Does Inequality Increase Crime? The Effect of Income Inequality on Crime Rates in California Counties

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Abstract

This article estimates the effect of county level income inequality on violent and property crime rates using data on eight years of data on California counties. Initial cross-sectional analysis suggests income inequality decreases most categories of crime. However, the impact of income inequality on all crime categories is statistically significant using a well structured panel data estimation.

1 Introduction

In recent years, the growing gulf in income and wealth in the United States has renewed interest in determining the impact of inequality on general well being. One avenue of great interest to researchers in recent decades has been the potential effect of inequality on rates of violence and crime.

Earlier developments in the economic theory of crime theorized by Becker (1968) suggest that criminal behavior is driven by largely rational individual responses to costs and benefits. Potential criminals consider deterents to crime, such as likelihood of apprehension and potential legal ramifications including lost wages from incarceration. They also respond to opportunities, and consider the potential gains to criminal activity.

Making rational decisions, particularly in regards to crimes with income gains for the perpetrator, income inequality could lead to an increase in potential gains. Considering robbery for instance, we would expect to see the liklihood of an individual engaging in robbery if they expect, on average, their victims to have higher incomes. Contrary to this, we could consider an area that is ubitquitiously poor. Here, we would expect a potential criminal to face significantly less potential gain from any act of robbery, decreasing the likelihood they make an attempt.

Though less direct, if one were to consider income inequality as a strong indicator of decreased social mobility then an alternative mechanism suggests itself. Here, high risk individuals face little opportunity cost if caught committing a crime, as their potential future earnings foregone if apprehended is relatively small. Considered this way, income inequality may effect violent crime even in the absence of pecuniary gains.

Here, we be estimate the effect of income inequality on eight specific and two aggregate crime rates using eight years of California county level data. In addition to income inequality, we include several measures effecting potential criminal activity. These include measures of education, poverty and unemployment to control for the opportunities foregone by potential criminals if apprehended. To control for the greater propensity of young males to commit most varieties of crime, we included population measures of sex and age. We controlled for population density as well, given the potential effect on opportunities for and potential deterence of some categories of crime.

Though we initially included measures of policing within counties, we eventually left this out of our model. We observed no noticable effect on the rest of our model coefficients or their significance whether we included police activity or not. However, we strongly suspect this is due to policing levels being endogeneously determined, not because it has no impact on crime rates.

Initial cross-sectional estimation methods, similar to those from previous work by others, yielded interesting results, including a crime reducing effect from greater income inequality. However, after utilising panel estimation methods to control for county level fixed effects we found income inequality had no effect on crime rates.

2 Literature Review

The effect of inequality on crime rates has been of interest to economists for decades. Earlier work, and some contemporary work, has focused on cross country comparisons or single country time series analysis. However, several concerns arise from this. In comparisons across countries, a multitude of difficult to quantify factors, including different legal and enforcement systems, make these comparisons potentially meaningless.

Work on the subject using county level units of observation include a paper by Kelly (2000) on Inequality and Crime where they were motivated by potential crime inducing effects from the proximity of low and high income individuals. To measure inequality, they calculated a Gini coefficient of income, as well a a Gini coefficient of education for each urban U.S. county. Building on previous research, they also included measures of population density, the proportion of the population in single female-head households as a measure of family instability, the percent of the population that are nonwhite, the unemployment rate, the poverty rate, the proportion of the population that lived elsewhere five years previous to indicate a lack of community cohesion, the percent of the population between 16 and 24 as young people are more likely to commit crimes, and a measure of adults over 25 with a college education. In some models, they also consider the impact of policing levels on crime. They note that there is likely an endogeneity issue, but find similar results with policing levels excluded from their model. Ultimately, using cross-sectional data, Kelly finds that income inequality affects violent crime rates at the county level, but not property crime.

More recent work on United States income inequality uses panel data. A recent study by Choe (2008) uses county and year level data, as well as a lagged crime rate to account for dynamic effects. When initially excluding the lagged crime rate income inequality appeared to have a statistically significant positive effect on most of the categories of crime considered. This included burglary, larceny, rape, and overall rates of violent and property crimes. When dynamic effects were included, Choe found income inequality had an effect on burglary and robbery rates. Notably though, they don't address law enforcement's effect on crime.

