Inequality and Crime Revisited: Effects of Local Inequality and Economic Segregation on Crime

Songman Kang

Hanyang University

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Abstract

Economic inequality has long been considered an important determinant of crime. Existing evidence, however, is mostly based on inadequately aggregated data sets, making its interpretation less than straightforward. Using tract- and county-level U.S. Census panel data, I decompose county-level income inequality into its within- and across-tract components and examine the extent to which county-level crime rates are influenced by local inequality and economic segregation. I find that the previously reported positive correlation between violent crime and economic inequality is largely driven by economic segregation across neighborhoods instead of within-neighborhood inequality. Moreover, there is little evidence of a significant empirical link between overall inequality and crime when county- and time-fixed effects are controlled for. On the other hand, a particular form of economic inequality, namely, poverty concentration, remains an important predictor of county-level crime rates across various specifications.

JEL: K4, I3

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Contact Information:

College of Economics and Finance, Hanyang University,

222 Wangsimni-ro, Seongdong-gu, Seoul, South Korea

email: songmankang@hanyang.ac.kr

1 Introduction

In light of high levels of economic inequality and crime in the U.S., economists have spent much effort on studying the link between inequality and crime.[1] Under a simple economic model of criminal behavior (Becker 1968), an individual chooses to commit a crime if his potential criminal gains net of the potential costs of punishment are greater than his potential gains from legitimate work. As inequality rises, those near the bottom of the income distribution may be left with little increase in the legitimate earnings potential but much larger increases in potential criminal gains, because there are now more wealthy potential victims who possess goods worth taking. This additional incentive to offend may result in higher levels of crime. The argument that high inequality generates more crimes through increased potential criminal gains has been further developed in a number of recent theoretical models (Bourguignon, Nuñez and Sanchez 2003; Burdett, Lagos and Wright 2003, 2004; Chiu and Madden 1998; Imrohoroglu, Merlo and Rupert 2004). Empirical studies generally find that inequality and crime are positively linked, based on both U.S. and international data (Fajnzylber, Lederman and Loayza 2002; Kelly 2000; Soares 2004).

A potential drawback of the existing empirical evidence is that the geographic level of aggregation used in many studies, e.g., counties and countries, may be inappropriately large while crime mostly remains as a local phenomenon.[2] For example, burglary victimization data from Philadelphia, PA and Wilmington, DE show that 46 percent of burglaries take place within 1 mile of the offender's residence (Rengert, Piquero and Jones 1999), and more than 70 percent of robberies in Chicago are committed inside the census tract in which the offender lives (Bernasco and Block 2009). Given that disproportionately many crimes take place near the offender's residence, the level of economic inequality aggregated up to county- or country-level may not be as relevant to a potential offender's criminal decision as the level of economic inequality near his own neighborhood.

[1] There is an extensive sociology literature on the link between inequality and crime, dating back to Merton's strain theory (1938) and Shaw and McKay's social disorganization theory (1942).

[2] Weisburd, Bernasco and Bruinsma (2009) discuss the importance of the aggregation level choice in empirical criminology research.

Moreover, highly aggregated inequality measures necessarily confound within-neighborhood economic inequality with across-neighborhood inequality, which should have different effects on crime. A positive empirical relationship between within-neighborhood inequality and crime would be consistent with the traditional explanation offered by economists; a potential offender should associate presence of wealthier neighbors with greater gains from crime and be more likely to offend. On the other hand, sociologists have long argued that high across-neighborhood inequality and the resulting concentration of poverty in a few disadvantaged neighborhoods would be particularly criminogenic via greater social disorganization and less informal social control (Sampson, Raudenbush and Earls 1997; Wilson 1987).

In this paper, I use a method of inequality decomposition to separate county-level inequality into its within- and across-tract components, and estimate their effects on crime using the U.S. Census and FBI Uniform Crime Reporting (UCR) data covering the years 1990 through 2009. The Census data used in this study are collected at three time points, the 1990 and 2000 decennial Census data and 2005-2009 American Community Survey (ACS), and is merged with the county-level UCR data from corresponding years.[3] Two key findings emerge from the estimation results. First, the previously reported positive correlation between inequality and crime is likely driven by the effects of economic segregation (across-tract inequality) instead of local inequality (within-tract inequality). In fact, I find that within-tract inequality is often negatively correlated with crime rates. Second, when the regression specification includes county and time fixed effects, the link between within- and across-tract inequality and crime becomes modest and statistically insignificant for all seven Part I index crimes considered.[4]

The observation that the inequality effect of crime mostly come from economic segregation across neighborhoods, rather than local inequality, may appear inconsistent with the rational choice model of crime, but this is not necessarily the case. The conventional economic explanation predicts that increased wealth in the community raises potential offenders' criminality

[3]Information on socioeconomic characteristics of the population at the tract-level is not available in the 2010 decennial Census, as the "long form" Census questionnaire, which elicited such information from respondents, has been replaced by the annual ACS.

[4]Part I index crimes are murder, rape, robbery, aggravated assault, burglary, larceny, and motor vehicle theft.

via greater gains from successful crimes (Ehrlich 1973). But crimes against high-income individuals may also pose greater probabilities of apprehension and punishment to offenders as the wealthy are more likely to invest on self-protection measures and/or choose to live in areas with more effective police forces. If this additional risk of apprehension and punishment outweighs additional gains from victimizing the wealthy, a potential offender prefers to victimize the poor. At the same time, the offending rates are likely to be higher among the poor, who may find crime as a more attractive "work option" than legitimate work. Then, neighborhoods of concentrated poverty (and thus little economic inequality) are heavily populated by individuals with high risks of both offending and victimization. The resulting high supply and demand of criminal opportunities (Cook 1986) make these neighborhoods particularly vulnerable to high crime risks. The key assumption that offenders may prefer to victimize the poor because of lower risks of apprehension and punishment is consistent with the observed crime victimization pattern from National Crime Victimization Survey (NCVS) data; low-income households are much more likely to become victims of crime and less likely to report to the authority after victimized, while the differences in economic loss to victim do not differ as much. Further discussion on the theoretical link between inequality and crime and the victimization data are presented below.

This paper makes the following contributions to the existing literature on the effect of inequality on crime. First, I find evidence that the previously reported positive relationship between inequality and crime is largely driven by economic segregation across communities, and the link between inequality and crime becomes more modest when unobserved time and county characteristics are controlled for. However, violent crime remains significantly and positively correlated with poverty concentration, a particular form of economic inequality, under various specifications. Second, I provide a novel explanation on the relationship between crime and inequality by extending the traditional economic model of crime. Under the assumption that crimes against the poor not only provide smaller gains to criminals, but also pose lower risks of apprehension and punishment, low-income individuals have higher risks of both offending and victimization. Poverty-concentrated neighborhoods then have high supply and demand of criminal opportunities, resulting in high criminal risks. Thirdly, this study highlights the importance of the choice of aggregation level in empirical studies of crime. Economics of crime literature paid relatively little attention to the appropriate geographic level of aggregation, although misspecification of the proper aggregation level is likely to lead to empirical results that can be difficult to interpret and misleading.

The rest of the paper is organized as follow. Section 2 briefly reviews the existing literature on inequality and crime. Section 3 describes the data and the inequality decomposition technique. Section 4 discusses the empirical strategy and reports the estimation results. Section 5 discusses the theoretical link between the crime, economic segregation and poverty concentration and presents empirical evidence. Section 6 concludes.

2 Background

Economists traditionally explain the theoretical link between inequality and crime using a simplified version of the rational choice model of criminal activity (Becker 1968; Ehrlich 1973). An individual chooses whether to commit crime or work in the legal sector. If he chooses to offend, he is apprehended with the probability p and receives disutility of u_f from the ensuing punishment. If he is not apprehended, he receives utility of u_s from successful completion of crime. If he abstains from crime, his utility level is equal to his earnings from legitimate work, $\underline{u}$. The individual chooses to commit crime if:

$$(1-p)u_s - pu_f > \underline{u}. \tag{1}$$

Ehrlich (1973) notes that that the level of criminal gains, u_s, is likely to depend on the level of transferable goods in a community, and claims that more crimes would take place in areas with high inequality, because of large differences between the expected criminal gains and legitimate earnings, $u_s - \underline{u}$. This explanation on the link between inequality and crime via increased criminal gains has been rigorously developed in the theoretic models of Chiu and

Madden (1998) and Imrohoroglu, Merlo and Rupert (2004). Consistent with the theoretical prediction, empirical research generally reports a positive, albeit relatively weak, link between inequality and crime. Based on the cross-sectional data on the crime and inequality levels in the U.S. counties in 1990, Kelly (2000) finds that inequality is a significant predictor of violent crime rates. Fajnzylber, Lederman and Loayza (2002) and Soares (2004) also find similar results using country-level, international panel data.[5]

However, the conventional economic explanation on inequality and crime has two important limitations. First, the key prediction that potential offenders become more likely to offend when their neighbors are richer via greater gains from crime does not appear to be consistent with the observed pattern of crime victimization in the U.S. Victimization is disproportionately concentrated among the poor, who should provide little criminal gains to offenders. This inconsistency may be explained by several factors. First, given the high degree of residential segregation in the U.S., many potential offenders who live in disadvantaged neighborhoods may have to incur significant travel costs before finding high-income victims living in affluent neighborhoods.[6] High victimization rates among the poor may also be explained by theoretical models in which committing a crime is used as a defensive strategy. For example, one may have to kill another to avoid being killed (O'Flaherty and Sethi 2010), or want to build a reputation of being a thug to lower his risk of victimization (Silverman 2004; Bjerk 2010). With these assumptions, economic models can explain the observed high victimization rates among the poor, especially for violent crimes.

An alternative explanation is that the probability of apprehension and punishment for criminals (p from Equation 1) may differ across the types of victims, similar to how the gains from successful crimes (u_s from Equation 1) are allowed to vary across different types of victims. In particular, potential criminals may associate crimes against high-income victims with higher

[5] Hsieh and Pugh (1993) and Soares (2004) provide more comprehensive reviews of earlier empirical studies on the relationship between inequality on crime.

