Crime and economic conditions in the United States Revisited

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Abstract

Conventional wisdom shows that crime exhibits a countercyclical pattern-trending up during recessions and down during economic expansion. This observation makes the analyzes of the determinants of the crime of interest to researchers to inform policy. To this end, the present study employs historical data to analyze the effects of economic conditions on crime rates in the U.S. The analysis is based on balanced panel data from all 50 states and the district of Columbia on violent and property crime rates covering from 1976-2019. We employed the linear and dynamic panel models, while four indicators of economic conditions were considered in this study. The empirical results show that these commonly used economic indicators significantly affect crime rates. Specifically, we found that unemployment rates and income inequality increased crime rates, while personal income and economic growth decreased crime rates. This shows that continued efforts to reduce unemployment and inequality coupled with policies to boost personal income and economic growth are vital to restrain future crime increases in the U.S. However, these findings are supported by the linear and dynamic model specifications employed in this study.

Keywords: Crime rates, Property crime, Violent crime, economic conditions, determinants, U.S

1 Introduction

The rates of crime in the United States have adopted a cyclical behavior pattern over the decades. For instance, available statistics show that crime rates, both property and violent crime, increased in the 1960s-1980s, drop in the 1990s, and decline in the 2000s, as shown in Figure 1. The downward trend has continued in the 1990s (Kearney et al., 2014), as the decrease in crime rates during the 1990s and the 2000s has been considered the longest and largest since World War II (James 2018). While property crime is much more common than violent crime in the U.S, it is also evident that the overall patterns are the same. The historical surge in crime rates in the 1980s has been linked to the crack cocaine epidemic (Grogger and Willis 2000). The declining period of the 1990s and the 2000s has been linked to better-policy strategies and changes in criminal justice sanctions (Levitt 2004; Shoesmith 2010). Fajnzylber et al. (2000) also argue that the decrease in the crack cocaine epidemic that began in the early 1990s has been linked to the decline in crime rates after 1991. The authors noted further that the long period of economic expansion and increase incarceration since the mid-1980 has undoubtedly contributed to the decrease in crime rates after 1991. Raphael and Winter-Ebmer (2001) reveal that a decline in crime rates during the 1990s could reduce the unemployment rate during the same period. Others claim that changes in demographic composition and economic conditions affect how crime rates fluctuate over the years in the United States (Witt et al., 1999; Blumstein, 2000). For example, some researchers theorize that economic expansion decreases crime (Blumstein and Wallman, 2006), while others argue that economic conditions do not always reduce crime (Lafree 1998). [1]

The economic theory of crime initially proposed by Becker (1968) and extended by Ehrlich (1973) provides a theoretical framework for understanding the puzzling relationship between crime and economic indicators such as unemployment, income inequality, consumer price index, economic growth, and wage/salary, among others. The theory assumes that crime is a rational act made by individuals to engage in criminal activity by carrying out the benefit-cost calculation under uncertainty. Many studies have established that economic activity can affect crime, although with mixed and often contradictory results (for details see: Detotto and Otranto, 2010; UNODC, 2012; Fajnzylber et al., 2002; Habibullah and Baharom, 2009; Witt et al., 1999; Levitt 2004; Raphael and Winter-Ebmer 2001; Rosenfeld and Fornango 2007; Machin and Meghir 2004;

[1] Economic conditions can be viewed as indicators of the broad underlying socio-economic situation in a country.

Rosenfeld 2009). UNODC (2012) revealed that property crime appeared to be the most affected during a period of economic stress. The UNOCS report further showed that violent and property crimes increased up to two-fold during the global food crisis of 2008/2009. Increased wealth leading to increased investment can also increase vandalism opportunities and property crime, and the demand for illegal goods and services such as the consumption of drugs and alcohol (Ragnarsdottir, 2014). In addition, economic growth and greater affluence can produce more crimes (Ehrlich 1973). For example, greater wealth means a higher level of transferable assets, which increase lucrative targets for potential criminals.