In another panel data analysis on violent and property crimes in England by Han et al. (2010) controls for law enforcement rates. Using instrumental variables they control for potential crime deterring effects of the police. As law enforcement rates are likely endogenous in any model of crime, they included lagged crime detection rates and the national prison population. Their model is based on relative small Police Force Areas and provides more finely grained analysis of the impact of relevant factors on crime. Unfortunately, because of the small unit size, they don't include measures of income inequality within each PFA. Rather, they use national level income inequality measures. They find no significant impact of income inequality on crime. This result might be irrelevant to our own analysis of pecuniary crime rates (i.e. robbery, burglary, motor vehicle theft). We would expect local inequality to motivate these crimes as it increases potential financial gains.

Compared with the papers shown above, Neumayer (2005) strongly argues against the link between income inequality and violent crime. His interpretation for the relation was that income may be correlated with social culture. The research was implemented in looking for robbery and violent theft as dependent variables and urbanization rates, the female labour force participation rate and the polity which measures of democracy as control variables. As for research method the data was collected from the year 1980-1997 to eliminate abnormal impact in one single year. As well, the log-form model was used to reduce heteroskedasticity of the error term. The result showed that income inequality is insignificant in fixed-effect and dynamic estimation but significant only in random effect estimation. The reason is that fixed-effect estimation measures the time-variant factors. When either controlling for the country-specific fixed effect or using a relative large sample size, the coefficient of income inequality became insignificant in all the models.

The interesting result was found on the paper *Does income inequality lead to more crime?* by Brush (2007). This paper estimates the effect using different categories of data. It shows that income inequality has a positive relationship with crime rates in a county-level cross-sectional analysis when using different ways to measure income inequality with crime rate. However the result indicates that the relationship between income inequality and crime rates is unclear because the negative or insignificant coefficient in the regression when using time-series data in the fixed-effect model. Whether or not the divergent results were due to the bias in both estimation models, this paper concluded that other factors should be taken into consideration when crime rates were analysed rather than focusing on income inequality.

3 Data Sources and Summary

County level data used in this study span eight years from 2005 to 2012 and cover 33 of the more heavily populated California counties. Crime rates we used as dependent variables in our models include broad aggregate crime rates for property and violent crime. Sub-categories we considered as well include homicide, forcible rape, robbery, aggravated assault, burglary, motor vehicle theft, theft and arson[1]. As noted by Brush (2007) reported crime rates are likely lower than actual incidence of crime as reported in victimization surveys. This crime data bias may be correlated with poverty and income inequality, possibly due to a lower perceived level of law enforcement efficacy. Additionally, we chose to focus solely on California county data to provide greater consistency in reporting rates and requirements, as well as greater consistency in the definition of each crime of interest. 1

A county level Gini coefficient for each county-year was generated as a measure of income inequality[2]. To help isolate the impact of income inequality from the crime inducing effects of poverty, we included the county-year poverty rate[3] as well as the county-year mean income[4]. High school dropout[5]

[1]Reported crime incidents data comes from Criminal Justice Statistics Center for the California Attorney Generals Office. Each crime rate given is the calculated rate per 100 000 residents.

[2]Except where noted differently, the remaining variables are generated from American Community Survey data taken from Integrated Public Microdata Surveys. The Gini index was calculated using non-negative total personal income for the county-year population over age 18. Values are between 0 and 1, where higher values represent greater income inequality. Missing values for 25 low population counties in IPUMS data led to their exclusion from this study.

