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Social Consequences of Economic Segregation*

Yoonseok Lee** · Donggyun Shin*** · Kwanho Shin****

The empirical literature has not been successful in generating robust results for a positive relationship between income inequality and social unrest outcomes such as crime and suicide. This paper questions the use of standard income inequality measures (e.g., Gini coefficient) in such studies and shows that income-mobility-based measures are effective in explaining outcomes of social unrest. Analyses of Korean and the United States region-by-year data suggest that crime and suicide rates are better explained by income immobility (i.e., the degree of economic segregation) rather than the inequality aspects of income distribution. The explanatory power improves as a heavier weight is placed on the poor group's degree of immobility. Findings in the current study will be helpful for guiding future efforts to develop more effective measures of social unrest.

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I. Introduction

The level of social unrest has often been represented by economic inequality. While various inequality measures such as the Gini coefficient have been used to explain outcomes of social unrest,[1] empirical studies have not been successful in finding strong supporting evidence. For example, in the literature of the crime-

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** Department of Economics, Syracuse University, U.S.A.
*** Corresponding author: Department of Economics, College of Political Science and Economics, Kyung Hee University, Seoul 130-701, Korea, E-mail: dgshin@khu.ac.kr
**** Department of Economics, Korea University 5-1, Anam-Dong, Sungbuk-Ku, Seoul 136-701, Korea, E-mail: khshin@korea.ac.kr

[1] See Demombynes and Özler (2005) and Fajnzylber, Lederman, and Loayza (2002) and references therein for crime, Andrés (2005) for suicide, and Kawachi and Kennedy (1999), Kawachi et al. (1997), and Wagstaff and Doorslaer (2000) among others for health and mortality.

inequality relationship, most cross-sectional comparisons across U.S. states and cities or across countries find that inequality is associated with high property or violent crime rates. These studies, however, may be subject to an omitted-variable bias problem, as they do not control for unobserved fixed-effects that are specific to the cross-sectional unit and possibly correlated with the unit's inequality. When fixed-effects are included in the analysis to avoid the potential bias, Lee (1993, cited in Freeman, 1996) finds insignificant coefficient estimates from the regression of changes in crime among metropolitan areas between 1970 and 1980 against changes in inequality. Based on the U.S. state-level panel data of the crime rates, Doyle, Ahmed, and Horn (1999) also adopt the first-differenced model to produce insignificant coefficients of the Gini index. On the contrary, using cross-country panel data, Fajnzylber, Lederman, and Loayza (2002) report significantly positive coefficients of inequality for both homicide rates and robbery rates even after country-specific fixed-effects are controlled for.[2]

More recently, some alternative measures that highlight the [bi]polarization aspects of income distribution have been developed to represent social unrest. As emphasized by Esteban and Ray (1994) and Wolfson (1994), income bipolarization is conceptually different from inequality.[3] Conventional inequality measures (e.g., Gini coefficient) describe the overall dispersion of income distribution, and hence are used to represent an individual's relative social status or income aspiration as an indicator of unhappiness at a point in time (e.g., Alesina, Di Tella and MacCulloch, 2004). In contrast, bipolarization emphasizes the within-group clustering as well as the distance between different income groups (e.g., Esteban and Ray, 1994; Esteban, Gradin and Ray, 2007; Foster and Wolfson, 1992; Wolfson, 1994, 1997), so that it can describe phenomena of the disappearing middle class and formation of two segregated income classes, which have a strong implication on between-group income mobility. In fact, as noted by Esteban and Ray (1994) and Wolfson (1994), their bipolarization indices have been developed as a result of dissatisfaction with the conventional inequality index as a measure of social unrest. They further go on to explain that bipolarization has implications on political cohesion and democratic decision making: a more bipolarized distribution of individuals' attributes in a society implies that a social consensus is costly to achieve. In this aspect, bipolarization indices reflect the level of social conflict or social unrest, resulting in

[2] Apparently, how to represent income inequality has been one of the central issues in this literature since results can vary depending on which aspect of income distribution is used to measure the degree of income inequality (e.g., Bourguignon, Nunez, and Sanchez, 2003). For example, some use the Gini coefficient (e.g., Ehrlich, 1973; Blau and Blau, 1982; Fajnzylber, Lederman, Loayza, 2002), or the proportion of the population below a certain percentage of the median income (e.g., Nilsson, 2004; Bourguignon, Nunez, and Sanchez, 2003), while the others exploit the mean log deviation as a special case of generalized entropy measure (e.g., Demombynes and Özler, 2005).

[3] Two income distributions with the same level of inequality can have different degrees of bipolarization.

'collective crime'.[4]

Although the theoretical foundation of the polarization-conflict relationship is sound and strong, there are not many empirical studies that support for the prediction, presumably because not enough observations exist that reflect conflicts between groups, such events as riots or revolts, although history has witnessed them occasionally. Unlike the aforementioned studies focusing on group conflicts, Lee and Shin (2011) and Lee and Shin (2012) emphasize the importance of [bi]polarization as a determinant of individual crime behaviors. Why is [bi]polarization also important in explaining 'individual' crime behaviors? From an inter-temporal point of view, with other things being equal including the probability of detection, even a low income earner would not have high crime incentive if he/she had better prospects in the future: economically, if one had higher expectation of upward income mobility, then his/her expected lifetime income would be high and so be the marginal cost of crime. Psychologically, the current relative deprivation felt by the poor would be mitigated if they had better prospects in the future. These arguments suggest that individual crime incentive could be understood better by considering the distribution of expected lifetime income rather than that of current income. What matters in an individual's current decision of crime or labor supply is his/her expectation of future as well as current position, and the expectation is affected by the statistical properties of the current income distribution: the poor tend to have lower expectation of upward income mobility in the future when the current income distribution is more bipolarized. This is so because bipolarization, that is, the disappearing middle class, is recognized by the poor as a collapse of the income ladder to the rich group.

Lee and Shin (2011) also argue that, for a better representation of social unrest, we need to generalize the Esteban-Ray type polarization measures by allowing asymmetric feelings of alienation between the rich and the poor and by developing a more plausible 'identification' function. Based on an individual's utility maximization framework, Lee and Shin (2012) derive an alternative measure of income immobility that effectively explains the individual's monetary crime incentives. All these theories can be applied to the cases of suicide, health, and labor supply, among others, in the most straightforward manner imaginable.

