Senior Project
Department of Economics

The Effect of Income Inequality on Property Crime in Ohio

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Abstract

This paper looks at the relationship between income inequality and property crime rates in Ohio. Using the Pooled OLS regression, results were inconclusive which led to the use of a Two-way Fixed Effects model. The Gini Coefficient, my variable for income inequality, was found to be statistically significant in leading to an increase in the property crime rates in Ohio, but income inequality may not be the most significant driving factor.

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I. Introduction

In 2013, the United States ranked fourth among the 34 countries in the Organization for Economic and Development (OECD) in homicide rates per 100,000 just behind Mexico, Turkey and Estonia. This statistic shows that there is a major issue of crime in our society today. The high rates of crime in America have caused many to be concerned with the safety of our nation, more specifically right where we live, in Ohio. Although since about 1990 our violent crime and property crime rates have fallen in the United States, the United States is still among the top in the world when it comes to crime rates. The State of Ohio has followed the same trends as the United States with property crime rates as shown in the graphs in Appendix 1. These graphs have been taken from The Office of Criminal Justice Services (OCJS) a Division of Ohio Department Safety.

With the political primary season in full swing, one of the main topics of discussion is about the income inequality in the United States. A study done in 2008 by Kevin Bryan and Leonardo Martinez concluded that in the past decades in the United States, the income inequality has been increasing. They show that the decreasing of real income by the lower income groups and the increase in real income by the top income groups in the United States is significantly impacting the income inequality levels in the United States (Bryan, 2008). In Appendix 2, you can see that the income inequality in the Unites States is rapidly growing.

This is the motivation for my research paper. I would like to see if this income inequality gap in the United States is causing people that are less fortunate to compensate for this inequality. It is interesting to note that these current trends actually do not follow

what the theory and past literally have said. Property crime, recently, has been decreasing, while income inequality has been steadily increasing. In this paper, I will be researching the effect of income inequality on property and violent crime in the 88 counties of Ohio. My hypothesis states that an increase in income inequality will lead to an increase in the property crime rate in Ohio. This is based on past literature and theory that will be explained in the coming sections of this paper.

II. Literature Review

"Income and Violent Crime" written by Pablo Fajnzylber, Daniel Lederman and Normal Loayza, looked at the link between income inequality and violent crime rates among countries. They used homicide data from the World Health Organization (WHO) and also used data from the United Nations World Crime Survey. For the income inequality data, they used the Gini Coefficient, which was calculated by the Klaus Deininger and Lyn Squire database. Fajnzylber, Leferman and Loayza created this database to get a better understanding of the income inequality among countries throughout the world. The econometric model that they used is called a GMM Estimator and is represented below:

$$y_{i,t} = \alpha y_{i,t-1} + \beta' X_{i,t} + \varepsilon_{i,t}$$

In this model, y represents the true crime rate (robbery or homicide); X is any explanatory variable (income inequality, GDP, etc.) "i" refers to the country and "t" represents time. They controlled for race, population density, and even age in their model. Their conclusion states that their results showed that income inequality had a "significant and positive effect" on crime (Fajnzylber, 2002).

Eric Neumayer published "Inequality and Violent Crime: Evidence from data on Robbery and Violent Theft" which stemmed from Fajnzylber, Lederman and Loayza. Neumayer questioned their findings in this research article because he felt they left out key variables in their data. Neumayer wanted to see how income inequality affects violent property crime. He used crime data from the United Nations and International Criminal Police Organization database. For income inequality data, he used data taken from UN-WIDER. Neumayer also used data from the Word Bank, for variables like GDP, growth rate, unemployment rate, etc. Below is his econometric model that was used as a fixed-effects model, which is given by the following equation:

$$\ln(y_{i,t}) = \propto + \beta x_{i,y} + (a_i + u_{i,t})$$

In the model, t is for time, countries are indicated by i, ln(y) is the logged rate of robbery and theft crime per one million people, x is explanatory variables, β is the vector of coefficients to be estimated. The fixed effects model is a model that is used to He found that income inequality "is not a statistically significant determinant, unless country-specific are not controlled." He found that income inequality is likely to be strongly correlated with country-specific fixed-effects like cultural differences (Neumayer, 2005).

Matz Dahlberg and Magnus Gustavsson took a different approach into looking at crime in their research article called "Inequality and Crime: Separating the Effects of Permanent and Transitory Income." Their main purpose of their research was to find the "effects of income in permanent income from the effects from the inequality in transitory income on crime." Dahlberg and Gustavsson gathered their transitory and permanent income data from a longitudinal database called LINDA. They used the data set from 1974

till 2000. They looked specifically at county level data in Sweden. The econometric model used in their study is as following

$$y_{iat} = p_t u_{it} + q_a \varepsilon_{it},$$

Dahlberg and Gustavsson's study found that it is important to distinguish between the two incomes. An increase in someone's transitory income has no effect on his or her chances of committing a crime. On the other hand, permanent income has a positive and significant impact on total crimes (Dahlberg, 2008).