Alternatively, improved economic activities can reduce crime. For instance, when a nation's economy becomes more vigorous, improvements in legitimate labor market opportunities make crime relatively less attractive (Becker, 1968). Also, increased employment opportunities deter potential offenders from committing crimes (Raphael and Winter-Ember 2001). For instance, the authors reveal that a decline in unemployment rates observed during the 1990s may have caused a decrease in the crime rates during the same period in the U.S. Although most studies predict that inequality increases crime (Fowles and Merva 1996; Choe 2008; Atems 2020; Fajnzylber et al., 2002). But Brush (2007) found a negative association between inequality and crime using time series analysis. Rosenfed et al. (2019) also show that continued low inflation rates restrain future crime increases in the United States. In contrast, Rosenfelf (2014) also argues that inflation is an important part of the story of acquisitive crime trends across the globe.

The present study offers continuity to the existing literature by investigating the effects of economic conditions on crime rates in the United States. A major drawback from previous studies that prevent reliable evidence from supporting how economic variables affect crime rates has been linked to an inadequate measure of economic indicators and model misspecification in the analyses (Greenberg 2001; Raphael and Winter-Ebmer 2001; Cerull et al. 2018). Most previous studies mainly analyzed each economic indicator individually. For example, Fowles and Merva (1996) focus on the effect of wage inequality on crime, while Rosenfield et al. (2019) examine the relationship between inflation and crime. Bushway et al. (2012) also note that other concern issues include how best to account for serial correlation in the term error terms and whether to have a lagged dependent variable in the model specification. In recognition of this, the present study considers four different indicators of economic conditions such as unemployment rates, income inequality, personal income, and gross domestic product (GDP) growth other than the unemployment rate or income inequality, which dominated previous studies. Rosenfeld (2009) argues that indicators of economic conditions that reflect different economic outputs yield a more substantial effect on crime rates than do unemployment rates in previous studies. Our study also accounts for the variation in educational attainment among states in the country. We consider both the linear and dynamic model specifications to address model misspecification issues in previous studies to allow for more reliable estimates. The study employs econometric procedures such as the Feasible Generalized Least Square (FGLS) and Common Correlated Effects Mean Group (CMG). The former accounts for serial correlation in the error terms, while the latter accounts for cross-sectional dependence in the data to minimize bias of overstating the effects of economic variables on crime rates in the study. The FGLS fits a fixed effect estimator for autocorrelation AR(1) disturbances.

The empirical results show that the four economic indicators considered significantly influence crime rates in the study. Specifically, we found that unemployment rates and income inequality increased crime rates, while personal income and economic growth decreased crime rates. This shows that continued efforts to reduce unemployment and inequality coupled with policies to boost personal income and economic growth are vital to restrain future crime increases in the U.S. These findings are supported by this study's linear and dynamic model specifications.

The remainder of the paper is organized as follows. In the next section, we describe the empirical model used. Section 3 describes the data used for the analysis, while in section 4, we present the results and discussion. The concluding remarks are presented in section 5.

[FIGURE 1 HERE]

2. Empirical Model Specification

The relationship between economic activities and crime has been investigated by modeling crime rates as a function of economic indicators (Fajnzylber et al., 2000; Witt et al., 1999; Levitt, 2004; Raphael and Winter-Ebmer 2001; Rosenfeld and Fornango 2007; Machin and Meghir 2004; Rosenfeld 2009). However, the exact specification of this relationship is unknown (Fowles and Merva 1996). To this end, we consider the linear and dynamic specifications. The economic indicators considered include in the study are unemployment rates, income inequality, personal income, and annual gross domestic product (GDP) growth. GDP growth is included to assess the potential influence of overall economic development on crime rates. In addition, crimes may differ by differences in education across states. In recognition of this, we include educational attainment measures such as the proportion of the population with high school diplomas and college degrees as control variables. However, the dependent variable is total violent and property crime rates. This is a departure from most previous studies that focus on property crime exclusively or reveals that economic conditions do not affect violent crimes other than robbery.