[6] On the other hand, residential segregation may be the outcome of the spatial distribution of crime. High-income households may have chosen to live far from high-crime, disadvantaged neighborhoods to avoid the risk of victimization. Cullen and Levitt (1999) describe empirical evidence on the "'urban flight"' of highly-educated households following increases in inner-city crime rates.

risks of apprehension and punishment. If this differential in risks between crimes against the low- and high-income victims outweighs the differential in criminal gains, rational potential offenders should prefer to victimize the poor. There are reasons to suspect that the risks of punishment may be higher in crimes against the wealthy. For example, given that security is a normal good, wealthier individuals are likely to invest more on private measures of self-protection (e.g., vehicle tracking devices, house alarm system), deterring potential offenders from committing crime against them (Ayres and Levitt 1998; Vollaard and Van Ours 2011).

This possibility that rational offenders may prefer to victimize the poor leads to an interesting theoretical prediction. From Equation 1, it is clear that the offending rates should be higher among the poor, who are more likely to find crime as a more attractive "work option" than legitimate work. Then, a high degree of economic segregation across neighborhoods should have a particularly criminogenic effect in a few disadvantaged, poverty-concentrated neighborhoods, as these neighborhoods now have a large number of individuals with high risks of both crime victimization and offending. In the language of the supply and demand of criminal opportunities (Cook 1986), the poor supply more criminal opportunities to potential offenders who find them preferable crime targets, and also demand more criminal opportunities because of their low legitimate earnings potential. A likely outcome is, then, exceedingly high levels of crime in the poverty-concentrated neighborhoods, as observed in the U.S. crime statistics.[7]

Another limitation of the existing literature is that empirical studies based on highly aggregated data sets may be inappropriate to test the empirical relevance of the theoretical link between inequality and crime. Given that many offenders commit crime near their residence (Bernasco and Block 2009; Rengert, Piquero and Jones 1999), potential offenders' criminal decisions should be more closely related to the extent of inequality of and near their own neighborhoods than overall inequality at the city-, state-, or country-level. Furthermore, large

[7]The above argument based on the supply and demand of criminal opportunities complements the existing peer effects literature on negative spillovers of criminality (Bayer, Hjalmarsson and Pozen 2009; Gaviria and Raphael 2001; Glaeser, Sacerdote and Scheinkman 1996; Kling, Ludwig and Katz 2005) and the economic models of "street culture" in which violence serves both offensive and defensive purposes (Bjerk 2010; O'Flaherty and Sethi 2010; Silverman 2004), both of which explain high concentration of crime in economically disadvantaged neighborhoods. This argument is also closely linked to the long sociological literature on the poverty concentration effect on crime (Sampson, Raudenbush and Earls 1997; Sampson and Wilson 1995; Wilson 1987).

geographic areas such as cities and counties are often composed of neighborhoods with relative economic homogeneity, some deprived and others affluent. Highly aggregated inequality measures may then confound local, within-neighborhood inequality with larger, across-neighborhood economic segregation, though the mechanisms through which these two components of inequality influence crime are likely to be distinctively different. Hipp (2011) shows the importance of disentangling the effect of economic segregation on crime from the effect of overall inequality. After constructing measures of city-level inequality and economic segregation separately based on the U.S. decennial Census Data between 1970 and 2000 and examining the extent to which crime rates are affected by overall inequality and economic segregation, he finds that the adverse effect of inequality on crime is more severe in economically segregated cities. In this paper, I exploit a mathematical property of a conventional inequality measure to precisely decompose overall county-level economic inequality into its within- and across-tract components, and directly examine how these two components of inequality affect crime rates.

It may be of great interest to directly examine the relationship between inequality and crime at a local level, e.g., regressing tract-level crime rates on tract-level inequality level. This approach would allow us to test the empirical relevance of local inequality effect on crime, but would not capture the effect of inter-neighborhood inequality and poverty segregation on crime. Moreover, even if we find a positive correlation between inequality and crime at the local level, its interpretation is not straightforward; greater local inequality can have a direct effect on local crime rates, or indirectly influence local crime rates via displacement of crime from and into other parts of the city (Hipp 2007). Perhaps due to the data availability issue, most existing empirical works on the link between inequality and crime at a local level come from cross-sectional analyses (Crutchfield 1989; Hipp 2007; Messner and Tardiff 1986). A notable exception is Freedman and Owens (2012), who examine the effect of local inequality on the residents' criminal risks using a plausibly exogenous variation in localized economic development.

3 Data

The empirical analyses in this paper are based on a panel data set of demographic and socioeconomic attributes and crime statistics in the 200 largest U.S. counties based on the 1990 population level.[8] Data on demographic and socioeconomic characteristics come from the 1990 and 2000 decennial Censuses and 2005-2009 ACS 5-year estimates. Corresponding county-level crime rates are taken from the FBI Uniform Crime Reporting (UCR) data from 1990, 2000, and 5-year average between 2005 and 2009. Regarding crime outcome variables, I focus on the seven Part I index crimes: murder, rape, robbery, aggravated assault, burglary, larceny, and motor vehicle theft.

The key variable of interest in the Census data is the levels of within- and across-tract economic inequality. A potential difficulty in computing these inequality measures is that the Census tract boundaries underwent non-negligible changes between Census years 1990 and 2000; approximately a half of the Census tract boundaries were redefined during the period. Instead of using the raw Census data, therefore, I use a standardized version of the decennial Census data from the Neighborhood Change Database (NCD), which normalizes the 1990 tract-level Census data according to the 2000 Census tract boundaries.[9] 2005-2009 ACS 5-year estimates use Census 2000 definitions for census tracts. In addition to the inequality measures, I also obtain from the Census data a number of variables on the demographic and socioeconomic attributes of sample counties: population, race distribution, unemployment and poverty rates, and shares of female-headed households and college graduates. Table A.1 provides a more detailed description of these variables.

[8]Counties in the state of Illinois are dropped from the sample because rape statistics were not available for these counties. Including these counties in the sample in the analyses for Part I index crimes other than rape, however, results in highly comparable results.

[9]Neighborhood Change Database is a product of Geolytics, inc (www.geolytics.com). See Tatian (2003) for technical details on the tract boundary normalization process used.

3.1 Inequality Measurement and Decomposition

This paper uses two conventional measures of economic inequality: the Theil index and Gini coefficient. The Theil index, a special case of the generalized entropy index, is particularly fitting for the present analysis because of its property of decomposability. Specifically, county-level Theil index can be expressed as a sum of its within- and across-tract components. While the main results of this paper are based on the Theil index as the inequality measure, I also run similar regression analyses using the Gini coefficient to explore whether my findings are robust to an alternative choice of inequality measure and how they compare to existing empirical studies based on the Gini coefficient. Unlike the Theil index, however, the Gini coefficient does not have the property of decomposability, and I can only examine the link between county-level Gini coefficient and county-level crime rates. I also compute the dissimilarity index and isolation index to measure the extent of poverty concentration in sample counties, and use these indices to study the effect of poverty concentration on crime.

First, the Theil index is represented by the following expression:

$$T = \frac{1}{N}\sum_{i=1}^{N}\frac{y_i}{\mu}ln\frac{y_i}{\mu}, \tag{2}$$

where N is the number of households, y_i is household i's income level, and μ is the population average household income level. If the population of interest is composed of several subgroups, the Theil index can be written as a sum of the within- and across-subgroup Theil indices:

$$T = T_{within} + T_{across}. \tag{3}$$

T_{within} can be written as a weighted average of Theil index computed within each group:

$$T_{within} = \sum_{g=1}^{G}\frac{N_g}{N}T_g, \tag{4}$$

where

$$T_g = \frac{1}{N_g}\sum_{i=1}^{N_g}\frac{y_{ig}}{\mu_g}ln\frac{y_{ig}}{\mu_g}. \tag{5}$$

Finally, T_{across} is represented by the following function of the population-level expected household income, μ, as well as N_g, N, and μ_g:

$$T_{across} = \sum_{g=1}^{G}\frac{N_g}{N}\frac{\mu_g}{\mu}ln\frac{\mu_g}{\mu}. \tag{6}$$

Note that the computation of the within-tract Theil index requires information on the income level of each individual household in sample counties ($y_{ig}\ \forall\ i \in g$). However, the computation can be substantially simplified if income is assumed to be log-normally distributed. Suppose that the income distribution in a Census tract g is log-normal i.e., $\log(y_{ig}) \sim N(\mu_g, \sigma_g^2)$. Then, following Crow and Shimizu (1988), the within-tract Theil index can be expressed as:

$$T_{within} = \sum_{i=1}^{N_g}\frac{N_g}{N}\frac{1}{2}\sigma_g^2 \tag{7}$$

where σ_g^2 is the variance of the log income at tract t. Exploiting the properties of log-normal distribution, I can write mean(y) = $\exp(\mu + \frac{1}{2}\sigma^2)$ and median(y) = $\exp(\mu)$. Then, σ_g^2 is simply equal to twice the log ratio of mean tract income to median tract income.

The log-normal assumption of income distribution can also simplify the computation of the Gini coefficient. Again assume that the county income distribution is log-normal, i.e., log(y) $\sim N(\mu, \sigma^2)$. Crow and Shimizu (1988) show that the Gini coefficient is the following function of σ^2:

$$L = 2\Phi(\frac{\sigma}{\sqrt{2}}) - 1, \tag{8}$$

where Φ denotes the normal cumulative distribution function. Kelly (2000) computes the Gini coefficients in the same way.

I also use the dissimilarity and isolation indices to study the effect of poverty concentration on crime. While the Theil index and Gini coefficient are derived from the aggregate income distribution, dissimilarity and isolation indices focus only on individuals under the poverty line. Note that these indices reflect the number and distribution of individuals under the poverty line, but not the intensity of poverty among the poor. The two indices are computed in the following way:

$$Dissimilarity = \frac{1}{2}\sum_{t=1}^{T} \mid \frac{p_g}{P} - \frac{(1-p_g)}{(1-P)} \mid \tag{9}$$

$$Isolation = \sum_{t=1}^{T}(\frac{p_g}{P} \cdot \frac{p_g}{n_g}) \tag{10}$$

In both equations, p_g represents the rate of poverty in tract g, and P the county-level poverty rate. n_g corresponds to the number of individuals in tract g.

