World-wide Crime

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This draft: January 2023

Abstract

This paper analyzes theoretically and empirically the determinants of crime. We develop a dynamic general equilibrium search model that builds on the Burdett et al. (2003) framework in four directions. We include an exogenous police force, which affects crime through a lower opportunity to commit crime and a higher probability of being caught. We include the government's budget constraint, with an endogenous tax rate. We specify a distribution function of wages, including location and Theil index parameters. Finally, we derive analytically the effects of key variables on the crime rate. The empirical specification follows closely our theoretical model for the crime rate, measured by the national homicide rate. Dynamic system GMM estimations are applied to aggregate data for a world panel of 68 advanced and developing countries for the 1974-2018 period. The results show that homicide rates are highly persistent, depend negatively on income levels, and positively on income inequality, the police force, and illegal drug prevalence.

Keywords: Crime, determinants of crime rates, cross-country study
JEL: O10, K42, C23

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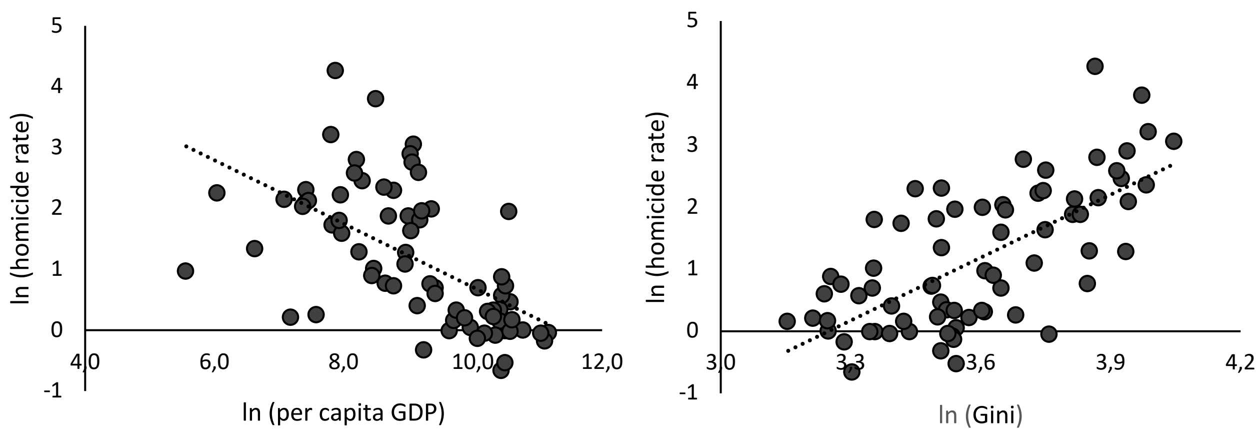
1. Introduction

Crime represents a major policy concern in most countries of the world. It has negative consequences for the well-being of citizens and the efficient performance of the economy.

Crime rates differ between countries and over time. Latin America and the Caribbean and Sub-Saharan Africa are the regions with the highest incidence of violent crime in the world.[1] Countries also differ substantially in many dimensions that may matter for crime, including average income, income inequality, unemployment, education, police force, severity of penalties, and illegal drug activity. Figure (1) depicts the negative cross-country correlation between the homicide rate and per capita GDP, and the positive cross-country correlation between the homicide rate and inequality.

Figure 1: Cross-country correlations between the homicide rate and per capita GDP, and between the homicide rate and the Gini coefficient



Note: data are presented in natural logarithms (ln). Data points represent long-term averages of each variable for each country included in the empirical section of this paper. The dotted lines depict statistical cross-country correlations estimated by OLS regressions.

The objective of this paper is to analyze theoretically and empirically the determinants of crime. We develop a dynamic general equilibrium search model of crime to identify the main determinants of world-wide crime. Then we perform econometric estimations of an empirical specification – that follows closely our theoretical model – for a large world panel database.

The economic literature on crime starts with Becker (1968), which shows that crime is the result of a rational decision based on an ex ante cost-benefit calculation of the criminal act. A higher expected value of the loot incentivizes crime, while a larger probability of being

[1] Dills and Miron (2010), Cook et al. (2011), and Tonry (2011) provide detailed descriptions of international crime data.

captured and a more drastic punishment discourage criminal actions. Then Stigler (1970) and Ehrlich (1973) examined the effects of some economic variables on the incidence of crime. Since then, the theoretical and empirical economic literature on crime has grown rapidly.

Becker's framework has some limitations. In particular, it is a static model and does not account for the mechanisms by which certain variables affect crime. Burdett et al. (2003, 2004) and Huang et al. (2004) develop innovative equilibrium search models for crime and other illegal activities. Burdett et al. (2003, 2004) model an environment where unemployment, income inequality, and crime are simultaneously determined in equilibrium, and analyze the effects of anti-crime policies on these three endogenous variables. Using a similar framework, Huang et al. (2004) add individuals' schooling decisions and investigate the equilibrium relations between educational attainment, labor market opportunities, poverty, and crime.

Empirical research has focused on the benefits and costs related to criminal actions.[2] [3] Empirical studies identify the following variables as the key determinants of crime rates in the world: the level and growth rate of income (Fleisher, 1966; Ehrlich, 1973; Ehrlich, 1976; Fleisher, 1996; Kelly, 2000; Fajnzylber et al., 2001; Soares, 2004; Dills and Miron, 2010), income inequality (Fleisher, 1966; Ehrlich, 1973; Fajnzylber et al., 2002; Dills and Miron, 2010), unemployment rate (Fleisher, 1966; Ehrlich, 1973; Fougère et al, 2000), educational level (Ehrlich, 1975; 1994; Soares, 2004; Lochner, 2010), police force (Levitt, 1996; Levitt, 1997; Lin, 2009), and the severity of criminal penalties (Ehrlich, 1973; Ehrlich 1975; Mathieson and Passell, 1976; Levitt, 1996 ; Levitt, 1997; Iyengar, 2010; Mocan and Gittins, 2010). Other studies have focused on sociological and institutional factors, such as social capital (Lederman et al., 2002), demographic composition by ethnic and age groups (Fajnzylber et al., 2002, Saridakis, 2004; Dills and Miron, 2010; Soares, 2010; Feld and Bishop, 2012), and the political system (Lin, 2007). Among the research based on international panel data, the largest cross-section dimension spans 45 countries and the longest time series covers from 1970 to 1994.

Starting from the economic theory of crime, we develop a dynamic general equilibrium search model to better understand the determinants of crime rates. Our theoretical specification builds on the model developed by Burdett et al. (2003) in their section I. We extend the Burdett et al. framework in four directions. We include an exogenous police force, which affects crime through a lower opportunity to commit crime and a higher probability of being caught. The second extension is the inclusion of the government's budget constraint, with an endogenous tax rate. Third, we specify a distribution function of

[2] Tonry (2011) provides a comprehensive review of the legal literature on criminology and criminal justice, focusing on the organization of the justice system, and the pattern of crime and victimization rates and their trends.

[3] Wilson and Petersilla (2011) review the literature on the effectiveness of public policies in preventing crime. Di Tella et al. (2010) survey the literature on the determinants of crime in Latin America.

wages, including location and Theil index parameters. Finally, we derive analytically the effects of key variables on the crime rate.

Note that this model is about common crime. As is the case of Burdett et al. (2003), our model is not well suited to analyze white-collar crime. For example, in a model of white-collar crime, the likelihood of committing crime could increase with the wage level, while in common-crime models the opposite relation is specified. Note also that there is no cross-country data available for an empirical specification of white-collar crime.

The empirical specification follows closely our theoretical model for the crime rate. The econometric analysis focuses on the determinants of intentional homicide rates for a world-wide panel of countries. Our world sample is comprised by 68 advanced and developing countries with 5-year data for the 1974-2018 period. We use the dynamic system GMM estimator as our main method of estimation, using alternative estimators selectively.

The empirical results generally provide evidence in favor of our model of criminal behavior. The results show that world-wide crime rates are highly persistent. They depend robustly and negatively on income levels, and robustly and positively on income inequality, the police force, and illegal drug prevalence.

The paper is organized as follows. Section 2 develops the dynamic general equilibrium search model of crime and labor-market variables, and derives analytically the effects of key variables on the crime rate. Section 3 presents the empirical specification, the estimation method, the world data sample, and the econometric results. Section 4 concludes.

2. A search model of criminal behavior

2.1 The Model

In this section we present a search model of crime that builds on the basic model developed by Burdett et al. (2003) in their section I. We extend their specification in four dimensions that are key for our analysis and subsequent empirical specification. As we progress in our model derivation, we point out our extensions.

The economy is populated by five classes of agents and the government. All agents are infinitely lived and risk neutral. There is a $[0,1-\alpha]$ continuum of homogeneous workers and a continuum $[0,\alpha]$ of homogeneous police officers, where $\alpha \in (0,1)$ is exogenous. The numbers of workers in each state are e (employed), u (unemployed), and n (jailed). There is neither capital nor saving; consumption in each state is restricted to wage income or government payments. At any point in time agents are either employed (at some wage w), unemployed, in jail or in the police force. The fifth agent class is a $[0,N]$ continuum of homogeneous firms. Each firm posts a wage that it is willing to pay any worker. In order to analyze explicitly the effects of changes in the average wage and in wage dispersion on crime, we depart from Burdett et al. by introducing below an explicit functional form for their generic cumulative distribution function (cdf) of wages, *F(w)*.

