UNIVERSIDADE ESTADUAL DE CAMPINAS
INSTITUTO DE ECONOMIA

TEMIDAYO JAMES ARANSIOLA

# Four empirical essays about crime and violence in an economic and interdisciplinary approach

# Quatro ensaios empíricos sobre crime e violência em uma abordagem econômica e interdisciplinar

Campinas
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**Prof. Dr. Marcelo Justus dos Santos – orientador**

**Prof.ª Dr.ª Vânia Aparecida Ceccato – coorientadora**

Tese de Doutorado apresentada ao Programa de Pós-Graduação em Ciências Econômicas do Instituto de Economia da Universidade Estadual de Campinas para obtenção do título de Doutor em Ciências Econômicas, área de Teoria Econômica.

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# ABSTRACT

The main objective of this study is to provide specific discussions concerning the determinants of crime and violence in four empirical essays from an economic and multidisciplinary approach. The first essay investigates the space-temporal growth of homicide rates in Brazil by providing empirical evidence of a convergence process and identifying predictors of the country's geography of homicides growth. The second investigates the effect of absolute deprivation (proxy unemployment) and relative deprivation (proxy income inequality) on homicide levels in Brazil. The data for these first two essays were obtained from the Brazilian Information System about Mortality and Census, but the empirical strategy for both differ – spatial autoregression model for the first and negative binomial model for the second. The third essay empirically tests four competing hypotheses of the causes of cargo theft – the space-time dynamics hypothesis, the economic attractiveness hypothesis, the social structure hypothesis, and the deterrence hypothesis – focusing on the São Paulo case. The Autoregressive-Distributed Lag model was estimated to test these hypotheses. The fourth essay investigates the effect of economic conditions on lethal crimes by testing the hypotheses that the relationship between GDP and homicide rates is non-linear and influenced by levels of income inequality. This last essay used data panel data of the OECD member countries to estimate GMM models for testing these hypotheses. As to results, the first paper confirms that the convergence of lethal violence exists in Brazil and is happening faster due to the increasing growth observed in the North and Northeast regions of the country. The second essay found that unemployment and income inequality increase lethal crimes and their effects are intertwined in that the effect of one exacerbates that of the other. The third essay found that the number of cargo thefts of a geographic area can be predicted by itself and that of neighboring areas. The result for economic attractiveness and social structure is inconclusive but police activity reduces cargo theft. The fourth essay found a non-linear relationship between GDP and homicide rates. Besides having a predominant effect on homicide rates, income inequality conditions the effect of GDP on homicide rates.



**Keywords**: Crime. Violence. Causes. Economics.

**RESUMO**

O principal objetivo deste estudo é apresentar discussões específicas sobre os determinantes de crime e violência em quatro ensaios a partir de uma abordagem econômica e multidisciplinar. O primeiro ensaio investiga o crescimento espacio-temporal da taxa de homicídios no Brasil, fornecendo evidências empíricas do processo de convergência e identificando preditores da geografia do crescimento de homicídios do país. O segundo ensaio investiga o efeito de privação/pobreza absoluta (proxy desemprego) e privação/pobreza relativa (proxy desigualdade de renda) sobre níveis de homicídio no Brasil. Os dados para os primeiros dois artigos foram obtidos do Sistema de Informações sobre Mortalidade e censos, mas a estratégia empírica de ambos varia – modelo autorregressivo especial para o primeiro e modelo binomial negative para o segundo. O terceiro artigo testa quatro hipóteses sobre as causas de roubo de carga – da dinâmica espacio-temporal, da atratividade econômica, da estrutura social, e da dissuasão – focando no caso de São Paulo. Modelos Autorregressivos de Defasagens Distribuídas foram estimadas para testar essas hipóteses. O quarto ensaio investiga o efeito de condições econômicas em crimes letais, testando a hipótese da não-linearidade da relação entre o PIB e taxa de homicídio, e que essa relação é condicionada ao nível de desigualdade. Essas hipóteses foram testadas usando painel de dados de países membros da OECD para estimar modelos de painel dinâmico (GMM). Quanto a resultados, o primeiro ensaio confirma a existência de convergência de violência letal no Brasil, e esse processo está acontecendo cada vez mais rápido devido ao crescimento de violência observada nas regiões Norte e Nordeste do país. Encontrou-se no segundo artigo que desemprego e desigualdade de renda aumentam crimes letais e seus efeitos são interligados de tal maneira que o efeito de um agrava do outro. No terceiro artigo, encontrou-se que o número de roubos de carga de uma área pode ser previsto usando seus valores anteriores e o de áreas vizinhas. Os resultados para atratividade econômica e estrutura social foram inconclusivos, mas a atividade policial reduz roubo de carga. O quarto artigo encontrou uma relação não linear entre o PIB e a taxa de homicídios. Além de ter efeito ressaltado sobre a taxa de homicídio, a desigualdade de renda condiciona o efeito do PIB sobre a taxa de homicídios.

Palavras-chave: Crime. Violência. Causas. Economia.

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# 1. INTRODUCTION

Public safety is a public good that every individual should have a right to. However, countries such as Brazil have become the global reference of crime and violence, whereby this public good is unavailable to all and a privilege to some.

In the year 2016 alone, about 62.517 homicides caused by aggression and legal interventions were recorded, giving a rate of about 30.3 for every one hundred thousand population. This rate was three times the world average; twice the average of countries in America; thirty times the average of countries in Europe, and; third highest in South America, following Peru and Colombia (Cerqueira et al., 2018). The homicide rate was even higher in the year 2017 and was declared to be the country's highest historical homicide rate (Cerqueira et al., 2019). This position makes Brazil a noteworthy case study for the literature to better understand the dynamics and causes of crime and lethal violence. Nonetheless, this study also explores the context of developed countries that have low crime rates to better understand the dynamics and effect of economic conditions and social structure on lethal violence.

This study compiles four empirical essays that provide specific discussions concerning the determinants of crime and lethal violence, exploring attributes of time, space, and context. Moreover, given the understanding that crime is an aftermath of the mix of various social and economic factors, these essays adopt an interdisciplinary approach by combining a diverse range of theoretical frameworks from economic and criminological researches.

The first essay investigates the space-temporal growth of homicide rates in Brazil by providing empirical evidence of a convergence process from 2000 to 2017 and identifying predictors of the country's geography of homicides. Specifically, this first essay aims to investigate the prospect of the homicide rates to converge towards similar high values in Brazil (henceforth, convergence) due to the growth pattern of violence observed across regions; identify the geographic clusters of homicide rates and their evolution in time by using spatial statistics, and; model and identify the covariates of the growth of homicide rates, emphasizing social disorganization factors such as ethnical heterogeneity, economic disadvantage, inequality, and unemployment. On one hand, this essay innovates by bridging crime and economic theories to test for the convergence of homicide rates, thereby promoting theoretical interdisciplinarity. On the other hand, the empirical strategy of this essay explores time and space by combines spatial statistics, GIS (Geographical Information Systems), and growth modeling techniques to achieve the proposed objectives.

The second essay investigates the effect of absolute deprivation (proxy unemployment) and relative deprivation (proxy income inequality) on homicide levels. Besides, this essay explores the effect of various contexts of deprivation on homicide levels by empirically interacting the unemployment rate and income inequality to verify how homicide levels react to distinct combinations of the magnitudes of these deprivation measures. The importance of such interaction is that it enables to answer critical questions such as, how does homicide levels respond to low unemployment under the conditions of high income inequality, or vice-versa. Apart from this interaction, this essay also innovates in the use of unemployment as a measure of absolute deprivation instead of poverty, whereas income inequality is used as a measure of relative deprivation. This is because poverty is, by construct, confounded in the lower tail of the distribution of income inequality measures (PRIDEMORE, 2011) and unemployment is a state which does not relate one person to another, hence absolute. Moreover, unemployment better characterizes the temporary lack of the means of individuals to change their deprivation situation, which may emphasize the feeling of frustration and, consequently, may trigger violence (MERTON, 1938).

The third essay diverges from lethal violence to property crimes by investigating the causes of cargo theft, addressing geographical, economic, social structure, and deterrence factors. Cargo theft is one of the major concerns of logistics systems worldwide in that it is costly to businesses and economies either directly through shrinkage (BAILEY, 2006) or indirectly through the cost of prevention measures and/or insurance (ALSTETE, 2006), which may be swift in crippling small and medium businesses. Specifically, in this essay, the space-time dynamic of cargo theft is identified; the role of economic attractiveness on cargo theft is investigated using market factors such as sales and prices; the role of the unemployment rate on cargo theft is assessed, and, last but not least important; the effect of policing (a proxy for deterrence) on cargo theft is identified. The Brazilian context is also resorted for the testing of these objectives since this modality of crime is most severe in South America, whereby Brazil takes the lead.

The fourth essay shifts from the Brazilian context which is characterized by high rates of violent crimes and high unemployment and inequality to the context of OECD member countries which is characterized by low rates of crime and low level of deprivation reflected by high absolute income and low inequality. Resorting to the context of developed countries enables to better identify the relationship between economic growth, inequality, and crime, whereby other socioeconomic conditions such as poverty, unemployment, low education attainment, etc. are less pronounced. The main objective here is to fill some gaps in the literature regarding the association between economic conditions, measured in GDP, and homicide rate.

In specific, the effect of GDP growth on crime is investigated, and the hypothesis of non-linearity (U-shape) is tested. Also, similarly to the third essay, this fourth essay tests the interaction between GDP and income inequality and investigates its effect on the association between the former and homicide rates.

Although the topics investigated are linked, this study is structured into four essays with independent structures, whereby each one has its introduction, theoretical and empirical background, method, results, and conclusion.

## 2. GROWTH OF LETHAL VIOLENCE IN BRAZIL 2000 - 2017: A SPACE-TEMPORAL ANALYSIS OF HOMICIDES

**Temidayo James Aransiola [1]**
**Vania Ceccato[2]**
**Marcelo Justus[3]**

### ABSTRACT

*Objectives*: This study investigates the space-temporal growth of homicide rates in Brazil by providing empirical evidence of a convergence process from 2000 to 2017 and identifying predictors of the country's geography of homicides.

