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Inequality and criminality revisited: further evidence from Brazil

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Abstract The objective of this study is to shed light on the determinants of criminality rates in Brazil. A panel data model was estimated using Brazilian states' data. Our main result suggests that income inequality plays an important role in the determination of the crime rate. Furthermore, there are evidence suggesting that both unemployment and urbanization rates are positively related to crime. Based on a GMM approach we find the existence of an "inertial effect" on criminality. Besides that, the GMM results show that public security spending is effective in reducing criminality rates. Contrary to the common wisdom, we could not find evidence that poverty increases violent crimes. Finally, we have evidence that income inequality Granger causes crime, but not the reverse.

Keywords Criminality · Inequality · Panel data model · GMM estimator · Granger causality

JEL Classification K42 · C23 · Z13

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1 Introduction

In a seminal paper, Becker (1968) constructs a model of rational criminal behavior where he/she compares how much he/she can earn in the labor market without risk with the expected income from an illegal activity. Therefore, Becker (1968) focuses on the effect of the relationship between the return and the risk of a criminal act has on criminality rates. However, the analysis of this issue from a strictly financial standpoint may lead us to underestimate the problem, by incompletely identifying the mechanisms through which criminality operates. In certain contexts, it is possible to verify a continuous growth in criminal activities along with an extremely severe law enforcement state and unattractive returns.

In order to incorporate the above consideration, we do consider the relationship between return and risk as very relevant in explaining criminality; however, we also want to point out the existence of other factors that contribute to the evolution of the phenomenon like social determinants, emphasizing, in particular, the adverse effect that social inequality exerts on criminality rates. Hence, it would be interesting to analyze the criminal behavior in a country where income inequality is much higher than those prevailing in the US and other developed economies. Brazil has one of the highest Gini coefficients in the world, appearing in 148th place in an ascending list of 150 national Gini coefficients. Brazil also has one of the highest rates of intentional homicides around the world. Thus, this country appears as an attractive candidate for our case study, potentially being a significant contribution for a better understanding about the relationship between income inequality and criminality.

Kelly (2000) shows that, for violent crime, the impact of inequality is large, although it has no effect on the property crime. Grogger (1997),Witte and Witt (2001), Imai and Krishna (2001), Lochner (2001) and others have empirically studied the effect of various socioeconomic factors on criminal behavior. For the Brazilian case, Mendonca et al. (2002) and Loureiro et al. (2009) have also shown that violent crimes, such as homicides and rapes, are more related to factors l of a social interaction nature like family heritage and family instability variables than non-violent crimes (such as theft).

Most empirical studies on crime use data on US or other developed countries. The reason for this is the lack of data in developing countries. In this paper, we try to mitigate this gap by collecting and analyzing crime rates data of a rich state level in Brazil. We believe that this will help us better understand criminal behavior in developing countries where the problem of crime is much more severe than in developed countries. We also believe that the empirical analysis of criminal behavior in countries with different time trends of crime compared to the US case will enrich our understanding of the crime determinants. Contrary to the US, the Brazilian homicide rate has been steadily increasing during the 1980s and 1990s. However, this increase was not uniform among regions in Brazil.

This study aims at shedding light on the main determining factors motivating criminal activity in Brazil. A first sight analysis of recently released data shows that Brazil experienced a surge in criminal activities not only in levels but also in growth rates. The fundamental aim of this study is to estimate an econometric model of criminality for Brazil based on disaggregated data by states from 1981 to 1995. Specifically, our econometric analysis will focus on the determinants of intentional homicides. This study is structured as follows. Section 2 provides the literature review on the theories modeling the relationship between criminal behavior and social inequality. In Sect. 3, we introduce the main variables considered in the literature related to the phenomenon of criminality. The dataset is described in Sect. 4. In Sect. 5, we develop an econometric model for criminality using panel data. Here we apply a "system GMM" approach to control endogeneity between criminality and public security spending. Further analysis based on Granger causality approach is performed in order to find the true causality relationship between these two variables. Finally, some concluding remarks appear in Sect. 6.

2 Inequality and criminality: background

Both economists and sociologists have extensively studied the relationship between crime and inequality. Merton (1938) strain theory and Hagan and Petersen (1995) argue that the frustration felt by lower income individuals when perceiving the prosperity of others, also called "relative privation", may explain the effect inequality has on criminality. Some studies also point out, in a more specific sense, that poverty is a factor that influences criminality. The argument here is that the social disorganization generated by poverty reduces the influence of informal social norms on the individual, resulting in an increase in criminality (Hagan and Petersen 1995). Kennedy et al. (1998) hypothesized that the growing gap between the rich and the poor reduces social cohesion, or social capital. That decreased social capital is, in turn, associated with increased firearm homicide and violent crime. This is also related to the social disorganization theory that argues that crime happens when the social mechanisms supporting society, like a community's ability to regulate its members, are weakened. The influential study of Blau and Blau (1982) found a strong relationship between income inequality and homicide rates. Daly et al. (2001) also support the proposition that the degree to which resources are unequally distributed is a stronger determinant of levels of lethal violence in modern nation states than is the average level of material welfare.