Unemployed workers consume b (unemployment insurance paid by the government) and receive independently and identically distributed (i.i.d.) wage offers from *F* at rate λ. Employed workers consume w, pay taxes at a rate t, receive i.i.d. wage offers from *F* at rate λ [4], and are laid off at rate δ. Jailed workers consume z (a government transfer), receive no job offers until released, and are released into unemployment at rate ρ. Note that that all sentences have the same expected length.

We extend Burdett et al. by introducing police officers who consume w_p (the police officers' wage, which is paid by the government) and their job is to prevent crime and capture criminals. Once captured, criminals are jailed. Police officers hold their jobs indefinitely and do not commit crime.

We also extend Burdett et al. by introducing the government. Its budget constraint determines an endogenous tax rate on wages, required to finance unemployment insurance payments, transfers to jailed workers, and the wage bill of police:

(1)
$$t\int_0^\infty w dF(w) = bu + \alpha w_p + zn$$

Employed and unemployed workers find opportunities to commit crimes at rate $\mu(\alpha)$. Departing from Burdett et al., where μ is a constant, we specify $\mu(\alpha)$ as a function that decreases with the number of police officers, reflecting the crime-prevention role of police. A crime opportunity is a chance to steal some amount g. The probability of being caught by police and sent to jail is $\pi(\alpha)$. Departing from Burdett et al., where π is a constant, we specify $\pi(\alpha)$ as a function that increases with the number of police officers, reflecting the crime-repression role of police. We define $\phi_1(w)$ (ϕ_0) as the probability that an employed (unemployed) worker commits a crime given an opportunity. The value functions are $V_1(w)$, V_0 , J, and P for employed workers, unemployed workers, jailed workers, and police officers, respectively. Let r be the rate of time preference.

The expected pay-off from crime for an employed (unemployed) worker is $K_1(w)$ (K_0), where:

(2)
$$K_0 = g + \pi(\alpha)J + \big(1 - \pi(\alpha)\big)V_0$$

(3)
$$K_1 = g + \pi(\alpha)J + \big(1 - \pi(\alpha)\big)V_1(w)$$

[4] For simplicity, λ is equal for employed and unemployed workers.

An unemployed worker commits a crime if and only if (iff) $K_0 > V_0$ and an employed worker commits a crime iff $K_1(w) > V_1(w)$. We assume for convenience that tie-breaking rules go the right way when agents are indifferent. Hence, the crime decision satisfies:

$$\phi_0 = \begin{cases} 1 & if \quad V_0 - J < \dfrac{g}{\pi(\alpha)} \\ 0 & if \quad V_0 - J > \dfrac{g}{\pi(\alpha)} \end{cases} \tag{4}$$

$$\phi_1(w) = \begin{cases} 1 & if \quad V_1(w) - J < \dfrac{g}{\pi(\alpha)} \\ 0 & if \quad V_1(w) - J > \dfrac{g}{\pi(\alpha)} \end{cases} \tag{5}$$

Employed and unemployed workers also fall victim to crime, at an exogenous rate γ. When victimized an employed (unemployed) worker suffers a loss equal to her wage: $l_1(w) = w$ (equal to her unemployment benefit: l_0 = b).[5]

The Bellman equations for unemployed, employed, and jailed workers, and for police officers, are:

$$rV_0 = b(1-\gamma) + \mu(\alpha)\phi_0(K_0 - V_0) + \lambda \mathrm{E}\left[\max_x\{V_1(x) - V_0, 0\}\right] \tag{6}$$

$$rV_1(w) = w(1-\gamma)(1-t) + \mu(\alpha)\phi_1(w)(K_1(w) - V_1(w)) + \delta\big(V_0 - V_1(w)\big) + \lambda \mathrm{E}\left[\max_x\{V_1(x) - V_1(w), 0\}\right] \tag{7}$$

$$rJ = z + \rho(V_0 - J) \tag{8}$$

$$rP = w_p \tag{9}$$

The flow return of an unemployed worker is her instantaneous unemployment benefit income (net of expected benefit income loss if victimized) plus the net expected value of receiving either a crime or a job opportunity. The flow return of an employed worker is her instantaneous wage income (net of expected wage loss if victimized and net of tax payment) plus the net expected value of income loss from being dismissed from her job and of receiving either a crime opportunity or a new job offer. The flow return of a jail inmate is the instantaneous government transfer plus the expected value of being released from jail

[5] We depart from Burdett et al. (2003), which assumes an exogenous loss that is equal for employed and unemployed workers. Our results reported below hold if we assume an exogenous loss that is equal for employed and unemployed workers.

into unemployment. Finally, the flow return of a police officer is her instantaneous police wage.

In order to analyze the job decision, we characterize the relation between the value functions of employed and unemployed workers. From equations (6) and (7) it can be shown that $V_1(0) < V_0$. As unemployed and employed workers are equally likely to commit crime and participate in the labor market, an employed worker earning a zero wage is strictly worse off than an unemployed worker who receives the government subsidy. We show in Appendix A that $V_1(w)$ in equation (7) is increasing and convex in w[6]. Therefore, an employed worker will accept any outside wage offer above his current wage, and an unemployed worker will accept any $w \geq R$, where R is the labor reservation wage defined by $V_1(R) = V_0$. Figure 2 depicts the job decision and the determination of reservation wage R.

Regarding the crime decision we focus now on the difference between the expected pay-off from crime and the value function for unemployed and employed workers. Unemployed workers will commit a crime iff $K_0 - V_0 > 0$. For employed workers, as $V_1(w)$ is increasing in w, equation (3) implies that $K_1(w) - V_1(w)$ is decreasing and concave in w, as shown in Appendix A. This implies that workers are less likely to commit a crime when their wages are higher. A condition for a positive crime rate is that $K_0 - V_0 > 0$. At the reservation wage, we have $K_0 - V_0 = K_1(R) - V_1(R)$. This implies that employed workers at the reservation wage engage in crimes iff unemployed workers do. Thus, if $\phi_0 = 0$, then $\phi_1(w) = 0$ for all w, and if $\phi_0 = 1$, then $\phi_1(R) = 1$. As $K_0 - V_0 < K_1(0) - V_1(0)$ and the decision to commit a crime decreases with the wage, then there exists a unique crime reservation wage (C) that satisfies: for any w < C, $\phi_1(w) = 1$, and for any w > C, $\phi_1(w) = 0$. Note that C satisfies $K_1(C) = V_1(C)$. By equation (3), at w = C the expected gain of crime is equal to the expected cost of crime; the latter is the likelihood of losing the job and going to jail: $g = \pi(\alpha)(V_1(C) - J)$. Figure 3 depicts the crime decision and the determination of crime reservation wage C.

In Appendix A we solve for the reservation wage and the crime wage. The corresponding equations are the following. Using (6) and (7) evaluated at w = R and rearranging yields:

(10)
$$R = \frac{b}{1-t}$$

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[6] V_0 is flat because the unemployed have a future wage expectation which is a constant that does not depend on the wage: it is the last term in equation (6).

Figure 2: Job Decision

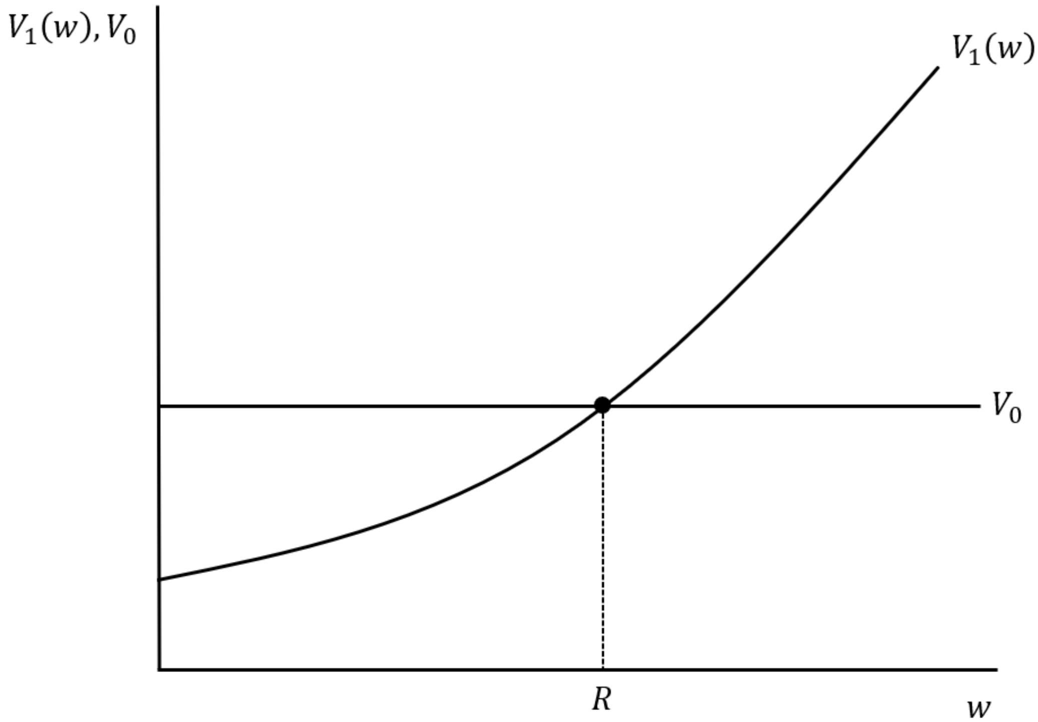
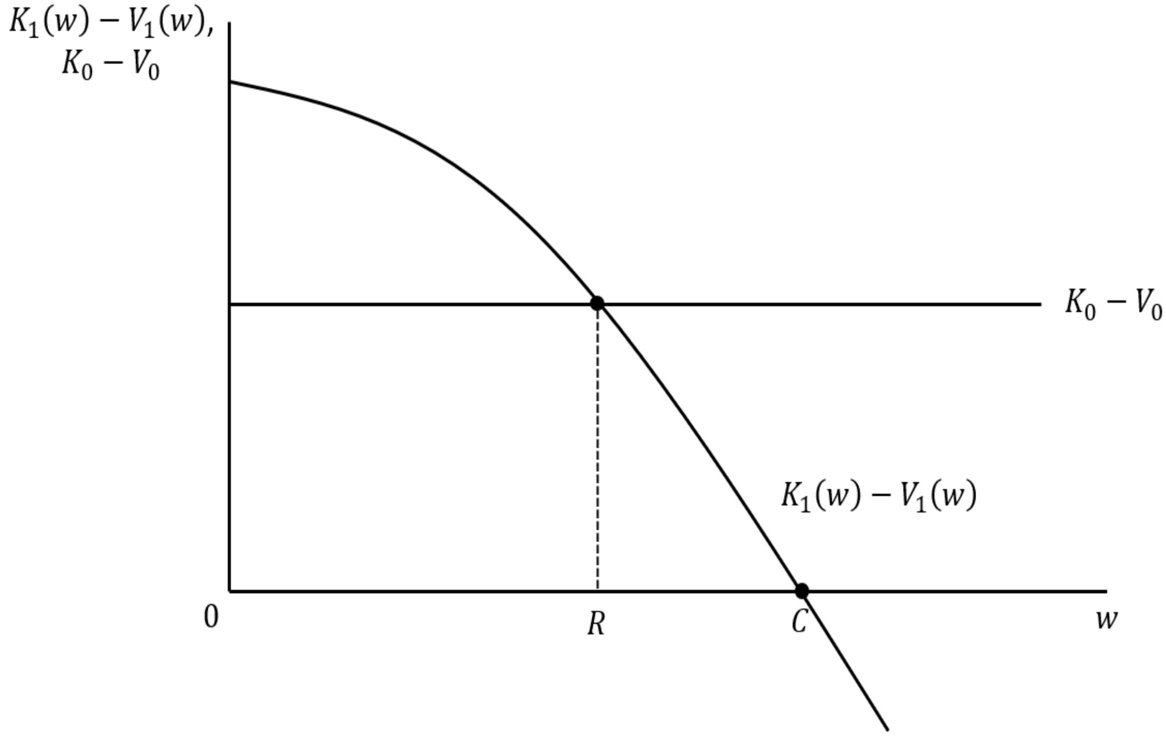


