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Mobility-Based Explanation of Crime Incentives*

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The canonical economic model of crime is extended to include individuals' expectation of future income mobility as an additional crime determinant. The model predicts that with all else being held constant including net gain from current criminal activity, reduced upward mobility among the poor increases crime rate whereas enhanced downward immobility among the rich decreases crime rate. These predictions are empirically supported by country-level panel data. In addition, a typical change in income distribution was implemented, such that both the poor and the rich groups contribute to crime rate with a greater contribution among the poor.

JEL Classification: C10, D63, K42
Keywords: crime, immobility, income distribution

I. Introduction

Many economic and sociological studies have attempted to determine the relationship between inequality and crime, as well summarized by Kelly (2000); Fajnzylber, Lederman, and Loayza (2002); and Demombynes and Özler (2005). The canonical economic model of crime[1] states that the more unequal income distribution results in a greater gap between benefits and costs of crime committed by low income earners and thus a higher (property) crime rate, which is largely based on the differential returns from legal and illegal activities. However, economic and sociological theories vary depending on which aspect of social phenomena is

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[1] See Becker (1963).

operative in these theories. According to sociological theories, inequality makes individuals in lower strata feel alienated from society, generally undermines the ability of society to control its members, and reduces demand for public safety, all of which contribute toward increasing crime rate. However, as argued by Fajnzylber, Lederman, and Loayza (2002, p. 2), whether the positive crime-inequality relation, if any, results from economic incentives-disincentives of crime or from social strain or disorganization is difficult to identify empirically.

Based on empirical evidence,[2] most cross-sectional comparisons across states and cities in the United States or those across countries conclude that inequality leads to property and/or violent crime (e.g., the survey by Demombynes and Özler, 2005). However, findings in these studies may be subject to an omitted variable bias problem because they do not control for unobserved fixed effects that are specific to the cross-sectional unit and possibly correlated with the unit's inequality. Evidence remains insufficient and contradicting even for panel data models with fixed effects. For example, Lee (1993, cited in Freeman, 1996) regressed changes in crime in a metropolitan area between 1970 and 1980 against changes in inequality and discovered insignificant coefficient estimates. The first-difference model of Doyle, Ahmed, and Horn (1999) also produced insignificant coefficients of the Gini index. On the contrary, based on international panel data for 39 countries, Fajnzylber, Lederman, and Loayza (2002) reported significantly positive coefficients for both homicide rates and robbery rates even after country-specific fixed-effects were controlled for.

Despite the repeated theoretical and empirical efforts to connect the crime rate with cross-sectional inequality, little effort has been exerted to understand the relationship between the crime rate and inequality in the distribution of lifetime income. This situation is surprising considering that many studies such as that of Backer and Solon (2003) have emphasized that long-term inequality is even more consequential than instability of transitory earnings. From a theoretical viewpoint, the decision of an individual regarding whether to supply his labor to the legal or illegal labor market is based on his relative position in the distribution of the expected lifetime income rather than in the current distribution. The latter is related to the conventional static inequality measure such as the Gini coefficient, while the former is determined by the mobility of the person to the income group other than the one to which he belongs. Existing measures of cross-sectional inequality do not sufficiently capture these mobility aspects of lifetime income distribution (e.g., Yitzhaki and Wodon, 2002) and therefore may not be adequate in explaining individual or collective violence.

This paper is the first that attempts to present a mobility-based explanation of crime incentives of individuals. We first extend the canonical crime model by

[2] The first empirical study dates back to Ehrlich (1973).

including expectation of individuals regarding their future mobility as an additional crime determinant. Each individual forms his expectation of future mobility based on the information obtained from the current distribution. In particular, mobility aspects of income distribution, which are not adequately captured by conventional inequality measures, are important in decision-making; individuals feel a greater extent of income class separation and so expect less mobility in the future either when between-group income distance is longer or when within-group income distribution is more clustered around its local mean, and therefore they recognize less of the income bridge to the other income group. Then, using country-level panel data, we directly estimate the equation generated by the utility maximization process that connects the crime rate with a measure of the subjective mobility of individuals along with other crime determinants. As such, we attempt to provide a more structural explanation of the crime incentives of individuals.

