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What causes violent crime?

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Abstract

This study uses panel data of intentional homicide and robbery rates for a sample of developed and developing countries for the period 1970–1994, based on information from the United Nations World Crime Surveys, to analyze the determinants of national crime rates both across countries and over time. A simple model of the incentives to commit crimes is proposed, which explicitly considers possible causes of the persistence of crime over time (criminal inertia). A panel-data based GMM methodology is used to estimate a dynamic model of national crime rates. This estimator controls for unobserved country-specific effects, the joint endogeneity of some of the explanatory variables, and the existence of some types of measurement errors afflicting the crime data. The results show that increases in income inequality raise crime rates, crime tends to be counter-cyclical, and criminal inertia is significant. © 2002 Elsevier Science B.V. All rights reserved.

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1. Introduction

The heightened incidence of criminal and violent behavior in recent years has become a major concern across the world. From Eastern Europe to the developing countries of Latin America, violence and crime threaten social stability and

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are becoming major obstacles to development. Between the early 1980s and the mid 1990s, the rate of intentional homicides increased by 50% in Latin America and by more than 100% in Eastern Europe and Central Asia. In countries such as Colombia, Russia, and Thailand, the homicide rate more than tripled in about the same period. The concern with crime is well justified given its pernicious effects on economic activity and, more generally, on the quality of life of people who must cope with the reduced sense of personal and proprietary security. Despite the fact that violent crime is emerging as a priority in policy agendas worldwide, we know little regarding the economic, social, and institutional factors that make some countries have higher crime rates than others or make a country experience a change in its crime rate. The objective of this paper is to help understand the social and economic causes of violent crime rates in a worldwide sample of countries.

The economics literature on crime has followed Becker's (1968) paradigm, according to which criminal acts result from a rational decision based on a cost–benefit analysis.[1] The expected benefits are given by the difference between the loot and the opportunity cost of crime; and the costs are given by the penalties imposed to apprehended criminals. Thus, research on crime has focused on either deterrence issues or economic factors that affect the costs and benefits related to criminal actions. The literature on the efficacy of punishment to prevent crime began in the 1970s. Ehrlich (1973, 1975a) found that crime rates were sensitive to the expected size of punishment. Using variation across U.S. states, Ehrlich (1975a) concluded that capital punishment had a significant impact on major crime rates. Working with sub-city data, Mathieson and Passell (1976) also find large deterrence elasticities of crime. On the other hand, Archer and Gartner (1984) find no impact of capital punishment on murders in their cross-national study. The endogeneity of punishment with respect to crime makes difficult the interpretation of simple deterrence elasticities. Taylor (1978) and, more recently, Grogger (1991) and Levitt (1996, 1997) have taken into account endogeneity issues to study and quantify the effectiveness of punishment to prevent crime. Using micro-level data in the U.S., these authors find a significant effect of policing and punishment on crime reduction.

The literature focusing on the benefits and opportunity costs of crime has also been rich, particularly in the U.S. In their work on U.S. cities, Fleisher (1966) and Ehrlich (1973) examined the effect of unemployment rates, income levels, and income disparities on the incidence of crime. Though their findings on the effects of average income levels are contradictory, both authors find a significant crime-inducing impact of unemployment and income inequality. Using the National Longitudinal Survey of Youth in the U.S., Freeman (1992) finds that

[1] For brief reviews of the economics literature on crime, see Glaeser (1999) and Fajnzylber et al. (1999).

youth in poverty are more likely to be arrested and go to jail. Tauchen and Witte (1994) find that in a sample of young men, going to work or school tends to reduce the probability of being involved in criminal activities. On the other hand, the effect of education on crime reduction is controversial in most studies. For example, Ehrlich (1975b) finds a positive relationship between the average number of school years completed by the adult population and property crimes committed across the U.S. in 1960.

Recently, in somewhat of a departure from Becker's paradigm, some research has turned to sociological aspects that affect the incidence of crime. DiIulio (1996) links the lack of 'social capital' to the rise of crime rates in U.S. cities. Similarly, Freeman (1986) finds a strong association between church attendance and lower crime participation rates for needy youths. Demographic factors and social interactions has also been the subject of recent research. Using a survey of disadvantaged youths in Boston, Case and Katz (1991) find that an individual's propensity to commit a crime rises when his peers are also engaged in criminal activities. In a related paper, Glaeser et al. (1996) emphasize the role of social interactions in explaining the continuous prevalence of high crime rates in certain places and the significant variance of crime rates across space.

The literature surveyed above is a point of departure for this paper. In choosing the variables to explain the incidence of crime, we follow Becker's paradigm and its recent extensions emphasizing sociological and demographic aspects. We consider the variables that the literature favors as determinants of crime rates. However, rather than using micro-level data or concentrating on a single city or country, we use cross-country data to explain national crime rates with social and economic variables at the same level of aggregation.

Our basic regression considers economic variables that may affect the incidence of crime. Then, we extend the basic model along four dimensions. The basic (or core) model includes as explanatory variables the lagged crime rate, the output growth rate, the average income of the population, the level of income inequality, and the average educational attainment of the adult population. The four extensions are the following. First, we consider deterrence factors by estimating, alternatively, the effects of police presence in the country and the existence of capital punishment. Given the importance of deterrence in the crime literature, we would have wanted to include these variables in the core model. We decided against it because we only have limited cross-sectional data for these variables. The second extension deals with the effects of illegal drugs in two aspects, namely, the production of drugs in the country and the rate of drug possession. The third extension considers demographic issues. In particular, we study whether the degree of urbanization and the age composition of the population, respectively, have an effect on the incidence of violent crime. Finally, we begin to explore cultural issues by considering the effect of geographic region and religion dummies.

One of the reasons cross-country studies are uncommon is that it is difficult to compare crime rates across countries. The issues of mismeasurement associated with aggregate variables are quite severe for most types of crime data. Underreporting is widespread in countries with low-quality police and judicial systems and with poorly educated populations. In fact, Soares (1999) finds that the extent of underreporting is negatively correlated with the level of development. Underreporting is most pronounced for low-value property crime (e.g., common theft) and for crimes carrying a social stigma for the victim (e.g., rape). We attempt to reduce the biases caused by measurement errors by, first, choosing the types of crime that are least likely to be affected by underreporting and, second, employing an econometric methodology that deals with systematic measurement error. The types of crime we work with are intentional homicides and robberies. Intentional homicide statistics suffer the least from underreporting because corpses are more difficult to ignore than losses of property or assaults. Robberies are crimes against property that include a violent component, which means that the victim has two reasons to report the crime. To the extent that intentional homicide and robbery are good proxies for overall crime, our conclusions apply to criminal activities broadly understood. However, if these types of crime proxy mostly for violent crime, our results apply more narrowly. We assembled a new data set on intentional homicide and robbery rates based on information from the United Nations World Crime Surveys. The data set consists of an unbalanced panel of 45 countries for homicides and 34 countries for robberies, covering the period 1970–94.

Panel data permits a rich model specification. First, we can consider both variables that vary mostly across countries (e.g., income inequality) and those that vary in the time and country dimensions (e.g., output growth rates and measures of development). Second, by considering the patterns of crime rates for a given country over time, we can test whether there is inertia in the incidence of crime. Third, we can control for the joint endogeneity of some of the explanatory variables, through the use of their lagged values as instruments. Controlling for joint endogeneity is essential to obtain consistent estimates of the effect of various economic and social variables on crime rates. For instance, in assessing the impact of output growth on crime rates, we must control for the possibility that higher crime rates scare away domestic investment and hurt economic growth. Finally, the use of panel data allows us to control for the effect of unobserved variables that vary little over time and can, thus, be considered as country-specific effects. In the context of crime regressions, possibly the most important unobserved country-specific effect is the systematic error involved in the measurement of crime rates. By controlling for these specific effects, we are reducing the estimation bias due to the underreporting of crime. Our econometric methodology follows the generalized method of moments (GMM) estimator applied to dynamic models of panel data (see Holtz-Eakin et al., 1988, particularly; Arellano and Bond, 1991; Arellano and Bover, 1995).

