This thesis, submitted by Jose Ramos in partial fulfillment of the requirements for the Degree of Master of Science in Applied Economics from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

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July 24, 2014
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PERMISSION

Title	Estimating the Effect of Poverty on Violent Crime
Department	Economics
Degree	Master of Science in Applied Economics

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Jose Ramos
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ABSTRACT

I examine the effect of poverty on violent crime in the United States during the years between 2000 and 2012. My analysis contributes to the literature by utilizing state-level poverty rates as the main variable of interest, and directly studying its effect on violent crime rates. I use panel data and a group (state) and time fixed effects estimation method in the study. The results confirm prior research that concludes that poverty does not have a significant effect on violent crime.

CHAPTER I

INTRODUCTION

In the literature, some researchers have developed a theory of crime by creating economic models that explain illegal behavior. Others have focused on analyzing historical data to measure and identify the determinants of crime. The effect of the business cycles on various measures of crime has also been an important part of the research on this topic.

However, not much research has focused specifically on the relationship between poverty and violent crime. For example, Huang, Laing and Wang (2004) propose a dynamic general equilibrium model to understand the link between crime and poverty, but poverty rates do not figure anywhere in their model. Bjerk (2010) found a connection between individual poverty and property and violent crimes, where his focus was neighborhood poverty and economic segregation. The poverty rate was not the main independent variable in Bjerk's study. A brief review of the related literature, which we detail in chapter II, suggests that poverty has been indirectly linked to crime rates via proxy economic indicators, such as the per capita income and the unemployment rate.

In the popular mass-media on the other hand, there are reports supporting the link between crime and poverty. For example, Blaine and Sauter (2013) suggest the existence of a relationship between violent crime and poverty in their well-publicized article "The Most Dangerous States in America", which was reproduced by several news outlets.

They pointed out that “of the 10 states with the highest rates of violent crime, eight have lower rates of adults with bachelor’s degrees, and most of them had median income levels below the national figure in 2012”[1].

A quick glance at the poverty and violent crime rate data for the years 2000 – 2012 leaves us with a taste of uncertainty between these two factors.

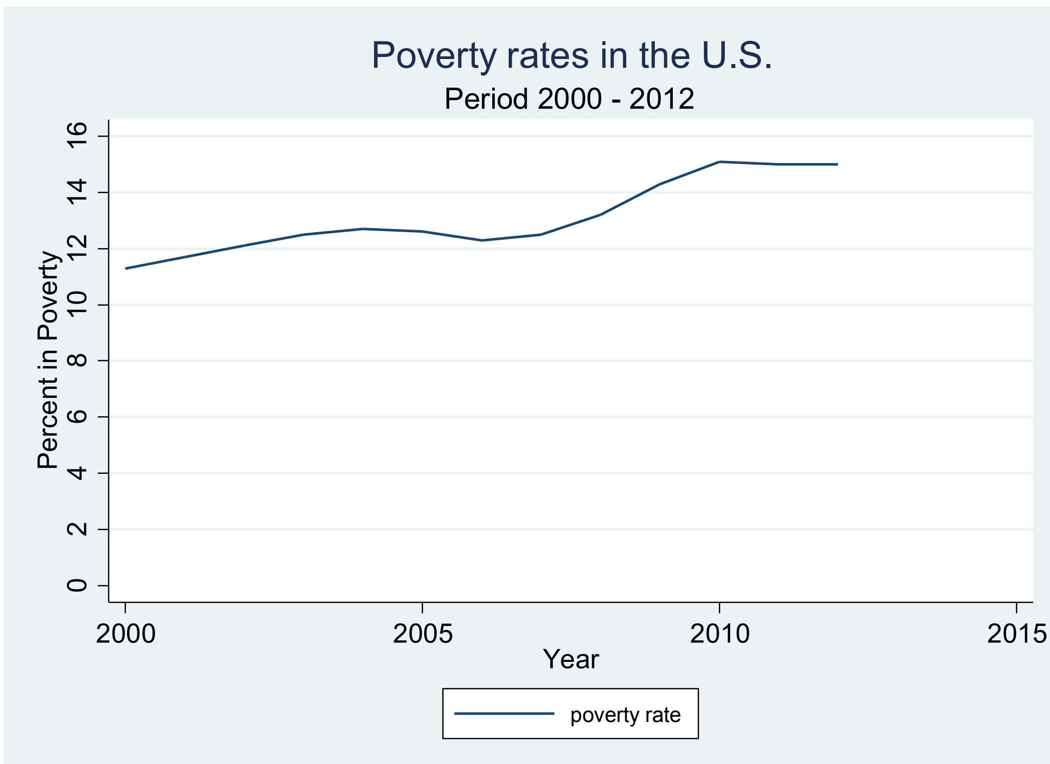

Figure 1. Poverty rates in the U.S. Source: U.S. Bureau of the Census.

1 Blaine, C. & Sauter, M. (October 4, 2013). The Most Dangerous States in America. 24/7 Wall St. Available at: http://247wallst.com/special-report/2013/10/04/the-most-dangerous-states-in-america

During the 13-year period covered by Figure 1, poverty rates have been consistently increasing in the United States, from a low of 11.3% in the year 2000 to a high of 15% in 2012. The highest jump seems to have occurred in 2007/2008 and the rate stabilized around the year 2010. This behavior, which officially started in December of 2007 and ended in June of 2009, coincided with the worst of the great recession.

When we look at different types of violent crimes, which are displayed in Figure 2, we observe a trend that is in the opposite direction during that same period.