*Methods*: Data from the Brazilian Information System on Mortality and Censuses are used to estimate growth models combined with spatial statistics and GIS (Geographical Information Systems).

*Results*: Not only is there evidence of convergence, but it is also happening faster in recent years than that observed in the past. This process is characterized by a steady increase in the North and Northeast regions combined with a reduction in growth in the South and Southeast regions of Brazil. The predictive strength of income inequality (measured using the GINI coefficient) on the growth of homicide rate is slightly reduced over time, whereas that of unemployment rate has become expressively dominant from 2010 to 2017.

*Conclusion*: Homicide rates are increasing more in regions that had lower rates, mainly due to social disorganization, causing the dislocation and expansion of homicide hotspots, and the homogenization of homicide rates at high values in Brazil. The theoretical and practical implications of these results are discussed.

***Keywords*:** Violence. Homicide. Evolution. Pattern detection. Homogenization.

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# 1. INTRODUCTION

Brazil has one of the highest homicide rates in the world and, according to Cerqueira et al. (2019), a historically high rate was observed in the year 2017 (around 31.6 homicides per 100.000 populations). In the year 2016, this rate was around 30.3, which was three times the world average; twice the average of countries in America; thirty times the average of countries in Europe, and; the third highest in South America, following Peru and Colombia. This position makes Brazil a relevant case of the so-called Global South for the literature on violent crimes (CERQUEIRA et al., 2018). Besides, the pattern of these murder rates has been affected by the redistribution of overall violence across Brazilian municipalities in the last decades (ANDRADE and DINIZ, 2013; CECCATO and CECCATO, 2017), showing signs of convergence whereby most regions evolve towards similarly high levels of violence (WAISELFISZ, 2011).

Drawing on the Brazilian experience from the year 2000 to 2017, this study aims to investigate the prospect of homicide rates to converge towards similar high values (henceforth, convergence) due to the growth pattern of violence across regions; identify the geographic clusters of homicide rates and their evolution in time by using spatial statistics, and; model and identify the covariates of the growth of homicide rates, emphasizing social disorganization factors such as ethnical heterogeneity, economic disadvantage, inequality, and unemployment.

The objectives are achieved by, firstly, characterizing the patterns of homicide rate and, thereafter, using spatial statistics and GIS (Geographical Information Systems) to identify the clusters of homicide rates.

Given the lack of a specific theoretical framework for the understanding of the growth of violence in the criminological literature, this study improvises by bridging crime and economic theories to test for the convergence of homicide rates, thereby promoting theoretical interdisciplinarity. A similar theoretical mix has been previously applied for Brazil by Justus and Santos Filho (2011) to test for the convergence of homicide rates from the early 1990s to the mids 2000s. However, no similar application was found in the international literature exploring also the spatial dimension of this process. Another novelty of this study is the use of spatial statistics in identifying significant pockets of homicide rates over time. Official homicide rates combined with spatial statistics, such as cluster analysis, and GIS underlie the methodology of this study. The application of the convergence and spatial concentration theories and empirical strategies gives a better understanding of how convergence affects the spatial clusters of homicide rates, i.e., the association of time and space.

The structure of this study is as follows. Section 2 presents the theoretical background on the determinants of violent crime and its distribution in Brazil over time. Section 3 provides the contextual framework and forwards the hypotheses. The source of data, empirical strategies, and model specification are detailed in Section 4. The descriptive and empirical results are reported in Section 5 and discussed in Section 6. Conclusions, limitations, and future research are provided in Section 7.

# 2. THEORETICAL BACKGROUND

## 2.1 TRENDS AND PATTERNS OF HOMICIDES: INTERNATIONAL AND BRAZILIAN PERSPECTIVES

Trends of violence are commonly explained in the criminological literature using specific events in time and space. For instance, the rise in violence in the U.S. in the 1980s is attributed to the appearance of cocaine in the drug market, and the decline observed in the 1990s is attributed to stricter gun laws, economic development, and policing (BLUMSTEIN *et al.*, 2000). Although similar trends were observed in Australia during the same period, most homicides were associated with interpersonal violence (MUKHERJEE, 2002). Similarly to the U.S., the increase and spread of homicides in Brazil in the 2000s is commonly attributed to demography and criminal organizations (CERQUEIRA et al.; 2019; WEISHEIT, 2011), whereas the significant drop has been associated with greater policing and police intelligence (JUSTUS *et al.*, 2018).

Such specific analyses are relevant to retrospectively understand the oscillations of homicide rates but the lack of a general theoretical framework of the growth of homicide rates (or violence in general) does not enable to conjecture trends in such a way that it supports public safety planning.

An alternative is to draw on growth theories from other fields, whereby this study resorts to the convergence growth theory from economics proposed by Solow (1970) and tested and extended by Mankiw *et al.* (1992). This theory is rooted in the observation that poorer economies grow faster in terms of national income per capita compared to richer economies and, by consequence, all economies would converge to similar levels and development gaps will reduce in the long-run. This process occurs due to the diminishing returns of capital, i.e., the limits imposed by physical and human capital make economic growth reduce over time, given that other factors are held constant. This economic growth framework is considered applicable to crime since the limit of homicide rate of a location is restricted, at maximum, to the population size of the same.

Therefore, the theoretical assumption of this study is that, other things equal, homicide rates will grow lesser in municipalities with already high rates compared to those with lower rates and, by consequence, homicide rates may converge in the long run. Different from the economic framework, the convergence of homicide rates is not desired since this implies that all regions will have similarly high rates.

### ***Homicide trends and geography in Brazil***

Brazil is ranked as one of the most violent countries in the world in terms of homicide absolute numbers and rates, and has recently broken its historical record of high rates (CERQUEIRA *et al.*, 2019). This global position has increased the body of research that investigates the trends, geography, and determinants of violence in Brazil (ANDRADE and DINIZ, 2013; CECCATO *et al.*, 2007; JUSTUS *et al.*, 2016; JUSTUS *et al.*, 2018 SCORZAFAVE *et al.*, 2015). In most cases, these studies explain violence by resorting to criminological theories in the international literature and adapt to regional peculiarities.

In Brazil, homicide rates are increasing in regions that had lower rates and stagnant or reducing in those which had higher rates, leading to the homogenization of homicide rates in Brazil. Waiselfisz (2011) and Waiselfisz (2016) characterize this process as the *interiorization* and *dissemination* of homicides and explain that the mechanisms behind such a trend are the socio-cultural and demographic factors highlighted by the social disorganization and subcultural theories of crime in the international literature. Justus and Bearing on the conflict theory, Cerqueira *et al.* (2019) explain that conflicts between criminal organizations associated with narcotraffic operations and land conflicts in specific regions are also responsible for the growth and regional differences of homicide rates in Brazil.

### ***The spatial concentration of crime***

The level of crime of a location is a result of the social structures and interactions that exist within and around the location (FREEMAN et al., 1996; SHAW and MCKAY, 1942). This makes crime not random in space and, therefore, concentrated in specific locations, commonly referred to as crime hotspots – locations of high crime rate surrounded by locations of high crime rate (ANSELIN *et al.*, 2000). The Moran's I and local indicators of spatial association (LISA) are two of the common statistics used for measuring spatial concentration. Although they both measure the deviation from randomness, the Moran's I statistic provides a single global statistic for the whole territory while the LISA statistic provides specific values by location that indicates the degree of dependence of a location on its neighbors.

Therefore, the theoretical assumption of this study is that, other things equal, homicide rates will grow lesser in municipalities with already high rates compared to those with lower rates and, by consequence, homicide rates may converge in the long run. Different from the economic framework, the convergence of homicide rates is not desired since this implies that all regions will have similarly high rates. Moreover, as to spatial distribution, we expect that other things equal, municipalities with high homicide rates will be surrounded by municipalities with relatively high rate forming, therefore, clusters of homicide rates in Brazil.

## 2.2 FACTORS AFFECTING VIOLENCE: AN INTERNATIONAL PERSPECTIVE

The international literature has shown that violence, in particular lethal violence, is associated with social disorganization, which is commonly reflected by weak informal social controls (SHAW and MCKAY, 1942), housing mobility, weak social ties, population heterogeneity, and poor normative social structures. The strain theory (AGNEW, 1999; MERTON, 1938) advocates that crime is caused by the disparity between aspirations and the possibility of achieving them. This disparity is caused, especially, by social structures such as absolute and relative deprivation. The effect of strain on crime is even higher, according to Cloward and Ohlin (1960), if the structural disadvantage is explicit to specific groups of the population that feels blocked out of the legitimate opportunity structure.

Cultural differences in terms of values, believes and norms of people are pointed by Messner and Rosenfeld (1997) to explain the variation of violence rates across regions. The subcultural theory of crime addresses crime as a normalized learned behavior that is not viewed as wrong due to internalized normative values and codes and can be perpetuated through peer influence (ANDERSON, 1990; BLACK, 2014). Noneconomic institutions such as family, government, education, and religion have a significant mitigating impact on the level of violence of a society (MESSNER and ROSENFELD, 1997). Profound institutional changes may also create anomic conditions such as a breakdown of social norms and values, and create favorable conditions for crime, including violence (MERTON, 1938).

Violence is also commonly associated with conflicts, which could range from land, domestic, gang to political conflict. Rosenfeld *et al.* (1999) show that youth homicides are directly related to gang activities and gang members' conflicts. The conflict theory also explains that family violence may result from power relations and socio-cultural antagonistic elements of relationships (WITT, 1987).

Researches have also emphasized that the mechanisms that cause crime may be manifested differently in urban and rural settings due to the peculiarity of contexts (CECCATO, 2016; WEISHEIT and DONNERMEYER, 2000).

Therefore, it is expected that factors related to social disorganization such as ethnic heterogeneity, economic disadvantage, inequality, and unemployment are significant determinants of homicide rates in Brazil.