Table 1 presents the descriptive statistics of the data set. Consistent with the literature that documents an increase in income inequality in recent decades (e.g., Autor, Katz, and Kearney 2008), both the Theil index and Gini coefficient rose during the sample period. The widening economic inequality are reflected by increases in both local inequality and economic segregation across neighborhoods; within-tract Theil index rose from 0.191 in 1990 to 0.220 in 2005-2009, and across-tract Theil index from 0.064 in 1990 to 0.074 in 2005-2009. Curiously, much of the increase in the average within-tract Theil index took place in the 1990s, while that in the average across-tract Theil index took place in the 2000s. The extent of poverty concentration remains relatively unchanged. The Index of Dissimilarity changes from 0.360 in 1990 to 0.358 in 2005-2009, and the Index of Isolation from 0.204 in 1990 to 0.218 in 2005-2009.

[Table 1]

Consistent with the historic drop in crime rates during the 1990s, crime rates in sample counties have significantly declined across all seven Part I index crimes. Rates of murder, robbery and motor vehicle theft dropped by more than 35 percent between 1990 and 2000, and burglary rate by about 45 percent. The change in crime rates during the 2000s is much smaller; the rates for murder, robbery, and burglary in fact slightly increased. The large differential in the levels of different crime types underscores the need to estimate the effect of inequality on each crime type separately. For example, time trends in violent crime rates (i.e., the sum of rates of murder, rape, aggravated assault, and robbery) are mostly driven by the rates of aggravated assault and robbery, though the inequality effect on murder and rape are also of great interest.[10]

[Figure 1]

To illustrate the time trends of economic inequality during the sample period in more detail, Figure 1 compares the distribution of county-level Theil index across the three time points: 1990, 2000, and 2005-2009. The rightward shift of the distribution over time is evident, and consistent with the rise in the average county-level Theil index from Table 1. The inequality decomposition technique enables me to further examine the extent to which changes in county-level inequality is driven by local inequality within each neighborhood and economic segregation across neighborhoods. Corresponding histograms of within- and across-tract Theil indices over the sample period are presented in Figures 2 and 3, respectively. The distributions of both inequality components show significant rightward shifts over the sample period as well.

[Figure 2]

[Figure 3]

Figure 4 provides a graphical illustration of the relationship between crime and decomposed inequality measures. Specifically, Figure 4 presents a scatterplot of the first differences of within- and across-tract Theil indices and the rates of violent and property crimes, as well as local linear estimates of the relationship.[11] Three notable patterns emerge. First, across-tract Theil index seems to be positively related with violent crime rates. Second, based on the local linear regression results, the empirical link between across-tract Theil index and property crime is much weaker and virtually flat. Finally, the relationship between within-tract inequality and crime rates tends to be *negative*, except in the region of few outliers that experienced unusually large declines in within-tract inequality. The graphical evidence suggests that the previously

[10]Following the official UCR classification, I define murder, rape, robbery, and aggravated assault as violent crimes and burglary, larceny, and motor vehicle as property crimes.

[11]Local linear regression results in all four panels of Figure 4 are computed using the triangle kernel with a bandwidth size of 0.02.

reported positive empirical relationship between inequality and violent crime rates may have been driven by the adverse effects of the economic segregation across neighborhoods, instead of the effect of local inequality.

[Figure 4]

4 Empirical Results

My main regression model is the following fixed effects model:

$$log(crime_{ijt}) = \alpha_j INQ_{it} + \beta_j X_{it} + \theta_t + \eta_i + \epsilon_{ijt}, \tag{11}$$

where $log(crime_{ijt})$ represents the log rate (per 100,000) of type-j crime in county i at time t, INQ_{it} indicates the measure of inequality, and X_{it} represents other time-variant county characteristics.[12] θ_t and η_i correspond to time and county fixed effects, respectively. ϵ_{ijt} represents an idiosyncratic error term. Time fixed effects control for nationwide variations in crime rates for a given time period, and county fixed effects account for time-invariant, unobserved county characteristics related to criminal risks. Inclusion of time fixed effect is particularly important here, given that the large fluctuation in crime rates during 1990s cannot be fully accounted by variations in observed economic and demographic variables (Levitt 2004). All estimation results are obtained using robust standard errors clustered at the county level.

I first estimate the model in which the dependent variable is the log rate of violent crime, using three different inequality measures: the Gini coefficient, county-level Theil index, and within- and across-tract components of the Theil index, and report the estimation results in Table 2. Panels A, B, and C correspond to the different choices of inequality measure used. In each panel, the first column corresponds to the pooled OLS specification, and the second and third columns to the specifications in which time and county fixed effects are introduced. First consider Panel A, in which the Gini Coefficient is the choice of inequality measure. The estimation results should be highly comparable to previous findings based on the Gini Coefficient

[12] I also estimated Equation 11 using the rate of arrest as the dependent variables and obtained similar results.

as the choice of inequality measure (e.g., Kelly (2000)). Under both the pooled-regression and time fixed effect specification (first and second columns of Panel A), the Gini coefficient is positively and significantly correlated with violent crime rates. The magnitude of the coefficient on inequality is substantial. For example, a one standard deviation increase in the Gini coefficient is associated with a 8.7 percentage point increase in violent crime rates under the pooled specification and a 9.8 percentage point increase under the time fixed effect specification. However, when both county and time fixed effects are included, the correlation between inequality and violent crime is small and no longer significant.

[Table 2]

Panel B repeats the analysis using the Theil Index as the inequality measure. As in Panel A, the Theil index is a positive predictor of violent crime rates in both the pooled specification (column (4)) and time fixed effects specification (column (5)). In the preferred specification with both county and fixed effects, the correlation between the Theil index and violent crime rates is again small and insignificant. Comparing the estimates from Panels A and B, I find that my estimates are not particularly sensitive to whether the Gini coefficient or Theil index was used as the inequality measure. A one standard deviation increase in the Theil Index is associated with a 11 percentage point increase in violent crime rates under both pooled-regression and time fixed effect specifications. The signs and magnitudes of coefficients on other sociodemographic variables are also highly comparable between Panels A and B.

In Panel C, the regression now controls for both within- and across-tract components of the county-level Theil index. Consistent with Figure 4, I find that the effects of the two components on violent crime rate are markedly different. Within-tract Theil index has a modestly positive impact on violent crime rates under the pooled and time fixed effects specifications, and is negatively correlated with violent crime when both time and county fixed effects are controlled for. On the other hand, the correlation between across-tract Theil index and violent crime is large and significantly positive under the pooled and time fixed effects specifications, and remains sizable when time- and county fixed effects are introduced. Under the pooled regression specification, a one standard deviation increase in within-tract (across-tract) Theil index is associated with a 3.4 (9.4) percentage point increase in violent crime rates. When both time- and county-fixed effects controlled for, a one standard deviation increase in within-tract Theil index decreases violent crime rates by a 0.4 percentage point but that in across-tract Theil index increases violent crime rates by a 4 percentage point.

The large disparity between cross-sectional and panel estimates suggests that the positive empirical link between inequality and crime, documented previously, may be mostly driven by the cross-sectional nature of the data set used. Indeed, studies based on U.S. panel data often find little evidence of inequality effects on crime (Brush 2007; Choe 2008; Doyle, Ahmed and Horn 1999). It is important to note, however, that the fixed effect specification still leads to inconsistent estimates if there are systematic, time-varying differences in criminal risks across sample counties. One important source of such variations may come from the criminal justice system. For example, many researchers find that crime rate is significantly influenced by the size of police force (Di Tella and Schargrodsky 2004; Evans and Owens 2007; Klick and Tabarrok 2005) and the severity of sentencing (Hjalmarsson 2009; Kessler and Levitt 1999; Zimring, Hawkins and Kamin 2001). The current empirical strategy does not control for potential time-varying systematic differences in policing and sentencing strategies among counties.[13]

Next, I repeat the estimation using the log rate of property crime as the dependent variable, and present the results in Table 3. Estimation results from Panels A and B show that the correlation between county-level inequality and property crime is mostly weak and tend to be negative. As in Table 2, however, the weak correlation at the county-level masks the opposite effects of within- and across-tract inequality on property crime. In Panel C, I find that within-tract inequality has large, negative effects on property crime rates, while across-tract inequality is mostly positively correlated to property crime rates under the pooled and time fixed effect specifications. In the pooled regression specification, a one standard deviation increase in within-tract (across-tract) Theil index is associated with a 8.5 percentage decrease (a 5.7 percentage

[13] I attempted to extend the regression specification by including (log) police expenditure per population to control for the difference in police resource across counties, but obtained similar results on the inequality effect on crime. The police expenditure variable is omitted from the main specification in order to avoid the well-known problem of reverse causality between police resource and crime.

increase) in property crime rates.

[Table 3]

Crime statistics aggregated up to violent and property types may obscure important variations in rates of specific crime types. For example, the time trend of violent crime rates is overwhelmingly driven by that of aggravated assault and robbery, and much less so by murder and rape statistics. Therefore, I repeat the analysis using each of the seven Part I index crimes as the dependent variable, and estimate how their rates are affected by within- and across-tract components of the Theil index. The results are presented in Tables 4 (for violent crime types) and 5 (for property crime types). There are few county-year observations with zero counts of murder and rape, whose log murder and rape rates are not defined. Omission of these few observations, however, seems to have little impacts on estimation results; I ran comparable negative binomial regressions using crime counts as dependent variables instead of crime rates, and obtained similar results.