[3]Percent of households that earning 100% or below of the poverty rate per federal guidelines

[4]Mean income from IPUMS data in given county-year

[5]Percent of county-year population over the age of 18 that did not complete the 12th grade

and college graduate rates[6] were also included to control for the effect of changes to potential future earnings on crime. As a significant social stressor and potential inducement to committing pecuniary crimes, we included county-year unemployment rates[7]. 2

Crime rates appear to be overwhelming driven by young males so we included county-year variables representing the percent of the population that is male, young, and both male and young[8]. We also included the population density[9] to control for the effect of increased opportunity for crime in dense areas or the effect of anonymity on criminality. 3

We also looked at the correlation between each explanatory variable. The results show that poverty is highly correlated with the high school dropout and youth rates. Mean income is highly correlated with youth and unemployment rates. Income inequality appears to be highly correlated with the high school dropout rate which 0.43 and low correlated with mean income which is -0.0814. 4

4 Empirical Analysis and Econometric Specification

In our model of criminal activity we have included several variables potentially correlated with crime. On the individually level, we would expect factors like poverty and lack of income opportunity to reduce the costs of potential loss of income as a result of committing a crime while at the same time increasing the relative payoff.Given that these and the other factors included in our model would, both individually and when aggregated to the county-year level, have a multiplicative effect on crime we used logged versions of each variable of interest in the following model[10]. This provides the

[6] Percent of county-year population over 23 that have completed a bachelor's degree or equivalent

[7] Percent of county-year labor force that is currently unemployed

[8] Percentage of the county-year population that is male, between 16 and 25, and both male and between 16 and 25

[9] In residents per square mile using the county-year population and the county area from the National Association of Counties

[10] As some homicide rates were 0, we replaced them with the lowest non-zero value in our sample.

additional benefit of reducing the effect of outliers.

$$ln(CrimeRate_{it}) = \beta_0 + \mathbf{Y}_t\delta + \beta_1 ln(Gini_{it}) + ln(\mathbf{X}_{it})\beta_2 + a_i + u_{it} \qquad (1)$$

Where $ln(CrimeRate_{it})$ is the crime rate of interest for county i in year t. $\mathbf{Y}_t$ is a vector of binary year variables, $ln(Gini_{it})$ is the log value of the county-year Gini coefficient, and $ln(\mathbf{X}_{it})$ are the log values of a vector of the remaining explanatory variables. As these are log versions of the variables, each β should be interpreted as an elasticity.

Initially, to control for the crime reducing effects of law enforcement we included a variable representing the number of sworn law enforcement officers per 100 000 county residents[11]. Unfortunately, we expect law enforcement rates to be effected strongly by crime rates, as we would expect higher crime rates to spur increased police highering. In our initial results, likely due to this endogeneity issue, policing levels had no statistically significant effect on any crime category. We eventually dropped policing rates from our model. We verified that this did not effect the direction, magnitude or statistical significance of any of our other explanatory variables to any large degree, suggesting we were not introducing significant bias by excluding policing from our model.

We expect the proportion of the population that is male and young to have positive effect on crime, particularly violent crime, as young males are, on average, more aggressive and impulsive than the general population. We would expect the percentage of high school dropouts to have a positive impact on crime while the percentage of college graduates to have a negative impact. Both are significant predictors of potential future income and serve as a proxy for the potential lost income as a result of committing a crime.

Population density remains more ambiguous in it's potential effect. Kelly (2000) suggests density would have a positive effect on crime rates by increasing both opportunities for criminal activity and anonymity. Alternatively though, higher density may reduce incidence of some property crimes by increasing the likelihood of being observed and apprehended. Higher unemployment and poverty rates would be expected to increase crime rates for a few reasons. Both may increase potential gains from property crimes while reducing expected losses in the event of being caught. Additionally, people in poverty are more easily victimized, increasing incidence of both property

[11] As with the crime rates, law enforcement data were from the California CJSC

and violent crimes. When controlling for poverty, we would expect median income to have a positive effect on property crimes, by increasing potential benefits, while having no effect on violent crime.

We expect income inequality to have a positive effect on property crime rate, but little or no significant impact on violent crime. To reiterate, a larger value Gini indicates greater county level income inequality. Given that we have controlled for the crime inducing effects of poverty and median income, the Gini represents purely the effect of unequal distribution of income on crime, and so should have a larger impact on pecuniary crimes relative to crimes not motivated by financial gain.