## 3. CONCEPTUAL FRAMEWORK AND HYPOTHESES

Brazil is a Global South country located in Latin America with 26 states and one federal district that comprises 5570 municipalities with a total population of about 210 million inhabitants (IBGE, 2019). Brazil has been experiencing historically high and increasing rates of violence, which, in the year 2017 alone, resulted in 65.602 deaths, giving a rate of 31.6 per 100 thousand populations (CERQUEIRA *et al.*, 2019). Apart from being heterogeneously distributed, the geography of violence is steadily changing in a way that may stimulate the homogenization of homicide rates at high values in Brazil (WAISELFISZ, 2011). As theorized in the international literature, researches on Brazil suggest that social disorganization expressed, especially, by socioeconomic deprivation, inequality and social exclusion combined with demographic changes and conflicts in specific regions are potential causes of the growth of homicide rates (CECCATO and CECCATO, 2017; JUSTUS*ET al.*, 2016; SCORZAFAVE *et al.*, 2015; WAISELFISZ, 2011). Given the theoretical and empirical background reviewed thus far, the hypotheses put forward are

*H1* – Homicide rates are increasing significantly more in Brazilian municipalities that in previous decades showed relatively lower rates of lethal violence than in those that showed relatively higher homicide rates - "the convergence hypothesis".

*H2* – Homicides show concentrated patterns both in space and time – municipalities with high homicide rates are surrounded by municipalities with high rates of homicide and this concentrated pattern tend to persist over time - "the clustering hypothesis"

*H3* – The growth of homicide rates is linked to *social disorganization* factors such as ethnic heterogeneity, economic disadvantage, inequality, and unemployment at the municipal level.

# 4. DATA AND METHODS

## 4.1 DATA

The analyses of this paper are centered on Brazilian municipalities for the years 2000, 2010, and 2017, which is the most recent data available in the year 2019.

Homicide countis defined as the number of deaths provoked by external causes through aggression (group X85–Y09 of the International Classification of Diseases, ICD 10) and this data was obtained from the Information System about Mortality (ISM). The counts were transformed into rates by dividing by population size and multiplying by 100.000, hence, the homicide rate by 100.000 populations. The population and other socioeconomic and demographic data were obtained from national censuses available in the database of the Brazilian Institute of Geography and Statistics (IBGE).

## 4.2 METHODS

The empirical strategy used to verify the hypotheses of this study is a mix of descriptive and confirmatory analyses as illustrated in Figure 3. First, homicide rates and growth are presented using tables and maps. Thereafter, hypothesis 2, regarding the spatial concentration of homicide rates, was tested using spatial cluster statistics. Hypotheses 1 and 3 on convergence were tested using regression analysis, whereby the appropriate empirical model was chosen based on due statistics. The details and procedures of these methods are developed in the following subsections.

### *Growth trend and pattern – Absolute Convergence*

The growth of homicide rates is investigated by combining descriptive and empirical methodologies. Similar to Mankiw *et al.* (1992), the latter is performed by estimating growth models using the Ordinary Least Square (OLS) method. This involves the regression of the growth of homicide rates from an initial period $(t_0)$ to a recent period $(t_1)$ as the dependent variable against the magnitude of the rates at the initial period $(t_0)$ as the dependent variable. This is represented as

$$Y_i = \beta_0 + \beta_1 \log\left(homicide_{i,t0}\right) + \varepsilon_i \quad (1)$$
$$Y_i = \frac{\log\left(homicide_{i,t1}/homicide_{i,t0}\right)}{\Delta t}$$

Where $homicide_{i,t0}$is homicide rateper 100.000 population for the municipality, *i,* at the initial period $t_0$ and $homicide_{i,t1}$ is the rate for the same municipality in the posterior or steady-state period $t_1$; $\Delta t$ is the number of years between the two periods, and; $\varepsilon_i$ is the error term. This equation, referred to as the *absolute convergence* model, is similar to that estimated by Justus and Santos Filho (2011). However, this model is limited since other structural factors, apart from time, contribute to explain homicide growth. The exclusion of these factors implicitly assumes that all municipalities are similar at the steady state in terms of structural factors.

The hypothesis of absolute convergence is confirmed if $\beta_1$ is significant and negative, meaning that the homicide rate of municipalities with already higher rates in the initial period grew at diminishing values during the period in question compared to those which had lower rates.

The rate or speed at which convergence occurs (β-convergence) and the length of time, in years, necessary to reach halfway of the complete convergence (half-life) is given by $\gamma = -\frac{\ln(1+\beta T)}{T}$ and$\frac{\ln(2)}{\gamma}$, respectively (MANKIW *et al.*, 1992).

Separate convergence models are estimated for different periods (2000 – 2010, 2000 – 2017, and 2010 – 2017) to verify if the convergence is span-specific or more pronounced in different moments from the year 2000 to 2017.

### *Spatial Distribution – Cluster Analysis*

The changes reported in previous studies regarding the geographical patterns of lethal violence in Brazil are descriptively illustrated by plotting the maps of homicide rates for the years 2000, 2010 and 2017. Besides, the existence and evolution of the clusters/concentration of these rates were verified by calculating spatial statistics.

First, the Moran's index was calculated to verify the existence and degree of global spatial correlation of homicide rates. Subsequently, the Local Indicator of Spatial Association (LISA) was used to show the regional clusters of homicides across municipalities. These statistics are calculated thusly

$$MORAN's\ I = \left(\frac{n}{S_0}\right)\left(\frac{z_i' w_{ij} z_i}{z_i' z_i}\right) \qquad LISA_i = z_i \sum_{j=1}^{J} w_{ij} z_{ij} \tag{2}$$

where $z_i$ is the standardized value of homicide rate in municipality $i$; $w_{it}$ is the spatial weight matrix that bears the *queen* type of neighboring structure between the municipality, *i,* and its neighbors,$j$;$n$isthetotalnumberofmunicipalitiesand$S_0$isthesumofallthe elements in the weight matrix. The LISA values are classified into categories of High-High (hotspot), Low-Low (cold spot), Low-High, and High-Low. For instance, a hotspot is a municipality that has a high homicide rate and is surrounded by municipalities also with high rates. Other clusters are interpreted analogously. Consult Le Sage and Pace (2009) for more details concerning these spatial correlation measures.

The presence of spatial correlation violates assumptions of the Ordinary Least Square (OLS) method due to the omission of relevant variable and error correlation, thus, estimates are biased and inconsistent (ANSELIN, 2013). Therefore, if clusters are identified by the LISA and Moran's statistics, this will be addressed in the empirical model (Equation 1) by the inclusion of spatial autoregressive controls of the dependent variable ($homicide$) or the error term ($\varepsilon_i$) as shown below

Spatial lag model: $Y_i = \beta_0 + \beta_1 \log(homicide_{i,t0}) + \rho W * Y_i + \varepsilon_i$

Spatial error model: $Y_i = \beta_0 + \beta_1 \log(homicide_{i,t0}) + \varepsilon_i$, and $\varepsilon_i = \lambda W * \varepsilon_i + u$

where $W$ is a matrix of the spatial neighboring structure of municipalities (*queen* type) to control for possible spatial spillovers of homicide rates across municipalities as suggested by Andrade and Diniz (2013). The best fit model between the traditional model estimated by OLS method (Equation 1) and these spatial models are chosen by using the Moran's Statistics and the best fit model between the spatial lag and error models were chosen using the coefficient of determination denoted by $R^2$, Akaike information criterion (AIC), Lagrange Multiplier (LM), and Robust Lagrange Multiplier (Robust LM) statistics. High values of $R^2$, LM and Robust LM indicate a better fit, whereas a low value of AIC indicates a better fit.

The spatial analyses of this study are performed with Geo Da version 1.12.1.131 of the year 2018 and the regression analyses are guided by the decision tree provided by Anselin (2005).

***Covariates of Homicide Growth – Conditional and Club Convergence***

The absolute convergence model presented in Equation 1 is limited since important socioeconomic and demographic covariates of homicide growth are not controlled, thus, convergence estimates may be biased (MANKIW *et al.*, 1992). Therefore, based on the theoretical review provided in Section 2, Equation 1 was extended by controlling some relevant factors thusly

$$Y_i = \beta_0 + \beta_1 \log\left(homicide_{i,t0}\right) + \beta_2 Z_{i,t0} + \varepsilon_i \tag{3}$$
$$Y_i = \frac{\log\left(homicide_{i,t1}/homicide_{i,t0}\right)}{\Delta t}$$

where all other variables are the same as in Equation 1, except $Z_i$ which is a set of independent variables at the initial period. This new equation is referred to as the *conditional convergence* model. Note that spatial controls are not specified in Equation 3 but will be controlled accordingly based on the spatial statistic test results.

The hypothesis of conditional convergence is confirmed if $\beta_1$ is significant and negative, however, here it is concluded that there is evidence of convergence or not after holding other important structural factors constant.

Given the differences in the nature and context of crimes in rural and urban areas discussed by Ceccato (2016) and Weisheit and Donner Meyer (2000), this study assumes that the growth of homicide may vary across levels of urbanization. Waiselfisz (2011) hinted that the convergence of homicide rates may be towards local levels and not to a singular national value. Following a similar application by Johnson and Takeyama (2003), the possibility of group convergence is controlled by interacting the categorical variable, $D_i$, for three levels of urbanization (urban, suburban, and rural) with $homicide_{i,t0}$ and all other regressors in the model. This model is called the *club convergence* model and is written as

$$Y_i = \beta_0 + \beta_1 \log(homicide_{i,t0}) + \beta_2 Z_{i,t0} + \beta_3 W * Y_i + \beta_4 D_i * Z_{i,t0} + \beta_5 D_i * \log(homicide_{i,t0}) + \varepsilon_i \quad (4)$$

where the evidence of club convergence is given by the negative sign and statistical significance of $\beta_1$ and $\beta_5$. It is important to highlight that the coefficients obtained for the interaction variables should not be interpreted independently but rather added to the main coefficients, which are for urban municipalities.