The rest of the paper is organized as follows. Section 2 presents a simple economic model of criminal behavior. It begins with a cost–benefit analysis for the individual and ends with a framework to study the determinants of national crime rates. Section 3 presents the data and the econometric methodology. Section 4 discusses the results for, respectively, intentional homicide rates and robbery rates. Section 5 summarizes the main conclusions.

2. A simple reduced-form model of criminal behavior

In this section we present a simple model that helps us organize ideas and motivate the explanatory variables of crime rates used in the empirical section of the paper. We first model criminal behavior from the perspective of the individual and then aggregate to the national level to obtain a reduced-form equation of the causes of national crime rates.

The basic assumption is that potential criminals act rationally, basing their decision to commit a crime on an analysis of the costs and benefits associated with a particular criminal act. Furthermore, we assume that individuals are risk neutral. For a given individual, the expected net benefit (nb) of committing a crime is equal to its expected payoff (that is, the probability of not being apprehended ($1 - pr$) times the loot (l)), minus the total costs associated with planning and executing the crime (c), minus the foregone wages from legitimate activities (w), minus the expected punishment for the committed crime ($pr * pu$):[2]

$$nb = (1 - pr) * l - c - w - pr * pu. \tag{1}$$

We can model the presence of moral values by assuming that the expected net benefits of a crime would have to exceed a certain threshold before the individual commits a crime. This threshold would be determined by her moral stance (m), to which we can assign a pecuniary value to make it comparable to the other variables in the model. Eq. (2) establishes the relationship between the decision to commit a crime and the net benefits of such behavior:

$$\begin{aligned} d &= 1 \quad \text{when } nb \geq m, \\ d &= 0 \quad \text{when } nb < m, \end{aligned} \tag{2}$$

where d stands for the decision to commit the crime ($d = 1$) or not ($d = 0$).

[2] Lower-case letters represent the variables related to a particular individual (not necessarily a representative individual in society). Upper-case letters represent society's averages for the corresponding variables.

In the empirical section of the paper, we estimate a model in which the dependent variable is the national crime rate and the explanatory variables are a number of national economic and social characteristics. In what follows of this section, we first link those characteristics with the elements entering the individual decision to commit a crime (as given in Eqs. (1) and (2)). Then, we aggregate over individuals in a nation to obtain a reduced-form expression for the country's crime rate as a function of the underlying socioeconomic variables.

The first underlying variable is the individual's past criminal activities (d_{t-1}). It affects the decision to commit a crime in several ways. First, convicts tend to be stigmatized in the legal labor market, thus having diminished employment opportunities and expected income (lower w). Second, criminals can learn by doing, which means that the costs of carrying out criminal acts (c) may decline over time. Third, people tend to have a reduced moral threshold (m) after having joined the crime industry. Furthermore, the past incidence of crime in society (D_{t-1}) affects the individual's decision by reducing the costs of carrying out criminal activities (lower c), lowering the perceived probability of apprehension (lower pr), and impairing civic moral values (lower m). These arguments strongly suggest the possibility of criminal hysteresis or inertia.

The level and growth of economic activity (EA) in society create attractive opportunities for employment in the legal sector (higher w) but, since they also improve the wealth of other members of society, the size of the potential loot from crime (l) also rises. Therefore, the effect of heightened economic activity on the individual's decision to commit a crime is, in principle, ambiguous. The effect of income inequality in society ($INEQ$) will depend on the individual's relative income position. It is likely that in the case of the rich, an increase in inequality will not induce them to commit crimes. However, in the case of the poor, an increase in inequality may be crime inducing, because such an increase implies a larger gap between the wages of the poor and those of the rich, thus reflecting a larger difference between the income from criminal and legal activities (higher $l - w$). A rise in inequality may also have a crime-inducing effect by reducing the individual's moral threshold (lower m) through what we could call an 'envy effect'. Therefore, a rise of inequality is likely to have a positive impact on (at least some) individuals' propensity to commit a crime.

An individual's education level (e) may impact on the decision to commit a crime through several channels. Higher levels of educational attainment may be associated with higher expected legal earnings (raising w). Also, education, through its civic component, may increase the individual's moral stance (m). On the other hand, education may reduce the costs of committing crimes (reducing c) or may raise the loot from crime (l). Hence the net effect of education on the individual's decision to commit a crime is, a priori, ambiguous. We can conjecture, however, that if legal economic activities are more skill- or education-intensive than illegal activities, then it is more likely that education will induce individuals not to commit crimes.

The existence of profitable criminal activities in some countries means that the expected loot from crime is larger in those countries than in others. The most important example of profitable criminal activities is the illicit drug trade (*DRUGS*); other examples are contraband, gambling, and prostitution. Countries where the raw materials for illicit drugs are easily obtained (such as Colombia, Bolivia, and Peru in the case of cocaine) or countries that are located close to high drug consumption centers (such as Mexico in relation to the United States) have frequent and highly profitable opportunities for criminal activities. These activities not only consist of drug production and trade themselves, but also involve elements of violence and corruption.

The strength of the police and the judicial system (*JUST*) increases the probability of apprehension (*pr*) and the punishment (*pu*) for criminal actions, thus reducing the incentives for an individual to commit a crime. This is the crime-deterrence effect.

There are other factors that may affect an individual's propensity to commit crimes such as cultural characteristics (e.g., religion and colonial heritage), age and gender (young males are said to be more violent prone than the rest of the population) and the degree of urbanization or population density. These other factors can affect the individual's decision to commit a crime mainly through the cost of planning and executing the crime (*c*) and the moral threshold (*m*). Substituting these underlying variables into Eqs. (1) and (2), a given individual will commit a crime if the following inequality holds:

$$\begin{aligned} &d = 1 \text{ if} \\ &l(\overset{+}{EA}, \overset{+}{INEQ}, \overset{+}{e}, \overset{+}{DRUGS}, \overset{-}{JUST}) - c(\overset{-}{d_{t-1}}, \overset{-}{D_{t-1}}, \overset{-}{e}, other) \\ &\quad - w(\overset{+}{EA}, \overset{-}{d_{t-1}}, \overset{+}{e}) - pr(\overset{+}{JUST}, \overset{-}{D_{t-1}}) * pu(\overset{+}{JUST}) \\ &\quad - m(\overset{-}{d_{t-1}}, \overset{-}{D_{t-1}}, \overset{-}{INEQ}, \overset{+}{e}, other) \geq 0. \end{aligned} \tag{3}$$

Rewriting this condition as a function *f* of the underlying individual and social variables, we obtain the following reduced-form expression:

$$\begin{aligned} &d = 1 \text{ if} \\ &f(\overset{?}{EA}, \overset{+}{INEQ}, \overset{+}{d_{t-1}}, \overset{+}{D_{t-1}}, \overset{?}{e}, \overset{+}{DRUGS}, \overset{-}{JUST}, other) = f(\psi) \geq 0, \end{aligned} \tag{4}$$

where ψ is a vector of the underlying determinants of crime. Assuming *both* a linear probability model for the decision to commit a crime and a linear functional form for *f*, we obtain the following individual regression equation:

$$d = \beta'\psi + \mu. \tag{5}$$

The assumption of linearity in both the functional form of f and the probability model are, of course, arbitrary. They are chosen because they allow the aggregation of Eq. (5). Given that our data is not individual but national, our regression equation must be specified in terms of national rates, which is obtained by averaging Eq. (5) over all individuals in a country and over a given time period

$$D_t = \beta'\psi_t + \upsilon_t \tag{6}$$

i.e.

$$\begin{aligned} \mathit{Crime\ Rate}_{i,t} = \beta_0 &+ \beta_1 \mathit{Crime\ Rate}_{i,t-1} + \beta_2 EA_{i,t} + \beta_3 INEQ_{i,t} \\ &+ \beta_4 EDUC_{i,t} + \beta_5 JUST_{i,t} + \beta_6 DRUGS_{i,t} \\ &+ \beta_7 OTHER_{i,t} + \eta_i + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

where the subscripts i and t represent country and time period, respectively; and η is an unobserved country-specific effect.