"Crime and local Inequality in South Africa", which was written by Gabriel Demombynes and Berk Özler, was a research article the combined economic and sociology theories to help understand the concept that income inequality could lead to more crime. In this article, they analyze three-research questions pertaining to the country of South Africa. The first question is examining the effects of separating violent and property crime to test different sociological and economic theories. The second is looking at the economic positioning of neighborhoods and how that affects crime rates. Lastly, they look at whether crime exists in areas with high inequality between different racial groups. Demombynes and Özler obtained their data from three sources. They used data from the 1996 Population Census of South Africa, The South Africa Police Service (SAPS) and a 1995 October Household Survey and Income and Expenditure Survey. They used a model that looked at unobserved country-specific measures, which may be correlated with the explanatory variables. The model is shown below is Generalized Least squares econometric model:

$$\ln y_{ch} = \mathbf{x}_{ch}'\boldsymbol{\beta} + u_{ch}.$$

Where “c” represents a cluster, “h” per capita household expenditure, X observable effects found in the survey and SAPS. The results of their study found that income inequality is highly correlated with burglary and vehicle crime (property crime). They also found that violent crimes are “more likely to happen” in high inequality neighborhoods (Demombynes, 2005).

Morgan Kelly looked at the income inequality and crime among United States counties. Kelly’s data on crime to conduct this study came from a 1991 FBI Uniform Crime Reports which comprises of both violent and property crime. Kelly looks more at property crime in her study. Kelly also uses data from the 1994 County and City Data Book to calculate her income inequality variable, which is done by taking the means and medians of each county and using a formula derived by Shimizu and Crow in 1988. The equation to calculate the Gini Coefficient is as follows:

$$I = 2\Phi\left(\frac{\sigma_y}{\sqrt{2}}\right) - 1,$$

Kelly used a Poisson econometric model to test the hypothesis. The model is as follows:

$$\log(\lambda) = \log(N) + \beta_0 \log(d) + \beta_1 \log(I) + \beta_2 \cdot \log(x) - \beta_3 \log(p).$$

Where N is the total population in a region, D is the density in the region, L is a function of inequality that includes poverty, family instability, race and mobility, X is the fraction of people who will commit a crime when the opportunity arises and P is the police activity in an area. After running her data and using the Poisson econometric model, Kelly

concludes that violent crime had a large and significant impact on crime even when controlling for race, poverty, and family composition (Kelly, 2000).

For my niche in my study, I will apply these ideas gathered from the previous literature and translate them into looking specifically at the 88 counties in Ohio over the year of 2012-2014. The year's chosen are the most recent data available.

III. Theory

There are really four primary theories that link together income inequality and crime: Gary Becker's economic theory of crime through his work in Crime and Punishment, the Social Disorganization theory of Shaw and McKay; Merton's Strain Theory and also the Sociological Theory of Relative Deprivation. Gary Becker is the pioneer economist that developed a theory of crime and punishment. Becker states that an individual will look at his or her opportunity costs to determine whether or not it is worth committing a crime, based on the consequences and the probability that they will get caught white committing a crime (Becker, 1974).

The Social Disorganization theory, states that income inequality causes crime by indirectly being associated with the amount of poverty. This theory really emphasizes the social constraints to crime. Shaw and McKay identified three major categories that weaken the social control in communities. These three are poverty, ethnic heterogeneity, and residential mobility. Merton's Strain Theory states that individuals with that have a low status in society are frustrated with their failure to attain attributes of success. This frustration is even more so when they are around those individuals that have attained successful attributes. These unsuccessful individuals become isolated and then will more

likely commit a crime in response. This isolation of individuals is a mirror result from being in the minority racially or the disparity of income.

The sociological theory of relative deprivation explains, "Inequality breeds social tensions as the less well-off feel dispossessed when compared to wealthier people (Fajnzylber, 2002)." This sociological theory pretty much states that the poor feel disadvantage and unfairness against them which leads them to finding compensation and satisfaction through any means which includes committing crimes on the poor and the rich. As Kelly states it, the previous theories that were explained better noted as complements of one another rather than substitutes by focusing on a different component of the relationship between income inequality and crime (Kelly, 2000). Provided with these economic and sociological theories, I hypothesis that an increase income inequality will lead to an increase in the property crime rate in Ohio.

IV. Data and Methodology

This section will review the data and the econometric model that will be used to help get a better understanding of the research question. The first main source of data that I will be using is the American Community Survey (ACS), which has been obtained from Census.gov. The data that I will be using is not the micro level data of each individual but rather than a summary and statistics of the micro level data. This data is also knows as the American Fact Finder on Census.gov. This data provides the Gini coefficient, economic, social and demographic characteristics for the 88 counties in Ohio. The data from the American Fact Finder of the ACS is a 5-year estimate for the years 2012-2014. The data provided will be used for the independent variables for the study. The Gini coefficient

"measures the extent of which the distribution of income among individuals or households within a economy deviates from a perfectly equal distribution" (WorldBank).

The second data set being used is from the Office of Criminal Justice Services, which is a division of the Ohio Department of Safety. This website provides the property crime data by Ohio county for the years 2012-2014. This data set provides the dependent variables in this study.

In Appendix 3, the table lists all the variables being used in the study and where they will be obtained. The positive and negative signs located right next to the variable are the expected sign for each variable on property and violent crime. For example, it is expected that income inequality will have a positive effect on crime, or the more income inequality the more crime that county in Ohio will have.

