**Violent Crimes, Robbery Crimes and Income Inequality**

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**Abstract**

This paper examines the relationship between violent crime, robbery crime, and income inequality. First, cross-sectional data were used because the Gini was found vary not much from the statistical summary table from 2010 to 2014. For the two types of crimes, the key independent variable, Income Inequality, was statistically significant at the 10% level only in Violent Crime models. However, the coefficients of Gini are positive as expected. The study also considered other explanatory variables like Unemployment Rate, poverty, Law Enforcement per 10000 people, the percent of less than high school diploma, the percent of High Education people, the population density, the percentage of races, and Death Penalty. Besides, the study finally confirmed Law Enforcement, the percent of High Education are statistically significant at conventional levels for violent crimes. For the robbery crimes, only Law Enforcement and the percent of High Education people are statistically significant at conventional levels. As a result, the study strongly suggests that the government increase the percent of High Education people by creating more equal opportunists for every citizen within the USA.

**Introduction:**

Income inequality and violent crime are important aspects affecting social stability and harmony. In recent years, the polarization between the rich and the poor is significantly increasing; income inequality has gradually changed over time. All most everyone could relate Income Inequality with Crimes. People’s recognition of this phenomenon believes the number of violent crimes continues to grow, and criminal activities are becoming more and more rampant at the same time. This social phenomenon creates a severe threat to the long-term stability of society. Therefore, it is of great practical significance to explore the relationship between violent crime and income inequality and analyze the influence mechanism of both. The past studies show there is still a debate by many scholars about whether income inequality would positively affect crimes. Fajnzylber et al. (1998) and Imrohoroglu et al. (2004) state that income inequality will increase crime rates in their findings and the results they found had a significant effect on crime rates. On the contrary, some scholars concluded that income inequality had no significant impact on crime ((Durante, 2012), (Neumayer, 2005), (Chen & Keen, 2014), (Simpson, 1985)). Besides, some scholars divided crime rates into specific crime types, economic crimes, and violent crimes. The results show that income inequality may cause an increase in economic crimes (Chiu and Madden, 1998; Imrohoroglu et al., 2004), and income inequality will cause an increase in violent crimes(Fajnzylber et al., 2002). On the contrary, some scholars concluded that income inequality had no significant effect on crime ((Durante, 2012), (Neumayer, 2005), (Chen & Keen, 2014); (Simpson, 1985)).

**Literature Review**

**Significant Income Inequality**

Fajnzylber et al. (1998) found increasing income inequality will lead to higher crime rates. Fajnzylber et al. (1998) used the extensive countries panel data from 1970 - 1994 based on the United Nations World Crimes Survey to analyze the income inequality with specific crime types, national homicides, and robbery rates. They examined the effects of variables that do not change much over time with the cross-sectional data with OLS. In studying the homicide rates, they found that GDP and lagged homicide rates are statistically significant as control variables. Drug producers dummy and Gini loses significance while considering the time effects. The robbery rates study shows GDP, urbanization rates, and drug possession crime rates are statistically significant as control variables. Undoubtedly, Fajnzylber et al.'s (1998) research provided much information for many scholars because their study is one of the most popular research cited by many scholars. The limitation of the data is the explanatory variables. More variables may be considered, and considering the reliability of the dataset, according to Neapolitan (1997) suggests that data from before the 1980s are far less reliable than later data.

Fajnzylber et al. (2002) found that crime rates and income inequality are positively correlated. They used panel data that contained 39 countries data from 1965-95 for homicides and 37 countries data from 1970-94 for robbers, and the Gini index for income inequality. The methodology of how they found the relationship between crimes and income inequality began with the OLS model. However, they noticed that the pooled OLS model has biased for three reasons. The first reason is the previous crime rates may influence the current crime rates. Secondly, dependent variables may affect some of the explanatory variables. Thirdly, the crime rates may have some errors which might be relevant to income inequality. (Fajnzylber et al. 2002) Then, they tried to analyze the crime rates and income inequality with a dynamic model. Their findings found control variables, GDP, the rate of urbanization, average population income, and educational attainment are statistically significant with a negative sign.

Similar to Fajnzylber et al. (1998), the data they used is similar. The limitation of the data causes the reliability of the research. Limited variables caused the authors to fail to consider factors like Unemployment, high school dropout rate, police per capita, population density, racial %s, and drug activity.

Joogmook Choe (2008) explored the relationship between income inequality and different types of crimes. The author concluded that there is a robust relationship between income inequality and burglary. The effect on the robbery is also strong. However, the author did not find any strong relationship between income inequality and other crime categories. Joogmook Choe(2008) used disposable personal income per capita in constant(2000) dollars, Unemployment, the proportion of people who got bachelor's degree or more in the population 25 years and over, the proportion of people who are 18 to24 years old, the proportion of African-American people, urbanization rate, and poverty rate by U.S. Census Bureau. The dependent variable, crime rates from UCR. For the first model, Joogmook Choe(2008) did similar work as Simpson(1995) to use logistic transformation to reduce data range. The first model also indicates that the behaviors of every crime with regard to income inequality are fairly different from one another(Choe, 2008). For the second model, Joogmook Choe(2008) tried to use GMM, which FAJNZYLBER and LEADERMAN’s analysis used to avoid past crime tend to affect current crime rates. The paper by Joogmook Choe(2008) provides me a new thought related to my analysis. I could consider analyzing the relationship between income inequality and different types of crime because his findings show that there may not be a meaningful relation between income inequality and all types of crimes. The data from the US Census Bureau may help analyze the different types of crime individually.

Chen & Keen (2014) used 33 counties of California data from 2005 to 2012. The cross-sectional analysis suggested increasing income inequality decreases property crime and violent crimes based on the pooled OLS. However, increasing poverty and population density increased crime rates. They find that control variables like high school dropout rates and Unemployment significantly affect property crime rates. However, Chen and Keen believe the fixed effect model is the best model for their estimation when they consider the heterogeneity. Then, they found that the control variables like density and poverty are statistically significant, which also have a negative impact on violent and property crimes. The limitation of this study's data is that they only consider the counties in California; however, it will be a regional bias because the findings may differ when considering nationally. Furthermore, any economic indicators may be considered in the model as well.

**Insignificant Income Inequality**

Simpson(1985) found that high rates of crimes are not related to income inequality. Simpson used Blau and Blau’s (1982) dataset on 125 largest metropolitan areas in the USA. The dependent variable he used is the rates of major violent crime: murder, forcible rape, robber, and aggravated assault from FBI report; each type of crime is analyzed individually. And he used income inequality(Gini) as a measure of income inequality, the population size of SMSA, percent Black, percent poor, geographical region, percent divorced, and racial, socioeconomic inequality. Simpson(1985) also found that Southernness had an independent effect on all four types of violent crime and believed regional culture had an effect on homicide. Moreover, Simpson(1985) found if a city has more young whites, the city would have fewer crime rates even though his topic was about Crime, Income Inequality, and Regional Culture. However, the explanatory variables are related to Income inequality is not enough. Based on his independent variable, people's divorce rates and age may be seemingly obvious explanatory variables that Simpson (1985) used. Simpson(1985) did not consider the impact of unemployment, education attainment, GDP per capita, and poverty rate on Crime rates completely. Nevertheless, Simpson’s analysis (1985) helped me think of regional differences in the USA, and he suggested using log-transformation on percent variables when the dataset is large and has powerful curvilinear relationships.

Neumayer(2005) concluded a contrary finding with previous scholars that found income inequality is statistically significant to crimes. Neumayer(2005) utilized cross-sectional data to research two types of crime related to income inequality, robbery, and violent theft. Neumayer(2005) pointed out Fajnzylber et al. (2002) used an unreliable dataset. Because of this issue, Neumayer (2005) used the Interpol dataset that contains a broader of countries to avoid cherry-picking. In this case, the dataset that Fajnzylber et al.(2002) used have coverage of countries is limited and non-representative encompassing most of the Developed countries. He found income inequality is not a statistically significant determinant that affects robbery and violent theft. (Neumayer, 2005) However, Neumayer(2005) explains the reason cultural differences may cause income inequality is not statistically significant. This conclusion is similar to Simpson’s conclusion. (1985). Interestingly, Neumayer(2005) found that GDP had a positive and significant effect on crimes, and unemployment was positive and significant at both 1% significance level. Female Labor force participation was positive and significant at the 5% level. Even though he found cultural differences may cause income inequality to lose significance. In this present research, the data is also the cross-sectional data about states in the USA. The final finding may not conclude cultural difference; however, instead, an interesting story about states difference could be introduced.

Durante(2012) also found no significant relationship between income inequality and crime on a state level within the USA through panel data for the years 1981 to 1999. In his research, he studied the relationship between income inequality with multiple types of crimes. However, He found that the income inequality and the share of young people aged 18 to 24 have a negative relationship with violent crime rates, and the share of young people aged 18 to 24 had a negative relationship with property crime rates, but population density has a strong positive relationship with property crime rates.

**Present Study(This research)**

The objectiveness of this study is to discuss whether the large Gini coefficient (Income Inequality) will cause more crimes. However, this research question had been widely discussed by numerous scholars. Therefore, based on the literature review, this present study revised several points to improve the reliability of this study.:

* Considering using the latest data, which is more reliable.
* Since the key independent variable vary little in the five years data, I decided to use five years mean cross-sectional data rather than time-series with sufficient reasons below.
* Split the “crimes” into Violent Crime and Robbery Crime to study how different types of crime are affected by income inequality.
* Considering more explanatory variables
  + Unemployment, High School Dropout Rate, Law Enforcement, population density, races%.

