

# **VIOLENT CRIME AND INCOME INEQUALITY**

A Project

Presented to the

Faculty of

California State Polytechnic University, Pomona

In Partial Fulfillment

Of the Requirements for the Degree

Master in Science

In

Economics

By

Lei Zhang

2018

## **SIGNATURE PAGE**

**PROJECT :** VIOLENT CRIME AND INCOME INEQUALITY

**AUTHOR:** Lei Zhang

**DATE SUBMITTED:** Spring 2018

Economics Department

Dr. Craig Kerr  
Project Committee Chair  
Economics

---

Dr. Bruce Brown  
Economics

---

Dr. Carsten Lange  
Economics

---

## **ACKNOWLEDGMENTS**

Thanks to Dr. Craig A. Kerr, Dr. Kelly Forrester, and Dr. Mohammad Safarzedah for their guidance and mentoring as I further my knowledge in the field of Economics.

## **Abstract**

This paper examines the relationship between violent crime and income inequality within counties in California. First, a cross-sectional regression for two time periods (Great Recession period and the subsequent economic recovery period) suggests that Gini coefficient does not have a significant effect on violent crime. Secondly, a regression employing time fixed-effects indicates that Gini coefficient is positive and significantly effects violent crime during the Great Recession period, but is not statistically significant for violent crime rates during the economic recovery period.

# Contents

<b>Contents</b>	<b>v</b>
<b>List of Tables</b>	<b>vi</b>
<b>List of Figures</b>	<b>vii</b>
<b>1 Introduction</b>	<b>1</b>
<b>2 Literature Review</b>	<b>4</b>
<b>3 Data and Methodology</b>	<b>8</b>
3.1 Data . . . . .	8
3.1.1 The dependent variable . . . . .	8
3.1.2 The explanatory variables . . . . .	8
3.2 Summary of Data Statistics . . . . .	12
3.3 Methodology . . . . .	15
<b>4 Results</b>	<b>17</b>
4.1 Pooled Ordinary Least Square (OLS) . . . . .	17
4.2 Fixed Effect Model . . . . .	20
<b>5 Conclusion</b>	<b>22</b>
<b>Bibliography</b>	<b>24</b>
<b>A Appendix</b>	<b>26</b>

# List of Tables

3.1	Descriptive information on Variables . . . . .	11
3.2	Descriptive information on Variables 2007 - 2010 . . . . .	11
3.3	Descriptive information on Variables 2011 - 2015 . . . . .	11
3.4	Pairwise Correlation 2007-2015 . . . . .	14
3.5	Pairwise Correlation 2007 - 2010 . . . . .	14
3.6	Pairwise Correlation 2011 - 2015 . . . . .	15
4.1	Regression Results for Violent Crime Rates . . . . .	19
4.2	Regression Results for Violent Crime Rates . . . . .	21
A.1	Data Source . . . . .	26
A.2	Hausmen test . . . . .	27
A.3	Stationary . . . . .	27

# List of Figures

1.1	Gini coefficient and violent Crime rates, 2007 - 2015 (9-year average)	3
3.1	Gini coefficient . . . . .	9

# Chapter 1

## Introduction

The effect of economic inequality on crime rates has caught the attention of many researchers and policy analysts who have used empirical evidence to measure the relationship between income inequality (the Gini coefficient) and violent crime rates for one or more countries. Some of these researchers and policy analysts have concluded that inequality has had a significant and positive affect on crime, especially violent crime (Kelly, (2000); Blau & Blau, (1982); Fajnzylber, Lederman & Loayza (2000)) while others find that inequality has had no significant affect on crime (Durante, (2012); Neumayer, (2012); Chen & Keen, (2014)). According to Kelly (2000), the greater the inequality, the higher economic strain between low-status individuals and high-status individuals, making low-status individuals feel more frustration toward their economic situation. As a result, low-status individuals are more likely to commit crime. Kelly (2000) concludes that income inequality and its relative factors are ultimately responsible for the increase in criminal behavior. Weatherburn (2001) believes that income inequality, poverty, and unemployment are the three main factors that cause crime, but also concludes that income inequality plays a very important role as well.

Many studies, using different analytical methods, have indicated that income inequality and crime are positively correlated on a county, state, or national level. Hsieh and Pugh (1993) employ meta-analysis on 34 aggregate studies that are at



different geographic levels and conclude that income inequality is positively associated with violent crime. Choe (2008) uses fixed-effect model to study her panel data at the state level, and finds a strong correlation between income inequality and crime. Kelly (2000) conducts a Gaussian Mixture Model (GMM) to analyze the relationship between inequality and crime on metropolitan counties in the contiguous 48 states. He concludes that inequality has a strong and robust impact on violent crime. Other studies find that income inequality has no effect or negative effect on crime. Neumayer (2005) studies panel data on a national level and finds that inequality has no statistical significant determination on crime. Durante (2012) studies panel data on the state level, and finds that inequality does not have a positive relationship with crime. Chintrakarn (2012) uses panel cointegration technical analysis on a state-level and concludes that income inequality has a significant negative effect on crime. Because of these contradicting findings, I would like to investigate the impact that income inequality has by measuring the Gini coefficient and its relationship with violent crime rates. The possible factors are unemployment rates, high school dropout rates, poverty rates, per capita income, police officer ratios, female employment rates, population density, and the proportion of young males aged 15 to 29 in counties across California from the year 2007 to 2015. I will explain why those explanatory variables are used in this paper in the data section.