[4] The reason we focus on bipolarization, rather than on multi-polarization, of the distribution is as follows. First, most existing research has been dealing with bipolarization of the income distribution presumably because most researchers were preoccupied with the historical event of the disappearing middle class. Second, the very reason we are interested in polarization is that we want to know the degree of social unrest, and according to Esteban and Ray (1994), the degree of social tensions tends to be great when the society is split into a small number of significantly sized groups, presumably two groups. Third, focusing on two poles is desirable for the purpose of communicating with another popular bipolarization measure developed by Wolfson (1994). In fact, Esteban, Gradin, and Ray (2007) show that their extended index incorporates the Wolfson measure as its special case when the number of poles is two.

Despite repeated efforts to develop new measures of social unrest, no existing studies attempt to test the relative effectiveness of existing measures in terms of their ability to predict the consequences of social unrest. The primary purpose of this paper is to empirically evaluate the existing measures of social unrest in terms of their explanatory power of social deviance and crime. In particular, we compare the conventional inequality measure with the Esteban-Ray type bipolarization measures in explaining various outcomes of social unrest such as crime and suicide, using Korean and the United States region-by-year panel data. Findings in the current study will be helpful for guiding future efforts to develop more effective measures of social unrest.

This paper is organized as follows. Section 2 summarizes and compares the recent developments in the social unrest measures that are considered in this paper. Section 3 presents the description of data and estimation strategies. Section 4 reports the empirical findings of the main analysis. Section 5 concludes the paper by summarizing the main messages.

II. Recent Developments of Social Unrest Measures

Esteban and Ray (1994, henceforth ER) and Wolfson (1994) developed a new measure of social unrest, namely, a [bi]polarization index. While Wolfson index is purely based on the shape of an income distribution and focuses on how the distribution centrifuges from the median, the ER index is based on group behavioral functions that give more structure on the index.[5] More precisely, ER postulate that an individual feels two forces from income distribution of a society: *identification* toward her "own income group" that she belongs to, and *alienation* from the "other income groups." Effective antagonism an individual has in a society increases with alienation, which is fueled by some sense of identification as well. ER define polarization as the sum of all effective antagonism in a society. A practical question is how to define the identification and the alienation functions in an income space and how to construct the overall measure of polarization based on these functions. We introduce the ER and Esteban, Gradin, and Ray (2007, henceforth EGR) polarization indices, followed by a brief discussion of some more recent developments by Lee and Shin (2011, 2012).

For the expositional simplicity, we assume the population mean income level as the cut-off level[6] and divide the entire income distribution, normalized by its

[5] Also note that Esteban, Gradin, and Ray (1999, EGR) extend the simple ER index to show that the Wolfson index can be treated as a special case of the EGR index.

[6] This cut-off level can be analytically derived by minimizing the approximation error between the original Lorenz curve and the piece-wise linear approximation to it, using two income groups.

population mean, into two groups: the rich (H: high-income group) and the poor (L: low-income group). Let π be the population share of the low-income group. Then, the ER index is defined as

$$ER(\alpha) = |\mu_H - \mu_L| \pi(1-\pi)\{\pi^\alpha + (1-\pi)^\alpha\}, \tag{1}$$

Where μ_H and μ_L are the mean income level of each group, and α is some sensitivity parameter to group identity that falls into [1, 1.6] to satisfy a set of axioms. This index combines the group identity functions represented by population proportions of both groups, π^α and $(1-\pi)^\alpha$, with the alienation function represented by the between-group mean income distance, $|\mu_H - \mu_L|$. In the form of equation (1), therefore, the ER index increases in $|\mu_H - \mu_L|$. Furthermore, it can be verified that ER is maximized when $\pi = 0.5$, which implies that conflict between the two groups is the most likely when the two groups have equal shares of the entire population.

Note that equation (1) represents the total level of antagonism under the assumption that all individuals in each low- and high-income group share the same income level as μ_H and μ_L, respectively. This two-spike representation of the entire distribution is subject to some degree of measurement error and thus the ER index overstates the true degree of polarization. (On the other hand, when the true income distribution is more clustered around the local mean of each group so that individuals feel more identified, the grouping error becomes smaller.) To minimize such bias, EGR extend the ER index as

$$EGR(\alpha,\beta) = |\mu_H - \mu_L| \pi(1-\pi)\{\pi^\alpha + (1-\pi)^\alpha\} - \beta(G - \overline{G}), \tag{2}$$

Where G is the Gini index for the original income distribution and $\overline{G}$ is the Gini index computed by grouped data. The positive constant β represents the weight we put on the 'measurement error from grouping' $(G - \overline{G})$, and thus the last term in equation (2) downscales the original ER index that assumes the two-spike representation of the population distribution. Many existing studies compute the level of bipolarization using equation (2).[7]

[7] The current chapter is interested in bipolarization of the distribution for the following reasons. First, most existing research has been dealing with bipolarization of the income distribution presumably because most researchers were preoccupied with the historical event of the disappearing middle class. Second, the very reason we are interested in polarization is that we want to know the degree of social unrest, and according to EGR, the degree of social tensions tends to be great when the society is split into a small number of significantly sized groups, presumably two groups. Third, focusing on two poles is desirable for the purpose of communicating with another popular bipolarization measure developed by Wolfson (1994). As previously noted, EGR is proven to incorporate the Wolfson index as its special case when the number of poles is two.

The EGR index in equation (2), however, still has some limitations. First, as recognized by Lee and Shin (2011), both ER and EGR assume symmetry of the alienation function: the rich feel equally alienated against the poor just as the poor feel against the rich. Unlike EGR, Lee and Shin (2011) allow for the possibility that the poor feel greater antagonism against the rich than the rich do against the poor. This is important for the purpose of measuring social unrest more effectively. Second, β can be arbitrary and researchers often fix the value of β at unity following EGR. Such an arbitrary choice of β, however, makes the interpretation of group identification difficult in the EGR index. As explicitly explained in Esteban and Ray (1994), a person in the low income group feels more identified when the group's population share (π) is greater. Let us call this term as a 'scale effect.' At the same time, the person feels more identified when, for a given population share, individuals' income levels in the group she belongs to are more clustered around the local mean. Let us call this term as a 'clustering effect.' A sensible group identification function should depend on the group-specific clustering effect as well as the scale effect. Viewed from this perspective, the EGR does not consider group-specific clustering effects in their index, but merely corrects the overall bias in the 'clustering effect' that is inherent in the ER index. More importantly, the degree of correction is totally determined by the arbitrarily chosen value of β. Furthermore, when $\beta = 1$, the EGR index, by construction, puts more weight on the scale effect than the clustering effect, which is hardly justified.[8]

To overcome such limitations associated with the EGR index, Lee and Shin (2011) propose the following generalized bipolarization index:

$$B(\alpha,\theta) = (\mu_H - \mu_L)\pi(1-\pi)\{(1-\theta)[\pi(G_L / G)^{-1}]^{\alpha} + \theta[(1-\pi)(G_H / G)^{-1}]^{\alpha}\}, \quad (3)$$

where the degree of the asymmetry is determined by the value θ. Assuming $0 \le \theta \le 1/2$, the low-income group feels more alienation to the high-income group than the high-income group feels to the lower. The asymmetry gets severer as θ decreases to zero. As an extreme case, if $\theta = 0$ then the rich do not feel any alienation to the poor; if $\theta = 1/2$ then the degree of alienation is symmetric to both groups, which is the case of the EGR index. As noted by Lee and shin (2011), when $\theta = 1/2$ and the clustering effect $(G_k / G)^{-1}$ (for $k = L, H$) is ignored, $B(\alpha,\theta)$ in (3) becomes the simple $ER(\alpha)$ index in (1).