**Data&Methodology**

**Crime Dataset**

The dataset ( 250 observations) used for this study includes five years of data from 2011 to 2014. The crime variables were collected from Uniform Crime Reporting (UCR), and explanatory variables exclude Law enforcement and Death Penalty, and key independent variables were collected from the Census Bureau. Most of the data cleaning process was done through version 3.6.0. However, Since the Gini coefficients and other explanatory variables vary little from 2010 to 2014, it may tremendously show the income inequality(Gini) will not be significant.(Table 1) As a result, the final dataset that had been used is the mean value of all the variables. Then, the dataset only contains 50 observations. And partial data cleaning process and all analysis parts were done through Stata 16.1.

**Testable Hypothesis**

The large Gini coefficient (Income inequality) will cause more violent crimes/ robbery crimes.

**Basic Model**

Ycrimes = β0+β1\*Unemployment +β2\*Poverty+β3\*Law Enforcement +β4\*Family Mean Income\_10000 +β5\*LSTH(High School Dropout) Rate + β6\*High Education +β7\*Population Density +β8\*Black Per+ β9\*White Per + β10\*Asia Per

Where,

β0 = Constant

β1,2..3 = Coefficients of Independent Variables

**Dependent Variable**

The dependent variables used Violent Crime Rates and Robbery Crime Rates. As the different scholars’ findings indicate, income inequality will not impact different types of crimes. Besides, Table 1 explains each variable in detail.

**Independent Variable**

The specific definitions of each independent variable are in Table 1 below. It also contains the expected sign for each independent variable. For the Death Penalty, it’s a dummy variable, indicate the states that have the death penalty issue or not. However, this independent variable was considered to exist in the basic model based on previous studies. Because none of the scholars use this as an explanatory variable, I expected that the Death Penalty would have a negative impact on crime rates. It indicated the states which support the Death Penalty issue would have lower crime rates.

I also expect the Law Enforcement variable has a negative impact on crime rates. Because this variable shows how many law enforcement employs per 10000 people, the more value it is, people who violate the laws may face many negative consequences, therefore the less crime rates. Similarly, Fajnzylber (2002) found family income variable had a negative impact on crime rates. Because of the greater family income, people may dislike taking the risk of violating the laws, therefore, the less crime rates. In addition, education attainment variables are definitely in contrast with each other. Therefore, the more population rate of High educational people may negatively impact crime rates; on the contrary, the more population rate of less than high school rate will cause more crimes. This assumption had been demonstrated by Fajnzylber (2002). Percent of people below poverty, percent of people are unemployment and Gini. I believe these three independent variables' greater values will cause more crimes because these variables may potentially be correlated with each other in real situations. Neumayer(2005) also demonstrated unemployment has a positive relationship with crimes. And Simpson (1985) demonstrated poverty has a positive relationship with crimes as well. Population density is also a key explanatory variable because in a more dense area, crimes may decrease.

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| **Table 1: Variables** | | | | |
| Variables | Definition /Measurement | Sources | Expected Sign | Abbreviations in Model |
| Violent Crime rate | Violent crime rate is composed of four offenses: murder and nonnegligent manslaughter, forcible rape, robbery, and aggravated assault. | UCR |  | Violent |
| Robbery rate | literal | UCR |  | Robber |
| Death Penalty | A dummy variable. States still have death penalty will be marked as 1, States do not have death penalty will be marked as 0. There are three states abolished the death penalty.CT.(2012)IL.(2011)Maryland(2013)  This is marked in the dataset. | UCR | - | D\_Penalty |
| Law\_enforcement\_10000 | Law enforcement employ per 10000 people. Created by Law\_enforcement\_ratio \*10000. Rates | UCR | - | Law |
| Family\_mean income\_10000 | Mean of family income. Measured in 10000 dollars. | Census Bureau | - | FIncome |
| High\_ed25over | High Education, above Bachelor degree above 25 years old people in the state. Rates | Census Bureau | - | HighEdu |
| LTHS\_25over | Or High School Dropout Rate, 9-12th no diploma rates. | Census Bureau | + | LTHS |
| poverty\_rate\_18to64 | Percent below poverty level from AGE 18 to 64 years in the states. Rates | Census Bureau | + | Poverty |
| Unemployment\_rate\_20\_24 | Unemployment rate for Population 20 to 24 years and over in the state.Rates | Census Bureau | + | UNRATE |
| Gini | Gini coefficient represents the income inequality. | Census Bureau | + |  |
| White\_per | Number of white people in states / Total population in each states. Rates | Census Bureau |  |  |
| Black\_per | Number of black  people in states / Total population in each states. Rates | Census  Bureau |  |  |
| Asia\_per | Same as Above(Asia). Rates | Census Bureau |  |  |
| Population density | Population for each states/land area in sq\_Mi | Census Bureau | - | Pop\_den |
| ln\_fmincome | Ln form of FIncome, created this for dealing multicollinearity issue. |  | - |  |
| ln\_pov | Ln form of Poverty, created this for dealing multticollinearity issue. |  | + |  |
| ln\_Pop | Ln form of Population Density, created this for dealing outliers issue |  | - |  |
| ln\_vio | Ln form of Violent Crime rates, created this for dealing box-cox theta value is close to 0. |  |  |  |

**Summary of Data Statistics**

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| **Table 2.1: Summary Statistics Table 2010 - 2012** | | | | | | | | | | | | | |
|  | | 2010 | | | | 2011 | | | | 2012 | | | |
| Variable | Obs | Mean | Std.Dev | Min | Max | Mean | Std. Dev. | Min | Max | Mean | Std.Dev. | Min | Max |
| D\_Penalty | 50 | 0.7 | 0.46291 | 0 | 1 | 0.68 | 0.4712121 | 0 | 1 | 0.66 | 0.4785181 | 0 | 1 |
| Gini | 50 | 0.4522 | 0.0178303 | 0.419 | 0.499 | 0.456838 | 0.0204565 | 0.4081 | 0.5033 | 0.457682 | 0.0199177 | 0.4166 | 0.5009 |
| Violent | 50 | 366.45 | 142.8057 | 122.1 | 663 | 354.274 | 130.4724 | 123.3 | 610.1 | 355.406 | 128.3952 | 122.4 | 638.5 |
| Robbery | 50 | 90.426 | 48.92706 | 12.1 | 204.4 | 86.526 | 44.76294 | 11.9 | 177.1 | 86.528 | 43.84839 | 10.6 | 178.6 |
| UNRATE | 50 | 15.854 | 3.186913 | 7.1 | 24.2 | 15.476 | 3.718216 | 5.7 | 25.4 | 14.37 | 3.400675 | 6.1 | 21.9 |
| Poverty | 50 | 13.806 | 2.795142 | 8.1 | 20.3 | 14.326 | 3.04931 | 8.3 | 20.6 | 14.316 | 2.994237 | 9 | 21.7 |
| Law | 50 | 30.88667 | 5.768601 | 21.38801 | 45.4521 | 30.34773 | 5.852082 | 20.75426 | 45.01432 | 29.3218 | 6.024647 | 16.69519 | 42.71772 |
| FIncome | 50 | 7.735136 | 1.202836 | 5.8584 | 10.8218 | 7.934428 | 1.196799 | 6.0294 | 11.073 | 8.112586 | 1.245422 | 6.1606 | 11.4025 |
| LTHS | 50 | 7.846 | 1.981981 | 4.7 | 12.4 | 7.63 | 1.984146 | 4.7 | 12.3 | 7.326 | 1.881902 | 4.3 | 12 |
| HighEdu | 50 | 27.496 | 4.817568 | 17.5 | 39 | 27.856 | 4.840525 | 18.5 | 39.1 | 28.446 | 4.855975 | 18.7 | 39.3 |
| Pop\_den | 50 | 195.2117 | 261.2757 | 1.25148 | 1196.572 | 196.2533 | 262.2404 | 1.268503 | 1201.356 | 197.2486 | 263.0979 | 1.279801 | 1205.84 |
| Black\_per | 50 | 10.33063 | 9.602372 | 0.4879117 | 37.34802 | 10.34116 | 9.637885 | 0.4315067 | 37.46012 | 10.41285 | 9.582302 | 0.3585302 | 37.62394 |
| Asia\_per | 50 | 3.679826 | 5.64272 | 0.554413 | 38.9433 | 3.720719 | 5.521931 | 0.5727362 | 38.0098 | 3.83034 | 5.567294 | 0.6406801 | 38.24666 |
| White\_per | 50 | 78.0332 | 12.73448 | 24.61296 | 95.4332 | 77.848 | 12.71468 | 24.91436 | 95.17893 | 77.67745 | 12.7097 | 24.98054 | 95.16952 |

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| **Table 2.2: Summary Statistics Table 2013 - 2014** | | | | | | | | | |
|  | | 2013 | | | | 2014 | | | |
| Variable | Obs | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max |
| D\_Penalty | 50 | 0.64 | 0.4848732 | 0 | 1 | 0.64 | 0.4848732 | 0 | 1 |
| Gini | 50 | 0.462872 | 0.0198541 | 0.4083 | 0.5098 | 0.462474 | 0.0195445 | 0.4175 | 0.5111 |
| Violent | 50 | 351.832 | 124.5299 | 123.6 | 638.7 | 346.806 | 128.8192 | 99.3 | 635.8 |
| Robbery | 50 | 83.198 | 42.1128 | 12 | 185.7 | 80.13 | 41.38796 | 9.1 | 209.7 |
| UNRATE | 50 | 13.566 | 3.453576 | 3.8 | 20.3 | 11.6 | 2.965172 | 5 | 19.3 |
| Poverty | 50 | 14.386 | 3.042288 | 8.8 | 22.1 | 14.21 | 2.895123 | 8.9 | 20.3 |
| Law | 50 | 27.31445 | 7.474124 | 2.448614 | 40.88487 | 27.68168 | 6.292627 | 11.01503 | 43.3847 |
| FIncome | 50 | 8.390746 | 1.30407 | 6.1720 | 11.8345 | 8.5956 | 1.3379.81 | 6.4810 | 12.1975 |
| LTHS | 50 | 7.146 | 1.865171 | 4.4 | 11.3 | 7.008 | 1.83846 | 4.3 | 11.4 |
| HighEdu | 50 | 28.898 | 4.902706 | 18.9 | 40.3 | 29.238 | 4.961439 | 19.2 | 41.2 |
| Pop\_den | 50 | 198.5112 | 264.5139 | 1.291984 | 1211.79 | 199.4991 | 265.358 | 1.29106 | 1215.417 |
| Black\_per | 50 | 10.43833 | 9.593179 | 0.3173824 | 37.7073 | 10.50938 | 9.593556 | 0.5678115 | 37.82652 |
| Asia\_per | 50 | 3.892022 | 5.50615 | 0.5640391 | 37.70212 | 4.021964 | 5.513027 | 0.6291865 | 37.63058 |
| White\_per | 50 | 77.44325 | 12.68441 | 25.47766 | 94.94189 | 77.24307 | 12.72373 | 25.41004 | 94.7514 |