Organization of this paper is as follows: Section II presents a theoretical framework that helps explain how expectation of individuals regarding their future mobility affects their decision to engage in criminal activity. Given the paucity of reliable data, theoretical reasoning is necessary to analyze the relationship between crime and income distribution (e.g., Bourguignon, 1999). The canonical economic crime model is enriched by encompassing the subjective feeling of mobility of individuals as an additional crime determinant. The model is further extended to include crime incentives of the rich as an additional model element, which also is a unique feature of the current model. Section III presents evidence from country-level panel data. Consistent with our theoretical prediction, with all else being controlled for, the crime rate increases in relation to measured immobility among the poor. Moreover, enhanced immobility among the rich reduces the crime rate. As our measure of the feeling of immobility increases among the poor but decreases among the rich, both groups make positive contributions to the crime rate, albeit much greater contribution is observed among the poor. Section IV concludes.

II. Model

When a person decides whether to supply his labor in the legal or illegal labor market, the person considers his relative position in the distribution of expected lifetime income rather than in the current distribution. The latter is related to conventional static inequality measures such as the Gini coefficient, while the former is determined by the entire lifetime income stream of the person, which in turn depends on, among others, the mobility of the person to the income group other than the one to which he belongs. Given this perspective, even a current low-income earner would not have high crime incentive if he had better prospects in the future. If one has higher expectation of upward mobility, then expected lifetime income is high and so is the marginal cost of the current crime action; therefore, one has lower crime incentive.

More precisely, we consider a utility maximization problem to explain individual crime incentive. We assume that the individual has utility function $u(y_i, \eta_i) = V(y_i) + \eta_i$, where y_i is the income (or wealth) level of person i, $V(y_i) > 0$, $\partial V(y)/\partial y > 0$, $\partial^2 V(y)/\partial y^2 < 0$, and η_i is the psychological crime disincentive factor of person i. In the literature, the psychological crime disincentive factor η_i is normally specified as the individual level of honesty, which is independent of income level. We emphasize, however, that the expected lifetime income or expectation of future income mobility is another important determinant for the psychological crime disincentive. To model such idea, we assume that society is divided into two income groups, G_r (rich) and G_p (poor), whose average income and population sizes are denoted as μ_r, μ_p, and n_r, n_p, respectively. We then define

$$\eta_i = \eta_i(h_i, IM_i) = \eta(h_i, IM_i^p) \text{ if } i \in G_p \text{ and } = \eta(h_i, IM_i^r) \text{ if } i \in G_r,$$

where h_i represents the individual level of "honesty" as disincentive for crime, which is independent of income level. $h_i \sim iidU[0, H]$ with some $H > 0$. IM_i^k for $k = r, p$ captures heterogeneous and subjective immobility that each individual feels toward the current income distribution of society. Values of IM_i^k differ between groups and across individuals. For a given level of objective immobility, individuals in the poor group feel a greater extent of immobility than those in the rich group, resulting in greater crime incentive among the poor. $\partial\eta/\partial h > 0$, $\partial\eta/\partial IM_i^p < 0$, and $\partial\eta/\partial IM_i^r > 0$, which are satisfied by a simple specification that

$$\eta_i = h_i - IM_i^p \text{ for } i \in G_p, \text{ and } \eta_i = h_i + IM_i^r \text{ for } i \in G_r. \tag{1}$$

Consequently, the rich generally have a greater extent of crime disincentive than the poor do.

The crime pays x with probability $(1-q)$ and $-F$ (i.e., fine once the crime is detected) with q. Similar to the standard crime model (e.g., Bourguignon, 1999), individual i (assuming he is the only person to commit a crime; i.e., *ceteris paribus*) opts for criminal activity if

$$(1-q)V(y_i + x) + qV(y_i - F) > V(y_i) + \eta_i. \tag{2}$$

In this setup, crime action is an all-or-nothing decision. Existing studies assume that F is proportional to the income level y_i, and thus the rich for whom x is relatively small are not tempted to commit crimes even when they are sufficiently dishonest $(h_i = 0)$. This assumption simplifies the discussion by assuming that only the poor commit crimes, although this assumption may not be justified by the judicial system of each society. By contrast, our specification (1) of the disincentive factor works toward making the crime incentive greater for the poor than the rich even without the "proportionality" assumption; even with an equal amount of fine between the rich and the poor, the crime disincentive (η_i) is always smaller for the poor because of the feeling of blocked upward mobility, other things being held constant. Similarly, even when the fine is independent of the income level and even when the rich are sufficiently dishonest, they may not have strong crime incentive when they feel sufficiently secure about the future. In other words, compared with existing crime models, crime incentive of the poor is stronger than that of the rich in the current model. For the purpose of comparison of our crime model with existing ones, we first follow existing studies and assume that H, x, q, F, and IM_i^p are such that only the poor engage in criminal activity. Observing the crime rate between 0 and 1, equation (2) is satisfied for $\eta_i = -IM_i^p$ in group p (sufficiently dishonest) but not for $\eta_i = H - IM_i^p$ (sufficiently honest).[3]