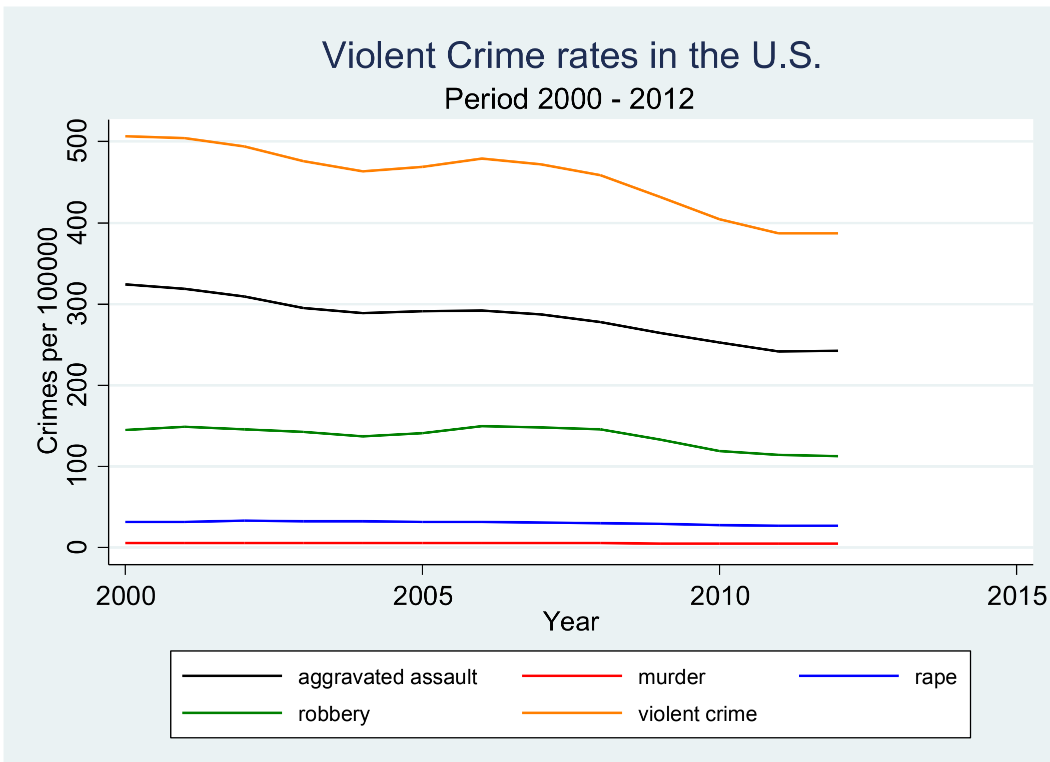

Figure 2. Violent Crime rates in the U.S. Source: Federal Bureau of Investigation Uniform Crime Reports (UCR)

For example, the overall violent crime rate decreased by roughly 20% between 2000 and 2012. Among others, rape and murder rates remained fairly constant, while robbery and aggravated assault rates dropped, especially the latter one. The reported data does not seem to support the positive link between poverty and violent crimes, as media outlets tend to propagate. There are certainly other factors at work that could explain the dramatic drop in violent crime in the last decade, and they could be possibly "cancelling" out the negative effect of poverty. A counterintuitive representation of our data is the comparison between the changes in violent crime rates and law enforcement personnel. As we can see from Figure 3 they both decreased in the period between 2000 and 2012.

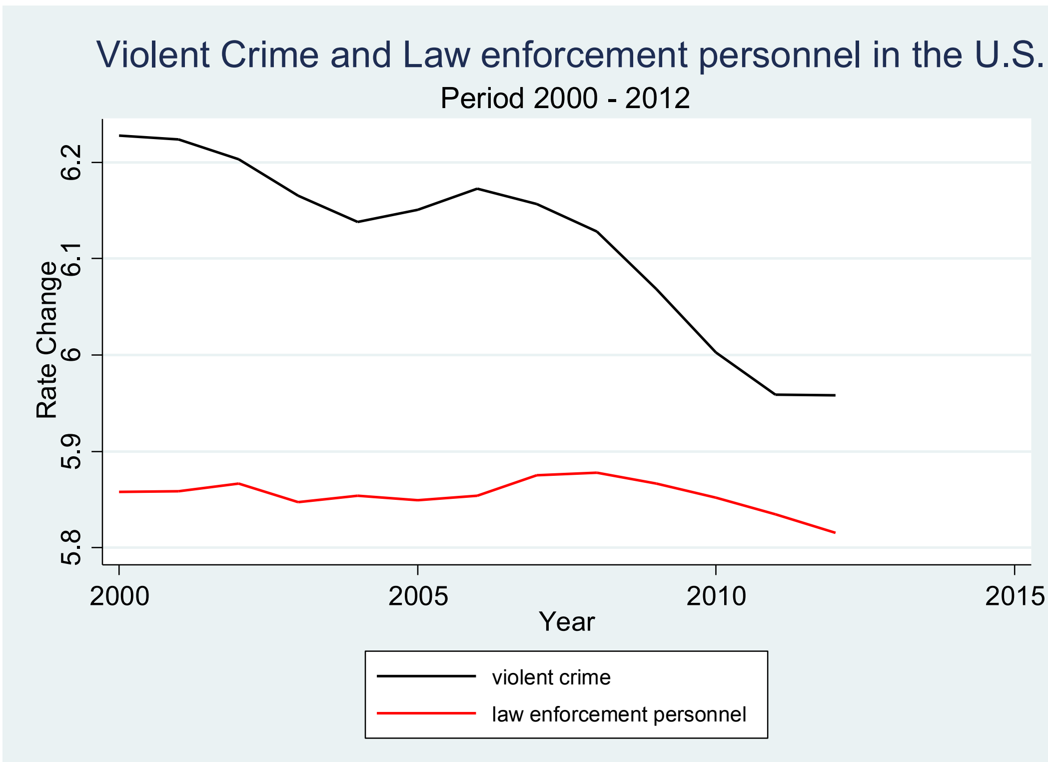

Figure 3. Change in Violent Crime and Law Enforcement personnel in the U.S.

