang activity. (FBI)

I chose to include this variable because crime rates had been used in related research paper. Violent crime seemed to be a better indicator for gun fatalities, since any crime committed using a gun qualifies as a violent crime. The FBI used the same scale as my data for $Deaths_i$, making it a clean fit for the regression.

Hypothesis for coefficient sign: This sign in theory be (+) positive, as violent crimes go hand in hand with gun violence. Gangs and criminals alike see guns as a badge of honor or sign of masculinity (Venkatesh 2012). This is one of my more confident predictions.

$URBAN_I$ → States are divided by those living in rural and urban areas. The variable $URBAN_i$, represents the percentage of civilians in each state living in Urban/Metropolitan areas. This data was provided from the U.S. Census Bureau survey from 2010. The use of percentages helps keep the data scaled regardless of how large or small a state may be.

Hypothesis for coefficient sign: Since most gang activity and violent crime is concentrated in the cities, I predict that the sign on URBAN will be (+) positive, as it increases the chance of gun violence.

First Regression

Below is my initial equation and the regression results before changing any functional form:

$$\widehat{DEATHS_i} = \underset{(4.384)}{6.1602} + \underset{(.1525)}{.1900}POVRT_i + \underset{(1.129)}{1.693}PARTY_i + \underset{(.0860)}{.1337}EDUC_i + \underset{(.0061)}{.0011}MENTAL_i$$

t-statistic	1.27	1.25	1.50	1.55	.18

$$-.0575URBAN_i - .0830LEGI_i + .0141CRIME_i$$

(.0373)	(.0248)	(.0032)	$\overline{R^2} = .6947$
-1.54	-3.35	4.38	$R^2 = .7384$

N = 50 df = N-K-1 = 50-7-1 = 42

Analysis

The coefficient β_1, on ***POVRT$_i$*** in equal to .1900. Meaning that for every unit change in the percent of those under the poverty line in each state, the number of people killed by firearms in every 100,000 will go up by .1900, holding all else equal. The sign on the coefficient matches the hypothesis and seems to have a large enough coefficient relative to the rest of the variables. The t-stat is under the threshold to be statistically significant as we will see with the below t-test.

<u>Testing for statistical significance:</u>

df = n-k-1 = 50-7-1 = 42→ critical t-stat for 95% confidence interval is $|t| \geq 1.684$

$H_0 \leq 0$ t-stat =$|1.25| \leq 1.684$

$H_A \geq 0$

There is not enough statistical evidence to reject the null hypothesis that the sign of β_1 is positive. Since the sign on ***POVRT$_i$*** aligns with the hypothesized sign and fits the theory of the regression, I will keep it in the regression for further analysis.

The dummy variable, **PARTY$_i$** has coefficient β_2, equal to 1.693. Which means that every Republican state, is expected to experience a 1.693 unit increase in gun deaths for every 100,000 people; holding all else equal. The coefficient sign is aligned with the hypothesis and well weighted for the equation. The national average or gun deaths per 100,000 people is 10.2, the value of β_2 is one-sixth of that.

<u>*Testing for statistical significance:* </u>**PARTY$_{\mathbf{i}}$**

df = n-k-1 = 50-7-1 = 42 → *critical t-stat for 95% confidence interval is* $|t| \geq 1.684$

$H_0 \leq 0$ t-stat = $1.50 \leq 1.684$

$H_A \geq 0$

There is not enough statistical evidence to reject the null hypothesis. This t-stat is significant at the 10% margin but not large enough to be statistically significant with 95% confidence. Since it has the hypothesized sign and it close to being statistically significant,

The variable **EDUC$_{\mathbf{i}}$** has a coefficient β_3 equal to .1337 units. This means that for every one unit change in the percentage of people with a bachelor's degree in a state, **DEATHS$_{\mathbf{i}}$** with change by .1337 units. The sign on this variable contradicts our earlier hypothesis as it was predicted to have a negative impact on firearm fatalities. The discrepancy with the coefficient sign could be an indicator of a potentially omitted variable. I will perform an omitted variable test after the analysis of this regression, *Testing for statistical significance:* **$EDUC_i$**

df = n-k-1 = 50-7-1 = 42 → *critical t-stat for 95% confidence interval is* $|t| \geq 1.684$

$H_0 \leq 0$ t-stat = $|1.55| \leq 1.684$

$H_A \geq 0$

The t-statistic is less than the critical t-score of 1.684, we do not have enough statistical evidence to reject the null hypothesis. Since the sign of **$EDUC_i$** is opposite of what was predicted, there may be an issue with functional form. We will check for these later in following regressions.