Figure 1.1 shows the simple correlation between the Gini coefficient and logged violent crime rates using panel data from 40 counties. By analyzing the simple correlation between logged violent crime rates and Gini coefficient, the relationship between logged violent crime rates and Gini coefficients appear positive but not significant.

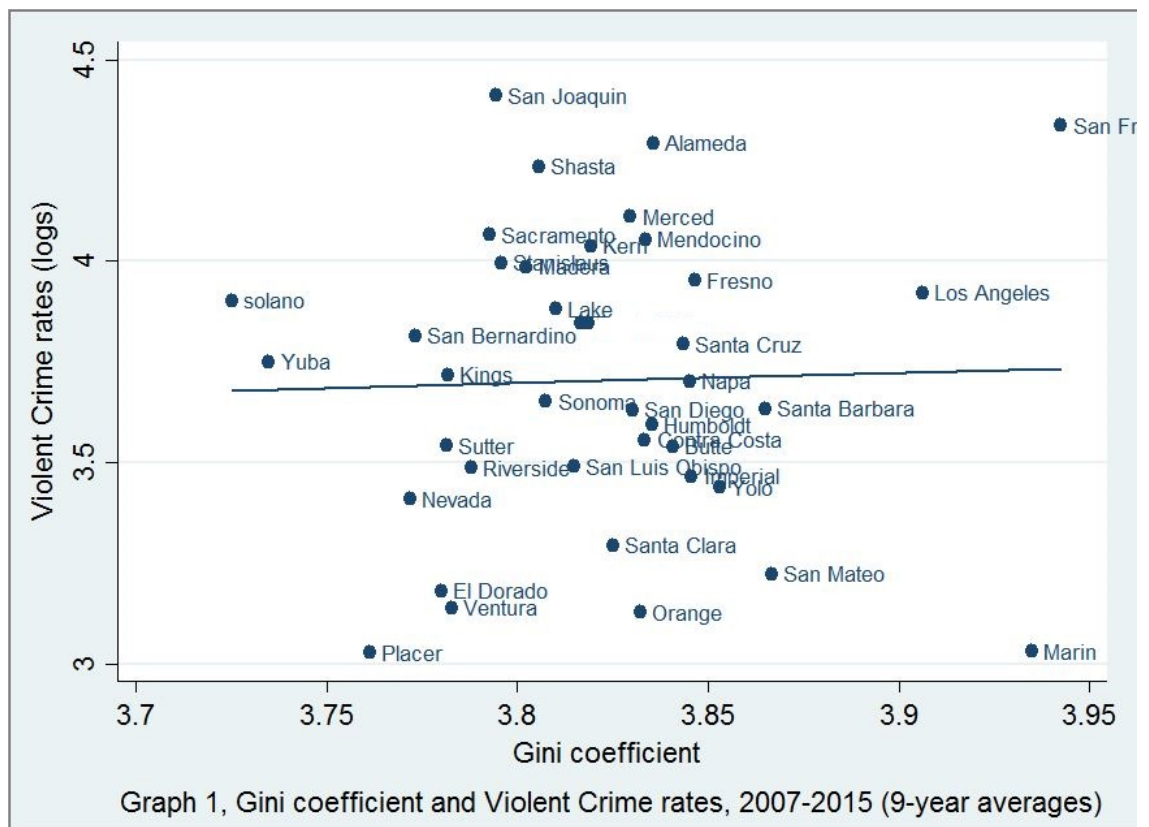


Figure 1.1: Gini coefficient and violent Crime rates, 2007 - 2015 (9-year average)

# Chapter 2

## Literature Review

Fajnzylber et al (2002) find that income inequality has a positive effect on crime rates across different nations. They use panel data from 39 countries from 1965 to 1995 for homicides rates, 37 countries from 1970 to 1994 for robbery rates, and the Gini index as an income inequality measurement. While other studies focus on the impact of income inequality on crime rates in different states or counties within a nation, Fajnzylber et al study the relationship between income inequality and crime from different countries. Fajnzylber et al (2002) believe that national borders limit the mobility of potential criminals more than neighborhood, city, or even provincial boundaries do. Their dependent variables are international homicide rates and robbery rates. The explanatory variables include Gross National Product per capita that is converted to U.S. dollars based on 1987 foreign exchange rates, the Gini coefficient, the income quintile, average years of education among adults over 15, GDP growth rate, police officer ratios per 100,000 people, and the percent of males aged 15 to 29. The Gini coefficient is income-based and the income quintile is the alternative measurement of the Gini coefficient, which is the ratio of the income of the population in the fifth quintile of the distribution of income to the first quintile of distribution of income (Fajnzylber et al). From using pooled ordinary least squares (OLS), they notice that the Gini coefficient has a positive and significant correlation with both international homicide crime and robbery crime. However, the

pooled OLS regression may be biased for three reasons. First, pooled OLS ignores the effect of crime rates of previous periods on the current period. Second, the estimates in pooled OLS are biased because dependent variables might affect some of explanatory variables. Third, the error term is contained while measuring crime rates, and the error term might be correlated with some other explanatory variables, especially income inequality (Fajnzylber et al). Because of this, the authors use dynamic (lag-dependent variable) models and find that income inequality measured by the Gini index and income disparity between rich and poor measured by the Gini index have a significant positive effect on homicide rates and robbery rates; however, the GDP growth rate has a significant negative effect on those same rates. This research shows correlation between income inequality and crime, but the authors fail to consider other factors, such as the unemployment rate or female labor force participation rates that might affect crime rates. Female in the workforce reduces the time spent they spend at homes, and contributes to low parental supervision to their children - some of which might become potential offenders. As a result, those potential offenders have more opportunities to commit crime (Witt and Witte, 2000).