Source: Federal Bureau of Investigation

In this research, I intend to fill the gap in the literature and study the effect poverty has on violent crime at an aggregate level, with poverty rates as the central variable of interest. Given the initial direction of the data, it is possible that poverty rates may not be an appropriate variable to use at the aggregate level, and instead a different economic indicator may have to be selected as a proxy for poverty levels.

My data-driven approach relies on contemporary econometric methods and existing theory. The expected results are that the poverty rates are strongly related to robberies but less so to aggravated assaults, murders and rapes. Also, the overall relationship between poverty and violent crime rates should not be statistically significant.

As a resident of Tennessee, the state with the highest violent crime rate in the country in 2012, this topic is of particular interest to me. If it is found that poverty does have a significant positive effect on violent crime, then the implication for policy-making is that reduction in poverty levels should go together with law enforcement initiatives in the pursuit of combating and reducing violent crime in the state. On the other hand, if poverty has a negative effect on violent crimes or no effect at all, efforts should be made to identify and study other variables that could have an impact in lowering the violent crime rates in the state.

CHAPTER II

LITERATURE REVIEW AND BACKGROUND

Among the numerous research that studies crime using alternative economic methods, probably the most widely quoted paper is "Crime and Punishment: an Economic Approach" by Gary Becker (1968). Becker (1968) developed a model of crime to find optimal public and private policies to combat illegal behavior using economic analysis. According to Becker's model, criminal acts result from a rational decision based on a cost-benefit analysis. As noted by Fajnzylber, Lederman and Loayza (2002), the expected benefits are given by the difference between the loot and the opportunity cost of crime; and the costs are given by the penalties imposed to apprehended criminals. The model's deterrence theory is that an increase in a typical offender's chance of being caught decreases crime. This intuitive prediction is at the core of many papers that mention Becker's research as seminal and as the starting point of analyzing crime using economic methods.

Departing from Becker's original model, Cantor and Land (1985) focused their research in studying whether economic conditions had an effect on crime. Using annual time-series data for the United States and the unemployment rate as a proxy for economic activity, they found a significant effect of the business cycles on crime. Their theoretical model, which used the criminal motivation and criminal opportunity effects, became the foundation for two decades of empirical research into the relationship between economic conditions and crime. Social strain and social controls are two of the sociological theories that support the relationship between criminal motivation and economic conditions.

Social strain is “the pressure individuals feel to reach socially determined goals” (Arvanites & Defina, 2006, p. 141). When these goals become out of reach via legal means, individuals are pressured to make use of illegitimate means to achieve them. For example, if we measure success in our society by the level of material wealth, an individual must have a good paying job or another source of legitimate income to be successful. When economic conditions are deteriorating, “success” becomes more elusive. Therefore, criminal motivation can arise from social strain.

Social control is usually described as “the ability of society to regulate its members” (Arvanites & Defina, 2006, p. 142). The lives of people are structured by work, parents, friends, stores, churches, libraries, etc. that provide routines, expectations and social support networks. If a person loses his/her job, the social aspect of work is greatly reduced. These institutions depend on the support of the people, and when economic conditions worsen, people cannot provide them with the same level of resources they are used to, weakening them. A result of that fact is that social control diminishes and criminal activities rise.

Besides motivation, the economic conditions also influence the opportunity to commit crimes. For example, in an improving economy, more wealth is generated and people are busy working or taking part in activities away from their homes. This creates the opportunity for criminals to target empty homes.

Based on the prior definitions Cantor and Land (1985) conclude that the criminal opportunity effect will run counter to the criminal motivation effect.

Prior to Cornwell and Trumbull's (1994) economic model of crime, estimating and testing what type of economic models was done using aggregate data, usually at the state or national level, with cross-sectional econometric techniques. Cornwell and Trumbull (1994, p. 360) argued that "ideally, the economic model of crime should be estimated with individual level data since the model purports to describe the behavior of individuals". Instead, they became one of the first to use county-level data for a lower level of aggregation, as well as panel data to control for unobserved heterogeneity.

In a related paper, Gould, Weinberg and Mustard (2002) examine the impact of both wages and unemployment on crime and found that even though those two factors are significantly related to crime, wages played a larger role in the crime trends in the last few decades. Their research not only focused on property crimes but also included violent crimes. They used county-level panel data and instrumental variables in their analysis.

Levitt (2004) studies the reasons why crime fell in the 1990s. He identifies four factors that appear to explain the drop in crime: increased incarceration, more police, the decline of crack and legalized abortion. Other factors often cited as important reasons for the decline do not appear to have played an important role: the strong economy, changing demographics, innovative policing strategies, gun laws and increased use of capital punishment.

Arvanites and Defina (2006) reexamine Cantor and Land's (1985) work to analyze the influence of business cycle fluctuations on street crime. Instead of using the unemployment rate as a proxy for economic strength, as previous studies had done, Arvanites and Defina (2006) determine that the inflation-adjusted per capita gross state product is a better measure of business cycle conditions. Using fixed-effects panel models, they find that a strong economy has a negative and statistically significant effect on property crimes and robbery - the only violent crime with a purpose of financial gain. The conclusion that the "stronger economy of the 1990s contributed to reductions in crime" (Arvanites & Defina, 2006, p. 161) is in stark contrast to Levitt's (2004) assertion that the strong economy did not play an important role in the decline of crime during the same period.