I examine the impact of the Gini coefficient and other explanatory variables on crime using states as a unit of analysis. However, Table 2.1 and Table 2.2 show the summary statistics from 2010 to 2014 for each year. Gini's key independent variable varies little between 2010 to 2014. The mean value of the Gini indicated that the range is 0.4522 to 0.4629. Also, the other control variables have not changed much over five year period within states. As a result, these variables may not be statistically significant. Since this issue, I decided to take five years means as cross-sectional data. More importantly, the summary statistics table(2.1) from 2010 to 2012 shows the Death Penalty changed the mean values. Because, CT.(2012), IL.(2011 ML(2013), these three states changed the death penalty policy to non-death penalty states. The code for modifications of the Death Penalty for these three states was also in the Stata code.

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| **Table 2.3: Summary Statistics - Five Years Mean** | | | | | |
| Variable | Obs | Mean | Std. Dev. | Min | Max |
| D\_Penalty | 50 | 0.664 | 0.463245 | 0 | 1 |
| Gini | 50 | 0.4584132 | 0.0191097 | 0.41618 | 0.50482 |
| Violent | 50 | 354.9536 | 129.9144 | 125.62 | 624.8 |
| Robbery | 50 | 85.3616 | 43.77228 | 11.7 | 185.66 |
| UNRATE | 50 | 14.1732 | 3.189477 | 5.54 | 22.22 |
| Poverty | 50 | 14.2088 | 2.928127 | 8.64 | 21 |
| Law | 50 | 29.11047 | 5.584757 | 18.5189 | 41.82009 |
| FIncome | 50 | 8.153699 | 1.252455 | 6.140.8 | 11.46586 |
| LTHS | 50 | 7.3912 | 1.898013 | 4.54 | 11.88 |
| HighEdu | 50 | 28.3868 | 4.863187 | 18.56 | 39.78 |
| Pop\_den | 50 | 197.3448 | 263.2926 | 1.276566 | 1206.195 |
| Black\_per | 50 | 10.40647 | 9.601071 | 0.4326285 | 37.59318 |
| Asia\_per | 50 | 3.828974 | 5.548995 | 0.6105723 | 38.10649 |
| White\_per | 50 | 77.64899 | 12.70657 | 25.07911 | 95.06339 |

Table 2.3 shows the summary statistics table for the five years' means. However, the values of observations indicate the dataset does not have any missing values. Instead, the Population Density may exist the outliers because of the large standard deviations. Moreover, for the three states previously noted, the mean value is coded based on the year that states changed their death penalty policy. Then, if the states changed the policy 2011, the states were denoted as 0; otherwise, the States were denoted as 1.

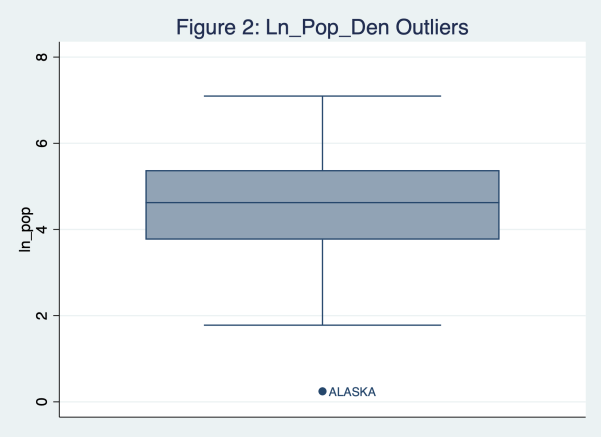
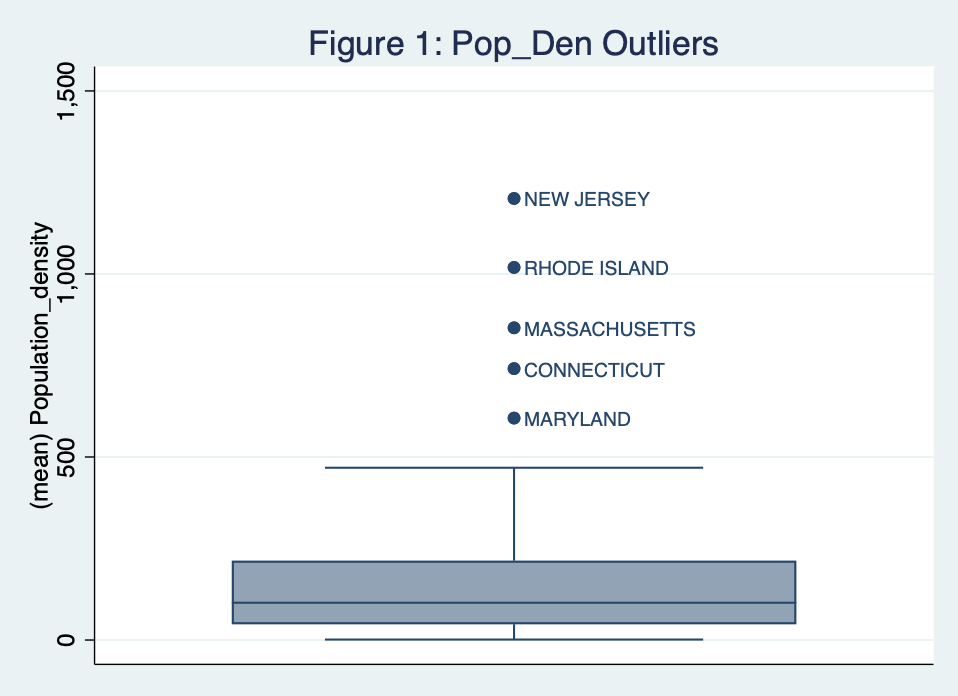


Figure 1 also shows NJ., RI., MA., CT, ML. are the sample's extreme values. However, Since the research is to study the Gini effect the crimes within the States, so there are only 50 observations; therefore, I decided to transform the data into Ln rather than remove all the five observations. Figure 2 shows the outlier check for ln form of Population Density. However, Figure 2 does not show the NJ., RI., MA., CT., ML. would cause any outliers issue. Instead, “ALASKA” becomes the smallest extreme observation for ln form of Population Density. Therefore, for the initial full model before any other modifications, I added a special regression which excluded the “ALASKA” behind thefull observation models in Appendices( Appendices Table 1)

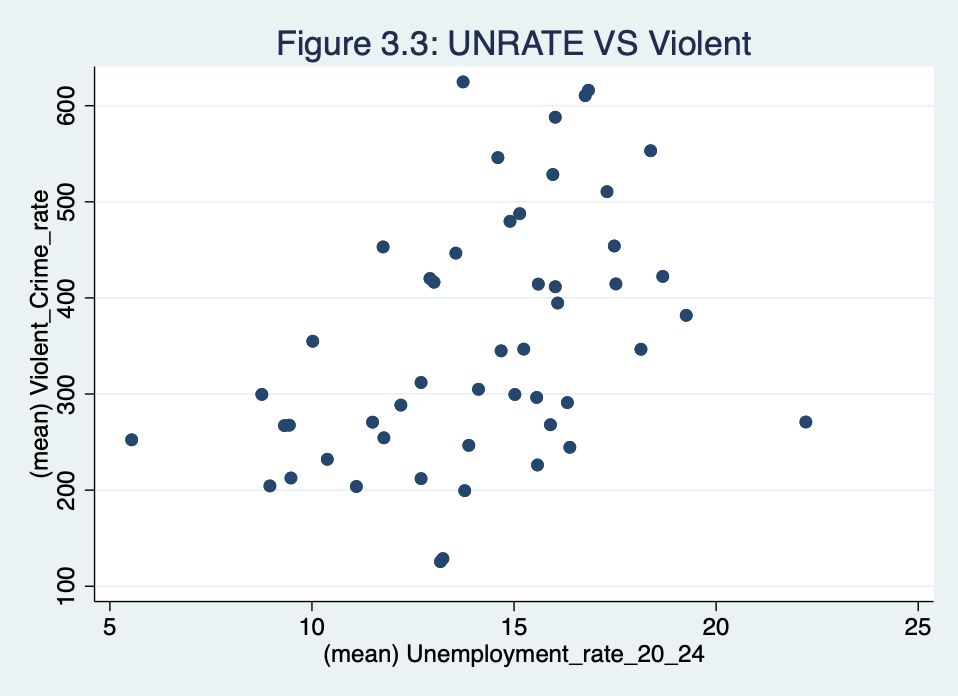
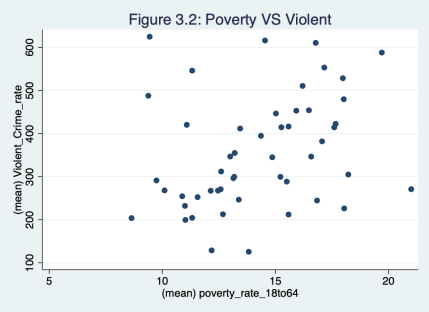
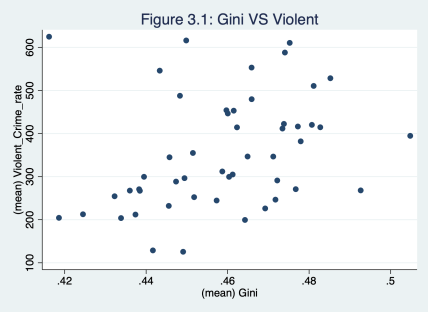


Figure 3.1 to 3.3 shows the overall trends that Gini has a positive relationship with Violent Crime rates because, with the greater Gini, the Violent Crime rates tend to increase. Poverty Rate and Unemployment both show they have a positive relationship with Violent Crime rates. These graphics confirmed my expectations of signs for these variables previously. However, the scatter plots and the summary statistics tables show that these dataset observations are too limited. Therefore, to determine the exact signs of the independent variables with the dependent variables. It’s necessary to check the regression results for Violent Crime rates and Robbery rates.