5 Results

5.1 Pooled OLS Estimation

For the purpose of comparison with previous articles, we began by evaluating the results from a pooled OLS estimation. We noted that income inequality decreased all categories of violent crime, as well as theft and aggregate property crime rates. We noted that, in those same categories, poverty increased crime as expected, as did population density with nearly all crime types. Interesting effects included a strong negative effect on homicide from the college graduate rate, but a positive effect on forcible rape. Highschool dropout rates increase robberies, as might be expected, but had no other effect. Unemployment had a positive impact on property crime rates and robbery, but no effect on other violent crime. With the exception of homicide, there appeared to be a strong downward trend over time for all categories of crime. 5 6

5.2 Fixed Effect Estimation

Testing suggested we must reject the pooled OLS model[12]. Using fixed effect estimation[13], and comparing with the results from our pooled OLS, we see that many of our results have changed. 7 8

[12]Testing on aggregated violent crime and aggregated property crime models using pooled data suggested we reject the null hypothesis that there was no county specific time invariant heterogeneity

[13]Testing led us to reject a random effects estimation method in favor of fixed effects.

Education no longer appears to have a statistically significant impact on crime. Using this method, we now see that density has a negative impact on many crime categories, including aggregate violent and property crime rates.

The county proportion that are male, youths, and male youths appear to no longer have a statistically significant impact on crime with two exceptions. A 1% increase in the proportion of males increases homicide by 4.11% and a 1% increase in the proportion on male youths decreases the forcible rape rate by 0.57%.

Poverty then appears to have a negative effect on most categories of property crimes as well as robbery. A 1% increase in the poverty rate decreases property crime by 0.60%. Mean county-year income only appears to affect burglary and aggravated assault. A 1% increase in mean income decreases burglary by 0.77% and decreases assault by 0.62%. A 1% increase in unemployment now appears to decrease homicide by 0.57%, motor vehicle theft by 0.27% and arson by 0.57%.

Though some crime categories appear to still be affected by broader trends over time, forcible rape, aggravated assault, and arson join homicide in having no statistically significant time effect.

Most interestingly, when we use a fixed effects estimation method to control for unobserved county specific effects on crime, we see no statistically significant effect of income inequality on crime rates.

6 Conclusion and Further Research

Initial results using cross-sectional data and pooled OLS estimation suggest that increasing income inequality decreases violent crime and theft. This result is interesting as it appears contrary to our initial expectation that income inequality would be an inducement to crime. Additionally, several of the control variables included in our model yield results consistent with our assumptions.

However, by utilising panel data we are able to used fixed effect estimation we are able to control for unobserved time-invariant county heterogeneity. Here, possibly due to elimination of bias from one or more omitted variables, we find strikingly different results. Many fewer control variables are statistically significant, and some effects, notably density and poverty, now appear to have the opposite effect from what we presumed. Most importantly, income inequality appears to have no effect on any category of crime.

Further research into the subject may benefit from inclusion of the effect of policing in the model, perhaps using an intrumental variable approach to deal with endogeneity issues. Most beneficial though might be expanding both scope of the data. Inclusion of a larger proportion of U.S. counties over a longer range of years might help increase the variance of a number of our variables[14].

7 Appendix

[14]Inclusion of lagged dependent variables had no significant effect on our results