Some studies such as the one is conducted by Alex Durante (2012) finds no significant relationship between income inequality and crime on a state and county level within a nation. Durante uses panel data for all fifty states and the District of Columbia from 1981 to 1999, and the Gini coefficient as a measure of income inequality for the purpose of his study. Violent crime includes murder, forcible rape, robbery, and aggravated assault; property crime includes burglary, larceny, and motor vehicle theft measured per 100,000 people. His independent variables are the Gini coefficient, poverty rates, unemployment rates, ratio of young people from 18 to 24, ratio of people older than 65, female to male ratio, and population density. Durante (2012) uses population density to “approximate the effect of urbanization on crime,” because he believes that urban areas contain clusters of low-income and

high-income groups that contributes to higher crime rates. He finds that the Gini coefficient 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 also have a negative relationship with property crime rates, but population density has a strong positive relationship with property crime rates. However, Durante (2012) does not consider out-of-state visitors who commit crime in that state and other factors that may affect crime rates, such as the police officer to general population ratios.

Chen and Keen (2014) examine the relationship between the change in income inequality, poverty rates, mean income, high school dropout rates, and college graduation rates on violent crime and property crime for 38 counties in California. Based on pooled ordinary least squares (OLS) analysis, the authors find that increasing income inequality decreased violent crime and property crime rates, but increasing poverty and population density increased crime rates. They find that high school dropout rates and unemployment rates have a significant effect on property crime rates. Pooled OLS does not distinguish various intercept and slopes among the counties and time period or deny the heterogeneity that may exist among counties. After testing aggregated violent crime and aggregated property crime models on their pooled data, Chen and Keen (2014) accept alternative hypothesis that at least one county at specific year has different explanatory variables other than what they use in the a. Then, they use another test - the Hausman test - and conclude that a fixed effect model is the best for their estimation. The results of the fixed effect model turn out different from the pooled OLS model. Based on their study, the high school dropout rates do not have any significant effect on crime rates. The population density, poverty rates, mean income and unemployment rate have a negative effect on crime rates. The authors notice that income inequality has no effect on any category of crime at the county level or below.

Jesse Brush (2007) explores the relationship between income inequality and crime by employing two economic models using the same independent variables

of reported crime rates, media income, density, share of young people aged 18 to 24, unemployment rates, and percentage of Black, Native American, Asian and Hispanic in the population, but different dependent variables of Gini coefficient and income inequality (ratio of percent of poverty and percent of income over \$100,000). After studying the cross-section analysis, he finds that the Gini coefficient and income inequality have a positive effect on crime rates on a county level within the nation, but he does not find a relationship between poverty rates and crime rates. He believes that this result is due to a higher police presence in wealthier counties. He notices while conducting a time-series analysis, that the change in the Gini coefficient and income inequality have a negative affect on crime rates because some factors such as increasing the number of police, and the rising prison population during 1990's resulted in lower crime.

# Chapter 3

## Data and Methodology

### 3.1 Data

#### 3.1.1 The dependent variable

Total violent crime is collected from the California Department of Justice website (SDJC), which includes homicide, forcible rape, robbery, and aggravated assault.<sup>1</sup> According to Kelly (2000), reported crime data are biased due to under-reporting, and this bias is likely correlated with the some explanatory variables, such as poverty, education, and police activity.

#### 3.1.2 The explanatory variables

The three main factors that are driving crime are inequality, poverty, and unemployment. Income inequality is measured by the Gini coefficient. A Gini coefficient of 0 indicates absolute equality and a Gini coefficient of 1 indicates absolute inequality. Figure 3.1<sup>2</sup> is graphic expression of the Gini coefficient. The formula of the Gini coefficient is:  $G = \text{area of A} / (\text{area of A} + \text{area of B})$ <sup>3</sup>. I expect that the Gini coefficient has a positive relationship with violent crime rates. Since children

---

<sup>1</sup> Reported Crime data comes from Criminal Justice Statistics Center for the California Attorney Generals Office. Each crime rate is calculated rate per 10,000 residents.

<sup>2</sup> Adapted from Wikipedia, the free encyclopedia.

<sup>3</sup> Gini coefficient formula is adapted from Wikipedia, the free encyclopedia.