The data of the independent variables being used are in decimal form. The decimals are the numeric value of the percent's in each county for a specific variable. For example, according to the data, in 2014 in Summit County of Ohio the percentage of the population that consisted of males was 48.8%. The dataset reads the 48.8% as 0.488.

There were multiple manipulations of the data. The first was creating a property crime rate variable. This was done by taking the total number of property crimes and dividing them by the total population. I was able to calculate the property crime rate in each Ohio County. Once this as done, I decided to take the log of the property crime rate for easier interpretation of the values in the results. I also created variables for the age groups in the regression. The variable "child" indicates the percentage of individuals in a specific county that are the age of 0-9 years old. "Teenager" represents the percentage of individuals in a specific county that are from the ages of 10-19 years old. "Early Adulthood"

is categorized as the percentage of individuals in a specific county that are the ages from 20-34. The variable "Mid Aged" is the percentage of individuals in a specific county that are the ages from 35-59 years old. Lastly, the variable "Sixty Plus" indicates the percentage of individuals in a specific county that are aged 60 and over. The last manipulation is combing the data for anyone who dropped out of school before ninth grade and adding it to anyone who dropped out of school while in high school. This new variable was names "dropout". It is important to note that Noble County was excluded from the dataset. This was because for a reason, which I could not find, they did not report any data on crime for the years 2012 and 2013. This explains why the number of observations that were used is an odd number at 261.

The descriptive statistics of the variables being used are located in Appendix 4. This table shows the descriptive statistics for the variables that was used in the three regression models. It is important to note the mean or average of each variable as it will give a better understanding of how to interpret the results from the regression that was run.

V. Econometric Model

In total, there were three regression models that were run for the research. The three models were a pooled OLS model, a one-way fixed effects model and a two-way fixed effects Model. The one-way fixed effects model was used to determine whether or not there was a county effect going on in the regression. The two-way fixed effects model was ran to see if there was a county and time effect that has happening in the regression. Below is the regression that was used for the OLS Model and the fixed effects model.

$$Log(Property\ Crime\ Rate_{i,t})$$

$$= \alpha_0 + \propto_1 Gini_{i,t} + \propto_2 Female_{i,t} - \propto_3 Education_{i,t} + \alpha_5 unemployed_{i,t}$$

$$+ \alpha_6 Nonwhite_{i,t} - Age_{i,t}$$

Where i and t represent the specific county and year, respectively. The Education variable in the equation above is a set of educational variables. The education variable consists of the percentage of people in a specific Ohio County that has dropout of high school before obtaining their high school or GED diploma, obtained a high school degree, has attended some college courses without completing a degree, bachelor's degree, and a graduate degree. I expect all the education variables all to have a negative effect on the property crime rate. This means that the more educated an area is, the lesser amount of property crime will happen in that area. The age is also a set of age variables. This includes the percentage of people in a specific county that are children, teenagers, early adulthood, and those that are over the age of sixty. I expect the older ages to have a negative effect on the property crime rate while the younger population has a positive effect on the property crime rate. The non-white variable is a variable that I created which includes every ethnicity except those that consider themselves white. This variable is explained by the percentage of individuals in a specific county who does not consider themselves as white. I expect the sign of this variable to be positive indicating the higher the percentage of minorities in an area, the higher property crime rate. The intercept is interpreted by the percentage of individuals in a specific county that are white and have dropped out of high school before obtaining their diploma.

VI. Results

The results of the Pooled OLS, One-way Fixed Effects and Two-way Fixed Effects are shown in appendices 5, 6 and 7, respectively. I first ran a pooled OLS model and it was not the results that I was expecting. The main variable of interest, the Gini Coefficient, was not statistically significant and also my educational variables were all positive. I then decided to run the one-way fixed effects and a two-way fixed effects model to account for any unobserved heterogeneity. After running the fixed effects, results were mush better than the OLS model. The F-value from running these three models suggests that the two-way fixed effects model is the best regression for my research. This states that there is a county effect and time effect that needs to be accounted for in my research.

I will be looking at the results of the two-way fixed effects model in Appendix 7. There are several statistical significant variables that are shown in the regression. My main variable of interest, the Gini Coefficient is statistically significant at the 99% confidence level with a t-value of 2.95. The coefficient of the variable is .131, which means that for every one-unit increase in the Gini Coefficient (income inequality) the property crime rate increases by .131 percentage points. Another statistically significant variable is one of the education variables, which is "Graduate_PHD". It is statistically significant at the 95% confidence level. This coefficient is -.211, which means that for every 1% increase in the population of a specific county with a masters or PHD degree, property crime rate will decrease by .211 percentage points. It is important to note that the signs for all the education variables are as expected. The negative signs associated with all the educational variables means that the higher percentage of people in a specific county that obtain a high education, the lower the property crime rate will be. The variable "Non-White" is another variable that is statistically significant. This variable is statistically significant at the 90%

confidence level. The coefficient for this variable is -.099, which means that a 1% increase in the percentage of non-white individuals in a specific county, the property crime rate will decrease by .099 percentage points. The rest of the variables in the model were not statistically significant, however the signs on the coefficients were what was expected.

