The Effects of the Abolition of the Death Penalty

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Abstract

The death penalty is used by most states as a punishment for several crimes, but most commonly for homicide. The debate on how effective the death penalty is as a deterrent for violent crime has been debated for decades, but as more states abolish the death penalty, a new question arises. How does the abolition of the death penalty affect violent crimes? This analysis is vital because it is important to understand how a policy change will affect crime if more states are to follow suit and abolish their death penalty statutes. In this paper, the analysis reports a decrease in homicides per 100,000 following the abolition of the death penalty in the short-term (1-3 years) and mid-term (4-6 years). These findings suggest the rejection of the hypothesis that homicide rates will increase without the death penalty; and support the stance that empirical evidence should be excluded when debating the death penalty statute. This work is significant in the death penalty debate as abolition has become more popular for states in the last 20 years as well as in the federal government as President Joe Biden has promoted the abolition of the federal death penalty.

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I. Introduction

The existence of empirical evidence for the effectiveness of the death penalty has been hotly debated for decades globally. The question is simple: does the death penalty have a deterrent effect on violent crimes? Another question often asked by economists: does the death penalty save lives? Fortunately, there is a wide variety of analysis and approaches used to determine the relationship between executions and crime rate. The empirical analysis of the death penalty debate is important as it is commonly referenced when making policy decisions and arguments for or against capital punishment.

In the 1972 *Furman v. Georgia* decision, the Supreme Court deemed capital punishment statutes unconstitutional, effectively abolishing the death penalty nationwide. Three years later, economist Isaac Ehrlich's analysis of national homicide and execution data from 1932 – 1969 led to claims that each execution saved eight lives (Ehrlich, 1975). This analysis was cited to the Supreme Court in 1976, which led to the end of the death penalty moratorium in the *Gregg v. Georgia* decision. The inclusion of Ehlrich's empirical analysis in political debate sparked contest from researchers, resulting in a plethora of analysis of the death penalty based on Ehrlich's model.

Today, the death penalty is legal in 28 states (3 with a gubernatorial moratorium) and illegal in 22 states (including Washington D.C.). There is also a federal death penalty statute in place, reinstated in 1988 under President Ronald Reagan, but the use was limited for many years. In July 2020, the first federal execution in 17 years was carried out under President Donald Trump (Carlisle, 2020). Between July 2020 and January 2021, 13 federal prisoners were executed, leading to the reignition of the death penalty debate. The Safe Justice act, supported by President Joe Biden, promotes the abolition of the federal death penalty as well as a variety of other justice reforms such as the decriminalization of marijuana and the abolition of private prisons (Scott, 2020).

Since the 1976 reinstatement, a major question for economists has been: how does the adoption of the death penalty affect a states' violent crime rate? This is still an important question, but zero additional states have reinstated the death penalty after the 1976 *Gregg v. Georgia* decision and twelve states have abolished. Now, a more potent question is: how does the abolition of the death penalty affect a states' violent crime rate? The purpose of this paper is to answer this question and to add to the discussion of death penalty deterrence. The rest of this paper is organized as follows, a literature review regarding empirical evidence for and against the death penalty's deterrent effects, a discussion of the data used in this project, and a brief theory discussion regarding the theory of deterrence.

II. Literature Review

A multitude of analyses followed the influential work of Isaac Ehlrich (1975). Many researchers used Ehlrich's model to either further solidify or discredit the claim of the deterrent effects of execution. Ten years after Ehrlich's publication, another study using his model was published by a former student, Stephen Layson, who further claims each execution prevents 18 homicides (Layson, 1985). Layson also testified to Congress that if he were to exclude the post-1960 data in his analysis, there would be very little to even no deterrent effects found (Gekas, 1988). One of the contesting papers written following Ehrlich's study done by Peter Passell and John B. Taylor points out that Ehrlich's claim of eight lives saved per execution heavily relies on the data from 1963-1969. They reexamine the data and limit the model to the years of 1932-1960 and find no deterrent effect on the homicide rate (Passell and Taylor, 1977). This reanalysis of Ehrlich's model led to the National Academy of Sciences to report, "the real contribution to the strength of

Ehlrich's statistical findings lies in the simple graph of the upsurge of the homicide rate after 1962, couple with the fall in the execution rate in the same period (Klein, 1978)." The claims of the National Academy of Sciences argue Ehlrich's model shows a superficial relationship, but many researchers continued to build upon his claim.

