INEQUALITY AND VIOLENT CRIME*

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Abstract

In this article we take an empirical cross-country perspective to investigate the robustness and causality of the link between income inequality and crime rates. First, we study the correlation between the Gini index and, respectively, homicide and robbery rates along different dimensions of the data (within and between countries). Second, we examine the inequality-crime link when other potential crime determinants are controlled for. Third, we control for the likely joint endogeneity of income inequality in order to isolate its exogenous impact on homicide and robbery rates. Fourth, we control for the measurement error in crime rates by modelling it as both unobserved country-specific effects and random noise. Lastly, we examine the robustness of the inequality-crime link to alternative measures of inequality. The sample for estimation consists of panels of non-overlapping 5-year averages for 39 countries over 1965-95 in the case of homicides, and 37 countries over 1970-1994 in the case of robberies. We use a variety of statistical techniques, from simple correlations to regression analysis and from static OLS to dynamic GMM estimation. We find that crime rates and inequality are positively correlated (within each country and, particularly, between countries), and it appears that this correlation reflects causation from inequality to crime rates, even controlling for other crime determinants.

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I. Introduction

The relationship between income inequality and the incidence of crime has been an important subject of study since the early stages of the economics literature on crime. According to Becker's (1968) analytical framework, crime rates depend on the risks and penalties associated with apprehension and also on the difference between the potential gains from crime and the associated opportunity cost. These net gains have been represented theoretically by the wealth differences between the rich and poor, as in Bourguignon (2000), or by the income differences among complex heterogeneous agents, as in Imrohoroglu, Merlo, and Rupert (2000). Similarly, in their empirical work, Fleisher (1966), Ehrlich (1973), and more recently Kelly (2000) have interpreted measures of income inequality as indicators of the distance between the gains from crime and its opportunity costs.

The relationship between inequality and crime has also been the subject of sociological theories on crime. Broadly speaking, these have developed as interpretations of the observation that "with a degree of consistency which is unusual in social sciences, lower-class people, and people living in lower-class areas, have higher official crime rates than other groups" (Braithewaite 1979, 32). One of the leading sociological paradigms on crime, the theory of "relative deprivation," states that inequality breeds social tensions as the less well-off feel dispossessed when compared to wealthier people (see Stack 1984 for a critical view). The feeling of disadvantage and unfairness leads the poor to seek compensation and satisfaction by all means, including committing crimes against both poor and rich.

It is difficult to distinguish empirically between the economic and sociological explanations for the observed correlation between inequality and crime. The observation that most crimes are inflicted by the poor on the poor does not necessarily imply that the economic theory is invalid given that the characteristics of victims depend not only on their relative wealth but also on the distribution of security services across communities and social classes. In fact, crime may be more prevalent in poor communities because the distribution of police services by the state favors rich neighborhoods (Behrman and Craig 1987; Bourguignon 2000) or because poor people demand lower levels of security given that it is a normal good (Pradhan and Ravallion 1998). Similarly, contrasting or consistent evidence on the effect of inequality on different types of crime cannot be used to conclusively reject one theory in favor of the other. For example, if income inequality leads to higher theft and robbery rates but not to higher homicide rates (as Kelly 2000 finds for the United States), the economic model could still be valid given that, first, homicides are also committed for profit-seeking motives and, second, homicide data are more reliable and produces more precise regression estimates than property crime data. By the same token, if income inequality leads to both higher robbery and higher homicide rates (as we find in this cross-country paper), we cannot conclude that the sociological model is incorrect because social deprivation can have both non-pecuniary and pecuniary manifestations. At any rate, the objective of this paper is not to distinguish between various theories of the link between inequality and crime; rather, we attempt to provide a set of stylized facts on this relationship from a cross-country perspective. This initial evidence could then be used in further, more analytically-oriented, research to discriminate among competing theories.

As the preceding remarks try to convey, the correlation between income inequality and crime is a topic that has intrigued social scientists from various disciplines. Most economic studies on the determinants of crime rates have used primarily microeconomic-level data and focused mostly on the U.S. (see Witte 1980; Tauchen, Witte and Griesinger 1994; Grogger 1997; and Mocan and Rees 1999). In the 1990s the interest on cross-country studies awakened, in part due to the appearance of internationally comparable data sets on national income and production (Summers and Heston 1988), income inequality (Deininger and Squire 1996), and crime rates (United Nations Crime Surveys and World Health Organization). In one of these cross-country studies, Fajnzylber, Lederman, and Loayza (2001) find that income inequality, measured by the Gini index, is an important factor driving violent crime rates across countries and over time. Far from settling the issue, this result opened a variety of questions on the plausible interactions between crime rates, measures of income distribution, and other potential determinants of crime. Some of these questions refer to the robustness of the crime-inequality link to changes in the sample of countries, the data dimension (time-series or cross-country), the method of estimation, the measures of inequality and crime, and the types of control variables. Other questions put in doubt the direct effect of inequality on crime. For instance, Bourguignon (1998, 22) argues that "…the significance of inequality as a determinant of crime in a cross-section of countries may be due to unobserved factors affecting simultaneously inequality and crime rather than to some causal relationship between these two variables."

In this article we take an empirical cross-country perspective to investigate the robustness and causality of the link between inequality and crime rates. Figures 1 and 2 plot the simple correlation between the Gini index and, respectively, the homicide and robbery rates in a panel of cross-country and time-series observations. In both cases the correlation is positive and significant. In what follows, we go behind this correlation to assess issues of robustness and causality. We present the stylized facts starting from the simplest statistical exercises and moving gradually to a dynamic econometric model of the determinants of crime rates. First, we study the correlation between the Gini index and, respectively, homicide and robbery rates along different dimensions of the data, namely, between countries, within countries, and pooled cross-country and time-series. Second, along the same data dimensions, we examine the link between income inequality and homicide and robbery rates when other potential crime determinants are controlled for. These include the level of development (proxied by real GNP per capita), the average years of education of the adult population, the growth rate of GDP, and the level of urbanization. We also include the incidence of crime in the previous period as an additional explanatory variable, thus making the crime model dynamic.

Third, we control for the likely joint endogeneity of income inequality in order to isolate its exogenous impact on the two types of crime under consideration. Fourth, we control for the measurement error in crime rates by modelling it as both an unobserved country-specific effect and random noise. We correct for joint endogeneity and measurement error by applying an instrumental-variable estimator for panel data. Fifth, using the same panel estimator, we examine the robustness of the inequality-crime link to alternative measures of inequality such as the ratio of the income share of the poorest to the richest quintile, an index of income polarization (calculated following Esteban and Ray 1994), and an indicator of educational inequality (taken from De Gregorio and Lee 1998). Lastly, we test the robustness of this link to the inclusion of additional variables that may be driving both inequality and crime, such as the population's ethno-linguistic fractionalization, the availability of police in the country, a Latin-America specific effect, and the share of young males in the national population.

As said above, this paper adopts a comparative cross-country perspective. Although there are well-known advantages to using micro-level data for crime studies, cross-national comparative research has the following advantage. Using countries as the units of observation to study the link between inequality and crime is arguably appropriate because national borders limit the mobility of potential criminals more than neighborhood, city, or even provincial boundaries do. In this way, every (country) observation contains independently all information on crime rates, inequality measures, and other crime determinants, thus avoiding the need to account for cross-observation effects.

The main conclusion of this article is that an increase in income inequality has a significant and robust effect of raising crime rates. In addition, the GDP growth rate has a significant crime-reducing impact. Since the rate of growth and distribution of income jointly determine the rate of poverty reduction, the two aforementioned results imply that the rate of poverty alleviation has a crime-reducing effect. The rest of the paper is organized as follows. Section II presents the data and basic stylized facts. Section III introduces the methodology and presents the results from the GMM estimations, including several robustness checks. Section IV concludes.

II. Data and stylized facts

This section reviews the data and presents the basic stylized facts concerning the relationship between violent crime rates and income inequality. Section II.A presents the sample of observations used in the various econometric exercises in the paper. Sections II.B and II.C review the quality and sources of data for the dependent variable (crime rates) and the main explanatory variable (income inequality), respectively. Detailed definitions and sources of all variables used in the paper are presented in Appendix Table A1. Section II.D examines the bivariate correlations between homicide and robbery rates and the Gini coefficient of income inequality. Finally, Section II.E presents OLS estimates of multivariate regression for both types of crime.

A. Sample of observations

We work with a pooled sample of cross-country and time-series observations. The time-series observations consist of non-overlapping five-year averages spanning the period 1965-1994 for homicides and 1970-1994 for robberies. The pooled sample is unbalanced, with at most 6 (time-series) periods per country. All countries included in the samples have at least two consecutive five-year observations. The sample for the homicide regressions contains 20 industrialized countries; 10 countries from Latin America and the Caribbean; 4 from Eastern and Central Europe; 4 from East Asia, South Asia, and the Pacific; and 1 from Africa. The sample for robberies contains 17 industrialized countries; 5 countries from Latin America and the Caribbean; 4 from Eastern and Central Europe; 10 from East Asia, South Asia, and the Pacific; and 1 from Africa. Appendix tables B1 and B2 show the summary statistics for, respectively, homicide and robbery rates for each country in the sample.

B. National crime statistics

We proxy for the incidence of violent crime in a country by its rate of intentional homicide and robbery rates. These rates are taken with respect to the country's population; specifically, they are the number of homicides/robberies per 100,000 people. Cross-country studies of crime have to face severe data problems. Most official crime data are not comparable across countries given that each country suffers from its own degree of underreporting and defines certain crimes in different ways. Underreporting is worse in countries where the police and justice systems are not reliable, where the level of education is low, and perhaps where inequality is high. Country-specific crime classifications, arising from different legal traditions and different cultural perceptions of crime, also hinder cross-country comparisons. The type of crime that suffers the least from underreporting and idiosyncratic classification is homicide. It is also well documented that the incidence of homicide is highly correlated with the incidence of other violent crimes (see Fajnzylber, Lederman, and Loayza 2000). These reasons make the rate of homicides a good proxy for crime, especially of the violent sort. To account for likely non-linearities in the relation between homicide rates and its determinants, we use the homicide rate expressed in natural logarithms.