Table 1: Crime Rates

Variable	Description	Source
Violent.Crime.Rate	Violent crimes reported to law enforcement per 100000 county residents	CJSC
Homicide.Rate	Homicides reported to law enforcement per 100000 county residents	CJSC
Forcible.Rape.Rate	Forcible rapes reported to law enforcement per 100000 county residents	CJSC
Robbery.Rate	Robberies reported to law enforcement per 100000 county residents	CJSC
Robbery.Firearm.Rate	Robberies involving a firearm reported to law enforcement per 100000 county residents	CJSC
Aggravated.Assault.Rate	Aggravated assaults reported to law enforcement per 100000 county residents	CJSC
Property.Crimes.Rate	Property crimes reported to law enforcement per 100000 county residents	CJSC
Burglary.Rate	Burglaries reported to law enforcement per 100000 county residents	CJSC
Burglary.Forcible.Entry.Rate	Burglaries with forcible entry reported to law enforcement per 100000 county residents	CJSC
Burglary.No.Force.rate	Burglaries without forcible entry reported to law enforcement per 100000 county residents	CJSC
Motor.Vehicle.Theft.Rate	Motor vehicle thefts reported to law enforcement per 100000 county residents	CJSC
Larceny.Theft.Rate	Thefts reported to law enforcement per 100000 county residents	CJSC
Arson.Rate	Arson crimes reported to law enforcement per 100000 county residents	CJSC
Gini	County level Gini index for income	IPUMS
Dropout	Percent of population over 18 that did not complete high school	IPUMS
College	Percent of population with a 4-year college degree.	IPUMS
Density	Persons per square mile	Census/NACO
Male	Percent of population which is male	IPUMS
Youth	Percent of population age 16 to 25	IPUMS
Male.Youth	Percent of population that is male and age 16 to 25	IPUMS
Poverty	Percent of population in poverty as measured by ACS	IPUMS
Mean.Income	Mean personal income	IPUMS
Unemployment	County unemployment rate	IPUMS

Table 2: Other Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Gini	264	.57	.03	.51	.67
Dropout	264	10.1%	4.7%	2.9%	24.9%
College	264	20.8%	9.2%	7.4%	44.6%
Density	264	1118.0	2913.7	36.9	17571.6
Male	264	49.3%	.2%	41.2%	61.9%
Youth	264	13.3%	2.4%	7.5%	23.7%
Male.Youth	264	6.9%	1.3%	4.0%	11.9%
Poverty300	264	47.41%	12.5%	21.6%	74.6%
Mean.Income	264	20920	10660.6	20920	76750
Unemployment	264	9.3%	3.4%	3.5%	18.3%

Table 3: Crime Rates

Variable	Obs	Mean	Std. Dev.	Min	Max
Violent Crime	264	447.4	175.4	188.0	917.2
Homicide	264	4.6	3.0	0	13.2
Rape	264	26.5	10.4	10.5	75.0
Robbery	264	126	95.2	24.0	525.8
Assault	264	289.9	113.1	110.8	674.9
Property Crime	264	2998.6	871.0	1468.5	5563.6
Burglary	264	717.5	241.7	319.3	1420.1
Theft	264	1827.0	514.6	825.2	3542.5
Auto Theft	264	454.0	251.6	96.1	1358.3
Arson	264	27.2	20.4	0.7	175.7

Table 4: Correlation amongst Explanatory Variable

	Gini	College	Dropout	Density	Male	Youth	Male.Youth	Unemployment
Gini	1.00	-0.10	0.43	0.08	0.32	0.21	0.31	0.22
College	0.01	1.00	-0.77	0.62	-0.24	-0.40	-0.44	-0.55
Dropout	0.48	-0.73	1.00	-0.19	0.24	0.54	0.55	0.47
Density	0.12	0.48	-0.07	1.00	-0.14	-0.22	-0.28	-0.26
Male	0.35	-0.20	0.30	0.00	1.00	0.10	0.30	0.16
Youth	0.24	-0.40	0.40	-0.17	0.10	1.00	0.95	0.32
Male.Youth	0.34	-0.44	0.46	-0.23	0.33	0.94	1.00	0.34
Unemployment	0.23	-0.53	0.49	-0.16	0.18	0.27	0.30	1.00
Poverty300	0.30	-0.83	0.81	-0.21	0.23	0.55	0.57	0.68
Mean.Income	-0.01	0.93	-0.70	0.33	-0.18	-0.53	-0.53	-0.57