One of the recent papers to spark debate was published by Dezhbakhsh, Rubin and Shepherd in 2003. They claim executions have a substantial and statistically significant deterrent effect on homicide rate. This study was reanalyzed by John Donohue III and Justin Wolfers in 2005. They state the Dezhbakhsh, Rubin and Shepherd analysis claims each execution results in around 150 fewer homicides, but after they review the analysis, they find that the estimated effect was potentially confounded (Donohue and Wolfers, 2005). In particular, Donohue and Wolfers suggest that the analysis does not present a control group for comparison, so there is no way to tell if the trends presented in a state that eliminate/instated the death penalty is due to this policy change or a general trend that would have taken place regardless (Donohue and Wolfers, 2005). The authors of the original study then replied, claiming Donohue and Wolfers' scope was too narrow and did not warrant a claim that the original study done in 2003 was confounded (Dezhbakhsh and Rubin, 2011). They claim, "our replication of their results shows that their reporting of the key model estimates is apparently selective, favouring the results that show 'no deterrence' (Dezhbakhsh and Rubin, 2011, p.3)." In other words, both groups of authors claim the existence of the same flaw, i.e., selective reporting in each other's analysis.

As these examples demonstrate, one of the main difficulties with analyzing the effect of the death penalty on violent crime is how easily the data can be manipulated to show a strong deterrent effect, or no deterrent effect at all. Economists, Gerritzen and Kirchgässner write, "our meta-analysis shows that the major and only significant driver of whether the author(s) claim(s) that the death penalty deters potential murderers is his/her profession (Gerritzen and Kirchgässner, 2013 p.24)." They show that a plethora of analyses has been presented for or against capital punishment, most with substantial evidence backing the claims, but the empirical evidence presented to date is too fragile (Gerritzen and Kirchgässner, 2013). For this reason, it is risky to make policy decisions based off empirical evidence of the deterrence effect because that evidence may be manufactured or confounded.

Economists have been debating the theory of deterrence for nearly a century, but the unfortunate truth is that it may be an unanswerable question with the current data and analytical approaches. The National Research Council explains this problem with two factors. The first deficiency in the research is the incomplete specification of the sanction for homicide (National Research Council, 2012). When analyzing the impact of capital punishment on homicide, existing research fails to clearly define what the counterfactual is. If the counterfactual was for an offender to be reintroduced into society, the capital punishment would most likely report a huge deterrent effect, but if the counterfactual is life imprisonment, then capital punishment offers little more of a deterrent effect beyond what life imprisonment already provides. The second deficiency is the lack of a credible model that captures the perceptions of potential murderers and the behavioral response to the risk of capital punishment (National Research Council, 2012). One of the fundamental assumptions of the theory of deterrence is that a potential murderer can act to their own best interest and can make rational decisions. In theory, the idea is instructive, but in practice, there is a significant dispute on whether a murderer acts rationally.

Although the question of death penalty deterrence has run the gauntlet of empirical approaches, there are still questions to be answered regarding the effects on overall crime rate.

How can the theory of deterrence account for a murder that is not premeditated? Many economists also focus on the number of executions performed, but does the mere presence of capital punishment influence violent crime rate? By answering these questions, insight may be offered on the effects of the abolition of the death penalty.