3. Empirical methodology

3.1. Approach and data

The empirical implementation of the theoretical model proposed above uses national crime rates as dependent variables. Specifically, our econometric analysis focuses on the determinants of intentional homicide and robbery rates for a worldwide sample of countries during the period 1970 and 1994.[3] We calculated crime rates on the basis of population data and the number of crimes reported by national justice ministries to the United Nations World Crime Surveys. All crime rates are expressed as the number of reported crimes in each category per 100,000 inhabitants.

The estimation relies on panel data of 5-year averages for both the dependent variables (homicide and robbery rates, respectively) and the explanatory variables. The sample of countries included in the regressions was selected according the quality of the available crime data and by the availability of at least three

[3] The United Nations World Crime Surveys define an 'intentional homicide' as a death purposely inflicted by another person (see Table 5). We chose to work with intentional rather than total homicides because we feared that the broader measure was subject to more definitional differences across countries than 'intentional' homicide. Exceptions to this rule are clearly noted in Table 6. The U.N. Crime Surveys define a 'robbery' as taking away property from a person, overcoming resistance by force or threat of force (see Table 6).

consecutive observations.[4] The resulting sample includes 45 countries in the homicide regressions, and 34 in the robbery regressions.[5] Both samples have a heavy representation of industrialized countries in Western Europe, the U.S., Canada, and Japan. This set of countries comprises 16 of the 45 countries in the homicide regressions, and 14 out of 34 in the robbery regressions. Hence the samples provide some balance between observations from developed and developing countries. However, both samples exclude countries from sub-Saharan Africa, due to the lack of data for three consecutive 5-year periods. The period covered by the crime data ranges from 1970–74 to 1990–94. Consequently, the highest number of observations per country is five. Appendix A describes in detail the definitions and sources of all variables used in the empirical analysis. Appendix B lists the countries and numbers of observations included in the homicide and robbery regressions.

3.1.1. Explanatory variables in the core model

As mentioned in Section 1, the explanatory variables in our core model are the lagged crime rate, the average income of the population, the GDP growth rate, the level of income distribution and average years of schooling of the adult population. All these variables are treated as endogenous in the empirical analysis. As the measure of average income we use gross national product (GNP) per capita, in prices of 1987. The figures were converted to U.S. dollars on the basis of the methodology proposed by Loayza et al. (1998), which is based on an average of real exchange rates.[6] To measure economic activity, we use the rate of growth of real GDP, calculated on the basis of data expressed in 1987 prices (in local currency).[7]

The degree of income inequality is measured by the Gini index. This variable was constructed on the basis of the data set provided by Deininger and Squire (1996). We use what these authors have termed 'high quality' data for the countries and years for which it was available; otherwise, we use the average of

[4] The panel of data used in the empirical analysis is unbalanced. The requirement on the minimum number of consecutive observations is dictated by our econometric methodology, as explained below.

[5] To control for quality we excluded countries that had 10-fold or greater increases in the reported number of crimes from one year to another. The presumption underlying this criterion is that such large jumps in the series could only be due to changes in definitions or reporting standards. For more detailed information on the how the data was cleaned, please refer to the appendix in Fajnzylber et al. (1998).

[6] Most of the data was provided by Loayza et al. (1998). For some countries not covered by these authors, however, the conversion factors were constructed on the basis of information from World Bank databases.

[7] The unemployment rate is an economic-activity variable commonly used in the theoretical and U.S. empirical literatures. We do not consider it here given that definitional disparities make unemployment rates not comparable across countries.

alternative Gini figures (also provided by Deininger and Squire 1996). The Gini coefficients originally based on expenditure information were adjusted to ensure their comparability with the indices based on income data.[8] The education variable is a measure of the stock of human capital in a given country and is given by the average years of schooling of the population over 15 years of age, as calculated by Barro and Lee (1996).

3.1.2. Deterrence

We use two variables to proxy for the probability of being caught and for the corresponding severity of the punishments. First, we use the number of police personnel per 100,000 inhabitants, constructed on the basis of data from the U.N. World Crime Surveys. This variable is introduced as the average for all time periods for which it is available and is treated as an exogenous variable in the regressions.[9] Second, we use the existence of the death penalty, whose information was obtained from Amnesty International. This variable is also introduced as the average for the whole period, and since some countries changed their stance towards the death penalty between 1970 and 1994, the average ranges between 0 and 1. It is also considered as an exogenous variable in the corresponding regressions.

3.1.3. Drugs

We use two specific variables as measures of the size of illegal drug activities in a country. The first is the number of drug possession offenses per 100,000 population, which we calculated on the basis of data from the United Nations World Crime Surveys. We introduce this variable as the average for all years for which it is available and is considered to be exogenous in the empirical exercises.[10] The second measure is a 'dummy' variable that takes the value of one when a country is listed as a significant producer of any illegal drug in any of the issues of the U.S. Department of State's *International Narcotics Control Strategy Report* – which has been published on an annual basis since 1986. This variable does not vary over time either and we treat it as exogenous in the corresponding regressions.

3.1.4. Demographics and culture

The demographic factors we consider are the rate of urbanization and the proportion of the total population encompassed by males belonging to the

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[8] We followed Deininger and Squire (1996, p. 582) by adding to the indices based on expenditure the average difference of 6.6 between expenditure-based and income-based coefficients.

[9] The limited over-time availability of these data prevented us from using its lagged values as instruments.

[10] As in the case of the 'deterrence' variables, the limited over-time availability of the drug-related variables prevented the use of their lagged values as instruments.

15–29 age group, as measured by World Bank statistics. These two demographic variables are introduced in the form of 5-year averages and are treated as endogenous in the corresponding regressions. To roughly account for cultural characteristics, we include religion and region 'dummies' in the empirical analysis. The religions we consider are Christian, Buddhist, Hindu, and Muslim. Each religion 'dummy' takes the value of one for countries in which the corresponding religion has the largest number of followers, according to information from the *CIA Factbook* and Regional dummies were assigned, respectively to, first, the industrialized countries of Western Europe, North America, Australia and New Zealand; second, countries of South and East Asia (including Japan); third, Eastern Europe and Central Asia; fourth, Latin America and the Caribbean; and, fifth, the Middle East and Northern Africa. Regions and religions are considered to be exogenous variables in the empirical analysis.

3.2. Econometric methodology

Working with panel data allows us to overcome, at least partially, some of the estimation problems that have troubled empirical studies on the causes of crime. Combining the time-series with the cross-country dimensions of the data can add important information and permit a richer model specification. First, we would like to consider the variables that drive the differences in crime rates across countries. These are variables that vary slowly over time but significantly from one country to the rest. Some of them are income inequality, the capacity for drug production, and the strength of the police and justice system. Second, we would like to consider the information provided by variables that vary significantly over time. This is the case of GDP growth, whose time-series variance can allow us to test business-cycle effects on the incidence of crime. Using panel data, we can also consider the effect of variables that vary both over time and across countries. This is the case of indicators of the overall level of development, such as per capita GNP, educational attainment, urbanization, and the age composition of the population.

Third, by considering the patterns of crime rates for a given country over time, we can test whether there is inertia in crime rates. In the regression model, we test for inertia by including the lagged crime rate as an explanatory variable. Fourth, we would like to control for the joint endogeneity of some of the explanatory variables. It is likely that the incidence of crime not only is driven but also affects a number of economic and social variables. For instance, if crime occurs mostly among the poor, more crime may result in higher income inequality. Likewise, higher crime rates may scare away domestic investment and, thus, hurt economic growth. In extreme cases, the incidence of crime and violence may alter the urban structure of the country and even its age composition. Controlling for joint endogeneity is essential to obtain consistent estimates of the effect of various economic and social variables on crime rates. As explained below, panel data allows the use of lagged values of the explanatory variables as instruments to deal with joint endogeneity issues. Finally, the use of panel data allows us to control for the effect of unobserved variables that vary little over time and can, thus, be considered as country-specific effects. Examples of these underlying factors are political institutions and regimes, ethnic structures, and cultural norms. Furthermore, in the context of crime regressions, possibly the most important unobserved country-specific effect is the systematic error involved in the measurement of crime rates. By controlling for these specific effects, we are reducing the estimation bias due to the underreporting of crime.