[Table 4]

[Table 5]

It appears that the link between local inequality and crime tends to be small and negative. In the preferred specification with both time and county fixed effects, for example, the coefficient on within-tract inequality is negative for all crime types except murder and aggravated assault. By contrast, the effect of across-tract inequality is positive for all crime types except robbery and motor vehicle theft under the preferred specification. In sum, the regression results show that 1) the estimated criminogenic effect of inequality is smaller when time- and county-specific unobserved characteristics are controlled for via fixed effects, and 2) economic segregation across neighborhoods and local inequality within neighborhoods are likely to have distinctively different effects on crime. Moreover, it seems that the previously reported inequality effect on crime is mostly driven by across-neighborhood inequality instead of within-neighborhood inequality.

One limitation of the current analysis is that it is difficult to give the estimates a causal interpretation, in the absence of exogenous variations in the level of inequality. Nevertheless, my analyses control for a series of time-varying demographic and socioeconomic characteristics, all of which have been traditionally considered as important determinants of crime, and also account for unobserved characteristics related to criminal risks using time and county fixed effects.

Another complication is that inequality and crime rates may influence households' residential location choices and change neighborhood composition. If greater economic segregation across neighborhoods results in higher crime rates in disadvantaged neighborhoods and induces low-risk residents from these neighborhoods to relocate, then this change in neighborhood composition should further increase crime rates in disadvantaged neighborhoods. However, the extent of this composition effect may not be large. For example, Ellen and O'Regan (2010) find that, when Cullen and Levitt's (1999) empirical analysis on urban flight is extended to the crime and Census data through the 1990s, there is little evidence that changes in crime rates resulted in significant changes in overall city population change and within-MSA migration pattern.

In order to control for the difference in the level of economic disadvantage across sample counties, the main regression specification controls for the county-level median income and poverty rate. However, the effect of local inequality and economic segregation on crime may be heterogenous depending on neighborhoods' economic characteristics. Under the "'supply and demand of criminal opportunity" explanation discussed above, an increase in local inequality in disadvantaged neighborhoods may lower crime risks in disadvantaged neighborhoods, but not necessarily in more affluent neighborhoods. On the other hand, if high economic segregation is more likely to result in poverty concentration when the overall income level is lower, the adverse effect of economic segregation on crime should be higher among low-income counties. To explore this possibility, I divided the sample counties into high- and low-income groups based on their 1990 median income level and estimated Equation 11 separately. Table 6 presents the subgroup estimation results, which tend to be imprecisely estimated. Although the estimates often differ in magnitudes and signs between high-income (first three columns) and low-income counties (last three columns), it is difficult to conclude there exist meaningful differences in estimated effects of inequality on crime between the two groups.

[Table 6]

5 Crime, Inequality and Poverty Concentration

The traditional economic explanation on inequality and crime focuses on the difference in expected criminal gains between high- and low-income victims. Potential offenders should expect higher gains from crime when victimizing the rich, and be more likely to offend when their wealthy neighbors become even wealthier. While simple and intuitive, the above description does not seem to be consistent with the observed pattern of crime victimization in the U.S. Crime victimization is disproportionately concentrated among the poor, who should provide less criminal gains to offenders (Levitt 1999; Thacher 2004). Consider Table 7, taken from the 2008 National Crime Victimization Survey (NCVS). Panel (a) reports the victimization rates across households of different income levels. Low-income households are much more likely to be victimized than higher income households for both violent and property crimes. Households with income level less than $7,500 are more than four times as likely as households with income level of $75,000 or more to be victims of an aggravated assault. Even for burglary, a typical example of financially motivated crime, the ratio of the victimization rates between the lowest and highest income groups is approximately 350%.

[Table 7]

Panel (b) of Table 7 presents the economic loss to crime victims, which should be roughly equal to the economic gain to the perpetrators.[14] The difference in economic loss across victims of different income groups is not negligible. Crime victims from the highest income group report the mean loss of $1,098 upon victimization, when victims from the lowest income group lose $445 on average. However, the disparity becomes much smaller when comparing the median economic losses, which range from $100 for the lowest income group to $150 for the highest income group. Given that crimes against rich victims appear to provide higher gains to criminals indeed, the high victimization rates among the poor appear puzzling.

One potential explanation for this apparent paradox is that crimes against the rich may provide not only higher expected criminal gains but also higher risks of detection and punishment

[14] Economic loss is defined as the value of cash and/or property taken upon victimization.

to potential offenders. Indeed, the original economic model of crime identifies the perceived level of risk of apprehension and punishment as a key factor in one's criminal decision (Equation 1), but the possibility that the perceived risk of punishment may differ across victim types has been mostly neglected in the literature on inequality and crime.[15] Although the NCVS questionnaire does not include questions on the level of private protection measures taken by individuals, it asks one interesting question closely associated with offenders' risks of apprehension and punishment: post-victimization reporting behavior to the authority. As Panel (c) of Table 7 indicates, low-income households are much less likely to report to the authority upon victimization than high income households. For instance, the reporting rate upon larceny victimization is 24.8% for victims in the lowest income group and 37.5% for the victims in the highest income group. As crimes unreported to the authority are unlikely to result in any form of punishment against the offenders, this sizable differential in reporting rates may lead offenders to perceive the poor as a more preferable target.[16]

As discussed above, if a potential offender feels that additional risks associated with crimes against the rich outweigh the additional gains and thus prefers offending against the poor, then poverty concentration in a few disadvantaged neighborhoods should be particularly criminogenic. These neighborhoods are populated by a large number of low-income individuals who have the high risks of both criminal victimization and offending. To test the empirical relevance of the effect of concentrated poverty on crime, I estimate Equation 11 using the index of dissimilarity and isolation as the measure of poverty concentration and present the results in Table 8. For brevity, the table only reports the coefficient on the poverty concentration index. Each entry corresponds to the coefficient on the poverty concentration index from a separate regression. In Column (1), the same list of observed demographic and economic county characteristics as in

[15] Empirical studies find that the deterrent effect of the perceived risks of punishment is substantial, often outweighing the deterrent effect of severity of punishment. Formal economic models linking the perceived risk of punishment with participation in criminal activity are presented in Sah (1991) and Lochner (2007).

[16] Several factors may account for the observed differential in reporting rates across victims of different income groups. First, poor victims may have less incentive to report to the authority because their economic loss from victimization tend to be smaller. Second, poor victims living in disadvantaged neighborhoods may feel that the police would be ineffective or biased against them. Lastly, they may fear retribution by perpetrators, who are likely to live in proximity.

Tables 2 and 3 are controlled for. Columns (2) and (3) introduces time- and county-fixed effects to the specification, respectively.

[Table 8]

Table 8 documents a strong, positive link between poverty concentration and crime. When the dissimilarity index is used as the measure of poverty concentration (Panel A), poverty concentration is a significantly positive predictor of murder, rape, aggravated assault, and robbery rates under the preferred specification with both time and county fixed effects controlled for. The coefficient on poverty concentration is smaller and more imprecise when the isolation index is used as the measure of poverty concentration (Panel B), but the coefficient on the index are still sizable and positive.

It is interesting to note that the estimated effect of poverty concentration on crime is particularly strong for violent crimes. In Panel A, a one standard deviation increase in the dissimilarity index would result in a 17 percentage point increase in murder, a 17 percentage point increase in rape, a 10 percentage point increase in aggravated assault, and a 14 percentage point increase in robbery. By contrast, a one standard deviation increase in the dissimilarity index is associated with a 2 percentage point increase in burglary, a 3 percentage point increase in larceny, and a 4 percentage point increase in motor vehicle theft.

This disparity between the concentrated poverty effects on violent and property crimes is consistent with the rational choice model of criminal behavior sketched above. Whether a potential offender prefers to victimize the poor or the rich depends on the differentials in expected gains from successful crime and risks of apprehension and punishment. Then, if violent crimes against the rich provide little additional gains but much larger risks to potential offenders, the poor are much more likely to be preferable victims. For these types of crime, the adverse effect of poverty concentration on crime would be substantially large. On the other hand, if property crimes against the rich victims provide larger gains and risks to potential offenders, the adverse effect of poverty concentration should be more mitigated. Therefore, it is reasonable that the adverse effect of poverty concentration is stronger on violent crimes, in which the link between criminal gains and victims' economic characteristics is less clear. Previous research also reported that the criminogenic effect of inequality was mostly concentrated among violent crimes, but did not offer a clear theoretical explanation as to why economic inequality matters more for violent crime than property crime. The possibility that the risks of apprehension and punishment perceived by a potential offender can vary across victim characteristics may have been the missing piece in the puzzle.

6 Conclusion

Economic inequality has long been considered an important determinant of crime by economists. Many of the existing empirical studies are based on cross-sectional and largely aggregated data. The use of largely aggregated data may be problematic because it confounds the effects of local (within-neighborhood) inequality and greater (across-neighborhood) inequality on crime. The effect of local inequality on crime, if any, is consistent with the traditional economic explanation on inequality and crime, in which potential offenders are more likely to offend against wealthier victims because of larger criminal gains. On the other hand, across-neighborhood inequality and concentration of poverty in a few disadvantaged neighborhoods may also increase crime through a different mechanism. In particular, potential offenders should prefer to victimize the poor if offenders face much higher risks of punishment when offending against high-income victims. Since the poor have higher risks of both offending and victimization, criminal risks in poverty-concentrated neighborhoods would be substantially high.

Using recent tract-level data in the U.S. between 1990 and 2009 and a conventional inequality decomposition technique, I find evidence that across-neighborhood inequality is responsible for the previously reported positive link between inequality and crime at the aggregated level. On the other hand, the correlation between local inequality and crime is mostly weak and negative. Under the specification that controls for both time and county fixed effects, a one standard deviation increase in within-tract Theil index decreases violent crime rates by a 0.4 percentage point but that in across-tract Theil index increases violent crime rates by a 4 percentage point. When poverty concentration is used as a measure of economic inequality instead, the estimation results show significantly positive effects of poverty concentration on violent crime.

These findings identify across-neighborhood economic segregation and poverty concentration as a potentially important criminogenic factor. Alleviating the extent of poverty concentration and promoting mixed-income residential environment in disadvantaged neighborhoods may then be highly helpful to successful urban crime control. Given the recent prominence of gentrification and public housing improvement project (e.g., HOPE VI), it would be of great interest to further explore whether and how these changes in neighborhood composition influence crime.