III. Data

The primary source for homicide data used in this paper is provided by the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) program, which has been collecting crime statistics since 1930. The data is collected from law enforcement agencies across the country who elected to submit an expanded homicide report. The UCR data provided describes the raw number of homicides in each state from 1985-2019 as well as population for each state. I then used this population data to calculate homicides per 100,000 for each state and each year by dividing the raw number of homicides by population, then multiplying the quotient by 100,000. This variable will be important for analysis because it will allow for comparison of homicide rates between states with different populations. Unfortunately, the FBI's data is not without flaw, as some years are missing or heavily underreported. This could be a product of law enforcement agencies failure to participate, but most states have complete data. Only Florida is heavily affected by this missing data. I decided to omit Florida from in the data to eliminate false readings, but most of the states' data is complete, with no significant outliers.

The next database used for this paper is the raw number of executions performed in each state from 1977-2019 provided by the Bureau of Justice Statistics (BJS). I used the years from 1985-2019 to match the FBI data. I also calculated the executions per 100,000 using the population data found in the FBI database by dividing the raw number of executions performed by the population, then multiplying the quotient by 100,000. This variable will be important for analysis because it will allow for comparison of execution rates in states with different populations as well as offer a predictor variable for homicides per 100,000.

This paper also uses economic databases used to provide more possible predictors for homicides per 100,000. Annual state unemployment rate from 1979-2019 is provided by the BJS and annual GDP by state from 1997-2019 is provided by the Bureau of Economic analysis (BEA). The U.S. Census Bureau is also used as a source for the median household income variable. Median household income is a measure of income in the past 12 months, including the income of the householder and all other individuals 15 years old and over in the household, whether they are related to the householder or not. Because it is common for a household to contain only one individual, average household income is generally less than average family income. This data is collected annually by the U.S. Census Bureau using a sample of over 3.5 million housing units (Census Bureau, 2020).

The last data source used in this paper is a state-level firearm ownership database developed by the RAND Corporation in 2020. The database provides this analysis with the Home Firearm Rate variable which is calculated given factor scores of other latent factors such as Gallup surveys, hunting licenses and firearm suicide numbers to estimate the number of firearms for each household in a state (Schell, 2020).

The use of comparison groups in this analysis is vital. Economists have learned the difficulty in building a convincing time-series analysis that describes a causal relationship. Therefore, researchers have turned to an approach used in medical studies, centered around the comparison in results of a group receiving a “treatment” (in this case, states that abolished the death penalty) with a control group (states that kept their death penalty statute). In the period of 1985-2019, most states start in the control group, but as they abolish their statute, they move to the treatment group. For example, when New York abolished the death penalty in 2007, they moved from control to treatment group. If homicide per capita is driven by executions, it is not expected to see a similar pattern in the control group, because no executions are being performed and there is no threat of execution. To separate states into a treatment and control group, it is necessary to build data frames for each state that abolished the death penalty known as units. A unit is comprised of one treatment state (for example, Illinois) and its surrounding states (Iowa, Wisconsin, Indiana, Kentucky, and Missouri). The surrounding states act as the control group within a unit if the states within the control group did not also undergo the policy change in the same year. It is important to note that New York and New Jersey abolished their statute in the same year, 2007, meaning the two states cannot be used as controls in each other's unit. Once all abolishing states are split into units, the units are compiled into a single dataset.

Before an analysis can be completed, the means for the treatment and control group need to be tested to see if they are comparable before the policy change takes place. Table 1 provides the T-test before the abolition for the variables used in this analysis. This is done to show how comparable the variables are before the policy change triggers the DID estimator with the After variable.