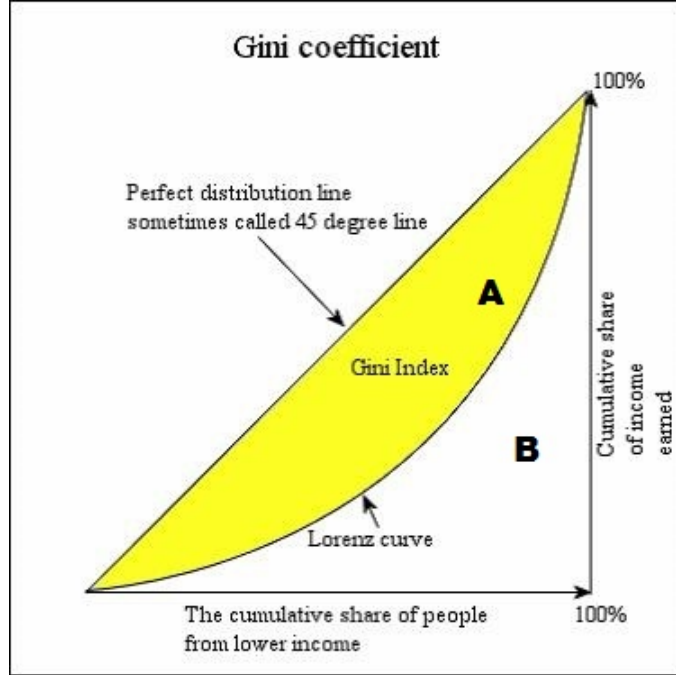


Figure 3.1: Gini coefficient

and the elderly are less likely to commit crime, I will focus on poverty rates <sup>4</sup> for people aged 15 to 64 years. Both the data for the Gini coefficient and poverty data are collected from American FactFinder. Unemployment rates<sup>5</sup> is the third main factor that leads to crime, and is collected from the Federal Reserve Bank of St. Louis website.

The other factors that could influence crime are: high school dropout rates, ratio of young males in the population, ratio of police officers, population density, female labor force participate rates and per capita income. I assume that because less educated people have limited opportunities, during financial hard times they are more likely to engage in crime. High school dropout data<sup>6</sup> is collected from American FactFinder. Most young males face adverse opportunities in labor market and only make minimum wage, but criminal opportunities that promise higher

<sup>4</sup> Percent of people aged from 15 to 64 below the poverty level.

<sup>5</sup> Percent of labor force that is unemployed.

<sup>6</sup> percent of population did not receive high school diploma and complete the 12th grade.



payoff that attract young males' attention to make more. According to Kanazawa and Still (2000), young men aged 15 to 34 commit majority of violent crime around the world. The data of young males aged 15 to 34 is collected from American FactFinder.<sup>7</sup> Neumayer (2005) uses opportunity cost to explain that working females who are living with potential offenders do not have time to look after their family members, which may give potential offenders more opportunities to commit crime. Female labor force participation rate<sup>8</sup> is included in this paper, and is collected from American FactFinder. I use per capita income as a measure of economic development because GDP data for counties is unavailable. Per capita income data is collected from U.S. Bureau of Economic Analysis. The police officer ratio<sup>9</sup> is also included because of the effect police activities has on crime. Population density<sup>10</sup> is included in this paper because high density counties may be associated with higher crime rates.

---

<sup>7</sup> Percent of male population aged 15 to 34.

<sup>8</sup> Percent of female population current employed.

<sup>9</sup> Percent of police officers population per 10,000.

<sup>10</sup> Population per square mile, 2014.

Table 3.1: Descriptive information on Variables

Variable	Obs	Mean	Std.Dev.	Min	Max
Violent crime rate per 10,000 people	360	43.8	17.7	16.1	175
Unemployment rate	360	10.0	4.3	3.4	28.9
Gini coefficient	360	.5	0.0	0.4	0.5
High school Dropout rate	360	33.8	12.7	9.4	69.2
% of aged 15-64 below poverty level	360	10.0	3.3	3.7	18.8
% of population male aged 15-34	360	14.8	2.0	9.6	23.3
Per capita income	360	44900	15800	24800	112000
Police officer ratio per 10,000 people	360	19.0	14.0	10.0	200
Density	360	954	2766	24.4	18400
Female employment rate	360	20.0	3.0	13.0	27.0

Table 3.2: Descriptive information on Variables 2007 - 2010

Variable	Obs	Mean	Std.Dev.	Min	Max
Violent crime rate per 10,000 people	160	46.5	19.2	20.6	175
Unemployment rate	160	10.0	4.3	3.7	28.8
Gini coefficient	160	0.5	0.0	0.4	0.5
High school Dropout rate	160	36.4	13.3	12.9	69.2
% of aged 15-64 below poverty level	160	9.0	2.9	3.7	15.7
% of population male aged 15-34	160	15.0	2.1	9.9	23.3
Per capita income	160	41500	13800	24800	91200
Police officer ratio per 10,000 people	160	21.9	19.7	9.7	200
Density	160	930	2710	24.4	17300
Female employment rate	160	20.2	2.7	13.5	25.9

Table 3.3: Descriptive information on Variables 2011 - 2015

Variable	Obs	Mean	Std.Dev.	Min	Max
Violent crime rate per 10,000 people	200	41.7	16.2	16.1	89.1
Unemployment rate	200	10.0	4.2	3.4	28.9
Gini coefficient	200	0.5	0.0	0.4	0.5
High school Dropout rate	200	31.8	11.8	9.4	66.9
% of aged 15-64 below poverty level	200	10.8	3.4	4.7	18.8
% of population male aged 15-34	200	14.6	1.9	9.6	19.7
Per capita income	200	47600	16800	29500	112000
Police officer ratio per 10,000 people	200	15.9	5.0	9.3	37.8
Density	200	972	2820	24.8	18400
Female employment rate	200	20.0	2.8	13.2	27.2

## 3.2 Summary of Data Statistics

I examine the impact of the Gini coefficient and other explanatory variables on violent crime rates using county as a unit of analysis. There are 58 counties in California, 98 percent of population and 98 percent of violent crime are accounted for in 40 of the 58 counties. The descriptive statistics of variables from 40 counties over a 9 year period is shown in the Table 3.1. Table 3.2 is the descriptive statistics of variables from 40 counties for the period from 2007 to 2010. Table 3.3 is the descriptive statistics of variables from 40 counties from the period from 2011 to 2015. All those three tables show for summary statistic for raw violent crime rates and its explanatory variables at different time line.