Our econometric methodology follows the generalized method of moments (GMM) estimator applied to dynamic models of panel data. This estimator was developed by Chamberlain (1984), Holtz-Eakin et al. (1988), and, particularly, Arellano and Bond (1991), and Arellano and Bover (1995). The following is a brief presentation of our dynamic GMM estimator.

Consider the following dynamic model with unobserved country-specific effects:

$$y^*_{i,t} = \alpha y^*_{i,t-1} + \beta' X_{i,t} + \eta_i + \varepsilon_{i,t}, \tag{8}$$

where y^* is the actual homicide rate, X is a set of explanatory variables, η_i is a country-specific unobserved factor, and ε is the regression error term. The country-specific factor η_i is a random effect possibly correlated with the explanatory variables; it varies across countries but not over time (see Chamberlain, 1984). The error term ε may be correlated with at least a subset of the explanatory variables, as detailed below. It varies both across countries and over time. The subscripts i and t denote country and time period, respectively.

Available data on crime rates suffers from measurement error. We assume that this error is driven by specific characteristics of each country. These characteristics vary little over time and, thus, can be modeled as a country-specific effect:[11]

$$y_{i,t} = y^*_{i,t} + \xi_i. \tag{9}$$

Substituting (9) into (8)

$$y_{i,t} = \alpha y_{i,t-1} + \beta' X_{i,t} + [\eta_i + (1-\alpha)\xi_i] + \varepsilon_{i,t},$$

$$y_{i,t} = \alpha y_{i,t-1} + \beta' X_{i,t} + \mu_i + \varepsilon_{i,t}. \tag{10}$$

[11] More generally, we could model the measurement error as having both a fixed country effect and a time-varying component. Given our lagged-dependent variable model, the time-varying measurement error would make the regression error term follow a moving average process of order 1. In this case, we could not use the most recent lags as instruments, which would reduce the efficiency of estimation. However, as explained later, we find no evidence that the regression error term is serially correlated once we account for country effects. This supports the way we model the measurement error in crime rates.

Therefore, the measurement error in crime rates is subsumed in the unobserved country-specific effect of our model.

Eq. (10) is our basic regression model. To estimate it we use the dynamic GMM estimator mentioned above. In particular, we base most of our estimates on the so-called *system GMM* estimator, which joins in a single system the regression equation in differences and in levels, each with its specific set of instrumental variables.

For ease of exposition, we discuss each section of the system separately, although 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 Eq. (10) yields

$$y_{i,t} - y_{i,t-1} = \alpha(y_{i,t-1} - y_{i,t-2}) + \beta'(X_{i,t} - X_{i,t-1}) + (\varepsilon_{i,t} - \varepsilon_{i,t-1}). \quad (11)$$

The use of instruments is required to deal with two issues: first, the likely endogeneity of the explanatory variables, X which is reflected in the correlation between these variables and the error term; and, second, the correlation, by construction, between the new error term, $(\varepsilon_{i,t} - \varepsilon_{i,t-1})$, and the differenced lagged dependent variable, $(y_{i,t-1} - y_{i,t-2})$. Instead of assuming strict exogeneity (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 crime 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:[12]

$$E[y_{i,t-s}(\varepsilon_{i,t} - \varepsilon_{i,t-1})] = 0 \quad \text{for } s \geq 2,\ t = 3, \ldots, T, \quad (12)$$

$$E[X_{i,t-s}(\varepsilon_{i,t} - \varepsilon_{i,t-1})] = 0 \quad \text{for } s \geq 2,\ t = 3, \ldots, T. \quad (13)$$

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

[12] The GMM estimator simply based on the moment conditions in (12) and (13) 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. See Alonso-Borrego and Arellano (1996) and Blundell and Bond (1997).

following stationarity property:

$$E[y_{i,t+p}\ \mu_i] = E[Y_{i,t+q}\mu_i] \quad \text{and} \quad E[X_{i,t+p}\mu_i] = E[X_{i,t+q}\mu_i]$$

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:[13]

$$E[(y_{i,t-s} - y_{i,t-s-1})(\mu_i + \varepsilon_{i,t})] = 0 \quad \text{for } s = 1, \tag{14}$$

$$E[(X_{i,t-s} - X_{i,t-s-1})(\mu_i + \varepsilon_{i,t})] = 0 \quad \text{for } s = 1. \tag{15}$$

Using the moment conditions presented in Eqs. (12)–(15), 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.

The consistency of the GMM estimator depends on whether lagged values of the explanatory variables are valid instruments in the crime-rate regression.[14] We address this issue by considering two specification tests suggested by Arellano and Bond (1991). The first is a Sargan test of over-identifying restrictions, which tests the null hypothesis of overall validity of the instruments by analyzing the sample analog of the moment conditions used in the estimation process. Failure to reject this null hypothesis gives support to the model. The second test examines the hypothesis that the error term $\varepsilon_{i,t}$ is not serially correlated. We test whether the differenced error term (that is, the residual of the regression in differences) is first- and 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, thus, that the instruments are misspecified. On the other hand, if the test fails to reject the null hypothesis of no second-order serial correlation, we conclude that the original error term is serially uncorrelated and the moment conditions are well specified.

[13] 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).

[14] Time-series non-stationarity of the variables included in the empirical model is not of concern in the present case. First, all of the asymptotic properties of our GMM estimator rely on the cross-sectional dimension of the sample (in our case, the time-series dimension is quite small). Given that all asymptotic moments are well defined in the cross-sectional dimension, normal statistical inference can be applied. Second, our econometric model belongs to the class of correlated random effects models. In this class of models, unbiased estimation is based on some of form of differencing, which is also the procedure used to eliminate unit roots.

4. Results

This section presents the results of the regressions on homicide and robbery rates. Our basic equation includes five explanatory variables: the GDP growth rate, the log of per capita GNP, the Gini coefficient, the average years of schooling of the adult population, and the lagged dependent variable (either lagged homicide or robbery rates). As explained in the previous section, our main econometric methodology is the GMM-*system* estimator. For comparative purposes, we also use the GMM-*levels* estimator, which does not control for country-specific effects. For this estimator, both the regression equation and the instruments are expressed in levels. In contrast to the GMM-*system* estimator, first-order serial correlation is a sign of misspecification in the case of the *levels* estimator.

The dependent variable is measured in logs so that each estimated coefficient should be interpreted as the relative change in the crime rate that is caused by a unit change in the corresponding explanatory variable. Given that the regressions include the lagged dependent variable, each estimated coefficient represents the short-run effect of the respective variable. To obtain long-run effects, each coefficient should be divided by 1 minus the coefficient on the lagged dependent variable.

Table 1 presents the regression results that allow a comparison of the GMM-*system* and GMM-*levels* estimators applied to the basic regressions of homicide and robbery rates. In Tables 2–5 we report the results of eight additional specifications for each type of crime, using only the GMM-*system* estimator. These additional regressions are designed to test both the robustness of our 'core' results and the relevance of other potentially important crime determinants.