Violent crime was specifically targeted by Rosenfeld (2009), who proposes that the economy stimulates violent crime indirectly through its effect on acquisitive crime. He questions social strain and social control theories because they imply that violent and property crimes are spuriously associated and they don't acknowledge the possibility of a causal connection between the two types of crime. Citing prior research by LaFree (1998), Rosenfeld (2009) notes that property and violent crime rates track one another closely over time, and that involvement in property crime is an important risk factor for violent victimization, including homicide. The existence of "underground" markets, where stolen goods are traded, contribute to the rise of violent crimes because violence is the main mode of enforcement of agreements in this space. Rosenfeld (2009) uses fixed-effects panel models of change in acquisitive crime and homicide rates to evaluate his hypothesis. The findings include a significant effect of acquisitive crime on homicide, which put pressure on studies that deny that economic conditions do not have an effect on violent crimes other than robbery.

Interestingly, poverty is not directly used as one of the principal factors affecting crime rates in the literature reviewed. Rather, it is implicit in the economic factors that are part of the various studies on crime. Bjerk (2010) is the only work that comes close with his model of crime, poverty and neighborhood composition. He concludes that "violent criminal behavior of poor individuals may be more influenced by their neighborhood economic characteristics than is the violent criminal behavior of non-poor individuals" (Bjerk, 2010, p. 243).

Therefore, my research not only complements the existing literature but also extends it to a new direction.

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CHAPTER III

DATA AND METHODOLOGY

Ideally, individual level data should be used when estimating an economic model of crime, since crime is the result of individual behavior. Data at the county or zip codes or metropolitan area level are preferred to aggregate level, such as state or national data. Due to difficulty in obtaining reliable annual poverty rate data prior to 2005, as well as data for other variables of interest, this paper uses state-level data for empirical work.

Data for this study covers the 13 year period 2000 – 2012 for each of the 50 states. Because the District of Columbia technically is not a state, it is excluded from the dataset. A more appropriate place to include Washington D.C. should be a study of crime comparing different metropolitan areas.

The FBI's Uniform Crime Report (UCR) is the source of data on violent crime rates, both for aggregate and individual categories (robbery, assault, murder, etc.). The annual report "Crime in the United States", from the same agency, provided information on state law enforcement personnel. The Census Bureau is the source of data for poverty rates, population growth rates, population aged 15-24, race and Hispanic origin, and educational attainment levels. The Bureau of Economic Analysis is the source of information on state GDP per capita and the National Bureau of Economic Research

(NBER) provided data on business cycles reference dates. In all, we have 650 observations per variable for a total of more than 7000 observations to work with.

Besides poverty rates, additional explanatory variables were selected based on prior studies and theories from the existing literature. State GDP per capita, state law enforcement per 100,000 population and population aged 15-24, also known as the "crime age", were selected following Rosenfeld's (2009) study on economic conditions and homicides. Arvanites and Defina (2006) also include a similar "crime age" variable in their model although their age range was 17-24. Gould, Weinberg and Mustard (2002) make use of multiple variables related to educational attainment when studying the relationship between crime and labor market conditions for less educated men. The variable population growth rate is included in my model based on the assumption that a larger population could result in more crimes reported, but not necessarily greater crime rates. Finally, race and ethnicity variables have been used by Arvanites and Defina (2006) and by Cornwell and Trumbull (1994). The categories selected in this paper, non-Hispanic white, non-Hispanic black and Hispanic, are the ones used by the Bureau of Justice Statistics in their prisoner census data.

The following equation (1) is our preliminary regression specification:

$$\mathbf{VC_{it} = \beta_0 + \beta_1 POV_{i,t} + \beta_2 POV_{i,t-1} + \beta_3 GDP_{i,t} + \beta_4 POP_{i,t} + \beta_5 AGED_{i,t} + \beta_6 LAWENF_{i,t} + \beta_7 HSGRAD_{i,t} + \beta_8 WHT_{i,t} + \beta_9 BLK_{i,t} + \beta_{10} HIS_{i,t} + U_{i,t}} \quad \mathbf{(1)}$$

where the main dependent variable $\mathbf{VC_{i,t}}$ is the violent crime rate in state i at time t. Among the set of main explanatory variables, $\mathbf{POV_{i,t}}$ is the poverty rate in state i at time t, $\mathbf{POV_{i,t-1}}$ is the lagged poverty rate in state i at time t-1, $\mathbf{GDP_{i,t}}$ is the GDP per capita in 2005 chained dollars in state i at time t, $\mathbf{POP_{i,t}}$ is the population growth rate in state i at time t expressed as a percentage, $\mathbf{AGED_{i,t}}$ is the percentage of the population aged 15-24 years in state i at time t, $\mathbf{LAWENF_{i,t}}$ is the law enforcement personnel per 100,000 in state i at time t, $\mathbf{HSGRAD_{i,t}}$ is the percentage of the population 25 years and older that graduated high school in state i at time t, $\mathbf{WHT_{i,t}}$ is the percentage of the population that is non-Hispanic white in state i at time t, $\mathbf{BLK_{i,t}}$ is the percentage of the population that is non-Hispanic black in state i at time t, $\mathbf{HIS_{i,t}}$ is the percentage of the population that is Hispanic of any race in state i at time t, and $\mathbf{U_{i,t}}$ is the error term.