The homicide data we use come from the World Health Organization (WHO), which in turn gathers data from national public health records. In the WHO data set, a homicide is defined as a death purposefully inflicted by another person, as determined by an accredited public health official. The other major source of cross-country homicide data is the United Nations World Crime Survey, which collects data from national police and justice records.[1] In this paper we use the WHO data set because of its larger time coverage for the countries included. Counting with sufficient time coverage is essential for the panel-data econometric procedures we implement (see Section III below).

To complement the analysis on the homicide rate, we consider the robbery rate as a second proxy for the incidence of crime. Although data on robberies is less reliable than homicide data for cross-country comparisons, it is likely to be more reliable than data on lesser property crimes such as theft. This is so because robberies are property crimes perpetrated with the use or threat of violence; consequently, their victims have a double incentive to report the crime, namely, the physical and psychological trauma caused by the use of violence and the loss of property. Robbery's close connection with property crimes, to which economic theory is more readily applicable, makes

[1] See Fajnzylber, Lederman, and Loayza (1998) for a description of the United Nations Crime Survey statistics.

its study a good complement to that of homicide. The robbery data we use come from the United Nations World Crime Survey. The robbery rates are also expressed in natural logs.

C. National income inequality data

Most of the empirical exercises presented below use the Gini coefficient as the proxy for income inequality. In a couple of instances, we also use the ratio of the income share of the poorest to the richest quintile of the population. In addition, we use income quintile shares to construct a measure of income polarization (see Appendix C for details).

Data on the Gini coefficient and the income quintile shares come from the Deininger and Squire (1996) database. We only use what these authors label "high-quality" data, which they identify through the following three criteria (p. 568-571). First, income and expenditure data are obtained only from household or individual surveys. In particular, high-quality Gini index and income quintile shares are not based on estimates generated from national accounts and assumptions about the functional form of the distribution of income taken from other countries. Second, the measures of inequality are derived only from nationally representative surveys. Thus, these data do not suffer from biases stemming from estimates based on subsets of the population in any country. Third, primary income and expenditure data are based on comprehensive coverage of different sources of income and type of expenditure. Therefore, the high-quality inequality data do not contain biases derived from the exclusion of non-monetary income.

D. Bivariate correlations

Table 1 presents the bivariate correlations between both crime rates and the Gini coefficient for three dimensions of the data, namely, pooled levels, pooled first-differences, and country averages. The first set contains the correlation estimated for the pooled sample in levels, that is, using both the cross-country and over-time variation of the variables. The second set presents the correlations between the first differences of the crime rates and the first differences of the Gini index. These correlations, therefore, reflect only the over-time relationship between crime rates and inequality, thus controlling for any country characteristics that are fixed over time, such as geographic location or cultural heritage. The third set shows the correlations across countries only, based on the country averages for the whole periods (1965-1994 for homicides and 1970-1994 for robberies). Consequently, these correlations do not reflect the influence of country characteristics that change over time. All correlations of both crime rates with the Gini coefficient are positive and statistically significant (the largest p-value is 0.12). The smallest, but still positive, correlations are those estimated using the data in first differences. While for the robbery rate there is not much disparity between the correlations estimated for the three data dimensions, in the case of homicides the correlation drops from 0.54 for the data in pooled levels and 0.58 for country averages to 0.26 for first differences. This result suggests that almost half of the correlation between the Gini and homicide rates is due to country characteristics that are persistent over time.

Table 2 presents a second group of bivariate correlations for two cuts of the cross-country sample, namely within countries and within time periods. The table contains the mean and the median of the correlations between each crime rate and the Gini index, obtained using, respectively, all the observations available for each country ("within-country") and for each five-year period ("within-period"). In addition, we report the percentage of, respectively, countries and periods for which the correlation between crime rates and inequality is positive. All the estimated mean and median correlations are positive. In fact, for each of the five-year periods, the cross-country correlation of crime and inequality is positive, while for about 60% of the countries, the time-series correlation is also positive. The fact that for both homicides and robberies the median within-country correlation is higher than the mean indicates that there are some outliers having negative correlations that depress the average.

An important problem for the interpretation of these bivariate correlations is that the apparent positive link between crime rates and income inequality might in fact be driven by other variables that are correlated with both of them. To address this issue, the following section studies the relationship between the Gini index and homicide and robbery rates, while controlling for other potential correlates of crime.

E. Multivariate regression analysis

Based on previous micro- and macro-level crime studies, we consider the following variables as the basic correlates of homicide and robbery rates in addition to inequality measures: 1) GNP per capita (in logs) as both a measure of average national income and a proxy for overall development (from Loayza et al. 1998). 2) The average number of schooling years of the adult population as a measure of average educational attainment (from Barro and Lee 1996). 3) The GDP growth rate to proxy for employment and economic opportunities in general (from Loayza et al. 1998). 4) The degree of urbanization of each country, which is measured as the percentage of the population in the country that lives in urban settlements (from World Bank data). Appendix Table A1 contains a detailed description of the data sources for these and the other variables used in this article.[2]

The basic OLS multivariate regression results are shown in Table 3. The homicide and robbery regressions were run on the same data dimensions as in Table 1. The first regression was estimated using the pooled sample in levels; the second uses pooled first differences, thus focusing on the within-country variation; and the third regression uses country averages to isolate the pure cross-country dimension of the data. The results indicate that the Gini index maintains its positive and significant correlation with both crime rates. As expected, the models estimated in first-differences present the lowest magnitudes for the coefficient on the Gini index. When the cross-country variation is taken into account, the coefficient on the Gini index increases from 0.02 to 0.06 in the case of homicides and from 0.04 to 0.11 in the case of robberies. Hence in both cases, two-thirds of the conditional correlation between crime rates and inequality seems to be due to country characteristics that do not change over time.

Of the additional crime regressors, the most important one seems to be the GDP growth rate. This variable appears consistently with a negative sign, as expected, for both crimes. It is also statistically significant, although only marginally so in the robbery regression using country averages. In contrast, the other crime regressors do not show a consistent sign or are not statistically significant in at least half of the specifications.

The OLS estimates just discussed might be biased for three reasons. First, these regressions do not take into account the possibility that crime tends to persist over time. That is, they ignore yet another potential determinant of crime, which is the crime rate of the previous period. Second, these estimates might be biased due to the possibility that crime rates themselves (our dependent variables) might affect the right-hand side variables. Third, it is very likely that the crime rates are measured with error, and this error might be correlated with some of the explanatory variables, particularly income inequality. The following section examines alternative specifications that include the lagged crime rate as an explanatory variable, account for certain types of measurement error, and allow for jointly endogenous explanatory variables.

[2] Appendix Table B3, panel A, contains the matrix of bivariate correlations among the basic set of dependent and explanatory variables. Note that the Gini is indeed significantly correlated with log of income per capita (negatively), educational attainment of the adult population (negatively), and the GDP growth rate (positively).

III. A Dynamic Empirical Model of Crime Rates

A. Econometric Issues

The evidence presented so far suggests that, from a cross-country perspective, there is a robust correlation between the incidence of crimes and the extent of income inequality. However, there are several issues we must confront in order to assure that this correlation is not the result of estimation biases. First, as mentioned, the incidence of violent crime appears to have inertial properties (i.e., persistence) that are noted in the theoretical literature and documented in the micro and macro empirical work (Glaeser, Sacerdote, and Scheinkman 1996; Fajnzylber, Lederman, and Loayza 1998). To account for criminal *inertia*, we need to work with a dynamic, lagged-dependent econometric model.

The second issue we must address is that the relationship between violent crime rates and their determinants is often characterized by a two-way causality. Failure to correct for the joint endogeneity of the explanatory variables would lead to inconsistent coefficients, which depending on the sign of the reverse causality would render an over- or under-estimation of their effects on violent crime rates. We address the problem of *joint endogeneity* by employing an instrumental-variable procedure applied to dynamic models of panel data. This is the Generalized-Method-of-Moments (GMM) estimator that uses the dynamic properties of the data to generate proper instrumental variables.

The third estimation difficulty is that despite our use of intentional homicide and robbery rates as the best proxies for the incidence of violent crimes, it is likely that measurement error still afflicts our crime data. Ignoring this problem might also result in biased estimates especially because crime underreporting is not random measurement error but is strongly correlated with factors affecting crime rates such as inequality, education, the average level of income, and the rate of urbanization. Even if measurement error were random, the coefficient estimates would still be biased given the dynamic nature of our model. To control for measurement error, we model it as either random noise or a combination of an unobserved country-specific effect and random noise.

Econometric methodology. We implement a generalized-method-of-moments (GMM) estimator applied to dynamic (lag-dependent-variable) models that use panel data. This method was developed in Arellano and Bond (1991) and Arellano and Bover (1995). It controls for (weak) endogeneity through the use of instrumental variables consisting of appropriately lagged values of the explanatory variables. When the model does not include an unobserved country-specific effect, the model is estimated in levels, for both the regression equation and the set of instruments. This is called the *GMM levels* estimator. When the model includes an unobserved country-specific effect (resulting from time invariant omitted factors such as systematic measurement error), the model is estimated in both differences and levels, jointly in a system. This is called the *GMM system* estimator. For each estimator, the correct specification of the regression equation and its instruments is tested through a Sargan-type test and a serial-correlation test.[3] Appendix D presents the econometric methodology in detail.