Log values above diagonal, Normal values below diagonal

Table 5: Pooled OLS - Violent Crime

VARIABLES	Violent Crime	Homicide	Rape	Robbery	Assault
Gini	-2.597***	-4.140***	-2.219***	-2.629***	-2.535***
	(0.544)	(1.064)	(0.524)	(0.713)	(0.592)
College	-0.0468	-0.894***	0.307**	0.0567	-0.24
	(0.141)	(0.276)	(0.136)	(0.185)	(0.154)
Dropout	0.215*	-0.05	-0.200*	0.341**	0.184
	(0.112)	(0.220)	(0.108)	(0.147)	(0.122)
Density	0.132***	0.384***	-0.0816***	0.386***	0.0403*
	(0.0223)	(0.0436)	(0.0215)	(0.0292)	(0.0242)
Male	-0.489	1.079	-0.0813	-0.745	-0.844
	(0.574)	(1.123)	(0.552)	(0.752)	(0.624)
Youth	-0.16	0.625	1.198***	0.451	-0.608
	(0.410)	(0.802)	(0.395)	(0.537)	(0.446)
Male_Youth	-0.328	-0.703	-1.000***	-0.699	0.139
	(0.395)	(0.772)	(0.380)	(0.517)	(0.429)
Poverty300	1.334***	1.537***	1.237***	0.873**	1.354***
	(0.260)	(0.509)	(0.251)	(0.341)	(0.283)
Mean_Income	0.526*	0.84	0.500*	0.0219	0.819**
	(0.310)	(0.607)	(0.299)	(0.406)	(0.337)
Unemployment	0.0849	0.138	0.132	0.427**	-0.0138
	(0.128)	(0.249)	(0.123)	(0.167)	(0.139)
Y2006	0.0583	0.12	0.0144	0.203**	0.00268
	(0.0701)	(0.137)	(0.0674)	(0.0918)	(0.0762)
Y2007	0.0494	0.0516	0.00121	0.204**	-0.014
	(0.0709)	(0.139)	(0.0682)	(0.0929)	(0.0771)
Y2008	0.0182	0.0748	-0.0663	0.191**	-0.0588
	(0.0719)	(0.140)	(0.0691)	(0.0941)	(0.0781)
Y2009	-0.108	-0.153	-0.218**	-0.109	-0.11
	(0.0895)	(0.175)	(0.0861)	(0.117)	(0.0972)
Y2010	-0.186*	-0.212	-0.248**	-0.241*	-0.167
	(0.101)	(0.197)	(0.0969)	(0.132)	(0.109)
Y2011	-0.249**	-0.121	-0.299***	-0.289**	-0.232**
	(0.101)	(0.198)	(0.0974)	(0.133)	(0.110)
Y2012	-0.184*	-0.324*	-0.342***	-0.157	-0.184*
	(0.0980)	(0.191)	(0.0942)	(0.128)	(0.106)
Constant	7.615	-0.911	1.197	10.71*	6.803
	(4.755)	(9.295)	(4.573)	(6.225)	(5.167)
Observations	264	264	264	264	264
R-squared	0.535	0.514	0.489	0.704	0.467