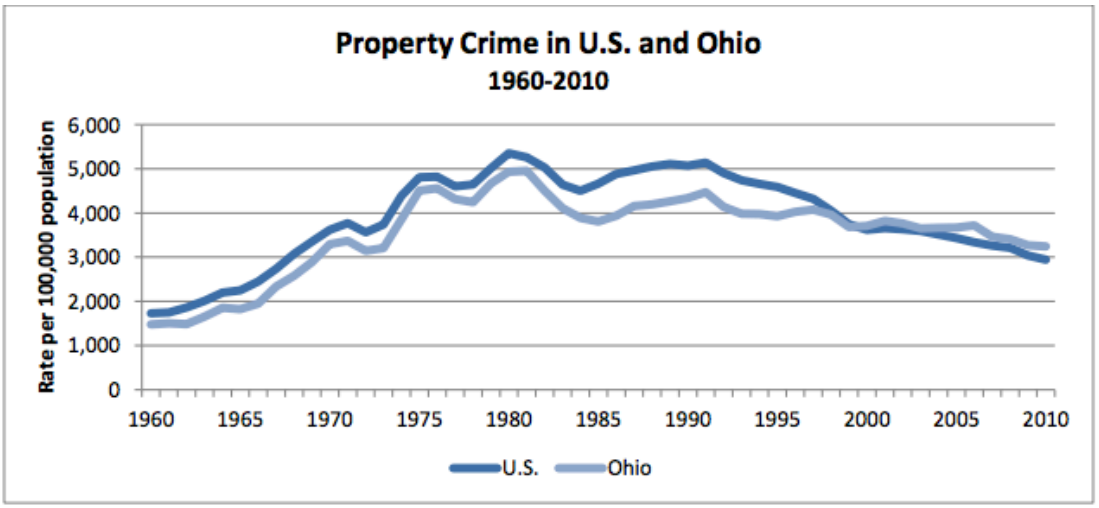
VII. Conclusion

In conclusion, after fixing for fixed effects, I can state that income inequality has a statistically significant effect on the property crime rate. My hypothesis, which came from the theory, that income inequality will lead to an increase in property crime rates turned out to be the case. However, other variables must have a larger effect on property crime in the property crime rate in Ohio is decreasing while the income inequality continues to increase. This is It is important to note that this study does not capture what exact variables are having more of an effect of the decrease of property crime rate.

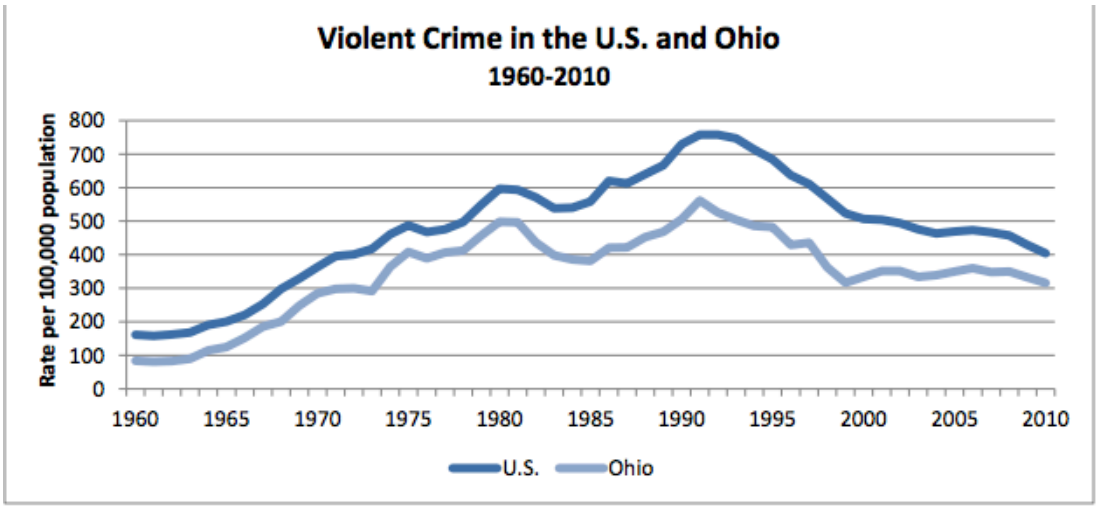
There are many limitations when it comes to this study. One limitations in this study is that it cannot account for any economic growth or decline in the counties. That data is available through the MSA, which looks at metropolitan areas and does not separate the data by county. I also do not have the data on the number of police officers in each county during this time. Also, due to time constraints on this project, income data was not included in this study. Also due to time constraints only three years of data was used from 2012-2014 because of the time it took to get the data ready to be able to run in SAS. I would have ultimately liked to use data dating back to when the property crime rate started to drop, which was around the year 1995. There also maybe some multicollinearity going on between my variables which maybe leads to some of the variables being statistically

insignificant. For further research, it would be interesting to get data on the neighborhood level to see the effects the income inequality has on the property crime rate.