4.1. Homicides

The first regression reported in Table 1 does not control for country-specific effects and omits the lagged dependent variable. Only the GDP growth rate and the Gini index have significant coefficients, with negative and positive signs, respectively. However, this specification is rejected by the tests of serial correlation, which indicate that we have either omitted variables with high over-time persistence or ignored dynamic effects coming from the lagged dependent variable. In the second regression reported in Table 1, we include the lagged homicide rate but continue to ignore country-specific effects. The inclusion of the lagged dependent variable is justified by the possible existence of inertia in crime rates, as stressed by recent theoretical models (e.g., Sah, 1991; Glaeser et al., 1996). The regression results indicate that this is in fact a relevant issue, as the coefficient of the lagged homicide rate is highly significant and the specification tests now support the estimated model. In this specification, only the GDP

Table 1
Homicide and robbery rates: Core model. Estimation technique: GMM-levels and GMM-system estimator (*t*-statistics are presented in parentheses below their corresponding coefficients)

	Dependent variable					
	Log of intentional homicide rate			Log of robbery rate		
Estimation technique Explanatory variables	GMM-levels [1]	GMM-levels [2]	GMM-system [3]	GMM-levels [4]	GMM-levels [5]	GMM-system [6]
Constant	− 1.8213	− 0.5548	− 0.3886	− 3.5994	0.1846	− 0.4965
	(− 1.02067)	(− 0.60248)	(− 0.52762)	(− 1.54279)	(0.27523)	− (0.86584)
Lagged dependent variable		0.8419	0.7263		0.9621	0.7673
		(14.9025)	(12.2731)		(21.6544)	(23.4132)
Growth rate (% annual change in real GDP)	− 0.0605	− 0.0455	− 0.0239	− 0.1705	− 0.0463	− 0.1468
	(− 1.6928)	(− 2.7900)	(− 2.9616)	(− 3.1040)	(− 2.3259)	(− 10.3282)
Average income (log of GNP per capita in U.S. $)	− 0.0307	− 0.0065	0.0090	0.3208	0.0111	0.1280
	(− 0.1926)	(− 0.0787)	(0.0783)	(1.8001)	(0.1804)	(2.4637)
Income inequality (Gini coefficient)	0.0813	0.0212	0.0146	0.1009	− 0.0009	0.0258
	(3.6855)	(1.8211)	(2.2671)	(2.8149)	(− 0.0977)	(3.7501)
Educational attainment (avg. yrs. of educ., adults)	0.0702	0.0270	0.0354	0.1454	0.0273	− 0.0016
	(1.1284)	(1.0440)	(0.6907)	(1.9388)	(1.5658)	(− 1.3333)
No. countries	45	45	45	34	34	34
No. obs.	136	136	136	102	102	102
Specification tests (*p*-values)						
(a) Sargan test	0.266	0.134	0.226	0.130	0.176	0.446
(b) Serial correlation						
First-order	0.000	0.975	0.068	0.039	0.037	0.043
Second-order	0.003	0.306	0.284	0.147	0.204	0.803

Table 2
Homicide rate: Deterrence and drugs. Estimation technique: GMM-system estimator (t-statistics are presented in parentheses below their corresponding coefficients)

Explanatory variables	Dependent variable: Log of intentional homicide rate			
	Deterrence		Drugs	
	[1]	[2]	[3]	[4]
Constant	− 3.5098	0.4234	− 1.0537	− 1.3046
	(− 4.6884)	(0.4549)	(− 1.5102)	(− 1.7084)
Lagged dependent variable	0.4820	0.7267	0.6007	0.6230
	(5.2070)	(12.0864)	(9.3867)	(9.6495)
Growth rate (% annual change in real GDP)	− 0.0395	− 0.0037	− 0.0316	− 0.0259
	(− 2.6655)	(− 0.4563)	(− 3.7848)	(− 2.0995)
Average income (log of GNP per capita in U.S. $)	0.4227	− 0.1185	0.0776	0.1076
	(2.8993)	(− 0.9845)	(0.7032)	(0.7627)
Income inequality (Gini coefficient)	0.0377	0.0178	0.0165	0.0306
	(4.3166)	(2.1770)	(2.5928)	(5.4550)
Educational attainment (avg. yrs. of educ., adults)	− 0.0554	0.0762	0.0492	− 0.0433
	(− 0.7109)	(1.6568)	(1.0932)	(− 0.6194)
Police (per 100,000 pop.)	− 0.0009			
	(− 1.8348)			
Death penalty (dummy)		− 0.3457		
		(− 2.5133)		
Drug production (dummy for drug producers)			0.6341	
			(4.1709)	
Drug possession (drug possession crime rate)				0.0020
				(2.2395)
No. countries	41	43	45	42
No. obs.	124	131	136	127
Specification tests (p-values)				
(a) Sargan test	0.306	0.421	0.34	0.434
(b) Serial correlation				
First-order	0.171	0.135	0.070	0.086
Second-order	0.636	0.318	0.306	0.340

growth rate and the Gini index are statistically significant and with the same signs as before.

A complementary way of dealing with the problem of autocorrelation in the residuals is to control for the presence of country-specific effects. One very important motivation for taking into account the existence of unobserved heterogeneity across countries is the possibility that countries differ in the degree to which their citizens underreport crimes. Likewise, the use of different

Table 3
Homicide rate: Demographics and culture. Estimation technique: GMM-system estimator (t-statistics are presented in parentheses below their corresponding coefficients)

Explanatory variables	Dependent variable: Log of intentional homicide rate			
	Demographics		Culture	
	[1]	[2]	[3]	[4]
Constant	− 0.0542	− 0.4549		
	(− 0.0932)	(0.7298)		
Lagged dependent variable	0.8294	0.8413	0.8031	0.8349
	(17.0926)	(19.9425)	(12.1633)	(9.1091)
Growth rate (% annual change in	− 0.0244	− 0.0101	− 0.0033	− 0.0298
real GDP)	(− 3.5504)	(− 1.1405)	(− 0.2934)	(− 3.5268)
Average income (log of GNP per capita	− 0.0194	− 0.1090	− 0.2852	0.4856
in U.S. $)	(− 0.2162)	(− 1.3164)	(− 1.7378)	(3.1283)
Income inequality (Gini coefficient)	0.0152	0.0194	0.0381	0.0379
	2.4394	2.4155	3.1492	4.8524
Educational attainment (avg. yrs. of	(0.0538)	(0.0820)	(0.1190)	(− 0.0434)
educ., adults)	1.2832	1.5793	1.7147	− 0.6786
Urbanization (% of pop. in urban	(− 0.0060)			
centers)	− 1.4097			
Young males (% males of ages		− 0.0352		
15–34 in pop.)		(− 1.3575)		
Region intercepts:				
Western Industrialized			0.7694	
			(0.7298)	
Latin America & Carribbean			0.2239	
			(0.2070)	
Eastern Europe & C. Asia			0.4257	
			(0.5469)	
Middle East & N. Africa			0.2621	
			(0.2539)	
South and East Asia			0.0685	
			(0.0702)	
Religion Intercepts:				
Christian				− 4.8910
				(− 4.5044)
Buddhist				− 4.9702
				(− 4.6520)
Hindu				− 3.7459
				(− 4.2614)
Muslim				− 4.3567
				(− 4.4248)
No. countries	45	44	45	45
No. obs.	136	133	136	136
Specification tests (p-values)				
(a) Sargan test	0.439	0.323	0.291	0.244
(b) Serial correlation				
First-order	0.042	0.105	0.083	0.044
Second-order	0.184	0.213	0.327	0.298

Table 4
Robbery rate: Deterrence and drugs. Estimation technique: GMM-system estimator (*t*-statistics are presented in parentheses below their corresponding coefficients)