Table 3.4 shows the simple correlations between violent crime rates and explanatory variables in logged form from 2007 to 2015. The table shows that the Gini coefficient is least correlated with violent crime rates. Poverty and high school dropout rates have a stronger positive correlation with violent crime rates among the explanatory variables. Per capita income has a stronger negative correlation with violent crime rates. Among potential explanatory variables, per capita income is the most strongly positive correlated with female employment rates and density, and per capita income is the most strongly negative correlated with unemployment rates and poverty rates. Female employment rates are strongly negatively correlated unemployment rates and high school dropout rates.

Table 3.5 shows simple correlation between violent crime rates and explanatory variables in logged form from 2007 to 2010. During this period, the Gini coefficient, density and police officer ratios have a stronger positive correlation with violent crime rates among the explanatory variables. Per capita income and female employment rates have a negative correlation with violent crime rates. Among potential explanatory variables, per capita income is the most strongly positive correlated with female employment rates. Unemployment rates is strongly posi-

tive correlated with poverty rates. High school dropout rates is the most strongly negative correlated with female employment rates. Per capita income is negative correlated with poverty rates, high school dropout rates, young males aged 15 to 34 ratios and unemployment rates. Poverty rates is negative correlated with female unemployment rates.

Table 3.6 shows simple correlation between violent crime rates and explanatory variables in logged form from 2011 to 2015. This tables shows that the Gini coefficient is weakly correlated with violent crime rates. Poverty rates and police officer ratios have a stronger positive correlation with violent crime rates among the explanatory variables. Per capita income and female employment rates have a negative correlation with violent crime rates. Per capita income is the most strongly positive correlated with female employment rates, and female employment rates is the most strongly negative correlated with unemployment rates and high school dropout rates. Unemployment rates are strongly positively correlated with high school dropout rates, and police officer ratios are strongly positively correlated with density. Per capita income is strongly negatively correlated with unemployment rates and poverty rates.

Table 3.4: Pairwise Correlation 2007-2015

variables	vcr	gini	une	pov	hsd	ymr	pof	pci	den	fer
vcr	1									
gini	0.011	1								
une	0.189	-0.251	1							
pov	0.388	0.087	0.528	1						
hsd	0.361	-0.167	0.514	0.326	1					
ymr	0.257	-0.056	0.203	0.430	0.374	1				
pof	0.274	0.261	-0.221	-0.019	0.007	0.115	1			
pci	-0.357	0.501	-0.659	-0.618	-0.603	-0.465	0.105	1		
den	0.014	0.321	-0.398	-0.444	-0.251	-0.085	0.161	0.645	1	
fer	-0.213	0.311	-0.711	-0.554	-0.695	-0.333	0.220	0.775	0.557	1

Note: All variables in logs.

vcr-violent crime rates. gini-Gini Coefficient. une-unemployment rates. pov-poverty rates. hsd-high school dropout rates. ymr-young males aged 15 to 34 ratios. pof-police officers ratios. pci-per capita income. den-population density. fer-female employment ratios.

Table 3.5: Pairwise Correlation 2007 - 2010

variables	vcr	gini	une	pov	hsd	ymr	pof	pci	den	fer
vcr	1									
gini	0.201	1								
une	0.017	-0.093	1							
pov	0.157	0.127	0.517	1						
hsd	0.189	-0.087	0.463	0.382	1					
ymr	0.04	-0.097	0.090	0.360	0.370	1				
pof	0.222	0.306	-0.181	0.136	-0.144	0.092	1			
pci	-0.153	0.442	-0.492	-0.642	-0.558	-0.511	0.039	1		
den	0.257	0.440	-0.187	-0.146	-0.19	-0.118	0.188	0.489	1	
fer	-0.011	0.267	-0.698	-0.508	-0.758	-0.431	0.173	0.730	0.385	1

Note: All variables in logs.

vcr-violent crime rates. gini-Gini Coefficient. une-unemployment rates. pov-poverty rates. hsd-high school dropout rates. ymr-young males aged 15 to 34 ratios. pof-police officers ratios. pci-per capita income. den-population density. fer-female employment ratios.

Table 3.6: Pairwise Correlation 2011 - 2015

variables	vcr	gini	une	pov	hsd	ymr	pof	pci	den	fer
vcr	1									
gini	0.012	1								
une	0.179	-0.308	1							
pov	0.401	-0.031	0.547	1						
hsd	0.278	-0.178	0.670	0.396	1					
ymr	0.207	0.042	0.277	0.462	0.351	1				
pof	0.311	0.387	-0.100	-0.034	-0.009	0.071	1			
pci	-0.259	0.573	-0.628	-0.652	-0.525	-0.367	0.339	1		
den	0.031	0.423	-0.245	-0.141	-0.216	0.118	0.670	0.520	1	
fer	-0.231	0.432	-0.702	-0.599	-0.735	-0.263	0.270	0.783	0.465	1

Note: All variables in logs.

vcr-violent crime rates. gini-Gini Coefficient. une-unemployment rates. pov-poverty rates. hsd-high school dropout rates. ymr-young males aged 15 to 34 ratios. pof-police officers ratios. pci-per capita income. den-population density. fer-female employment ratios.