A literature review shows that previous studies employed the linear and dynamic panel models to investigate the effects of economic conditions on crime rates (for details see: Rosenfeld and Fornango 2007; Witt et al. 1999; Bun et al. 2019; Fajnzylber et al., 2000; Rosenfeld 2009). To this end, the present study employs the linear and dynamic panel model specified below as Equations 1 and 2, respectively.

$$Crime_{it} = \beta Unemploy_{it} + \delta Inequality_{it} + \tau Income_{it} + \sigma GDPGrowth_{it} + \alpha HighSchool_{it} + \pi College_{it} + \gamma_i + \varepsilon_{it} \qquad 1$$

$$Crime_{it} = \rho Crime_{it-1} + \beta Unemploy_{it} + \delta Inequality_{it} + \tau Income_{it} + \sigma GDPGrowth_{it} + \alpha HighSchool_{it} + \pi College_{it} + \gamma_i + \varepsilon_{it} \qquad 2$$

where t= 1,…..T time period and i= 1…….N states; $Crime_{it}$ is a vector of total violent and property crime rates; $Crime_{it-1}$ is lagged $Crime_{it}$ included in Equation 2 to capture lags in criminal behavior or inertial in crime rates; $Unemploy_{it}$ is unemployment rate; $Inequality_{it}$ is income inequality (Gini index); $Income_{it}$ is personal income (annual); $GDPGrowth_{it}$ is annual Gross Domestic Product (GDP) growth computed as the first difference of GDP level ; $HighSchool_{it}$ is the proportion of the population with a high school diploma; $College_{it}$ is the proportion of the population with a college degree; β, δ, τ, σ, α, π, and ρ are parameters to be estimated; γ_i denotes state-specific effects accounting for unobserved heterogeneity; and ε_{it} represents the error term of the regression.

The estimation strategy employs to estimate the parameters of equation 1 are fixed-effect (FE), Common Correlated Effects Mean Group (CMG), and Feasible Generalized Least Square (FGLS) estimators. Because of the dynamic panel model specification in Equation 2, we employ the system generalized method of moments (GMM) estimator proposed by Blundell and Bond (1998) to estimate the parameters.[2] Farhadi et al. (2015) revealed that the GMM produces consistent estimates in the presence of endogeneity issues created by including the lagged dependent variable and collinearity of regressors in Equation 2. Endogeneity arises because the lagged dependent variable on the right side of Equation 2 is correlated with the error term, which creates a bias problem (Nickell 1981). The methodology can also mitigate the endogeneity problem in the explanatory variables (Blundell and Bond 1998). The GMM uses instruments based on lagged differences of the regressors to control the endogeneity problems. However, the instruments are appropriate under the assumption that the error term is not serially correlated (Blundell and Bond 1998; Arellano and Bond 1991). Arellano and Bond(1991) also noted that the generalized method of moment (GMM) could overcome the econometric problem of cross-sectional dependence and multi-correlation in macro panel data models.

3. Data description and correlation matrix of the explanatory variables

We employ state-level data covering 1976-2019 on violent and property crime rates from the Federal Bureau of Investigation through the Uniform Crime Reporting Statistics website.[3] Data from 50 states and the District of Columbia from the United States (i.e., 51 groups) yield a cross-state panel of 2244 observations in the analysis. The property and violent crime rates are measured as per capita of 100,000 inhabitants. Violent crime is an aggregation of murder and nonnegligent manslaughter, rape, robbery, and aggravated assault, while property crime includes burglary, larceny-theft, and motor vehicle theft.

The measure of economic conditions consider in the study includes unemployment rates, income inequality, average income per worker (personal income divided by employment) adjusted by inflation, and per capita real gross domestic product (GDP) growth. We obtained data from the Bureau of Economic Analysis (BEA) on average annual per capita personal income and per capita gross domestic product (GDP). Annual GDP growth was later computed from the GDP level and included in the analysis. Other data obtained includes unemployment rates from the Federal Reserve Economic Data[4]. In addition, data on income inequality (e.g., Gini coefficient) and the proportion of the population with high school graduates and college graduates were obtained

[2] The system GMM estimate jointly the regressions in levels and differences (for the instruments).
[3] See: http://www.ucrdata
[4] https://fred.stlouisfed.org

http://www.shsu.edu/eco_mwf/inequality.html. All variables are expressed in natural logarithm for the analysis to reduce the influence of measurement units.

While Table 1 provides summary statistics of the variables, Figure 2 describes the violent and property crime rates' distribution. Judging by the distribution of the crime rates in the Figure and the average size of the type of crime rates reported, it evident that property crime is much more common than violent crime in the country. Tables 2A, 2B, and 2C present the correlation matrix of the explanatory variables used in the regression. Most of the correlation coefficients among the explanatory variables are less than 0.50, suggesting that multicollinearity should not be a severe problem for the estimated models.