**Model Methodology**

Therefore my **Second model** before any test modifications is that:

Ycrimes = β0+β1\*Unemployment +β2\*Poverty+β3\*Law Enforcement +β4\*Family\_Mean\_Income\_10000+β5\*LSTH(High School Dropout) Rate + β6\*High Education +β7\*LN Population Density +β8\*Black Per+ β9\*White Per + β10\*Asia Per

Where,

β0 = Constant

β1,2..3 = Coefficients of Independent Variables

Noted: Only Population Density is in Ln form after removing the outliers.

**Box-Cox**

Then, prior to search for the final models for Violent Crime Rates and Robbery Rates.

The summary statistics table 2.3 indicates that the Violent Crime Rates variable should also be in logged form to confirm this finding. (Box and Cox, 1964) I performed Left-Hand Box-Cox based on the Second model above to determine whether I need to transform my two dependent variables.

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| **Table 3.1: Box-Cox For Violent Crime Rates** | | | | | | |
| Violent | Coef. | Std. Err. | z | P>z | [95% Conf. | Interval] |
| /theta | 0.2868782 | 0.3222321 | 0.89 | 0.373 | 0.344685 | 0.9184414 |

Table 3.1 shows the Violent Crime rates have a theta coefficient, which is close to 0. The coefficient suggests it’s necessary to log the dependent variable. Otherwise, if the coefficient of theta is closer to 1, then stick with linear form. Table 3.2 shows the Robbery Rate has a theta coefficient which is close to 1; therefore, I kept the robbery rate in the linear form.

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| --- | --- | --- | --- | --- | --- | --- |
| **Table 3.2: Box-Cox For Robbery Rate** | | | | | | |
| Robbery | Coef. | Std. Err. | z | P>z | [95% Conf. | Interval] |
| /theta | 0.6583431 | 0.1586627 | 4.15 | 0 | 0.3473699 | 0.9693163 |

As a result my **Third model** after the Box-Cox test changed to

**Violent Crime Rate:**

Ln YViolent = β0+β1\*Unemployment +β2\*Poverty+β3\*Law Enforcement +β4\*Family\_Mean\_Income\_10000+β5\*LSTH(High School Dropout) Rate + β6\*High Education +β7\*LN Population Density +β8\*Black Per+ β9\*White Per + β10\*Asia Per

Where,

β0 = Constant

β1,2..3 = Coefficients of Independent Variables

Noted: Dependent Variable is now in Ln form, Population Density is now in Ln Form.

**Robbery Crime Rate:**

YRobbery = β0+β1\*Unemployment +β2\*Poverty+β3\*Law Enforcement +β4\*Family\_Mean\_Income\_10000+β5\*LSTH(High School Dropout) Rate + β6\*High Education +β7\*LN Population Density +β8\*Black Per+ β9\*White Per + β10\*Asia Per

Where,

β0 = Constant

β1,2..3 = Coefficients of Independent Variables

Noted: Population Density is now in Ln Form.

**Heteroskedasticity Test**

For the heteroskedasticity issue, I performed two tests on both Full models (Third Model mentioned above) and two heteroskedasticity tests for final models for the two types of crimes(Tables below in results section). One is the Breusch-Pagan(BP) Test, and another one is the White’s Test. The null hypothesis of the BP Test indicates the error variances are all equal versus the alternative that error variances are a multiplicative function of one or more variables. (Williams, 2020) Besides, the White Test investigates whether the squared residuals can be explained by the equation’s independent variables, their squares, and their cross-products.(White, 1980).

The Heteroskedasticity Test

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table 3.3: Heteroskedasticity Test For Third Model | | | | |
| Violent | F(12,37) = 0.5 | Prob > F = 0.9019 | chi2(49) = 50.00 | Prob > chi2 = 0.4334 |
| Robbery | F(12,37) = 0.92 | Prob > F =0.5356 | chi2(49) = 50.00 | Prob > chi2 = 0.4334 |

Both BP Tests and White Tests after Box-Cox shows the p values for each of the models of crimes are larger than 0.05(Model 3). This indicated they fail to reject the null hypothesis; therefore, there is no heteroskedasticity issue so far.

**Multicollinearity Test**

As Appendices Table 1 and 2show, the last two models include all variables for each type of crime; however, while consistently adding new variables, it’s unavoidable to face multicollinearity issues. Thus, it’s necessary to plot a correlation plot and the VIF score from the VIF function that shows which variable would cause multicollinearity issues. Therefore, I performed two tests on both Full models (model 12 and model 13 in Appendices Table 1 and Appendices Table 2) and the final models for two types of crimes.

**Results&Discussion**

Appendices Table 1 shows all the models before the multicollinearity test and heteroskedasticity test. This table's purpose was to see how the statistical and economic significance changes over time as I consistently added new variables for Violent Crime Rate models. Model 1 includes the only key independent Gini. As expected, the Gini is statistically significant at a 5% significance level. This finding was confirmed by Fajnzylber (1998) and Fajnzylber et al.(2002). However, considering to use only the Gini coefficient is too biased for real situations even though everyone recognizes that the greater Income Inequality(Gini), the greater Violent Crimes.

However, the Adj R^2 shows 0.108, which is very low. The value indicates the model needs more explanatory variables; therefore, model 2 was built by adding Unemployment. However, model 2 loses Gini's significance; meanwhile, the Gini coefficient decreased while adding Unemployment. This suggests that Unemployment is highly correlated with the Gini coefficient in some ways. However, the obvious change in model 2 compared with model 1 was that the Adj R^2 increased significantly. This fact shows the adding Unemployment could better explain the variations in the response variable. In addition, Unemployment is statistically significant at a 10% significance level. This finding was confirmed by Neyumar(2005). Model 3 includes all model 2 and the new variable, Poverty. The significant changes were firstly the Unemployment lost its significance, indicating the variables in model 3 may highly be correlated.

Meanwhile, the Adj R^2 decreased from 0.158 to 0.144. The decreased Adj R^2 indicated the Poverty variable should not remain in the model. Other factors may also be considered. Model 4 added the Law Enforcement variable based on model 3. The variable is statistically significant at the 1% level; meanwhile, the Adj R^2 increased a lot. This indicates the Law Enforcement variable is worthy of keeping in the model. Even though the literature review scholars did not use this variable, luckily, I found it for my model. Most importantly, while adding the Law Enforcement in model 4, I unexpectedly found Gini's sign changed to negative. The multicollinearity issue may cause a suppression effect on models. Therefore, a multicollinearity test is necessary to perform while adding many explanatory variables.

As the Appendices Table 1 shows that most models have unexpected signs of Gini, as well as, the Adj R^2 is fluctuating around 0.3. This fact shows it’s necessary to check the correlation plot and the multicollinearity issue before determining the final models and making a conclusion for the testable hypothesis. However, model 12 and model 13 suggested removing “ALASKA ” Observation is highly necessary because model 13 excluded the extreme value and suggested Ln Population Density became statistically significant at 5% percent level. The sign of the Ln Population density suggested it has a positive relationship with Violent Crime Rates. This finding was not expected because this present research assumed that the greater population density indicates there are more people in one area. Criminals may do not want to take the risk of violating the law. Model 13, as expected, shows High Education is statistically significant at the 10% level with a negative sign. The race variables are all statistically significant at the 5 percent level. In addition, Law enforcement showed a significant positive impact on Violent Crime Rates. This is an “offsetting behavior.” Therefore, it’s necessary to talk about the findings in detail with statistical methods and econometric methods for the final models. The current findings before multicollinearity tests and heteroskedasticity tests are partially contradicted with my expectations.

The purpose of Appendices Table 2 is similar to the Appendices Table. However, all Robbery models' Adj R^2 values show explanatory variables could better explain the response variable's variations (Robbery) than all Violent Crime models. That’s because Unemployment is statistically significant at a 5% level in both model 12 and model 13. However, model 12 has a better Adj R^2 than model 13. Also, the Death Penalty in model 12 is statistically significant at the 10% level. This fact suggests removing “ALASKA” Observation may not be the best choice for Robbery Rates. I will still choose to use model 13 to make sure the model is more reliable.

Similarly, Gini is only statistically significant with a positive sign at a 1% significance level. However, the whole Appendices Table 2 shows Gini’s coefficient fluctuates between the negative and positive direction. This fact is also the same as the Violent Crime models. It indicates explanatory variables are correlated in some way. Therefore, the next step is to check the correlation plot and perform a multicollinearity test based on the Third Model, which is mentioned in the methodology before determining the best models for two types of crimes.