B. Basic Results

Table 4 shows GMM estimates for the basic set of determinants of the homicide and the robbery rates, respectively in the left- and right-hand side panels. The first two columns of each panel present the results obtained for the model that assumes no unobserved country-specific effects, estimated using the *GMM-levels* estimator. The difference between the first and the second column of each panel is related to the samples used in each case, which are restricted to, respectively, countries with at least two and three consecutive observations. The third column of each panel reports the results obtained for the model that allows unobserved country-specific effects, estimated using the GMM-*system* estimator. The *system* estimator uses not only levels but also differences of the variables and requires at least three consecutive observations for each country. Thus, results in the second and the third columns of each panel are obtained from the same samples but are based on different estimators.

In the basic *levels* specification for homicides, and using the largest possible sample (first column), the lagged homicide rate, the level of income inequality, and the growth rate of GDP have significant coefficients with the expected signs. The rate of urbanization also appears to be significantly associated with homicide rates but unexpectedly, in a negative way: countries with a larger fraction of their population in cities would appear to have lower crime rates. Qualitatively similar results are obtained with the smaller sample used in column 2, although in this case the population's average income and educational attainment are significant, both with negative signs. Regardless of the sample, both the Sargan and the serial correlation tests validate the results obtained using the *levels* estimator for homicides.

[3] In both tests the null hypothesis denotes correct specification. For the *GMM-levels* estimator, serial correlation of any order implies misspecification, while for the *GMM-system* estimator, only second- and higher-order serial correlation denotes misspecification (see Appendix D for details).

Column 3 shows the results using the GMM-*system* estimator. As in the case of the *levels* estimator, both the Sargan and the serial correlation tests support the specification of the *system* estimator. The main results are as follows.

First, homicide rates show a sizeable degree of inertia. The coefficient on the lagged homicide rate is close to unity (though not as large as when country-specific effects are ignored). The size of this coefficient implies that the half-life of a unit shock lasts about 17 years.[4]

Second, income inequality, measured by the Gini index, has a positive and significant effect on homicide rates. Using the corresponding coefficient estimate we can evaluate the crime-reducing effect of a decline in inequality in a given country. If the Gini index falls permanently by the *within-country* standard deviation in the sample (about 2.4 percentage points), the intentional homicide rate will decrease by 3.7 percent in the short run and 20 percent in the long run.[5] If the Gini index were to fall by its *cross-country* standard deviation, the decline in inequality would be much larger; however, a change in inequality by the magnitude of cross-country differences is implausibly large to be attained by a country in a reasonable amount of time. It is noteworthy that the estimated coefficient on the Gini index is much larger with the *system* estimator than with the *levels* estimator, although they are both based on a common sample of 27 countries. It is possible that the higher magnitude obtained with the *system* estimator is due to the fact that this estimator corrects for the positive correlation between inequality and the degree of crime under-reporting (i.e., the measurement error).[6]

Third, the GDP growth rate has a significantly negative effect on the homicide rate. According to our estimates, the impact of a permanent one-percentage point increase in the GDP growth rate is associated with a 4.3 percent fall in the homicide rate in the short run and a 23 percent decline in the long run. Fourth, our measure of educational attainment remains negative and significant but the GNP per capita and the urbanization rate now lack statistical significance. The pattern of significance (or lack thereof) of the basic explanatory variables is quite robust to all the

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[4] The half-life (*HL*) of a unit shock is obtained as follows: $HL=ln(0.5)/ln(\alpha)$, where α is the estimated autoregressive coefficient. According to column 3, Table 4, α=0.8137.

[5] The within country standard deviation is calculated after applying a "within" transformation to the Gini index, which amounts to subtracting to each observation the average value of that variable for the corresponding country and adding the global mean (based on all observations in the sample).

[6] This finding is interesting because we expected that the magnitude of the effect of the *levels* estimator would be higher, because the analysis of the bivariate and conditional OLS correlations showed that a large portion of the correlation between the crime rates and the Gini were due to country characteristics that do not change over time, and that are lost in the first-differenced data.

various empirical exercises of this paper. It is also similar to what we found in our first empirical cross-country study on violent crime rates (see Fajnzylber, Lederman, and Loayza 2001).

In the right-hand-side panel of table 4, we report analogous estimates for the determinants of robbery rates. For robberies, the results are qualitatively similar across samples and specifications. In the case of the lagged dependent variable, the growth rate, and income inequality, the results for robberies are similar to those for homicides. Indeed, there is evidence that robberies are also subject to a sizeable degree of inertia, although somewhat smaller than in the case of homicides: the half life of the effects of a permanent shock is between 11 and 12 years, depending on the specification. The coefficients on income inequality are also positive and significant in all specifications. Based on the results in column 6, a fall of one within-country standard deviation in the Gini coefficient (about 2.1 percent) leads to a 6.5-percent decline of the robbery rate in the short run and a 23.2-percent decline in the long run. Similarly, a permanent one-percentage point increase in the GDP growth rate produces an 11- and 45-percent fall of the robbery rate in the short and long runs, respectively. As in the case of homicides, note that the magnitude of the estimated impact of the Gini index on robbery rates is larger for the *system* than for the *levels* estimator (for equal samples, of course).

As for the other variables, their signs and significance vary from homicides to robberies. The average income appears with a negative sign, but is significant only for the smaller samples (columns 5 and 6). Educational attainment and urbanization are significant in all specifications, both with a positive sign. The latter result was expected, as robberies appear to be mostly an urban phenomenon. However, the finding that robberies are positively associated with education is puzzling.

Regarding the GMM specification tests for the robbery models, all regressions are supported by the Sargan test on the validity of the instrumental variables. However, in the *levels* regressions there is evidence that the residuals suffer from first-order serial correlation, especially in the case of the largest sample of 37 countries.

C. Alternative measures of inequality

This section studies the crime effect of alternative measures of income inequality and thus checks the robustness of the results obtained with the Gini coefficient. The alternative measures we consider are the ratio of income of the richest to the poorest quintile of the population, an index of income polarization, and the standard deviation of the educational attainment of the adult population.[7] Given the fact that the new variables lead to further restrictions in sample size, we choose to maintain our basic *levels* specification, which allows the largest possible sample in the context of a dynamic model. The results are presented in Table 5.

In columns 1 and 4 the ratio of the income shares of the 1st to the 5th quintile is substituted for the Gini coefficient in the basic regressions for homicides and robberies, respectively. The results are qualitatively analogous to those reported in table 4. The new measure of income inequality is positively and significantly associated with both crime rates. A permanent fall of one within-country standard deviation in the quintile ratio (about 1.3) leads to a 2-percent decline in the intentional homicide rate in the short-run and a 16.2-percent fall in the long run. The corresponding impacts on the robbery rate are 4.7 and 21.5 percent, respectively in the short and the long runs. In further exercises (not presented in the tables), we examined the significance of the income levels of the poor and rich separately. We found that when the income of the poor was included by itself, its coefficient was not generally significant. When we included the incomes of both the poor and the rich, neither was statistically significant, which can be explained by the fact that they are highly correlated with each other. These results contrast with the significant crime-inducing effect of the difference between the income levels of the rich and poor (or more precisely the log of the ratio of top to bottom income quintiles of the population). Coupled with the general lack of significance of per capita GNP in our crime regressions, the aforementioned results indicate that it is not the level of income what matters for crime but the income differences among the population.

In columns 2 and 5, we substitute an index of polarization for the Gini index. Some authors argue that a society's degree of polarization may be the cause of rebellions, civil wars, and social tension in general (Esteban and Ray 1994; Collier and Hoeffler 1998). Similar arguments can be applied to violent crime. The concept of polarization was formally introduced by Esteban and Ray (1994). Though linked to standard measures of income inequality, the polarization indicators proposed by these authors do not only consider the distance between the incomes of various groups but also the degree of homogeneity within these groups. Thus, the social tension that leads to violence and crime would be produced by the heterogeneity of internally strong groups. Following the principles proposed by Esteban and Ray, we constructed a polarization index from data on national income shares by quintiles (see Appendix C for details). The results concerning polarization presented in Table 5 are similar to those obtained with the other inequality indicators. The effect of

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7 Appendix Table B3, panel B, shows the bivariate correlations between the Gini index and the these three alternative indicators of inequality. As expected, these correlations are statistically significant and high in magnitude, ranging from

polarization on crime appears to be positive and significant for both homicides and robberies, and the signs and significance of the other core variables are mostly unchanged. As for the size of the polarization coefficient, a permanent reduction of one within-country standard deviation (about 7.6 percent) in this variable leads to a decline in the homicide and the robbery rate of, respectively, 3.8 and 3 percent in the short run. In the long run, the corresponding reductions are 28.7 and 19.2 percent for the homicide and robbery rates.

Columns 3 and 6 examine whether the underlying inequality of educational attainment has the same impact on crime rates as the Gini index does. We measure the inequality of educational attainment as the standard deviation of schooling years in the adult population, as estimated by De Gregorio and Lee (1998). The basic results discussed above remain essentially unaltered. When we substitute the measure of education inequality for the Gini index, the estimated coefficient of this variable acquires the sign of the Gini index in the benchmark regression, but appears significant only in the robbery regression. A fall of one within-country standard deviation (about 4 percent) in our measure of educational inequality leads to a reduction in the robbery rate of 3.6 and 27.6 percent in the short and long runs, respectively.