In equation (3), G is the Gini index of the entire sample, and G_L and G_H represent the group-wise Gini indices of the low and the high income class, respectively. In this specification, the within-group identity is measured by

[8] This is so because while the part of the simple ER index in the EGR, which has the form of a Gini index based on grouped data, is not divided by 2, whereas the error term, which is the difference between the usual Gini index and the Gini index based on grouped data, is divided by 2.

$[\pi(G_k / G)^{-1}]^{\alpha}$ (for $k = L, H$), which is the ratio of the scale effect to the clustering effect. The value of the identification function gets larger as either the group share becomes greater or individual income levels within group k become more identical. This measures the *relative* dispersion of the within-group income distribution, which can be more meaningful than the absolute dispersion measure ($\pi_k G_k^{-1}$), since changes in G_k also alter the overall income inequality G. Unlike the EGR index, the generalized bipolarization measure does not depend on β and places an equal weight between the scale and the clustering effects.[9]

In an effort to explain crime incentives based on income mobility, Lee and Shin (2012) extends the canonical economic model of crime by including individuals' expectation of future income mobility as an additional crime determinant. In their extended model, an individual makes a decision of whether to supply her labor in the legal or illegal labor market based on her relative position in the distribution of expected lifetime income rather than the current distribution, where an individual's expected life-time income depends on her expectation of future income mobility as well as her position in the current income distribution. Given that the individual forms her expectation of future mobility based on the properties of the current distribution, and that the average feeling of immobility of each income group is proportional to between-group income distance and inversely proportional to within-group dispersion, the crime rate (CR) in a society increases in the following immobility measure (Lee and Shin, 2012, p.58):

$$\begin{aligned} Immobility(\theta) = (\mu_H - \mu_L)\pi(1-\pi)\{&(1-\theta)\pi(G_L / G)^{-1} \\ &-\theta(1-\pi)(G_H / G)^{-1}\}, \end{aligned} \tag{4}$$

where the poor group feels a greater extent of income immobility either when between-group income distance gets greater or when within-group distribution is less dispersed. As in the aforementioned bipolarization measures, the clustering effect is adjusted by the group's size. Similar interpretations are applied to the immobility feeling of the rich. According to (4), greater feeling of immobility makes the poor involved in more criminal activity, whereas crime rates decrease as the rich feel their life-time income more secured.

Both the generalized bipolarization index $B(\alpha,\theta)$ in (3) and the immobility measure (4) share common elements of between-group income gap and size-adjusted within-group dispersion. Like $B(\alpha,\theta)$, the immobility measure increases in between-group income gap and in the feeling of immobility of the low income group. Individuals form their expectations of future income mobility based on these two aspects. Both measures can be therefore understood as the mobility-based

9 See Lee and Shin (2011) for a more detailed discussion of the generalized index.

measures.

Unlike the generalized bipolarization index $B(\alpha,\theta)$, however, the immobility feeling of the rich and that of the poor work in opposite directions in measuring social unrest: while enhanced immobility feeling of the poor increases social unrest, the rich group's feeling of more segregated income classes (i.e., feeling of more secured life-time income) reduces social unrest. In this sense, the immobility measure in (4) is more of a measure of economic motive. On the contrary, the generalized bipolarization measure is based on antagonism, where each group is antagonistic against the other group. Consequently, enhanced immobility feeling of the rich increases the level of social unrest in the bipolarization measure. In this sense, the bipolarization measure represents more of a psychological aspect of an income distribution.[10] In reality, the rich group feels two opposite forces following income class separation. As in the case of the generalized bipolarization measure, the rich feels antagonism against the poor and contribute to the level of social unrest. At the same time, as in the case of the immobility measure, they are less motivated to involve in criminal activity for monetary incentive. Which factor dominates and which of the immobility or the generalized bipolarization measure better represents social unrest are an empirical matter.[11] Overall, the current discussion suggests that mobility aspect of the income distribution should play a central role in measuring social unrest.

III. Data and Estimation Method

The goal of this section is to explain the data and methodology to empirically evaluate which of inequality or mobility-based measures (i.e. the Esteban-Ray type bipolarization measures) is more effective in representing the level of social unrest. This is done by including both inequality and mobility-based measures in the same equation and examining which one is more significant in explaining various outcomes of social unrest such as crime and suicide. To be specific, it is tested if (i) for a given level of inequality, mobility-based measures raise negative social

[10] Strictly speaking, even the immobility measure has some psychological elements in it. For example, as either the between-group income distance gets longer or the within-group clustering becomes stronger in each group, the poor group increases social unrest, whereas the rich group reduces the level. Assuming that the reduced social unrest by the rich is smaller than the elevated social unrest by the poor ($\theta < 0.5$), it can be predicted that the overall level of social unrest increases in the degree of income immobility. Of course, the this type of asymmetry is first introduced in the generalized bipolarization measure suggested by Lee and Shin (2011): while both the rich and the poor groups are antagonistic against each other, the poor feel more alienated against the rich than vice versa ($\theta < 0.5$), following income class separation.

[11] As another minor difference, the immobility measure does not depend on α.

outcomes; (ii) for a given level of between-group mobility, the poor feel more alienated against the rich than the latter against the former, so that placing a heavier weight on the poor increases the explanatory power of the mobility-based measures.