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Figure 1: Distribution of County-level Theil Index in the U.S.: 1990, 2000, and 2005-2009

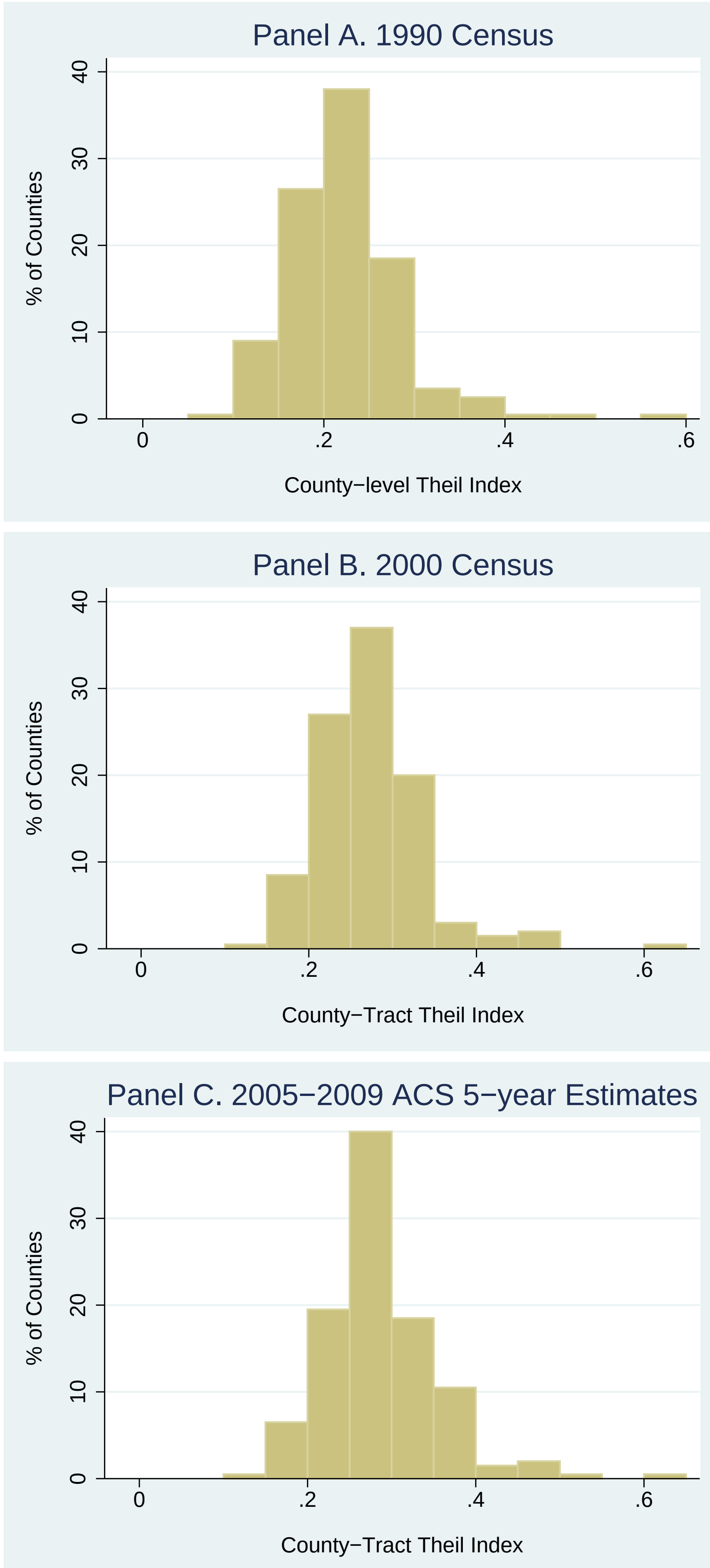


Figure 2: Distribution of Within-tract Theil Index in the U.S.: 1990, 2000, and 2005-2009

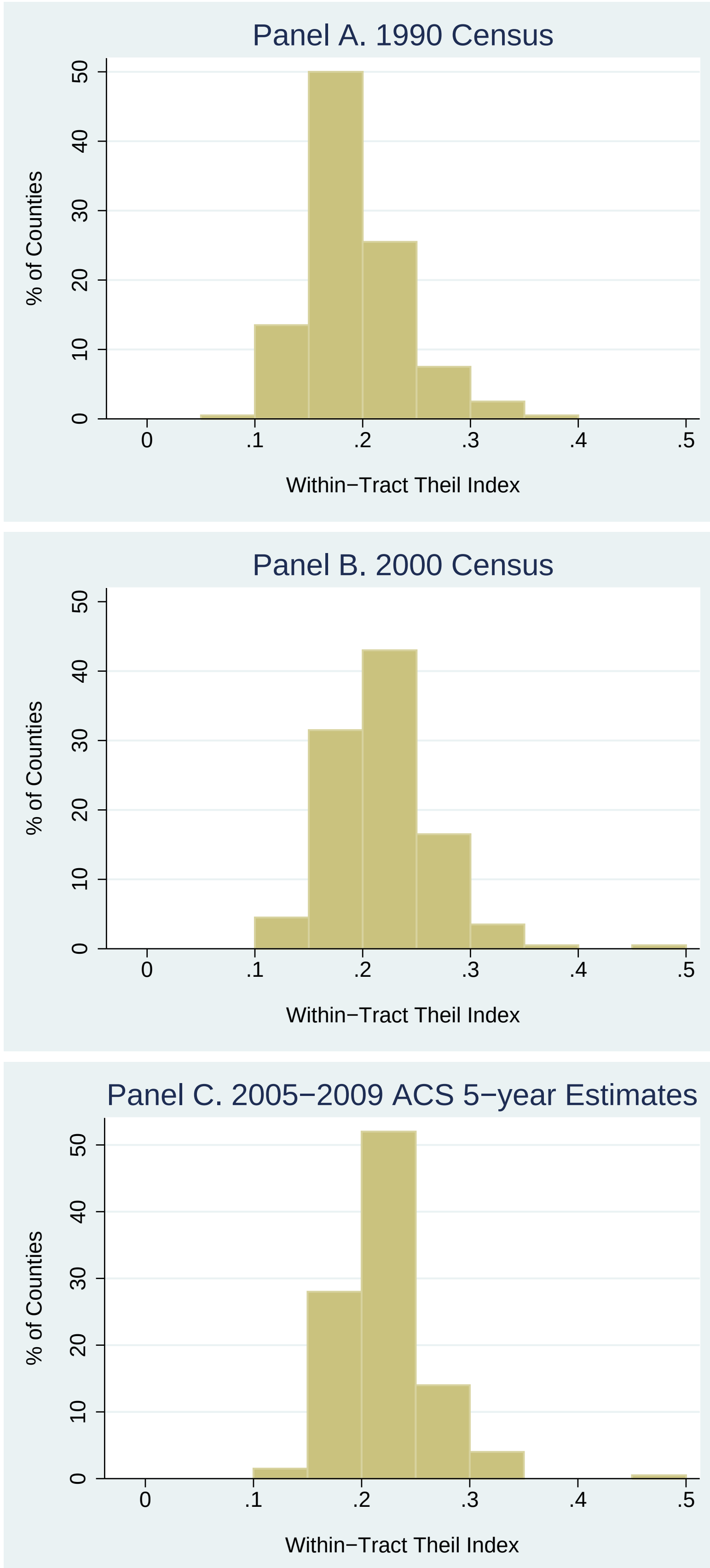


Figure 3: Distribution of Across-tract Theil Index in the U.S.: 1990, 2000, and 2005-2009