Given this simple specification, the crime rate (CR) in a society can be obtained as

$$\begin{aligned} CR &= n^{-1}\sum_{i\in G_p} \Pr(h_i < \{V(y_i+x)-V(y_i)\} - q\{V(y_i+x)-V(y_i-F)\} + IM_i^p\} \\ &= H^{-1}n^{-1}\sum_{i\in G_p} [\{V(y_i+x)-V(y_i)\} - q\{V(y_i+x)-V(y_i-F)\}] \\ &\quad + H^{-1}(n^{-1}\sum_{i\in G_p} IM_i^p) \end{aligned} \tag{3}$$

In equation (3), $\{V(y_i+x)-V(y_i)\}$ and $\{V(y_i+x)-V(y_i-F)\}$ represent the utility change when the crime is not detected and the utility change when it is detected, respectively. The second term implies that, other things being held constant, the crime rate increases as the feeling of immobility escalates among the poor.

Empirical implementation of equation (3) requires specification of the average group-specific subjective immobility as a function of observable variables. We postulate that individuals evaluate their future income mobility based on the properties of the current income distribution. Specifically, individuals in the poor group ***feel*** a greater degree of immobility to the rich group either when the between-

[3] For the rich class, even dishonest people usually do not involve themselves in criminal activity because of the feeling of economic safety. Equation (2) may not be satisfied even when $\eta_i = IM_i^r$.

group income gap is greater or when the within-group income distribution is less dispersed. When income levels of individuals are more clustered around a local mean, each individual feels a greater extent of group identity to members of their own group, which enhances income class separation and lessens the subjective probability of switching to the other group. To the extreme, if all individuals in the lower income group had the same income level as μ_p and all income levels of individuals in the higher group were identical to μ_r such that no bridge income level exists in the society, the crime incentive of the poor would be high even for a relatively small between-group income gap. Given these conditions, the average feeling of immobility of the poor group is specified as follows.

$$\overline{IM^p} = n_p^{-1} \sum_{i \in G_p} IM_i^p = \beta_p \mu^{-1} (\mu_r - \mu_p) \upsilon_p^{-1}, \tag{4}$$

where $\mu^{-1}(\mu_r - \mu_p)$ is a measure of income distance between the two groups normalized by the population mean (μ), and υ_p represents a measure of within-group income dispersion. Specification (4) implies that the average immobility feeling is proportional to the product of the between-group income distance and the degree of within-group income clustering, with β_p being the psychological proportionality factor. Consequently, the psychological crime incentive of the poor generated by their expectation of future mobility is assumed proportional to some observable statistical characteristics of the current distribution. We further assume that υ_p is represented by $Gini^{-1}Gini_p$, the within-group Gini coefficient relative to the overall Gini.[4] As each society has a different degree of income (or wealth) inequality, the feeling of identity of the poor group is determined by the relative inequality. Even given the same extent of within-group inequality among the poor, the poor feel more identification to their group members as the within-group income distribution among the rich (thus the entire distribution) becomes more unequal.

Inserting (4) into the parenthesis of the second term of equation (3) produces an expression of the group-size-adjusted crime incentive of the poor generated by their immobility feeling.

$$IM\_Poor = \beta_p \mu^{-1} (\mu_r - \mu_p) \upsilon_p^{-1} \pi_p \tag{5}$$

Equation (5) describes how the expectation of future mobility of the poor group affects the overall crime rate. To repeat, first, other things being equal, the between-group income distance raises the subjective immobility of the poor group, which

[4] In the empirical execution, we also attempt to use the ratio of within-group standard deviation to overall standard deviation as an alternative measure of υ_p and find little difference in the results.

increases the crime incentive of the poor. Second, as income levels of individuals are more clustered around μ_p, the poor feel a greater extent of income class separation (or group identity), which enhances the crime incentive of the poor (called the "clustering effect"). In addition, equation (5) emphasizes the group size as an additional crime determinant. Given the clustering effect, the poor feel a greater extent of group identity as the group size increases, which is positively associated with the crime incentive (called the "scale effect"). The poor tend to view the income class separation more as a structural problem when the population proportion of their income group increases; otherwise, income class separation is viewed as a personal problem.