[FIGURE 2 HERE]

[TABLES 2A, 2B, & 2C HERE]

4. Results and Discussion

4.1. Panel data specific tests: Hausman tests, cross-sectional dependence, and serial correlation

Table 3 presents the panel data specification tests, including the Hausman test, cross-sectional dependence test, and serial correlation test. The first row represents the Hausman (1978) specification test to compare the random-effect and fixed-effect models. The estimated p-value is less than 0.01. The differences between the random effects and fixed effects coefficient are systematic, as the fixed effect is more robust to the data than the random effect specification. The second row represents the Pesaran (2004) test of cross-section independence. Given the p-value less than 0.01, we reject the null hypothesis of cross-sectional independence, thus confirming cross-sectional dependence in the data. Finally, the third row represents the test for serial correlation using Wooldridge's (2002) test statistics. Again, with a p-value less than 0.01, we reject the null hypothesis of no serial correlation between the error terms across the data period.

Because of the clear evidence of cross-sectional dependency and a serial correlation between the error terms across the period, as shown in the data in Table 3, we employe the Common Correlated Effects Mean Group (CMG) and Feasible Generalized Least Square Method (FGLS) estimators to estimate the parameters of Equation 1 to address these problems. Baltagi (2005) noted that FGLS is robust to time series cross-sectional dependence contemporaneous correlation problem. Pesaran (2006) also pointed out that the Common Correlated Effects Mean Group (CMG) estimator is robust to cross-sectional dependence.

[TABLES 3 HERE]

4.2. Diagnostic test results for the dynamic panel model

Since all variables are considered endogenous in the empirical models, we believe further specification using the GMM models improves the estimated parameters' robustness. Hence, the diagnostic statistics of the GMM show the presence of first-order autocorrelation [AR(1)] in the model's residual, given the p-value less than 0.01. However, we observe the absence of second-order autocorrelation [AR(2)] in the model's residuals. GMM is consistent with no AR(2) in the model's idiosyncratic error term (Blundell and Bond 1998). The implication of this is that no serial correlation exists in the disturbance that might affect the estimated parameters' efficiency. The Sargan test result of overidentifying restriction tests the null hypothesis of the instruments' overall validity, which shows that the model specifications are valid or not misspecified.[5]

The educational attainment measures included in the model are assumed to be strictly exogenous and thus taken as an instrument for the levels equation. Also, lagged crime, unemployment, inequality, personal income, and GDP growth are considered endogenous in the model. Lags of the endogenous variables are taken as the instrument for the first differences equation and include lags from t-2 to t-3. We also collapse the instruments using a limited number of moment conditions to overcome instrument proliferation's difficulty following Roodman's (2009) advice.

4.3. Effects of economic conditions on violent and property crime rates

Tables 4 and 5 present the results of the effects of economic conditions on crime rates based on the linear and dynamic panel model specifications. In Table 5, the lagged dependent variable taken as a measure of the inertial effects of crimes or impact of previous crime is significant and positive, showing previous criminal behavior is a critical determinant of the current crime in the study. The implication of this is that the persistence in the flow of cime across the period is evident.

However, the effects of economic indicators show that the measures of economic activity considered significantly affect crimes in the study. Specifically, we find a significant positive impact of unemployment rates and income inequality on the property and violent crime rates across the specified models both in Tables 4 and 5, which means an increase in unemployment and

[5] The failure to reject the null hypothesis lends support to the validity of the model given the p-value.

income inequality increased crime rates in the U.S. The positive effect of unemployment rates on crime rates across the models shows that high unemployment induces crime activities. This means when there are fewer opportunities for legitimate income, people may turn to illegal activities or violent activities and reduce the opportunity cost of engaging in crime (Watt et al., 1999).[6] Raphael and Winter-Ember (2001) also noted that individual with low relatively potential wages during unemployment spell unambiguously increases the time devoted to criminal activity. Also, Fajnzylber et al. (2000) reveal that the positive link between inequality and crime shows that individuals with higher income inequality have lower expectations of improving their social and economic status through legal economic activities, thus decreasing the opportunity cost of participating in illegal endeavors.