Table 1 T-Test Before Abolition

Variable	Treatment Mean	Control Mean	Difference
Homicides per 100,000	5.00	4.43	0.57^{***}
State GDP	396,982.00	329,793.00	$67{,}189.00^{*}$
Unemployment	5.62	5.49	0.13

Median Household Income	48,457.00	44,938.00	3,519***
Black pop percent	12.8%	9.81%	2.99%***
Population	6732312	6337145	395,167
Home Firearm Rate	0.303	0.364	-0.061***

A very low p-value for Homicides per 100,000 suggests that the means of the treatment and control groups are different before the abolition. This shows that the homicide rates for states in the treatment and control groups were different to begin with, meaning the effects of the abolition may be dampened. This result in the T-test warrants the use of a parallel trend test. This test is used to determine if the trend of means for the treatment and control group were parallel to each other before policy change. The variable "relative year" was created for this test and will not be used in this paper again. It is a simple variable used to mark the year of policy change for each state in the treatment group without the use of units, this way the year of policy change is relative. Table 2 shows the results of the parallel trend test.

Table 2 Parallel Trend Test before Abolition

Variable	Parameter Estimate (Standard Error)
Trend Treatment	-0.006 (0.065)
Relative Year	-0.019

	(0.031)
Treatment	0.491
	(0.385)
Observations	436
Adjusted R^2	0.009
F- Statistic	2.35

These results show no statistical significance in any of the variables and an extremely low adjusted R^2 value, meaning the means of the two groups are parallel before the policy change occurs and therefore comparable and usable in this analysis.

IV. Theoretical Discussion

The theory of deterrence in relation to criminology expresses that the threat of consequence will deter potential offenders from committing crime. The logic is simple: if the cost of murder increases, homicide rate should decrease. A key assumption to the deterrence theory is that offenders will make rational choices, known as rational choice theory. The rational choice theory has several assumptions including: an offender will be able to weigh the probability of being caught, an offender will be fully aware of the punishment they will likely receive, an offender can choose their actions and behavior, and an offender will be able to weigh the consequence with the potential gain of committing a crime. The economic approach to deterrence theory was formalized by Gary Becker in his essay which was an attempt to “develop optimal public and private policies to combat illegal behavior” (Becker, 1988, p.43). The rational choice theory works well when considering premeditated murders but does not hold when considering other types of murders such as a “heat of passion” murder. This problem highlights one of the reasons why empirical analysis is necessary to determine if the death penalty has a deterrent effect on violent crime.

The death penalty inherently serves as another cost to committing a crime, therefore when this cost is removed, it is expected that homicides per capita should increase. If the abolition does not increase homicides per capita, but rather has no change or shows a decrease, it could be reasonable to claim the death penalty's deterrent effects are supplementary to the other costs of committing the crime. If the death penalty is abolished, there must be an alternative penalty available suitable for heinous crimes. In non-death penalty states, the most severe punishment an offender can receive is life imprisonment. If life imprisonment acts as a strong deterrent for violent crime, it is possible that there will be little movement in violent crime rate after abolition. It may be possible that life imprisonment is enough to keep people from committing murder, and the death penalty provides only supplemental deterrent effects.

V. Methodology

The research question being analyzed is "does the abolition of the death penalty affect violent crime rate?" In this analysis, states are categorized into a treatment and control group. The sudden exogenous change being analyzed is death penalty abolition; the control group includes states that maintain the death penalty (Death penalty states), and the treatment group consists of states that have abolished the death penalty between 1985 – 2019. As mentioned before, many states move from control to treatment group as they abolished their death penalty statute. This analysis uses quantitative data provided by the FBI Uniform Crime Reporting program, the CDC, BJS and BEA.