The economic literature on crime suggests that inequality can generate criminality. There is a vast literature on theories pointing out the exact economic mechanisms governing inequality and crime. First, based on the earliest works of Becker (1968) and Ehrlich (1973), individuals can allocate time between market and illegal activities by comparing the expected return from these alternatives. Inequality creates crime by placing low-income individuals who have low returns in the labor market next to high-income individuals. This proximity contributes to a feeling of frustration, or "envy effect", already mentioned before, becoming an important determining factor on criminality. This idea appeared in a more concise economic framework in Eastherlin's seminal work in 1980. In this study, Eastherlin (1980) tries to explain why people in the US, Japan, Continental Europe or Britain have not become happier, despite of the strong economic growth. One possible reason for this, in line with a major finding from happiness surveys, is that satisfaction/happiness depends on some "status ranking", that is, what matters is not only one's absolute economic well-being but also one's relative position in society.

Third, one similar theory is based on the idea that an agent has a targeted consumption. The agent derives dissatisfaction from the difference between the level of targeted consumption and the level of effective consumption out of of his/her income. Hence, dissatisfaction reduces utility, which implies the direct relationship between income inequality and criminality: a high level of inequality implies a high level of dissatisfaction. The agent requires a higher remuneration to participate in the labor market given an increase of the targeted consumption, in this framework, poverty by itself is not considered a direct factor leading to criminality but only an indirect one.

Finally, we can find more specific economic channels by which social inequality is related to criminality assuming that illegal activities also depend on economic growth. First, inequality manifests itself through capital market imperfections since the poor are deprived of resources for investment. Second, inequality influences the balance of power in the political system in such a way to generate pressures for government to reduce income inequality that, in turn, slows the incentives to work and, thereby, slows down economic growth. Finally, there is an ancient argument that inequality contributes to deviant behavior and non-compliance to social norms, therefore reducing the security of property rights which, in their turn, discourages investment and economic growth (Pearsson and Tabellini 1998; Bénabou 1996; Aghion and Howitt 1998).

We just highlighted the channels through which inequality causes crime, but can criminality also generate inequality? There are at least four arguments to explain the channels through which violence generates income inequality: (a) violent areas are less attractive to new investments, in this way, violent areas will gradually become poor and non-violent areas, receiving the investments, will gradually become richer; (b) the most skilled people will prefer to work in non violent areas. Hence, the better teachers (for example) will teach in safer places, and the education of the children living in violent areas, will be in charge of the worst teachers. That is, the children of violent areas will receive lower quality education than children who live in non-violent areas, which in the long run, will generate income inequality due to this difference in the acquired skills; (c) the most skilled individuals will prefer to live in non violent areas. On the belief that social interaction (or networks) is important to the future of the children, it is the case that children living in non-violent areas will have a better environment to their development than the children living in violent places. Again, the difference in the children's skills, generated by violence, will imply an income inequality in the future; and (d) statistical discrimination: two individuals, with the same human capital and working in the same area, will receive different wages, just because they live in places with different levels of violence. The reason for this is that the employer does not know the skills of each individual, so he attributes to each one the average characteristics of the employees in this region. Hence, the difference in the wages will generate income inequality, but the wage differential was originated by violence.

3 Other potential variables for criminality

In a first instance, we will use per capita intentional homicides[1] as a proxy for criminal activity. This is similar to Fajnzylber's approach (1998). However, there are some concerns regarding the use of this variable as a proxy for criminality. First, intentional

[1] Homicides intentionally caused by other people.

homicides are not always correctly classified. For instance, deaths caused from wounds are sometimes included in this statistics regardless of having been or not intentionally inflicted. A second problem is that some incidents end up not being reported. The underreporting is more frequent in rural areas. However, as pointed out by Cano and Santos (2000), the underreporting of deaths due to external causes is much lower than those resulting from natural causes. Also, if the under-registry remains stable over time, it may be controlled with the use of panel data with fixed effects (Fajnzylber and Araujo 2001).

In the literature on criminality, several variables haves been used to explain it in econometric models. Among them we can mention income, unemployment, schooling, structure of law enforcement, poverty, inequality, urbanization and so on. Yet, rationalizing the channels through which these variables affect crime has proved difficult for researchers.