**Correlation Plots**

Table 4.1 and Table 4.2 below show the correlation between each variable. Correlations measure the strength and direction of the linear relationship between the two variables. As a rule of thumb, the absolute value of correlation above 0.7 will show the highly correlated. From Table 4.1, the LTHS( High School Dropout) Rate is highly positively correlated with Unemployment(0.7236) and Poverty(.7942). This fact indicates if as one increases, so the other two variables increase as well. Besides, FIncome (Family Mean Income in 10000 dollars) shows a highly negative correlation with Poverty(-0.8222). This indicates one increases, so does the other decrease. Also, the High Education variable has a positive association with FIncome (0.8695). The result indicates as one increases, the other increases as well. Moreover, I found White Per has a very strong negative association with Asia Per. However, the other race variables have no strong association with each other. More importantly, I found Gini, Unemployment, Poverty, Law Enforcement, Black Per, and White per have a moderate association with the Ln Violent Crime Rates. With a rule of thumb, table 4.2 also shows the Gini, Unemployment, Law, LTHS, Ln Population Density, Black Per, White Per are moderate association with Robbery Crime Rate. The difference between Violent Crime Rate and the Robbery Crime Rate is obvious. Gini, Unemployment, Ln Population Density, Asia Per, White Per are more highly correlated with Robbery Crime. This fact indicates as one increases, the Robbery Crime Rate increases/decreases more than Violent Crime Rate. Even though the correlation plot tells the association between variables, it does not tell the causality to explain why variables have the changes in one variable actually cause the changes in the other variable. Studying the causality is also important; however, the present research is not about the causality between variables. Instead, a high correlation between each variable will raise the serious problem that may affect the reliability of fitting models. In other words, the high correlation may cause variables that are not really statistically significant, but it’s significant in the model. It may raise multicollinearity issues in the models.

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| **Table 4.1: Ln Violent Crime Rate Correlation Plot** | | | | | | | | | | | | | |
|  | ln\_vio | Gini | UNRATE | Poverty | Law | FIncome | LTHS | High Edu | ln\_pop | Black\_  Per | Asia\_  per | White\_  per | D\_Penalty |
| ln\_vio | 1 |  |  |  |  |  |  |  |  |  |  |  |  |
| Gini | 0.3557 | 1 |  |  |  |  |  |  |  |  |  |  |  |
| UNRATE | 0.423 | 0.631 | 1 |  |  |  |  |  |  |  |  |  |  |
| Poverty | 0.3098 | 0.4658 | 0.563 | 1 |  |  |  |  |  |  |  |  |  |
| Law | 0.4208 | 0.2912 | 0.0732 | -0.1191 | 1 |  |  |  |  |  |  |  |  |
| FIncome | -0.0974 | 0.0318 | -0.1738 | -0.8222 | 0.2462 | 1 |  |  |  |  |  |  |  |
| LTHS | 0.4911 | 0.5994 | 0.7236 | 0.7942 | 0.1037 | -0.5464 | 1 |  |  |  |  |  |  |
| High Edu | -0.2628 | 0.0233 | -0.1908 | -0.7228 | 0.1677 | 0.8695 | -0.6242 | 1 |  |  |  |  |  |
| ln\_pop | 0.091 | 0.5849 | 0.4337 | -0.0885 | 0.2105 | 0.4031 | 0.253 | 0.3705 | 1 |  |  |  |  |
| Black\_per | 0.4431 | 0.521 | 0.6829 | 0.3478 | 0.3027 | -0.1 | 0.6868 | -0.1742 | 0.437 | 1 |  |  |  |
| Asia\_per | 0.0067 | -0.0599 | 0.0123 | -0.2973 | 0.0725 | 0.4108 | -0.2152 | 0.2742 | 0.2393 | -0.1002 | 1 |  |  |
| White\_per | -0.4546 | -0.2996 | -0.4759 | -0.0636 | -0.2838 | -0.2264 | -0.3205 | -0.048 | -0.3218 | -0.544 | -0.7132 | 1 |  |
| D\_Penalty | 0.1991 | -0.0186 | 0.1792 | 0.3078 | 0.1075 | -0.3718 | 0.3629 | -0.2812 | -0.1021 | 0.2978 | -0.2261 | -0.0184 | 1 |

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| **Table 4.2: Linear Robbery Crime Rate Correlation Plot** | | | | | | | | | | | | | |
|  | Robbery | Gini | UNRATE | Poverty | Law | FIncome | LTHS | High Edu | ln\_pop | Black\_  Per | Asia\_  per | White\_  per | D\_Penalty |
| Robbery | 1 |  |  |  |  |  |  |  |  |  |  |  |  |
| Gini | 0.513 | 1 |  |  |  |  |  |  |  |  |  |  |  |
| UNRATE | 0.6275 | 0.631 | 1 |  |  |  |  |  |  |  |  |  |  |
| Poverty | 0.1097 | 0.4658 | 0.563 | 1 |  |  |  |  |  |  |  |  |  |
| Law | 0.3629 | 0.2912 | 0.0732 | -0.1191 | 1 |  |  |  |  |  |  |  |  |
| FIncome | 0.2117 | 0.0318 | -0.1738 | -0.8222 | 0.2462 | 1 |  |  |  |  |  |  |  |
| LTHS | 0.468 | 0.5994 | 0.7236 | 0.7942 | 0.1037 | -0.5464 | 1 |  |  |  |  |  |  |
| High Edu | 0.03 | 0.0233 | -0.1908 | -0.7228 | 0.1677 | 0.8695 | -0.6242 | 1 |  |  |  |  |  |
| ln\_pop | 0.5651 | 0.5849 | 0.4337 | -0.0885 | 0.2105 | 0.4031 | 0.253 | 0.3705 | 1 |  |  |  |  |
| Black\_per | 0.5801 | 0.521 | 0.6829 | 0.3478 | 0.3027 | -0.1 | 0.6868 | -0.1742 | 0.437 | 1 |  |  |  |
| Asia\_per | 0.2127 | -0.0599 | 0.0123 | -0.2973 | 0.0725 | 0.4108 | -0.2152 | 0.2742 | 0.2393 | -0.1002 | 1 |  |  |
| White\_per | -0.5787 | -0.2996 | -0.4759 | -0.0636 | -0.2838 | -0.2264 | -0.3205 | -0.048 | -0.3218 | -0.544 | -0.7132 | 1 |  |
| D\_Penalty | 0.1416 | -0.0186 | 0.1792 | 0.3078 | 0.1075 | -0.3718 | 0.3629 | -0.2812 | -0.1021 | 0.2978 | -0.2261 | -0.0184 | 1 |

**Multicollinearity Test**

|  |  |  |
| --- | --- | --- |
| **Table 5.1: Violent Model 13** | | |
| Variable | VIF | 1/VIF |
| Poverty | 27.65 | 0.036172 |
| FIncome | 23.3 | 0.042911 |
| White\_per | 22.55 | 0.044342 |
| Asia\_per | 16.17 | 0.061829 |
| LTHS | 12.23 | 0.08176 |
| Black\_per | 10.76 | 0.09295 |
| High Edu | 8.66 | 0.115413 |
| Gini | 7.19 | 0.139154 |
| ln\_pop | 5.38 | 0.185862 |
| UNRATE | 4.99 | 0.200201 |
| D\_Penalty | 1.63 | 0.615243 |
| Law | 1.52 | 0.655857 |
| Mean VIF | 11.84 |  |

Table 5.1 above is based on the last model from Appendices Table 1 for Violent Models. Since all the independent variables for each type of crime were used the same. Therefore, I only built the VIF test for Violent Crime Rates. As a rule of thumb, a VIF value that exceeds 5 or 10 indicates a problematic amount of collinearity. The concerned variables should be removed since the presence of multicollinearity implies that the information that this variable provides about the response is redundant in the presence of the other variables. (James et al. 2014) From the table, only Unemployment, Death Penalty, and Law Enforcement are below 5 VIF values. As noted from the correlation plot (Table 4.1), Poverty and FIncome are collinear (-0.8222), White Per and Asia Per are collinear(-.7132), White Per and Black Per are collinear (-0.544), High Edu and FIncome are collinear(-0.8695). High School Dropout Rate and High Education are collinear(0.8695). However, having these multicollinearity issues are expected; these collinearities follow the logical way. As mentioned previously, there was not an obvious causality between the two variables. More importantly, the VIF score demonstrated the findings found in Table 4.1 and Table 4.2.

To solve for the multicollinearity issues among the last model (model 13) for both Violent Crime Rate models and Robbery Crime Rate models. I decided to transform the Poverty and FIncome into Ln forms for Violent Crime Models and Robbery Crime Models firstly. However, Robbery Crime Models share the same explanatory variables. Therefore, I only built models for Robbery Crime Models without a VIF table. Table 6 shows that the first model excluded the family means Income variable instead kept the ln form of family mean income variable, for the second model excluded poverty, instead kept family mean income variable, the third model used ln forms of both family mean income and poverty. However, the Gini still had the negative coefficients for each models in Table 6, which is similar to the model 13 in Appendices Table 1. In addition, the Adj R^2 for the three models compared to Violent model 13 in Appendices Table 1 remained the same, around 0.5. In addition, the multicollinearity test(Table 6.1-6.3) for each models in Table 6 suggested Ln forms of Poverty and FIncome did not solved the issues. Since there are still many collinearity issues, among other variables, these facts are similar to the Robbery Crime models as well. However, the differences are for Robbery models compared to Violent models in Table 6 are obvious. The Adj R^2 are higher than any Violent Crime Models. In addition, the key independent variable Gini showed large differences in coefficient between two types of crimes. Even though Violent Crime model 3 is in Ln form, the dependent variable decreases by (exp(-2.009)-1) = 86% for every additional unit in Gini. However, for Robbery Crime, every additional unit in Gini will decrease by 495.4 Robbery. These findings contradicted my expectations for gini due to the multicollinearity issue. Moreover, the table found. Unemployment is statistically significant at a 5% significance level, which is better than the Violent model 3. However, the Poverty, Law, Black Per are not statistically significant in Robbery model 3. And Ln form of fmincome is statistically significant at 5% level. Most importantly, these findings of differences show the explanatory variables had a different impact on different types of crimes.