Explanatory variables	Dependent variable: Log of robbery rate			
	Deterrence		Drugs	
	[1]	[2]	[3]	[4]
Constant	− 0.5720	0.1357	0.3626	− 1.3643
	(− 1.7125)	(0.1710)	(0.7206)	(− 3.8803)
Lagged dependent variable	0.8026	0.9286	0.7862	0.8194
	(26.97260)	(23.64258)	(22.44189)	(28.2520)
Growth rate (% annual change in real GDP)	− 0.1555	− 0.1231	− 0.1288	− 0.1268
	(− 7.32060)	(− 8.84293)	(− 7.87440)	(− 5.8804)
Average income (log of GNP per capita in U.S. $)	0.0798	− 0.0211	0.0227	0.1907
	(2.21980)	(− 0.27525)	(0.43302)	(4.6464)
Income inequality (Gini coefficient)	0.0270	0.0257	0.0204	0.0292
	(5.42560)	(2.46288)	(4.12029)	(5.7035)
Educational attainment (avg. yrs. of educ., adults)	0.0002	− 0.0014	0.0005	− 0.0010
	(0.17400)	(− 0.60134)	(0.37695)	(− 1.1286)
Police (per 100,000 pop.)	0.0008			
	(2.88602)			
Death penalty (dummy)		0.0354		
		(0.27095)		
Drug production (dummy for drug producers)			− 0.4025	
			(− 4.10333)	
Drug possession (drug possession crime rate)				− 0.0007
				(− 1.8220)
No. countries	33	33	34	33
No. obs.	99	98	102	99
Specification tests (*p*-values)				
(a) Sargan test	0.452	0.433	0.682	0.398
(b) Serial correlation				
First-order	0.034	0.033	0.041	0.047
Second-order	0.766	0.821	0.625	0.842

definitions and criteria for recording crime statistics could also lead to country-specific measurement errors. Provided that the factors that determine the underreporting – or underrecording – of crime rates are relatively stable over time, their impact can be modeled by the inclusion of a time-invariant country-specific component in the error term, as explained in the previous section. In addition, this term could capture other non-observable crime determinants

Table 5
Robbery rate: Demographics and culture. Estimation technique: GMM-system estimator (*t*-statistics are presented in parentheses below their corresponding coefficients)

Explanatory variables	Dependent variable: Log of robbery rate			
	Demographics		Culture	
	[1]	[2]	[3]	[4]
Constant	0.4696	0.6048		
	(1.1148)	(1.3929)		
Lagged dependent variable	0.7605	0.8826	0.7657	0.7751
	(18.83861)	(37.23451)	(20.3349)	(29.2284)
Growth rate (% annual change in real GDP)	− 0.1082	− 0.1226	− 0.1165	− 0.1295
	(− 7.76782)	(− 10.71832)	(− 5.7405)	(− 8.3427)
Average income (log of GNP per capita in U.S. $)	− 0.0757	0.0206	0.0901	0.0282
	(− 1.15435)	(0.74065)	(1.3002)	(0.5712)
Income inequality (Gini coefficient)	0.0142	0.0225	0.0185	0.0239
	(2.79228)	(4.56249)	(2.7701)	(3.7311)
Educational attainment (avg. yrs. of educ., adults)	0.0010	− 0.0004	− 0.0004	0.0002
	(0.58750)	(− 0.63691)	(− 0.3813)	(0.1584)
Urbanization (% of pop. in urban centers)	0.0135			
	(3.63641)			
Young males (% males of ages 15–34 in pop.)		− 0.0360		
		(− 1.23784)		
Region intercepts:				
Western Industrialized			− 0.1149	
			(− 0.1654)	
Latin America & Carribbean			0.1657	
			(0.2539)	
Eastern Europe & C. Asia			0.0792	
			(0.1465)	
Middle East & N. Africa			− 1.5433	
			(− 1.1685)	
South and East Asia			− 0.1209	
			(− 0.2192)	
Religion Intercepts:				
Christian				0.2979
				(0.5356)
Buddhist				0.0298
				(0.0488)
Hindu				− 0.4612
				(− 0.9122)
Muslim				0.1659
				(0.2917)
No. countries	34	34	34	34
No. obs.	102	102	102	102
Specification tests (*p*-values)				
(a) Sargan test	0.722	0.591	0.46	0.541
(b) Serial correlation				
First-order	0.046	0.047	0.041	0.043
Second-order	0.548	0.375	0.659	0.647

related to each society's tolerance and inclination for violent or illegal activities, provided that these characteristics are relatively stable over time.

We use the GMM-*system* estimator to control for unobserved country-specific effects that are potentially correlated with the explanatory variables. The corresponding results are presented in column 3 of Table 1. These results are supported by the specification tests and, once again, suggest that in the basic model the only significant determinants of homicide rates are the GDP growth rate, the degree of income inequality as measured by the Gini index, and the lagged homicide rate.[15] The coefficients on per capita GNP and educational attainment are not statistically significant; thus, economic development, as measured by these variables, does not appear to have an effect on the incidence of homicides.

Our results indicate that homicide rates are counter-cyclical: stagnant economic activity induces heightened homicide rates. Assuming that the level of economic activity has a larger impact on the legal sector, economic growth reflects variations in the opportunity cost of crime. Therefore, the negative coefficient on the GDP growth rate indicates that crime, in general, and homicides, in particular, decrease with an improvement in the availability of job opportunities (or rising wages) in the legal vis-à-vis the criminal labor market. This result may indicate that a large share of homicides result from economically motivated crimes that become violent.[16]

The positive effect of income inequality on the homicide rate can be interpreted as the impact of the difference between the returns to crime (as measured by the income of the victims) and its opportunity cost (as measured by the legal income of the most disfavored citizens). However, this argument, initially made by Ehrlich (1973, pp. 538–540), is based on the assumption that homicide victims are relatively richer than their killers and may not apply to crimes where victims and perpetrators share common social and economic characteristics. An alternative interpretation of the positive link between inequality and crime is that in countries with higher income inequality, individuals have lower expectations of lifetime improvement of their social-economic status through legal economic activities, which would decrease the opportunity cost of participating in illegal endeavors more generally. Moreover, lower perceived opportunities of lifetime economic improvement through established institutions could also lead to the discrediting of the latter and thus to a lessening of the moral loss associated with breaking the law.

There may be other factors explaining the positive link between inequality and crime. Bourguignon (1998, p. 2) argues that "… the significance of

[15] As explained in the section on methodology, in the context of the GMM-*system* estimator, the residual of the regression is the original error term in differences and thus is expected to exhibit first-order but not second-order serial correlation.

[16] An alternative explanation is that economic conditions may have a cognitive impact on individuals by affecting their moral values or tolerance for crime.

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". One such factor that could lead to a spurious correlation between income inequality and crime rates is the limited amount and the unequal distribution of crime prevention efforts that could be present in more unequal countries. We explore this possibility below when we include proxies of deterrence in our estimating equation. Other factors that could affect both income inequality and crime are absolute and relative poverty, the existence of educational inequality, and the degree of income and ethnic polarization. We have explored the importance of these factors in a companion paper (Fajnzylber et al., 1999), and our empirical results indicate that the effect of income inequality on intentional homicide rates is robust to the inclusion of these factors. Soares (1999), using victimization rates derived from national surveys, also finds a significant crime-inducing effect of income inequality.

The estimated coefficients for the growth rate and the Gini index are not only statistically significant, but they are also economically important in magnitude. The estimated coefficient on the growth variable implies that a 1-percentage point increase in the GDP growth rate is associated with a short-run 2.4 percent decline in the homicide rate. The estimated coefficient on the inequality variable implies that a one-percentage point increase in the Gini is associated with a 1.5 percent increase in the homicide rate, in the short-run.

The size of the coefficient on the lagged homicide rate declines when country-specific effects are considered but continues to be large and significant (column 3).[17] According to the GMM-*system* estimator, the coefficient on the lagged dependent variable implies a half-life of a unit shock to the homicide rate of about 10.8 years (or 2.2 five-year periods). The channels through which past crime breeds future crime can be presented in two groups. First, there is an internal dynamic in criminal behavior. Thus, the costs of performing criminal activities decline over time as criminals learn by doing, the moral loss of breaking the law is reduced by crime itself and by the social interactions with other criminals, and the job opportunities in the legal labor market suffer by the stigma associated with past criminal records. A second channel through which high crime rates can be perpetuated over time is the failure of the police and judicial systems to respond to jumps in the incidence of criminal behavior. This can lead to a reduction in the perceived probabilities of apprehension and conviction of criminals.