Becker (1968) points out that criminal behavior can be well represented by a situation of choice involving risk. In this case the variable **average family income** as appears in Ehrlich (1973) can be used as a proxy for the return of participating in an illicit activity. Upwards shifts in this variable increase the probability of an agent engaging in criminal activity. Hence, a positive relationship between income and crime is expected. On the other hand, a positive income shift increases the opportunity cost to engage in illegal activity. Then we cannot state a priori the average income expected sign in criminality regression.

In the literature **schooling** has always been mentioned as having important effects on criminality. But, it is also not so easy to determine a priori the sign between criminality and schooling. It may be that schooling reduces crime because it increases the opportunity cost for engaging in an illegal activity. Hence, a negative correlation between both variables could be expected. Notwithstanding it, more schooling increases the ability to commit crime efficiently. Thus, the effect of schooling on criminality may be also positive. The majority of criminality cases is undertaken by males. So, it is fair to assume that the impact of schooling on criminality is more important to males than females. Schooling is represented by the average years of schooling for males above 15 years old.

The degree of **urbanization** (the ratio between urban population and total population) also appears as one variable that can explain crime. This is because of the interaction between groups of criminals and potential criminal, making it easier for the latter group to enter the criminality market with the exchange of information.

Some studies indicate the existence of a positive relationship between **unemployment** and criminality (Ehrlich 1973; Trumbull 1989; Gould 1979–1997). The literature points out that unemployment has two distinct effects on criminality. The first, denoted opportunity effect, refers to the negative influence that unemployment exerts upon crime due to the decrease in available wealth, because of the lower return from the activity. The second effect is known as criminal motivation. This effect is brought about by a reduction in the agent's income, as well as by the depreciation of human capital due to the period of absence from the labor market. Thus, the longer the agent remains unemployed, the greater the probability of taking part in crime (Ehrlich 1973).

Table 1 Explanatory variables for intentional homicides (crimes)

Explanatory variables (1)	Terminology (2)	Expected sign (3)
Average family income	Income	Not defined
Law enforcement spending	Public security	Negative
Rate of urbanization	Urbanization	Positive
Gini index	Gini	Positive
Rate of unemployment	Unemployment	Not defined
Schooling	Schooling	Not defined
Poverty	Poverty	Positive

Related to the structure of law enforcement, different variables are used in econometric studies on criminality. Some studies introduce the ratio of the number of convictions to the total number of reported incidents to identify the penalty imposed on the agent (Fajnzylber 1998). Another variable that could be used would be the size of each state's police force. Unfortunately, data for these variables are not available for Brazil. But under certain hypotheses and due to the availability of data, we can take the spending on **public security** as a proxy for these variables. At first sight, it is expected that criminality be negatively correlated with this variable. We must keep in mind, however, that for this variable endogeneity may occur: it is possible that a lower rate of criminality in a given region would have the effect of generating less public law enforcement spending or areas with high incidence of criminality have high rates of police expenditure. Studies that ignore endogeneity usually find that police activity has no impact on crime (Cameron 1988).

Finally, **poverty** measured by the percentage of the population below the poverty line appears in the literature among variables used to explain criminality. Poverty reduces the opportunity cost to enter in an illegal activity. Extreme poor individuals may see no big cost in getting caught and going to jail when the only available alternative choice is starvation and death. Furthermore, some researchers link poverty with social disorganization. If we accept that social disorganization makes it harder to find and punish criminals, then social disorganization, and consequently poverty, increases criminality. In spite of it, Kelly (2000) found an inverse correlation, although with no statistical significance, between violent crimes and poverty. Table 1 below provides a summary of the variables used in this study.

4 Database description and brief overview about inequality and crime in Brazil

According to the IBGE,[2] 14% of the nation's wealth belongs to the 1% of Brazilians. In 1998, the Gini index in Brazil was 0.60. It was 148th among 150 countries in terms of income inequality measured by the Gini index. The two countries that had the highest income inequality were Swaziland (Gini index: 0.612) and Sierra Leone (Gini index: 0.63). Furthermore, 19.6% of 45.2 million Brazilian families are poor, since they have

[2] Brazilian Institute of Geography and Statistics.

a per capita income of less than half minimum wage (R$ 42.00, approximately US$ 35.00) per month. The average income of the 10% richer is 150 times bigger than the average income of the 10% poorer.