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| --- | --- | --- | --- | --- | --- | --- |
| **Table 6: Intermediate Tables For Crimes** | | | | | | |
|  | -1 | -2 | -3 | -1 | -2 | -3 |
|  | ln\_vio | ln\_vio | ln\_vio | Robbery | Robbery | Robbery |
| Gini | -0.436 | -1.287 | -2.009 | -26.99 | -162.2 | -495.4 |
|  | (-5.723) | (-5.988) | (-5.78) | (-566.118) | (-615.456) | (-569.477) |
| UNRATE | -0.00213 | -0.00468 | -0.00359 | 6.623 | 5.447 | 5.513 |
|  | (-0.027) | (-0.026) | (-0.026) | (2.699)\*\* | (2.717)\* | (2.551)\*\* |
| Poverty | 0.0485 |  |  | -1.155 |  |  |
|  | (-0.073) |  |  | (-7.186) |  |  |
| Law | 0.0207 | 0.0208 | 0.0205 | 0.94 | 1.122 | 1.073 |
|  | (0.008)\*\* | (0.008)\*\* | (0.008)\*\* | (-0.827) | (-0.842) | (-0.801) |
| ln\_fmincome | 0.892 |  | 1.294 | 194.9 |  | 320.2 |
|  | (-1.399) |  | (-1.398) | -138.422) |  | (137.697)\*\* |
| LTHS | -0.0613 | -0.0593 | -0.0555 | -4.361 | -5.731 | -4.774 |
|  | (-0.071) | (-0.069) | (-0.069) | (-6.978) | (-7.111) | (-6.794) |
| High Edu | -0.0433 | -0.0408 | -0.0441 | -6.383 | -5.584 | -6.794 |
|  | (0.024)\* | (0.023)\* | (0.023)\* | (2.333)\*\*\* | (2.354)\*\* | (2.292)\*\*\* |
| ln\_pop | 0.137 | 0.139 | 0.134 | 14.9 | 17.57 | 16.03 |
|  | (0.067)\*\* | (0.065)\*\* | (0.065)\*\* | (6.663)\*\* | (6.663)\*\* | (6.403)\*\* |
| Black\_per | -0.0298 | -0.029 | -0.0279 | -2.252 | -2.08 | -1.644 |
|  | (0.013)\*\* | (0.013)\*\* | (0.013)\*\* | (1.305)\* | (-1.35) | (-1.287) |
| Asia\_per | -0.0808 | -0.0805 | -0.0801 | -5.635 | -5.37 | -5.109 |
|  | (0.027)\*\*\* | (0.027)\*\*\* | (0.027)\*\*\* | (2.719)\*\* | (2.799)\* | (2.663)\* |
| White\_per | -0.0439 | -0.0438 | -0.0429 | -3.128 | -3.052 | -2.647 |
|  | (0.014)\*\*\* | (0.014)\*\*\* | (0.014)\*\*\* | (1.425)\*\* | (1.455)\*\* | (1.387)\* |
| D Penalty | 0.136 | 0.132 | 0.125 | 16.55 | 17.43 | 15.65 |
|  | (-0.103 | (-0.102 | (-0.102) | (-10.142) | (-10.526) | (-10.066) |
| ln\_pov |  | 0.792 | 0.931 |  | 20.77 | 85.81 |
|  |  | (-0.965) | (-0.914) |  | (-99.156 | (-90.089) |
| FIncome |  | 0.111 |  |  | 21.35 |  |
|  |  | (-0.162) |  |  | (-16.662) |  |
| \_cons | 7.871 | 7.744 | 5.914 | 9.765 | 210.4 | -303.2 |
|  | (3.035)\*\* | (2.840)\*\*\* | (-3.93) | (-300.178) | (-291.959) | (-387.214) |
| N | 49 | 49 | 49 | 49 | 49 | 49 |
| AdjR-Sqr | 0.504 | 0.507 | 0.512 | 0.649 | 0.623 | 0.657 |
| SEE | 0.265 | 0.264 | 0.263 | 26.21 | 27.16 | 25.9 |
| F-ratio | 5.064 | 5.109 | 5.195 | 8.385 | 7.603 | 8.663 |
| SSR | 2.528 | 2.514 | 2.488 | 24739.1 | 26563.9 | 24148.2 |
| Standard errors in parentheses  \* p<.1, \*\* p<.05, \*\*\* p<.01 | | | | | | |

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| **Table 6.1** | | **Table 6.2** | | **Table 6.3** | |
| Variable | VIF | Variable | VIF | Variable | VIF |
| Poverty | 29.83 | FIncome | 28.07 | ln\_fmincome | 29.26 |
| ln\_fmincome | 28.86 | ln\_pov | 27.24 | ln\_pov | 24.74 |
| White\_per | 23 | White\_per | 22.34 | White\_per | 22.32 |
| Asia\_per | 16.19 | Asia\_per | 15.98 | Asia\_per | 15.91 |
| LTHS | 12.16 | LTHS | 11.76 | LTHS | 11.81 |
| Black\_per | 11.07 | Black\_per | 11.02 | Black\_per | 11.03 |
| High Edu | 9.17 | High Edu | 8.7 | High Edu | 9.08 |
| Gini | 7.5 | Gini | 8.25 | Gini | 7.77 |
| UNRATE | 5.28 | UNRATE | 4.98 | UNRATE | 4.83 |
| ln\_pop | 5 | ln\_pop | 4.66 | ln\_pop | 4.73 |
| D Penalty | 1.61 | D Penalty | 1.62 | D Penalty | 1.63 |
| Law | 1.51 | Law | 1.46 | Law | 1.46 |
| Mean VIF | 12.6 | 12.17 | | 12.05 | |

Models after Table 6, this is the **Fourth** Model

**Violent Crime Rate: (Table 6, Model 3)**

Ln YViolent = β0+β1\*Unemployment +β2\*Ln Poverty+β3\* Law Enforcement +β4\*LN Family\_Mean\_Income\_10000+β5\*LSTH(High School Dropout) Rate + β6\*High Education +β7\*LN Population Density +β8\*Black Per+ β9\*White Per + β10\*Asia Per

Where,

β0 = Constant

β1,2..3 = Coefficients of Independent Variables

Noted: Dependent Variable is now in Ln form, Population Density is now in Ln form. Poverty is now in Ln form, family Mean Income is now in Ln form

**Robbery Crime Rate:(Table 6, Model 3)**

YRobbery = β0+β1\*Unemployment +β2\*Ln Poverty+β3\*Law Enforcement +β4\*Ln Family\_Mean\_Income\_10000+β5\*LSTH(High School Dropout) Rate + β6\*High Education +β7\*LN Population Density +β8\*Black Per+ β9\*White Per + β10\*Asia Per

Where,

β0 = Constant

β1,2..3 = Coefficients of Independent Variables

Noted: Population Density is now in Ln form. Poverty is now in Ln form, family Mean Income is now in Ln form

**Final Models**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 7: Final Models** | | | | |
|  | ln\_vio | | Robbery | |
|  | -1 | -2 | -1 | -2 |
| Gini | -2.009 | 6.092 | -495.4 | 156.2 |
|  | (-5.78) | (3.059)\* | (-569.477) | (-358.691) |
| UNRATE | -0.00359 |  | 5.513 | 3.76 |
|  | (-0.026) |  | (2.551)\*\* | (-2.32) |
| ln\_pov | 0.931 |  | 85.81 |  |
|  | (-0.914) |  | (-90.089) |  |
| Law | 0.0205 | 0.0233 | 1.073 | 1.653 |
|  | (0.008)\*\* | (0.008)\*\*\* | (-0.801) | (0.870)\* |
| ln\_fmincome | 1.294 |  | 320.2 |  |
|  | (-1.398) |  | (137.697)\*\* |  |
| LTHS | -0.0555 |  | -4.774 |  |
|  | (-0.069) |  | (-6.794) |  |
| High Edu | -0.0441 | -0.0254 | -6.794 | -0.99 |
|  | (0.023)\* | (0.011)\*\* | (2.292)\*\*\* | (-1.105) |
| ln\_pop | 0.134 | 0.032 | 16.03 | 14.94 |
|  | (0.065)\*\* | (-0.051) | (6.403)\*\* | (5.243)\*\*\* |
| Black\_per | -0.0279 | 0.00314 | -1.644 | 0.282 |
|  | (0.013)\*\* | (-0.006) | (-1.287) | (-0.698) |
| Asia\_per | -0.0801 | 0.00602 | -5.109 | 1.127 |
|  | (0.027)\*\*\* | (-0.008) | (2.663)\* | (-0.847) |
| White\_per | -0.0429 |  | -2.647 |  |
|  | (0.014)\*\*\* |  | (1.387)\* |  |
| D Penalty | 0.125 | 0.139 | 15.65 | 14.37 |
|  | (-0.102) | (-0.103) | (-10.066) | (-10.615) |
| \_cons | 5.914 | 2.739 | -303.2 | -145.4 |
|  | (-3.93 | (1.358)\* | (-387.214 | (-144.421) |
| N | 49 | 49 | 49 | 49 |
| AdjR-Sqr | 0.512 | 0.404 | 0.657 | 0.565 |
| SEE | 0.263 | 0.29 | 25.9 | 29.18 |
| F-ratio | 5.195 | 5.656 | 8.663 | 8.782 |
| SSR | 2.488 | 3.457 | 24148.2 | 34058.6 |
| Standard errors in parentheses  \* p<.1, \*\* p<.05, \*\*\* p<.01  Note: Violent Model 2(P value) Gini: 0.053 Death Penalty :0.185  Robbery Model 2(P value) Unemployment: 0.113, Asia Per: 0.191, Death Penalty:0.183 | | | | |

Since the six models in Table 6 shows Ln forms of Poverty and Family Mean Income could not make the models better. Because the multicollinearity in this present research is a severe problem, as the multicollinearity Test (Table 6.1 to 6.3) and the correlation plots above showed Poverty and FIncome are collinear, White Per and Asia Per are collinear, White Per and Black Per are collinear, High Edu and FIncome are collinear, High School Dropout Rate(LTHS) and High Education are collinear. Therefore, I dropped “Ln Poverty”, “LTHS”, “Ln FIncome”, and “White” due to the multicollinearity issue. For Violent models, I also found “Unemployment” is not statistically significant at any level in model 1 from Table 7. Therefore, I only dropped the Unemployment variable only for the final Violent model.