Finally, by substituting (5) into (3), the crime rate is determined by the following equation.

$$CR = f(IM\_Poor,\quad H,\ \ ng(x,F,q)), \tag{6}$$

where $ng(x,F,q \mid y_i) = n^{-1}\sum_{i\in G_p}[\{V(y_i + x) - V(y_i) - q\{V(y_i + x) - V(y_i - F)\}]$. This result implies that the crime rate is a function of the feeling of immobility of the poor group, a unique feature of our crime model, as well as the extent of honesty in the society H, which in turn may depend on various economic and demographic observable characteristics such as education, age, and gender as well as unobservable characteristics specific to that society and the net gain from the current crime action ng.[5] The net gain of crime depends on the crime premium (x), which depends on the average income (or wealth) level (if the victim is randomly selected from the society), the current income level of the potential criminal (y_i), fine F, which is determined by the judicial system, and the effort level of crime prevention, q (e.g., police size, arrest rate, and conviction rate, among others).

We can further enrich the above crime model by including the feeling of immobility of the rich group as an additional psychological crime disincentive factor, as in equation (1). That is, we consider a more general situation where both the rich and the poor groups have a positive level of crime incentives, although the level of the rich is presumably lower than that of the poor. For both groups to have a positive level of crime activity, values of H, x, q, F, IM_i^p, and IM_i^r are such that equation (2) is satisfied for $\eta_i = -IM_i^p$ in group p but not for $\eta_i = H - IM_i^p$ and for $\eta_i = IM_i^r$ in group r but not for $\eta_i = H + IM_i^r$. Even the rich have positive crime incentives when they are sufficiently dishonest or when they expect strong downward income mobility in the future.

Given this addition, the crime rate in a society is now expressed as

[5] Although not explicit in the current model, inclusion of the net gain from the current crime action partly reflects imperfection of the labor market.

$$
\begin{aligned}
CR &= n^{-1}\sum\nolimits_{i\in G_p} \Pr(h_i < \{V(y_i+x)-V(y_i)\} - q\{V(y_i+x)-V(y_i-F)\} + IM_i^p\} \\
&+ n^{-1}\sum\nolimits_{i\in G_r} \Pr(h_i < \{V(y_i+x)-V(y_i)\} - q\{V(y_i+x)-V(y_i-F)\} - IM_i^r\} \\
&= H^{-1}n^{-1}\sum\nolimits_{i=1}^{n} [\{V(y_i+x)-V(y_i)\} - q\{V(y_i+x)-V(y_i-F)\}] \\
&+ H^{-1}(n^{-1}\sum\nolimits_{i\in G_p} IM_i^p - n^{-1}\sum\nolimits_{i\in G_r} IM_i^r). \qquad (7)
\end{aligned}
$$

Finally, by obtaining comparable expressions for equation (4) and (5), the crime rate in a society is determined by the following equation.

$$CR = f(IM\_Poor,\ IM\_Rich,\ H,\ ng(x,F,q)), \qquad (8)$$

where $IM\_Rich = \beta_r \mu^{-1}(\mu_r - \mu_p)\upsilon_r^{-1}\pi_r$, and

$$g(x,F,q) = n^{-1}\sum\nolimits_{i=1}^{n} [\{V(y_i+x)-V(y_i)\} - q\{V(y_i+x)-V(y_i-F)\}].$$

In the present setup, the hypothesis is that $\beta_p > 0$ and $\beta_r < 0$; a unit increase in the group-specific measured immobility increases the crime rate among the poor and decreases it among the rich. Whether the overall crime rate will increase or decrease following a change in the current income distribution also depends on how the change affects within-group dispersions as well as group sizes. Specifically, given the hypothesis that $\beta_p > 0$ and $\beta_r < 0$, if the change in the income distribution enhances the size-adjusted group identity of the poor, $\upsilon_p^{-1}\pi_p$, and weakens that of the rich, $\upsilon_r^{-1}\pi_r$, then the overall crime rate increases, other things being equal. If the distribution change enhances the identification feelings of both groups, the overall crime rate increases if and only if $|\beta_p \Delta(\upsilon_p^{-1}\pi_p)| > |\beta_r \Delta(\upsilon_r^{-1}\pi_r)|$. This would be called weak asymmetry in the mobility-generated crime incentive between the rich and the poor. Even given an equal increase in the extent of the group-specific identification feeling, the crime rate increases if and only if $|\beta_p| > |\beta_r|$, which is called strong asymmetry in the crime incentive. The main goal of the next section is to verify that with all else being controlled for, our immobility variable increases the crime rate among the poor in equation (6), and enhanced immobility increases the crime incentive of the poor but reduces that of the rich in equation (8) (or in the following equation (9)). Our sample also was tested for the existence of asymmetry.