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Pooled OLS - Property Crime

VARIABLES	Property Crime	Burglary	Theft	Auto Theft	Arson
Gini	-1.224***	-0.271	-1.804***	-0.699	-1.631
	(0.422)	(0.487)	(0.419)	(0.777)	(1.066)
College	0.0169	-0.104	0.0364	-0.0575	0.109
	(0.109)	(0.126)	(0.109)	(0.202)	(0.277)
Dropout	0.0484	-0.118	0.0781	0.111	-0.125
	(0.0871)	(0.101)	(0.0865)	(0.161)	(0.220)
Density	0.0807***	0.0258	0.0609***	0.265***	0.0838*
	(0.0173)	(0.0199)	(0.0172)	(0.0319)	(0.0437)
Male	0.452	-0.737	1.316***	-0.615	3.882***
	(0.445)	(0.513)	(0.442)	(0.820)	(1.125)
Youth	0.610*	0.313	0.853***	0.121	1.912**
	(0.318)	(0.367)	(0.316)	(0.586)	(0.804)
Male_Youth	-0.606**	-0.496	-0.698**	-0.441	-1.06
	(0.306)	(0.353)	(0.304)	(0.564)	(0.774)
Poverty300	0.410**	0.291	0.644***	-0.0379	0.812
	(0.202)	(0.233)	(0.200)	(0.372)	(0.510)
Mean_Income	0.131	-0.285	0.657***	-0.883**	0.289
	(0.240)	(0.277)	(0.239)	(0.443)	(0.608)
Unemployment	0.444***	0.531***	0.366***	0.701***	0.452*
	(0.0989)	(0.114)	(0.0982)	(0.182)	(0.250)
Y2006	0.0172	0.0649	-0.0046	0.0287	-0.034
	(0.0543)	(0.0626)	(0.0539)	(0.100)	(0.137)
Y2007	-0.0477	0.0136	-0.0659	-0.094	-0.124
	(0.0550)	(0.0634)	(0.0546)	(0.101)	(0.139)
Y2008	-0.102*	-0.0109	-0.108*	-0.260**	-0.221
	(0.0557)	(0.0642)	(0.0553)	(0.103)	(0.141)
Y2009	-0.402***	-0.302***	-0.378***	-0.738***	-0.593***
	(0.0693)	(0.0800)	(0.0689)	(0.128)	(0.175)
Y2010	-0.475***	-0.390***	-0.423***	-0.929***	-0.822***
	(0.0781)	(0.0900)	(0.0775)	(0.144)	(0.197)
Y2011	-0.456***	-0.379***	-0.399***	-0.925***	-0.928***
	(0.0785)	(0.0905)	(0.0779)	(0.145)	(0.198)
Y2012	-0.346***	-0.265***	-0.323***	-0.658***	-0.837***
	(0.0759)	(0.0876)	(0.0754)	(0.140)	(0.192)
Constant	6.426*	11.96***	-1.826	18.49***	-15.54*
	(3.684)	(4.250)	(3.659)	(6.788)	(9.312)
Observations	264	264	264	264	264
R-squared	0.488	0.524	0.432	0.574	0.327

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Fixed Effect - Violent Crime

VARIABLES	Violent Crime	Homicide	Rape	Robbery	Assault
Gini	0.409	-1.764	-0.0109	-0.265	0.547
	(0.424)	(1.255)	(0.505)	(0.433)	(0.536)
College	-0.0375	0.526	-0.185	0.0621	-0.00773
	(0.174)	(0.515)	(0.207)	(0.178)	(0.220)
Dropout	-0.0635	-0.598*	0.121	0.103	-0.128
	(0.112)	(0.332)	(0.134)	(0.115)	(0.142)
Density	-2.721***	-0.324	-1.916**	-3.079***	-2.750***
	(0.636)	(1.883)	(0.757)	(0.650)	(0.804)
Male	-0.0214	4.113***	0.345	0.0931	-0.0147
	(0.411)	(1.218)	(0.490)	(0.420)	(0.520)
Youth	-0.28	-0.0756	0.521*	-0.00254	-0.449
	(0.249)	(0.739)	(0.297)	(0.255)	(0.315)
Male_Youth	-0.0499	-0.0234	-0.565**	0.0448	0.0205
	(0.201)	(0.595)	(0.239)	(0.205)	(0.254)
Poverty300	-0.232	-0.00888	-0.364	-0.515**	-0.0922
	(0.209)	(0.620)	(0.249)	(0.214)	(0.265)
Mean_Income	-0.439*	-1.182*	0.445	-0.451*	-0.620**
	(0.235)	(0.696)	(0.280)	(0.240)	(0.297)
Unemployment	-0.0697	-0.566***	0.13	-0.0556	-0.0866
	(0.0680)	(0.202)	(0.0810)	(0.0696)	(0.0860)
Year 2006 to 2012	- to ***	- to *	-	***	- to *
Y2006	0.0814**	0.0977	0.0257	0.173***	0.0489
	(0.0348)	(0.103)	(0.0415)	(0.0356)	(0.0440)
Y2007	0.113***	0.0717	0.00609	0.206***	0.0915*
	(0.0391)	(0.116)	(0.0466)	(0.0400)	(0.0494)
Y2008	0.134***	0.171	-0.0372	0.272***	0.0970*
	(0.0432)	(0.128)	(0.0515)	(0.0442)	(0.0546)
Y2009	0.157***	0.281*	-0.0755	0.284***	0.131*
	(0.0526)	(0.156)	(0.0626)	(0.0538)	(0.0665)
Y2010	0.124**	0.272	-0.054	0.255***	0.0883
	(0.0604)	(0.179)	(0.0719)	(0.0617)	(0.0764)
Y2011	0.063	0.326	-0.0609	0.213***	0.0122
	(0.0689)	(0.204)	(0.0821)	(0.0704)	(0.0871)
Y2012	0.152**	0.0788	-0.0817	0.325***	0.107
	(0.0706)	(0.209)	(0.0840)	(0.0722)	(0.0892)
Constant	26.83***	7.838	9.461	29.29***	27.79***
	(5.259)	(15.58)	(6.262)	(5.377)	(6.648)
Observations	264	264	264	264	264
R-squared	0.362	0.187	0.345	0.39	0.282
Number of CountyID	33	33	33	33	33