The first analysis done in this paper is a comparison of homicide rates before and after a state's policy change. There are four models used to compare the effects of abolition in the short-term, mid-term and long-term. The first model uses all years in the dataset for the response variable, Homicides Per 100,000 to report the overall effect of the policy change. The short-term model uses a 1–3-year average Homicide per 100,000 value after the policy change as the response variable. The mid-term model uses a 4-6-year average Homicide per 100,000 value and the long term uses a 7-9-year average Homicide per 100,000 value for the response variable. All years are accounted for before the policy change in each model. Then, the difference of means in treatment and control groups are calculated, effectively making this analysis a difference-in-differences (DID). DID models are useful to evaluate what a treatment group would do had they not passed the policy versus what happened and are used to measure the effects of a sudden change in economic environment or policy. Equation 1 shown below corresponds with the difference-in-differences model that uses all years in the dataset in the response variable. The response variable in this case is homicide per 100,000. On the right side of the equation, there is a constant term (α) and unknown parameters represented by the Greek letters β, γ, δ and ε_i is a random unobserved "error" term. The "treatment" variable is an indicator variable that takes the value of 1 for all states that are treated. The "after" variable is another indicator variable that takes the value of 1 for all years after the treatment (both in treatment and control states). The "DID" variable is an interaction term between "after" and "treatment" and an indicator variable. The δ coefficient will produce the true effect of the treatment and is the main variable of interest (also known as the difference-in-differences estimator). The "controls" variable is a collection of other variables used as predictors in this analysis such as Black population, state GDP, state unemployment, median household income and average home firearm rate.

Equation 1

$$Homicide\ Rate_{it} = \alpha + \beta Treatment + \gamma After + \delta DID + Controls_{it} + \varepsilon_{it}$$

The Equations for each of the other three models, short-term, mid-term and long-term models, is similar with only the response variable changing. As mentioned before, the short-term model uses a 1-3-year post policy change average of homicide per 100,000, the mid-term model uses a 4-6-year post policy change average homicide per 100,000 and the long-term uses a 7-9-year post policy change average homicide per 100,000.

The second analysis is a simple ordinary least squares regression (OLS) to determine the relationship between executions per 100,000 and homicides per 100,000, as they should be related in theory. We should expect to see homicides per 100,000 decreasing as executions increases because the theory of deterrence states that if the death penalty is frequently used, the cost of committing murder is higher.

VI. Results

The results of the main difference in differences analysis are presented below in Table 3. The table reports 4 models used for this analysis, one for all years included in the dataset, one for short-term effects (1–3-year average homicides per 100,000 after the policy change), mid-term effects (4–6-year average homicides per 100,000 after the policy change) and long-term effects (7–9-year average). Each model has an adjusted r^2 value of ~30 meaning roughly 30% of the data is explained by the models. The number of observations decrease as time progresses because it is impossible to do a difference in difference analysis in the long-term for a few of the states that have abolished in the last 7 years. For example, New Hampshire abolished their statute in 2019, so the data is not yet available for the long-term model. The DID parameter estimate (the interaction term between after and treatment) is the parameter that shows the effects of the abolition of the death penalty on homicides per 100,000. Column two shows that the effects of the abolition of the death penalty causes a decrease in homicide per 100,000 in the short-term of 0.067, with a relatively low statistical significance. This effect drops off after the 1–3-year model as the DID estimator is not statistically significant in the mid-term or the long-term model suggesting the effects of the abolition are temporary. This is rather surprising as these results contradict the theory of deterrence and suggest that the hypothesis that abolition will increase homicide rate should be rejected.

Table 3: Difference in Differences Results

	Dependent Variable: Homicides Per 100,000			
	All	Short-Term (1-3 Years)	Mid-Term (4-6 Years)	Long-Term (7-9 Years)
DID	-6.736e-01*	-6.455e01*	-3.922e-01	-5.459e-01
	(3.149 e-01)	(3.022e-01)	(3.042e-01)	(3.566e-01)
Unemployment	3.664e-02	2.978e-02	3.169e-02	6.682e-02·
	(3.456e-02)	(3.318e-02)	(3.358e-02)	(3.562e-02)
State GDP	-6.906e-06***	-6.964e-06***	-7.480e-06***	-7.634e-06***
	(5.737e-07)	(5.507e-07)	(5.544e-07)	(6.124e-07)
Median	-1.992e-05*	-1.869e-05*	-1.743e-05*	-1.185e-05
Income	(7.784e-06)	(7.472e-06)	(7.617e-06)	8.757e-06
Black Pop	3.033e-06***	3.016e-06***	3.130e-06***	3.179e-06***
	(1.961e-07)	(1.883e-07)	(1.895e-07)	(2.040e-07)