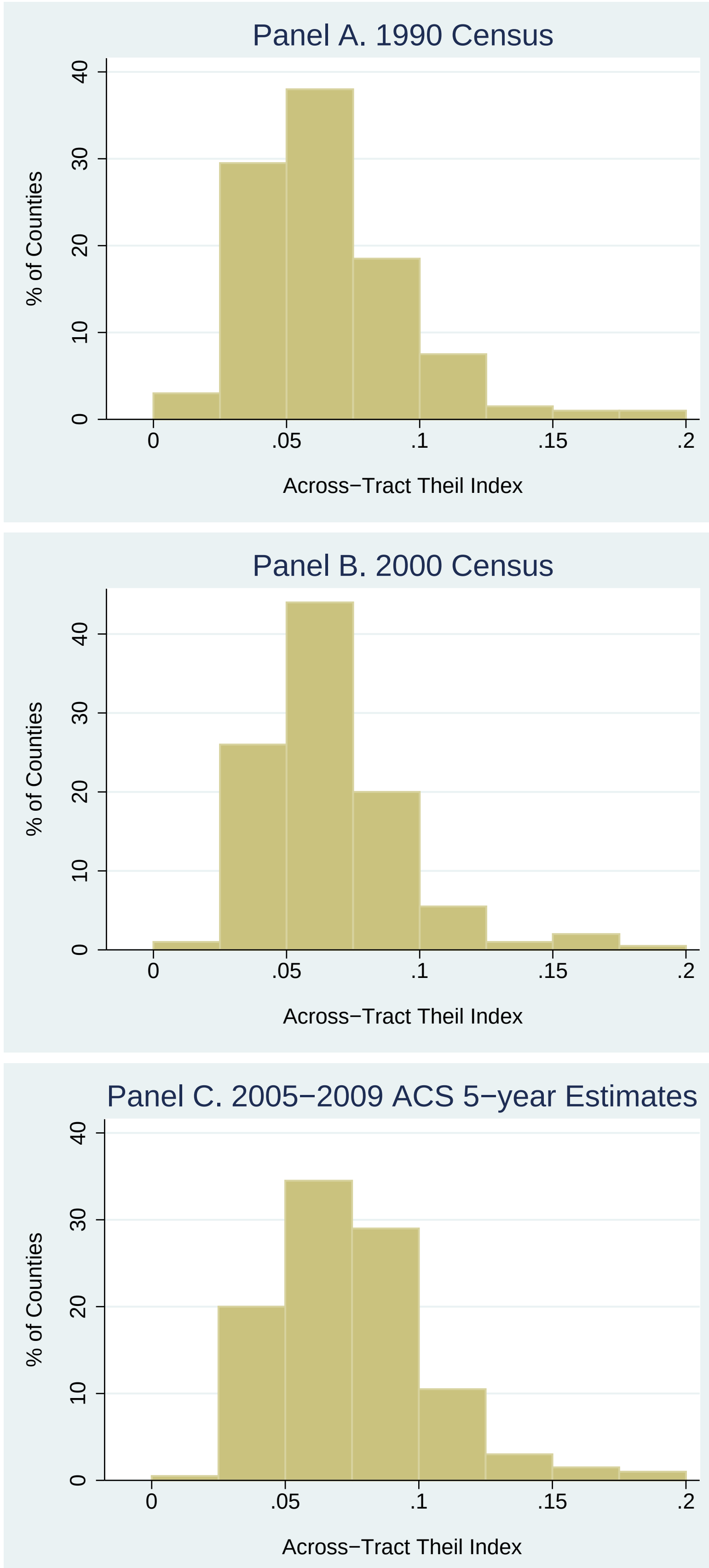
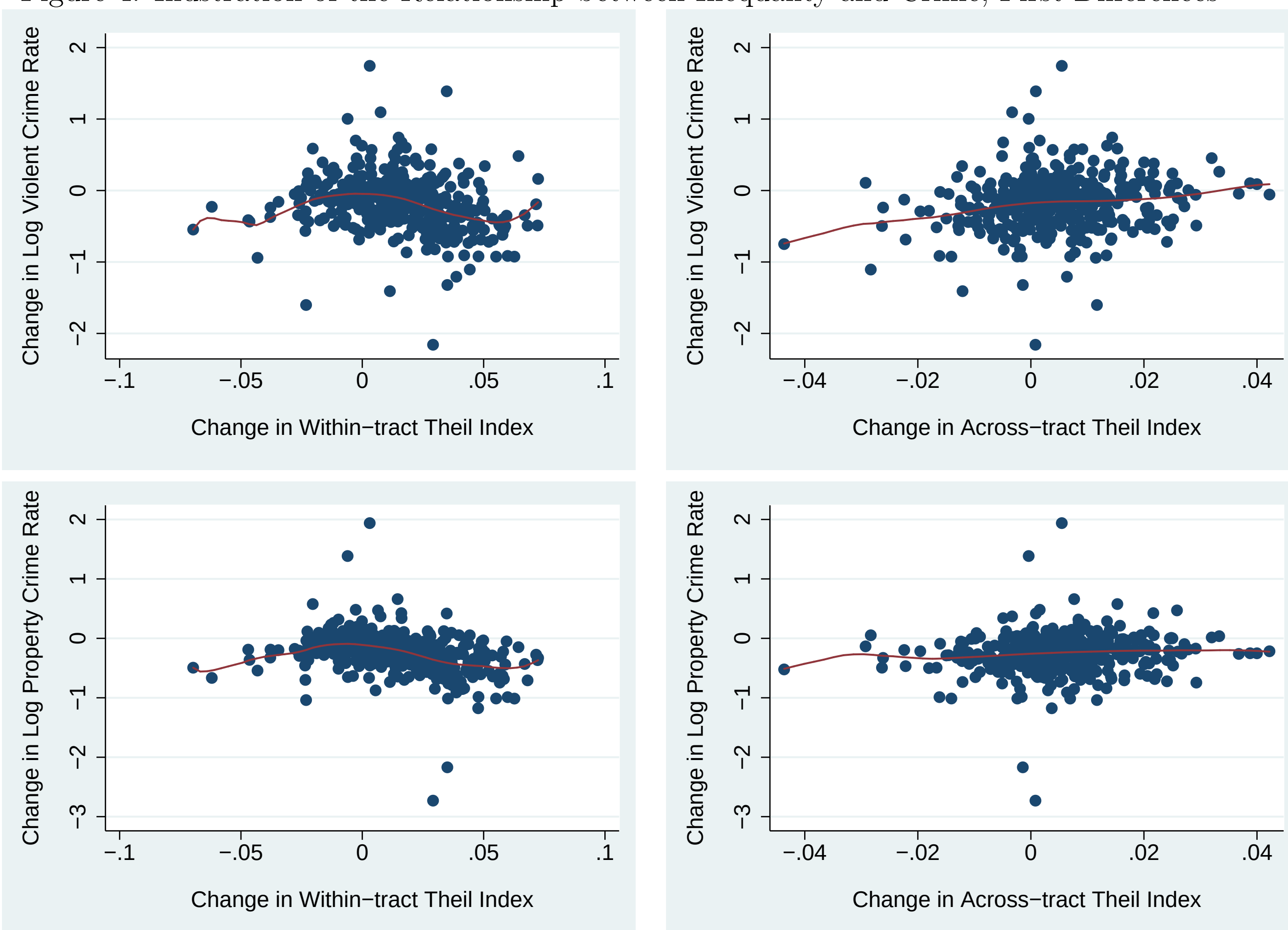


Figure 4: Illustration of the Relationship between Inequality and Crime, First Differences



Note: Dots represent first differences in inequality level and crime rates between Census years 1990 and 2000, and between years 2000 and 2005-2009. Solid curves represent local linear regression estimates; triangular kernel with a bandwidth of 0.02 is used.

Table 1: Summary Statistics

	Aggregate		1990 Census		2000 Census		2005-2009 ACS	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
County Characteristics								
Population (in 100,000)	7.407	8.098	6.663	7.398	7.514	8.171	8.044	8.656
Female-headed Household	0.220	0.077	0.228	0.070	0.244	0.071	0.187	0.078
Black	0.137	0.133	0.130	0.130	0.149	0.141	0.134	0.128
Hispanic	0.120	0.148	0.086	0.130	0.122	0.147	0.152	0.159
Unemployment	0.066	0.023	0.064	0.023	0.060	0.024	0.075	0.019
Poverty	0.120	0.056	0.116	0.061	0.116	0.054	0.129	0.052
College	0.273	0.088	0.234	0.073	0.278	0.085	0.306	0.090
Theil Index	0.279	0.067	0.257	0.066	0.285	0.065	0.296	0.063
Within-tract Theil Index	0.210	0.046	0.192	0.046	0.219	0.045	0.221	0.042
Across-tract Theil Index	0.069	0.030	0.065	0.030	0.066	0.028	0.075	0.030
Gini Coefficient	0.386	0.047	0.359	0.045	0.395	0.041	0.405	0.042
Index of Dissimilarity	0.356	0.067	0.360	0.074	0.350	0.065	0.358	0.061
Index of Isolation	0.206	0.081	0.204	0.088	0.195	0.076	0.218	0.075
Crime Rate (per 100,000)								
Murder	7.4	8.2	9.6	10.3	6.0	6.5	6.7	7.0
Rape	37.1	20.8	47.2	25.6	33.2	16.5	30.8	14.6
Aggravated Assault	366.1	257.4	457.5	315.2	333.1	223.0	307.8	193.6
Robbery	213.9	211.0	283.8	295.9	176.9	148.3	180.9	130.5
Burglary	978.2	550.5	1388.1	604.5	767.3	377.4	779.3	388.8
Larceny	2913.3	1214.4	3659.2	1249.9	2697.5	1124.2	2383.2	851.2
MV Theft	549.3	429.8	747.8	548.4	486.1	332.7	414.0	287.6
Obs.	600		200		200		200	

Note: Statistics are computed from the 200 largest U.S. counties in terms of the 1990 population. See Appendix Table A.1 for the definition and data source of each variable.

Table 2: Inequality and Violent Crime Rates

	Outcome: Log(Violent Crime Rate per 100,000)								
Measure of Inequality =	A. Gini Coefficient			B. Theil Index			C. Decomposed Theil Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Gini Coefficient	1.841**	2.085**	0.059						
	(0.894)	(0.878)	(1.385)						
Theil Index				1.622**	1.644**	0.193			
				(0.614)	(0.584)	(0.835)			
Within-tract Theil							0.733	0.933	-0.082
							(0.865)	(0.902)	(0.992)
Across-tract Theil							3.136**	2.768**	1.333
							(1.256)	(1.223)	(1.692)
Log(Population)	0.201**	0.194**	-0.018	0.196**	0.193**	-0.020	0.174**	0.178**	-0.012
	(0.044)	(0.043)	(0.185)	(0.044)	(0.043)	(0.186)	(0.047)	(0.045)	(0.190)
Log(Median Income)	-1.040**	-1.079**	1.741**	-0.988**	-1.146**	1.751**	-0.937**	-1.156**	1.768**
	(0.128)	(0.410)	(0.525)	(0.123)	(0.408)	(0.500)	(0.131)	(0.408)	(0.495)
Female-headed Household	0.426	1.209*	-0.655	0.343	1.074	-0.666	0.496	1.133	-0.665
	(0.614)	(0.707)	(0.544)	(0.606)	(0.699)	(0.543)	(0.616)	(0.701)	(0.545)
Black	1.892**	1.752**	0.880	1.880**	1.774**	0.890	1.770**	1.708**	0.897
	(0.332)	(0.333)	(0.588)	(0.332)	(0.333)	(0.587)	(0.334)	(0.332)	(0.582)
Hispanic	0.315	0.376	-2.264**	0.356	0.470	-2.258**	0.323	0.463	-2.391**
	(0.268)	(0.305)	(0.676)	(0.265)	(0.299)	(0.673)	(0.267)	(0.299)	(0.724)
Unemployment	6.203**	4.196**	1.979	5.840**	4.114**	1.985	5.699**	4.227**	2.089
	(1.836)	(2.009)	(1.410)	(1.803)	(1.989)	(1.410)	(1.826)	(1.983)	(1.402)
Poverty	-1.601	-1.945	5.150**	-1.753	-2.460	5.082**	-1.356	-2.319	4.964**
	(1.315)	(1.957)	(1.696)	(1.294)	(1.974)	(1.751)	(1.339)	(1.955)	(1.736)
College	0.017	-0.122	-3.260**	-0.169	-0.145	-3.292**	-0.285	-0.172	-3.398**
	(0.583)	(0.708)	(1.281)	(0.595)	(0.685)	(1.232)	(0.610)	(0.683)	(1.260)
Constant	13.313**	13.777**	-11.179**	13.189**	14.910**	-11.280**	12.999**	15.251**	-11.540**
	(1.426)	(4.291)	(5.649)	(1.402)	(4.239)	(5.104)	(1.405)	(4.288)	(5.083)
Year Fixed Effect		✓	✓		✓	✓		✓	✓
County Fixed Effect			✓			✓			✓
Obs.	600	600	600	600	600	600	600	600	600
R^2	0.585	0.596	0.412	0.588	0.598	0.412	0.591	0.599	0.413

Note: * $p < 0.10$, ** $p < 0.05$. Robust standard errors, clustered at the county level, are in parenthesis. Violent crime consists of murder, rape, aggravated assault and robbery. Data is obtained from the U.S. Census and FBI Uniform Crime Reports at three time periods (1990, 2000, and 2005-2009). See text for details.