Appendix 1

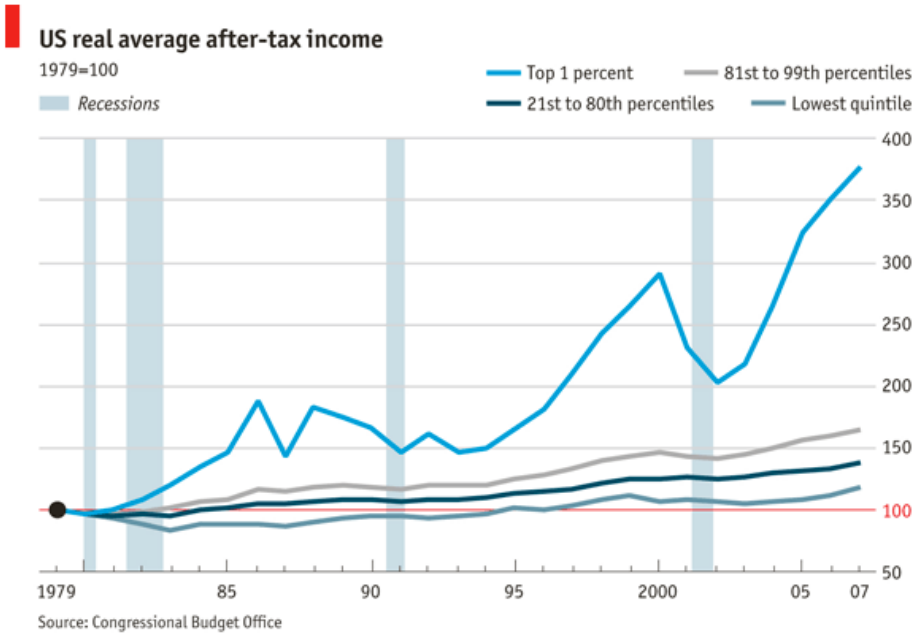


Source: Federal Bureau of Investigation, Uniform Crime Reports data, prepared by the National Archive of Criminal Justice Data
Source: Federal Bureau of Investigation, Crime in the United States 2010



Source: Federal Bureau of Investigation, Uniform Crime Reports data, prepared by the National Archive of Criminal Justice Data
Source: Federal Bureau of Investigation, Crime in the United States 2010

Appendix 2



Source: "The 99 Percent." *The Economist*. The Economist Newspaper

Variables	Definition	Source

Appendix 3

Gini Coefficient (+)	The Gini is a calculation of income inequality in each Ohio County.	http://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ACS_14_5YR_B19083&prodType=table
Unemployment rate (+)	% of unemployed in that specific county	https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/2014/
Sex (+/-)	% of people in that specific county who are male or female	https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/2014/
Age (+/-)	% of people in a specific county in a specific age range i.e. 25-34 years old, 35-44 years old, etc.	https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/2014/
Race (+/-)	% of people in a specific county with a specific race i.e. White, Black, Hispanic	https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/2014/
Population	Total number of people living in that specific county	http://www.ocjs.ohio.gov/crime_stats_reports.stm
Property Crime	Total number of property crimes committed in that specific county	http://www.ocjs.ohio.gov/crime_stats_reports.stm
Education (-)	% of people in a specific county with a certain level of education i.e. high school grad, college grad, dropout, etc.	hhttps://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/2014/
Economic Growth (-)	Time permitting and availability of data	N/A

Appendix 4

Variable	N	Mean	Std. Dev.	Min	Max
Gini Coefficient	261	.424	.026	.355	.503
Bachelor	261	.116	.049	.048	.329
Dropout	261	.129	.048	.037	.448
High School	261	.412	.067	.203	.528
Some College	261	.194	.024	.100	.255
Graduate-PHD	261	.067	.032	.024	.184
Female	261	.506	.011	.451	.530
Unemployed	261	.058	.013	.027	.107
Non-White	261	.078	.070	.010	.368
Child	261	.127	.014	.080	.200
Teenager	261	.138	.012	.112	.180
Early Adulthood	261	.177	.026	.122	.337
Sixty-Plus	261	.215	.026	.140	.290

Appendix 5

Pooled OLS

The REG Procedure
Model: MODEL1
Dependent Variable: lnRate

Number of Observations Read	261
Number of Observations Used	261

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	0.01218	0.00093671	13.12	<.0001
Error	247	0.01763	0.00007138		
Corrected Total	260	0.02981			

Root MSE	0.00845	R-Square	0.4085
Dependent Mean	0.02010	Adj R-Sq	0.3774
Coeff Var	42.03646		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-0.09350	0.05447	-1.72	0.0873
Gini_Index	1	0.05684	0.03736	1.52	0.1294
Bachelor	1	0.15082	0.05196	2.90	0.0040
dropout	1	0.15880	0.04541	3.50	0.0006
High_School	1	0.15889	0.04935	3.22	0.0015
some_college	1	0.26498	0.06193	4.28	<.0001
Graduate_PHD	1	0.13100	0.07939	1.65	0.1002
Female	1	-0.14155	0.06205	-2.28	0.0234
unemployed	1	0.07351	0.05085	1.45	0.1495
Non_White	1	0.04574	0.01506	3.04	0.0026
Child	1	0.04937	0.07210	0.68	0.4942
Teenager	1	-0.12049	0.07856	-1.53	0.1264
Early_Adulthood	1	0.05494	0.04293	1.28	0.2019
Sixty_Plus	1	-0.04570	0.04950	-0.92	0.3568