### 3.3 Methodology

The model employed includes nine potential explanatory variables that are correlated with violent crime. All variables are in logged form in order to avoid outliers. The model is to be estimated as follows:

$$\ln(y_{it}) = \alpha + \beta \ln(X'_{it}) + \mu_i + \nu_{it} \quad (3.1)$$

where  $\ln(y_{it})$  is transformed to natural log value on total violent crime rates for county  $i$  in year  $t$ .  $\ln(X_{it})$  is transformed to natural log values on vectors of explanatory variables for county  $i$  in year  $t$ .  $\beta$  is the coefficient of the independent variables.  $\alpha$  is a constant.  $\mu_t$  is an unobserved effect for counties in different year, and errors are independent identically distributed.  $\nu_{it}$  is error terms (Wooldridge, 2009).

I expect the Gini coefficient, unemployment rate, the ratio of young males aged 15 to 34, high school dropout rates, poverty rates, female employment rates and density to have a positive affect on violent crime. Kang (2018) mentions that young males have higher crime rates because crime has a higher pecuniary payoff

than their minimum wage. The reason is that young people have higher dropout rates from high school, and therefore have less opportunity in the labor market. Since crime promises higher pecuniary payoffs, they would be more likely to take the risk of getting caught. People who are in poverty need more income and as such, criminal activity will attract people in poverty. When a female is living with a potential offender and she has a job, then she will not have time to look after the potential offender. As a result, the potential offender is more likely to commit crime. High population density increases opportunities to potential criminals. On the other hand, I expect ratios of police officers and per capita income to have a negative effect on violent crime. The more police officers there are in a community, the greater the effect they will have in the community.

In the following estimations, I use a pooled OLS estimator to test two time periods, which assumes a constant intercept and slopes regardless of time period. Then, I estimate a fixed-effects estimator for two time periods, which explores the relationship between dependent variables and explanatory variables within a time period. The fixed-effects estimator is more efficient than the random-effects estimator and is designed to study the causes of changes within an entity by conducting a Hausman test.

Before running the regressions, I search for non-stationary in any of the variables. I find that high school dropout rates, per capita income and ratios of police officers are non-stationary, the rest of the variables are stationary, therefore, all variables used in regression are in logged transform. After using unit root test, all logged variables are stationary.

# Chapter 4

## Results

### 4.1 Pooled Ordinary Least Square (OLS)

The pooled ordinary least square (OLS) regression is employed for 2 periods. Period 1 is from 2007 to 2010 that includes the Great Recession, and period 2 is from 2011 to 2015 that is part of the economic recovery period. First, I would like to examine if the slopes of regressors are the same across different time periods. As such, the Chow test is employed. The null hypothesis is that all slopes of regressors are the same across different time periods, and the alternative hypothesis is that at least one slope of regressors is different from all slopes of regressors in different time periods. If null hypothesis is rejected, panel data is not poolable. In other words, data in different time periods have their own slope. The restricted sum of squared residuals ( $SSR_r$ ) is 13.01, which is from running a pooled regression with different time intercepts for period 1, and the unrestricted sum of squared residuals ( $SSR_{ur}$ ) is sum of sum of squared residual from running a regression for each year and is 10.60. There are 9 explanatory variables in 4 years for 40 counties, then  $F = 1.02$  and  $p\text{-value} = 0.44$ . I fail to reject the null hypothesis, and conclude that all the slopes are the same over 9 years and the panel data are poolable. The fixed effect or random effect can appeal it. For period 2, the restricted sum of squared residuals ( $SSR_r$ ) is 17.6, and the unrestricted sum of



squared residuals ( $SSR_{ur}$ ) is 16.3. Since there are 9 explanatory variables in 5 years for 40 counties, then  $F = 0.33$  and  $p\text{-value} = 0.99$ . I also fail to reject the null hypothesis of poolablility. Second, testing heteroskedasticity of errors for period 1, I estimated a chi-square of 6.78 and a  $p\text{-value} = 0.01$  that is smaller than the critical  $p\text{-value}$  at 5% significant level, which indicates the presence of heteroskedasticity. Since OLS's assumed error terms are independent and identically distributed, I obtain heteroskedasticity-robust standard errors to correct biased error terms and to estimate accurate  $p\text{-values}$  (William, 2015). Period 2's chi-square is 1.83, and  $p\text{-value} = 0.18$  that is greater than the critical  $p\text{-value}$  at 5% significant level. I fail to reject null hypothesis that indicates standard errors are homoskedasticity.

I use pooled ordinary least squares (OLS) with robust standard errors to test data in a logged version, which reduced the effect of outliers. According to Table 4.1 for period 1, I notice that high school dropout rates, female employment rates, and population density have a positive significant effect on violent crime rate at a 5% significant level. Young males aged 15 to 34 and per capita income have a negative significant effect on violent crime rates at a 5% significant level. For period 2, poverty rates, high school dropout rates, police officer ratios, and population density have a positive and significant effect on violent crime rates at a 5% significant level. Unemployment rates and per capita income have a negative and significant effect on violent crime rates at a 5% significant level. Young males aged 15 to 34 have a negative and significant effect on violent crime rates at a 10% significant level. The Gini coefficient does not have any significant effect on violent crime rates.