**Statistical & Economic Significance**

Table 7 shows the final model (2) results for Violent Crime and Robbery Crime. Even though removing some variables cause the Adj R^2 to lose some Adj R^2, however, for both models, the Adj R^2 is still above 0.3. As a result, the models are good with the rule of thumb. Also, the heteroskedasticity tests for both final models indicate no heteroskedasticity issues. (Appendices Table 3)

For the Violent Crime model, Holding other variables constant, the dependent variable (Violent Crime Rate) increases by (exp(6.092)-1) =44130.5% for every one measurement of Gini. This large coefficient sounds reasonable because if we consider increasing Gini's hundredth unit, the Violent Crime Rate will increase by (exp(6.092/100) -1) = 0.0628\*100% = 6.28%. In addition, Gini is statistically significant at the 10% percent level; however, the significance value of Gini is almost 0.05. This finding is demonstrated by Fajnzylber et al. (1998) and Fajnzylber et al. (2002). More importantly, the positive and significant Gini accepted the testable hypothesis of the large Gini coefficient (Income inequality) will cause more Violent crimes. Similarly to the final Robbery model, Gini was found positive but insignificant. This fact suggested Gini has a large significance value; instead, it indicated Income Inequality would not have a huge impact on Robbery, particularly. The different significance values of Gini suggested Income Inequality will not be a huge impact on all types of crimes. However, Gini is insignificant in the Robbery model. It is kind of unacceptable for me. Because the purpose of Robbery is obvious to obtain any valuable things, it happens if criminals’ economic situations are severe. However, the limitation of the dataset may cause Gini is not significant for Robbery. Therefore, considering more observations in further research will make the finding more reliable.

Gini's economic significance is not obvious, even though the increase in Gini would significantly increase violent crime from a statistical perspective. Furthermore, People know the Gini coefficient measures income inequality. To some extent, decreasing income inequality does not sound like an easy thing with a macro-view. It’s a long term goal. Especially, the Gini is indirectly associated with tons of people’s income. Through this perspective, tons of people may result in a high Gini because it’s hard to balance social class differences. In other words, Gini could think of as a barometer that tells polarization between the rich and the poor for the whole society. However, if one state/country is generally all the blue-collar people or generally all people are billionaires, it may result in a low Gini because it has an equal distribution. However, this assumption is not practical to tell how to make the Gini small. But considering this perspective in-depth, the government could shrink the income inequality between the citizens through improving people’s education, reducing racial bias, reducing the unemployment rate, and the percent of below poverty. Similar to the other explanatory variables, the economic significance of affecting crimes is not obvious.

As expected, the Unemployment Rate has a positive effect on Robbery Crimes. But it was found statistically insignificant at the conventional level. This is also partially demonstrated by Neumayer(2005), even he found the variable is statistically significant. The small dataset may cause the variable is sufficient to conclude the significance. However, for unemployment, particularly, creating more jobs, occupants would afford more unemployed people opportunities to make livings. The government could reduce the unemployment rate by supporting all business types with lower taxes, reducing loan interests to stimulus markets. Therefore, the companies will not take more risks of bankruptcy while they face some financial issues. Thus, the unemployment rate will not be increased in this way; as a result, the crimes will not increase by the increase in the unemployment rate. For percent of high education, it has little economic significance as well. However, the government could consider providing more equal opportunities for people to study. In short, the government could be more flexible about financial aids, which could help people get high educations.

Unexpectedly, Law Enforcement per 10000 people shows an offsetting behavior because the coefficient indicated that if Law Enforcement increase1 unit, the Violent Crime rate will increase by (exp(0.0233) -1) =0.0236\*100% =2.36%. Meanwhile, the Law Enforcement is statistically significant at 1 percent level. This finding is unexpected because Vollard(2012) found police numbers have no effect on recorded violent crime. Additionally, in real situations, people may relate this variable with more police officers than the government. Therefore, Criminals maybe not willing to take the risk of violating the laws. Moreover, within the states, the logic follows the more crime rates within one state. Therefore, the state government would hire more law employees to control society's stability. But the positive coefficient was also found by Vollard(2012), explained the reason that why the coefficient is positive by saying that “ the impact of measurement error in police statistics is large and can not be ignored when assessing the impact of police numbers on crime.” (Vollard, 2012). In other words, it’ is likely because it is endogenous and hence biased > Police =f(Crime). That is, areas with high crime rates are likely to increase the number of police to combat them.

Percent of High Education was expected with a negative impact on both crimes. This fact shows increase in one unit in High Education, the violent crime will decrease by (exp(-0.0254) -1)\*100% = -2.51%. in violent crime. However, High Education was found statistically significant at a 5% level only in violent crime rather than robbery crime. On the contrary, Ln of Population density was only statistically significant at a 5% level in robbery crime. The coefficient indicated the robbery crime rate increases by 0.1494 for every one percent increase in Ln of Population density. Even though the regression table only shows Ln of Population is not statistically significant in the Violent model, however, the sign of its coefficient met the expectation for the variable previously.

Unexpectedly, removing the percent of white people caused the other percent of races to lose its significance in both crimes. This proved the collinearity that White per existed in Black per and Asia per. The issue caused the model unreliable due to the multicollinearity issue. However, the two percent of races' coefficient and significance value show a really small impact on each crime.

Lastly, the coefficients of the Death penalty shows the movement of it from 0(No Death penalty) to 1(Support Death Penalty) produces a 13.9% more in violent crime rates, which is similar to the robbery crime. However, the death penalty is statistically insignificant. And the sign of coefficients is not expected because, within the states, the small sample of the data is not sufficient in this case.

**Conclusion**

To sum up the findings above, The Gini was found statistically significant at 10 percent level only for violent crimes with a positive sign as expected. The result supports the testable hypothesis of the large Gini coefficient (Income inequality) will cause more violent crimes at a 10% percent level, but not exactly for robbery crimes. I also found Law enforcement and Death Penalty are the two interesting variables in this study because the signs of coefficients tell it will create more crime rates, while one explanatory variable increases. However, it’s insufficient to conclude that way due to the limited data. Instead, I found Gini and percent of High Education are worthy for the government to consider the policy that benefits the variables. Therefore, the government could consider improving people’s education, reducing racial bias, reducing the unemployment rate, and poverty percent of below poverty to solve the polarization between the rich and the poor. Also, the correlation plot demonstrated this argument. However, it’s a long-term goal to solve income inequality in order to reduce crimes. In the short term, the government could help students get equal opportunities to attend high education. The government could lower the loan interests for individuals and companies.

**Limitations & Further Research**

1. Law enforcement per 10000 people maybe not the best explanatory variable, instead, the efficiency of police officers may show reliable results.
2. Considering using more observations to study whether death penalty would impact crimes. The sufficient data and bias within the states cause the death penalty has an unexpected sign.
3. Considering regional differences as control variables. Within this study particularly, four regions(West, East, North, South) are worthy to discuss.
4. This study is an cross-sectional data due to the gini coefficient vary little from 2010 to 2014, however, it’s necessary to consider how the time affect the crimes as well.