Income is also unevenly distributed across regions[3] and states, the Northeast being the region where the poverty situation is the worst with 38.2% of workers earning less than half a minimum wage. In the Southeast, this percentage falls to 10.8%. In the North it is 26%. In the Midwest 15.9%, while 13% fall under this category in the South. In Brazil, in 1998, only 9.9% of the 45 million Brazilian families receive earnings that are more than _five times the minimum wages (R$ 420.00 or US$ 350.00) a month. According to IPEA[4] and IETS,[5] based on data of 1996–1997, the richest state of Brazil, São Paulo, has 8.4 million people below the poverty line. That is 40% of people that lives in this state are considered to be poor (receive a monthly wage less than R$ 83 or US$ 69) and 10% can be considered indigent (less than R$ 40.5 or US$ 33.75 a month), according to the indexes utilized by WHO[6] to quantify misery. Furthermore, 35% of individuals that live in the state of Rio de Janeiro live below the poverty line. And in the state of Minas Gerais, 51% of the population is also below that line.

In Brazil, recent data show a huge increase in the criminality rates. For example, the average rate of deaths due to homicide jumps from 14.8 per 100,000 inhabitants to 22.6 per 100,000 habitants during the period 1984–1995; that is, an increase of 52% in the period. In some states, the statistics on homicides are even more disturbing. Andrade and Lisboa (2001) show that the number of homicides in the state of São Paulo for men between 15 and 24 years old jumped from 54.4 per 100,000 inhabitants in 1981 to 128.4 in 1995. For men between 25 and 44 years old, that same rate rose from 49.3 to 106.2. This means a growth of 136 and 115%, respectively, between the years of 1981 and 1995. In Rio de Janeiro, another important Brazilian state, the number of murders among men between 15 and 24 years old per 100,000 inhabitants, rose from 148.9 to 275.3 between 1981 and 1995, representing a growth of 85%.

According to Sachsida et al. (2008), for Distrito Federal, homicides have increased from 14.3 per 100,000 inhabitants in the period 1980–1984 to 33.7 during 1990–1995, an incredible increase of 135% in a decade. Although larger states like Rio de Janeiro and São Paulo are by far the most violent ones in Brazil, we should expect a lower level of homicides in Distrito Federal, because of the following reasons: (a) the per capita income in Distrito Federal is the highest in the country, (b) the state has the highest security budget among the other states of the federation; (c) the living standards are considered high by international parameters. In this sense, we believe that income inequality rather than only economic conditions might have an important role in affecting the criminal behavior of individuals.

3 There are five regions in Brazil, namely, North, Northeast, South, Southeast and Midwest.

4 Institute of Applied Economic Research.

5 Institute for the Study of Work and Society.

6 World Health Organization.

Information regarding intentional homicides is available for all Brazilian regions. This information is collected by DATASUS.[7] With regard to the variables average family income, the Gini index, poverty, schooling, unemployment and the urbanization rate, the data used in this study were obtained from the following databases: (i) the series on average family income, male schooling, unemployment and the Gini index were extracted from the PNAD;[8] and (ii) the rate of urbanization was obtained from the Demographic Census. Both the PNAD and the Demographic Census were produced by the IBGE.[9] Information on state law enforcement spending was obtained from the Brazilian Finance Report produced by NTS.[10] Last, the population that will be used to normalize the intentional and homicides was obtained from the Demographic Census produced by IBGE. In the years for which no census was taken, the values were obtained by interpolation.

5 Econometric model of criminality

5.1 A panel data analysis for Brazilian states

As the extensive survey of Land, McCall and Cohen (1990) shows, empirical results that appear in literature on crime can be biased because of the strong collinearity among measures like inequality, poverty, unemployment and other variables used in econometric models. So, first of all, we have to undertake a study in order to identify collinearity among the variables and drop some variables to avoid multicollinearity.

Following Kelly (2000), in Table 2, we present simple correlations for grouped data or pooling among potential explanatory variables, which were described in Sect. 3. Table 2 indicates that income, schooling, and poverty are strongly correlated. The reason why income and schooling are correlated is simple. There is an extensive literature on returns on schooling that identifies the positive relationship between income and schooling (Mincer 1958; Becker 1975; Card 2001, inter alia). Another important correlation is between income and poverty or schooling and poverty, albeit the last one is more tenuous. In fact, after performing a number of OLS regressions and using the VIF[11] instrument, we conclude that we cannot run a regression with schooling and income in the same set of regressors. Based on it and in order to isolate the true impact of each explanatory variable, we decide not to include income in the econometric model and present the results based on two set of variables: one with schooling and poverty in the same set and, another one, in which we exclude schooling in views of the existence of multicollinearity existing between schooling and poverty.

To estimate the crime model, panel data analysis was used for data on crime rates and other variables for the Brazilian states from 1981 to 1995. The panel data analysis

[7] Data base on population health collected by the Brazilian Ministry of Health.

[8] National Home Sampling Survey.

[9] Brazilian Geographic and Statistics Institute.

[10] National Treasury Secretary.