III. Empirical Findings

1. Data, empirical specifications, and estimation method

The most challenging aspect of this empirical study is to compute our immobility variable using micro data on individual households, which requires a large sample size for each unit of analysis. In particular, for each unit of analysis in which crime is examined, our immobility variable requires dividing the sample into the poor and the rich and computing the Gini coefficient as well as various group-level statistics for each group. Thus, a unit smaller than the country is difficult to consider in the analysis.[6] On the contrary, differences in the definition of household income often make the comparison of various inequality and income mobility measures across different countries difficult. Thus, we adopt country data from the Luxembourg Income Study (LIS) database, which includes micro income data obtained from many countries at different times. The LIS uses the same definition and components of household income across countries, which renders more significance to a cross-country comparison of income-related statistics. We use household disposable income adjusted by the "OECD equivalency scale" (e.g., Atkinson, Rainwater, and Smeeding, 1995) and household sample weights.

One more advantage of using country data is that when the unit of analysis is very small, the local crime rate does not necessarily reflect the economic conditions of the region. Criminals travel to neighborhoods in search of higher returns (e.g., Demombynes and Özler, 2005), or those who are frustrated in one region transfer to another region where they have better prospects and thus decide to supply labor to the legal labor market. This increased geographical interdependence makes the analysis extremely complicated. By contrast, the crime market is closed at the country level. The original LIS includes a large number of countries in its data set, while our final regression sample has 100 country-year observations for 24 countries, where the sampling frequency is approximately five years on average.[7] The LIS serves as our main data set, although we also supplement the results with another country-level data set, the Cross-National Equivalent File (CNEF). The CNEF uses sources of income data different from the LIS. Unlike the LIS, the CNEF contains only longitudinal micro data sets for all member countries, enabling longitudinal cross-country research on topics like employment and earnings

[6] This may explain why none of the studies that investigate the relationship between crime and inequality using the unit of observation smaller than the level of country include inequality measures in their regression models (e.g., Cornwell and Trumbell, 1994; Glaeser, Sacerdote, and Scheinkman, 1996; Wilson and Daly, 1997; Kelly, 2000).

[7] They are Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Mexico, Netherlands, Norway, Poland, Slovenia, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

dynamics. This exercise is meaningful because the crime rate is affected by measured characteristics of an income distribution such as the Gini coefficient and our immobility variable, and those measured characteristics are often different depending on the data sets used in the analysis, even when the same income definition is adopted in a country. The main disadvantage of the CNEF is that it includes only five countries (Australia, Canada, Germany, the U.K., and the U.S.). The final regression sample, which contains all valid observations on all variables used in the regression analysis, includes 30 country-year observations, where the sample frequency is approximately two years on average.[8] As in the LIS, we use household disposable income adjusted by the "OECD equivalency scale" and household sample weights. In the LIS, most observations pertain to the 1980s and the 1990s, while those of the CNEF refer to the 1990s and the 2000s.

Our primary goal is to not distinguish empirically between the economic and sociological explanations of the relationship between crime and income distribution; our immobility measure reflects both economic and psychological motives of crime. Thus, the overall crime rate is the relevant variable used to test the hypotheses. The crime data we use are obtained from the United Nations Surveys on Crime Trends and the Operations of Criminal Justice Systems (CTS). Regarding other control variables, police size (POLICE) is imported from the CTS. Average years of education (EDUCATION), percentage of urban population among the total population (URBAN POPULATION), and population density (DENSITY) are obtained from the World Bank. The proportion of men aged 15 to 29 among the total population (YOUNG MEN), unemployment rates (UNEMPLOYMENT), and the percentage of tax revenue among gross domestic product (TAX-GDP-RATIO) to be used as an instrumental variable for POLICE, are obtained from the Organization for Economic Cooperation and Development (OECD).

Due to lack of data, penalties (F) are neglected, and the probability of apprehension (q) is instead determined by the police size. The net gain from the current criminal activity, if succeeded, is measured by $(1-\mu^{-1}\mu_p)$ given that the potential victim and potential criminal are randomly selected from the entire population and the poor group, respectively. The dependent variable is the logarithm of the crime rate as measured by the number of reported crimes per 100,000 people.