The **$MENTAL_i$** variable has a positive coefficient β_4 equal to .0011 units. This means that for every one unit change in the per capita funding of mental health programs in each state, there will be a .0011 unit change in expected gun related deaths. Although this variable has a relatively insignificant coefficient, I would have predicted the sign to be negative. Higher mental health spending would in theory lead to fewer instances of violence caused by mental health issues within a state. This outcome suggests that mental health in not a huge factor in the overall number of deaths from firearms in each state.

Testing for statistical significance: **$MENTAL_i$**

df = n-k-1 = 50-7-1 = 42 → *critical t-stat for 95% confidence interval is* $|t| \geq 1.684$

$H_0 \leq 0$ t-stat = $0.18 \leq 1.684$ p-value = .855

$H_A \geq 0$

Since the t-statistic is less than the critical t-score of 1.684, we do not have enough statistical evidence to reject the null. Since the sign of **$MENTAL_i$** is opposite of what was predicted and has a low t-statistic, it might be irrelevant. The p-value of .855 makes $MENTAL_I$ statistically irrelevant. I will remove it for the next regression.

$URBAN_i$→ With a (-) negative coefficient β_5 of .0575 coefficient on $Urban_i$ means that all else equal, for each one unit change in the percent of people living in Metropolitan areas, $Deaths_i$ will change by .251 units. Holding all else equal.

Testing for statistical significance:

df = n-k-1 = 50-7-1 = 42→ critical t-stat for 95% confidence interval is $|t| \geq 1.684$

t-stat = $|-1.54| \leq 1.684$

$H_0 \geq 0$

$H_A \leq 0$

Since the t-statistic is less than the critical t-score of 1.684, we do not have enough statistical evidence to reject the null. Since the sign of $Urban_i$ is opposite of what was predicted there may be an issue with functional form or problems with omitted or irrelevant variables. We will check for these later in following regressions.

$LEGI_i$→ The (-) negative coefficient β_5 of .0830 signifies, that every state with a one unit change in their *Brady Score*, will experience a .0830 unit change in firearm deaths; holding all else equal. This coefficient is the same as predicted and while slightly smaller than expected is well correlated with the data.

Testing for statistical significance:

df = n-k-1 = 50-7-1 = 42→ critical t-stat for 95% confidence interval is $|t| \geq 1.684$

t-stat = $|-3.32| \geq 1.684$

$H_0 \geq 0$

$H_A \leq 0$

With a t-statistic greater than the critical t-score of 1.684, we do have enough statistical evidence to reject the null hypothesis. This enables our study to rely on the Reg_i as a correlated and relevant variable in the study of gun violence.

$CRIME_i$→ The $CRIME_i$ variable has a (+) positive coefficient β_7 of .0141 in the above regression. This is in line with our predicted sign. This coefficient means that for each one unit change in the number of violent crimes committed for every 100,000 people, that same state will incur a .0141 change in $DEATHS_i$; holding all else constant.

Testing for statistical significance:

df = n-k-1 = 50-7-1 = 42→ critical t-stat for 95% confidence interval is $|t| \geq 1.684$

t-stat = $|4.38| \geq 1.684$

$H_0 \geq 0$
$H_A \leq 0$

With a t-statistic greater than the critical t-score of 1.684. Therefore, we do have enough statistical evidence to reject the null hypothesis. This enables our study to view $Crime_i$ as a positively correlated and relevant variable in the study of gun violence.

Testing for Omitted Variables

Due to how irrelevant and uncorrelated $MENTAL_i$ was in the past regression. I am going to start by removing it as an irrelevant variable. If the regression continues to have uses, I will return to looking for a potentially omitted variable.

Removing Irrelevant Variables

After running the past regression, it is time to use the analysis of the data to remove any variables that are not statistically significant and thus irrelevant.

$MENTAL_i$, the per capital funding allocated to mental health programs in each state, tested with results that signify an irrelevant variable. While the literature around mental health is encouraging as it has shown progress reducing Depression or Bi-polar in those struggling it does not seem to be correlated with the data in this study. Perhaps in another study only looking at suicides in each state, we would see a higher correlation. Unfortunately, it did not fit as hoping and will be removed for the next regression. Another part to consider is that mental health is still stigmatized by many in parts of our country, leaving those in need of assistance, unable to get help they need. As the United States continues to progress, we may see an increase in the effectiveness mental health programs have in detouring such events.