Separately, I test regressions (1) for secondary dependent variables for 4 different categories of violent crime: robbery rates (RB_{it}), aggravated assault rates (AA_{it}), murder rates (MU_{it}) and rape rates (RP_{it}). These secondary regressions have the same explanatory variables as Equation 1. The only difference is the dependent variable on the left hand side. Cherry and List (2002) argue that economic models of crime suffered from aggregation bias and it isn't appropriate to pool different crime types into a single decision model. Therefore, running separate regressions for specific categories of violent crime in addition to the aggregate violent crime rate is an effective attempt to address this issue.

All variables included in this study are summarized in Table 1.

Table 1. Variables and summary statistics.

Variables	Description	Obs	Mean	Standard deviation	Min	Max
year	Year	650	2006	3.74	2000	2012
Dependent variables						
vc	Violent crime rate per 100000	650	397.59	169.40	78.20	828.10
aa	Aggravated assault rate per 100000	650	257.42	124.57	42.60	627.00
mu	Murder rate per 100000	650	4.61	2.37	0.60	14.60
rp	Rape rate per 100000	650	33.31	11.34	11.10	93.30
rb	Robbery rate per 100000	650	102.25	56.90	6.80	282.00
Independent variables						
pov	Poverty rate %	650	12.42	3.29	4.50	23.10
lagpov	Lag of poverty rate	600	12.27	3.24	4.50	23.10
gdp	GDP per capita in 2005 chained dollars	650	40538.46	7512.18	26644.00	64900.00
pop	Population growth rate %	650	1.08	1.17	-4.87	11.58
aged	Percent population aged 15-24	650	14.31	0.99	11.89	19.81
lawenf	Law enforcement personnel per 100000	650	324.52	64.91	206.57	557.53
hsgrad	High school graduation rate % for population 25+ years old	650	86.50	3.70	77.10	93.00
wht	Percent population non-Hispanic white	650	73.30	15.15	22.71	96.62
blk	Percent population non-Hispanic black	650	10.01	9.43	0.28	37.02
his	Percent population Hispanic any race	650	9.52	9.55	0.68	46.73

All variables show a certain amount of variation. Poverty rates had a fairly low standard deviation of 3.70, where the lowest poverty rate was 4.50% and belonged to New Hampshire in the year 2000; the highest poverty rate in our data set was 23.10%, which belonged to Mississippi in the year 2009. In those same years, the violent crime rate for New Hampshire was 175.4 and for Mississippi was 286.3. In both instances, well below the mean violent crime rate of 397.59 for the 13-year period between 2000 and 2012. Could this be an indication that there is no relationship between poverty and violent crime? Another variable, the percentage of the population aged 15-24 years, had the smallest standard deviation of 0.99, indicating most of its data is clustered around the mean of 14.31%. Connecticut had the smallest share of its population between ages 15-24 in the year 2000, at 11.89%, while Utah had the largest concentration of young people in the years 2000 and 2001, with 19.82% of its population in that age bracket. The violent crime rates for these states in the year 2000 were 324.7 and 255.7 respectively. The variable per capita GDP had the largest dispersion around its mean, with a standard deviation of 7,512.18. Expressed in 2005 chained dollars, Delaware had the highest per capita GDP in 2007 at $64,900 while Mississippi had the lowest per capita GDP in 2001 at $26,644. In those same years, the violent crime rate for Delaware was 705.4 and for Mississippi was 349.9. This suggests a possible positive relationship between per capita GDP and violent crime rates.

The estimation method selected for this study is the fixed effects method. None of the explanatory variables are time-invariant, a requirement for using this method. Panel data allows us to control for unobserved heterogeneity, which decreases the chance for endogeneity, where the explanatory variable is correlated with the error term of the regression. The fixed effects estimator allows for arbitrary correlation between the unobserved effects and the explanatory variables in any time period (Wooldridge, 2013, Ch. 14). Using changes within each group (states) from our panel, the fixed effects can be eliminated by subtracting the individual means of the variables in the model. The alternative random effects method assumes there is no correlation between the unobserved effects and the explanatory variables. However, as Wooldridge (2013, p. 496) points out, "we cannot treat our sample as a random sample from a large population, especially when the unit of observation is a large geographical unit", which in our case is a state. Because we have data for 13 years, an additional regression that also includes time fixed effects will be tested. This regression results in adding year dummies, except for the first year, to our original state fixed effects regression.

Natural logarithms are applied to our dependent variables and to the explanatory variables real GDP per capita and law enforcement personnel. This helps to achieve stationarity in the time-series part of the data, transform any non-linear distributions and normalize data where non-normal distributions are present (Yearwood & Koinis, 2011). The remaining variables are already given as percentages so there is no need to apply logarithmic transformations. After transformation, the regression equation (1) becomes equation (2):

$$\mathbf{Ln(VC_{i,t}) = \beta_0 + \beta_1 POV_{i,t} + \beta_2 POVi_{,t-1} + \beta_3 Ln(GDP_{i,t}) + \beta_4 POP_{i,t} + \beta_5 AGED_{it} + \beta_6 Ln(LAWENF_{i,t}) +}$$

$$\mathbf{\beta_7 HSGRAD_{i,t} + \beta_8 WHT_{i,t} + \beta_9 BLK_{i,t} + \beta_{10} HIS_{i,t} + U_{i,t} \qquad (2)}$$

Correlation results between violent crime rates and the explanatory variables are presented in Table 2:

Table 2. Correlation diagnostics between violent crime rates and explanatory variables.