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Fixed Effect - Property Crime

VARIABLES	Property Crime	Burglary	Theft	Auto Theft	Arson
Gini	-0.127	0.0467	-0.209	0.0508	0.172
	(0.246)	(0.364)	(0.279)	(0.494)	(1.158)
College	-0.114	-0.0936	-0.198*	0.21	1.200**
	(0.101)	(0.149)	(0.115)	(0.203)	(0.475)
Dropout	0.137**	0.0449	0.189**	-0.00329	0.586*
	(0.0650)	(0.0963)	(0.0739)	(0.131)	(0.306)
Density	-1.286***	-2.211***	-0.785*	-1.360*	-2.469
	(0.368)	(0.546)	(0.419)	(0.742)	(1.737)
Male	-0.0294	0.0803	0.1	-0.0937	-1.012
	(0.238)	(0.353)	(0.271)	(0.480)	(1.124)
Youth	-0.12	0.0682	-0.13	-0.532*	-0.136
	(0.145)	(0.214)	(0.164)	(0.291)	(0.681)
Male_Youth	0.0282	-0.169	0.0739	0.236	-0.0286
	(0.116)	(0.172)	(0.132)	(0.234)	(0.549)
Poverty300	-0.603***	-0.429**	-0.616***	-0.748***	-0.219
	(0.121)	(0.180)	(0.138)	(0.244)	(0.572)
Mean_Income	-0.238*	-0.772***	0.0889	-0.4	-0.309
	(0.136)	(0.202)	(0.155)	(0.274)	(0.642)
Unemployment	-0.045	-0.0834	0.0254	-0.272***	-0.566***
	(0.0394)	(0.0584)	(0.0449)	(0.0794)	(0.186)
Y2006	-0.0165	0.00566	-0.0167	-0.061	-0.0674
	(0.0202)	(0.0299)	(0.0230)	(0.0406)	(0.0951)
Y2007	-0.0582**	-0.00281	-0.0567**	-0.191***	-0.117
	(0.0227)	(0.0336)	(0.0258)	(0.0456)	(0.107)
Y2008	-0.0567**	0.0601	-0.0592**	-0.283***	-0.136
	(0.0251)	(0.0371)	(0.0285)	(0.0504)	(0.118)
Y2009	-0.0756**	0.0824*	-0.109***	-0.248***	0.0383
	(0.0305)	(0.0452)	(0.0347)	(0.0614)	(0.144)
Y2010	-0.0624*	0.102*	-0.0964**	-0.272***	-0.066
	(0.0350)	(0.0519)	(0.0398)	(0.0705)	(0.165)
Y2011	-0.0333	0.113*	-0.058	-0.259***	-0.143
	(0.0399)	(0.0592)	(0.0454)	(0.0804)	(0.188)
Y2012	0.0488	0.205***	0.00333	-0.0986	-0.113
	(0.0409)	(0.0606)	(0.0465)	(0.0823)	(0.193)
Constant	21.27***	29.03***	14.23***	22.14***	21.63
	(3.049)	(4.518)	(3.468)	(6.136)	(14.37)
Observations	264	264	264	264	264
R-squared	0.663	0.272	0.547	0.758	0.391
Number of CountyID	33	33	33	33	33

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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