The first two columns of Table 2 report the results of the regressions that include indicators related to crime prevention efforts. They are the average

[17] It appears that when unobserved time-invariant determinants of homicide rates are not considered in the estimation, their effect is captured by the lagged dependent variable, which causes an upward bias in its coefficient.

number of policemen per 100,000 population and the existence of the death penalty. The police variable is intended to capture the probability of detection and punishment, while death penalty is employed as a rough indicator for the severity of punishment of offenders. Limited data availability (police) and narrow over-time variability (death penalty) prevents us from treating the two variables as endogenous in the GMM-*system* estimator. Since countries with a high incidence of homicides could react by increasing the size of their police force and by toughening their criminal legislation, there would be a positive bias in the estimated coefficients of police and death penalty. Note, however, that the estimated coefficients are negative for the two variables. Therefore, given the possible presence of positive bias in their estimates, the negative coefficients on police and death penalty provide support for the notion that crime-prevention efforts do have a negative impact on the incidence of homicides. We should, however, take these results with caution given that the indicators of crime-prevention efforts we use are only rough proxies. The strength of police and the death penalty are themselves the result of complex political and cultural processes, and, thus, our control for country-specific effects may not have been sufficient to isolate their exogenous effect on crime rates.

The last two columns of Table 2 present regressions that include two different indicators of illegal drug activities. The first is a dummy variable that identifies the countries that are significant producers of illegal drugs; the second is the rate of drug possession crimes per 100,000 population. As it is well known, the illegal drug trade generates very high profits and is usually accompanied by violent disputes for market shares among different networks of producers and distributors. The presence of such networks can also have an indirect impact on national homicide rates, through the provision of externalities to other organized criminal activities. Furthermore, the intellectual and moral decay associated with the consumption of illegal drugs can contribute to the proliferation of other violent crimes. These arguments are consistent with our finding that both drug-related variables have positive and significant coefficients in their respective homicide regressions. However, as in the case of deterrence, lack of data prevents us from treating the drug-related variables as endogenous. Therefore, their positive coefficient may also reflect reverse causality. This is particularly the case of the drug possession crime rate.[18] On the other hand, the drug production dummy may be less subject to estimation biases due to the fact that the production of illegal drugs respond mostly to climatic characteristics (e.g., abundant rain in the high-altitude forests of Colombia and Bolivia) and geographic location of the country (such as the proximity of Mexico to the U.S.) and less so to prevalent crime rates.

[18] Furthermore, it is important to highlight the fact that the results in column (4) cannot be interpreted as reflecting the effects on homicides of drug consumption per se. A high number of drug possession crimes does not necessarily reflect a high incidence of drug consumption, because it can also be the result of tough legislation regarding the punishment of illegal drug consumers.

The first two columns of Table 3 examine the effect of demographic variables. As argued in the theoretical section, some demographic characteristics may promote an environment conducive to criminal activities. For instance, the interaction between criminals and would-be criminals may be easier in urban agglomerations than in rural areas (Glaeser and Sacerdote, 1999). Also, a high proportion of young males in total population may promote more violent acts. Although these arguments may be compelling, we do not find evidence that demographic factors per se affect homicide rates. In the first regression, we test the effect of the degree of urbanization and find that, after controlling for basic economic conditions, larger fractions of the population leaving in urban areas are not associated with higher homicide rates. Column 2 shows that, although victims and perpetrators of homicides are most commonly young males, there is no evidence that an increase in the relative size of this demographic group leads to a rise in national homicide rates.

The inclination for criminal activity may also be influenced by cultural characteristics. To account for cultural traits that may have an impact on crime rates, we group countries on the basis of their geographical location and the most common religious affiliation of the population.[19] Then, we introduce group-specific intercepts in our core regression, first on the basis of regional groups (Table 3, column 3) and second on the basis of the most common religion in each country (Table 3, column 4). In the core regression we have countries representing the following regions: Latin America and the Caribbean, Eastern Europe and Central Asia, Middle East and North Africa, South and East Asia, and Western Europe, the U.S., Canada, Australia, and New Zealand (Western Industrialized, for short). Our results indicate that none of the regional intercepts are significantly different from zero. However, when we test for the equality of the regional intercepts, we find that countries in the Western industrialized group have higher homicide rates than those in Latin America, South and East Asia, and the Middle East and North Africa, beyond what should be expected given their economic characteristics. Regarding the religion groups, we have countries representing the Buddhist, Hindu, Muslim, and Christian religions. All the religion intercepts are significantly negative. When we compare these intercepts with each other, we find that Hindu countries have lower homicide rates than any other group (controlling for the economic differences captured by the core regressors).[20]

[19] Note that we are including country-group dummies in a model that controls for country-specific effects. Therefore, in this case, the unobserved country-specific effect is what remains after common group characteristics are controlled for. The inclusion of group dummies can be regarded as a partial solution to the problem of unobserved country effects.

[20] In Table 3, we report only the estimated group intercepts and the corresponding t-statistics. Naturally, the relevant conclusions on country-group effects should be drawn not from the intercepts themselves but from the differences between them. Therefore, in order to make statistical inferences on intercept differences, we use the full variance–covariance of the estimated coefficients.

As mentioned before, we conducted the extensions to our basic model not only to test for the effects of additional variables but also to check the robustness of the basic results reported in Table 1. In this respect, we can say that the sign and significance of the coefficients on the Gini index and the lagged homicide rate were not affected by the inclusion of any of the additional control variables. As for the GDP growth rate, the sign of its coefficient remained negative in all of the eight exercises. However, it lost its significance when the death penalty, the fraction of young males, and the regional dummies were included. The signs and significance of our two other basic variables – per capita GNP and educational attainment – did not show a consistent pattern.

4.2. Robberies

The results of the basic robbery regression are similar to those of the homicide rate. As Table 1 shows, the regressions that ignore country-specific effects fail the first-order serial correlation test and have borderline p-values for the Sargan test. This is the case whether the lagged robbery rate is ignored (column 4) or taken into account (column 5). In contrast, the regression that uses the GMM-*system* estimator (column 6) passes the specification tests, having p-values for the Sargan and second-order serial correlation tests well above standard significance levels. Therefore, as in the case of homicide regressions, we base our analysis of the core and extended models for the robbery rate on the GMM-*system* estimator. In the core model (column 6), we find that the significant variables in the homicide regression are also significant and with the same sign in the robbery regression. The coefficient on the lagged robbery rate reveals a large degree of inertia, slightly higher than for the homicide rate. Note that the estimated inertial coefficient is larger when country-specific effects are ignored (column 5). However, the fact that it retains its significance under the GMM-*system* estimator means that the persistence in robbery rates follows from the dynamic properties of crime, as emphasized in Section 1 and the theoretical model. In this case, the implied half-life of a unit shock to the robbery rate is about 13.1 years (or 2.6 five-year periods).

An increase in the growth rate is associated with a significant fall in the robbery rate. The magnitude of the estimated coefficient using the system estimator implies that a 1 percentage-point increase in the GDP growth rate is associated with a short-run 13.7% decline in the robbery rate, which is a much larger impact than for homicides. This result supports the view that economic conditions related to the economic cycle, such as employment opportunities and salaries in legal activities, have a strong impact on the incidence of crime. The effect of inequality on robbery rates is also significant. The estimated coefficient in column 6 of Table 1 implies that a one percentage point increase in the Gini is associated with a short-run increase of 2.6% in the robbery rate, which is similar in magnitude to the estimated impact of inequality on homicide rates. When we combine the crime-inducing impact of higher inequality with that of lower GDP growth, we can conclude that the *rate* of poverty alleviation is a significant determinant of crime rates.

It is noteworthy that the lagged robbery rate, the GDP growth rate, and the Gini index, are always significant in the extensions to our basic model (Tables 4 and 5). Thus, these results are robust to the inclusion of variables related to deterrence, illegal drug activities, and demographic and cultural factors. The fact that the main results in the robbery regression are similar to those in the homicide regression supports the contention that homicides also reflect property crimes and, thus, can be analyzed with an economic model.

Regarding the other core variables, educational attainment does not carry a statistically significant coefficient. This result, already present in the homicide regression, confirms the 'education puzzle' first noticed by Ehrlich (1975b). The average level of income appears to be positively related to the robbery rate. This result, however, is not robust to the inclusion of additional variables.