Appendix 6

One-Way Fixed Effects

The PANEL Procedure
Fixed One Way Estimates

Model Description	
Estimation Method	FixOne
Number of Cross Sections	87
Time Series Length	3

Fit Statistics			
SSE	0.0013	DFE	161
MSE	0.0000	Root MSE	0.0029
R-Square	0.9560		

F Test for No Fixed Effects			
Num DF	Den DF	F Value	Pr > F
86	161	23.30	<.0001

Parameter Estimates						
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|	Label
Intercept	1	-0.03618	0.0836	-0.43	0.6660	Intercept
Gini_Index	1	0.124487	0.0453	2.75	0.0067	
Bachelor	1	-0.07335	0.0829	-0.88	0.3776	
dropout	1	0.012611	0.0612	0.21	0.8370	
High_School	1	-0.05266	0.0631	-0.83	0.4055	
some_college	1	-0.03798	0.0688	-0.55	0.5815	
Graduate_PHD	1	-0.20791	0.0954	-2.18	0.0308	
Female	1	0.108964	0.1098	0.99	0.3223	
unemployed	1	0.086604	0.0559	1.55	0.1235	
Non_White	1	-0.13934	0.0501	-2.78	0.0060	
Teenager	1	0.068287	0.0730	0.94	0.3511	
Child	1	-0.0075	0.0701	-0.11	0.9149	
Early_Adulthood	1	0.068719	0.0856	0.80	0.4231	
Sixty_Plus	1	-0.14941	0.0427	-3.50	0.0006	

Appendix 7

Two-Way Fixed Effects

The PANEL Procedure
Fixed Two Way Estimates

Model Description	
Estimation Method	FixTwo
Number of Cross Sections	87
Time Series Length	3

Fit Statistics			
SSE	0.0012	DFE	159
MSE	0.0000	Root MSE	0.0028
R-Square	0.9588		

F Test for No Fixed Effects			
Num DF	Den DF	F Value	Pr > F
88	159	24.16	<.0001

Parameter Estimates						
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|	Label
Intercept	1	-0.004	0.0858	-0.05	0.9629	Intercept
Gini_Index	1	0.131027	0.0444	2.95	0.0037	
Bachelor	1	-0.08058	0.0808	-1.00	0.3201	
dropout	1	-0.06352	0.0640	-0.99	0.3228	
High_School	1	-0.0898	0.0629	-1.43	0.1555	
some_college	1	-0.07335	0.0679	-1.08	0.2819	
Graduate_PHD	1	-0.21128	0.0929	-2.27	0.0243	
Female	1	0.073904	0.1081	0.68	0.4954	
unemployed	1	0.04382	0.0652	0.67	0.5025	
Non_White	1	-0.09728	0.0512	-1.90	0.0593	
Teenager	1	0.016906	0.0753	0.22	0.8227	
Child	1	-0.04826	0.0728	-0.66	0.5083	
Early_Adulthood	1	0.067851	0.0840	0.81	0.4202	
Sixty_Plus	1	-0.02788	0.0565	-0.49	0.6221	

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SAS Code

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set crime_2012;
run;
data crime_2012;
set crime_2012;
      Keep
            county
            year
            property_crime;
run;
data crime_2013;
set crime_2013;
      Keep
            county
            year
            property_crime;
run;
data crime_2014;
set crime_2014;
Keep
            county
            year
            property_crime;
run;
data crime1;
      merge crime_2012 crime_2013;
      by county year;
run;
data crime2;
      merge crime1 crime_2014;
      by county year;
run;
data social_2012;
set social_2012;
      rename __High_school_graduate__includes = High_School;
      rename __Some_college__no_degree = some_college;
      rename __Associate_s_degree = associate;
      rename __Bachelor_s_degree = Bachelor;
      rename __Graduate_or_professional_degre = Graduate_PHD;
      rename __Naturalized_U_S__citizen = USCitizen;
      rename __Not_a_U_S__citizen = non_UScitizen;
      rename __Family_households__families_ = Family_House;
      rename ____Married_couple_family = Married_Family;
      rename ____Male_householder__no_wife_p = male_house;
      rename ____Female_householder__no_husb = female_house;
      rename __9th_to_12th_grade__no_diploma = Nodip_9_12;
      rename __Less_than_9th_grade = Less_9;
run;
data social_2012;
set social_2012;
      dropout = Less_9 + Nodip_9_12;
run;
data social_2013;
set social_2013;
      rename ______High_school_graduate__incl = High_School;
```