Home Firearm	2.108e+00***	2.059e+00***	2.328e+00***	2.334e+00***
Rate	(5.258e-01)	(5.047e-01)	(5.116e-01)	(5.610e-01)
Total Obs.	752	752	749	674
Adj-R^2	0.2886	0.2978	0.3032	0.2991
F-Statistic	39.53	41.28	42.17	37.38

The unemployment parameter shows that unemployment is only statistically significant in the long-term model with a low level of significance. The parameter estimate is 6.682e-02 which means when unemployment increases by 100,000, homicides per 100,000 will increase by 0.7 7-9 years later. The fact that unemployment has no statistical significance in the short-term or mid-term models suggests the variable's effects are lagged, which means when unemployment increases, we will not see the effects on crime rate for several years following. In the model using all years in the dataset for analysis, unemployment has no statistical significance, and in the long-term, changes in unemployment only account for 0.7 more homicides per 100,000, so this variable offers little explanation for homicides per 100,000 in this analysis. This is somewhat surprising as unemployment is often used as a key estimator when modeling for a variety of crime rates.

State GDP on the other hand, presents high significance in all 4 models with increasing effects as time progresses. In the short-term model, state GDP has a parameter estimate of -6.964e-06 with very high statistical significance, meaning when state GDP increases by $100,000, homicides per capita will decrease by 0.696. In the mid-term, this effect is greater at a decrease of .748 homicides per capita after a $100,000 increase, and in the long-term, homicides per 100,000 decrease by 0.734. This suggests that if a state has healthy economic growth, they should experience decreasing homicide rates as a result. This could assist in explaining why homicide per 100,000 is so high in Louisiana, as they reported the 5th lowest 5-year annualized GDP growth rate through Q1 in 2020 of +0.2% (Lenze & Newman, 2020). Louisiana has been experiencing high homicide rates relative to the rest of the US for over 20 years now and this could be due to the stagnated economic growth.

Median household income shows statistical significance in 3 out of 4 models, as it seems the effects drop off in the long-term. The effects also decrease in impact as time goes on. Median household income has a negative relationship with homicides per 100,000, which makes sense given state GDP also had a negative relationship. As economic health in general increases, homicides per 100,000 will most likely decrease. According to the parameter estimates, as median household income increases by $10,000, homicides per 100,000 should decrease by 0.187 in the short-term and 0.1743 in the mid-term. The variable is not statistically significant in the long-term, so we cannot expect homicides per 100,000 to be affected by median household income in the long-term.

Black population has very high statistical significance in all four models with parameter estimates in each model around 3.10e-06. This means, as black population increases by 100,000, homicides per 100,000 increases roughly 0.31 in all time periods. There appears to be no lag in this variable as the parameter estimates are very close in all models, meaning when black population increases, homicides per 100,000 will also increase at all time periods.

Home firearm rate (HFR) provides parameter estimates that are very significant with high effect in all 4 models. In the all-years model, HFR presents a parameter estimate of 2.108 with very high significance and a standard deviation of 0.5258. This means, as HFR increases by 0.5 (one standard deviation), homicide per 100,000 will increase by 1.108. This is a very significant effect, and the models show the effect increases as time progresses. In the short-term model, as HFR increases by 0.5, homicides per 100,000 increases by 1.039 and in the long-term, as HFR increases by 0.56, homicides per 100,000 increases by 1.309. This suggests that states with high firearm ownership levels will generally experience higher homicide rates compared to states with minimal firearm ownership. This is counter-intuitive to the popular belief that owning firearms will prevent crime.

One reason for the lack of movement in homicides per 100,000 after abolition could be due to the deterrent effects of the life imprisonment sentence. It is possible that the death penalty offers only supplementary effects of deterrence alongside life imprisonment, meaning life imprisonment offers more of a deterrent effect than the death penalty.