The control variables included in the conditional and club convergence models are based on the theoretical and empirical review and can be classified into three groups: socioeconomic, demographic, and geographical factors. The socioeconomic controls are: income inequality measured by the GINI index, *GINI*; average household income per capita, *fam income*; average years of schooling, *education*, and; unemployment rate, *unemployment*. The demographic controls are: population size, *population*; an indicator developed by Blau (1977) forrace/ ethnicity heterogeneity calculated by subtracting one from the squared proportion of the population in each racial/ethnic group, *ethnicity*, and; the proportion of young men between age 20 to 29, *young men*. The geographic controls are: a binary that is 1 for coastal municipality and 0 if other wise, *coastal*¸ and; a categorical variable for the level of urbanization – *urban* (reference group) for municipalities that are predominantly urbanized, *suburban* for municipalities with the intermediary level of urbanization and, *rural* for predominantly rural municipalities. Details concerning how these typologies of urbanization were created are available in Table 3.

All the specified variables are transformed by applying natural logarithm and one is added to the rates of homicide before applying natural logarithm to avoid missing values in the cases where zero homicide was registered in municipalities.

# 5. RESULT

## 5.1 HOMICIDE RATE AND GROWTH IN BRAZIL FROM 2000 TO 2017

Homicide rates increased steadily in Brazil from the year 2000 to 2017 and the spatial distribution of these rates changed significantly over this period. According to the data from the

Information System on Mortality (ISM), the rates of homicide caused by aggression were around 29.01, 29.44, and 30.70 per 100 thousand persons in Brazil in the years 2000, 2010, and 2017 (Table 1).

In the year 2000, the homicide rate was highest in the Southeast region followed by the Midwest, whereas, in the year 2017, the highest rates were observed in the North followed by the Northeast, and the lowest in the Southeast. Regarding growth, homicide rates reduced consistently in the Southeast from the year 2000 to 2017, but it more than doubled in the North and Northeast. The combination of such a growth pattern signalizes the convergence of homicide rates in Brazil.

The homicide rates were calculated by municipalities and plotted in Figures 1 (a), (b), and (c) to observe greater detail of the geographical distribution and changes over time. It is clear that, in the year 2000, only very few coastal municipalities were responsible for the high homicide rate in the Southeast. In the same year, high homicide rates were spread across many municipalities of the Midwest region, especially in the states that share international borders with Bolivia and Paraguay.

In the year 2010, there was notable dissemination of higher homicide rates in many states in Brazil compared to the year 2000 (Fig. 1 (b)). However, a more pronounced increase was observed in the North and the coastal municipalities of the Northeast and Southeast. The reduction observed in Table 1 for the Southeast region seems to be mostly stimulated by the reduction in the coastal municipalities of the state of São Paulo. In the year 2017, homicide rates were even expressively higher in the North and Northeast compared to the previous years and these rates became more distinguished in coastal municipalities (Fig. 1 (c)).

By comparing Fig. 1 (a) and (c) for the year 2000 and 2017, respectively, we are more convinced of the homogenization of homicide rates in Brazil. This is further emphasized by Fig. 2 that shows the growth of homicide rate from the year 2000 to 2010 and from 2010 to 2017, respectively. It is perceptible that most of the municipalities which already had high homicide rates in the year 2000 experienced a modest increase or reduction from the year 2000 to 2010. The stagnation or reduction is more evident for the entire Midwest region, the state of São Paulo in the Southeast, and Pernambuco in the Northeast region which had higher rates in the year 2000. From the year 2010 to 2017, stagnation was more evident compared to reduction but the increase in homicide rates was still very perceptible.

## 5.2 SPATIAL CLUSTERS OF HOMICIDE RATES

The locations concentrated with high homicides rates were not only persistent over time but also expanded in space. This is expressed by the significance of the Moran's index at 1% for the years 2000, 2010, and 2017 with values of 0.267, 0.213, 0.394, respectively. This clustering pattern is heterogeneously spread across Brazil as illustrated in Figures 1 (d), (e), and (f) which presents the significant hotspots (clusters of high rates) and colds pots (clusters of low rates) of homicide rates, measured by the LISA indicator.

Apart from being concentrated, the geography of homicide clusters changed significantly from the year 2000 to 2017. In the year 2000, most of the hotspots were located in the Midwest region, emphasizing the borders with Bolívia and Paraguay (Fig. 1 (d)). Almost the entire states of Roraima in the North and Pernambuco in the Northeast were isolated hotspots in the same year. The concentration of high homicide rates in the Southeast is located in the coastal municipalities of the states of São Paulo, Rio de Janeiro, and Espírito Santo. The colds pots were mostly located in the inland of the Northeast and Southeast regions.

In the year 2017 (Fig. 1 (f)), the concentration of hotspots in the North and the coastal municipalities of the Northeast and Southeast regions becomes more evident. Moreover, a higher concentration of colds pots is observed in the state of São Paulo (Southeast), Piauí (Northeast) and some parts of Rio Grande do Sul and Santa Catarina (both South).

The most noticeable observation for the cluster analysis over time is the regional shift of the clusters of homicide rates, characterized by: the upward shift of hotspots from the Midwest to the Northern region; the expansion of coastal hotspots, and; the drastic reduction of colds pots in the Northeast region.

## 5.3 MODELING THE CONVERGENCE OF THE RATE OF VIOLENTCRIMES

The steady increase in time and spatial expansion of homicide rates stimulated a tendency of convergence, that is, the homogenization of homicide rates at high values in Brazil. This was observed by estimating spatial regressions with model specifications following the convergence theory borrowed from economics.

As discussed in Section 2.2, the classic OLS regression, spatial lag, and spatial error models were estimated using the same specification and the best fit model was chosen using due statistic tests as suggested by Anselin (2005). Table 2 presents the results and tests. Moran's statistics for all the models estimated using the OLS method uphold the existence of spatial correlation even after the inclusion of control variables. The coefficient of determination ($R^2$), Akaike information criterion (AIC), Lagrange Multiplier (LM) and Robust Lagrange Multiplier (Robust LM) statistics show that the spatial error model is the best fit among the models and is, therefore, chosen for result analyses. Note that the coefficients observed for the control variables are consistent with the associations suggested in the literature and are similar across various model specifications, i.e., the estimates are stable (Table 2).

Table 3 presents the results obtained from spatial error models for the absolute, conditional, and club convergence of homicide rates. Separate growth models were estimated for three periods: 2000 to 2010, 2010 to 2017, and 2000 to 2017. This enables to characterize the convergence process in different stages between the year 2000 and 2017. The control for the spatial error ($\lambda W * \varepsilon_i$) is significant at $1\%$ in all the models, showing that there are variables not controlled in the model that are concentrated in space.

The negative and significant coefficients for $initial\_homicide$ in the models for absolute convergence show evidence of the convergence of homicide rates in Brazil given that other structural factors are the same across municipalities. In other words, municipalities with lower homicide rates in the initial period experienced higher growth compared to municipalities with already higher rates and, thus, homicide rates are prone to converge in the long run. Although a similar conclusion is drawn for the three different time spans in terms of convergence, the speed of convergence and half-life vary significantly. Specifically, the convergence process is slower and, consequently, the half-life is higher from the year 2000 to 2010 compared to the period from the year 2010 to 2017. Using homicide data from the year 2000 to 2017, the model shows that the halfway of convergence will be attained in approximately nine years, i.e, around the year 2026.

Recognizing that Brazilian municipalities are not identical, as implicitly assumed in the absolute convergence models, conditional convergence models were estimated to control for socioeconomic, demographic, and geographic differences. Still, the hypothesis of convergence is sustained by the negative and significant coefficient for$initial_homicide$. The convergence speed increased and the half-life reduced expressively in all models, indicating that the long-run convergence of homicide rates will be half-way completed in lesser time if structural socioeconomic, demographic, and geographic differences among municipalities are controlled and held constant. The comparison of specific periods within the entire period shows that the convergence process was slower at the initial period from the year 2000 to 2010 but gained pace from the year 2010 to 2017.

Regarding the socioeconomic variables controlled in the conditional convergence models for the overall period from the year 2000 to 2017, it was found that homicide rates increased more in municipalities with high income inequality and unemployment in the initial period. However, such growth is mitigated by higher levels of education and average family income. The strength of the association of these socioeconomic variables with the growth of homicide rates varied significantly over time. The predictive strength of income inequality (measured using the GINI coefficient) on the growth of homicide rate slightly reduced over time, whereas that of unemployment became expressively dominant from the year 2010 to 2017. During this latter period, the growth of homicide rates also became more elastic to average income. Education level seems to have been influential on homicide growth only from the year 2010 to 2017.

As to demographic factors, the size of the population is positively associated with the growth of homicide rates throughout the period between the year 2000 and 2017. The model also shows that, besides size, the ethnicity and gender composition of the population also positively correlates with the growth of homicide rates. Specifically, the higher the ethnical heterogeneity or population of young men, the higher the growth of homicide rates and both factors were more influential in the earlier period from the year 2000 to 2010.

As to geographic factors, the control for coastal municipalities confirms the observation provided in Figure 1 that homicide rates increased significantly in the coastal municipalities, especially in more recent years. The statistical evidence of the growth of homicide is not clear for the levels of urbanization. From the year 2010 to 2017, the model indicates a lower growth of homicide in predominantly rural municipalities compared to urban ones. However, for the whole period between the year 2000 and 2017, the growth of homicide was higher in predominantly suburban municipalities compared to urban and rural ones.

The relative influence of these socioeconomic, demographic, and geographic controls on the growth of homicide rates may have been time-specific or more or less pronounced at specific levels of urbanization. Apart from shedding more light on this, the club convergence models also provide evidence that the growth of the homicide rate of municipalities may not converge to a similar national level but to the levels of other municipalities with a similar degree of urbanization. The negative and significant coefficient for $initial\_homicide$ confirms the existence of club convergence among urban municipalities throughout the whole period but the evidence of club convergence among rural and suburban municipalities, given by $rural * initial\_homicide$ and $suburban * initial\_homicide$, respectively, was only confirmed for the period between the year 2010 and 2017. Therefore, the hypothesis of club convergence for levels of urbanization can not be consistently sustained since the convergent growth patterns observed for recent years may be due to time shocks.