Figure 3: Crime Decision



At w = C, the gain of crime equals the expected cost of crime. Using equation (7) at w = C and (6), we have:

$$C = \frac{1}{(1-\gamma)(1-t)}\left(z + \frac{g}{\pi(\alpha)}(r+\delta) + (\rho-\delta)(V_0 - J) - \lambda\Delta C\right) \tag{11}$$

where:

$$\Delta C = \int_C^\infty \frac{(1-t)(1-\gamma)(1-F(x))}{r+\delta+\lambda(1-F(X))}dx \tag{12}$$

In order to obtain $V_0 - J$, we subtract (6) from (8) which yields:

$$V_0 - J = \frac{b(1-\gamma) - z + \mu(\alpha)g + \lambda\Delta R}{r + \rho + \mu(\alpha)\pi(\alpha)} \tag{13}$$

Let $\sigma = 1 - F(C)$ be the fraction of firms offering at least C. Departing from Burdett et al., we specify the following Pareto cdf for *F:*

$$F(w) = 1 - \left(\frac{R-\varphi}{w}\right)^\beta \tag{14}$$

where φ is the location parameter of the cdf, and $\beta > 1$ is the Theil Index parameter. An increase in φ reflects a higher average wage and an increase in β (or a decline in σ) reflects higher wage dispersion or income inequality. We solve the model for $\varphi = 0$ and subsequently analyze the effect of higher values of φ. Then $\sigma = \left(\frac{R}{C}\right)^\beta$ decreases with β, as R is smaller than C.

Now we derive the transition dynamics for employed, unemployed, and jailed workers, where s denotes a time period. Employed workers are divided into high-wage workers e_H (those that earn w > C) and low-wage workers e_L (those that earn a wage that satisfies R < w < C). The workers' flows are the following:

$$e_{H,s+1} = (1-\delta)e_{H,s} + \lambda\sigma e_{L,s} + \lambda\sigma u_s \tag{15}$$

$$e_{L,s+1} = (1-\delta-\mu(\alpha)\pi(\alpha)-\lambda\sigma)e_{L,s} + \lambda(1-\sigma)u_s \tag{16}$$

$$u_{s+1} = (1-\lambda-\mu(\alpha)\pi(\alpha))u_s + \delta e_{L,s} + \delta e_{H,s} + \rho n_s \tag{17}$$

$$n_{s+1} = (1-\rho)n_s + \mu(\alpha)\pi(\alpha)e_{L,s} + \mu(\alpha)\pi(\alpha)u_s \tag{18}$$

Now let's turn to the economy's steady-state equilibrium. In steady state any variable X satisfies $X_{s+1} - X_s = 0$. Imposing the latter condition on equations (15) - (18), we obtain:

$$\delta e_H^{ss} = \lambda\sigma e_L^{ss} + \lambda\sigma u^{ss} \tag{19}$$

$$e_L^{ss}(\delta + \mu(\alpha)\pi(\alpha) + \lambda\sigma) = \lambda(1-\sigma)u^{ss} \tag{20}$$

$$u^{ss}\big(\lambda + \mu(\alpha)\pi(\alpha)\big) = \delta e_L^{ss} + \delta e_H^{ss} + \rho n^{ss} \tag{21}$$

$$\rho n^{ss} = \mu(\alpha)\pi(\alpha)e_L^{ss} + \mu(\alpha)\pi(\alpha)u^{ss} \tag{22}$$

Solving the latter system of equations yields:

$$e_H^{ss} = \frac{(1-\alpha)(\delta + \mu(\alpha)\pi(\alpha) + \lambda)\rho\lambda\sigma}{\Omega} \tag{23}$$

$$e_L^{ss} = \frac{(1-\alpha)(1-\sigma)\rho\delta\lambda}{\Omega} \tag{24}$$

$$u^{ss} = \frac{(1-\alpha)(\delta + \mu(\alpha)\pi(\alpha) + \lambda\sigma)\rho\delta}{\Omega} \tag{25}$$

$$n^{ss} = \frac{(1-\alpha)(\delta + \mu(\alpha)\pi(\alpha) + \lambda)\mu(\alpha)\pi(\alpha)\delta}{\Omega} \tag{26}$$

where $\Omega = (\rho\delta + \rho\lambda\sigma + \delta\mu(\alpha)\pi(\alpha))(\delta + \mu(\alpha)\pi(\alpha) + \lambda)$, which is the variable that makes $e_L^{ss} + e_H^{ss} + n^{ss} + u^{ss} = 1 - \alpha$.

The stationary equilibrium equations (23) - (26) are similar to those derived by Burdett et al. The differences stem from our introduction of the government budget constraint (and its endogenous tax rate) and the introduction of the police force. The latter variables affect the dynamics and the stationary equilibrium of our model, as shown by our analytical derivation of crime determinants below.

Finally, we define the per capita crime rate (c), consistent with our model, as:

$$c = \frac{\mu(\alpha)(u + e_L)}{1 - \alpha - n} \tag{27}$$

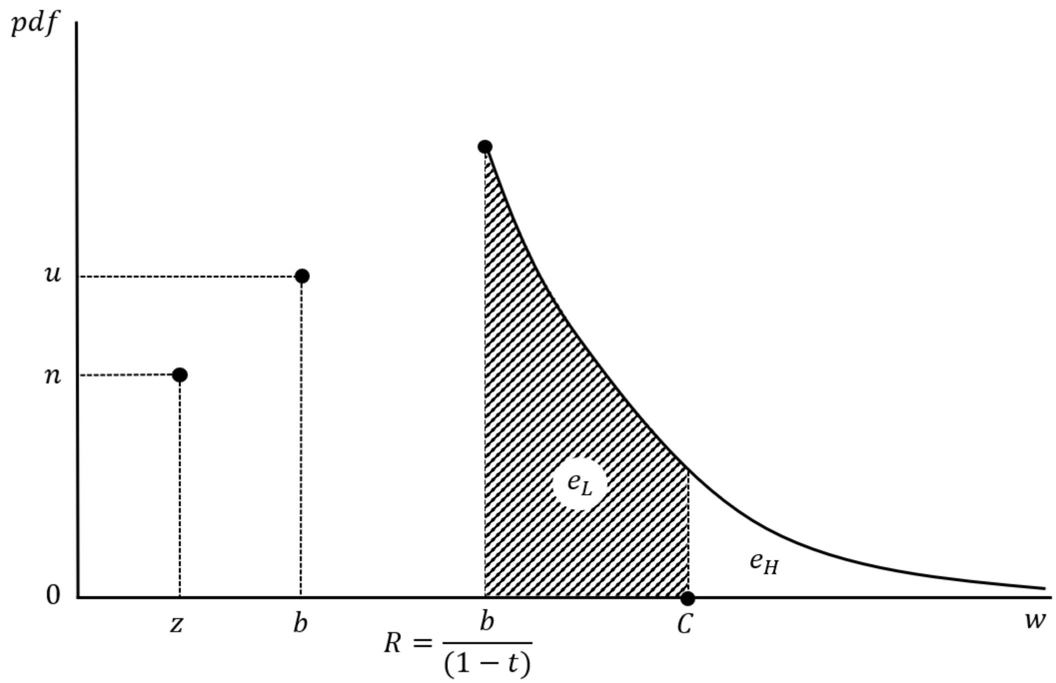
The latter equation reflects the crime rate as the ratio between the likelihood of committing a crime applied to the sum of unemployed and low-wage workers, and the sum of total employed and unemployed workers.