The ordinary least squares regression results showed high levels of significance in the Executions per 100,000 variable with a parameter estimate of 0.84235, but a very low adjusted R-squared value of 0.02. This R-squared value is somewhat surprising, so a covariance function was run on the model and produced a value of 0.07 leading me to believe the execution per 100,000 and homicides per 100,000 are statistically significant only because they are using the same population values to calculate for rates instead of raw numbers. In other words, executions per 100,000 is statistically significant, but not robust potentially due to normalizing for population.

VII. Conclusion

The purpose of this paper was to offer insight on the effects of the abolition of the death penalty and to add to the discussion of the death penalty debate. Understanding the effects of the death penalty is vital if the country intends to continue the use of such a punishment. It is also vitally important to understand how abolishing the death penalty affects a state's violent crime rate as the policy change has become more popular in recent years. It may also be important to note the difference in effects in different areas of the country, as the policy change may be a good idea for one state and the opposite for another. Still, there is a necessity of more analysis on the death penalty's effects as empirical analysis is not trusted as reliable evidence when making policy decisions. Based on the results of the difference in difference analysis completed, the abolition of the death penalty does not result in an increase in homicides per 100,000 as hypothesized; rather a decrease is shown after the policy change. This suggests the death penalty may be considered unnecessary from a statistic point of view, which gives credit to the National Research Council's statement that empirical evidence should not be used when debating the death penalty. These results lead to the same conclusion: empirical evidence should be considered but should not be a determinant on the status of the statute, and the death penalty debate should be centered around ethics and politics rather than statistics.

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IX. Appendix: R Code

```
rm(list=ls())

library(dplyr)

library(foreign)

library(rstatix)

library(caTools)

library(rms)

#Load Data

Unit_All    <- read.table("E:\\Senior project\\Units\\Unit_All_edit1.csv", sep = ",",
        header=TRUE)

Unit_Treatment    <- read.table("E:\\Senior project\\Units\\Treatment.csv", sep = ",",
        header=TRUE)
```

```
#Create the Post homicide average variables

df <- Unit_All%>%

  group_by(Location)%>%



  mutate(post_short = roll_mean(Homicides_per_100000, 3, na.rm=TRUE, align="left", fill =
        NA))%>%

  mutate(post_med = roll_mean(dplyr::lead(Homicides_per_100000,3), 3, na.rm=TRUE,
        align="left", fill = NA))%>%

  mutate(post_long = roll_mean(dplyr::lead(Homicides_per_100000,6), 3, na.rm=TRUE,
        align="left", fill = NA))%>%

  ungroup()



#DID Models

didreg =  lm(formula = Homicides_per_100000 ~ Treatment + After + DID + GDP + Unemploy
        + Black_pop + HFR + Median_income, data=df)

didregshort=  lm(formula = post_short ~ Treatment + After + DID + GDP + Unemploy +
        Black_pop + HFR + Median_income, data=df)

didregmed=  lm(formula = post_med ~ Treatment + After + DID + GDP + Unemploy +
        Black_pop + HFR + Median_income, data=df)

didreglong=  lm(formula = post_long ~ Treatment + After + DID + GDP + Unemploy +
        Black_pop + HFR + Median_income, data=df)

summary(didreg)

summary(didregshort)

summary(didregmed)

summary(didreglong)
```

```
#T-test for robustness check

df %>%

  group_by(After=0, Treatment)%>%

  get_summary_stats(Median_income, type="mean")


res <- t.test(Median_income~Treatment, After=0, data = df)

res




#Parallel Trend

trendtreatment = (df$Treatment * df$year_relative)

regpar= lm(formula= Homicides_per_100000 ~ Treatment + year_relative + trendtreatment,
        data=df)

summary(regpar)


#OLS

str(df)

summary(df)


model <- lm(sqrt(Homicides_per_100000) ~ sqrt(Executions_per_100000), data=df)

summary(model)

cor(df$Homicides_per_100000, df$Executions_per_100000)
```