Second Regression

Model

$$\widehat{DEATHS_i} = 6.5583 + .18189POVRT_i + 1.6650PARTY_i + .13390EDUC_i$$

(4.2717) (.14432) (1.1059) (.08501)

t-stat 1.54 1.26 1.51 1.58

$$-.06004URBAN_i - .08192LEGI_i + .01415CRIME_i$$

(.03442) (.02381) (.00317) $\overline{R^2} =$ .7016

-1.74 -3.44 3.88 $R^2 =$ .7381

N = 50 df = N-K-1 = 50-6-1 = 43

Analysis

It is immediately noticeable that the t-statistics for many coefficients increased, along with the $\overline{R^2}$ value, slightly from .6947 to .7016. These are small, but positive changes in the data. Showing that the loss of the $MENTAL_i$ variable was not significantly correlated to any other variables and shows an overall increase in the rest of the equations correlation to the regression.

After running the regression without $MENTAL_i$, there are a few notable changes to the regression. $URBAN_i$ is now a statistically significant variable.

<u>*Testing for statistical significance:*</u> ***URBAN$_i$***

df = n-k-1 = 50-6-1 = 43 → critical t-stat for 95% confidence interval is $|t| \geq 1.684$

t-stat = $|-1.74| \geq 1.684$

$H_0 \geq 0$

$H_A \leq 0$

The variable $Urban_i$ now has a high enough t-statistic to reject the null hypothesis and be considered statistically significant in the regression.

Regression 3: Testing for Multicollinearity

Now that we have found a theoretically sounds are correctly specified equation, it is time to test for Multicollinearity. When an independent variable is a perfect linear function of one of more independent variables, Classical Assumption VI is violated, qualifying the equation as Multicollinearity. Since we have shown the regression has a sound specification, if it were to have multicollinearity, it would be classified as pure multicollinearity. Impure has the same symptoms as pure, but happens due to incorrect functional form such as omitted variable bias.

We will be running a variance inflation factor (VIF) test and a correlation matrix for all variables. These tests are essentially the same, differing in how they present the data. The VIF test takes the correlation values calculated from the matrix and converts them into numbers that if greater than 5 will quality as being highly correlated. Equation for VIF in below:

$$VIF = \frac{1}{(1 - R^2{}_i)}$$

After running the VIF test, there were no correlations exceeding 5; shown in the following table:

VARIABLE	VIF	1/VIF
LEGI	2.38	.420969
URBAN	2.19	.456652
PARTY	1.84	.544027
POVRT	1.46	.683105
CRIME	1.40	.714467
EDUC	1.25	.797891
MEAN VIF	1.75	

After this regression, we can conclude that this regression does not exhibit any signs of multicollinearity. If, however we were to have experienced signs of multicollinearity, there are a few solutions. The first recommendation is to do nothing. Insinuating that although an independent variable may be highly correlated with one of more other variables it is still important to the theory and most likely will not affect t-stats enough to render any statistically insignificant. Another solution is to drop an irrelevant variable, in a situation where a regression has two variables essentially measuring the same data. Finally, if possible, increasing the size of the sample can confirm if the variables are correlated or if it was the lack of sufficient data.

Regression 4: Serial Correlation

Serial Correlation occurs when Classical Assumption IV is violated; stating that different observations of the error term are uncorrelated with each other. While most common with time-series data, serial correlation can occur in any data set. The error term from one period is dependent on the value of a previous error term, known as pure serial correlation. Impure serial correlation is when we see these same patterns in the error term, created from an incorrect specification in the model and not a product of the data itself. This can be corrected by reviewing theory to fix the specification error.

Some symptoms of serial correlation are that the Ordinary Least Squares (OLS) equation is no longer the minimum variance estimator. This leads the estimates of the standard error $SE\ (\widehat{\beta})$ to be biased and therefore make any hypothesis testing unreliable.

To test for serial correlation, we will be using the Durban-Watson Test. Using this test, checks for positive serial correlation which is the most common form.