The most challenging aspect of this empirical study is to compute the generalized bipolarization index for each unit of analysis in which crime or suicide is examined. In particular, the index requires dividing the sample into the poor and the rich in each unit, and computing various group-level statistics including the Gini coefficient for each group, which requires a large number of observations in each analysis unit. It is therefore tempting to use country level data because the sample size of micro data on individual households is large in general at the country level. As emphasized by several researchers (e.g., Cornwell and Trumbull, 1994), however, when the crime-distribution relationship is investigated, it is desirable to adopt an analysis unit that is small enough to reflect the local labor market condition in which the crime rate is determined. In addition, differences in the definition of household income often make it difficult to compare various inequality and polarization measures across different countries. Furthermore, countries often use different definitions of crime categories and have different crime-related legal traditions. For these reasons, we look for evidence from regional rather than country data. More specifically we rely on Korean region-by-year data. Evidence from Korea is particularly interesting because most existing evidence is concentrated on continents other than Asia. To check the robustness of the results, however, we supplement Korean data with the U.S. state-by-year data.

For Korea, we use household disposable income received from the Korea Labor and Income Panel Survey (KLIPS), adjusted by the 'OECD equivalency scale' (see, e.g., Atkinson, Rainwater, and Smeeding, 1995) and household sample weights. By excluding Jeju-Do and including Busan into Gyeongsangnam-Do and Incheon into Gyeonggi-Do, we have a balanced sample of 90 region-by-year observations for 9 regions.[12] Crime and suicide rates, normalized by 100,000 people, as well as other demographic/economic variables are obtained from *Statistics Korea* (http://kostat.go.kr).

For the United States, the Current Population Survey (CPS) data are used to calculate mobility-related variables by state and year. Excluding states that do not have valid observations for some relevant control variables, we work with annual observations on 40 states from 1991 (the first year the CPS reports state codes) through 2005. As the CPS does not report disposable income, before-tax-transfer income (also adjusted by the 'OECD equivalency scale' and household sample weights) is used in the analysis, although the former is more relevant for crime behavior. The U.S. sample consists of 600 state-by-year balanced observations for 40

[12] They are Seoul metropolitan area, Gyeonggi-Do, Gangwon-Do, Chungcheongbuk-Do, Chungcheongnam-Do, Jeolabuk-Do, Jeolanam-Do, Gyeongsangbuk-Do, and Gyeongsangnam-Do.

states. The crime data, along with police size, are directly drawn from the Federal Bureau of Investigation Uniform Crime Reports for the period of 1991 through 2005. Among other control variables, DENSITY, YOUNG MEN, and the percentage of those who have earned bachelor's degrees or higher among the population over 25 years old, all measured by state and by year, are drawn from the U.S. Census Bureau; and state unemployment rates are from the Bureau of Labor Statistics.

In the regression equation, the logarithm of the crime (or suicide) rate is explained by the generalized bipolarization (or immobility) measure as well as other demographic, economic and crime-prevention variables. Because, as noted by Fajnzylber, Lederman, and Loayza (2002, p.2), it is difficult to identify whether the observed positive crime-inequality relationship results from monetary incentives of crime or from social strain or disorganization, and because the above mobility-based variables reflect both economic and psychological motives of crime, the overall crime rate is the relevant dependent variable to be used for the test of our hypotheses. As one of the primary goals is to test if crime is better explained by bipolarization than inequality, the model also includes the Gini index as an additional explanatory variable. In the estimation, the simultaneity between the crime rate and the crime deterrent variable, police size, is addressed using instrumental variables described below. Unobservable unit-specific fixed effects are included in every regression model and 2-step fixed-effects Generalized Method of Moments (GMM) estimation is applied with Heteroskedasticity and Autocorrelation Consistent (HAC) standard error estimates.

Existing studies, on U.S. data in particular, often emphasize the importance of police activity as a crime determinant, focusing on the effectiveness of crime deterrent efforts measured by police size, the arrest rate, and the imprisonment rate, for example. Omitting these effects may result in bias of the estimated coefficients of the mobility-based variable and the Gini index if the demand for public safety is correlated with these variables. The following three variables are used as excluded instruments. The first one is the percentage of tax revenue among gross domestic product (TAX_GDP_RATIO). As argued by Cornwell and Trumbull (1994), countries with residents who have greater preferences for law enforcement will reveal their preferences by voting for higher tax rates to finance larger police forces. Such countries would have larger police sizes for reasons not directly related to the crime rate. The second instrumental variable, CRIME_COMPOSITION, also suggested by Cornwell and Trumbull (1994), is defined by the ratio of the number of violent crimes to that of property crimes. While this ratio is not directly related with the total number of crimes, crime composition is believed to be related to police size. For example, with the total number of crimes fixed, a greater proportion of violent crimes calls for more police activity and for more policemen involved. The last one is NEIGHBORHOOD_POLICE, a population-weighted average of police sizes in neighboring states.

IV. Findings

Table 1 presents cross-correlations of the distribution-related variables: the Gini coefficient and four mobility-based measures, economic immobility measures for two different values of θ and generalized bipolarization measures for two different values of θ. Our first interest lies in correlation of the inequality index and the other four mobility-based measures. For Korea, the Gini coefficient is more highly correlated with the economic immobility measure than the antagonism-based bipolarization measures. When an equal weight is placed between the rich and the poor ($\theta = 0.5$), the estimated correlation of the Gini and the economic immobility is 0.72, whereas that of the Gini and the generalized bipolarization measure is only 0.59. As a heavier weight is placed on the poor ($\theta = 0.25$), these two correlations become similar. This happens because, when $\theta = 0.25$, the estimated correlation between the two immobility-based measures becomes quite high as 0.94,[13] compared to an estimated correlation of 0.32 when $\theta = 0.5$. Although the Gini coefficient becomes more highly correlated with mobility-based measures for lower values of θ, the estimated correlations are still far from unity (0.76 to 0.80), implying that they are different measures. All these characteristics are preserved for the U.S. data in a qualitative sense, although estimated correlations are generally higher for the U.S. than for Korea.