Our expanded regression based on equation (8) has the following form.

$$\begin{aligned}\log CR_{it} &= \beta_p immobility\_poor_{it} + \beta_r immobility\_rich_{it} + \\ &\delta_1 netgain_{it} + \delta_2 \log(police)_{it} + \gamma' X_{it} + \lambda' \alpha_i + \varepsilon_{it}\,, \qquad (9)\end{aligned}$$

[8] The small sample problem in the final regression is also attributed to large missing values of some control variables with crime- and police- related variables being the most important sources missing.

where $\log CR_{it}$ represents the logarithm of the crime rate of country i in year t, $immobility\_poor = \mu^{-1}(\mu_r - \mu_p)\upsilon_p^{-1}\pi_p$, $immobility\_rich = \mu^{-1}(\mu_r - \mu_p)\upsilon_r^{-1}\pi_r$, and $netgain = (1-\mu^{-1}\mu_p)$. $\log(police)$ is the logarithm of the police size. X_{it} represents a vector of time-varying economic and demographic variables. α_i is a vector of country-specific time-invariant characteristics, observable or not. ε_{it} is the error term. 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 two-step fixed-effect Generalized Method of Moments (GMM) estimation is applied with Heteroskedasticity and Autocorrelation Consistent (HAC) standard error estimates.

In the fixed-effect GMM, the endogenous right hand side variable, $\log(police)$, is instrumented by two excluded variables, TAX-GDP-RATIO and CRIME COMPOSITION. First, as argued by Cornwell and Trumbull (1994), countries with residents who are more agreeable toward 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. As for CRIME COMPOSITION, defined by the ratio of the number of violent crimes to that of property crimes,[9] while this ratio is not directly related with the total number of crime, the crime composition is related with 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.

2. Findings

Based on the LIS data, Figure 1 displays the sample correlation between the total crime rate and our measure of immobility of the poor group, while Figure 2 shows the result for the rich group. We normalize the total crime rate and the immobility variable by the country-specific mean of each variable, exploiting within-variation of each variable. Apparently, crime is positively correlated with the feeling of immobility of the poor group and negatively correlated with the immobility of the rich group. Although not reported for brevity, the CNEF also reveals similar patterns.[10] Technically speaking, these observed correlations would be obtained by applying fixed-effect estimation of the crime rate with only the immobility variable included in the right hand-side variable. In the following exercises, we test if these observed patterns survive controlling for other variables.

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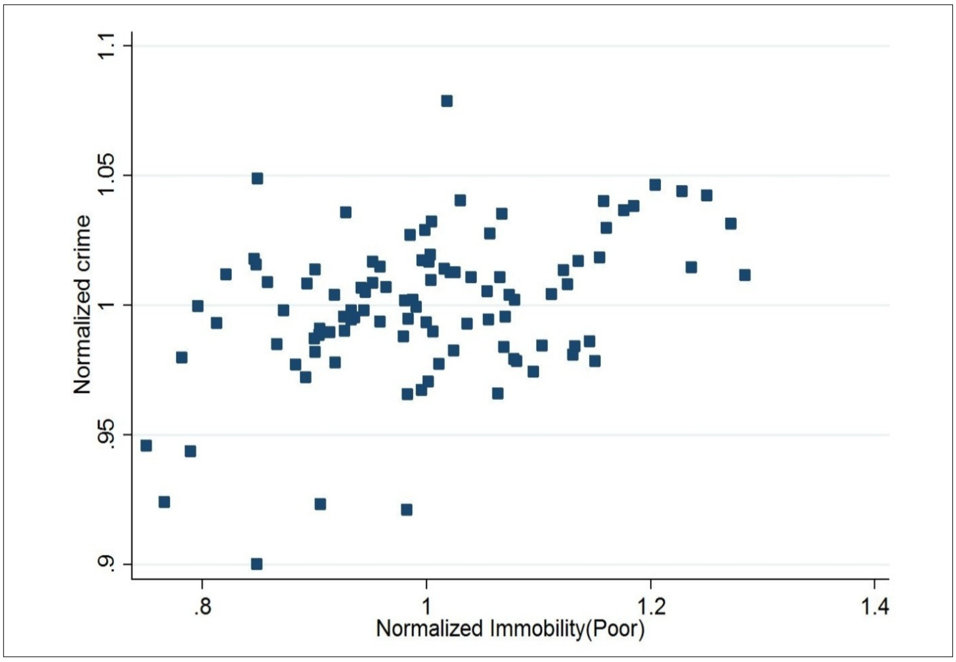
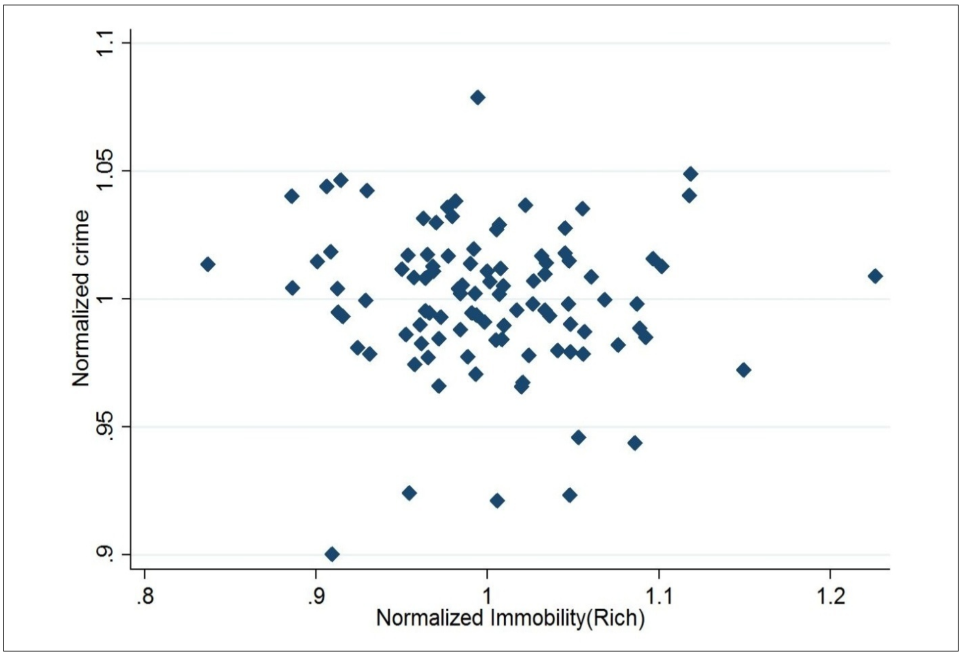
[9] A similar instrumental variable is suggested by Cornwell and Trumbull (1994). Information on the numbers of violent and property crimes is obtained from the CTS.