The statistical significance of the socioeconomic, demographic, and geographic controls in the club convergence models shows that the results found for Brazil as a whole in the conditional convergence model may be the reflection of urban municipalities. Only the control for population size shows a consistent positive association with homicide growth, indicating a higher effect in the rural areas compared to suburban and urban ones.

The associative effect of income on homicide growth is significant only in predominantly urban and rural municipalities, and the effect is lower in the latter. Unemployment played a significant role in increasing homicide growth in urban municipalities only from the year 2000 to 2010 and, thereafter its role becomes significant and dominant in the suburban municipalities. The evidence of a negative association of education with homicide growth was only observed in urban municipalities from the year 2010 to 2017. The direct association of ethnic/racial heterogeneity with homicide growth was modest and limited to suburban municipalities from the year 2010 to 2017.

## 6. DISCUSSION OF THE RESULTS

The growth of crime in Brazil has been a trending topic in the literature due to its unanticipated growth pattern across regions, states, and municipalities. For instance, Justus *et al.* (2018) investigated the “mystery” around the striking reduction of homicides in the State of São Paulo in the 2000s, which was also clearly observed in the spatial analysis of this study. Scorzafave *et al.* (2015) found that crime rates are higher in urban areas but have been increasing more in rural areas. Weisheit (2011) alerted regarding these “new patterns” of the geographic distribution of homicide rates in the 2000s, which was upheld in this study by showing that regions which had lower rates in the early 2000s now have leading rates, while those which had leading rates in the early 2000s now have relatively lower rates. Weisheit (2011) and Justus *et al.* (2016) forwarded that such a growth pattern may lead to the convergence of homicide rates in Brazil in the long-run and, therefore, called for more empirical investigation.

This study contributes to the chain of evidence on the growth pattern and trajectory of homicide rates in Brazil by empirically confirming its convergence towards similar national levels in the long-run, i.e., the homogenization of homicide rates in Brazil. Although the empirical results uphold the evidence of convergence from Justus and Santos Filho (2011), it was noted that homicide rates are converging faster in recent years (from the year 2000 to 2017) compared to the period studied by these authors (from mids 1990s to mids 2000s). Justus and Santos Filho (2011) predicted that the halfway of the convergence will be attained in about 27 years from the mids 2000s and, using recent data, we predict about 9 years from the year 2017. This implies that the estimate provided by Justus and Santos Filho (2011) continues feasible. However, this time estimate becomes lower if socioeconomic, demographic, and geographic factors are taken into account.

The descriptive and cluster analyses support the reports provided in Weisheit (2011) and Cerqueira *et al.*(2019) regarding the steady increase of homicide rates in the North and Northeast regions combined with the reduction in the South and Southeast regions. Specifically, Cerqueira *et al.*(2019) reported that the increase observed in North and Northeast is mostly the aftermath of the increasing narcotraffic operations and conflicts in those regions. Similarly, Weisheit (2016) reported that such operations are especially common in municipalities that share international borders, making them routes for drug and firearm trafficking. Nonetheless, Cerqueira *et al.* (2019) also showed that the growth of homicide rate was restrained by the Statute of Disarmament and reduced by demographic factors such as, for example, population aging. The results add that, from the year 2000 to 2017, the growth of homicide increased alongside income inequality, unemployment, total population size, young male population, and ethnical heterogeneity and reduced with average income and years of schooling. This study provides descriptive and empirical evidence that show that homicide rates increased significantly in coastal municipalities, especially in recent years. Weisheit (2011) posited that such an increase is due to "predatory tourism" and suggested the need for empirical investigation of this hypothesis. Nonetheless, the regionalization of homicide hotspots observed for recent years may be positively exploited by directing focal regional policies to high-risk locations.

This study showed that, as suggested by the social organization theory, socioeconomic factors such as income inequality (*proxy* for relative deprivation), income level, unemployment and education, and demographic factors such as population size, gender composition, and ethnical heterogeneity are important covariates of the growth of homicide rates. However, the strength of the association of these factors varies over different spans between the year 2000 and 2017. Specifically, from the year 2000 to 2010, the proportion of young men was the dominant covariate of homicide rates, whereas, from the year 2010 to 2017, the unemployment rate became more dominant. This is particularly unsettling since unemployment has been steadily increasing in Brazil (POCHMANN, 2015).

## 7. CONCLUSIONS

The objective of this study is to investigate the space-temporal growth of homicide rates in Brazil and, concurrently, test the hypothesis of convergence. This was achieved by applying a mix of criminological and economic growth theories to guide the empirical modeling of the growth of homicide rates.

This study found evidence of the convergence and significant changes in the geography of homicide rates, alongside some determinants of the growth dynamics of homicide rates in Brazil. That is to say, high levels of lethal violence, represented by homicide rates in this study, are very likely to increase and spread across all municipalities in Brazil in the close future. However, the results from the cluster and regression analyses help to know the hotspot locations of homicides and the factors that could be used as countermeasures.

Specifically, the convergence analysis showed that apart from the overall increase and heterogeneous distribution of homicide rates, the "new" growth patterns experienced across Brazilian regions from the year 2000 to 2017 portray a convergent pattern which may cause homicide rates to homogenize at high levels throughout Brazil in the close future. Moreover, this convergence process is occurring at a faster rate than conjectured in previous studies.

The spatial analysis shed more light on changes in the geography of homicide rates which may have stimulated the faster rate of convergence in Brazil. The geographic clusters of high homicide rates reduced expressively in the south and southeast regions that had higher rates in the past but expanded significantly in the North and Northeast regions that had lower rates in the past, especially in coastal municipalities.

Socioeconomic and demographic factors such as income inequality, unemployment, family income, education, and population gender and ethnic composition are significantly correlated with this growth pattern of homicide rates and, specifically, the empirical results spotlight the role of unemployment in the recent period (from the year 2010 to 2017).

A limitation of the study, as many others that test for convergence, is that it addresses growth from a specific period to the other and, consequently, does not take time shocks between periods into account. Therefore, it is most appropriate to read the results as time-specific events and not generalize the associations showed in this study, although they are strongly in line with those in the literature. Another limitation is that the empirical models do not exhaustively control for the determinants of homicide suggested in the theoretical literature. However, the focus here is more on the growth characteristics of homicide rates and not the determinants of homicides *per se* and no theoretical framework was found concerning the former in the criminological literature. Therefore, the results are associative and not causal, thus, the conclusions are only suggestive.

The lack of applications of the convergence theory to crime studies in the international literature does not enable to compare the results provided here with others from abroad. Future research on homicide in Brazil should further investigate the causes of the regional heterogeneity of homicide rates, focusing on the role of social, economic, and political institutions and their interaction with social factors, beyond the hypotheses tested in this study. The presence or lack of solid institutions may potentialize or mitigate the effect of social structural factors affecting homicide rates and, consequently, help explain the regional heterogeneous patterns as observed in this study.

Despite these limitations, this study applies a novel methodology of spatial analysis and contributes to the area homicide studies by offering an insight into the patterns and trends of homicide growth in a country of Global South, so far lacking in the international literature.

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**REFERENCES**


AGNEW, R. A general strain theory of community differences in crime rates. *Journal of research in crime and delinquency*, 36 (2), 123-155. 1999.

ANDRADE, L. T., and DINIZ, A. M. A. A reorganização espacial dos homicídios no Brasil e a tese da interiorização. *Revista Brasileira de Estudos de População*, 30(1), 171-191. 2013.

ANSELIN, L., COHEN, J., COOK, D., GORR, W., and TITA, G. Spatial analyses of crime. *Criminal justice*, *4*(2), 213-262. 2000.

ANSELIN, L. Exploring spatial data with Geo DaTM: a workbook. *Center for spatially integrated social science*. 2005

ANSELIN, L. *Spatial econometrics: methods and models*. Springer Science & Business Media. 2013.

ANDERSON, E. *Streetwise*. Chicago: University of Chicago Press. 1990.

BLACK, P. Subcultural Theories of Crime. In D. Weisburd and G. Bruinsma (Eds.). *The Encyclopedia of Criminology and Criminal Justice* (pp. 1-3). New York, NY: Springer. 2014.

BLAU, P. M. *Inequality and heterogeneity: A primitive theory of social structure*. Free Press New York. 1977.

BLUMSTEIN, A., Rivara, F. P., and ROSENFELD, R. The rise and decline of homicide—and why. *Annual review of public health*, *21*(1), 505-541. 2000.

CECCATO, V. A. *Rural crime and community safety*. Abingdon: Routledge. 2016.

CECCATO, V., and CECCATO, H. Violence in the rural global south: trends, patterns, and tales from the Brazilian countryside. *Criminal Justice Review*, *42*(3), 270-290. 2017.

CECCATO, V., Haining, R., and KAHN, T. The geography of homicide in São Paulo, Brazil. *Environment and Planning A*, *39*(7), 1632-1653. 2007.

CLOWARD, R. A., and OHLIN, L. E. (1960). *Delinquency and opportunity: A study of delinquent gangs*. Routledge. 1960.

FREEMAN, S., Grogger, J., and SONSTELIE, J. The spatial concentration of crime. *Journal of Urban Economics*, *40*(2), 216-231. 1996.

IBGE. *Classificação e caracterização dos espaços rurais e urbanos do Brasil.* Technical report, Instituto Brasileiro de Geografia e Estatística. 2017.

IBGE. *Estimativas da população residente no Brasil e Unidades da Federação com data de referência em 1º de julho de 2019*. Instituto Brasileiro de Geografia e Estatística. 2019.

CERQUEIRA, D. R. C. et al. *Atlas da violência 2018.* Instituto de Pesquisa Econômica Aplicada (IPEA) e Fórum Brasileiro de Segurança Pública (FBSP), 2018.

CERQUEIRA, D. R. C. et al. *Atlas da violência 2019.* Instituto de Pesquisa Econômica Aplicada (IPEA) e Fórum Brasileiro de Segurança Pública (FBSP), 2019.