A review of the literature shows that the positive effect of unemployment on crime is consistent with the finding of Raphael and Winter-Ember (2001) and a review of earlier literature by Freeman (1999). Also, Philip et al. (1985) and Rosenfeld (2009) found significant negative effects of unemployment on violent and homicide crimes, respectively. Further literature review shows that the positive association between inequality and crime rates observed in the present study is consistent with most empirical studies (see for details Fowles and Merva 1996; Choe 2008; Atems 2020; Fajnzylber et al., 2000). But Brush (2007) found a negative association between inequality and crime using time series analysis.

Other results show that personal income has a significant negative impact on the violent and property crime rates. This indicates that an increase in personal income induced lower crime rates. We also found that GDP growth, which measured overall economic development, does appear to have an effect on crime across the estimated models. Generally speaking, stagnant economic conditions increased criminal activity. However, a negative impact of GDP growth on crimes implies that a GDP growth increase is associated with a decline in the crime rates. A literature review shows that Arvanites and Defina (2006) found a significant negative impact of economic growth on property crime and robberies, while Fajnzylber et al. (2000) found no significant effect of GDP growth and average income on homicide crime.

[6] The unemployment rate may be negatively correlated with the crime rates during periods of increasing unemployment because there may be decreased criminal opportunities due to increase guardianship of property and reduce availability of property (Watt et al. 1999).

Because crime-fighting actions are most effective when the incidence of crime is low, the significance of inequality and personal income can be interpreted as evidence that poverty does induce criminal behavior in the study. For example, when social programs that address inequality and policies that raise wages are combined, it increases poverty reduction with crime-reducing consequences. The positive correlation between unemployment rates and crime rates shows that improving job opportunities and raising wages can potentially reduce crime rates. These findings also raise the issue of creating employment opportunities and income redistribution programs in the country as tools to reduce criminal activity. The negative association between GDP growth and crimes shows that efforts to improve overall economic opportunities have a crime-reducing effect.

4.4 Effects of education on violent and property crime rates

The effects of educational attainment defined by the proportion of the population with a high school diploma and a college degree on crime rates give mixed results in the linear model presented in Table 4. But the effects are not statistically significant in Table 5. For example, Table 4 shows that crime rates decrease significantly as the proportion of the population with a college degree increases. In contrast, it increased significantly as the proportion of the population with high school diplomas increases. Machin et al. (2011) reveal that education increases expected wages, and higher wages increased crime opportunity costs. Fajnzylber et al. (2000) argued that when education raises productivity in illegal activities to a greater extent than in legal ones, education's positive effect on crime is evident.[7] The puzzling education effects on crimes is first observed by Ehrlich (1975).

Despite the puzzling empirical findings, higher educational attainment remains an effective policy tool to mitigate crime surge in any society. But education by itself is no panacea for preventing crime, as noted by Fajnzylber et al. (2000). To this end, we highlight the importance of public policies that promote enrollment in colleges in combination with policies that promote job opportunities and reduce inequality as an essential component of the program to decrease future crime increases in the United States.

[TABLES 4 & 5 HERE]

[7] Usher (1997) also noted that a negative relationship between education and crime could arise due to a civic externality of education, which is assumed to affect one’s willingness to commit an offense.

5. Concluding Remarks

The puzzling relationship between economic activities and crime rates has been linked to factors such as the inadequate measure of economic activity, model misspecification, and how best to account for serial correlation in the term error terms. In recognition of this, the present study re-examines the effects of economic conditions on crime rates in the United States. The analysis is based on balanced panel data from all 50 states and the district of Columbia on violent and property crime rates covering 1976-2019. We employ the linear and dynamic panel models, while four indicators of economic conditions were considered in the study. These specifications were necessary to address model misspecification's problematic issues in the previous studies. The study also employs econometric procedures that account for serial correlation in the error terms and cross-sectional dependence in the data to minimize bias of overstating economic variables' effects on crime rates.

The empirical results show that economic indicators considered significantly affect crime rates in the study. Specifically, we found that unemployment rates and income inequality increased crime rates, while personal income and economic growth decreased crime rates. However, these findings are supported by the linear and dynamic model specifications employed in the study. The effect of education on crime rates captured by the population's proportion with a high school diploma and a college degree shows mixed findings with the linear specification. Our results indicate that crime significantly reduces among the population with a college degree while increasing among the high school diploma population. The impact of educational attainment is not statistically significant in the dynamic model. Despite these puzzling empirical findings, higher educational attainment remains an effective policy tool to mitigate crime surge in the country, especially college enrollment.