Based on Korean region-by-year panel data, Figures 1, 2, and 3 display the sample correlations between the crime rate and the Gini coefficient, between the crime rate and the immobility measure, and finally between the crime rate and the generalized bipolarization measure. We normalize each variable by the region-specific mean of each variable, and to focus on statistical properties of mobility-based measures, θ is set at 0.5. Figures show that, while the crime rate is unrelated with the Gini coefficient, it is positively correlated with either the economic immobility measure or the generalized bipolarization measure. As we exploit only within-variation of each variable, the observed correlations would be obtained by applying fixed-effects estimation to the crime regression model with no control variables included. In subsequent analyses, we examine if these observations survive including both inequality and mobility-based measures and controlling for other variables in the regression model.[14]

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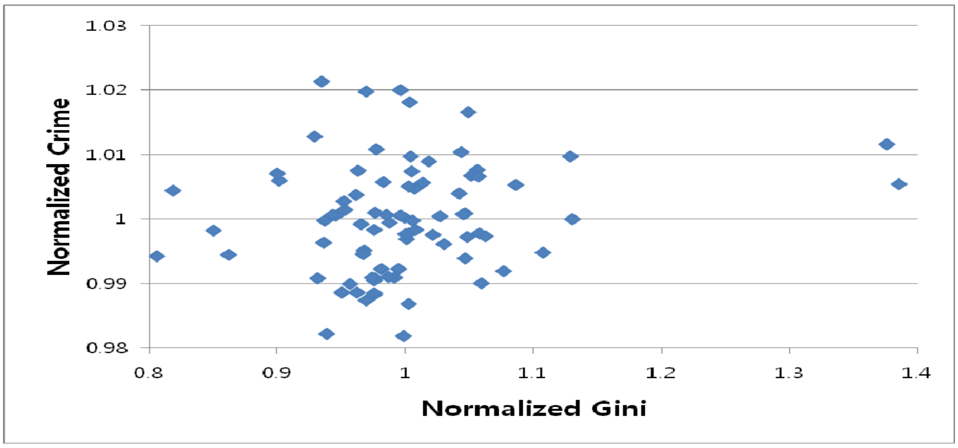
[13] When $\theta = 0$, $Immobility(\theta)$ and $B(1,\theta)$ become identical.

[14] When fixed-effect estimation is applied to the regression of the crime rate against the social unrest measure with no controls, the estimated coefficients of the Gini index, the generalized bipolarization, and the immobility measure are 0.348, 0.706, and 0.524, respectively, which are generally imprecise. When θ is lowered to 0.25, however, the coefficients of the generalized bipolarization and immobility measures are precisely estimated at 0.538 and 0.448, respectively.

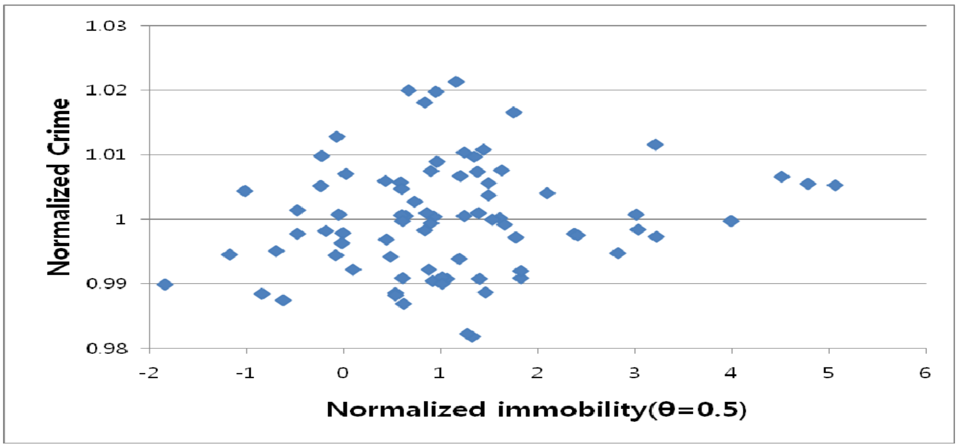
[Table 1] Cross-Correlation Matrix of Income-Distribution-Related Variables

	Gini	Economic immobility (θ=0.5)	Economic immobility (θ=0.25)	Generalized bipolarization (θ=0.5)	Generalized bipolarization (θ=0.25)
Korea					
Gini	1				
Economic immobility(θ=0.5)	0.7155	1			
Economic immobility(θ=0.25)	0.7963	0.8202	1		
Generalized bipolarization(θ=0.5)	0.5918	0.3150	0.8006	1	
Generalized bipolarization(θ=0.25)	0.7640	0.5760	0.9369	0.9545	1
United States					
Gini	1				
Economic immobility(θ=0.5)	0.9127	1			
Economic immobility(θ=0.25)	0.8629	0.9459	1		
Generalized bipolarization(θ=0.5)	0.6854	0.7432	0.9200	1	
Generalized bipolarization(θ=0.25)	0.8242	0.8768	0.9841	0.9717	1

[Figure 1] Crime and Gini Coefficient



[Figure 2] Crime and Economic Immobility Measure ($\theta = 0.5$)



[Figure 3] Crime and Generalized Bipolarization Measure ($\theta = 0.5$)

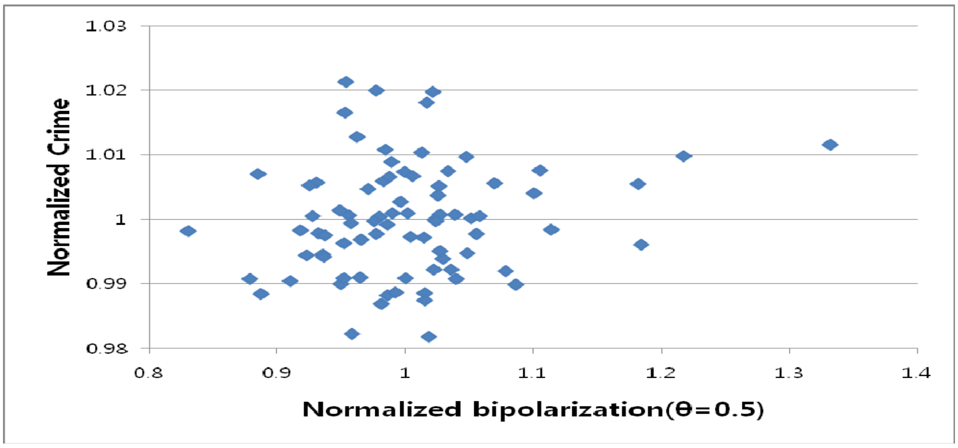


Table 2 presents estimation results of the crime regression model described in the previous section, where the crime rate is for the total crime including property and violent crimes. Estimates in the first four columns show the results for Korea, and the last four columns those for the United States. The dependent variable is the logarithm of the number of total crimes per 100,000.[15] Unobservable region-specific fixed effects are included in every regression model, and two-step fixed-effects GMM estimation is applied with HAC standard error estimates. For Korea, the endogenous regressor, log (police), is instrumented by three excluded variables,

[15] Following existing studies (e.g., Demombynes and Özler, 2005; Fajnzylber, Lederman, and Loayza, 2002), we take the logarithm of the dependent variable. Consequently, the estimated coefficient of a regressor represents percentage change in the number of crimes reported per 100,000 individuals associated with a unit change in the regressor.