```
      rename ______Some_college__no_degree = some_college;
      rename ______Associate_s_degree = associate;
      rename ______Bachelor_s_degree = Bachelor;
      rename ______Graduate_or_professional_d = Graduate_PHD;
      rename ______Naturalized_U_S__citizen = USCitizen;
      rename ______Not_a_U_S__citizen = non_UScitizen;
      rename ______Family_households__familie = Family_House;
      rename ________Married_couple_family = Married_Family;
      rename ________Male_householder__no_wi = male_house;
      rename ________Female_householder__no = female_house;
      rename ______Less_than_9th_grade = Less_9;
      rename ______9th_to_12th_grade__no_dip = Nodip_9_12;
run;
data social_2013;
set social_2013;
      dropout = Less_9 + Nodip_9_12;
run;
data social_2014;
set social_2014;
      rename ______High_school_graduate__incl = High_School;
      rename ______Some_college__no_degree = some_college;
      rename ______Associate_s_degree = associate;
      rename ______Bachelor_s_degree = Bachelor;
      rename ______Graduate_or_professional_d = Graduate_PHD;
      rename ______Naturalized_U_S__citizen = USCitizen;
      rename ______Not_a_U_S__citizen = non_UScitizen;
      rename ______Family_households__familie = Family_House;
      rename ________Married_couple_family = Married_Family;
      rename ________Male_householder__no_wi = male_house;
      rename ________Female_householder__no = female_house;
      rename ______Less_than_9th_grade = Less_9;
      rename ______9th_to_12th_grade__no_dip = Nodip_9_12;
run;
data social_2014;
set social_2014;
      dropout = Less_9 + Nodip_9_12;
run;
data social1;
      merge social_2012 social_2013;
      by county year;
run;
data social2;
      merge social1 social_2014;
      by county year;
run;
data econ_2012;
set econ_2012;
      rename __In_labor_force= labor_force;
      rename ____Civilian_labor_force = Civil_labor;
      rename ______Employed = employed;
      rename ______Unemployed = unemployed;
      rename ____Armed_Forces = armed_forces;
      rename __Not_in_labor_force = not_labor_force;
run;
data econ_2013;
set econ_2013;
      rename ______In_labor_force= labor_force;
```

```
      rename ________Civilian_labor_force = Civil_labor;
      rename __________Employed = employed;
      rename __________Unemployed = unemployed;
      rename ________Armed_Forces = armed_forces;
      rename ______Not_in_labor_force = not_labor_force;
run;
data econ_2014;
set econ_2014;
      rename ______In_labor_force= labor_force;
      rename ________Civilian_labor_force = Civil_labor;
      rename __________Employed = employed;
      rename __________Unemployed = unemployed;
      rename ________Armed_Forces = armed_forces;
      rename ______Not_in_labor_force = not_labor_force;
run;
data econ1;
      merge econ_2012 econ_2013;
      by county year;
run;
data econ2;
      merge econ1 econ_2014;
      by county year;
run;
data demo_2012;
set demo_2012;
      rename ____Total_population = Total_Pop;
      rename ____White = White;
      rename ____Black_or_African_American = Black;
      rename __Male = Male;
      rename __Female = Female;
      rename ____White = White2;
      rename ____Black_or_African_American = Black2;
      rename __Under_5 = Less_5;
      rename __5_to_9 = _5_9;
      rename __10_to_14 = _10_14;
      rename __15_to_19 = _15_19;
      rename __20_to_24 = _20_24;
      rename __25_to_34 = _25_34;
      rename __35_to_44 = _35_44;
      rename __45_to_54 = _45_54;
      rename __55_to_59 = _55_59;
      rename __60_to_64 = _60_64;
      rename __65_to_74 = _65_74;
      rename __75_to_84 = _75_84;
      rename __85__and_over = _85_Over;
      rename __White = White;
      rename __Black_or_African_American = Black;
      rename __American_Indian_and_Alaska_Nat = American_Indian;
      rename __Asian = Asian;
      rename __Native_Hawaiian_and_Other_Paci = Hawaiian;
      rename __Some_other_race = Other;
      rename __18__and_over = Eighteen_Over;
      rename __21__and_over = Twentyone_Over;
      rename __62__and_over = Sixtytwo_Over;
      rename __65__and_over = Sixtyfive_Over;
run;
data demo_2012;
```

```
set demo_2012;
      Child = Less_5 + _5_9;
      Teenager = _10_14 + _15_19;
      Early_Adulthood =_20_24 +_25_34;
      Mid_Aged = _35_44 + _45_54 + _55_59;
      Sixty_Plus = _60_64 + _65_74 +_75_84 + _85_Over;
      Non_White = Black + American_Indian + Asian + Hawaiian + Other;
run;
data demo_2013;
set demo_2013;
      rename ____Total_population = Total_Pop;
      rename ________White = White2;
      rename ________Black_or_African_America = Black2;
      rename ______Male = Male;
      rename ______Female = Female;
      rename ____White = White;
      rename ____Black_or_African_American = Black;
      rename ______Under_5 = Less_5;
      rename ______5_to_9 = _5_9;
      rename ______10_to_14 = _10_14;
      rename ______15_to_19 = _15_19;
      rename ______20_to_24 = _20_24;
      rename ______25_to_34 = _25_34;
      rename ______35_to_44 = _35_44;
      rename ______45_to_54 = _45_54;
      rename ______55_to_59 = _55_59;
      rename ______60_to_64 = _60_64;
      rename ______65_to_74 = _65_74;
      rename ______75_to_84 = _75_84;
      rename ______85__and_over = _85_Over;
      rename ______White = White;
      rename ______Black_or_African_American = Black;
      rename ______American_Indian_and_Alaska = American_Indian;
      rename ______Asian = Asian;
      rename ______Native_Hawaiian_and_Other = Hawaiian;
      rename ______Some_other_race = Other;
      rename ______18__and_over = Eighteen_Over;
      rename ______21__and_over = Twentyone_Over;
      rename ______62__and_over = Sixtytwo_Over;
      rename ______65__and_over = Sixtyfive_Over;
run;
data demo_2013;
set demo_2013;
      Child = Less_5 + _5_9;
      Teenager = _10_14 + _15_19;
      Early_Adulthood = _20_24 + _25_34;
      Mid_Aged = _35_44 + _45_54 + _55_59;
      Sixty_Plus = _60_64 + _65_74 + _75_84 + _85_Over;
      Non_White = Black + American_Indian + Asian + Hawaiian + Other;
run;
data demo_2014;
set demo_2014;
      rename ____Total_population = Total_Pop;
      rename ________White = White2;
      rename ________Black_or_African_America = Black2;
      rename ______Male = Male;
      rename ______Female = Female;
```