Appendix A derives the corresponding stationary crime rate as:

(28)
$$c^{ss} = \frac{\mu(\alpha)\delta}{\delta + \lambda\sigma}$$

Figure 4 depicts the stationary distribution of employed, unemployed, and jailed workers.

Figure 4: Stationary distribution of workers, unemployed, and jailed workers



Note: the distributions of unemployed and jailed workers are u and n, respectively.

2.2 Determinants of crime

In this section we derive and discuss the effects on the crime rate of key variables: the average wage, wage inequality, number of police officers, and crime penalty. Appendix A derives the partial derivatives of crime with respect to the latter variables and to crime gain.

In analyzing the effects of each of these variables on crime, we note the transmission mechanisms at work. There is a first mechanism similar to Burdett et al. (2003), where changes in exogenous variables modify the optimal solution of the agents' decisions, and therefore the reservation wages of work and crime. This modifies the distribution of individuals in jail, unemployment, and employment, and hence the crime rate. Our model develops a second mechanism, which is through the government budget constraint. Changes in exogenous variables also modify variables in the latter constraint, requiring an endogenous tax rate adjustment. This affects both labor and crime reservation wages and therefore modifies the crime rate, too.

To analyze the effect of a higher average wage, we increase the wage distribution's location parameter φ. If the expected value of F(w) is $\overline{w}$, then the average wage with a non-zero value of φ is:

$$\int_0^\infty w dF(w-\varphi) = \int_0^\infty (w-\varphi+\varphi) dF(w-\varphi) = \overline{w} + \varphi \tag{29}$$

The first mechanism of a higher location parameter is a reduction of the crime reservation wage through a higher opportunity cost of committing crime, caused by the prospect of a higher wage. This raises σ and lowers u, n, and e_L, and then lowers the crime rate. The second mechanism works through a reduced tax rate, which lowers further the crime reservation wage and the labor reservation wage. Both reservation wages are directly affected by the tax rate. However, the effect of a lower tax is smaller for the crime reservation wage than for the labor reservation wage because the former effect takes into account the prospects of higher net future wages. A lower tax rate raises σ (as C declines by more than R), lowering the crime rate even further. Hence a higher average wage unambiguously lowers the crime rate.

Now we analyze the effects of higher wage inequality, reflected by an increase in the Theil index parameter β[7]. The first mechanism of a higher level of inequality is by reducing the likelihood of finding higher wage opportunities. This leads to a higher crime reservation wage. As salary prospects have worsened, individuals are more willing to commit crime. This leads to higher numbers of jailed and unemployed individuals and a lower number of employed workers. The second mechanism is analogous to that in the previous case but with a higher tax rate that raises the labor and crime reservation wages. A higher tax rate lowers σ (as C rises by more than R), increasing the crime rate even further. Hence higher wage inequality unambiguously raises the crime rate (Figure 5).

Let's consider now a higher proportion of police officers, i.e., a higher α. A larger police force reduces the probability of finding crime opportunities and raises the probability of being caught after committing crime. Both effects increase the cost of committing crime. Through this first mechanism the crime reservation wage declines, lowering u, n, e_L, and the crime rate. However, the second mechanism goes in the opposite direction. The larger share of police officers is financed by a higher tax rate, which raises the crime reservation and labor reservation wage. Therefore a higher tax rate lowers σ (as C rises by more than R), raising the crime rate. Hence the overall effect on crime of a higher proportion of police officers is ambiguous.

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[7] A higher β of the Pareto distribution (a higher Theil index) represents an increase in income inequality. However, given the functional form of the Pareto distribution, a higher β also changes the expected value of the mean. To overcome the latter feature, we added a location parameter to isolate the effect of the expected value of the mean from the change in the Theil index.

More severe crime penalties can be represented by a lower level of net transfers of the government to jailed individuals. In fact, z could be negative if the value of punishment (including fines) exceeds the value of gross transfers to prosecuted criminals. The first mechanism of transmission of a higher z implies that the crime reservation wage declines and fewer individuals are willing to commit crime. This reduces u, n, e_L, and the crime rate. Again the second mechanism works through taxes. As government spending declines – with less expenditure per jailed individual, fewer jailed individuals, and fewer unemployed workers –, the tax rate declines. This leads to lower crime and labor reservation wages – as discussed above, the effect on C is larger than the effect on R. Therefore both transmission mechanisms have the same sign, lowering u and n, and raising e. Hence more severe penalties unambiguously lower the crime rate (Figure 6).

Figure 5: More inequality raises crime

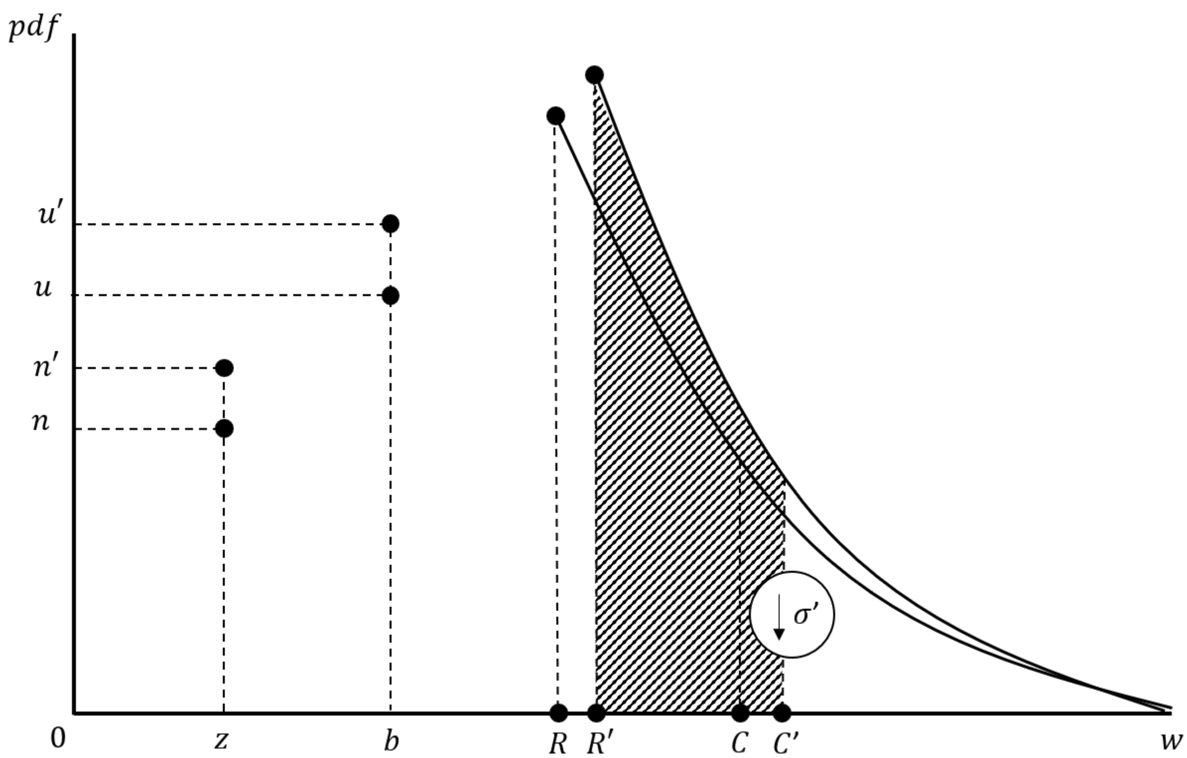
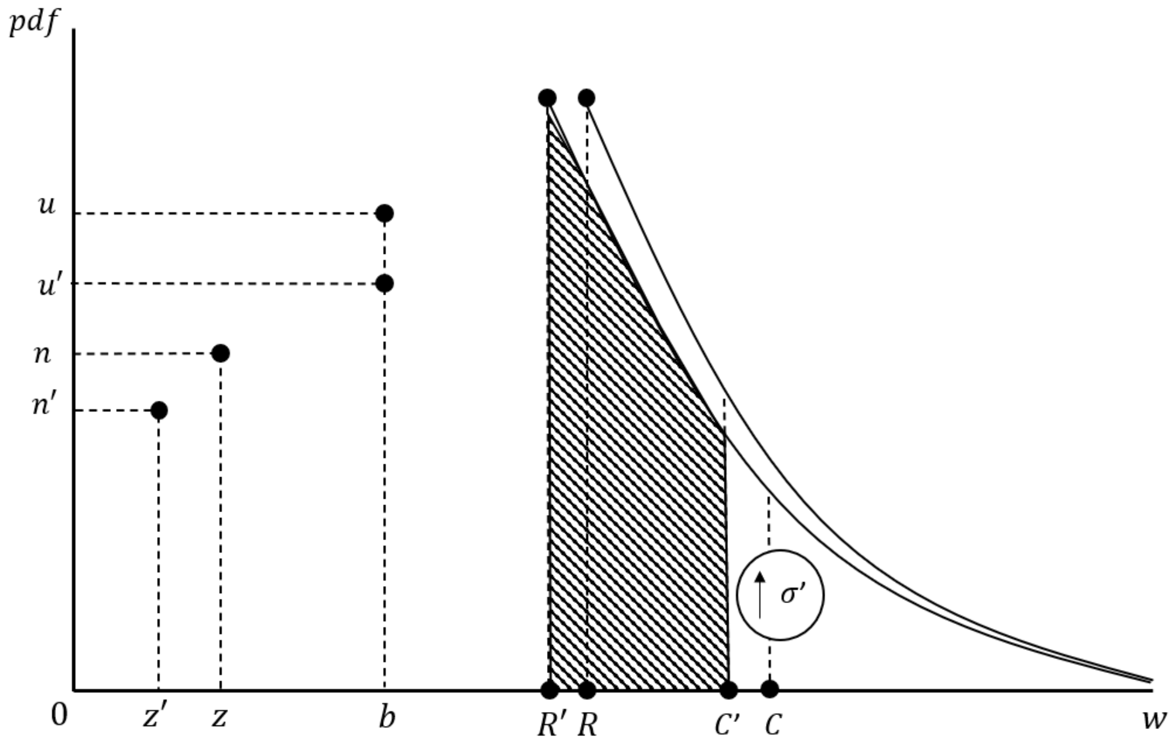