[11] Variation Inflation Factor.

Table 2 Correlations among explanatory variables (pooling data: 1981–1995)

	Income	Schooling	Poverty	Gini	Public security	Unemployment	Urbanization
Income	1.000						
Schooling	0.8559	1.000					
Poverty	−0.8642	−0.6920	1.000				
Gini	−0.1959	−0.2116	0.4075	1.000			
Public security	0.3603	0.2565	−0.2600	0.3256	1.000		
Unemployment	0.0768	0.3148	0.1539	0.1100	0.1443	1.000	
Urbanization	0.6610	0.6640	−0.4778	0.1122	0.5160	0.3487	1.000

allows us to estimate the parameters of the model even when there is state specific unobserved heterogeneity. The results of the econometric model are presented in Table 3.

Following Kelly (2000), all the variables were transformed into logarithms, which means the estimated coefficients are in the form of elasticities. We also perform it for the variable Public Security. It must be noted that the dependent variable, intentional homicide, is measured with error. However, we have assumed the hypothesis in which this error has a normal distribution with mean zero and constant variance.

The estimated results are shown in Table 3. Columns (1)–(2) illustrate the estimation by simple OLS based on grouped data or pooling where individual effects are not taken into account. The OLS estimation is shown only for comparative analysis. Notwithstanding it, OLS estimation allows us to identify whether there is multicollinearity with the use of the VIF instrument that calculates the impact upon the variance of the one variable resulting from the correlations among the other regressors. The literature states that, in order for an indication of multicollinearity to exist, the value that indicates the highest VIF should be greater than 5 (Judge et al. 1985).

The rest of them list the results estimated by panel data. Columns (3)–(4) and columns (5)–(6) present the estimates for the random effect and fixed effect, respectively. The RHO statistics indicate the proportion of the variance of individual effect in the variance of ordinary noise. In our case, its value is greater than 80% in all cases., suggesting the importance of the individual component as a source of variability in the model.

The Breusch–Pagan test[12] tests the null hypothesis of no individual effect (the variance individual component is zero). This test clearly suggests that there are specific individual effects. If this accepted the null, the pooling OLS estimator would be appropriated to estimate the model (Baltagi 1995).

The random effect estimates are based on the assumption that they are uncorrelated with the explanatory variables. The fixed effect estimates are unbiased and consistent whether or not there is correlation between it and the explanatory variables. In other words when the random effect is valid, the fixed effect estimator will produce consistent estimates, although not efficient. That is the why the fixed effect is, in general, to be

12 This is based on adjusted Lagrange Multiplier (LM) principle.

Table 3 Econometric model for intentional homicide

Independent Variables	OLS (1)	OLS (2)	RE (3)	RE (4)	FE (5)	FE (6)
Poverty	−0.032	−0.208	−0.112	−0.155	−0.089	−0.107
	(0.804)	(0.049)	(0.106)	(0.021)	(0.114)	(0.090)
Gini	−2.012	−1.989	0.634	0.781	0.718	0.801
	(0.001)	(0.001)	(0.005)	(0.003)	(0.008)	(0.026)
Urbanization	1.683	1.911	0.807	1.401	0.793	1.150
	(0.000)	(0.000)	(0.058)	(0.000)	(0.088)	(0.001)
Unemployment	0.279	0.374	0.122	0.142	0.120	0.129
	(0.004)	(0.000)	(0.012)	(0.003)	(0.012)	(0.007)
Public security	−0.268	−0.281	−0.027	−0.024	0.073	0.083
	(0.000)	(0.000)	(0.605)	(0.647)	(0.214)	(0.152)
Schoolmale15	0.469	_	0.512	_	0.303	_
	(0.000)		(0.031)		(0.242)	
Constant	−9.642	−10.020	−7.724	−9.502	−8.719	−9.904
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
VIF	2.451	1.830	_	_	_	_
R^2	0.401	0.390	0.200	0.139	0.246	0.242
Rho	_	_	0.822	0.814	0.846	0.878
Hausmann test	_	_	15.73	20.11	_	_
			(0.010)	(0.000)		
Breusch–Pagan test	_	_	833.34	843.33	_	_
			(0.000)	(0.000)		
Observations	319	319	319	319	319	319

The values in parentheses are the *P* values of the variables

preferred to the random effects estimator unless we can measure all the time-invariant factors correlated with other regressors. In our case the Hausmann test indicates that the hypothesis that the specific individual is correlated with the independent variable cannot decisively be rejected. Therefore, this result points out that the estimation by random effect does not generate consistent estimators for the model. In this way, we should focus on the fixed effect results.