```
      rename ____White = White;
      rename ____Black_or_African_American = Black;
      rename ______Under_5 = Less_5;
      rename ______5_to_9 = _5_9;
      rename ______10_to_14 = _10_14;
      rename ______15_to_19 = _15_19;
      rename ______20_to_24 = _20_24;
      rename ______25_to_34 = _25_34;
      rename ______35_to_44 = _35_44;
      rename ______45_to_54 = _45_54;
      rename ______55_to_59 = _55_59;
      rename ______60_to_64 = _60_64;
      rename ______65_to_74 = _65_74;
      rename ______75_to_84 = _75_84;
      rename ______85__and_over = _85_Over;
      rename ______White = White;
      rename ______Black_or_African_American = Black;
      rename ______American_Indian_and_Alaska = American_Indian;
      rename ______Asian = Asian;
      rename ______Native_Hawaiian_and_Other = Hawaiian;
      rename ______Some_other_race = Other;
      rename ______18__and_over = Eighteen_Over;
      rename ______21__and_over = Twentyone_Over;
      rename ______62__and_over = Sixtytwo_Over;
      rename ______65__and_over = Sixtyfive_Over;
run;
data demo_2014;
set demo_2014;
      Child = Less_5 + _5_9;
      Teenager = _10_14 + _15_19;
      Early_Adulthood = _20_24 + _25_34;
      Mid_Aged = _35_44 + _45_54 + _55_59;
      Sixty_Plus = _60_64 + _65_74 + _75_84 + _85_Over;
      Non_White = Black + American_Indian + Asian + Hawaiian + Other;
run;
data demo1;
      merge demo_2012 demo_2013;
      by county year;
run;
data demo2;
      merge demo1 demo_2014;
      by county year;
run;
data gini_2012;
set gini_2012;
run;
data gini_2013;
set gini_2013;
run;
data gini_2014;
set gini_2014;
rename gini = gini_index;
run;
data gini1;
      merge gini_2012 gini_2013;
      by county year;
run;
```

```
data gini2;
      merge gini1 gini_2014;
      by county year;
run;
data one;
      merge crime2 social2;
      by county year;
run;
data two;
      merge one econ2;
      by county year;
run;
data three;
      merge two gini2;
      by county year;
run;
data final;
      merge three demo2;
      by county year;
run;
data final;
set final;
if county = 'Noble' then delete;
run;
ods pdf file = "F:\WWW\Portfolios\Fall2014\226\kmb222\Senior
Project\Project\Senior+Project.pdf";
data final;
set final;
      keep  county
                  year
                  gini_index
                  bachelor
                  associate
                  some_college
                  high_school
                  dropout
                  high_school
                  Female
                  Male
                  graduate_PHD
                  male_house
                  female_house
                  unemployed
                  property_crime
                  Total_Pop
                  Child
                  Teenager
                  Early_Adulthood
                  Mid_Aged
                  Sixty_Plus
                  Black
                  American_Indian
                  Asian
                  Hawaiian
                  Other
                  White
                  Married_family
```

```
                    Family_House
                    non_white
                    USCitizen
                    Employed;
run;
proc means;
run;
data final;
set final;
 Rate = Property_Crime/Total_pop;
 lnRate = log(rate+1);
 lnpropertycrime= log(Property_Crime+1);
 lnTotalPop = log(Total_Pop);
 run;
/*pooled ols*/
proc reg plots = none;
model lnrate = Gini_index bachelor dropout high_school some_college
graduate_PHD Female Unemployed Non_White child Teenager early_adulthood
Sixty_Plus;
Title 'Pooled OLS';
run;
quit;
proc sort;
by county year;
run;
/*One-Way Fixed Effects*/
proc panel plots = none;
id county year;
model lnrate = Gini_index bachelor dropout high_school some_college
graduate_PHD Female Unemployed Non_White Teenager child early_adulthood
Sixty_Plus/FIXONE;
Title ' One-Way Fixed Effects';
run;
quit;
/*Two-Way Fixed Effects*/
Proc Panel plots = none;
id county year;
model lnrate = Gini_index bachelor dropout high_school some_college
graduate_PHD Female Unemployed Non_White Teenager child early_adulthood
Sixty_Plus/FIXTWO;
Title ' Two-Way Fixed Effects';
run;
quit;

ods pdf close;
```