[Table 2] Total Crime

Variables	Korea				United States			
	Economic immobility		Generalized bipolarization		Economic immobility		Generalized bipolarization	
	θ=0.5	θ=0.25	θ=0.5	θ=0.25	θ=0.5	θ=0.25	θ=0.5	θ=0.25
Gini	-0.149	-0.327	0.045	-0.339	**-1.471*****	**-1.638*****	-0.458	**-1.372*****
	(0.282)	(0.311)	(0.231)	(0.290)	**(0.249)**	**(0.302)**	(0.342)	**(0.304)**
Immobility or Bipolarization	**0.598***	**0.681****	0.348	**0.759****	**1.219*****	**1.049*****	-0.436	**0.685****
	(0.310)	**(0.315)**	(0.570)	**(0.371)**	**(0.323)**	**(0.313)**	(0.548)	**(0.286)**
log(police)	-0.599	-0.628	-0.685	-0.709	**-3.877*****	**-3.882*****	**-3.929*****	**-3.883*****
	(0.590)	(0.589)	(0.522)	(0.566)	**(0.995)**	**(0.994)**	**(1.000)**	**(0.991)**
education level	**-0.187*****	**-0.189*****	**-0.180*****	**-0.187*****	-0.174	-0.195	-0.157	-0.209
	(0.059)	**(0.059)**	**(0.055)**	**(0.058)**	(0.415)	(0.413)	(0.423)	(0.413)
population density	**0.001***	**0.001***	**0.001****	**0.001***	**-0.004*****	**-0.004*****	**-0.005*****	**-0.004*****
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
young ratio	0.021	0.032	-0.440	-0.152	**-5.354*****	**-5.441*****	**-5.605*****	**-5.600*****
	(1.415)	(1.406)	(1.288)	(1.353)	**(1.763)**	**(1.775)**	**(1.839)**	**(1.801)**
unemployment rate	**-4.404***	**-4.608***	-4.345	**-4.867***	**1.465*****	**1.372*****	0.832	1.162**
	(2.551)	**(2.545)**	(2.678)	**(2.589)**	**(0.524)**	**(0.523)**	(0.536)	(0.525)
First-stage F-test	0.0001	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000
Hansen J-test	0.3697	0.4085	0.3674	0.4672	0.2975	0.2682	0.2019	0.2191
Observation [Region]	90 [9]				600 [40]			

The dependent variable is log (total reported crimes per 100,000).Unobservable unit-specific fixed effects are included in every regression model and 2-step fixed-effects Generalized Method of Moments (GMM) estimation is applied with Heteroskedasticity and Autocorrelation Consistent (HAC) standard error estimates. The endogenous right hand side variable, log(police size), is instrumented by the percentage of tax revenue among gross domestic product (TAX_GDP_RATIO), the ratio of the number of violent crimes to that of property crimes(CRIME_COMPOSITION), and the population-weighted average of police sizes in neighboring states (NEIGHBORHOOD_ POLICE). Numbers in parentheses are estimated standard errors. *, **, *** = significant at the 10%, 5%, and 1%, respectively.

CRIME_COMPOSITION, TAX_GDP_RATIO, and log (NEIGHBORHOOD_ POLICE). For the United States, the endogenous variable is instrumented by CRIME_COMPOSITION and TAX_GDP_RATIO.[16] An F-test rejects the null hypothesis that these instruments are not correlated with the endogenous regressor at any conventional significance level, and a Hansen J-test cannot reject the null hypothesis that each set of instrumental variables are not correlated with the error term in the crime model. For all tables, we let $\alpha = 1.6$ for generalized bipolarization indices, $B(\alpha,\theta)$.

The results mostly show that mobility-based measures, the economic immobility ($Immobility(\theta)$) and the generalized bipolarization measures ($B(\alpha,\theta)$), explain the crime rate significantly, while the Gini index does not. For both countries, estimated coefficients of the Gini index are negative and sometimes even significantly negative.[17] On the contrary, with the exception of using an equal weight in the generalized bipolarization index, estimated coefficients of mobility-based measures (again economic immobility or generalized bipolarization) are positive and statistically significant. Note that a negative coefficient of the Gini index implies that, with between-group income immobility controlled for, income distance works as an incentive to supply labor so as to increase income, and as such, as a disincentive of crime. Positive coefficients of mobility-based measures imply that, with all else being controlled for, including between-individual income gaps, between-group immobility induces higher crime rates.

Consistent with Lee and Shin (2012), the explanatory power of the generalized bipolarization index becomes higher when a greater weight ($\theta = 0.25$) is placed on the poor than when an equal weight ($\theta = 0.5$) is applied. Although not reported, compared to the case of $\theta = 0.25$, the explanatory power of the generalized bipolarization index is somewhat reduced when the rich are entirely eliminated in designing the index ($\theta = 0$). This motivates us to further explore the 'optimal' value of θ that gives the generalized bipolarization index the greatest power in explaining crime rates. To that effect, we re-estimate the crime model by fixed-

[16] A sequence of validity tests suggest that log (NEIGHBORHOOD_POLICE) cannot be used as an instrument for the U.S. case.

[17] When we estimate the crime regression model in Table 2 with mobility-based measures excluded from the equation, the estimated coefficients of the Gini index is 0.153 with standard error estimate 0.193.The insignificantly positive estimate is quite consistent with existing studies (e.g., Lee (1993, cited in Freeman, 1996). For the U.S., the corresponding figures are -0.697 and 0.192, respectively. In comparison, based on the U.S. state-level panel data over the years 1984-93, Doyle, Ahmed, and Horn's (1999) fixed-effects GMM estimation of their crime model produces negative but insignificant coefficient estimates of the Gini index. The current study's finding of the significantly negative estimate for the United States is partly understood by considering that the current study incorporates more recent observations relative to Doyle et al.. As well recognized by many researchers (see Levitt (2004) for example), crime rates have been falling in the U.S. since the early 1990s. At the same time, income distribution has become unequal since the 1980s.

effects GMM, repeatedly changing the value of θ from 0 to 0.5 by 0.01. The results show that the estimated coefficients on the generalized bipolarization index appear as a concave function of θ for both countries, and the largest coefficient estimate of the bipolarization index is obtained at around $\theta = 0.27$. Due to the large standard error estimates, however, differences in the estimated coefficient for different values of θ are generally insignificant. This type of asymmetric effect in the feeling of alienation does not appear in the immobility measure, which focuses more on economic incentives/disincentives rather than antagonism.[18]

For both countries, estimated coefficients of the police size, as measured by the number of policemen per 100,000 people, are negative: They are highly significant for the case of the United States, though not for Korea. Although not reported for brevity, little change occurs in our main conclusions even when police size is treated as an exogenous variable. Higher education levels, as measured by the average years of schooling, are associated with lower crime rates, though estimates are not significant for the case of the U.S. The higher proportion of young men aged between 15 and 29 leads to a lower crime rate, especially in the U.S. The effects of the population density and those of the overall unemployment rate appear somewhat inconsistent between the two countries.