JOHNSON, Paul A. and TAKEYAMA, Lisa N. *Convergence among the U.S. states: Absolute, conditional, or club?* Faculty Research and Reports, 75. 2003.

JUSTUS, M., and SANTOS FILHO, J. I. Convergência das taxas de crimes no território brasileiro. *Revista Economia*, *12*(1), 131-147. 2011.

JUSTUS, M., L. G. Scorzafave, and E. G. Sant'Anna. Crime and victimization in rural Brazil. In J. Donnermeyer (Ed.), *The Routledge International Handbook of Rural Criminology* (pp. 211–221). Routledge. 2016.

JUSTUS, M., de Castro Cerqueira, D. R., Kahn, T., and MOREIRA, G. C. The "São Paulo Mystery": The role of the criminal organization PCC in reducing the homicide in 2000s. *EconomiA*, *19*(2), 201-218. 2018.

LESAGE, J., and Pace, R. K. *Introduction to spatial econometrics*. Chapman and Hall/CRC. 2009.

MANKIW, N.G., D.Romer, and D.N.Weil. A contribution to the empirics of economic growth. *The quarterly journal of economics 107* (2), 407–437. 1992.

MERTON, R. K. Social structure and anomie. *American Sociological Review 3*(5), 672-682. 1938.

MESSNER, S. F., and R. Rosenfeld. Political restraint of the market and levels of criminal homicide: Across-national application of institutional-anomie theory. *Social Forces75* (4), 1393-1416. 1997.

MUKHERJEE, S. Trends and Patterns of Homicide in Australia. In R. A. Silverman, T. P. Thornberry, B. Cohen, and B. Krisberg (Eds.), *Crime and Justice at the Millennium* (pp. 121-134). Boston, MA: Springer. 2002.

POCHMANN, M. Ajuste econômico e desemprego recente no Brasil metropolitano. *Estudos Avançados*, 29(85), 7-19. 2015.

ROSENFELD, R., Bray, T. M., and EGLEY, A. Facilitating violence: A comparison of gang-motivated, gang-affiliated, and nongang youth homicides. *Journal of Quantitative Criminology*, *15*(4), 495-516. 1999.

SCORZAFAVE, L. G., M. Justus, and P. F. A. Shikida. Safety in the global south: criminal victimization in Brazilian rural areas. *Journal of Rural Studies* 39(1), 247–261. 2015.

SHAW, C. R., and MCKAY, H. D. *Juvenile delinquency and urban areas.* Chicago, IL, US: University of Chicago Press. 1942.

SOLOW, R. *Growth Theory. An exposition*. Oxford University Press, Oxford. 1970

VOLD, G. B. *Theoretical criminology.* Oxford, England: Oxford Univer. Press. 1958.

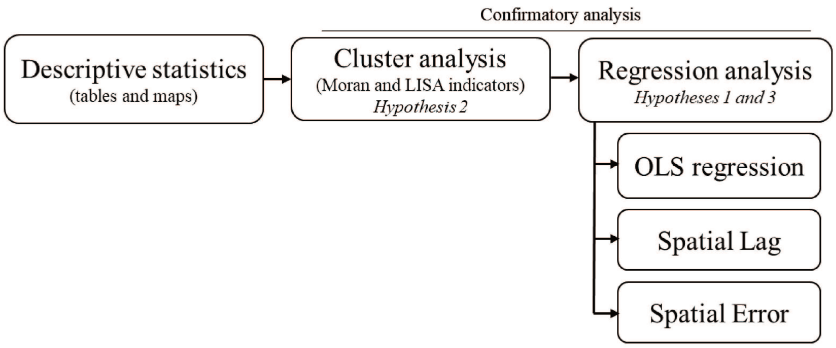
WAISELFISZ, J. J.. *Mapa da violência 2010 – os novos padrões da violência homicida no Brasil.* Technical report, Instituto Sangari. 2011.

WAISELFISZ, J. J.. *Mapa da violência 2016: homicídios por armas de fogo.* Technical Report. Flasco Brasil. 2016.

WEISHEIT, R. A., and J. F. Donnermeyer. Change and continuity in crime in rural America. *Criminal justice*, *1*(1), 309-357. 2000.

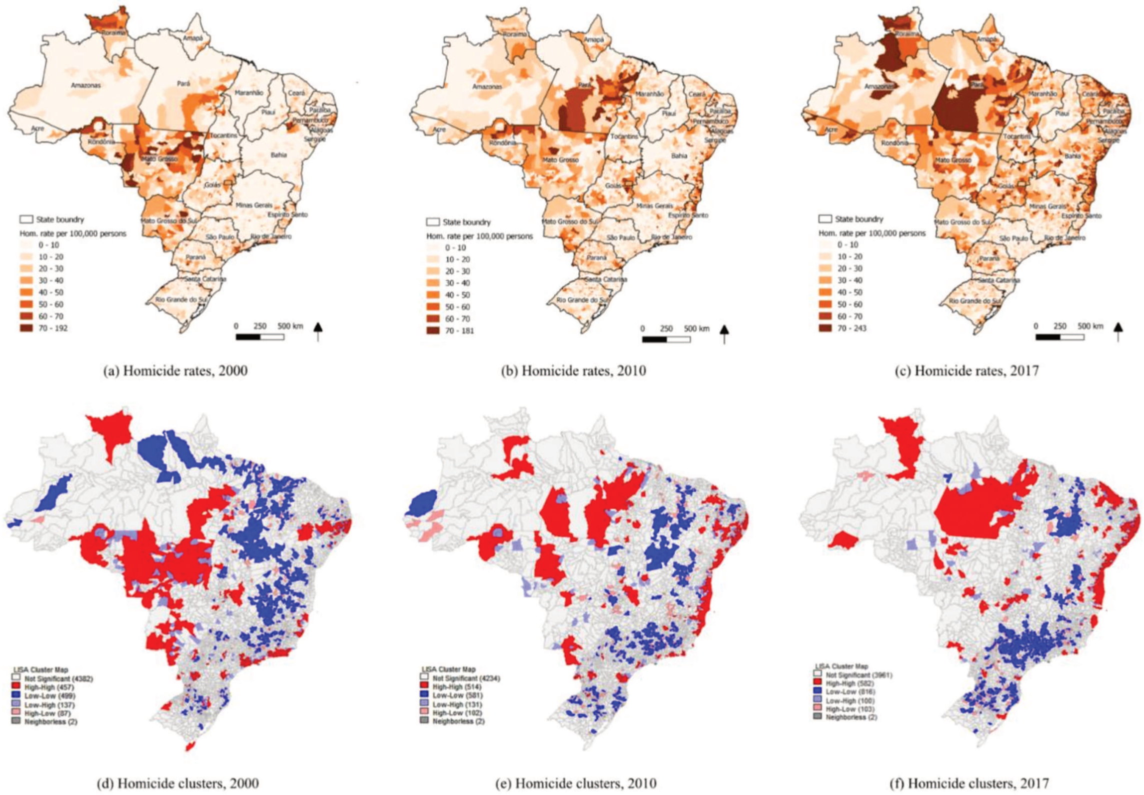
WITT, D. D.. A conflict theory of family violence. *Journal of Family Violence*, *2*(4), 291-301. 1987.

**Figure 1: Methodological procedure.**



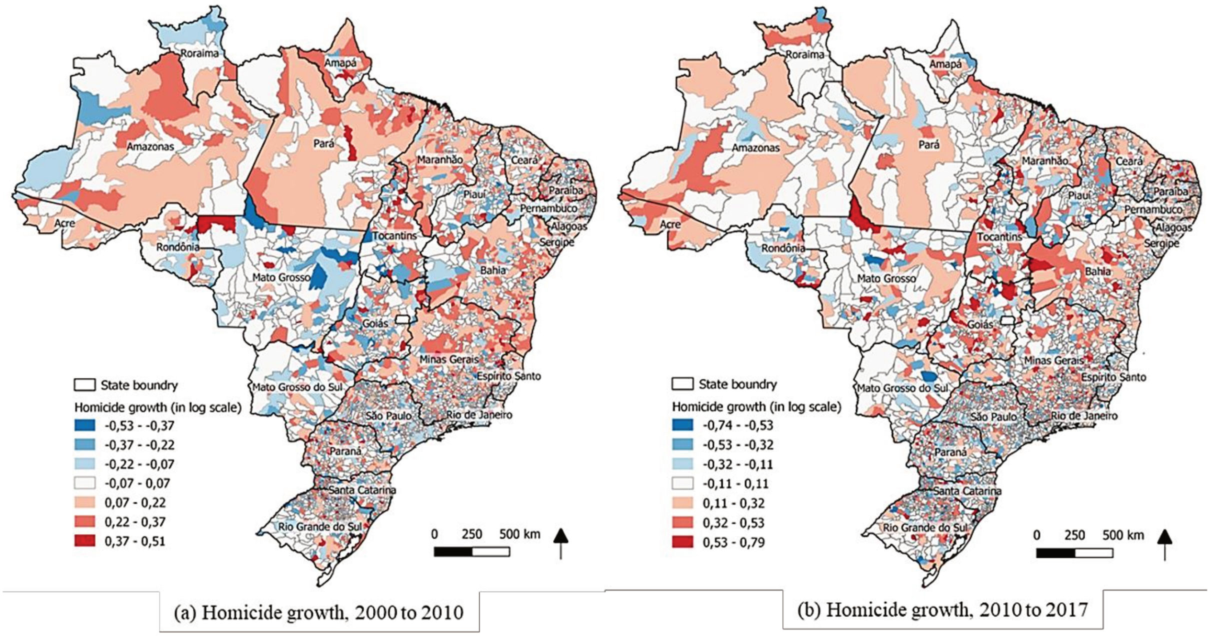

Source: Elaborated by the authors.
Note: The regression analysis is guided by the decision procedure in Anselin (2005)

**Figure 2: Homicide rates and clusters of the Brazilian municipalities per 100 thousand population, years 2000, 2010, and 2017**