Figure 6: More severe criminal penalties lower crime



3. Empirical Specification and Estimation Results

3.1 Empirical Specification, Estimation Method, and Data

We specify an empirical model for the crime rate, which will be applied to a country panel data sample. We consider the following dynamic model with unobserved country-specific effects:

$$Y_{i,t} = \gamma Y_{i,t-1} + \theta' X_{i,t} + \eta_i + \varepsilon_{i,t} \qquad (30)$$

where the dependent variable *Y* is the crime rate, *X* is the set of independent variables, γ is the regression coefficient of the lagged dependent variable, θ is a vector of regression coefficients, η_i is a country-specific factor (which could be correlated with explanatory variables), and $\varepsilon_{i,t}$ is the error term. Subscripts i and t denote country and time period, respectively. The model includes the lagged dependent variable as an additional explanatory variable, reflecting the existence of inertia in crime rates, as stressed in crime theoretical models (e.g., Sah, 1991; Glaeser et al., 1996), including ours, and to account for possible short-term dynamics found in the data. All empirical variables are national (country-wide) averages, available for many years, as discussed below. These variables are the most reliable measures at the national level and therefore they are comparable internationally (Fajnzylber et al., 2002; Feld and Bishop, 2012).

Our empirical core model is comprised by measures of key variables identified in our theoretical model. Our dependent variable, the crime rate (c), is measured by the national intentional homicide rate defined as ratio to the national population. [8] We include four independent variables in our core model. As a proxy for the average wage level ($\overline{w} + \varphi$), we use per capita GDP. The Gini coefficient of income concentration is used as a proxy of wage dispersion (β). For unemployed workers (u), we use the unemployment rate. The ratio of the number of police officers to the national population is used as a measure of police (α).

In addition to the variables in our core model, we add the following variables in our extended specifications. Interpreting literally our theoretical model's government net transfer to jailed criminals (z), we use as an extreme proxy of the negative of this net transfer ($z \to -\infty$) a country dummy for the death penalty. Then we include a country dummy for prevalence of drugs (large national drug production and/or trafficking), as a variable that reflects a higher value of the loot obtained by criminals (g). Therefore this dummy for drug prevalence captures a country feature that reflects more profitable crime opportunities (Fajnzylber et al., 2002). Finally, as a key determinant of the average wage level ($\overline{w} + \varphi$), we add educational attainment as a measure of human capital.

Consistent with our theoretical model (the correlation between crime and unemployment in equation (27), and the partial derivatives of crime with respect to exogenous variables in Appendix A), the expected signs of the coefficients of crime rate determinants are positive (for the Gini coefficient, the unemployment rate, and drug prevalence), negative (for education, per capita GDP, death penalty, and education), and ambiguous (for the police ratio).

For estimating equation (28), we adopt the generalized method of moments (GMM) estimator in its dynamic system version, which performs jointly regressions in levels and in first differences.[9] All independent variables are treated as potentially endogenous, using their first and second lags as internal instruments.

We also perform two specification tests: the Hansen test for the null hypothesis of overall validity of instruments and the Arellano and Bond test for first and second-order serial correlation of errors.

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[8] We considered using the national robbery rate as an additional, separate dependent variable, complementary to the homicide rate. However, we dismissed this option, as the available world data on robbery rates is of much lower quality than that for homicide. This is due to several factors, including significant under-reporting of robberies, as discussed by Fajnzylber et al. (2002) and Lederman et al. (2002).

[9] The dynamic panel data model was initially developed by Chamberlain (1984), with an arbitrary intertemporal covariance matrix of errors. Arellano and Bond (1991) propose a GMM estimator used to estimate dynamic models of panel data and present procedures and specification tests for consistent estimation of parameters and their asymptotic covariance matrix for the dynamic system extension of the GMM panel data model. Arellano and Bover (1995) specify valid instruments for the equations in levels, in addition to those available for the equations in first differences or deviations from individual means.

We construct our data sample as a cross-country time-series panel database extending from 1974 to 2018. The country sample was selected according to the availability of at least three consecutive observations in any five-year period and the quality of available crime data. The resulting sample includes 68 countries for the homicide rate regressions. The 68-country sample comprises 33 advanced countries and 39 emerging-market and developing economies. The frequency of our original data is annual, from which we compute five-year averages, which we use in our estimations. Due to lack of complete data availability for all countries, the panel is unbalanced. Therefore, the time period for individual countries covers at most 1984-2018, with seven five-year observations and two additional five-year observations (at most 1974-1983) for lagged variables used as instruments. To the best of our knowledge, the data sample assembled here represents the largest panel dataset assembled in cross-country empirical research on crime. Regarding sample size, the largest cross-country panel sample used in previous empirical research spans 45 countries and covers from 1970 to 1994 (Fajnzylber et al., 2002).

The data on intentional homicides and police personnel are reported by national justice ministries to the United Nations Office on Drugs and Crime (UNODC). Crime (and police) rates are expressed as the number of reported crimes in each category (and of police personnel) per 100,000 inhabitants, using the population reported by the World Bank Database.[10] All definitions and sources of dependent and independent variables are summarized in Appendix B.[11]

3.2 Estimation Results

Table 1 reports the results for the homicide rate for different specifications. Columns (1) and (2) present results for the core model, consistent with a set of variables included in our theoretical model. Both columns report results of two-step Dynamic System GMM estimations; the first without the Windmeijer correction for the variance of GMM estimations and the second with the Windmeijer correction. We also apply the latter estimation model in the extended model results reported in columns (3)-(5). The extended specifications in columns (3)-(5) add sequentially to the core model the death penalty dummy, the drug prevalence dummy, and educational attainment.

All regression results reported in Table 1 pass the standard specification tests. Most signs of coefficient estimates and their significance levels are consistent with expected signs of the corresponding variables in our theoretical model.

[10] Both crime rates (and the police rate) enter regressions in logs, so that estimated coefficients can be interpreted as the relative change in the corresponding crime rate caused by a unit change in the corresponding explanatory variable (i.e., as an elasticity or semi-elasticity).

[11] The full data base, a detailed explanation of data selection and construction procedures, and the regression files are available by request from the authors.

The coefficients of the lagged homicide rate are positive and highly significant, reflecting significant crime inertia. Their large size implies that long-term coefficients[12] of all other independent variables are on average eight times the size of the reported short-term coefficients.

Higher per capita GDP – our proxy for the average wage – has a negative and significant effect on the homicide rate, which is robust across different specifications. Considering the coefficient estimate of -0.272 in column (2), a 10% increase of the sample average per capita GDP (for example, from Korea's average US$ 15,800 to Czech Republic's average US$ 17,200) is associated to a decline in the homicide rate by 2.7%. The latter result confirms the mechanism at work that was derived in the theoretical model of section 2: the prospects of finding a higher wage – proxied empirically by higher per capita income – raise the alternative cost of crime and thereby lead to lower crime incidence.

Income inequality raises the homicide rate significantly and robustly. Based on the average coefficient estimate reported in columns (1) to (5), a 10-percentage point rise in the Gini coefficient (for example, from UK's average 35 Gini to Argentina's average 45 Gini) raises the homicide rate by 5%. This result is consistent with our analytical model, where the positive link between inequality and crime is based on the decline in expectations of wage improvement when inequality rises, which reduces the opportunity cost of engaging in crime.

The unemployment rate does not exhibit a consistent effect on the homicide rate across different specifications. Its unambiguously positive effect predicted by our theoretical model is not confirmed by our results.

According to our model, the effect of the number of police officers on the incidence of crime is ambiguous. This is due to two offsetting consequences of a higher number of police officers: the negative effects of crime prevention and detection by police on crime, and the positive effect on crime of a higher tax rate on wages (or income) to finance the larger policy force (which reduces the alternative cost of crime). Our empirical results suggest that the second mechanism dominates the first mechanism: the police force raises significantly and robustly (except in column (3)) the homicide rate. Hence the effectiveness of police in crime prevention and detection is weak, relative to the stronger incentives to engage in crime as a result of higher taxes on wages (or income).

Now we turn to the additional variables included in the extended-model results reported in columns (3)-(5). In column (3), the coefficient estimate for the death penalty dummy would suggest that countries where capital punishment is legal have a 5.4% lower homicide rate than in countries without the death penalty. However, this estimate is significant only at a 10% level; in subsequent columns no significant effect of capital punishment is obtained.

[12] The long-term coefficients are calculated for the steady state, by multiplying the short-term coefficents by $\frac{1}{1-\gamma}$.