[10] The negative association of the crime rate and the immobility of the rich group is even more apparent in the CNEF.

[Figure 1] Crime and Immobility of the Poor Group



[Figure 2] Crime and Immobility of the Rich Group



[Table 1] Determinants of Total Crime: Basic Model

Variables	LIS			CNEF
	Specification 1	Specification 2	Specification 3	Specification 3
Immobility_Poor	-	0.630*** (0.238)	0.562** (0.236)	1.607** (0.643)
Net gain of crime	1.044 (0.812)	-	0.907 (0.774)	7.302** (3.058)
Log(police)	0.906 (0.782)	0.855 (0.787)	0.784 (0.710)	0.443** (0.195)
Urban population	0.060*** (0.011)	0.050*** (0.010)	0.051*** (0.010)	0.076 (0.082)
Young men	1.110 (0.902)	0.815 (0.809)	1.114 (0.952)	-15.760* (8.748)
Unemployment rate	0.020 (0.016)	0.034*** (0.012)	0.023* (0.014)	-0.035 (0.033)
Education	0.052 (0.042)	-0.012 (0.035)	0.023 (0.043)	-1.136*** (0.434)
Population density	0.009*** (0.003)	0.013*** (0.003)	0.010*** (0.002)	0.115*** (0.042)
F-test of excluded instrument: Prob>F	0.220	0.260	0.238	0.096
Hansen J-test	0.244	0.589	0.541	0.139
N: country-year [country]		100 [24]		30 [5]

The dependent variable is the logarithm of the number of total crimes per 100,000. Our immobility variable is measured based on household income data from the LIS and the CNEF. Fixed-effect GMM estimation with HAC standard error estimates. The police size is instrumented by the TAX-GDP-RATIO and CRIME COMPOSITION. *, **, *** = significance at 10%, 5%, and 1%, respectively.

Table 1 presents estimation results of equation (6). As in existing studies, Table 1 assumes that only the poor are involved in criminal activity. What has changed in our model is the inclusion of the feeling of immobility of the poor group as an additional crime determinant. Estimates in the first three columns are obtained from the LIS, and those in the last column are obtained from the CNEF. Focusing on the effects of the two distribution-related variables, immobility and net gain of crime, when only the net gain is included in the regression (conventional specification), the estimated coefficient is positive but insignificant (column 1). However, when only the feeling of immobility of the poor group is included in the regression, it increases the crime rate significantly (column 2). When both variables are included in the regression (our preferred specification), the estimated immobility effect is still positive and significant (column 3); the feeling of immobility of the poor group significantly increases the crime rate whether or not the net gain is controlled for. Evidence from the CNEF also suggests that although the crime rate increases in the net gain, the income immobility also increases the crime rate significantly even after the net gain is controlled for. The effects of other control variables are generally consistent with those in existing studies. Overall, other things held constant, the crime rate increases in the population share of those living in urban areas, the population density, and the unemployment rate.