Source: Elaborated by the authors using the data from IMS-DATA

**Figure 3: Growth of homicide rates of Brazilian municipalities, from 2000 to 2010 and 2010 to 2017**.




Source: Elaborated using data from IMS-DATASUS

**Table 1: Homicide rate per 100.000 population by region, 2000, 2010, and 2017**

| Region | 2000 | 2010 | 2017 | 2000-2010 (Δ %) | 2010-2017 (Δ %) |
|---|---|---|---|---|---|
| Midwest | 32.45 | 33.78 | 32.77 | 4.11 | -3.01 |
| Northeast | 22.10 | 38.06 | 47.43 | 72.22 | 24.62 |
| North | 21.36 | 40.19 | 47.01 | 88.13 | 16.96 |
| Southeast | 38.08 | 21.90 | 18.36 | -42.49 | -16.18 |
| South | 18.34 | 26.42 | 23.61 | 44.06 | -10.66 |
| Brazil | 29.01 | 29.44 | 30.70 | 1.48 | 4.26 |

Source: Elaborated using data from IMS-DATASUS

| | OLS | | | Spatial Lag | | | Spatial Error | | |
|---|---|---|---|---|---|---|---|---|---|
| | 2000-2010 | 2010-2017 | 2000-2017 | 2000-2010 | 2010-2017 | 2000-2017 | 2000-2010 | 2010-2017 | 2000-2017 |
| $\rho W * Y_i$ | | | | 0.124*** | 0.126*** | 0.184*** | | | |
| | | | | (0.017) | (0.017) | (0.016) | | | |
| $\lambda W * \varepsilon_i$ | | | | | | | 0.329*** | 0.351*** | 0.359*** |
| | | | | | | | (0.019) | (0.018) | (0.018) |
| $\boldsymbol{log\ (initial\_homicide)}$ | **-0.0813*** ** | **-0.114*** ** | **-0.0498*** ** | **-0.0801*** ** | **-0.113*** ** | **-0.0484*** ** | **-0.0871*** ** | **-0.124*** ** | **-0.0526*** ** |
| | **(0.001)** | **(0.002)** | **(0.001)** | **(0.001)** | **(0.002)** | **(0.001)** | **(0.001)** | **(0.002)** | **(0.001)** |
| $log\ (GINI)$ | 0.0998*** | 0.0595** | 0.0398*** | 0.0962*** | 0.0576** | 0.0357*** | 0.0833*** | 0.0621** | 0.0297*** |
| | (0.016) | (0.023) | (0.009) | (0.015) | (0.023) | (0.009) | (0.016) | (0.024) | (0.010) |
| $log(famincome)$ | -0.0217*** | -0.0565**** | -0.0224*** | -0.0157*** | -0.0510*** | -0.0144*** | -0.018*** | -0.0624*** | -0.017*** |
| | (0.005) | (0.008) | (0.003) | (0.005) | (0.008) | (0.003) | (0.006) | (0.009) | (0.004) |
| $log(unemployment)$ | 0.0843** | 0.355*** | 0.172*** | 0.0784** | 0.337*** | 0.158*** | 0.0783** | 0.300*** | 0.158*** |
| | (0.037) | (0.090) | (0.022) | (0.037) | (0.089) | (0.022) | (0.040) | (0.094) | (0.024) |
| $log(education)$ | -0.0024 | -0.117*** | -0.0196*** | -0.002 | -0.109*** | -0.0175** | -0.0121 | -0.0917*** | -0.0273*** |
| | (0.012) | (0.027) | (0.007) | (0.012) | (0.026) | (0.007) | (0.014) | (0.029) | (0.008) |
| $log(population)$ | 0.0471*** | 0.0544*** | 0.0259*** | 0.0457*** | 0.0546*** | 0.0249*** | 0.0479*** | 0.0607*** | 0.0272*** |
| | (0.002) | (0.003) | (0.001) | (0.002) | (0.004) | (0.001) | (0.002) | (0.004) | (0.001) |
| $log(ethnicity)$ | 0.0613*** | 0.0357*** | 0.0681*** | 0.0645*** | 0.0352*** | 0.0657*** | 0.0742 | 0.0344*** | 0.0701*** |
| | (0.021) | (0.007) | ( 0.013) | (0.021) | (0.007) | (0.012) | (0.002) | (0.009) | (0.015) |
| $log(youngmen)$ | 0.111 | 0.004 | 0.0308*** | 0.111*** | 0.003*** | 0.0308*** | 0.113*** | 0.0241 | 0.0217* |
| | (0.018) | (0.021) | (0.011) | (0.018) | -0.021 | ( 0.011) | (0.019) | (0.023) | (0.012) |
| $coastal$ | 0.0234*** | 0.0518 | 0.0245*** | 0.020** | 0.0485*** | 0.0198*** | 0.0118 | 0.0297** | 0.0137** |
| | (0.008) | (0.012) | (0.005) | (0.008) | (0.012) | (0.005) | (0.009) | (0.014) | (0.006) |
| $rural$ | -0.012* | -0.0353 | -0.004 | -0.0115 | -0.0336*** | -0.0025 | -0.0192*** | -0.0419*** | -0.007* |
| | (0.007) | (0.010) | (0.004) | (0.007) | (0.010) | (0.004) | (0.007) | (0.010) | (0.004) |
| $suburban$ | 0.004 | 0.0139 | 0.0138*** | 0.003 | 0.0142 | 0.0135*** | -0.0021 | 0.0077 | 0.0104*** |
| | (0.007) | (0.009) | (0.004) | (0.007) | (0.009) | (0.004) | (0.006) | (0.008) | (0.008) |
| $constant$ | 0.157** | 0.432*** | 0.102** | 0.123* | 0.365*** | 0.0504 | 0.154** | 0.428*** | 0.0547 |
| | (0.068) | (0.091) | (0.041) | (0.068) | (0.017) | (0.041) | (0.072) | (0.098) | (0.043) |
| Moran's I | 0.1433*** | 0.1501*** | 0.1634*** | | | | | | |
| $R^2$ | 0.4168 | 0.3997 | 0.4498 | 0.4234 | 0.4064 | 0.4649 | 0.4562 | 0.4454 | 0.4954 |
| AIC | -6867.45 | -2661.70 | -12432.9 | -6913.96 | -2706.96 | -12552 | -7143.58 | -2973.06 | -12778.10 |
| LM | | | | 47.49*** | 44.68*** | 128.32*** | 310.85*** | 340.91*** | 404.48*** |
| Robust LM | | | | 151.29*** | 212.84*** | 57.72*** | 414.66*** | 509.07*** | 333.89*** |

Note: *, **, and *** denote significance at 10%, 5%, and 1%, respectively; $W$is thespatial weights matrix that expresses the neighboring structure (*queen* type), $Y_i$ is the growth of homicide rate in logarithm scale and $\varepsilon_i$ is the error term;$R^2$is the coefficient of determinant; AIC is the Akaike information criterion, LM is the Lagrange Multiplier, and Robust LM is the Robust Lagrange Multiplier.

**Table 1: Estimation results and tests for OLS, spatial lag and error models.**

**Table 2: Estimation results for absolute, conditional and club convergence of homicide rates**

| | Absolute convergence | | | Conditional convergence | | | Club convergence | | |
|---|---|---|---|---|---|---|---|---|---|
| | 2000-2010 | 2010-2017 | 2000-2017 | 2000-2010 | 2010-2017 | 2000-2017 | 2000-2010 | 2010-2017 | 2000-2017 |
| $\lambda W * \varepsilon_i$ | 0.3834*** | 0.413*** | 0.470*** | 0.124*** | 0.126*** | 0.184*** | 0.313*** | 0.331*** | 0.336*** |
| | (0.018) | ( 0.017) | (0.017) | (0.017) | (0.017) | (0.016) | (0.019) | (0.019) | (0.019) |
| **log ($initial\_homicide$)** | **-0.0684*** ** | **-0.0983*** ** | **-0.0430*** ** | **-0.0801*** ** | **-0.113*** ** | **-0.0484*** ** | **-0.0859*** ** | **-0.107*** ** | **-0.0526*** ** |
| | **(0.001)** | **('0.002)** | **(0.001)** | **(0.001)** | **(0.002)** | **(0.001)** | **(0.004)** | **(0.005)** | **(0.002)** |
| log ($GINI$) | | | | 0.0962*** | 0.0576** | 0.0357*** | 0.077* | 0.116** | 0.0494* |
| | | | | (0.015) | (0.023) | (0.009) | (0.043) | (0.049) | (0.026) |
| $log(famincome)$ | | | | -0.0157*** | -0.0510*** | -0.0144*** | -0.034** | -0.0923*** | -0.0320*** |
| | | | | (0.005) | (0.008) | (0.003) | (0.016) | (0.018) | (0.010) |
| $log(unemployment)$ | | | | 0.0784** | 0.337*** | 0.158*** | 0.276** | 0.138 | 0.0639 |
| | | | | (0.037) | (0.089) | (0.022) | (0.108) | (0.226) | (0.064) |
| $log(education)$ | | | | -0.002 | -0.109*** | -0.0175** | -0.0634 | -0.137** | -0.0492* |
| | | | | (0.012) | (0.026) | (0.007) | (0.046) | (0.071) | (0.028) |
| $log(population)$ | | | | 0.0457*** | 0.0546*** | 0.0249*** | 0.0297*** | 0.030*** | 0.0135*** |
| | | | | (0.002) | (0.004) | (0.001) | (0.004) | (0.006) | (0.003) |
| $log(ethnicity)$ | | | | 0.0645*** | 0.0352*** | 0.0657*** | 0.0681 | 0.003 | 0.0499 |
| | | | | (0.021) | (0.007) | (0.012) | (0.053) | (0.021) | (0.032) |
| $log(youngmen)$ | | | | 0.111*** | 0.003*** | 0.0308*** | 0.0744 | 0.0066 | 0.0341 |
| | | | | (0.018) | -0.021 | ( 0.011) | (0.050) | (0.050) | (0.029) |
| $coastal$ | | | | 0.020** | 0.0485*** | 0.0198*** | 0.0147 | 0.0318 | 0.017*** |
| | | | | (0.008) | (0.012) | (0.005) | (0.009) | (0.014) | (0.005) |
| $rural$ | | | | -0.0115 | -0.0336*** | -0.0025 | -0.546*** | -1.154*** | -0.564*** |
| | | | | (0.007) | (0.010) | (0.004) | (0.182) | (0.228) | (0.110) |
| $suburban$ | | | | 0.003 | 0.0142 | 0.0135*** | -0.259 | -0.920*** | -0.310** |
| | | | | (0.007) | (0.009) | (0.004) | (0.257) | (0.314) | (0.154) |
| $\boldsymbol{rural * initial\_homicide}$ | | | | | | | **-0.0013** | **-0.0210*** ** | **-0.0001** |
| | | | | | | | **(0.004)** | **(0.006)** | **(0.965)** |
| $rural * GINI$ | | | | | | | -0.0013 | -0.0964* | -0.0411 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | (0.047) | (0.056) | (0.028) |
| $rural * income$ | | | | | | | 0.0311* | 0.0624*** | 0.0247** |
| | | | | | | | (0.017) | (0.020) | (0.010) |
| $rural * educ$ | | | | | | | 0.0629 | 0.077 | 0.0285 |
| | | | | | | | (0.047) | (0.076) | (0.028) |