A meaningful deduction from these findings is that continued efforts to reduce unemployment and inequality coupled with policies to boost personal income and economic growth are vital to restrain future crime surge. To put our results into perspective, policies aimed at improving employment prospects and improve income redistribution can be effective tools for combating crime in the county. Another potential policy implication from this result is that policies that promote enrollment in colleges combine with policies that promote job opportunities and reduce inequality are essential inputs to decrease future crime increases in the United States.

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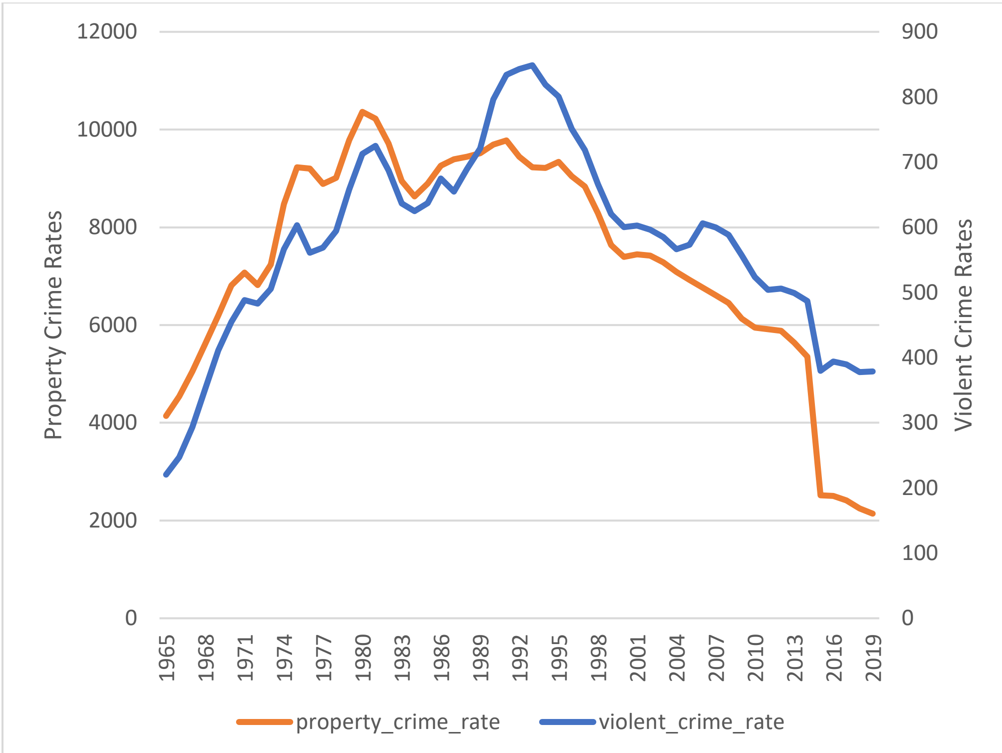