Through Stata, the Durbin-Watson value is 1.6338. From the table of critical values for Durbin-Watson tests we get a margin of $d_L = 1.24$ and $d_U = 1.84$. Since the given value of 1.6338 is in between d_L and d_u the results for positive serial correlation are inconclusive.

The Lagrange Multiplier test is another way to check for serial correlation. From Stata, we receive a value of $.388 = NR^2$. With seven independent variables at a confidence interval of 95 % the chi-squared table read a value of 14.07. Since $14.07 > .388$, the same as

$Chi - Squared > NR^2$. Therefore, there is not enough evidence to reject the null hypothesis of no serial correlation.

The Lagrange Multiplier helped confirm that there is no serial correlation in the regression after getting an inconclusive result from the Durbin-Watson test. Concluding that there is no need to perform a Newey-West or Prais-Winsten test to correct the $SE\ (\widehat{\beta})$ of the variables. Although my current regression does not test positive for any signs of serial correlation.

Regression 5: Heteroscedasticity

Heteroscedasticity is the result when Classical Assumption V is violated, which states that the error terms in a regression should have a constant variance. There are two forms of heteroscedasticity, pure and impure. Pure Heteroscedasticity occurs when the regression equation is in correct functional form and experiences an error term without constant variance. For example, I took the total number of gun fatalities in each state without scaling it by every 100,000 people, it would be difficult to decipher which states where experiencing higher rates of gun deaths from those that are high due to a larger population. Impure heteroscedasticity, similarly to serial correlation, occurs when there is an error in the specification of the regression being run. Such as incorrect functional form or omitted variable.

Typical is cross-sectional data, this was of high concern when finding data from all fifty states, as they vary significantly in population size. In the below equation, the variance in the error term is explained by the *proportion factor*, Z.

$$VAR(\in_i) = \sigma^2 Z_i$$

The higher the value of Z, the larger the distribution of the i^{th} observation of the error term. In this research paper, Z can we viewed as the number of states observed.

The more states we get data from, the more likely it is to have a data with small and large values. Consequences of heteroscedasticity are causing OLS to no longer be a minimum variance indicator, leading to inaccurate $SE\ (\widehat{\beta})$ standard errors. Typically, in the case of heteroscedasticity, $SE\ (\widehat{\beta})$ standard errors tend to be too small. Leading to unreliably high t-scores, which increase the probability of rejecting the null hypothesis and committing a Type I error.

As highlighter earlier in the model, scalers used on $DEATHS_i$ and $CRIME_i$, in additional to percentages of the population used to represent $POVRT_i$, $EDUC_i$, and $URBAN_i$, have minimalized the likely hood of Heteroscedasticity. To confirm that this data set is not experiencing heteroscedasticity, we can perform either the White test or Breusch-Pagan test.

In the White test, like the LaGrange Multiplier test (used to test serial correlation) we will be comparing our NR^2 value to the Chi-Squared value. If $NR^2 > CHI^2$ there is enough statistical evidence to reject the null hypothesis, H_0: no heteroscedasticity, implying the regression is heteroscedastic.

The NR^2 value from the White test is 22.25 and the CHI^2 value for 26 degrees of freedom is 38.89. Which means $NR^2 < CHI^2$, therefore we do not have enough evidence to reject the null hypothesis. This concludes that our regression is confirmed with 95 % certainty to not be heteroscedastic.

In this situation, my data is not showing any signs of heteroscedasticity. If I did have a data set with heteroscedastic data, I would prefer the *Heteroscedasticity Adjuster Standard Errors Test.* This test generates new standard error value to

Conclusion

After testing our model for multiple specification errors, we can confirm a correctly specified regression. In the regression, there are two negatively correlated independent variables: $URBAN_i$ &$LEGI_i$ and four positively correlated independent variables: $POVRT_I$ $CRIME_I$ $EDUC_I$ $PARTY_I$. I would recommend emulating gun legislation from states that have scored in the upper 25% of the Brady Score. This statistic has been used countless times in relevant studies (Lanza 2014) (Kalesan 2016)(Kwon 2005) all showing a negative correlation between the Brady Score and firearm mortality rates.

Additionally, Kalesan's study on ammunition background tests, testing a 84% reduction in gun deaths, followed by universal background checks that take into account private sales of guns. Overall, we need to limit gun into the system as best we can and limit ammunition the most. Without ammunition, there will be no gun left to escalate perfectly manageable situations. American should not be dying more than the rest of the world.

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