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**Appendices**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Appendices Table 1: Ln Violent Model Changes | | | | | | | | | | | | | |
|  | -1 | -2 | -3 | -4 | -5 | -6 | -7 | -8 | -9 | -10 | -11 | -12 | -13 |
|  | ln\_vio | ln\_vio | ln\_vio | ln\_vio | ln\_vio | ln\_vio | ln\_vio | ln\_vio | ln\_vio | ln\_vio | ln\_vio | ln\_vio | ln\_vio |
| Gini | 7.137 | 2.958 | 2.65 | -1.502 | -4.921 | -7.883 | -5.398 | -3.104 | -3.234 | -3.445 | -0.682 | 0.411 | 0.741 |
|  | (2.707)\*\* | -3.392 | -3.47 | -3.355 | -5.043 | -5.13 | -5.19 | -5.807 | -5.883 | -6.375 | -5.598 | -5.728 | -5.626 |
| UNRATE |  | 0.0397 | 0.0352 | 0.0376 | 0.0295 | 0.00474 | 0.0158 | 0.0207 | 0.0173 | 0.0174 | 0.0184 | 0.0195 | -0.00103 |
|  |  | (0.020)\* | -0.022 | (0.020)\* | -0.022 | -0.025 | -0.025 | -0.026 | -0.028 | -0.028 | -0.025 | -0.025 | -0.028 |
| Poverty |  |  | 0.0109 | 0.029 | 0.0845 | 0.0831 | 0.0824 | 0.0572 | 0.0641 | 0.0665 | -0.000111 | 0.0000848 | 0.0296 |
|  |  |  | -0.021 | -0.02 | -0.064 | -0.062 | -0.061 | -0.067 | -0.071 | -0.076 | -0.069 | -0.069 | -0.07 |
| Law |  |  |  | 0.0306 | 0.0316 | 0.028 | 0.0282 | 0.0266 | 0.0259 | 0.0261 | 0.0206 | 0.0192 | 0.0206 |
|  |  |  |  | (0.009)\*\*\* | (0.009)\*\*\* | (0.009)\*\*\* | (0.009)\*\*\* | (0.009)\*\*\* | (0.009)\*\*\* | (0.009)\*\*\* | (0.008)\*\* | (0.009)\*\* | (0.008)\*\* |
| FIncome |  |  |  |  | 0.113 | 0.186 | 0.272 | 0.245 | 0.254 | 0.26 | 0.0559 | 0.073 | 0.0499 |
|  |  |  |  |  | (0.125) | (0.127) | (0.132)\*\* | (0.136)\* | (0.140)\* | -0.159 | -0.149 | -0.151 | -0.149 |
| LTHS |  |  |  |  |  | 0.0978 | 0.038 | 0.0572 | 0.0457 | 0.0445 | -0.0291 | -0.0506 | -0.0613 |
|  |  |  |  |  |  | (0.051)\* | -0.06 | -0.064 | -0.073 | -0.075 | -0.068 | -0.072 | -0.071 |
| High Edu |  |  |  |  |  |  | -0.0394 | -0.0339 | -0.0351 | -0.0358 | -0.0403 | -0.0472 | -0.0393 |
|  |  |  |  |  |  |  | (0.022)\* | -0.023 | -0.023 | -0.025 | (0.022)\* | (0.023)\*\* | (0.023)\* |
| Ln\_Pop |  |  |  |  |  |  |  | -0.0467 | -0.0463 | -0.0445 | 0.0828 | 0.091 | 0.138 |
|  |  |  |  |  |  |  |  | -0.052 | -0.053 | -0.057 | -0.061 | -0.061 | (0.068)\*\* |
| Black\_per |  |  |  |  |  |  |  |  | 0.00271 | 0.00265 | -0.0354 | -0.0372 | -0.0313 |
|  |  |  |  |  |  |  |  |  | -0.008 | -0.008 | (0.013)\*\*\* | (0.013)\*\*\* | (0.013)\*\* |
| Asia\_per |  |  |  |  |  |  |  |  |  | -0.000942 | -0.0929 | -0.0954 | -0.0822 |
|  |  |  |  |  |  |  |  |  |  | -0.01 | (0.027)\*\*\* | (0.027)\*\*\* | (0.028)\*\*\* |
| White\_per |  |  |  |  |  |  |  |  |  |  | -0.0507 | -0.0522 | -0.0455 |
|  |  |  |  |  |  |  |  |  |  |  | (0.014)\*\*\* | (0.014)\*\*\* | (0.014)\*\*\* |
| D\_Penalty |  |  |  |  |  |  |  |  |  |  |  | 0.095 | 0.138 |
|  |  |  |  |  |  |  |  |  |  |  |  | -0.107 | -0.103 |
| \_cons | 2.531 | 3.885 | 3.934 | 4.655 | 4.598 | 5.115 | 4.685 | 4.102 | 4.147 | 4.174 | 10.45 | 10.23 | 9.064 |
|  | (1.242)\*\* | (1.392)\*\*\* | (1.406)\*\*\* | (1.284)\*\*\* | (1.288)\*\*\* | (1.279)\*\*\* | (1.270)\*\*\* | (1.432)\*\*\* | (1.454)\*\*\* | (1.500)\*\*\* | (2.149)\*\*\* | (2.165)\*\*\* | (2.254)\*\*\* |
| N | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 49 |
| AdjR-Sqr | 0.108 | 0.158 | 0.144 | 0.305 | 0.303 | 0.343 | 0.376 | 0.372 | 0.359 | 0.342 | 0.502 | 0.5 | 0.5 |
| SEE | 0.362 | 0.352 | 0.355 | 0.32 | 0.32 | 0.311 | 0.303 | 0.304 | 0.307 | 0.311 | 0.271 | 0.271 | 0.266 |
| F-ratio | 6.951 | 5.586 | 3.754 | 6.385 | 5.254 | 5.267 | 5.209 | 4.634 | 4.043 | 3.549 | 5.489 | 5.089 | 4.999 |
| SSR | 6.295 | 5.822 | 5.789 | 4.597 | 4.512 | 4.153 | 3.857 | 3.784 | 3.774 | 3.773 | 2.783 | 2.719 | 2.549 |

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| Appendices Table 2: Linear Robbery Model Changes | | | | | | | | | | | | | |
|  | -1 | -2 | -3 | -4 | -5 | -6 | -7 | -8 | -9 | -10 | -11 | -12 | -13 |
|  | Robbery | Robbery | Robbery | Robbery | Robbery | Robbery | Robbery | Robbery | Robbery | Robbery | Robbery | Robbery | Robbery |
| Gini | 1175 | 445.4 | 613.7 | 374.3 | 372.1 | 20.43 | 209.3 | -146.3 | -150.9 | -48.55 | 127.1 | 327.2 | 322.5 |
|  | (283.800)\*\*\* | -328.992 | (305.402)\* | -316.321 | -479.918 | -476.312 | -487.959 | -536.807 | -544.527 | -588.376 | -562.861 | -559.865 | -567.609 |
| UNRATE |  | 6.928 | 9.381 | 9.521 | 9.516 | 6.575 | 7.417 | 6.661 | 6.538 | 6.465 | 6.528 | 6.734 | 7.029 |
|  |  | (1.971)\*\*\* | (1.959)\*\*\* | (1.892)\*\*\* | (2.094)\*\*\* | (2.314)\*\*\* | (2.357)\*\*\* | (2.378)\*\*\* | (2.585)\*\* | (2.614)\*\* | (2.479)\*\* | (2.416)\*\*\* | (2.790)\*\* |
| Poverty |  |  | -5.978 | -4.936 | -4.9 | -5.066 | -5.116 | -1.213 | -0.966 | -2.123 | -6.358 | -6.322 | -6.747 |
|  |  |  | (1.871)\*\*\* | (1.874)\*\* | (-6.102) | (-5.778) | (-5.706) | (6.203) | (6.558) | (7.033) | (6.912) | (6.731) | (7.085) |
| Law |  |  |  | 1.765 | 1.766 | 1.344 | 1.354 | 1.599 | 1.576 | 1.512 | 1.166 | 0.898 | 0.878 |
|  |  |  |  | (0.845)\*\* | (0.861)\*\* | -0.833 | -0.822 | (0.827)\* | (0.856)\* | (0.874)\* | (0.841) | (0.834) | (0.849) |
| FIncome |  |  |  |  | 0.0734 | 8.7 | 15.23 | 19.47 | 19.79 | 16.55 | 3.557 | 6.695 | 7.026 |
|  |  |  |  |  | (11.857) | (11.761) | (12.453) | (12.600) | (12.992) | (14.706) | (15.020) | (14.735) | (15.004) |
| LTHS |  |  |  |  |  | 11.61 | 7.063 | 4.078 | 3.666 | 4.268 | -0.408 | -4.337 | -4.184 |
|  |  |  |  |  |  | (4.711)\*\* | (5.607) | (5.878) | (6.735) | (6.911) | (6.854) | (7.040) | (7.166) |
| High Edu |  |  |  |  |  |  | -2.999 | -3.857 | -3.9 | -3.573 | -3.858 | -5.122 | -5.235 |
|  |  |  |  |  |  |  | (2.065) | (2.116)\* | (2.167)\* | -2.289 | (2.173)\* | (2.236)\*\* | (2.322)\*\* |
| Ln\_Pop |  |  |  |  |  |  |  | 7.234 | 7.246 | 6.352 | 14.44 | 15.93 | 15.25 |
|  |  |  |  |  |  |  |  | (-4.848) | (-4.908) | -5.283 | (6.099)\*\* | (6.000)\*\* | (6.820)\*\* |
| Black\_per |  |  |  |  |  |  |  |  | 0.0974 | 0.13 | -2.291 | -2.612 | -2.696 |
|  |  |  |  |  |  |  |  |  | (-0.746) | (-0.756) | (1.265)\* | (1.245)\*\* | (1.317)\*\* |
| Asia\_per |  |  |  |  |  |  |  |  |  | 0.457 | -5.391 | -5.849 | -6.039 |
|  |  |  |  |  |  |  |  |  |  | (-0.934) | (2.668)\* | (2.611)\*\* | (2.782)\*\* |
| White\_per |  |  |  |  |  |  |  |  |  |  | -3.224 | -3.493 | -3.589 |
|  |  |  |  |  |  |  |  |  |  |  | (1.387)\*\* | (1.360)\*\* | (1.445)\*\* |
| D\_Penalty |  |  |  |  |  |  |  |  |  |  |  | 17.37 | 16.75 |
|  |  |  |  |  |  |  |  |  |  |  |  | (9.909)\* | (-10.426) |
| \_cons | -453.3 | -217 | -244 | -202.4 | -202.5 | -141.1 | -173.7 | -83.33 | -81.73 | -94.66 | 304.2 | 264 | 280.7 |
|  | (130.208)\*\*\* | -135.024 | (123.753)\* | -121.11 | -122.624 | -118.756 | -119.392 | -132.366 | -134.545 | -138.399 | -216.053 | -211.634 | -227.41 |
| N | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 49 |
| AdjR-Sqr | 0.248 | 0.392 | 0.491 | 0.526 | 0.515 | 0.565 | 0.576 | 0.588 | 0.578 | 0.57 | 0.614 | 0.634 | 0.632 |
| SEE | 37.96 | 34.14 | 31.22 | 30.14 | 30.48 | 28.86 | 28.49 | 28.09 | 28.43 | 28.7 | 27.21 | 26.5 | 26.84 |
| F-ratio | 17.14 | 16.77 | 16.78 | 14.59 | 11.42 | 11.62 | 10.52 | 9.751 | 8.462 | 7.495 | 8.073 | 8.06 | 7.856 |
| SSR | 69178.4 | 54781.8 | 44829.5 | 40869.3 | 40869.2 | 35811.1 | 34099.6 | 32343.6 | 32329.8 | 32133.2 | 28136 | 25977.8 | 25942.7 |

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| Appendices Table 3.1: Heteroskedasticity Test For Final Model | | | | |
| Violent | F(7 , 41) = 1.37 | Prob > F = 0.2424 | chi2(34) = 38.30 | Prob > chi2 = 0.2806 |
| Robbery | F(8,40)=0.86 | Prob>F=0.5553 | chi2(43) =48.70 | Prob > chi2 = 0.2546 |