The first two columns of Table 4 address the issue of deterrence. In this case, the results for the robbery rate are different from those of the homicide rate. First, the number of police, relative to the size of the population, carries a positive and significant coefficient, which is likely to reflect a direction of causality running from robbery rates to police personnel. Second, the death penalty dummy has no significant relationship with the robbery rate. One possible interpretation for this finding is that the death penalty has a deterrent effect for only major crimes. However, the fact that we do not control for the joint endogeneity of the death penalty (beyond the control of economic conditions and country-specific effects) obscures the interpretation of its different effects on homicide and robbery rates.

The last two columns of Table 4 consider variables related to illicit drug activities. Both the dummy for drug production and the drug possession crime rate carry a surprisingly negative and significant coefficient. A possible explanation is that drug activities are substitutes of economically motivated crimes. Whereas homicides can be considered a byproduct of illegal drug activities (which explains their positive association), robberies may compete for resources with those activities (resulting in a negative coefficient). However, the fact that we do not control for the joint endogeneity of drug possession and production obscures the interpretation of their negative association with the robbery rate.

Table 5 deals with the effect of demographic and cultural factors on robbery rates. The first two columns consider the degree of urbanization of the country and the fraction of young males in the population. In contrast to the homicide regression, an increase in the degree of urbanization leads to a rise in the robbery rate. This type of property crime seems to be an urban phenomenon, apparently more than homicides. The last two columns of Table 5 consider region and religion intercepts. Only the intercept corresponding to the Middle East and Northern Africa is significantly different from zero (with a negative sign). However, when we compare the region intercepts with each other, we find not only that countries in the Middle East and North Africa have a lower incidence of robberies than any other region (controlling for economic conditions, of course). We also find that Latin America has a higher incidence of robberies than any other region. Regarding the effect of the country's major religion, the comparison across intercepts yields a significantly negative Hindu dummy variable. Recalling the results from the previous section, we conclude that Hindu countries have lower homicide and robbery rates than any other religion group, controlling for the economic conditions captured by the core regressors.

5. Conclusions

The results from cross-country analysis provide strong evidence in favor of a model of criminal behavior that emphasizes the role of economic variables and accounts for inertial effects. Both economic growth and income inequality are robust determinants of violent crime rates. Furthermore, even after controlling for country-specific effects (including systematic measurement error), there is clear evidence that violent crime is self-perpetuating. These variables – economic growth, inequality, and past crime rates – worked well for homicides and remarkably well for robbery rates. Their sign and statistical significance survived the addition of other explanatory variables, including measures of crime deterrence, illicit drug activities, demographic characteristics, and cultural traits.

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Appendix A

Table 6 describes in detail the definitions and sources of all the variables used in the empirical analysis.

Table 6
Descriptions and sources of the variables

Variable	Description	Source
Intentional homicide rate	Death purposely inflicted by another person, per 100,000 population.	Constructed from the United Nations World Crime Surveys of Crime Trends and Operations of Criminal Justice Systems, various issues, except for Argentina, Brazil, Colombia, Mexico, and Venezuela. The data is available on the internet at http://www.ifs.univie.ac.at/ ~ uncjin/wcs.html # wcs123. The data on population was taken from the World Bank's International Economic Department database. For the five Latin American countries listed above, the source for the number of homicides was the Health Situation Analysis Program of the Division of Health and Human Development, Pan-American Health Organization, from the PAHO Technical Information System. This source provided us with data on the annual number of deaths attributed to homicides, which come from national vital statistics systems. Another exception is the United States for the 1990-94 period, for which 'intentional' homicide data is not available. In this case we used the ratio of 'intentional' homicides to total homicides in 1975–76 (72%) to deduce a proxy for the intentional homicides during 1990–94 based on the total number of homicides.
Robbery rate	Total number of robberies recorded by the police, per 100,000 population. Robbery refers to the taking away of property from a person, overcoming resistance by force or threat of force.	Same as above. No exceptions.

Police	Number of police personnel per 100,000 population.	Same as above.
Drug possession crime rate	Number of drug possession offenses per 100,000 population.	Same as above.
Drug producers dummy	Dummy that takes the value one for the countries which are considered significant producers of illicit drugs.	International Narcotics Control Strategy Report, U.S. Department of State, Bureau for International Narcotics and Law Enforcement Affairs, various issues.
Gini index	Gini coefficient, after adding 6.6 to the expenditure-based data to make it comparable to the income-based data.	Constructed from Deininger and Squire (1996). The dataset is available on the internet from the World Bank's Server, at http://www.worldbank.org/html/prdmg/grthweb/datasets.htm
Average years of schooling	Average years of schooling of the population over 15.	Barro and Lee (1996). The dataset is available on the internet from the World Bank's Server, at http://www.worldbank.org/html/prdmg/grthweb/datasets.htm
GNP per capita	Gross National Product expressed in U.S. dollars prices, based on an average of each country's real exchange rate.	Loayza et al. (1998).
Growth of GDP	Growth in the gross domestic product expressed in constant 1987 local currency prices.	The dataset is available on the internet from the World Bank's Server, at http://www.worldbank.org/html/prdmg/grthweb/datasets.htm
Urbanization rate	Percentage of the total population living in urban agglomerations.	Same as above.

Table 6. (*Continued*).

Variable	Description	Source
Buddhism dummy	Dummy for countries where Buddhism is the religion with the largest number of followers.	CIA Factbook. The data is available on the internet at http://www.odci.gov/cia/publications/pubs.html.
Christian dummy	Dummy for countries where Christian religions are the ones with the largest number of followers.	Same as above.
Hindu dummy	Dummy for countries where Hinduism is the religion with the largest number of followers.	Same as above.
Muslim dummy	Dummy for countries where Islam is the religion with the largest number of followers.	Same as above.
Asia dummy	Dummy for developing countries of East and South Asia.	Same as above.
Europe and Central Asia dummy	Dummy for developing countries of Europe and Central Asia.	Same as above.
Latin America dummy	Dummy for developing countries of Latin America.	Same as above.

Middle East dummy	Dummy for developing countries of the Middle East and Northern Africa.	Same as above.
Death penalty	Dummy for countries whose laws do (1) or do not (0) allow the death penalty. Some countries experienced changes, either abolishing or imposing the death penalty during 1970–94. Hence period averages range between 0 and 1.	Amnesty International. List of Abolitionist and Retentionist Countries at http://www.amnesty.org/ailib/intcam/dp/abrelist.htm#7.
Ratio of males aged 15–34 to total population	Ratio of number of males aged 15–34 to total population.	Pre-formatted projection tables in the World Development Indicators database of the World Bank.

Appendix B

Table 7 shows the countries and number of observations included in the homicide and robbery regressions.

Table 7
Countries included in the core regressions on homicide and robbery rates (observations correspond to 5-year averages)

Regions and Countries	Number of observations	
	Homicides	Robberies
Whole sample	181	136
Western industrialized	67	57
Australia	5	5
Austria	4	4
Canada	5	5
Denmark	5	
Finland	4	5
Germany	5	5
Greece	3	3
Italy	5	4
Netherlands	4	4
New Zealand	4	4
Norway	5	5
Spain	4	
Sweden	5	5
United Kingdom	4	3
United States	5	5
Latin America and the Caribbean	41	20
Argentina	4	
Brazil	3	
Barbados	3	3
Chile	3	3
Colombia	5	
Costa Rica	4	
Jamaica	3	4

Table 7. (*Continued*).

Regions and Countries	Number of observations	
	Homicides	Robberies
Mexico	5	
Peru	3	3
Trinidad & Tobago	3	3
Venezuela	5	4
Eastern Europe & Central Asia	15	11
Bulgaria	4	4
Czech Republic	4	
Hungary	3	3
Poland	4	4
Middle East & North Africa	10	3
Egypt	3	
Israel	3	3
Jordan	4	
Asia	48	45
Bangladesh	3	3
Hong Kong	3	3
India	5	5
Indonesia	5	5
Japan	5	5
Korea, Republic of	4	4
Malaysia	4	4
Nepal	3	3
Pakistan	3	
Singapore	4	4
Sri Lanka	4	4
Thailand	5	5

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