	lvc	pov	lgdp	pop	aged	llawenf	hsgrad	wht	blk	his
lvc	1									
pov	0.301	1								
lgdp	0.122	-0.468	1							
pop	0.196	-0.104	0.0434	1						
aged	-0.114	0.040	-0.081	-0.016	1					
llawenf	0.480	0.174	0.224	0.071	-0.049	1				
hsgrad	-0.452	-0.617	0.369	-0.094	0.058	-0.302	1			
wht	-0.553	-0.319	-0.217	-0.183	0.065	-0.421	0.402	1		
blk	0.506	0.375	-0.093	-0.033	-0.098	0.498	-0.530	-0.388	1	
his	0.365	0.239	0.198	0.251	0.001	0.272	-0.288	-0.631	-0.141	1

Violent crime rates have the strongest positive correlation with the percentage of the population that are black (51%), percentage of the population that are Hispanic (37%), law enforcement personnel (48%) and poverty rates (30%). The strongest negative correlation are with the percentage of the population that are white (-55%) and with high school graduation rates (-45%). It is not counterintuitive that more law enforcement personnel is linked to higher violent crime rates. "Previous empirical work suggests that the greater the number of police, the greater the number of reported crimes…this result may be due to a dependency of the size of the police force on the crime rate" (Cornwell & Trumbull, 1994, p. 363). Data for our 13-year period shows that as violent crime rates dropped, the number of police per capita has remained constant or has also dropped slightly. The race and ethnicity variables may be signaling that people of certain race/ethnicity are more exposed to violent crime than others, for example they could live or work in areas that have a higher crime rate. The relationships between violent crime and poverty rates and educational attainment, seem to validate, at least initially, the widespread belief that more poverty breeds more violent crime, and better educational attainment levels help reduce crime.

Among the set of explanatory variables, the highest negative correlations are between the population of Hispanics and whites (-63%), between the black population and high school graduation rates (-53%), and between poverty and high school graduation rates (-62%). On the positive side, the relationships between the black population and the number of law enforcement personnel (50%) and between per capita GDP and high school graduation rates (37%) are the ones that stand out. These results all conform to standard expectations that better education and a stronger economy help reduce poverty, and a better education fuels better incomes. It also points out that the black population is victim of more violent crimes therefore more police resources are dispatched to areas where they live and work. This environment is not conducive to achieving high school graduation rates. And lastly, the population growth of Hispanics is linked directly to the population decline of whites. A high correlation among independent variables can be a sign of multicollinearity. Overall, the highest correlation among our independent variables is the negative 63% between the population of Hispanics and whites, though it can be argued that this level of correlation is not extremely high, such as 75% or more in absolute values. Wooldridge (2013, Ch. 3) emphasizes that it is better to have less correlation among independent variables.

Multicollinearity can be a problem because it can increase the variance of the coefficient estimates and make the estimates very sensitive to minor changes in the model. In other words, we get unstable parameter estimates, which makes it very difficult to assess the effect of explanatory variables on dependent variables. A multicollinearity test is our next logical step before setting up and running our actual regression. Results of that test are shown in Table 3.

Table 3. Multicollinearity diagnostics results of explanatory variables.

Explanatory variable	VIF	Tolerance
pov	2.19	0.456
lgdp	1.94	0.515
pop	1.15	0.872
aged	1.03	0.974
llawenf	1.72	0.583
hsgrad	2.52	0.398
wht	2.87	0.348
blk	3.21	0.311
his	3.27	0.306
Mean VIF	2.21	

Table 3 results suggest that the Variance Inflation Factor (VIF) for our explanatory variables are all less than 3.5. A rule of thumb is that a VIF should be less than 10, and ideally less than 2.5, to not be overly concerned about multicollinearity in our model. The tolerance is defined as 1/VIF, and values of 0.4 (equivalent to a VIF of 2.5) or above should provide us some valid justification for their inclusion. Four out of nine explanatory variables have VIFs above 2.5 but not by much. It is expected to have some degree of correlation among some of our explanatory variables. In this case, the test results do not warrant excluding any of our variables from our regression model.

Notice that we did not include the variable lag of poverty rate in our correlation and multicollinearity tests. The reason being is that this variable is generated from the poverty rate variable and is very likely to have a high correlation coefficient and VIF, which can affect the test results of the other variables and prompt us to incorrectly exclude them from our regression.

CHAPTER IV

RESULTS

Using the model specification from equation (2), we run a within group (state) fixed effects regression for violent crime rates, represented by equation (3):

$$\mathbf{Ln(VC_{i,t}) = \beta_0 + \beta_1 POV_{i,t} + \beta_2 POVi_{,t-1} + \beta_3 Ln(GDP_{i,t}) + \beta_4 POP_{i,t} + \beta_5 AGED_{it} + \beta_6 Ln(LAWENF_{i,t}) +}$$

$$\mathbf{\beta_7 HSGRAD_{i,t} + \beta_8 WHT_{i,t} + \beta_9 BLK_{i,t} + \beta_{10} HIS_{i,t} + A_i + U_{i,t}} \qquad \mathbf{(3)}$$

where the term A_i represents the group (state) fixed effects in state i.

A random effects regression is also estimated and the Hausman test is performed to determine if random effects are appropriate. We test the null hypothesis that the coefficients estimated by the random effects estimator are the same as the ones estimated by the fixed effects estimator. The p-value of 0.000 is significant and it signals we should use fixed effects but our results are also not positive definite. This means the Hausman statistic has not yielded the best possible value and we cannot trust this result. We apply the Stata command xtoverid: this is a Hausman test for fixed vs random effects that allows for clustered standard errors. The result is a p-value of 0.000, which means that random effects assumptions do not hold and we should use fixed effects.