D. Additional Controls

This section focuses on the potential role played by additional control variables in the crime-inducing effect of income inequality.[8] The regression results are presented in Table 6. Columns 1 and 5 show the results for the regression on the basic explanatory variables, with the addition of a measure of ethnic diversity. This measure is the index of ethno-linguistic fractionalization employed by Mauro (1995) and Easterly and Levine (1997) in their respective cross-country growth studies. Our results indicate that this index is significantly associated with higher homicide rates but its link with robberies is not significant (with a negative point estimate). As to its quantitative effect on homicides, an increase of one standard deviation (about 4 percent) in ethno-linguistic fractionalization is associated with an increase in the homicide rate of 3.8 and 31.6 percent in the short and long runs, respectively. Most importantly for our purposes, the Gini index keeps its sign, size, and significance in the homicide and robbery regressions even controlling for ethnic diversity as a crime determinant.

0.62 to 0.88.

[8] Appendix Table B3, panel C, contains the bivariate correlations between these new control variables and the set of basic variables used in the paper. Of the additional control variables, only the share of young males in the national population exhibits a high and significant correlation with the Gini index. This variable is also positively and significantly correlated with both crime rates.

Columns 2 and 6 consider the possibility that the crime-inducing effect of the Gini coefficient in fact reflects an unequal distribution of protection from the police and the judicial system. We do this by adding the number of police per capita to the core explanatory variables.[9] This is an average measure for the whole population and may not represent egalitarian protection by the police and the law. However, it is an appropriate control under the assumption that an unequal distribution of protection is more likely to occur when there is scarcity of police resources. Although for homicides the number of police per capita does present the expected negative sign, for both crimes this variable presents statistically insignificant coefficients. Most importantly, the sign, size, and statistical significance of the Gini coefficient appear to be unaltered by the inclusion of this proxy for police deterrence.

In columns 3 and 7 we add a Latin American dummy to the basic explanatory variables. We do it to assess whether the apparent effect of inequality on crime is merely driven by a regional effect, given that countries in Latin America have among the highest indices of income inequality in the world and, in many cases, also very high crime rates. We find that in fact the Latin American dummy has a positive coefficient in the regressions for both crimes, although it is statistically significant only in the case of robberies. Quantitatively, the results suggest that in Latin America the rate of robberies is 35 percent higher than what our basic model predicts, given the economic characteristics of the countries in that region. Most importantly for our purposes, the signs and significance of our basic explanatory variables, especially the Gini index, are not altered by the inclusion of the Latin American dummy.

Finally, columns 4 and 8 report results of regressions in which we introduce the percentage of young males (aged 15 to 29 years) in the population as an additional explanatory variable. It is well known that the rate of crime participation of individuals is highest at the initial stages of adulthood, so that one could expect countries with large populations in those ages to have high crime rates. At the same time, countries with younger adult populations may experience more income inequality, through a Kuznets-like effect. The inclusion of the proportion of young males as a determinant of crime allows us to test whether the inequality-crime link is driven by this demographic factor. Our results indicate that after controlling for our basic crime determinants, the share of young males in the population does not have a statistically significant effect on either

[9] We average the available observations of this variable for the 1965-95 period, and then we use the average as a constant observation for all five-year periods in the regression. We do this to increase the number of usable observations per country and, most importantly, to minimize the reverse causation of this variable to over-time changes in homicide rates (though this does not solve the cross-country dimension of reverse causation).

homicide or robbery rates. In fact, for the former crime, the point estimate of that variable is actually negative. As in previous robustness exercises, controlling for the proportion of young males does not lead to any substantial change in the estimated effect of inequality on crime.

E. Poverty Alleviation and Crime

Although the main objective of this article is to analyze the relationship between income inequality and crime, our empirical findings suggest that there is also an important correlation between the incidence of crime and the rate of poverty alleviation. This relationship exists as a consequence of the joint effects of income inequality and economic growth on crime rates. The level of poverty in a country is measured as the percentage of the population that receives income below a threshold level, which is usually determined by the necessary caloric intake and the local monetary cost of purchasing the corresponding food basket. Simply put, the level of poverty is jointly determined by the national income level and by the pattern of distribution of this income. When a reduction in income inequality is coupled with a rise in economic growth, the rate of poverty alleviation improves.

Through the several econometric exercises performed in the paper, we find that the GDP growth rate and the Gini index are the most robust and significant determinants of both homicide and robbery rates. Consequently, these results also indicate that the rate of change of poverty is also related to the incidence of crime. That is, when poverty falls more rapidly, either because income growth rises or the distribution of income improves, then crimes rates tend to fall. Estimating the precise effect of poverty reduction on violent crime and designing a strategy for crime-reducing poverty alleviation remain important topics for future research.

IV. Conclusions

The main conclusion of the paper is that income inequality, measured by the Gini index, has a significant and positive effect on the incidence of crime. This result is robust to changes in the crime rate used as the dependent variable (whether homicide or robbery), the sample of countries and periods, alternative measures of income inequality, the set of additional variables explaining crime rates (control variables), and the method of econometric estimation. In particular, this result persists when using instrumental-variable methods that take advantage of the dynamic properties of our cross-country and time-series data to control for both measurement error in crime data and the joint endogeneity of the explanatory variables.

In the process of arriving at this conclusion, we found other interesting results. The following are some of them. First, the incidence of violent crime has a high degree of inertia, which justifies early intervention to prevent crime waves. Second, violent crime rates decrease when economic growth improves. Since violent crime is jointly determined by the pattern of income distribution and by the rate of change of national income, we can conclude that faster poverty reduction leads to a decline in national crime rates. And third, the mean level of income, the average educational attainment of the adult population, and the degree of urbanization in a country are not related to crime rates in a significant, robust, or consistent way.

The main objective of this paper has been to characterize the relationship between inequality and crime from an empirical perspective. We have attempted to provide a set of stylized facts on this relationship: Crime rates and inequality are positively correlated (within each country and, particularly, between countries), and it appears that this correlation reflects causation from inequality to crime rates, even controlling for other crime determinants. If any, the contribution of this paper is empirical. Analytically, however, this paper has two important shortcomings. First, we have not provided a way to test or distinguish between various theories on the incidence of crime. In particular, our results are consistent with both economic and sociological paradigms. Although our results for robbery (a typical property crime) confirm those for homicide (a personal crime with a variety of motivations), this cannot be used to reject the sociological paradigm in favor of the economic one. The reason is that the satisfaction that the "relatively-deprived" people in sociological models seek for can lead to both pure manifestations of violence and illicit appropriation of material goods. A more nuanced econometric exercise than what we offer here is required to shed light on the relative validity of various theories on the inequality-crime link.

The first shortcoming of the paper leads to the second, which is that we have not identified the mechanisms through which worse inequality leads to more crime. Uncertainty about these mechanisms raises a variety of questions with important policy implications. For instance, should police and justice protection be redirected to the poorest segments of society? How important for crime prevention are income-transfer programs in times of economic recession? To what extent should public authorities be concerned with income and ethnic polarization? Do policies that promote the participation in communal organizations and help develop "social capital" among the poor also reduce crime? Hopefully, this paper will help stir an interest on these and related questions on the prevention of crime and violence.

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Figure 1: Income Distribution and Intentional Homicide Rates, 1965-1994
(5-year-averages)

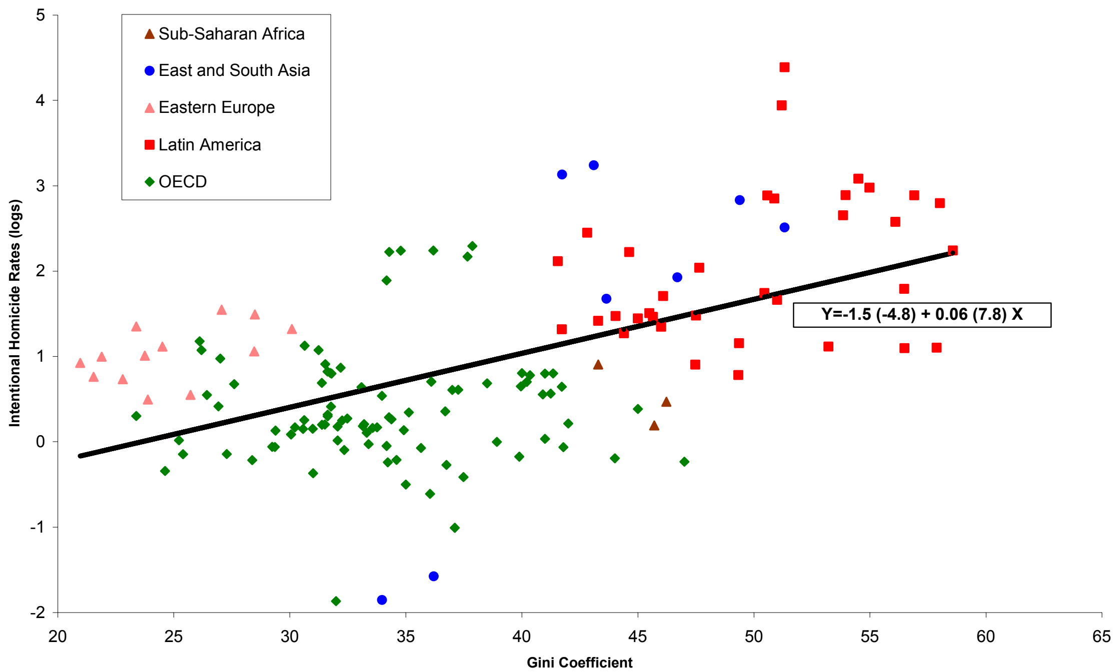

Figure 2: Income Distribution and Robbery Rates, 1970-1994
(5-year-averages)