Figure 1: Trend in the average property and violent crime rates, 1965-2019

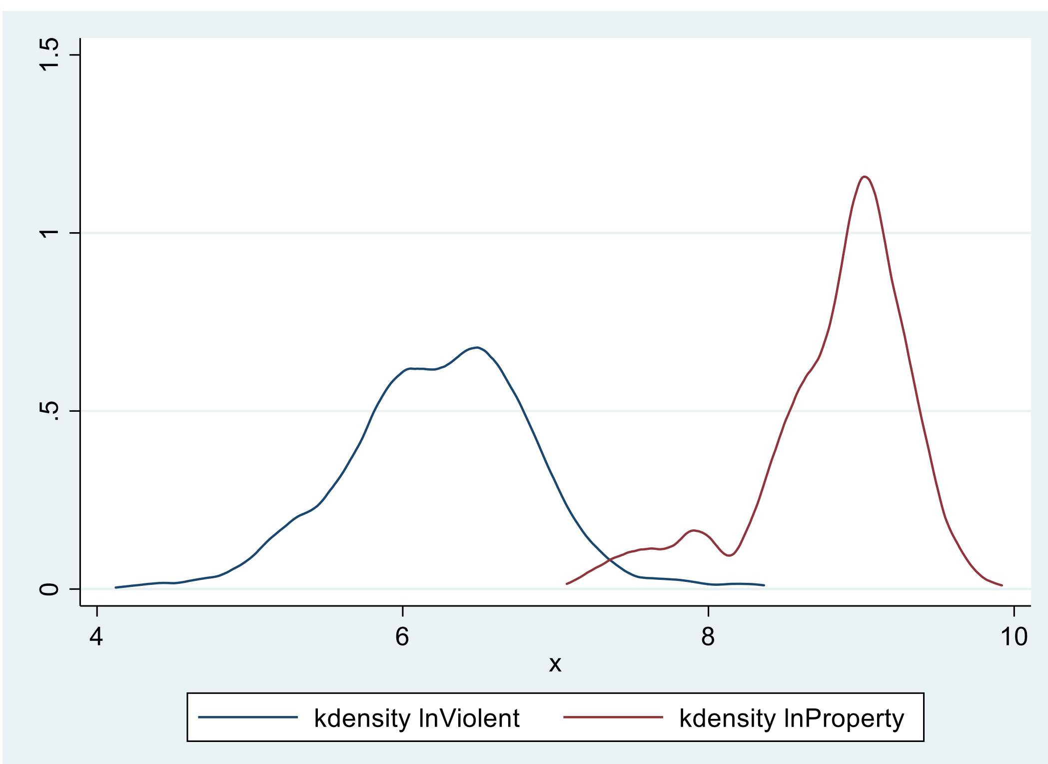

Figure 2: Distribution of the violent and property crime rates

Table 1: Summary statistics of variables used.

Variable	Mean	Std. Deviation
The violent crime rate (per capita of 100,000 inhabitants)	617.26	431.33
The property crime rate (per capita of 100,000 inhabitants)	7,542.50	3,101.03
Unemployment rates	5.91	2.08
Income inequality (Gini Index)	0.5630	0.0537
Average real personal income per worker (annual)	27, 682.41	14,905.29
Gross domestic product (GDP)	33522.86	21466.26
The proportion of the population with a college degree	0.1594	0.0550
The proportion of the population with a high school diploma	0.5920	0.0758

Table 2 A: Correlation tabulation of the explanatory variables used for the linear model.

	Unemployment rate$_t$	Inequality (Gini)$_t$	Personal Income$_t$	GDP Growth$_t$	High school$_t$	College$_t$
Unemployment rate$_t$	1.0000					
Inequality (Gini)$_t$	-0.1932	1.0000				
Personal Income$_t$	-0.2941	0.4012	1.0000			
GDP Growth$_t$	-0.0734	-0.4942	-0.4199	1.0000		
High school$_t$	-0.3421	0.3640	0.3769	-0.4598	1.0000	
College$_t$	-0.2616	0.3401	0.3680	-0.3966	0.4389	1.0000

Table 2 B: Correlation tabulation of the explanatory variables used for the dynamic models (violent crime rates)

	Violent$_{t-1}$	Unemployment rate$_t$	Inequality (Gini)$_t$	Personal Income$_t$	GDP Growth$_t$	High school$_t$	College$_t$
Violent$_{t-1}$	1.0000						
Unemployment rate$_t$	0.0591	1.0000					
Inequality (Gini)$_t$	0.0199	-0.1853	1.0000				
Personal Income$_t$	-0.1631	-0.2873	0.4995	1.0000			
GDP Growth$_t$	0.0647	-0.0787	-0.4909	-0.5169	1.0000		
High school$_t$	-0.1223	-0.3325	0.3608	0.3760	-0.4575	1.0000	
College$_t$	-0.1146	-0.2506	0.3385	0.3678	-0.3946	0.4347	1.0000

Table 2 C: Correlation tabulation of the explanatory variables used for the dynamic models (property crime rates)