Table 1
Panel regressions: Homicide Rate (68 countries, 1984-2018)
Estimation Method: Dynamic System GMM

	Dependent variable: log of homicide rate				
Explanatory Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Lagged dependent variable	0.930*** (0.013)	0.841*** (0.345)	0.888 *** (0.018)	0.886 *** (0.015)	0.847 *** (0.022)
Log per capita GDP	-0.212*** (0.011)	-0.272** (0.137)	-0.105*** (0.015)	-0.421*** (0.022)	-0.096** (0.021)
Income Concentration	0.077*** (0.033)	0.108*** (0.033)	0.011*** (0.002)	0.046*** (0.002)	0.007** (0.002)
Unemployment Rate	-0.006*** (0.002)	-0.017 (0.040)	-0.010*** (0.003)	0.010 (0.011)	-0.006* (0.003)
Log Police Rate	0.050** (0.026)	0.127** (0.067)	-0.003 (0.050)	0.294*** (0.061)	0.107** (0.045)
Death Penalty			-0.054** (0.026)	-0.020 (0.061)	0.019 (0.028)
Drug Prevalence				0.486*** (0.170)	0.130*** (0.070)
Educational Attainment					0.005 (0.007)
Constant	0.000 (0.013)	-0.143 (0.179)	-0.121 (0.124)	-0.071 (0.131)	0.362 (0.195)
Time dummy	Yes	Yes	Yes	Yes	Yes
Country dummy	Yes	Yes	Yes	Yes	Yes
Observations	364	364	364	364	364
Countries	68	68	68	68	68
Specification tests (p-values)					
Hansen test	0.694	0.929	0.911	0.845	0.493
Serial correlation:					
(i) First order	0.017	0.005	0.018	0.017	0.018
(ii) Second order	0.355	0.623	0.306	0.331	0.342

Note: statistical significance levels are denoted by *** (1%), ** (5%), and *(10%). Column (1) presents results without the Windmeijer correction and column (2)-(5) presents results using the Windmeijer correction.

Table 1 reports a large, positive, and significant effect of high drug prevalence on the homicide rate. In countries where drug production and/or drug trafficking is large, the homicide rate is 13% to 49% higher than in other countries. This huge increase in homicides reflects that illegal drug activity involves criminal activity and, in addition, is likely to spill over to other criminal activities involving homicides that are not directly related to drug production and trade.[13] Our statistical result suggests that large drug prevalence raises the average value of the criminal loot. This is consistent with the model in section 2, where a larger gain from criminal activity raises crime.

Finally, educational attainment – a key determinant of wages (and income) – does not have a statistically and economically significant effect.

Table 2
Panel regressions: Homicide Rate (68 countries, 1984-2018)
for Different Estimation Methods

	Dependent variable: log of homicide rate			
Explanatory Variables	**(1) Cross-section BE**	**(2) Pooled OLS**	**(3) IV-FE**	**(4) GMM**
Lagged dependent variable		0.890*** (0.025)	0.464*** -0.078	0.841*** -0.345
Log per capita GDP	-0.432*** -0.035	-0.074*** (0.018)	-0.386** -0.187	-0.272** -0.137
Income Concentration	0.058*** -0.005	0.009*** (0.003)	-0.009 -0.01	0.108*** -0.033
Unemployment Rate	0.001 -0.009	-0.005 (0.005)	-0.005 -0.007	-0.017 -0.04
log Police Rate	0.242** (0.078)	0.029 (0.034)	0.134** (0.067)	0.127** (0.067)
Observations	68	364	364	364
Countries	68	68	68	68

Notes: statistical significance levels are denoted by *** (1%), ** (5%), and *(10%). BE is the Between Estimator and IV-FE is the Instrumental Variable Fixed Effect estimator.

[13] Ilegal drug production and trade generates very high profits and goes with violent disputes for market shares between different networks of drug producers and distributors. The indirect impact on national homicide rates, through the provision of externalities to other organized criminal activities, is discussed by Boyum et al., 2011.

To check for robustness of our core-model results, we report regression results for alternative estimation models in Table 2. For reference, we replicate in column (4) of Table 2 the core-model results for our preferred estimation method (system GMM with Windmeijer correction), presented in column (2) of Table (1). Columns (1)-(3) report results for alternative regression models (which econometrically are dominated by the model used in column (4)). Column (1) presents a cross-section estimation based on the Between Estimator (BE), column (2) reports results for the Pooled OLS Estimator, and column (3) presents results based on the Instrumental Variable Fixed Effect Estimator (IV-FE). Most signs of coefficient estimates and their significance levels are consistent with the results reported in Table 1. Therefore our core-model results are largely robust to alternative estimation models.

4. Conclusions

This paper has analyzed theoretically and empirically the determinants of crime in the world. We have developed a dynamic general equilibrium search model to better understand crime determination. Our model builds on Burdett et al. (2003), extending the latter framework in four directions: an exogenous police force (which affects crime through a lower opportunity to commit crime and a higher probability of being caught), the government's budget constraint (with an endogenous tax rate), a distribution function of wages (with location and Theil index parameters), and an analytical derivation of the effects of key variables on the rate of crime.

The solution of our model is similar to that derived by Burdett et al. (2003). Our differences stem from the introduction of the abovementioned variables, which affect the dynamics and the stationary equilibrium of the model. These differences also modify the transmission mechanisms at work in our model. There is a first mechanism similar to Burdett et al. (2003), where changes in exogenous variables modify the optimal solution of the agents' decisions, and therefore the reservation wages of work and crime. This modifies the distribution of individuals in jail, unemployment, and employment, and hence the crime rate. Our model develops a second mechanism, which is through the government budget constraint. Changes in exogenous variables also modify variables in the latter constraint, requiring an endogenous tax rate adjustment. This affects both labor and crime reservation wages and therefore modifies the crime rate, too.

The first mechanism of a higher average wage (or a lower wage inequality or more severe penalties) on crime is a reduction of the crime reservation wage through a higher opportunity cost of committing crime, caused by the prospect of a higher wage. This raises the proportion of higher wage workers, and lowers unemployed, jailed, and lower wage workers, lowering the crime rate. The second mechanism works through a reduced tax rate, which lowers further the crime reservation wage and the labor reservation wage. Both reservation wages are directly affected by the tax rate. A lower tax rate also raises the proportion of higher wage workers, lowering the crime rate even further. Hence a higher average wage income (or a lower wage inequality or more severe penalties) unambiguously lowers the crime rate. For these variables, the effect of the first mechanism is enhanced by the effect of the second mechanism.

However, this does not occur when analyzing the effect of a higher proportion of police officers. A higher ratio of police officers lowers the probability of finding crime opportunities and raises the probability of being caught. Both effects increase the cost of committing crime, hence the crime reservation wage declines and so does the crime rate. However, a larger share of police officers has to be financed by a higher tax rate, which raises the crime reservation and labor reservation wage, therefore raising the crime rate. Hence the overall effect on crime of a higher proportion of police officers is ambiguous.

Then we have performed an empirical test of the model, based on a specification that follows closely our theoretical model for the crime rate. The econometric analysis has focused on the determinants of the intentional homicide rate for a world-wide panel of countries. Our world sample is comprised by 68 advanced and developing countries with 5-year data for the 1974-2018 period – to the best of our knowledge, this is the largest database used to date in country panel research on crime. We have used the dynamic system GMM method as our main estimator, reporting also results for alternative estimation models.

The empirical results have supported our model of criminal behavior. The dependent variable is the national intentional homicide rate. We include four independent variables in our core model: per capita GDP, the Gini coefficient of income concentration, the unemployment rate, and the ratio of the number of police officers to inhabitants.

The coefficients of the lagged homicide rate is positive, reflecting significant crime inertia. Higher per capita GDP has a negative and significant effect on the homicide rate, which is robust across different specifications. Income inequality raises the homicide rate significantly and robustly. However, the unemployment rate does not exhibit a consistent effect on the homicide rate across different specifications. The police force raises significantly and robustly the homicide rate. The latter result suggests that the effectiveness of police in crime prevention and detection is weak, relative to the stronger incentives to engage in crime as a result of higher taxes – required to pay for police officers – on wages (or income).

We have checked our core-model results for robustness using alternative estimation models. In addition to our core model, we have also estimated extended specifications that include the death penalty, a country dummy for prevalence of drugs, and educational attainment as additional regressors. Neither the death penalty nor educational attainment affect the homicide rate robustly and/or significantly. However, high drug prevalence raises significantly the homicide rate.

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Appendix A: proofs and derivations

$V_1(w)$ is increasing and convex

Proof

Deriving equation (7) with respect to w, we obtain:

$$rV'_1(w) = (1-\gamma)(1-t) - \delta V'_1(w) - \mu(\alpha)\phi_1(w)V'_1(w) + \lambda\frac{\partial \mathrm{E}\left[\max_w\{V_1(w) - V_0, 0\}\right]}{\partial w}$$

Using the Leibniz integral rule, the last term of the right-hand side yields:

$$\frac{\partial \mathrm{E}\left[\max_w\{V_1(w) - V_0, 0\}\right]}{\partial w} = -V'_1(w)(1 - F(w))$$

Replacing the latter equation in the previous yields:

$$V'_1(w) = \frac{(1-\gamma)(1-t)}{r + \delta + \mu(\alpha)\phi_1(w)\pi(\alpha) + \lambda(1 - \mathrm{F}(w))} > 0$$

Deriving again with respect to w yields:

$$V''_1(w) = \frac{(1-\gamma)(1-t)\lambda \mathrm{F}'(w)}{(r + \delta + \mu(\alpha)\phi_1(w)\pi(\alpha) + \lambda\big(1 - \mathrm{F}(w)\big))^2} > 0$$

As $V_1(w)$ is increasing, we have that $V_1(0) < V_1(R)$.