The results of our group (state) fixed effects estimation are reported in Table 4.

Table 4. State fixed effects results on violent crime rates.

Explanatory variable	Beta coefficient
pov	-0.008^{*}
	(0.004)
lagpov	-0.008^{**}
	(0.003)
lgdp	0.749^{**}
	(0.121)
pop	0.004
	(0.008)
aged	-0.024^{*}
	(0.011)
llawenf	0.598^{**}
	(0.096)
hsgrad	-0.005
	(0.004)
wht	-0.064^{**}
	(0.017)
blk	0.041
	(0.026)
his	-0.145^{**}
	(0.024)
_cons	1.095
	(2.385)
N	600
r2	0.404
rmse	0.0970

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

The variables population growth rate, high school graduation rate and the percentage of population that is non-Hispanic black are not statistically significant. The variables poverty rate and percentage of population aged 15-24 years, are significant at the 5% level. Variables lag of poverty rate, log of GDP per capita, log of law enforcement per 100,000, percentage of population that is non-Hispanic white, and percentage of population that is Hispanic, are significant at the 1% level. Of the ten explanatory variables in our regression, seven are statistically significant at 5% or 1% levels.

Next, we add time fixed effects to the model specification from equation (3) and run a group (state) and time fixed effects regression for violent crime rates, represented by equation (4):

$$\mathbf{Ln(VC_{i,t}) = \beta_0 + \beta_1 POV_{i,t} + \beta_2 POVi_{,t-1} + \beta_3 Ln(GDP_{i,t}) + \beta_4 POP_{i,t} + \beta_5 AGED_{it} + \beta_6 Ln(LAWENF_{i,t}) +}$$

$$\mathbf{\beta_7 HSGRAD_{i,t} + \beta_8 WHT_{i,t} + \beta_9 BLK_{i,t} + \beta_{10} HIS_{i,t} + A_i + Y_t + U_{i,t}} \qquad \mathbf{(4)}$$

The term Y_t in equation (4) represents the time fixed effects at time t.

The year dummy variables are not included in our results table since we only use them to control for time fixed effects. The results of our group (state) and time fixed effects regression are shown in Table 5.

Table 5. State and time fixed effects results on violent crime rates.

Explanatory variable	Beta coefficient
pov	-0.004
	(0.004)
lagpov	-0.005
	(0.004)
lgdp	0.683**
	(0.142)
pop	0.003
	(0.008)
aged	-0.031*
	(0.014)
llawenf	0.476**
	(0.100)
hsgrad	-0.001
	(0.005)
wht	-0.060**
	(0.020)
blk	0.038
	(0.027)
his	-0.152**
	(0.025)
_cons	1.999
	(2.634)
N	600
r2	0.443
rmse	0.0947
t test $\beta_1 = \beta_2 = 0$	$Pr(\|T\| > \|t\|) = 0.0000$

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Including time fixed effects provides different results. This time only five out of the ten explanatory variables are statistically significant. At the 1% level, the positive coefficient of the change in GDP per capita indicates that a 1% increase in this variable results in a 0.68% jump in violent crime; a 1% increase in the number of the police force is due to a 0.48% increase in violent crime, a 1% increase in the Hispanic population is linked to a 15% reduction in violent crime, and a 1% increase in the non-Hispanic white population is connected to a 6% decrease in violent crime. At the 5% significance level, a 1% increase in the population aged 15-24 years goes along with a 3% decline in violent crimes. The positive link between law enforcement personnel per capita and violent crime is not unexpected as evidenced by prior empirical work (see page 17) and by Figure 3 from chapter I where as violent crime rates dropped, law enforcement personnel per capita remained mostly flat with a slight drop in the last few years.

The biggest surprise in Table 5 is that our main variable of interest, poverty rate, is no longer statistically significant. Its coefficient is still negative, but now a 1% increase in poverty results in a decrease in violent crime of 0.4%, as opposed to the 0.8% drop when time fixed effects were not considered. The negative relationship between poverty and violent crime, however small, seems to be a reflection of what Figure 1 in chapter I displayed: during the period of this study, while poverty increased, violent crime rates experienced a sharp drop. The same can be said about the variable lag of poverty rate: its negative relationship with violent crime rates and significance mirrors that of the original poverty rate variable. The last row in Table 5 displays a t test where the null hypothesis states that the coefficients of poverty rate and lag of poverty rate are equal to 0. The result is a p-value of 0, that leads us to reject the null and confirm that the coefficients of poverty rates and lag of poverty rates are significantly different than 0 at a 5% level.

Two separate models, one with only the poverty rate and the other with only the lag of the poverty rates as explanatory variables, are tested. The results are in table 6.

Table 6. State and time fixed effects results of poverty rates on violent crime rates.

Explanatory variable	Model (1) Beta coefficient	Model (2) Beta coefficient
pov	-0.013^{**}	
	(0.004)	
lagpov		-0.013^{**}
		(0.004)
_cons	6.073^{**}	6.058^{**}
	(0.045)	(0.045)
N	650	600
r2	0.172	0.180
rmse	0.117	0.114

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

In both instances, without any other explanatory variables in the models, poverty rate and lag of poverty rate have a negative sign, as we found out in our previous regression results, and they are both statistically significant at the 1% level. This confirms the negative relationship between poverty and violent crime. As a side note, Model (2) has only 600 observations because the lagged variable starts in year 2.