The findings of the OLS estimates partially support my assertion that an increase in high school dropout rates and population density result in an increase in violent crime rates and that increasing per capita income will decrease violent crime rates for both periods. However, the following findings are contrary with my assertion. The increase ratios of police officers are correlated with the increase in violent crime rates because areas with more criminal activity will need more po-

lice officers. Young males aged 15 to 34 have a negative and significant effect on violent crime rates. In this data, the amount of young males aged 15 to 34 has an ambiguous effect because it includes all races and education levels. The Gini coefficient does not have any effect on violent crime for both of periods. Neither unemployment rates nor poverty rates have any effect on violent crime rates during the Great Recession; however, during the economic recovery period, unemployment rates have a negative effect on violent crime rates, and poverty rates have a positive effect on violent crime rates. Female employment rates have a positive effect on violent crime rates for period 1, but do not have any effect during period 2. The pooled OLS model fits the data at 5 percent significance level where F statistics is 19.40 (period 1) and 15.90 (period 2) and both periods of the  $p$ -value are zero.  $R^2$  is around 0.4 for both periods, which indicates that explanatory variables explain 40% of variance in violent crime rates, and I conclude is good for cross sectional data. Although pooled OLS fits the data well, each year has different initial violent crime rates. Pooled OLS denies individual effect (heterogeneity), as a result, the pooled OLS model is rejected.

Table 4.1: Regression Results for Violent Crime Rates

variable	Pooled OLS (2007-2010)	Pooled OLS (2011-2015)
Gini coefficient	0.97 (0.89)	-0.45 (0.65)
unemployment rates	-0.19 (0.14)	-0.20 (0.09)**
poverty rates	0.13 (0.27)	0.67 (0.14)*
high school dropout rates	0.31 (0.01)*	0.28 (0.10)*
young male ratios	-0.49 (0.24)	-0.40 (0.20)***
police officer ratios	0.17 (0.10)	0.27 (0.09)*
per capita income	-1.03 (0.31)*	-0.48 (0.24)**
density	0.12 (0.03)*	0.09 (0.02)*
employed female ratios	1.09 (0.43)	0.33 (0.33)
Constant	1.87 (4.79)	4.11 (3.77)

Note: Robust standard errors in parentheses for Pooled OLS (2007-2010).

Standard errors in parentheses for pooled OLS (2011-2015).

\* Significant at 1% level

\*\* Significant at 5% level

\*\*\* Significant at 10 % level

## 4.2 Fixed Effect Model

Fixed-effect estimator is employed for 2 time periods because I want to know the difference between effects of potential explanatory variables have on violent crime separately during the Great Recession and the economic recovery period. The first time period is from 2007 to 2010 (Great Recession period) and second time period is from 2011 to 2015 (economic recovery period). During the 1st time period, the chi square and  $p$ -value for heteroskedasticity test are 3580 and 0.00, which indicates presence of heteroskedasticity. Huber/White estimators are employed to obtain heteroskedasticity-robust standard errors. For the 2nd time period, the chi-square and  $p$ -value for heteroskedasticity test are 18067 and 0.00, which indicates the presence of heteroskedasticity. By using Hausman test for both time periods, I conclude that fixed effect model should be used.

By comparing the results across different periods using pooled OLS and fixed effect models, I note that my results changed during the period of the Great Recession. The Gini coefficient and high school dropout rates have a positive and significant effect on violent crime rates at a 5% significant level. A 1% increase in the Gini coefficient will increase violent crime rates by 2.24%, and a 1% increase in the high school dropout rate will increase violent crime by 0.29%. Per capita income has a positive and significant effect on violent crime rates at a 10% level. A 1% increase in per capita income will increase violent crime rates by 1.6%. Unemployment rates and police officers ratios have a positive effect on violent crime rates at a 15% level, but this effects are not significant. Young males aged from 15 to 34 and population density appear to no longer have a statistically significant impact on violent crime rates. During economic recovery period, only population density shows negative and significant effect on violent crime. A 1% increase in population density will decrease violent crime by 3.82%. The rest of explanatory variables do not show any significant effect on violent crime at all. The most interesting finding

from fixed-effect estimator is that the Gini coefficient and high school dropout rates have a positive and significant effect on violent crime during the Great Recession, but do not have any significant effect on violent crime during the economic recovery period; on the other hand, density has a positive and significant effect on violent crime during the economic recovery period, but does not have any significant effect on violent crime during the Great Recession.

Table 4.2: Regression Results for Violent Crime Rates

variable	Fixed effect (2007-2010)	Fixed effect (2011-2015)
Gini coefficient	2.24 (0.68)*	0.04 (0.29)
unemployment rates	0.55 (0.36)	-0.07 (0.26)
poverty rates	-0.22 (0.17)	0.01 (0.11)
high school dropout rates	0.29 (0.14)**	-0.13 (0.10)
young male ratios	-0.22 (0.26)	0.38 (0.68)
police officer ratios	0.24 (0.17)	-0.00 (0.08)
per capita income	1.60 (0.95)***	0.05 (0.50)
density	-1.18 (1.77)	-3.83 (1.32)*
employed female ratios	-0.19 (0.40)	-0.01 (0.20)
Y2008	-0.08 (0.13)	
Y2009	-0.25 (0.23)	
Y2010	-0.38 (0.28)	
Y2012		0.05 (0.04)
Y2013		0.04 (0.08)
Y2014		0.05 (0.14)
Y2015		0.13 (0.20)
Constant	-17.30 (16.60)	22 (7.50)

Note: Robust standard errors in parentheses for Fixed Effect(2007-2010) and Fixed Effect(2011-2015).

\* Significant at 1% level

\*\* Significant at 5% level

\*\*\* Significant at 10 % level

# Chapter 5

## Conclusion

The results from the pooled OLS model show that increases in high school dropout rates, population density, and ratios of police officers are associated with violent crime rates. This result appears to partially support my initial expectation that high population density will increase criminal activities. Areas with more criminal activities require more police presence. The Gini coefficient does not have significant effect on violent crime which appears contrary to my initial expectation.