Table 3: Inequality and Property Crime Rates

	Outcome: Log(Property Crime Rate per 100,000)								
Measure of Inequality =	A. Gini Coefficient			B. Theil Index			C. Decomposed Theil Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Gini Coefficient	-0.806	-1.169*	-0.595						
	(0.599)	(0.624)	(1.021)						
Theil Index				-0.458	-0.555	-0.668			
				(0.421)	(0.407)	(0.538)			
Within-tract Theil							-1.840**	-1.984**	-0.796
							(0.640)	(0.625)	(0.641)
Across-tract Theil							1.896**	1.702*	-0.138
							(0.882)	(0.867)	(1.248)
Log(Population)	0.052	0.058	-0.090	0.050	0.052	-0.084	0.016	0.021	-0.080
	(0.040)	(0.039)	(0.121)	(0.040)	(0.039)	(0.121)	(0.042)	(0.040)	(0.124)
Log(Median Income)	-1.322**	-1.737**	1.692**	-1.342**	-1.650**	1.701**	-1.264**	-1.668**	1.708**
	(0.092)	(0.277)	(0.385)	(0.087)	(0.278)	(0.358)	(0.088)	(0.262)	(0.357)
Female-headed Household	-0.924**	-0.552	-0.389	-0.910**	-0.492	-0.357	-0.673*	-0.372	-0.357
	(0.403)	(0.457)	(0.431)	(0.404)	(0.468)	(0.431)	(0.404)	(0.462)	(0.430)
Black	1.317**	1.326**	0.800**	1.315**	1.292**	0.777**	1.144**	1.161**	0.781**
	(0.208)	(0.201)	(0.380)	(0.207)	(0.202)	(0.380)	(0.201)	(0.196)	(0.380)
Hispanic	0.506**	0.720**	-2.286**	0.497**	0.658**	-2.321**	0.447**	0.645**	-2.382**
	(0.193)	(0.215)	(0.445)	(0.193)	(0.212)	(0.437)	(0.186)	(0.204)	(0.469)
Unemployment	1.933	1.481	5.495**	2.061	1.378	5.510**	1.843	1.604	5.558**
	(1.287)	(1.342)	(1.218)	(1.273)	(1.342)	(1.201)	(1.276)	(1.338)	(1.221)
Poverty	-0.933	-2.432**	1.530	-1.067	-2.254*	1.729	-0.450	-1.970*	1.674
	(0.776)	(1.177)	(1.175)	(0.753)	(1.202)	(1.214)	(0.741)	(1.150)	(1.210)
College	1.397**	1.793**	-4.149**	1.382**	1.624**	-4.133**	1.203**	1.570**	-4.183**
	(0.363)	(0.439)	(0.798)	(0.364)	(0.427)	(0.732)	(0.368)	(0.420)	(0.761)
Constant	21.599**	25.970**	-6.968*	21.662**	24.878**	-7.207**	21.367**	25.563**	-7.327**
	(1.110)	(2.967)	(4.177)	(1.093)	(2.971)	(3.632)	(1.046)	(2.799)	(3.645)
Year Fixed Effect		✓	✓		✓	✓		✓	✓
County Fixed Effect			✓			✓			✓
Obs.	600	600	600	600	600	600	600	600	600
R^2	0.540	0.552	0.684	0.539	0.550	0.685	0.553	0.563	0.685

Note: * $p < 0.10$, ** $p < 0.05$. Robust standard errors, clustered at the county level, are in parenthesis. Property crimes consist of burglary, larceny and motor vehicle theft. Data is obtained from the U.S. Census and FBI Uniform Crime Reports at three time periods (1990, 2000, and 2005-2009). See text for details.

Table 4: Effects of Within- and Across-tract Inequality on Violent Crime Rates

	Outcome: Log(Crime Rate per 100,000)											
Crime Type		Murder			Rape			Aggravated Assault			Robbery	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Within-tract Theil	-0.018	0.250	0.383	-3.444**	-4.213**	-0.654	1.515	1.637	0.453	0.426	0.942	-0.979
	(1.008)	(1.087)	(1.582)	(0.927)	(0.919)	(1.041)	(0.967)	(1.003)	(1.113)	(1.045)	(1.090)	(1.150)
Across-tract Theil	5.950**	5.514**	1.883	4.122**	3.816**	1.355	2.214	1.873	2.477	5.100**	4.577**	-0.595
	(1.356)	(1.326)	(2.384)	(1.320)	(1.204)	(2.135)	(1.501)	(1.474)	(1.781)	(1.391)	(1.359)	(2.132)
Log(Population)	0.157**	0.161**	-0.689**	-0.021	-0.006	0.247	0.144**	0.148**	-0.134	0.280**	0.282**	0.137
	(0.052)	(0.051)	(0.230)	(0.063)	(0.057)	(0.168)	(0.055)	(0.054)	(0.207)	(0.054)	(0.053)	(0.248)
Log(Median Income)	-1.061**	-1.285**	2.407**	-0.752**	-2.023**	1.604**	-0.937**	-1.214**	1.472**	-0.920**	-0.961*	2.605**
	(0.140)	(0.436)	(0.695)	(0.133)	(0.392)	(0.602)	(0.149)	(0.437)	(0.532)	(0.153)	(0.492)	(0.625)
Female-headed HH	-2.091**	-1.326	-0.814	1.053*	1.441**	0.168	0.550	1.133	-0.676	0.333	1.273	-0.250
	(0.710)	(0.849)	(0.789)	(0.594)	(0.646)	(0.757)	(0.712)	(0.784)	(0.638)	(0.713)	(0.855)	(0.711)
Black	3.895**	3.817**	1.299	0.007	0.144	-0.035	1.299**	1.254**	0.670	2.922**	2.788**	1.064
	(0.350)	(0.360)	(0.815)	(0.311)	(0.294)	(0.726)	(0.448)	(0.445)	(0.659)	(0.328)	(0.340)	(0.694)
Hispanic	0.517	0.669*	-1.315	-0.687**	-0.104	-2.690**	0.444	0.606*	-1.807**	0.316	0.399	-3.390**
	(0.331)	(0.375)	(0.945)	(0.321)	(0.326)	(0.775)	(0.318)	(0.353)	(0.846)	(0.314)	(0.356)	(0.870)
Unemployment	7.127**	5.296**	2.675	-1.339	-0.523	-3.292**	4.616**	3.387	1.315	8.643**	6.047**	4.673**
	(2.267)	(2.337)	(2.149)	(1.798)	(1.910)	(1.590)	(2.096)	(2.299)	(1.538)	(2.345)	(2.449)	(1.940)
Poverty	-0.185	-1.207	5.126**	3.790**	-0.814	7.373**	-1.296	-2.450	4.188**	-2.752	-3.182	6.028**
	(1.600)	(2.104)	(2.128)	(1.371)	(1.909)	(2.083)	(1.517)	(2.168)	(2.083)	(1.678)	(2.367)	(2.034)
College	-1.124*	-1.029	-2.195	0.160	1.411**	-2.295	-0.577	-0.393	-3.539**	-0.064	-0.189	-3.493**
	(0.609)	(0.735)	(1.545)	(0.578)	(0.645)	(1.433)	(0.728)	(0.775)	(1.425)	(0.665)	(0.798)	(1.439)
Constant	10.134**	12.452**	-14.427**	11.631**	24.812**	-16.101**	12.939**	15.804**	-7.411	9.939**	10.349**	-23.402**
	(1.521)	(4.592)	(6.808)	(1.666)	(4.284)	(6.039)	(1.626)	(4.637)	(5.741)	(1.589)	(5.090)	(6.136)
Year Fixed Effect		✓	✓		✓	✓		✓	✓		✓	✓
County Fixed Effect			✓			✓			✓			✓
Obs.	596	596	596	599	599	599	600	600	600	600	600	600
R^2	0.663	0.670	0.306	0.405	0.442	0.376	0.474	0.482	0.338	0.624	0.635	0.330

Note: * $p < 0.10$, ** $p < 0.05$. Robust standard errors, clustered at the county level, are in parenthesis. Data is obtained from the U.S. Census and FBI Uniform Crime Reports at three time periods (1990, 2000, and 2005-2009). See text for details.