Table 3 displays results when the dependent variable is replaced by the suicide rate. Official statistics show that, as of 2011, suicides per 100,000 people were about 32 in Korea. This figure was the highest among all OECD member countries and was about three times as high as that of the U.S.. The two countries also differ in the determinants of the suicide rate. For Korea, the single most important determinant of the suicide rate is the mobility-related variable, the economic immobility measure or the generalized bipolarization measure. For Korea, it is immobility not inequality that matters in the suicide model, which is quite consistent with the estimated results of the crime model. The estimated coefficients of the Gini index are even more significantly negative than in the crime model, implying that, with between-group income immobility controlled for, greater inequality works as a disincentive for suicide (an incentive for labor supply). On the contrary, for the U.S., income-distribution-related variables (inequality or immobility) are generally insignificant in the suicide model. Instead, the overall labor market condition, as measured by the unemployment rate, affects the suicide rate significantly.

[18] Unlike the current study, Lee and Shin (2012) include in the crime equation the extent of group-specific immobility feeling, as measured by the ratio of the between-group income distance (normalized by the population mean) to the extent of size-adjusted within-group clustering, and compare the marginal effect of a unit-increase in the immobility feeling of the poor and that of the rich. Their results from the Luxemburg Income Study (LIS) data show another type of asymmetric effects: Given an equal increase in the extent of immobility feeling for both groups, the rise in the crime incentive of the poor is greater than the reduction in the crime incentive of the rich (Op. cit.,p. 65).

[Table 3] Suicide

Variables	Korea				United States			
	Economic immobility		Generalized bipolarization		Economic immobility		Generalized bipolarization	
	θ=0.5	θ=0.25	θ=0.5	θ=0.25	θ=0.5	θ=0.25	θ=0.5	θ=0.25
Gini	**-0.954***** **(0.341)**	**-1.420***** **(0.430)**	**-0.950**** **(0.434)**	**-1.662***** **(0.442)**	-0.036 (0.202)	-0.015 (0.241)	**0.601**** **(0.300)**	0.172 (0.255)
Immobility or Bipolarization	**1.273***** **(0.447)**	**1.562***** **(0.478)**	**1.880*** **(1.012)**	**2.038***** **(0.541)**	0.293 (0.230)	0.187 (0.222)	**-0.806*** **(0.436)**	-0.016 (0.209)
log(police)	**-1.638**** **(0.695)**	**-1.796***** **(0.687)**	**-2.290***** **(0.750)**	**-2.208***** **(0.694)**	**-1.197*** **(0.691)**	**-1.206*** **(0.693)**	**-1.244*** **(0.705)**	**-1.225*** **(0.698)**
education level	0.069 (0.110)	0.058 (0.109)	0.063 (0.112)	0.048 (0.110)	-0.184 (0.327)	-0.185 (0.328)	-0.143 (0.336)	-0.176 (0.331)
population density	0.001 (0.001)	0.001 (0.001)	0.002* (0.001)	**0.001*** **(0.001)**	**-0.001***** **(0.000)**	**-0.001***** **(0.000)**	**-0.001***** **(0.000)**	**-0.001***** **(0.000)**
young ratio	**-16.481***** **(1.750)**	**-16.581***** **(1.681)**	**-18.282***** **(1.818)**	**-17.319***** **(1.644)**	-0.902 (1.510)	-0.949 (1.520)	-0.939 (1.526)	-1.010 (1.536)
unemployment rate	2.447 (3.264)	1.990 (3.358)	2.192 (3.333)	1.205 (3.536)	**1.489***** **(0.430)**	**1.429***** **(0.428)**	**1.269***** **(0.419)**	**1.324***** **(0.426)**
First-stage F-test	0.0001	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000
Hansen J-test	0.0743	0.1030	0.2184	0.2392	0.0570	0.0623	0.0622	0.0696
Observation [Region]	90 [9]				600 [40]			

The dependent variable is log (suicides per 100,000).

Interestingly, the estimated coefficient of the police size is negative and significant for both countries. While inclusion of the variable in the suicide model is justified by the nature of an individual's choice among crime, suicide, and labor supply (so crime deterrent efforts are assumed to affect their choice of either suicide or labor supply as well as criminal activities), no existing study considers police-related variables in the suicide model.[19] To obtain estimates comparable to those of existing studies, we re-estimated the suicide model without the police size. Although not reported in separate tables for brevity, this exercise makes little change in the estimated results.

In line with the Beckerian economic models of crime (Becker, 1963) that focus on monetary incentives-disincentives of crime, we conduct similar analyses using the property crime rate as the dependent variable. While these models hypothesize that, the more unequal the income distribution is, the greater the gap between benefits and costs of crime, and thus the higher the property crime rate is, it is believed in the current study and others that the net gain is better represented by immobility than inequality: the between-group income gap works as an incentive of human capital investment and/or labor supply, not crime, when sufficient mobility is guaranteed.

The upper panel of Table 4 shows the results.[20] With the property crime rate being the dependent variable, crime composition can no longer be a valid instrument for police size. For the U.S., we apply fixed-effect Instrumental Variable (IV) estimation with TAX-GDP-RATIO being the only relevant instrument.[21] The estimates show that, relative to the results for the total crime in Table 2, explanatory power of the mobility-based variables increases to some degree, especially for Korea. More importantly, it is again not inequality but immobility that matters in the crime model. In the lower panel of Table 4, we redo the same analysis using the drug crime as the dependent variable, which is measured by the logarithm of the number of those who are arrested for drug-related crimes per 100,000 people. It is believed that this variable reflects aspects of both crime and suicide. While estimates are generally less precise compared to the previous cases, patterns of estimating more significant coefficients for mobility-based variables are still preserved even in this exercise.

[19] Since the error term in the crime model is likely to be contemporaneously correlated with the error term in the suicide model, a system estimation may be preferable in a general set-up. As proved in Theil (1970), however, in our case a system-estimation produces identical results to separate OLS estimations since all equations share identical regressors.

[20] Table 4 reports the estimated coefficients of distribution-related variables only. Although not reported for brevity, estimates of the other coefficients are very similar to our previous cases in terms of signs and significance.