A robust positive relationship between the Gini coefficient and violent crime is estimated from the fixed-effect model and reflects the direction of these two variables from 2007 to 2010. This result is the same as Kelly's (2000) finding that inequality has a strong and robust impact on violent crime. However, Gini coefficient does not have any effect on violent crime from fixed-effect model during economic recovery period from 2011 to 2015. This result is consistent with Chen and Keen (2014), who find income inequality does not have any effect on any category of crime. I do not find any result that indicates that increase of the Gini coefficient will increase violent crime.

The high school dropout rate shares a positive significant relationship with violent crime during the Great Recession, but does not appear to have any relationship during the economic recovery period. This suggests that during great recession, high school dropouts have even lesser opportunities in labor market compared to normal

economic periods. Because criminal activities can result in high payoff, high school dropouts are more likely to commit crime. The economic recovery resulted in more opportunities in the labor market, even for low skilled people many of which are high school dropouts.

In addition, unemployment rates and police officer ratios are positive correlated with violent crime rates, but they are not significant effect to violent crime rates during the Great Recession period. Unemployment rates were very high during Great Recession and people become frustrated due to their financial situation, and many go into debt. As a result, these people might have had an incentive to commit crime. With higher crime rates, more police officers have to be hired.

For future research, I should include different races as dummy variables in the model, then I can distinguish different race groups on violent crime rates. Also, the time period of data should be extended. Some data, such as violent crime rates and young males aged from 15 to 34 in counties from neighboring states should be collected because people may travel to different counties and commit crime, and as a result, the crime rate will be over estimated.

# Bibliography

Brush, J. (2007). Does Income Inequality Lead to More Crime? A comparison of cross-sectional and time-series analyses of United States counties. *Economic Letters*, 96 p(2), 264-268.

Chen, W., and Keen, M. (2014). Does inequality increase crime? The effect of income inequality on crime rates in California counties. *Working Paper*.

Chintrakarn, P., and Herzer, D. (2012). More inequality, more crime? A panel cointegration analysis for the United States. *Economic Letters*. 116(3), 389-391.

Choe, J. (2008). Income Inequality and Crime in the U.S. *Economic Letters*. 101(1), 31-33.

Durante, A. (2012). Examining the Relationship between Income Inequality and Varieties of Crime in the United States. *A Senior Thesis in Economics*.

Fajnzylber, P., Lederman, D., and Loayza, N. (2002). Inequality and Violent Crime. *Journal of Law and Economics*. 45(1), 1-39.

Gini coefficient.(n.d). In *Wikipedia*. Retrieved May 31, 2018, from [https://en.wikipedia.org/wiki/Gini\\_coefficient](https://en.wikipedia.org/wiki/Gini_coefficient)

Kanazawa, S., and Still, M. (2000). Why Men Commit Crimes (and Why They Desist). *Sociological Theory* 18(3), 434-47.

Kelly, M. (2000). Inequality and Crime. *Review of Economics and Statistics* 82(4):530-539.

Neumayer, E. (2005). Inequality and Violent Crime: Evidence from Data on Robbery and Violent Theft. *Journal of Peace Research*. 42(1), 101-112.

Kang, S. (2018). Why do young men commit more crimes? *Economics of Crime*. Hanyang University.

Weatherburn, D. (2001). What Causes Crime?. *BOCSAR NSW Crime and Justice Bulletins*, 11.

William, R. (2015). Heteroskedasticity. [www3.nd.edu/~rwilliam](http://www3.nd.edu/~rwilliam). University of Notre Dame.

Witt, R., and Witte, A. (2000). Crime, Prison, and Female labour Supply, *Journal of Quantitative Criminology*, 16(1), 69 - 85.

Wooldridge, J. (2009). The Introductory Econometrics: *A Modern Approach*. OH: South Western, Cengage Learning, Print.



# Appendix A

## Appendix

Table A.1: Data Source

Variable	Defination	Source
violent Crime rate	Violent Crime rate per 10,000 people	CJSC
police officer ratio	Number of police officer per 10,000 people	CJSC
population density	Population per square mile	CSAC
unemployment rate	Percent of labor force that is unemployed	U.S. Bureau of Economic Analysis
poverty rate	Percent of population aged 15 to 64 in poverty	U.S. Bureau of Economic Analysis
per capita income	Mean personal income	U.S Bureau of Economic Analysis
Gini coefficient	Pre-Tax, Pre-Transfer Gini Coefficient	American Fact Finder
high school dropout rate	Percent of population not have high school diploma or equivalence	American FactFinder
young male share	Percent of population Between ages 15 and 34	American FactFinder
female employment rate	percent of employed female among whole population	American FactFinder

Table A.2: Hausmen test

	Chi Square	P-value
Pooled OLS (2007-2010)	6.78	0.0092
Pooled OLS (2011-2015)	1.83	0.1761
Fixed-Effect (2007-2010)	3580.14	0.0000
Fixed-Effect (2011-2015)	18067.54	0.0000

Table A.3: Stationary

variables	z-statistics	p-value
Violent crime rate	10.7	0.00
Gini	8.15	0.00
Unemployment rate	2.16	0.02
Poverty rate	11.2	0.00
high school dropout rate	8.72	0.00
Young male	13.1	0.00
police officer	11.7	0.00
per capita income	23.5	0.00
density	25.9	0.00
employed female	6.60	0.00