Table 5: Effects of Within- and Across-tract Inequality on Property Crime Rates

	Outcome: Log(Property Crime Rate per 100,000)								
Crime Type		Burglary			Larceny			MV Theft	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Within-tract Theil	-1.473*	-1.473*	-0.704	-1.877**	-2.178**	-0.548	-2.058**	-1.926*	-1.083
	(0.810)	(0.780)	(0.738)	(0.627)	(0.611)	(0.621)	(0.955)	(1.032)	(1.466)
Across-tract Theil	2.975**	2.553**	0.380	1.218	1.049	0.052	4.078**	4.164**	-0.790
	(1.163)	(1.123)	(1.684)	(0.886)	(0.868)	(1.086)	(1.394)	(1.407)	(2.685)
Log(Population)	0.010	0.017	-0.053	-0.038	-0.031	-0.199	0.333**	0.330**	0.340
	(0.052)	(0.049)	(0.141)	(0.042)	(0.040)	(0.129)	(0.060)	(0.061)	(0.251)
Log(Median Income)	-1.595**	-2.112**	1.681**	-1.107**	-1.663**	1.294**	-1.487**	-1.228**	3.627**
	(0.105)	(0.322)	(0.468)	(0.087)	(0.258)	(0.337)	(0.153)	(0.415)	(0.750)
Female-headed Household	-1.810**	-1.112*	-1.003**	-0.491	-0.255	0.061	0.338	0.215	-2.100**
	(0.490)	(0.566)	(0.472)	(0.385)	(0.433)	(0.436)	(0.712)	(0.811)	(0.689)
Black	1.468**	1.443**	0.925**	0.915**	0.965**	0.591*	1.694**	1.672**	2.103**
	(0.249)	(0.248)	(0.460)	(0.206)	(0.197)	(0.351)	(0.393)	(0.403)	(0.702)
Hispanic	0.365	0.639**	-2.923**	0.374*	0.633**	-2.070**	0.895**	0.773**	-2.217**
	(0.260)	(0.297)	(0.569)	(0.190)	(0.207)	(0.447)	(0.298)	(0.344)	(1.013)
Unemployment	4.717**	3.523**	6.866**	-0.943	-0.772	4.312**	10.857**	10.813**	9.332**
	(1.536)	(1.620)	(1.377)	(1.284)	(1.349)	(1.184)	(2.027)	(2.155)	(2.324)
Poverty	-1.370	-3.406**	2.613*	0.670	-1.364	0.710	-4.696**	-3.743**	3.933
	(0.964)	(1.428)	(1.410)	(0.745)	(1.144)	(1.343)	(1.226)	(1.828)	(2.405)
College	0.528	0.941*	-4.748**	1.399**	1.934**	-3.065**	1.036	0.789	-9.409**
	(0.481)	(0.527)	(0.906)	(0.356)	(0.411)	(0.745)	(0.638)	(0.756)	(1.650)
Constant	23.583**	28.936**	-8.806*	20.056**	25.821**	-2.138	16.789**	14.100**	-33.997**
	(1.312)	(3.502)	(4.861)	(0.993)	(2.722)	(3.331)	(1.788)	(4.440)	(8.005)
Year Fixed Effect		✓	✓		✓	✓		✓	✓
County Fixed Effect			✓			✓			✓
Obs.	600	600	600	600	600	600	600	600	600
R^2	0.588	0.607	0.753	0.480	0.495	0.615	0.534	0.535	0.494

Note: * $p < 0.10$, ** $p < 0.05$. Robust standard errors, clustered at the county level, are in parenthesis. Data is obtained from the U.S. Census and FBI Uniform Crime Reports at three time periods (1990, 2000, and 2005-2009). See text for details.

Table 6: Inequality and Crime: Subgroup Analysis

Crime Type	Inequality Measure	A. High Income Counties			B. Low Income Counties		
		(1)	(2)	(3)	(4)	(5)	(6)
Murder	Within-tract Theil	-0.354	0.107	0.908	0.525	1.054	3.117
		(1.562)	(1.660)	(3.149)	(1.046)	(1.117)	(2.341)
	Across-tract Theil	3.723**	3.492*	6.391	4.976**	4.867**	-1.111
		(1.846)	(1.861)	(6.773)	(1.697)	(1.741)	(4.195)
Rape	Within-tract Theil	-4.797**	-5.275**	1.488	-2.374**	-1.921*	-0.473
		(1.240)	(1.050)	(1.775)	(1.042)	(1.063)	(1.284)
	Across-tract Theil	1.671	2.041	11.405**	4.847**	4.743**	-2.188
		(1.513)	(1.430)	(4.619)	(1.411)	(1.424)	(2.396)
Aggravated Assault	Within-tract Theil	0.890	1.205	-0.745	2.483**	3.340**	0.784
		(1.274)	(1.335)	(2.099)	(1.087)	(1.121)	(1.438)
	Across-tract Theil	0.693	0.527	1.520	0.646	0.510	4.825
		(1.827)	(1.846)	(4.063)	(1.798)	(1.814)	(3.231)
Robbery	Within-tract Theil	0.253	0.686	-0.952	1.022	2.320**	0.403
		(1.509)	(1.600)	(1.789)	(1.101)	(1.030)	(1.437)
	Across-tract Theil	2.791	2.537	1.797	4.283**	3.957**	-1.321
		(1.945)	(1.971)	(5.609)	(1.777)	(1.763)	(3.653)
Burglary	Within-tract Theil	-2.849**	-2.669**	-1.673	-0.607	0.253	0.166
		(1.119)	(1.054)	(1.125)	(0.943)	(0.913)	(1.082)
	Across-tract Theil	1.583	1.539	4.121	2.402*	2.226	-2.174
		(1.424)	(1.425)	(4.636)	(1.389)	(1.391)	(2.861)
Larceny	Within-tract Theil	-2.305**	-2.323**	-1.259	-1.678**	-1.498**	-0.700
		(0.837)	(0.804)	(1.130)	(0.762)	(0.718)	(0.816)
	Across-tract Theil	0.501	0.554	4.445	0.888	0.862	-1.852
		(1.027)	(1.025)	(3.198)	(1.143)	(1.155)	(2.183)
MV Theft	Within-tract Theil	-4.642**	-4.456**	-1.062	-0.633	1.222	-0.508
		(1.518)	(1.584)	(1.769)	(1.015)	(1.088)	(2.015)
	Across-tract Theil	3.546*	3.399*	4.423	3.426*	3.288*	-4.768
		(1.973)	(1.968)	(6.708)	(1.792)	(1.827)	(4.624)
	Year Fixed Effects		✓	✓		✓	✓
	County Fixed Effects			✓			✓

Note: * $p < 0.10$, ** $p < 0.05$. Robust standard errors, clustered at the county level, are in parenthesis. Data is obtained from the U.S. Census and FBI Uniform Crime Reports at three time periods (1990, 2000, and 2005-2009). See text for details.

Table 7: Patterns of Victimization, Economic Loss, and Victims' Reporting Behaviors

	Household Income Level						
	Less than $7,500	$7,500- $14,999	$15,000- $24,999	$25,000- $34,999	$35,000- $49,999	$50,000- $74,999	$75,000 or More
(a) Victimization Rate per 100,000							
Robbery	5.9	4.8	3	3.7	2	1.3	1.4
Aggravated Assault	9.3	8.6	5.3	3.4	3.8	3	1.9
Burglary	56.6	52.6	32.3	33	26.8	21.1	16.3
MV Theft	9.4	7.8	6.2	6	7.5	7.6	5.9
Larceny	138.3	114.6	123.2	111.5	108.5	97	111.2
(b) Total Economic Loss to Victims							
Mean Dollar Loss	445	604	677	611	779	1,163	1,098
Median Dollar Loss	100	120	100	100	100	150	150
(c) Post-victimization Reporting Rate							
Burglary	53.7	43.4	56.7	57.2	57.4	62.1	68.0
MV Theft	75	65.2	79.4	84.5	80.6	77.9	87.9
Larceny	24.8	28.5	28.4	29.1	36.5	32.5	37.5

Source: 2008 National Crime Victimization Survey. Tables are taken from the official USDOJ report (Rand and Robinson 2011).

†Defined as the value of cash and/or property taken upon victimization.

Table 8: Poverty Concentration and Crime

A. Measure of Inequality = Dissimilarity Index	(1)	(2)	(3)
Murder	1.737**	1.805**	2.598**
	(0.508)	(0.518)	(0.740)
Rape	0.968*	1.188**	2.588**
	(0.492)	(0.520)	(0.605)
Aggravated Assault	0.249	0.313	1.482**
	(0.527)	(0.563)	(0.681)
Robbery	2.120**	2.138**	2.105**
	(0.543)	(0.550)	(0.668)
Burglary	0.747*	0.771*	0.247
	(0.410)	(0.408)	(0.482)
Larceny	0.335	0.399	0.467
	(0.344)	(0.353)	(0.404)
MV Theft	0.704	0.628	0.639
	(0.518)	(0.532)	(0.892)
Year Fixed Effects		✓	✓
County Fixed Effects			✓
B. Measure of Inequality = Isolation Index			
Murder	2.309**	2.261**	1.795
	(1.050)	(1.044)	(1.250)
Rape	1.843**	2.073**	2.180**
	(0.875)	(0.875)	(1.072)
Aggravated Assault	0.923	0.967	0.778
	(0.950)	(1.002)	(1.264)
Robbery	3.419**	3.308**	1.971
	(1.026)	(1.016)	(1.195)
Burglary	1.378**	1.308*	-0.001
	(0.692)	(0.676)	(0.812)
Larceny	0.615	0.659	0.172
	(0.559)	(0.564)	(0.686)
MV Theft	0.773	0.642	-0.619
	(0.885)	(0.912)	(1.331)
Year Fixed Effects		✓	✓
County Fixed Effects			✓

Note: * p < 0.10, ** p < 0.05. Robust standard errors, clustered at the county level, are in parenthesis. Data is obtained from the U.S. Census and FBI Uniform Crime Reports at three time periods (1990, 2000, and 2005-2009). See text for details.

Appendix

Table A.1: Description of Explanatory Variables

Data Source	Variable	Description
1990, 2000 Decennial Census;	Population	County-level population in 100,000s
2005-2009 ACS 5-year Estimates	Female-headed Household	Share of family households with female head
	Black	Share of African American population
	Hispanic	Share of Hispanic population
	Unemployment	Share of population unemployed
	Poverty	Share of population under the poverty line
	College	Share of population above age 25 who have more than 16 years of education

Note: Data are taken from 1990 and 2000 Decennial Census and 2005-2009 American Community Survey 5-year estimates.