The results related to the fixed effect in columns (5)–(6) indicate that unemployment level, income inequality and urbanization rates increase homicides. Poverty has a negative effect on criminality; however the results are not statistically significant at the 5% level. This result is close to the one that appears in Kelly (2000) for violent crime. According to Kelly (2000) most people in poverty are children, single mothers or elderly. These groups have no comparative advantage to resort in criminality. We can note too that public security and schooling are not statistically significant in the determination of intentional homicides.[13]

[13] The exclusion of these variables do not change qualitatively the results presented in Table 3.

Regarding the unemployment rate, it may be stated that the result obtained for the sign and value of the coefficient is in agreement with most of the studies appearing in the literature (Ehrlich 1973; Trumbull 1989; Wong 1995; Gould 1979–1997). We can note that an increase of 10% in unemployment generates an increase of about 1.2% in the intentional homicides. Fajnzylber and Araujo (2001) in a study for the Brazilian case, and Magalhães (1997) in a study for the Federal District State (Brazil) using time series, show that unemployment has a net positive effect on criminality. In the same way, an increase of 10% in the income inequality, represented by the Gini index, generates an increase of about 8% in intentional homicides. This strong evidence suggests the importance of inequality on criminality for Brazil during the period 1981–1995.

In the random and fixed effects estimated coefficients for inequality, results shown in columns (3)–(6) in Table 3 turn out to be positive, whereas their OLS estimated coefficients have the opposite sign. This seems to be due to the fact that the Gini index is correlated with the state specific unobserved heterogeneity, resulting in bias of the OLS estimates. The consideration of these factors is extremely relevant because they may greatly alter the estimated coefficient of a variable. If a methodology that allows us to consider the differences among the individual units (states) is not incorporated into this study, we would have a completely distorted idea of how income inequality affects criminality. Confirming our initial intuition, income inequality represented by the Gini index has significant influence in explaining criminality.

It is also interesting to notice that the estimated coefficient of the public security variable is negative in columns (3) and (4) when random effect specification is used, but becomes positive in columns 5 and 6 when fixed effect specification is used. Indeed, the fixed effects estimator is able to control for endogeneity due to the correlation between the individual specific component of the error term and the regressor. But in the case of public security, it is possible that the source of endogeneity is related to reverse causality. To be more specific, here the source of endogeneity probably comes from not the correlation of this variable with error's individual component, but with the non-specific component of disturbance.[14] In order to investigate this issue, we will apply a panel database in the GMM[15] methodology. GMM controls unobserved unity-specific effects too, but it also controls the joint endogenity of the explanatory variables and some types of measurement errors in the dependent variable.

Our econometric model follows the methodology developed by Arellano and Bond (1991) and Arellano and Bover (1995). In fact, we base our estimation on the so-called "system GMM"[16] approach (Blundell and Bond 1998) and not on the later version

[14] In the panel data model, the disturbance u_{it} is made up of two random components, the individual effect α_i, and the non-specific disturb ε_{it}, so that $u_{it} = \alpha_i + \varepsilon_{it}$ (Hsiao 2003).

[15] Generalized method of moments

[16] A problem with the original Arellano–Bond estimator is that lagged levels are often poor instruments for first differences, especially for variables that are close to a random walk. Arellano and Bover (1995) described how, if the original equations in levels were added to the system, additional moment conditions could be brought to bear to increase efficiency. In these equations, predetermined and endogenous variables in levels are instrumented with suitable lags of their own first differences. Blundell and Bond (1998) articulate the necessary assumptions for this augmented estimator more precisely and tested it with Monte Carlo simulations (Bond 2002).

Table 4 Econometric model for intentional homicide: panel data GMM system estimator

Independent variables	(1)	(2)	(3)	(4)
Mortp_1	_	0.617 (0.000)	_	0.932 (0.000)
Poverty	−0.235 (0.022)	−0.127 (0.058)	−0.620 (0.000)	−0.154 (0.007)
Gini	0.803 (0.003)	0.667 (0.012)	0.672 (0.000)	0.780 (0.024)
Urbanization	0.860 (0.064)	0.787 (0.056)	0.720 (0.000)	0.408 (0.101)
Unemployment	0.202 (0.097)	0.071 (0.109)	0.364 (0.000)	0.050 (0.050)
Public Security	−0.322 (0.064)	−0.078 (0.000)	−0.373 (0.000)	(−0.048) (0.059)
SchoolMale15	0.948 (0.002)	0.071 (0.006)	_	_
Constant	−4.561 (0.0080)	1.473 (0.001)	5.586 (0.000)	1.007 (0.007)
Serial correlation AR(1)	−1.300 (0.002)	−3.100 (0.002)	−1.300 (0.002)	−4.640 (0.002)
Serial correlation AR(2)	0.062 (0.952)	0.300 (0.765)	0.005 (0.982)	−0.180 (0.858)
Sargan test	91.71 (0.992)	121.90 (0.587)	97.52 (0.982)	143.09 (0.459)
Observations	309	263	309	263