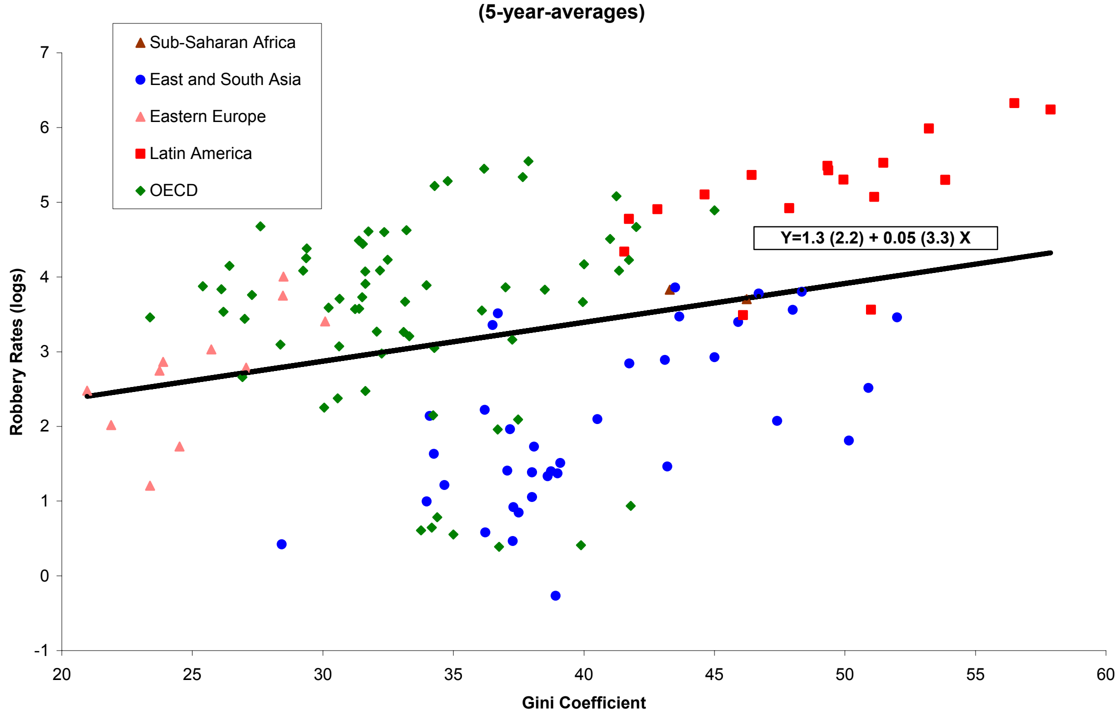

Table 1: Pairwise Correlations between the Gini Index and, respectively, Homicide and Robbery Rates

(p-values in parenthesis below the corresponding correlation. N is the number of observations)

	Homicides	Robberies
Pooled Levels	0.54	0.28
	(0.00)	(0.00)
	N=148	N=132
Pooled First Differences*	0.26	0.21
	(0.01)	(0.05)
	N=106	N=94
Country Averages	0.58	0.26
	(0.00)	(0.12)
	N=39	N=37

Source: Authors' calculations using data from WHO, *Mortality Statistics* , UN, World Crime Surveys, and Deininger and Squire (1997), A New Data Set Measuring Income Inequality. Crime rates expressed in natural logarithms. (*) Differences are obtained from consecutive country-period observations. Three observations are lost for homicides (one for robberies), for countries for which we have non-consecutive data.

Table 2: Within-Country and Within-Period Pairwise Correlations between the Gini Index and, respectively, Homicide and Robbery Rates (in logs)

(N is the number of observations)

	Homicides		Robberies	
	Within-Country	**Within-Period**	**Within-Country**	**Within-Period**
Mean Correlation	0.22	0.52	0.23	0.28
Median Correlation	0.48	0.55	0.58	0.25
Percentage of Positive Correlations	62 (N=39)	100 (N=6)	59 (N=37)	100 (N=5)

Source: Authors' calculations using data from WHO, *Mortality Statistics* , UN, *World Crime Surveys* , and Deininger and Squire (1997), *A New Data Set Measuring Income Inequality.* Crime rates expressed in natural logarithms.

Table 3: Basic Economic Model (OLS estimation)
Homicides Data Source: *World Health Organization Mortality Statistics (WHO)*
Robbery Data Source: *United Nations (UN) World Crime Surveys*
(t-statistics are presented below their corresponding coefficients)

Sample:	**Pooled Levels**	**Pooled First-Differences**	**Country-Averages**	**Pooled Levels**	**Pooled First-Differences**	**Country-Averages**
Dependent Variable (in logs):	Homicide Rate	Homicide Rate	Homicide Rate	Robbery Rate	Robbery Rate	Robbery Rate
	[1]	[2]	[3]	[4]	[5]	[6]
Income Inequality	0.064	0.023	0.067	0.105	0.039	0.111
(Gini Coefficient)	6.418	3.121	2.923	7.634	2.476	4.204
Growth Rate	-7.959	-2.032	-12.026	-11.963	-4.963	-9.751
(% Annual Change in Real GDP)	-2.785	-2.184	-1.668	-3.371	-2.294	-1.251
Average Income	-0.343	0.106	-0.351	-0.053	-0.223	-0.101
(Log of GNP per capita in US $)	-2.966	0.620	-1.391	-0.349	-0.624	-0.351
Urbanization	0.000	0.039	0.003	0.026	0.015	0.030
(% urban population)	-0.050	3.068	0.254	3.449	0.518	2.089
Educational Attainment	0.081	-0.023	0.044	0.153	0.254	0.175
(Avg. Yrs. of Educ., Adults)	1.646	-0.520	0.360	2.260	2.332	1.304
Intercept	1.112		1.165	-2.422		-2.838
	6.418		0.579	-2.427		-1.527
Adjusted R-Squared	0.38	0.24	0.34	0.49	0.25	0.49
No. Countries	39	39	39	37	37	37
No. Observations	148	106	39	132	94	37

Source: Authors' calculations. For details on definitions and sources of variables, see Appendix Table A1.

Table 4: Basic Economic Model (GMM estimation)
Homicides Data Source: *World Health Organization Mortality Statistics (WHO)*
Robbery Data Source: *United Nations (UN) World Crime Surveys*
(t-statistics are presented below their corresponding coefficients)

Dependent Variable (in logs):	Homicide Rate			Robbery Rate		
Regression Specification:	Levels	Levels (*)	Levels and Differences	Levels	Levels (*)	Levels and Differences
	[1]	[2]	[3]	[4]	[5]	[6]
Lagged Dependent Variable	0.8957	0.9282	0.8137	0.7254	0.7528	0.7222
	46.2310	114.5404	25.4593	12.3614	23.1968	50.0311
Income Inequality	0.0069	0.0032	0.0155	0.0331	0.0223	0.0307
(Gini Coefficient)	3.9761	2.3130	7.0490	3.5354	4.8849	11.8691
Growth Rate	-1.9270	-3.3952	-4.2835	-8.4505	-7.1754	-11.1536
(% Annual Change in Real GDP)	-2.9066	-6.5945	-4.9471	-7.2343	-9.3441	-18.1176
Average Income	-0.0570	-0.0396	0.0151	-0.0541	-0.0923	-0.0287
(Log of GNP per capita in US $)	0.0187	-4.0141	0.8876	-0.7641	-2.9946	-2.0664
Urbanization	-0.0032	-0.0023	-0.0019	0.0078	0.0106	0.0053
(% of Pop. In Urban Centers)	-4.9258	-5.9852	-0.8959	4.0733	6.9098	6.0005
Educational Attainment	-0.0090	-0.0153	-0.0300	0.0901	0.0634	0.0382
(Avg. Yrs. Of Educ., Adults)	-1.1584	-2.7694	-3.4280	3.9416	4.2398	6.5551
Intercept	0.7935	0.7584		-0.5486	0.0669	
	5.3834	9.7501		-0.8663	0.2277	
No. Countries	39	27	27	37	29	29
No. Obs.	106	91	91	94	85	85
SPECIFICATION TESTS (P-Values):						
(a) Sargan Test	0.651	0.581	0.958	0.531	0.314	0.430
(b) Serial Correlation :						
First-Order	0.683	0.873	0.048	0.035	0.103	0.082
Second-Order	0.239	0.498	0.240	0.147	0.225	0.879

Source: Authors' calculations. For details on definitions and sources of variables, see Appendix Table A1.
(*) The sample is restricted to the countries that have at least three consecutive observations.

Table 5: Alternative Inequality Measures (GMM levels estimation)
Homicides Data Source: *World Health Organization Mortality Statistics (WHO)*
Robbery Data Source: *United Nations (UN) World Crime Surveys*
(t-statistics are presented below their corresponding coefficients)

Dependent Variable (in logs):	Homicide Rate			Robbery Rate		
	[1]	[2]	[3]	[4]	[5]	[6]
Lagged Dependent Variable	0.8780	0.8688	0.9268	0.7818	0.7784	0.8698
	48.8267	56.5593	58.2480	18.7384	25.1457	18.9108
Growth Rate	-3.2533	-3.1665	-0.9411	-4.1422	-4.7806	-6.9070
(% Annual Change in Real GDP)	-3.8806	-4.2468	-1.2659	-3.6406	-4.1412	-2.3018
Average Income	-0.0666	-0.0761	-0.0590	-0.0666	-0.1135	0.0373
(Log of GNP per capita in US $)	-4.2536	-4.1829	-2.8788	-1.8281	-3.1697	0.6770
Urbanization	-0.0019	-0.0023	-0.0031	0.0078	0.0095	0.0028
(% of Pop. In Urban Centers)	-2.1161	-2.4541	-2.5615	3.6231	4.3303	0.9051
Educational Attainment	-0.0205	-0.0151	-0.0083	0.0568	0.0699	0.0632
(Avg. Yrs. Of Educ., Adults)	-3.1268	-2.5024	-0.7124	2.6936	2.9841	1.9850
Intercept	1.0556	0.7916	0.9411	0.4020	0.0463	-0.7550
	8.5890	5.6564	5.1455	1.5376	0.1752	-1.2889
Ratio of the 1st to the 5th quintile	0.0152			0.0426		
	3.7918			4.0275		
Income Polarization		0.0019			0.0037	
(Log of Income Polarization Index)		4.9967			3.6931	
Educational Inequality			0.1036			0.8976
(Standard Deviation of Schooling Years)			0.8801			2.0666
No. Countries	39	39	37	36	36	35
No. Obs.	96	96	103	86	86	91
SPECIFICATION TESTS (P-Values):						
(a) Sargan Test	0.533	0.789	0.512	0.168	0.201	0.180
(b) Serial Correlation :						
First-Order	0.662	0.742	0.829	0.145	0.078	0.023
Second-Order	0.272	0.272	0.174	0.283	0.136	0.359

Source: Authors' calculations. For details on definitions and sources of variables, see Appendix Table A1.