[21] For Korea, log (NEIGHBORHOOD_POLICE) and TAX_GDP_RATIO pass a series of validity tests of instrumental variables.

[Table 4] Property Crime and Drug

Variables		Korea				United States			
		Economic immobility		Generalized bipolarization		Economic immobility		Generalized bipolarization	
		θ=0.5	θ=0.25	θ=0.5	θ=0.25	θ=0.5	θ=0.25	θ=0.5	θ=0.25
Property Crime	Gini	0.207 (0.684)	-0.420 (0.835)	-0.214 (0.927)	-0.505 (0.948)	**-1.511***** **(0.244)**	**-1.683***** **(0.296)**	-0.534 (0.341)	**-1.426***** **(0.301)**
	Immobility or Bipolarization	**2.024**** **(0.864)**	**1.616***** **(0.576)**	**1.266*** **(0.662)**	**1.410**** **(0.604)**	**1.222***** **(0.316)**	**1.055***** **(0.306)**	-0.365 (0.543)	**0.700**** **(0.281)**
Drug	Gini	-2.294 (3.281)	**-6.653*** **(3.646)**	-3.751 (2.905)	**-5.903*** **(3.570)**	**-4.182**** **(1.793)**	-2.912 (1.934)	-1.180 (1.631)	-2.012 (1.976)
	Immobility or Bipolarization	4.838 (7.739)	**8.713**** **(4.326)**	5.967 (3.640)	**7.208*** **(3.787)**	**5.645**** **(2.456)**	1.904 (1.460)	0.509 (1.753)	1.199 (1.670)

The dependent variable is log (reported property crimes per 100,000) or log (those arrested for drug per 100,000).

V. Conclusion

This paper compares the conventional income-inequality index with income-mobility-based measures to explain outcomes of social unrest such as crime and suicide. The conclusion of theoretical discussions and empirical analyses can be summarized in twofold: For the income distribution, it is immobility not inequality that matters in explaining social deviance and crime; and both monetary and psychological aspects of income distribution are important in designing a measure of social unrest.

As emphasized by Esteban and Ray (1994), social tensions are expected to be most aggravated when the society is split into a small number of significantly sized groups, presumably two groups. This is the reason why we focus on immobility between the poor and the rich in investigating social consequences of economic segregation. However one may argue that a three-group representation of the income distribution may be more appropriate in measuring social unrest: the poor feel higher crime incentives when their mobility to the middle class is more restricted, and the middle may be frustrated by their immobility to the rich.[22] This issue could be investigated in future research.

[22] We thank an anonymous referee for raising this point.

References

Alesina, A., R. Di Tella and R. MacCulloch (2004), "Inequality and happiness: Are Europeans and Americans different?" *Journal of Public Economics*, 88, 2009-2042.

Andrés, A. R. (2005), "Income Inequality, Unemployment, and Suicide: A Panel Data Analysis of 15 European Countries," *Applied Economics*, 37, 439-451.

Atkinson, A. B., L. Rainwater, and M. Smeeding (1995), Income Distribution in OECD Countries: Evidence from the Luxembourg Income Study, OECD Social Policy Studies No. 18, Paris: OECD.

Becker, G. S. (1963), "Crime and Punishment: An Economic Approach," *Journal of Political Economy*, 76, 169-217.

Blau, J. R., and P. M. Blau (1982), "The Cost of Inequality: Metropolitan Structure and Violent Crime," *American Sociological Review*, 47, 114-129.

Bourguignon, F., J. Nunez, and F. Sanchez (2003), What Part of the Income Distribution does matter for Explaining Crime? The Case of Columbia, DELTA Working Paper No. 2003-04.

Cornwell, C., and W. N. Trumbull (1994), "Estimating the Economic Model of Crime with Panel Data," *Review of Economics and Statistics*, 76, 360-366.

Demombynes, G., and B. Özler (2005), "Crime and Local Inequality in South Africa," *Journal of Development Economics*, 76, 265-292.

Doyle, J. M., E. Ahmed, and R. N. Horn (1999), "The Effects of Labor Markets and Income Inequality on Crime: Evidence from Panel Data," *Southern Economic Journal*, 65, 717-738.

Ehrlich, I. (1973), "Participation in Illegitimate Activities: A Theoretical and Empirical Investigation," *Journal of Political Economy*, 81, 521-565.

Esteban, J., C. Gradin and D. Ray (2007), "An Extension of a Measure of Polarization, with an Application to the Income Distribution of Five OECD Countries," *Journal of Economic Inequality*, 5, 1-19.

Esteban, J. and D. Ray (1994), "On the Measurement of Polarization," *Econometrica*, 62,819-851.

Fajnzylber, P., D. Lederman, and N. Loayza (2002), "Inequality and Violent Crime," *Journal of Law and Economics*, 45, 1-39.

Foster, J. E., and M. C. Wolfson (1992), "Polarization and the Decline of the Middle Class: Canada and the U.S.," mimeo, Vanderbilt University.

Freeman, R. B. (1996), Why Do So Many Young American Men Commit Crimes and What Might We Do About It?," *Journal of Economic Perspectives*, 10, 25-42.

Kawachi, I. and B. P. Kennedy (1999), "Income Inequality and Health: Pathways and Mechanisms," *Health Services and Research*, 34, 215-227.

Kawachi, I., B. P. Kennedy, K. Lochner, and D. Prothrow-Stith (1997), "Social Capital, Income Inequality, and Motality," *Journal of Public Health*, 87, 1491-1498.

Lee, Y. and D. Shin (2011), "Measuring Social Unrest Based on Income Distribution," mimeo, University of Michigan.

Lee, Y. and D. Shin (2012), "Mobility-Based Explanation of Crime Incentives," *Korean Economic Review*, 28, 51-67.

Levitt, S. D. (2004), "Understanding Why Crime Fell in the 1990s: Four Factors that Explain the Decline and Six that Do Not," *Journal of Economic Perspective*, 18, 163-190.

Nilsson, A. (2004), "Income Inequality and Crime: The Case of Sweden, Institute for Labor Market Policy Evaluation," Working Paper 2004:6.

Theil, Henri, *Principles of Econometrics*, New York: Wiley, 1971.

Wagstaff, A. and E. V. Doorslaer (2000), "Income Inequality and Health: What Does the Literature Tell Us?" *Annual Review of Public Health*, 21, 543-67.

Wolfson, M. C. (1994), "When Inequalities Diverge," *American Economic Review: Papers and Proceedings*, 84, 353-358.