The values in parentheses are the P values of the variables
Mortp = terminology for intentional homicide; Mortp_1 = first lag of Mortp

known as "difference GMM"[17] approach. These estimators, instead of assuming strict exogeneity, are more flexible, allowing for the limited form of simultaneity and reverse causality. Specifically, we adopt the more flexible assumption of weak exogeneity, that is, current values of the explanatory variables may be affected by past and current realizations of dependent variable but not its future innovations. The results obtained by "system GMM" approach are shown in Table 4.

Due to the possible existence of multicollinearity above discussed, we present two results where the regressors are subsets of the set of all potential controls. In addition, we include the lag of the dependent variable. The motivation behind the use of lag is its dynamic appeal. There are three specification tests in Table 4. First, the Sargan test reports a test of over-identifying restrictions, which test the null hypothesis of overall validity of the instruments. Failure to reject this hypothesis gives support to the model. We also conduct two additional tests to check for both autocorrelation AR(1) and AR(2). In Table 4, we see that the coefficient on the lagged homicide rate is positive and significant in all of the two specifications where the variable is included. This result supports the claim that past homicides have "inertial effect" on current criminal behavior.

The dynamic appeal is related to some kind of "inertial effect" on homicides (Fajnzylber et al. 2000). We can see that the current homicide rate has a positive effect in future values of this variable. In all regressions presented in Table 4, the sign of the variable public security is negative, so in view of Sargan test's results we can state that the GMM system estimator has been able to control the endogeneity for public security. So, another achievement of this study is to establish a negative link

[17] This estimator has low asymtotic precision and large biases in small samples Blundell and Bond (1997).

between public expenditure in public security and crime. That is, for the Brazilian case spending in public security is effective to control criminality.

5.2 The Granger causality test for income inequality and public security

Considering the fundamental importance between inequality and crime in this study, our task now is to verify the consistency of this relation. In other words, we shall attempt to verify the correct causality relationship between these variables. In the last section, we verified the existence of statistical correlation between crime and inequality. But, as we had already stressed in Sect. 2 it is possible that criminality causes inequality. In order to check the true causality of this relationship we will implement the Granger causality approach (Granger 1969).

In order to adapt the Granger Causality test to a panel data context, a representative procedure used to test causality in a panel appears in Holtz-Eakin et al. (1988). This model is expressed as follows

$$y_{it} = \alpha_0 + \sum_{j=1}^{m} \alpha_j y_{it-j} + \sum_{j=1}^{n} \delta_j x_{it-j} + f_i + u_{it}, \tag{1}$$

where $i = 1, \ldots, N$, represents the units, and $t = 1, \ldots, m$, represents the time index.

Eliminating the fixed effect f_i, the model in differences assumes the following form

$$y_{it} - y_{it-1} = \sum_{j=1}^{m} \alpha_j (y_{it-j} - y_{it-j-1}) + \sum_{j=1}^{m} \delta_j (x_{it-j} - x_{it-j-1}) + (u_{it} - u_{it-1}). \tag{2}$$

Such a specification introduces a simultaneity problem due to the fact that the disturbance is correlated with $y_{it-j} - y_{it-j-1}$. In this case, a consistent alternative is estimating the model by using the two-stage instrumental variable method (2SLS). To verify whether x causes y, we only need to test the joint hypothesis $\delta_1 = \delta_2 = \cdots = \delta_m = 0$ (Nair-Reicheit and Weinhold 2001).

Introducing the issue into the current context, to verify whether income inequality expressed by the Gini index causes crime, we must prove that $\delta_1 = \delta_2 = \cdots = \delta_m = 0$ in the following model[18]

$$\begin{aligned} \text{mortp}_{it} - \text{mortp}_{it-1} &= \sum_{j=1}^{m} \alpha_j (\text{mortp}_{it-j} - \text{mortp}_{it-j}) \\ &\quad + \sum_{j=1}^{m} \delta_{11} (\text{gini}_{it-j} - \text{gini}_{it-j}) + u_{it} - u_{it-1} \end{aligned} \tag{3}$$

[18] Mortp = terminology for intentional homicide.