[Table 2] Asymmetry between the Rich and the Poor in the Immobility Effect

Variables	LIS	CNEF
Immobility_Poor	0.534*	0.959*
	(0.287)	(0.613)
Immobility_Rich	-0.138	-3.026**
	(0.924)	(1.417)
Net gain of crime	0.954	11.374***
	(0.741)	(3.362)
Log(police)	0.890	0.473***
	(0.650)	(0.169)
Urban population	0.052***	0.136*
	(0.011)	(0.080)
Young men	1.158	-13.662
	(0.986)	(8.464)
Unemployment rate	0.022*	-0.009
	(0.013)	(0.036)
Education	0.025	-0.682*
	(0.040)	(0.354)
Population density	0.010***	0.122***
	(0.003)	(0.037)
F-test of excluded instrument: Prob>F	0.205	0.066
Hansen J-test	0.554	0.222
N: country-year	100	30
[country]	[24]	[5]

Refer to the caption of Table 1.

Table 2 shows estimation results of equation (9). Consistent with our hypothesis that enhanced immobility increases crime incentive of the poor but decreases that of the rich, both data sets show that estimated β_p is positive and estimated β_r is negative. As a minor difference between the two data sets, while the LIS reveals that the estimated coefficient of the immobility of the rich group is negative but insignificant, the corresponding estimate obtained from the CNEF data is negative both statistically and substantially. Also consistent with the conventional belief, the crime rate increases when criminals expect higher returns net of their opportunity costs. Estimated coefficients of other control variables remain similar to those in

Table 1.

Our model addresses how the poor and the rich groups behave differently in response to a change in the income distribution. Note that the extent of the feeling of immobility of each group ($immobility\_poor$ or $immobility\_rich$ in equation (9)) is measured by the product of the between-group income distance and the extent of size-adjusted within-group clustering. Estimates presented in Table 2 indicate the marginal effect of a unit-increase in the feeling of immobility of each group. Evidence obtained from the LIS data supports the strong asymmetry hypothesis; given an equal increase in the extent of the feeling of immobility for both groups, the rise in the crime incentive of the poor is greater than the reduction in the crime incentive of the rich. Evaluation of whether the crime rate increases following a change in the income distribution requires information on how the distribution change affects the expectation of future immobility of each group. Our LIS sample shows that the average change between two adjacent years (on average, five years apart) in the measured immobility feeling is 0.015 and -0.001 for the poor and the rich group, respectively. Therefore, the feeling of immobility of the rich group has actually weakened albeit by a small extent, which resulted in an increase in the crime rate even among the rich. Finally, the estimated overall immobility effect generated by a distribution change is approximately 0.008 for the poor, while the comparable figure for the rich is 0.0001. Evidence obtained from the CNEF shows similar results. As previously stated, estimates obtained from the CNEF sample do not support the strong asymmetry hypothesis, as the estimated coefficient of the immobility variable is larger in an absolute value for the rich than the poor. However, even the CNEF sample observes a reduction in our measure of the feeling of immobility among the rich; the average change between two adjacent years (on average, two years apart) in the measured feeling of immobility is 0.007 and -0.0015 for the poor and the rich group, respectively. Consequently, the estimated overall immobility effect of the poor is approximately 0.007, while the comparable figure for the rich is 0.003.

In sum, estimates show that the feeling of income class separation or between-group immobility is an important determinant of the decision of individuals to engage in crime, and enhanced immobility increases the crime incentive of the poor but decreases the crime incentive of the rich. Evidence obtained from the LIS data also supports the hypothesis of strong asymmetry between the poor and the rich in the crime incentive/disincentive generated by enhanced feeling of immobility.

IV. Conclusion

Both our theoretical reasoning and empirical execution suggest that the decision of an individual on whether or not to become involved in criminal activities is based not just on the net gain of crime from the current action but also on expectation of future income mobility. Labor and education market policies that mitigate permanent income inequalities and ensure greater upward mobility among the poor are effective measures of reducing the crime rate. In this regard, future research could investigate determinants of income mobility rather than inequality.

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