Table 6: Additional Control Variables (GMM levels estimation)
Homicides Data Source: *World Health Organization Mortality Statistics (WHO)*
Robbery Data Source: *United Nations (UN) World Crime Surveys*
(t-statistics are presented below their corresponding coefficients)

Dependent Variable (in logs):	Homicide Rate				Robbery Rate			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Lagged Dependent Variable	0.8792	0.8987	0.9040	0.9106	0.8195	0.7358	0.7414	0.7849
	57.6962	62.3507	45.7224	42.0085	15.2561	12.9489	12.2210	16.3984
Income Inequality	0.0069	0.0055	0.0049	0.0073	0.0275	0.0307	0.0228	0.0226
(Gini Coefficient)	2.7692	3.4744	2.1574	3.8160	3.3464	3.3330	2.4784	3.8775
Growth Rate	-1.3845	-1.0327	-1.8185	-0.9918	-7.8263	-8.6606	-7.1703	-8.1747
(% Annual Change in Real GDP)	-2.8885	-1.3381	-2.4141	-1.1735	-6.9305	-6.2523	-4.9902	-6.0847
Average Income	-0.0335	-0.0689	-0.0432	-0.0448	0.0115	-0.0332	-0.0477	-0.0865
(Log of GNP per capita in US $)	-1.2479	-6.2284	-2.4857	-2.9894	0.1548	-0.5184	-0.7148	-1.6034
Urbanization	-0.0033	-0.0029	-0.0033	-0.0031	0.0047	0.0065	0.0045	0.0078
(% of Pop. In Urban Centers)	-5.6910	-4.7985	-5.0455	-4.9780	2.4969	2.9605	2.3226	4.6855
Educational Attainment	-0.0203	-0.0042	-0.0103	-0.0029	0.0453	0.0832	0.1081	0.0707
(Avg. Yrs. Of Educ., Adults)	-2.1061	-0.6974	-1.2640	-0.4580	3.0588	3.7235	4.5435	4.6855
Intercept	0.6323	0.8846	0.7445	0.7186	-0.6947	-0.6327	-0.2877	0.0029
	2.5482	8.5859	4.7312	6.5509	-1.0287	-1.0006	-0.4495	0.0089
Ethno-Linguistic Fractionalization	0.1706				-0.1092			
	2.1826				-0.7786			
Police		-0.0001				0.0004		
(per 100,000 population)		-0.9153				1.5252		
Latin America			0.0493				0.3486	
(dummy variable)			0.9198				2.7248	
Young Male Population				-0.0103				0.0039
(15-29 years old as % of total population)				-1.5412				0.1930
No. Countries	34	35	39	39	31	36	37	37
No. Obs.	96	97	106	106	83	92	94	94
SPECIFICATION TESTS (P-Values):								
(a) Sargan Test	0.674	0.533	0.471	0.536	0.554	0.575	0.349	0.539
(b) Serial Correlation :								
First-Order	0.486	0.702	0.732	0.782	0.060	0.025	0.044	0.043
Second-Order	0.123	0.240	0.279	0.244	0.153	0.120	0.175	0.194

Source: Authors' calculations. For details on definitions and sources of variables, see Appendix Table A1.

Appendix A: Data Definitions and Sources

Table A1: Description and Sources of the Variables

Variable	Description	Source
Intentional Homicide Rate	Number of deaths purposely inflicted by another person, per 100,000 population.	Constructed from mortality data from the World Health Organization (WHO). Most of this data is available by FTP from the WHO server (WHO-HQ-STATS01.WHO.CH) in the directory '\FTP\MORTALIT'. Additional data was extracted from the WHO publication "World Health Statistics Annual." The data on population was taken from the World Bank's International Economic Department data base.
GNP Per Capita	Gross National Product expressed in constant 1987 US prices and converted to U.S. dollars on the basis of the "notional exchange rate" proposed by Loayza et al. (1998).	Most data was taken from Loayza et al. (1998). For some countries the variable was constructed on the basis of the same methodology using data from the World Bank's International Economic Department data base
Gini Index	Income-based gini coefficient. Constructed by adding 6.6 to expenditure-based indexes to make them comparable to income-based indexes. Data of "high quality" was used when available. Otherwise, an average of the available data was used.	Deininger and Squire (1996). The data-set is available on the internet from the World Bank's Server, at http://www.worldbank.org/html/prdmg/grthweb/datasets.htm.
Educational Attainment	Average years of Schooling of the Population over 15.	Barro and Lee (1996). The data-set is available on the internet from the World Bank's Server, at http://www.worldbank.org/html/prdmg/grthweb/datasets.htm.
GDP Growth	Growth in the Gross Domestic Product constructed as the log-difference of GDP at constant local 1987 market prices.	Loayza et al. (1998).
Standard Deviation of Educational Attainment	Standard deviation of the distribution of education for the total population over age 15. The population is distributed in seven categories: no formal education, incomplete primary, complete primary, first cycle of secondary, second cycle of secondary, incomplete higher, and complete higher. Each person is assumed to have an educational attainment of log(1+years of schooling).	De Gregorio and Lee (1998).

Variable	Description	Source
Ethno-Linguistic Fractionalization	Measure that two randomly selected people from a given country will not belong to the same ethno-linguistic group (1960).	Easterly and Levine (1997). The data-set is available on the internet from the World Bank's Server, at http://www.worldbank.org/html/prdmg/grthweb/datasets.htm.
Police per 100,000	Number of police personnel per 100,000 population.	Constructed from the United Nations World Crime Surveys of Crime Trends and Operations of Criminal Justice Systems, various issues. The data is available on the internet at http://www.ifs.univie.ac.at/~uncjin/wcs.html#wcs123.
Young male population share	Male population 15-29 years of age as a share of the total population.	World Bank data.
Income of the Fifth Quintile relative to the First Quintile	Income of the population in the fifth quintile of the distribution of income divided by the income of the first quintile.	Same as above.

Appendix B: Summary Statistics

Table B1. Summary Statistics, Homicide Rates
(number of homicides per 100,000 population)

Country	Obs.	Mean	Std. Dev.	Min.	Max.
Australia	4	1.91	0.06	1.84	1.98
Belgium	2	1.62	0.15	1.51	1.73
Brazil	3	12.97	3.49	9.39	16.36
Bulgaria	3	3.41	0.92	2.71	4.45
Canada	6	2.08	0.34	1.51	2.48
Chile	5	3.45	0.61	3.00	4.33
China	2	0.18	0.03	0.16	0.21
Colombia	4	42.80	29.43	17.28	80.61
Costa Rica	4	4.21	0.43	3.56	4.51
Denmark	4	1.07	0.25	0.69	1.23
Dominica	3	4.70	0.89	4.12	5.72
Finland	6	2.84	0.36	2.22	3.24
France	4	0.94	0.16	0.79	1.14
Germany	4	1.22	0.05	1.18	1.29
Greece	2	0.89	0.07	0.84	0.94
Hong Kong	5	1.68	0.35	1.24	2.18
Hungary	5	2.65	0.68	2.08	3.75
Ireland	2	0.87	0.09	0.81	0.93
Italy	5	1.69	0.50	1.03	2.38
Japan	6	1.04	0.31	0.61	1.41
Mauritius	3	1.76	0.65	1.21	2.48
Mexico	4	18.37	0.83	17.92	19.62
Netherlands	4	0.94	0.14	0.81	1.14
New Zealand	5	1.57	0.43	1.09	2.02
Norway	6	0.92	0.30	0.54	1.28
Panama	2	4.23	2.49	2.46	5.99
Peru	2	2.68	0.70	2.19	3.17
Philippines	2	14.65	3.29	12.32	16.98
Poland	3	2.09	0.69	1.64	2.89
Romania	2	4.28	0.59	3.86	4.70
Singapore	4	2.13	0.19	1.84	2.23
Spain	4	0.63	0.43	0.15	1.01
Sri Lanka	2	6.10	1.07	5.35	6.85
Sweden	4	1.27	0.08	1.18	1.35
Thailand	2	24.22	1.88	22.89	25.55
Trinidad & Tobago	3	4.85	0.97	3.74	5.52
United Kingdom	6	0.97	0.21	0.71	1.35
United States	6	8.89	1.17	6.62	9.91
Venezuela	5	10.20	2.68	7.68	14.19

Source: Homicide data from the World Health Organization; population data from the World Bank.