	Property$_{t-1}$	Unemployment rate$_t$	Inequality (Gini)$_t$	Personal Income$_t$	GDP Growth$_t$	High school$_t$	College$_t$
Property$_{t-1}$	1.0000						
Unemployment rate$_t$	0.2195	1.0000					
Inequality$_t$	-0.3877	-0.1853	1.0000				
Personal Income$_t$	-0.4149	-0.2873	0.4995	1.0000			
GDP Growth$_t$	0.2906	-0.0787	-0.4909	-0.4169	1.0000		
High school$_t$	-0.4813	-0.3325	0.3608	0.3760	-0.4575	1.0000	
College$_t$	-0.4891	-0.2506	0.3385	0.3678	-0.3946	0.4347	1.0000

Table 3: Panel data specific tests

Tests	Violent Crime Rates		Property Crime Rates	
	Statistics	p-value	Statistics	p-value
Hausman test of fixed effect vs. random effect	39.96	0.000	76.47	0.000
Pesaran (2004) test of cross-section independence	90.69	0.000	172.37	0.000
Woodridge's (2002) test of serial correlation of error component	464.63	0.000	1925.52	0.000

Pesaran (2004) test statistic of the null hypothesis of cross-sectional independence
Woodridge (2002) test statistic of the null hypothesis of no serial correlation

Table 4: Linear specification of the effect of economic indicators on crime rates

Independent Variables	Dependent Variable: Violent Crime Rates			Dependent Variable: Property Crime Rates		
	Fixed Effect Model	CMG Model	FGLS Model	Fixed Effect Model	CMG Model	FGLS Model
Inequality-Gini Index	0.6073*** [0.1404]	1.6004*** [0.2325]	0.0542*** [0.0238]	1.3260*** [0.1653]	2.8113*** [0.3274]	0.3759*** [0.0235]
Unemployment rate	0.0703*** [0.0022]	0.0878*** [0.0282]	0.0285*** [0.0041]	0.1468*** [0.0259]	0.1321*** [0.0370]	0.1099*** [0.0034]
Personal income	-0.2078*** [0.0421]	-0.4713*** [0.0866]	-0.2078*** [0.0421]	-0.9590*** [0.0495]	-1.0257*** [0.1349]	-0.5271*** [0.0185]
GDP Growth	-0.0661*** [0.0174]	-0.1509*** [0.0261]	-0.0076*** [0.0011]	-0.0483*** [0.0204]	-0.1297*** [0.0323]	-0.0084*** [0.0011]
High school	1.3283*** [0.1385]	1.1141*** [0.3119]	0.0212 [0.0191]	2.1293*** [0.1631]	1.0755* [0.6366]	0.2682*** [0.0131]
College	-0.3664*** [0.0806]	-0.4765*** [0.1509]	-0.0100 [0.0078]	-0.4085*** [0.0949]	-0.3457* [0.1934]	-0.0565*** [0.0473]
Constant	8.1585*** [0.5871]	11.8659*** [1.0905]	6.7119*** [0.1538]	19.3814*** [0.6910]	20.5850*** [1.7715]	14.2099*** [0.1939]
Prob >F or chi2	0.000	0.000	0.000	0.000	0.000	0.000
# states	51	51	51	51	51	51
# observation	2193	2193	2193	2193	2193	2193

**** p < 0.01, ** p < 0.05, * p < 0.1; all variables are expressed in logarithm.*

Table 5: Dynamic specification of the effect of economic indicators on crime rates based on a system GMM.

Independent Variables	Dependent Variable: Violent Crime Rates	Dependent Variable: Property Crime Rates
Lagged Crime Rate	0.9877***[0.0163]	0.9501***[0.0079]
Inequality-Gini Index	0.4160***[0.0879]	0.5459***[0.0593]
Unemployment rate	0.0684***[0.0119]	0.0454***[0.0093]
Personal income	-0.0871***[0.0291]	-0.1691***[0.0258]
GDP Growth	-0.0363* [0.0199]	-0.0291* [0.0159]
High school	0.0006 [0.0560]	0.0220 [0.0524]
College	-0.0057 [0.0272]	0.0301 [0.0239]
Constant	1.1553***[0.4497]	2.4343*** [0.3756]
Prob>F	0.000	0.000
AR (1) p-value	0.000	0.000
AR (2) p-value	0.968	0.911
Sargan test p-value	0.736	0.658
# instruments	18	18
# states	51	51
# observation	2193	2193

**** p < 0.01, ** p < 0.05, * p < 0.1; all variables are expressed in logarithm.; Sargan test is use to test the null hypothesis of overall validity of the instruments*