$K_1(w) - V_1(w)$ is decreasing and concave

Proof

Rearranging equation (3) yields:

$$K_1 - V_1(w) = g + \pi(\alpha)J - \pi(\alpha)V_1(w)$$

Deriving the previous equation with respect to w yields:

$$(K_1 - V_1(w))' = -\pi(\alpha)V_1{}'(w) < 0$$

$$(K_1 - V_1(w))'' = -\pi(\alpha)V_1{}''(w) < 0$$

As $V_1(w)$ is increasing and convex, $K_1(w) - V_1(w)$ is decreasing and concave. Also, as $K_1(w) - V_1(w)$ is decreasing, we have that $K_1(0) - V_1(0) < K_1(R) - V_1(R)$.

Derivation of reservation wage and crime wage

Proof of equation (10)

Using $V_1(R) = V_0$ and equations (6) and (7) evaluated at w = R (which implies $\phi_0 = \phi_1(R) = 0$), we have:

$$rV_0 = b(1-\gamma)$$

$$rV_1(w) = R(1-\gamma)(1-t)$$

Combining the previous equations, we have:

$$R = \frac{b}{1-t}$$

Definition of $\Delta(\boldsymbol{Z})$

We first define $\Delta(Z)$ for $Z \geq R$ as:

$$\Delta(Z) = \mathrm{E}\left[\max_x\{V_1(x) - V_1(Z),0\}\right] = \int_z^\infty (V_1(x) - V_1(Z))dF(x)$$

Integrating by parts yields:

$$\Delta(Z) = \lim_{x\to\infty}(V_1(x) - V_1(Z))F(x) - (V_1(Z) - V_1(Z))F(Z) - \int_z^\infty V'_1(x)F(x)dx$$

$$\Delta(Z) = \lim_{x\to\infty}(V_1(x) - V_1(Z))F(x) - \int_z^\infty V'_1(x)F(x)dx$$

By definition of a cdf, we have $\lim_{x\to\infty} F(x) = 1$. Then we have:

$$\Delta(Z) = \lim_{x\to\infty} V_1(x) - V_1(Z) - \int_z^\infty V'_1(x)F(x)dx$$

Rearranging the latter equation yields:

$$\Delta(Z) = \int_z^\infty V'_1(x)dx - \int_z^\infty V'_1(x)F(x)dx = \int_z^\infty V'_1(x)\big(1-F(x)\big)dx$$

Proof of equation (11)

Using equation (7), evaluated at w = C, we have:

$$V_1(C) = \frac{C(1-\gamma)(1-t) + \delta V_0 + \lambda\Delta(C)}{r+\delta}$$

Subtracting J from the previous equation yields:

$$V_1(C) - J = \frac{C(1-\gamma)(1-t) + \delta(V_0 - J) + \lambda\Delta(C) - rJ}{r+\delta}$$

Using equation (8) yields:

$$V_1(C) - J = \frac{C(1-\gamma)(1-t) - (\rho-\delta)(V_0 - J) + \lambda\Delta(C) - z}{r+\delta}$$

Equating the previous equation to $\frac{g}{\pi(\alpha)}$, we have:

$$C = \frac{1}{(1-\gamma)(1-t)}\left(z + \frac{g}{\pi(\alpha)}(r+\delta) + (\mathrm{\rho} - \mathrm{\delta})(V_0 - J) - \lambda\Delta\mathrm{C}\right)$$

Proof of equation (13)

Using equations (6) and (8), we have:

$$r(V_0 - J) = b(1-\gamma) + \mu(\alpha)(K_0 - V_0) + \lambda\Delta\mathrm{R} - \mathrm{z} - \mathrm{\rho}(V_0 - J)$$

Then:

$$V_0 - J = \frac{b(1-\gamma) - z + \mu(\alpha)g + \lambda\Delta\mathrm{R}}{r + \mathrm{\rho} + \mu(\alpha)\pi(\alpha)}$$

Proof of equations (23) - (26)

From equation (20), we have:

$$e_L^{ss} = \frac{\lambda(1-\sigma)u^{ss}}{(\delta + \mu(\alpha)\pi(\alpha) + \lambda\sigma)}$$

Using the previous equation in (19) yields:

$$\delta e_H^{ss} = \lambda\sigma\frac{\lambda(1-\sigma)u^{ss}}{(\delta + \mu(\alpha)\pi(\alpha) + \lambda\sigma)} + \lambda\sigma u^{ss}$$

$$e_H^{ss} = \frac{\lambda\sigma}{\delta}\left(\frac{\delta + \mu(\alpha)\pi(\alpha) + \lambda}{(\delta + \mu(\alpha)\pi(\alpha) + \lambda\sigma)}\right)u^{ss}$$

Combining the previous results in (22), we have:

$$\rho n^{ss} = \mu(\alpha)\pi(\alpha)\frac{\lambda(1-\sigma)u^{ss}}{(\delta + \mu(\alpha)\pi(\alpha) + \lambda\sigma)} + \mu(\alpha)\pi(\alpha)u^{ss}$$

$$n^{ss} = \frac{\mu(\alpha)\pi(\alpha)}{\rho}\left(\frac{\delta + \mu(\alpha)\pi(\alpha) + \lambda}{(\delta + \mu(\alpha)\pi(\alpha) + \lambda\sigma)}\right)u^{ss}$$

Then, using $e_H^{ss} + e_L^{ss} + u^{ss} + n^{ss} = 1 - \alpha$, yields:

$$\frac{\lambda\sigma}{\delta}\left(\frac{\delta + \mu(\alpha)\pi(\alpha) + \lambda}{(\delta + \mu(\alpha)\pi(\alpha) + \lambda\sigma)}\right)u^{ss} + \frac{\lambda(1-\sigma)u^{ss}}{(\delta + \mu(\alpha)\pi(\alpha) + \lambda\sigma)} + u^{ss} + \frac{\mu(\alpha)\pi(\alpha)}{\rho}\left(\frac{\delta + \mu(\alpha)\pi(\alpha) + \lambda}{(\delta + \mu(\alpha)\pi(\alpha) + \lambda\sigma)}\right)u^{ss} = 1 - \alpha$$

$$u^{ss}\left(\frac{\rho\delta(\delta + \mu(\alpha)\pi(\alpha) + \lambda\sigma) + \rho\delta\lambda(1-\sigma) + \rho\lambda\sigma(\delta + \mu(\alpha)\pi(\alpha) + \lambda) + \delta\mu(\alpha)\pi(\alpha)(\delta + \mu(\alpha)\pi(\alpha) + \lambda)}{\rho\delta(\delta + \mu(\alpha)\pi(\alpha) + \lambda\sigma)}\right) = 1 - \alpha$$

$$u^{ss} = \frac{(1-\alpha)\rho\delta(\delta + \mu(\alpha)\pi(\alpha) + \lambda\sigma)}{(\rho\delta + \rho\lambda\sigma + \delta\mu(\alpha)\pi(\alpha))(\delta + \mu(\alpha)\pi(\alpha) + \lambda)}$$

Replacing the latter equation in e_H^{ss}, e_L^{ss}, and n^{ss}, yields:

$$e_H^{ss} = \frac{(1-\alpha)(\delta + \mu(\alpha)\pi(\alpha) + \lambda)\rho\lambda\sigma}{(\rho\delta + \rho\lambda\sigma + \delta\mu(\alpha)\pi(\alpha))(\delta + \mu(\alpha)\pi(\alpha) + \lambda)}$$

$$e_L^{ss} = \frac{(1-\alpha)(1-\sigma)\rho\delta\lambda}{(\rho\delta + \rho\lambda\sigma + \delta\mu(\alpha)\pi(\alpha))(\delta + \mu(\alpha)\pi(\alpha) + \lambda)}$$

$$n^{ss} = \frac{(1-\alpha)(\delta + \mu(\alpha)\pi(\alpha) + \lambda)\mu(\alpha)\pi(\alpha)\delta}{(\rho\delta + \rho\lambda\sigma + \delta\mu(\alpha)\pi(\alpha))(\delta + \mu(\alpha)\pi(\alpha) + \lambda)}$$

We define Ω as the variable that makes $e_L^{ss} + e_H^{ss} + n^{ss} + u^{ss} = 1 - \alpha$, where:

$$\Omega = (\rho\delta + \rho\lambda\sigma + \delta\mu(\alpha)\pi(\alpha))(\delta + \mu(\alpha)\pi(\alpha) + \lambda)$$

Stationary crime rate

The stationary representation of equation (27) is:

$$c^{ss} = \frac{\mu(\alpha)(u^{ss} + e_L{}^{ss})}{1 - \alpha - n^{ss}}$$

Using equations (20) - (22), we obtain the following stationary crime rate:

$$c^{ss} = \frac{\mu(\alpha)\rho\delta(\delta + \mu(\alpha)\pi(\alpha) + \lambda))}{\Omega - (\delta + \mu(\alpha)\pi(\alpha) + \lambda)\mu(\alpha)\pi(\alpha)\delta}$$

Replacing Ω yields:

$$c^{ss} = \frac{\mu(\alpha)\rho\delta(\delta + \mu(\alpha)\pi(\alpha) + \lambda)}{(\rho\delta + \rho\lambda\sigma + \delta\mu(\alpha)\pi(\alpha))(\delta + \mu(\alpha)\pi(\alpha) + \lambda) - (\delta + \mu(\alpha)\pi(\alpha) + \lambda)\mu(\alpha)\pi(\alpha)\delta}$$

Therefore:

$$c^{ss} = \frac{\mu(\alpha)\delta}{\delta + \lambda\sigma}$$

Determinants of the stationary crime rate

We calculate the total differential of the crime rate for a given change of an exogenous variable ω that implies a higher tax rate, we obtain:

$$\Delta c^{ss} = \frac{\partial c}{\partial \sigma}\left(\frac{\partial \sigma}{\partial \omega} + \frac{\partial \sigma}{\partial \mathrm{t}}\frac{\partial t}{\partial \omega}\right)$$

where:

$$\frac{\partial c}{\partial \sigma} = \frac{-\mu(\alpha)\delta\lambda}{(\delta + \lambda\sigma)^2} < 0$$

In order to obtain the effect of each variable, we focus on the sign of $\frac{\partial \sigma}{\partial \omega} + \frac{\partial \sigma}{\partial \mathrm{t}}\frac{\partial t}{\partial \omega}$.