Table 5 Granger causality test

Regression 1 Dependent variable = Dmortp[a]		Regression 2 Dependent variable = Dgini	
Dmortp_1[b]	−0.0671 (0.346)	Dgini_1	−0.5055 (0.000)
Dmortp_2	−0.0522 (0.477)	Dgini_2	−0.2750 (0.008)
Dmortp_3	−0.1636 (0.030)	Dgini_3	−0.3335 (0.001)
Dgini_1	0.5824 (0.061)	Dmortp_1	−0.0050 (0.801)
Dgini_2	−0.2067 (0.574)	Dmortp_2	0.0275 (0.185)
Dgini_3	−0.4670 (0.183)	Dmortp_3	0.0016 (0.940)
Causality test	7.08 (0.069)	Causality test	2.02 (0.569)
$\delta_1 = \delta_2 = \delta_3 = 0$		$\delta_1 = \delta_2 = \delta_3 = 0$	
Regression 3 Dependent variable = Dmortp[a]		Regression 4 Dependent variable = Dpublicsecurity	
Dmortp_1[b]	0.0265 (0.706)	Dpublicsecurity_1	−0.5643 (0.000)
Dmortp_2	−0.0998 (0.148)	Dpublicsecurity_2	−0.4601 (0.000)
Dmortp_3	−0.1311 (0.070)	Dpublicsecurity_3	−0.2676 (0.020)
Dpublicsecurity_1	−0.1838 (0.002)	Dmortp_1	−0.0243 (0.820)
Dpublicsecurity_2	−0.0101 (0.880)	Dmortp_2	0.1351 (0.199)
Dpublicsecurity_3	0.0816 (0.279)	Dmortp_3	−0.3452 (0.002)
Causality test	14.22 (0.002)	Causality test	12.66 (0.005)
$\delta_1 = \delta_2 = \delta_3 = 0$		$\delta_1 = \delta_2 = \delta_3 = 0$	

[a] Dmortp = mortp − mortp(-1)
[b] Dmortp_1 = mortp(-1) − mortp(-2), Dmortp_2 = mortp(-2) − mortp(-3) *P* values in parentheses; OBS: 189

where mortp is the ratio between intentional homicides and the population. In order to estimate this model, we may use mortp_{it-2} or $\text{mortp}_{it-2} - \text{mortp}_{it-3}$ as instruments (Hsiao 1986). Table 5 below presents the results of the Granger procedure to identify the consistency of the relationship between income inequality, crime and public security.

The reason to perform the Granger causality approach for public security and crime is because in the last section we found existence of endogeneity between these variables. If there is a bi-directional causality or reverse causality, Granger causality test stresses the identication problem between these variables. In Table 5 we present the results of four regressions used to perform the test of Granger causality. Due to short temporal dimension of the sample, we decided to include just three lags in the model.

Considering the results from regressions 1 and 2, Granger causality tests show that inequality causes crime, but the reverse is not true. In regression 1, we can reject the null hypothesis of the non-significance of the coefficients of the Gini index in the mortality regression. The reverse is not true because we can not reject the null that the coefficient of mortality in Gini equation is zero. This shows that income inequality does not cause criminality in Granger sense.

In regression 3 and 4, we want to verify whether the spending on public security really reduces criminality, or conversely, more crime attracts more public expenditure on security. In this case, the Granger causality tests reveal there is a bi-causality relation between crime and public security. Furthermore, regression 4, also shows that crime Granger causes public security. In other words, the Granger causality test confirms the identification problem between these variables.

This exercise stresses the true relationship between inequality and criminality. Bourguinon (1999) argues that the "positive link between these variables in a cross-section countries may be due to unobserved factors affecting simultaneously inequality and criminality rather than to some causal relationship between these variables". In a view of the results obtained in this section we showed that the correlation between inequality and criminality is not spurious. Our results are in accordance with Fajnzylber et al. (1999) and Soares (1999). Both studies concluded in favor of a significant crime-inducing effect of income inequality.

6 Conclusions

The objective of this study was to shed light on the main determinants of criminality in Brazil. To do so we used panel data methods for the state level data on crime rates and other variables in Brazil. One of the advantages of the panel data approach is that it allows for unobserved state level heterogeneity. This is important because there are large disparities in income across Brazilian states. Our results show that income inequality has a statistically and economically significant positive effect on criminal behavior.

The econometric results also showed that others variables like unemployment and urbanization are positively related to crime. We also used panel data GMM methodology to estimate the dynamic effects of past criminal activity on current crime, and we found it to be positive, which suggests an "inertial effect" on criminal behavior. Panel data GMM estimator was also used to control the existence of endogeneity related to the variable public security. In this case, the results showed that public security spending is effective in decreasing criminal behavior. Contrary to the common wisdom, we could not find evidence that poverty increases crime. In fact, the results indicate a negative relationship between poverty and criminality.

Finally, considering the results from the Granger causality tests, it was possible to show that inequality Granger causes crime. This result supports the view that income inequality is an important determinant of criminality in Brazil.

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