Additional group (state) and time fixed effects regressions for individual violent crime categories were ran to verify their behavior with respect to the overall violent crime rates. The results are summarized in Table 7.

Table 7. Regression results for individual violent crime categories.

Expl. variable	Aggravated Assault Beta Coeff.	Murder Beta Coeff.	Rape Beta Coeff.	Robbery Beta Coeff.
pov	-0.005	-0.008	-0.009^{*}	-0.003
	(0.005)	(0.007)	(0.004)	(0.004)
lagpov	-0.005	-0.008	-0.006	-0.002
	(0.005)	(0.007)	(0.004)	(0.004)
lgdp	0.847^{**}	0.607^{*}	0.345^{*}	0.353^{*}
	(0.181)	(0.267)	(0.152)	(0.151)
pop	0.002	0.010	0.002	0.004
	(0.010)	(0.014)	(0.008)	(0.008)
aged	-0.030	0.028	-0.059^{**}	-0.015
	(0.018)	(0.026)	(0.015)	(0.015)
llawenf	0.613^{**}	0.199	0.429^{**}	0.209
	(0.128)	(0.189)	(0.107)	(0.107)
hsgrad	-0.003	0.005	-0.002	0.002
	(0.006)	(0.009)	(0.005)	(0.005)
wht	-0.055^{*}	0.002	0.013	-0.098^{**}
	(0.025)	(0.038)	(0.021)	(0.021)
blk	0.052	0.113^{*}	0.072^{*}	-0.000
	(0.035)	(0.052)	(0.029)	(0.029)
his	-0.155^{**}	-0.063	-0.037	-0.188^{**}
	(0.032)	(0.047)	(0.027)	(0.027)
_cons	-1.283	-7.546	-2.806	8.513^{**}
	(3.367)	(4.967)	(2.819)	(2.806)
N	600	600	600	600
r2	0.341	0.175	0.327	0.481
rmse	0.121	0.179	0.101	0.101
t test $\beta_1 = \beta_2 = 0$	Pr(|T| > |t|) = 0.0000	Pr(|T| > |t|) = 0.0000	Pr(|T| > |t|) = 0.0000	Pr(|T| > |t|) = 0.0000

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

We observe that the poverty rates are only statistically significant with rape rates at the 5% level, where a 1% increase in poverty results in a 0.9% drop in rapes. In the remaining violent crime categories, poverty does not have a significant effect. The other unexpected result is that robbery is not significantly affected by poverty rates, and the direction of the insignificant relationship is negative, meaning that a 1% increase in poverty results in a 0.3% decrease in robbery rates. The only variable that is statistically significant across all violent crime indices is the GDP per capita. Increases in this variable result in higher violent crimes, with the effect on aggravated assault being the largest, where a 1% increase in the GDP per capita generates a 0.8% jump in aggravated assaults.

The empirical results confirm our initial expectations that poverty does not have a significant effect on violent crimes. However, the no-effect on robberies but the significant effect on rape rates comes as a surprise. The negative sign of the coefficients seems to contradict the assumption that more poverty should result in more violent crimes. A possible explanation may be found in the criminal opportunity theory: when there is less poverty, there is more opportunity to commit crimes due to more people being away from their homes working, and better incomes make it possible to have more material wealth, which turns more people into attractive targets for criminals. If we add that more people have the discretionary income to go out and engage in behavior conducive to violence, such as drinking more, gambling and drug consumption, it is not far-fetched to conclude that poverty and violent crimes go in opposite directions.

The positive sign of the GDP per capita variable with all indices of violent crime is the other side of the coin. An economic expansion results in higher GDP per capita, which could have the effect of reducing poverty rates.

With that said, these results should be taken with caution due to the aggregate-level nature of the study. It is possible that within a state, communities with high levels of poverty experience higher rates of violent crimes while the majority of the state experiences the opposite. The total effect could be what we have seen: less poverty overall but more localized violent crime. A targeted study of smaller communities with high levels of poverty and violent crime could yield completely different conclusions.

An interesting result is the sign of the coefficient for law enforcement personnel per capita: it is positive for every violent crime category, whether statistically significant or not. The interpretation is that a larger police force exists where there are more violent crimes. This result is consistent with findings from previous empirical work. In Tables 2, 4 and 5, the sign of the coefficient of high school graduation rates is negative and although not statistically significant, it implies that higher graduation rates help decrease violent crime rates. When looking at the individual violent crime categories in Table 7 however, this variable has a coefficient with positive sign for murder and robbery rates, when the opposite is expected. At worse, we can conclude that educational attainment does not have an impact on violent crime.

CHAPTER V

CONCLUSION

The assumption that more poverty leads to more violent crime may still be up for debate, and more research is necessary to arrive to a definitive answer. In this paper, using aggregate level data for a 13-year period and a group and time fixed effects estimation model, we have arrived to the conclusion that poverty does not have a significant effect on violent crime in the United States. It can be argued that poverty does have a significant negative effect on violent crime when poverty rates are the only variable in our regression, as Table 6 results showed. However, poverty does not occur in a vacuum and including variables that have a strong link to poverty levels, such as per capita GDP, helps us paint a more accurate picture of the effect of poverty on violent crime.

Poverty rates do have a significant negative effect on rape rates, an unexpected result that demands more thorough research. Robbery is not significantly affected by poverty rates. These results do not mean that poverty doesn't matter when analyzing the determinants of crime. More research at the individual level, utilizing city and county level data for larger periods of time is necessary to confirm or deny my results. Due to the local nature of crime, this result cannot be extrapolated to other parts of the world, where poverty conditions may be more critical than in the United States.

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