Effect of t on $\boldsymbol{\sigma}$

$$\frac{\partial \sigma}{\partial t} = \beta\sigma\left(\frac{\frac{\partial R}{\partial t}}{R} - \frac{\frac{\partial C}{\partial t}}{C}\right)$$

Note that:

$$\frac{\frac{\partial R}{\partial t}}{R} = \frac{1}{(1 - \mathrm{t})}$$

$$\frac{\frac{\partial C}{\partial t}}{C} = \left(\frac{r+\delta+\lambda\sigma}{r+\delta}\right)\left(\frac{1}{1-\mathrm{t}}\right) + \left(\frac{\mathrm{R}}{C}\right)\left(\frac{\lambda(r+\delta+\lambda\sigma)}{(r+\delta+\mu(\alpha)\pi(\alpha)+\lambda)(r+\rho+\mu(\alpha)\pi(\alpha))(1-\mathrm{t})}\right)$$

Then:

$$\frac{\partial\sigma}{\partial t} = -\left(\frac{\beta\sigma\lambda}{1-\mathrm{t}}\right)\left(\frac{\sigma}{r+\delta} + \frac{(r+\delta+\lambda\sigma)}{(r+\delta+\mu(\alpha)\pi(\alpha)+\lambda)(r+\rho+\mu(\alpha)\pi(\alpha))}\right) < 0$$

c is decreasing in φ

The first mechanism is a direct effect of φ on C:

$$\frac{\partial \mathrm{C}}{\partial\varphi} = \frac{\lambda}{(r+\rho+\mu(\alpha)\pi(\alpha))}\left((\rho-\delta)\int_R^C \frac{(r+\delta+\mu(\alpha)\pi(\alpha))F'(x-\varphi)}{(r+\delta+\mu(\alpha)\pi(\alpha)+\lambda(1-F(x-\varphi))^2}dx - (r + \delta+\mu(\alpha)\pi(\alpha))\int_C^\infty \frac{(r+\delta)F'(x-\varphi)}{(r+\delta+\lambda(1-F(x-\varphi))^2}dx\right) < 0$$

Then we have that a lower C implies a higher σ:

$$\frac{\partial\sigma}{\partial\varphi} > 0$$

The second mechanism is an indirect effect of a lower tax rate on R and C. As $\frac{\partial t}{\partial\varphi} < 0$ and $\frac{\partial\sigma}{\partial t} < 0$, we have:

$$\frac{\partial\sigma}{\partial \mathrm{t}}\frac{\partial t}{\partial\varphi} > 0$$

Finally, we have:

$$\Delta c^{ss} = \frac{\partial c}{\partial\sigma}\left(\frac{\partial\sigma}{\partial\varphi} + \frac{\partial\sigma}{\partial \mathrm{t}}\frac{\partial t}{\partial\varphi}\right) < 0$$

c is increasing in $\boldsymbol{\beta}$

The first mechanism is a direct effect of β on C:

$$\frac{\partial \mathrm{C}}{\partial\beta} = \frac{(r+\delta+\lambda(1-\mathrm{F}'(\mathrm{C})))}{(1-\gamma)(1-t)(r+\rho+\mu(\alpha)\pi(\alpha))(r+\delta)} > 0$$

Then we have that a higher C implies a lower σ:

$$\frac{\partial \sigma}{\partial \beta} < 0$$

The second mechanism is an indirect effect of a higher tax rate on R and C. As $\frac{\partial t}{\partial \beta} > 0$ and $\frac{\partial \sigma}{\partial t} < 0$, we have:

$$\frac{\partial \sigma}{\partial \mathrm{t}}\frac{\partial t}{\partial \beta} < 0$$

Finally, we have:

$$\Delta c^{ss} = \frac{\partial c}{\partial \sigma}\left(\frac{\partial \sigma}{\partial \beta} + \frac{\partial \sigma}{\partial \mathrm{t}}\frac{\partial t}{\partial \beta}\right) > 0$$

Police has an ambiguous effect on c

The total differential of a higher α, considering the effect on t, is:

$$\Delta c^{ss} = \frac{\partial \mathrm{c}}{\partial \sigma}\frac{\partial \sigma}{\partial \alpha} + \frac{\partial \mathrm{c}}{\partial \sigma}\frac{\partial \sigma}{\partial t}\frac{\partial t}{\partial \alpha} + \frac{\partial \mathrm{c}}{\partial \alpha}$$

The first mechanism is a direct effect of α on C:

$$\frac{\partial \mathrm{C}}{\partial \alpha} = \frac{-(V_0 - J)(r + \delta + \mu(\alpha)\pi(\alpha))(r + \delta + \lambda(1 - \mathrm{F(C)}))}{(1-\gamma)(1-t)(r + \rho + \mu(\alpha)\pi(\alpha))(r+\delta)} < 0$$

Then we have that a lower C implies a higher σ:

$$\frac{\partial \sigma}{\partial \alpha} > 0$$

The second mechanism is an indirect effect of a higher tax rate on R and C. As $\frac{\partial t}{\partial \alpha} > 0$ and $\frac{\partial \sigma}{\partial t} < 0$, we have:

$$\frac{\partial \sigma}{\partial \mathrm{t}}\frac{\partial t}{\partial \alpha} < 0$$

The third mechanism is a direct effect of a lower probability of finding crime opportunities. Deriving equation (28) yields:

$$\frac{\partial \mathrm{c}}{\partial \alpha} = \frac{\delta\left((\delta + \lambda\sigma)\mu'(\alpha) - \mu(\alpha)\lambda\frac{\partial \sigma}{\partial \alpha}\right)}{(\delta + \lambda\sigma)^2} < 0$$

The latter sign follows from having $\mu'(\alpha) < 0$ and $\frac{\partial \sigma}{\partial \alpha} > 0$. Therefore, there are two negative effects on crime (through a larger number of police officers and a lower probability of finding crime opportunities) and a positive effect on crime through taxes.

c is increasing in z

The first mechanism is a direct effect of z on C:

$$\frac{\partial \mathrm{C}}{\partial z} = \frac{(r + \delta + \mu(\alpha)\pi(\alpha))(r + \delta + \lambda(1 - \mathrm{F(C)}))}{(1 - \gamma)(1 - t)(r + \rho + \mu(\alpha)\pi(\alpha))(r + \delta)} > 0$$

Then we have that a higher C implies a lower σ:

$$\frac{\partial \sigma}{\partial z} < 0$$

The second mechanism is an indirect effect of a higher tax rate on R and C. As $\frac{\partial t}{\partial z} > 0$ and $\frac{\partial \sigma}{\partial t} < 0$, we have:

$$\frac{\partial \sigma}{\partial \mathrm{t}}\frac{\partial t}{\partial z} < 0$$

Finally, we have:

$$\Delta c^{ss} = \frac{\partial c}{\partial \sigma}\left(\frac{\partial \sigma}{\partial z} + \frac{\partial \sigma}{\partial \mathrm{t}}\frac{\partial t}{\partial z}\right) > 0$$

Appendix B: Definitions and Sources of Variables Used in Regression Analysis

Variable	Definition and Construction	Source
Log homicide rate	Log of the count of deaths purposely inflicted by other persons, per 100,000 inhabitants. Count of homicides reported by the United Nations Office on Drugs and Crime (UNODC) and population reported by the World Bank	UNODC, Homicide Statistics (2019), United Nations Surveys on Crime Trends and the Operations of Criminal Justice Systems (various issues), and World Bank database
Log per capita GDP	Log of the ratio between the series "GDP, PPP (constant 2017, international $)" and "Population" reported by the World Bank, thousands of dollars	World Development Indicators (World Bank)
Income concentration or inequality	Gini index	World Development Indicators (World Bank) and Deininger and Squire (1996)
Educational attainment	Average years of schooling of the population aged 25 and above	UNESCO (2017)
Unemployment rate	Reported by the World Bank	World Development Indicators (World Bank)
Log police rate	Log of the count of police personnel per 100,000 inhabitants. Count of police personnel reported by UNODC and population reported by the World Bank	UNODC, Homicide Statistics (2019), UN Surveys on Crime Trends and the Operations of Criminal Justice Systems (various issues), and World Bank database
Death penalty	Dummy for countries where the death penalty is legal (1) or not (0)	Amnesty International. List of Abolitionist and Retentionist Countries
Drug prevalence	Dummy for countries classified as major illicit drug-producing and/or drug-transit countries (1) or not (0)	U.S. Department of State, Bureau of International Narcotics and Law Enforcement Affairs, International Narcotics Control Strategy Report, various issues