Table B2. Summary Statistics, Robbery Rates
(number of robberies per 100,000 population)

Country	Obs.	Mean	Std. Dev.	Min.	Max.
Australia	4	44.34	18.70	23.61	68.60
Bangladesh	3	3.08	1.78	1.79	5.11
Belgium	2	38.83	34.67	14.31	63.35
Bulgaria	3	22.70	27.93	5.65	54.94
Canada	5	88.09	18.74	58.70	107.58
Chile	3	490.43	82.55	398.70	558.74
China	3	4.48	4.14	1.52	9.22
Denmark	2	70.72	44.52	39.24	102.21
Finland	5	37.61	5.97	31.18	46.33
Germany	3	27.84	7.17	21.58	35.66
Greece	2	2.03	0.74	1.50	2.55
Hong Kong	3	133.56	26.99	106.72	160.70
Hungary	3	19.22	9.64	11.91	30.14
India	5	4.12	0.98	2.87	5.63
Indonesia	5	4.54	2.12	2.51	8.14
Italy	4	35.42	23.46	7.09	59.51
Jamaica	4	177.73	35.63	137.08	213.61
Japan	5	1.83	0.26	1.47	2.19
Korea	4	5.88	2.35	3.37	8.51
Malaysia	4	31.02	13.61	12.36	44.80
Mauritius	2	43.28	3.86	40.55	46.01
Netherlands	4	53.79	26.28	22.11	79.89
New Zealand	4	19.33	11.49	9.50	34.85
Norway	4	14.34	7.40	8.11	24.68
Pakistan	2	1.18	0.58	0.76	1.59
Peru	3	240.25	12.04	227.64	251.63
Philippines	2	24.26	7.90	18.66	29.85
Poland	3	26.93	13.61	17.52	42.54
Romania	2	9.79	9.11	3.34	16.23
Singapore	4	65.63	18.25	47.59	90.82
Sri Lanka	5	37.10	8.05	28.66	47.40
Sweden	4	49.13	14.24	36.22	68.76
Thailand	4	12.29	6.14	6.11	17.99
Trinidad	3	62.27	49.05	32.70	118.89
United Kingdom	4	59.75	28.91	31.82	99.66
United States	5	216.00	28.83	184.85	256.83
Venezuela	4	144.26	52.39	76.62	200.40

Source: Robbery data from the United Nations World Crime Surveys; population data from the World Bank.

Table B3: Bivariate Correlations of Variables Included Simultaneously in Multivariate Regressions

(number of five-year-average observations in parentheses)

	Log of Homicide Rate	Log of Robbery Rate	Gini Index	Log of GNP per Capita	Educational Attainment	GDP Growth	Urbanization
A. Variables used in basic regressions							
Log of Homicide Rate	1.00						
Log of Robbery Rate	0.46 (96)	1.00					
Gini Index	0.54 (148)	0.28 (132)	1.00				
Log of GNP per Capita	-0.44 (148)	0.40 (132)	-0.46 (148)	1.00			
Educational Attainment	-0.31 (148)	0.35 (132)	-0.63 (148)	0.64 (148)	1.00		
GDP Growth	-0.07* (148)	-0.28 (132)	0.26 (148)	-0.15* (148)	-0.37 (148)	1.00	
Urbanization	-0.24 (148)	0.51 (132)	-0.19 (148)	0.68 (148)	0.41 (148)	-0.10* (148)	1.00
B. Alternative indicators of inequality used instead of the Gini index in GMM regressions							
Ratio of Income Share of Fifth to First Quintile	0.61 (96)	0.31 (86)	0.88 (96)	-0.45 (96)	-0.52 (96)	0.15* (96)	-0.23 (96)
Log of Income Polarization	0.53 (96)	0.35 (86)	0.88 (96)	-0.28 (96)	-0.45 (96)	0.23 (96)	-0.12* (96)
Std. Dev. of the log(1 + years of education)	0.31 (103)	-0.25 (91)	0.62 (103)	-0.53 (103)	-0.74 (103)	0.41 (103)	-0.07* (103)
C. Additional control variables used in GMM regressions							
Police per 100,000 Population	-0.18* (97)	0.38 (92)	0.03* (97)	0.06* (97)	-0.00* (97)	0.31 (97)	0.25 (97)
Young Male (15-29 years) Population as Share of Total	0.36 (106)	0.06 (94)	0.58 (106)	-0.36 (106)	-0.43 (106)	0.48 (106)	-0.04* (106)
Ethno-Linguistic Fraction. in 1960	0.20* (96)	-0.12* (83)	-0.03* (96)	-0.07* (96)	0.19* (96)	0.03* (96)	-0.14* (96)
Latin America Dummy	0.59 (148)	0.49 (132)	0.74 (148)	-0.49 (148)	-0.58 (148)	-0.01* (148)	-0.13* (148)

The * indicates correlations that are NOT significant at the 5% level.

Appendix C: On the Empirical Implementation of Esteban and Ray's (1994) Measure of Polarization

In this note we briefly describe a possible empirical implementation of the measure of polarization proposed by Esteban and Ray (1994: 834) – "ER". More precisely, we propose an implementation of ER's equation (3), extended to incorporate the possibility of identification between individuals belonging to different income groups.

We use data on the percentages of total income held by different quintiles of the distribution of income within a given country. We thus consider a population that is initially subdivided in five groups (the quintiles). Since we do not have information on the degree of income heterogeneity within each quintile, we assume that they are equally homogeneous and thus treat each quintile as having the same degree of "identification" (as defined by ER).

Following the suggestion contained in section 4 of ER, we also permit "identification across income groups that are 'sufficiently' close" (p. 846). We implement this idea by assuming that two or more quintiles may group themselves into a new unit if their incomes are sufficiently similar. As emphasized by ER, the definition of the "domain over which a sense of identification prevails"(p. 846) can not be specified a priori. Thus, we test with different values of the minimum logarithmic difference ("D") that gives rise to the merger of two quintiles into a new group. In our empirical exercise this minimum (percentage) distance is allowed to vary between 10 and 100%.

We also assume that individuals act as "social climbers": when a given quintile is within the range of identification with both a quintile with higher income and a quintile with lower income, the merger takes place first between the two "superior" quintiles. Moreover, once two (or more) quintiles have merged, the decision to form a larger group with another quintile rests upon the quintile with the highest income within the (pre-) existing grouping. That is, the new merger takes place only if the new "candidate" is within the range of identification of the highest quintile within the previously existing group.

In practice, given our assumptions, there are 16 (or 2 to the 4^{th} power) possible structures of groups, each formed by one or more quintiles: either the highest quintile merges with the 4^{th} or not, either the 4^{th} quintile (with or without the 5^{th}) merges or not with the third, etc. On the basis of the Deininger and Squire international data set on income inequality, we apply a simple algorithm that implements our assumptions and determines, for each country and for each value of the parameter D, the types of groups that are expected to emerge.

Once the structure of groups in a given country is defined, we calculate, for each year and country, the value of a measure of polarization "P", using a modified version of ER's equation (3), which intends to reproduce the "spirit" of equation (25) in this paper. Indeed, we assume that the degree of identification of a group depends positively on its size and negatively on the log-difference between the average income of the two quintiles that, within the group, are situated farthest away from each other:

$$P(\pi, y) = \sum_{i=1}^{n} \sum_{j=1}^{n} \left(\frac{\pi_i}{1+|y_i^{\max} - y_i^{\min}|}\right)^{1+\alpha} \pi_j |y_j - y_j|$$

where y_i is the log of the average income of group i (formed by one or more quintiles), y^{max}_i is the average income of the highest quintile within group i, y^{min}_i is the average income of the lowest quintile within group i, and π_i is twice the number of quintiles that form group i (it's the number of deciles that were merged to create group i). Following the analysis in ER, we allow the parameter α to vary between 1.0 and 1.6.

Our preliminary exercises show that the measure of polarization is increasing in D for sufficiently low values of this parameter, and then becomes decreasing in D. The value of D after which P starts to decrease with D is, in turn, increasing in α. As expected, the correlation between "P" and the Gini Index decreases with the parameter α, and varies from 0.74 for α equal to 1, to 0.58 for α equal to 1.6.

Appendix D: Dynamic-Panel GMM Methodology

i) Assuming no unobserved country-specific effects: moment conditions

We use a dynamic model to explain the homicide and robbery rates. The basic model is given by,

$$y^*_{i,t} = \alpha y^*_{i,t-1} + \beta' X_{i,t} + \xi_{i,t} \tag{D1}$$

where y^* is the "true" crime (homicide or robbery) rate, X is the set of explanatory variables, and ξ is the unexplained residual. The subscripts *i* and *t* denote country and time period, respectively.

Available crime data suffers from measurement error. For this section, let us assume that measurement error is only standard random noise (we relax this assumption below). Then,

$$y_{i,t} = y^*_{i,t} + \nu_{i,t} \quad and \ \ \nu_{i,t} \ is \ i.i.d. \tag{D2}$$

where y represents the measured crime rate. Substituting (D2) into (D1):

$$y_{i,t} = \alpha y_{i,t-1} + \beta' X_{i,t} + \varepsilon_{i,t} \quad where \ \ \varepsilon_{i,t} = \xi_{i,t} + \nu_{i,t} - \alpha \nu_{i,t-1} \tag{D3}$$

Equation (D3) is our basic regression model. Estimation via ordinary least squares (OLS) would lead to inconsistent parameter estimates because the explanatory variables are not independent with respect to the error term: $y_{i,t-1}$ is correlated by construction with $\nu_{i,t-1}$, and $X_{i,t}$ is potentially correlated with $\xi_{i,t}$. Consistent estimation requires the use of instrumental variables. Specifically, we use the Generalized-Method-of-Moments (GMM) estimators developed for dynamic models of panel data that were introduced by Holtz-Eakin, Newey, and Rosen (1990), Arellano and Bond (1991), and Arellano and Bover (1995). Given that for this section we assume that there is no country-specific effect, we base our estimates on the so-called *levels GMM* estimator. The use of instruments is required to deal with both the random noise measurement error in the lagged dependent variable and the likely endogeneity of the remaining explanatory variables, *X,* which may be affected by crime rates (reverse causation) and/or jointly caused by other variables (simultaneity). Instead of assuming strict exogeneity of *X* (i.e., that the explanatory variables be uncorrelated with the error term at all leads and lags), we allow for a limited form of simultaneity and reverse causation. Specifically, we adopt the more flexible assumption of weak exogeneity, according to which current explanatory variables may be affected by past and current realizations of the dependent variable (the homicide or the robbery rate) but not by its future innovations. Under the assumptions that (a) the error term, ε, is not serially correlated, and (b) the explanatory variables are weakly exogenous, the following moment conditions apply:

$$E\left[y_{i,t-s} \cdot \varepsilon_{i,t}\right] = 0 \quad for \ s \geq 2 \tag{D4}$$

$$E\left[X_{i,t-s} \cdot \varepsilon_{i,t}\right] = 0 \quad for \ s \geq 1 \tag{D5}$$

ii) Allowing and controlling for unobserved country-specific effects: moment conditions

Our second specification allows for the existence of persistent country-specific measurement error. This alternative model is given by,

$$y^*_{i,t} = \alpha y^*_{i,t-1} + \beta' X_{i,t} + \eta_i + \xi_{i,t} \tag{D6}$$

where y^* is the "true" crime rate, and η_i is a country-specific unobserved factor, which may be correlated with the explanatory variables. We now assume that the mismeasurement in crime rates is not only driven by random errors but most importantly by specific and persistent characteristics of each country. These characteristics can be related to the variables that explain crime rates, such as the average level of income, educational attainment, and income inequality. Then, we model measurement error as the sum of random noise and a country-specific effect:

$$y_{i,t} = y^*_{i,t} + \nu_{i,t} + \psi_i \tag{D7}$$

where ν is i.i.d. and ψ is a country-specific effect. Substituting (D7) into (D6):

$$y_{i,t} = \alpha y_{i,t-1} + \beta' X_{i,t} + \mu_i + \varepsilon_{i,t} \tag{D8}$$

where,

$$\mu_{i,t} = \eta_i + (1-\alpha)\psi_i \quad and \quad \varepsilon_{i,t} = \nu_{i,t} - \alpha\nu_{i,t-1} + \xi_{i,t}$$

Thus, the measurement error in crime rates is subsumed into both the unobserved country-specific effect and the time-varying residual. Equation (D8) is our second regression model. To estimate it we use the so-called *system GMM* estimator, which joins in a single system the regression equation in both differences and levels, each with its specific set of instrumental variables.

For ease of exposition, we discuss each section of the system separately, although the actual estimation is performed using the whole system jointly. Specifying the regression equation in differences allows direct elimination of the country-specific effect. First-differencing equation (D8) yields,

$$y_{i,t} - y_{i,t-1} = \alpha\left(y_{i,t-1} - y_{i,t-2}\right) + \beta'\left(X_{i,t} - X_{i,t-1}\right) + \left(\varepsilon_{i,t} - \varepsilon_{i,t-1}\right) \tag{D9}$$

In addition to the likely endogeneity of the explanatory variables, X, and the random measurement error of the lagged crime rate, the use of instruments is here required to deal with the correlation which, by construction, is generated between the new error term, ($\varepsilon_{i,t}$ - $\varepsilon_{i,t-1}$), and the differenced lagged dependent variable, ($y_{i,t-1}$ - $y_{i,t-2}$). Once again, we adopt the assumption of weak exogeneity, which together with the assumption of no serial correlation in the error term yields the following moment conditions:

$$E\left[y_{i,t-s} \cdot \left(\varepsilon_{i,t} - \varepsilon_{i,t-1}\right)\right] = 0 \quad for\ s \geq 3 \tag{D10}$$

$$E\left[X_{i,t-s}\cdot\left(\varepsilon_{i,t}-\varepsilon_{i,t-1}\right)\right]=0 \quad for\ s\geq 2 \qquad \text{(D11)}$$

The GMM estimator simply based on the moment conditions in (D10) and (D11) is known as the *differences* estimator. Although asymptotically consistent, this estimator has low asymptotic precision and large biases in small samples, which leads to the need to complement it with the regression equation in levels.[10]

For the regression in levels, the country-specific effect is not directly eliminated but must be controlled for by the use of instrumental variables. The appropriate instruments for the regression in levels are the lagged *differences* of the corresponding variables if the following assumption holds. Although there may be correlation between the levels of the right-hand side variables and the country-specific effect, there is no correlation between the *differences* of these variables and the country-specific effect. This assumption results from the following stationarity property,

$$E\left[y_{i,t+p}\cdot\eta_i\right]=E\left[y_{i,t+q}\cdot\eta_i\right] \ \ and \ \ E\left[X_{i,t+p}\cdot\eta_i\right]=E\left[X_{i,t+q}\cdot\eta_i\right] \ \ for\ all\ \ p\ and\ q$$

Therefore, the additional moment conditions for the second part of the system (the regression in levels) are given by the following equations:[11]

$$E\left[\left(y_{i,t-s}-y_{i,t-s-1}\right)\cdot\left(\eta_i+\varepsilon_{i,t}\right)\right]=0 \qquad for\ s=2 \qquad \text{(D12)}$$

$$E\left[\left(X_{i,t-s}-X_{i,t-s-1}\right)\cdot\left(\eta_i+\varepsilon_{i,t}\right)\right] = 0 \quad for\ s=1 \qquad \text{(D13)}$$

iii) Estimation

Using the moment conditions presented in equations (D4) and (D5) and, alternatively, (D10) to (D12), and following Arellano and Bond (1991) and Arellano and Bover (1995), we employ a Generalized Method of Moments (GMM) procedure to generate consistent estimates of the parameters of interest and their asymptotic variance-covariance. These are given by the following formulas:

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[10] Alonso-Borrego and Arellano (1996) and Blundell and Bond (1998) show that when the lagged dependent and the explanatory variables are persistent over time, lagged levels of these variables are weak instruments for the regression equation in differences. This weakness has repercussions on both the asymptotic and small-sample performance of the *differences* estimator. As persistence increases, the asymptotic variance of the coefficients obtained with the *differences* estimator rises (i.e., deteriorating its asymptotic precision). Furthermore, Monte Carlo experiments show that the weakness of the instruments produces biased coefficients in small samples. This is exacerbated with the variables' over-time persistence, the importance of the country-specific effect, and the smallness of the time-series dimension. An additional problem with the simple *differences* estimator relates to measurement error: Differencing may exacerbate the bias due to errors in variables by decreasing the signal-to-noise ratio (Griliches and Hausman, 1986). Blundell and Bond (1997) suggest the use of Arellano and Bover's (1995) *system* estimator that reduces the potential biases and imprecision associated with the traditional *differences* estimator.

[11] Given that lagged levels are used as instruments in the *differences* specification, only the most recent difference is used as instrument in the levels-specification. Other lagged differences would result in redundant moment conditions (Arellano and Bover 1995).

$$\hat{\theta} = (\overline{X}' Z\hat{\Omega}^{-1} Z' \overline{X})^{-1} \overline{X}' Z\hat{\Omega}^{-1} Z' \overline{y} \tag{D14}$$

$$AVAR(\hat{\theta}) = (\overline{X}' Z\hat{\Omega}^{-1} Z' \overline{X})^{-1} \tag{D15}$$

where θ is the vector of parameters of interest (α, β), $\overline{y}$ is the dependent variable (stacked first in differences and then in levels in the case of the *system* estimator), $\overline{X}$ is the explanatory-variable matrix including the lagged dependent variable (y_{t-1}, X) (also stacked first in differences and then in levels for the *system* estimator), Z is the matrix of instruments derived from the moment conditions, and $\hat{\Omega}$ is a consistent estimate of the variance-covariance matrix of the moment conditions.[12]

iv) Specification tests

The consistency of the GMM estimators depends on whether lagged values of the explanatory variables are valid instruments in the crime-rate regression. We address this issue by considering two specification tests suggested by Arellano and Bond (1991) and Arellano and Bover (1995). The first is a Sargan test of over-identifying restrictions, which tests the overall validity of the instruments by analyzing the sample analog of the moment conditions used in the estimation process. Failure to reject the null hypothesis gives support to the model. The second test examines the null hypothesis that the error term $\varepsilon_{i,t}$ is not serially correlated. As in the case of the Sargan test, the model specification is supported when the null of no serial correlation is not rejected. In our *levels* (basic) specification, we test whether the error term is first-order serially correlated. In our *system* (alternative) specification we test whether the differenced error term (that is, the residual of the regression in differences) is second-order serially correlated. First-order serial correlation of the differenced error term is expected even if the original error term (in levels) is uncorrelated, unless the latter follows a random walk. Second-order serial correlation of the differenced residual indicates that the original error term is serially correlated and follows a moving average process at least of order one. This would reject the appropriateness of the proposed instruments (and would call for higher-order lags to be used as instruments).

[12] In practice, Arellano and Bond (1991) suggest the following two-step procedure to obtain consistent and efficient GMM estimates. First, assume that the residuals, $\varepsilon_{i,t}$, are independent and homoskedastic both across countries and over time. This assumption corresponds to a specific weighting matrix that is used to produce first-step coefficient estimates. Then, construct a consistent estimate of the variance-covariance matrix of the moment conditions with the residuals obtained in the first step, and use this matrix to re-estimate the parameters of interest (i.e. second-step estimates). Asymptotically, the second-step estimates are superior to the first-step ones in so far as efficiency is concerned.