Continued from the previous page

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $rural * educ$ | | | | | | | 0.0629 | 0.077 | 0.0285 |
| | | | | | | | (0.047) | (0.076) | (0.028) |
| $rural\_pop$ | | | | | | | 0.0336*** | 0.0636*** | 0.0267*** |
| | | | | | | | (0.005) | (0.008) | (0.003) |
| $rural * ethnic$ | | | | | | | 0.0060 | 0.0414 | 0.0355 |
| | | | | | | | (0.056) | (0.021) | (0.034) |
| $rural * ymen$ | | | | | | | 0.0367 | 0.0244 | -0.0156 |
| | | | | | | | (0.053) | (0.055) | (0.032) |
| $\boldsymbol{suburban * initial\_homicide}$ | | | | | | | **-0.0040** | **-0.0191*** ** | **-0.0004** |
| | | | | | | | **(0.005)** | **(0.007)** | **(0.003)** |
| $suburban * GINI$ | | | | | | | -0.0299 | 0.0119 | 0.0123 |
| | | | | | | | (0.060) | (0.070) | (0.037) |
| $suburban * income$ | | | | | | | 0.0167 | 0.0549 | 0.0095 |
| | | | | | | | (0.022) | (0.026) | (0.013) |
| $suburban * unemp$ | | | | | | | -0.101 | 0.507* | 0.171** |
| | | | | | | | (0.141) | (0.308) | (0.084) |
| $suburban * educ$ | | | | | | | 0.0021 | 0.0186 | 0.0188 |
| | | | | | | | (0.057) | (0.090) | (0.034) |
| $suburban * pop$ | | | | | | | 0.0306*** | 0.0501*** | 0.0152*** |
| | | | | | | | (0.009) | (0.012) | (0.005) |
| $suburban * ethnic$ | | | | | | | 0.0621 | 0.0576** | -0.0081 |
| | | | | | | | (0.075) | (0.030) | (0.045) |
| $suburban * ymen$ | | | | | | | 0.0751 | -0.0389 | -0.0195 |
| | | | | | | | (0.069) | (0.069) | (0.041) |
| $constant$ | 0.133*** | 0.228*** | 0.105*** | 0.154** | 0.428*** | 0.0547 | 0.436*** | 0.990*** | 0.404*** |
| | (0.003) | (0.005) | (0.002) | (0.072) | (0.098) | (0.043) | (0.167) | (0.201) | (0.101) |
| $R^2$ | 0.3528 | 0.3552 | 0.4099 | 0.4562 | 0.4454 | 0.4954 | 0.4641 | 0.4545 | 0.5045 |
| $\beta$ −convergence speed | 11.5% | 16.5% | 7.7% | 20.% | 28.9% | 13.2% | 19.6% | 19.7% | 13.2% |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Half-life | 6.0 | 4.2 | 9.0 | 3.4 | 2.4 | 5.2 | 3.5 | 3.5 | 5.2 |

Note: *, **, and *** denote significance at 10%, 5%, and 1%, respectively; $\beta$ −convergence rate is the speed at which convergence occur; Half-life is the time (in years) necessary to reach half stage of the convergence; The speed of convergence and half-life calculated from log ($initial\_homicide$)in the model for club convergence is for urban municipalities. The values for predominantly suburban and rural municipalities are 30.6% (2.3 years) and 7.3% (9.6 years), respectively, for the period from 2010 to 2017. It is important to remember that the coefficients for the interaction variables should not be interpreted independently but rather added to the main coefficients (for urban municipalities).

**Table 3: Conceptual matrix for the rural-urban municipal typology.**

| | Percentage distribution of population in densely populated areas | | | |
|---|---|---|---|---|
| Total population ranges in dense occupation areas | More than 75% | 50% to 75% | 25% to 50% | Less than 25% |
| Population Units with more than 50,000 inhabitants in dense occupation area | Predominantly urban | | | |
| Population Units that have between 25,000 and 50,000 inhabitants in dense occupation area | Predominantly urban | Predominantly urban | Suburban | Predominantly rural |
| Population Units that have between 10,000 and 25,000 inhabitants in dense occupation area | Predominantly urban | Suburban | Predominantly rural | Predominantly rural |
| Population Units that have between 3,000 and 10,000 inhabitants in dense occupation area | Suburban | Predominantly rural | Predominantly rural | Predominantly rural |
| Population Units with less than 3,000 inhabitants in dense occupation area | Predominantly rural | | | |

Source: Adapted from IBGE (2017).

## 2. THE EFFECT OF ABSOLUTE AND RELATIVE DEPRIVATION ON HOMICIDES IN BRAZIL

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**Marcelo Justus[3]**

### ABSTRACT

This paper investigates the effect of absolute deprivation (proxy unemployment) and relative deprivation (proxy income inequality) on homicide levels in Brazil. A database from the Brazilian Information System about Mortality and Census of the year 2000 and 2010 are used to estimate negative binomial models of homicide levels controlling for socioeconomic, demographic, and geographic factors. Findings show that unemployment and income inequality affect homicides levels and that the effect of the former is more pronounced compared to the latter. Moreover, the combination of income inequality and unemployment exacerbates the overall effect of deprivation on homicide levels.

**Keywords:** Violence. Deprivation. Unemployment. Inequality. Interaction.

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# 1 INTRODUCTION

Brazil has one of the highest rates of lethal violence in the world. The rate of homicide is remarkably high and has been steadily increasing over time in the last few years. In the year 2017, homicide is the cause of about 46.6% of the death of individuals between the age of 15 and 29 in Brazil, being significantly higher among the male population (about 53.3%). In that year alone, this represents 65.602 homicides caused by aggression and legal interventions in Brazil, giving a rate of 31.6 for every one hundred thousand population, which is three times the world average (CERQUEIRA et al., 2018; 2019). This position of Brazil in the global chart of violent deaths makes the country a relevant case not only of the so-called Global South[4] but also for the international literature on the topic.

Homicides are heterogeneously distributed across Brazilian municipalities and this distribution correlates with that of some socio-economic structures such as deprivation and inequality in terms of poverty, employment opportunities, and health facilities, especially in metropolitan areas. The regional concentration of homicide rate is also linked to other criminal activities such as drugs and firearm production and traffic (CERQUEIRA et al., 2019). This study centers on the association of social and economic deprivation with the homicide rate of municipalities controlling for demographic, geographic, and other socioeconomic factors.

The objective of this study is to investigate the effect of absolute deprivation (proxy unemployment) and relative deprivation (proxy income inequality) on homicide levels. Moreover, the potential interaction between unemployment and income inequality is tested to verify how homicide levels react to distinct combinations of the magnitudes of these deprivation measures. The analysis of such interaction is important because it enables to answer critical questions such as, how does homicide levels respond to low unemployment under the conditions of high income inequality, or vice-versa.

Criminological literature has long indicated that deprivation and inequality are significant causes of violent crimes (BLAU and BLAU, 1982; CECCATO, 2014; MESSNER *et al.,* 2002). However, there is a long-established debate regarding the role of economic deprivation on homicide, especially when specified as absolute deprivation (the ability of individuals to meet their subsistence needs) and relative deprivation (the social position of individuals compared to their social group) (PRIDEMORE, 2011).

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[4]Global South – a term broadly used by the World Bank to refer to countries in Asia, Africa, Latin America, and Oceania.

This study builds on the previous international literature but in particular the study by Burraston *et al.*(2018) that tested the interaction effect of income inequality and disadvantage on homicide levels using data from United State counties. These authors used income inequality as a proxy measure for relative deprivation and a disadvantage indicator that combines poverty, unemployment, level of education and family structure and income, as a proxy measure for absolute deprivation.

This present study contributes to this literature with novel perspectives. Unlike in most previous studies, unemployment is used as a measure of absolute deprivation instead of poverty, whereas income inequality is used as a measure of relative deprivation. This is because poverty is, by construct, confounded in the lower tail of the distribution of income inequality measures (PRIDEMORE, 2011) and unemployment is a state which does not relate one person to another, hence absolute. Moreover, unemployment better characterizes the temporary lack of the means of individuals to change their deprivation situation, which may emphasize the feeling of frustration and, consequently, may trigger violence (MERTON, 1938).

The international literature on this topic is overrepresented by evidence from the North American and European countries, whereas examples from countries of the Global South are underrepresented. Therefore, providing evidence on Brazil is peculiar not only because of the remarkably high homicide level but also because it is informative of the global south perspective, where income inequality is high and unemployment is on the increase (POCHMANN, 2015).

This study is structured into eight sections. The association between deprivation and crime is discussed in Section 2 and used as a support for the contextual framework and hypotheses presented in Section 3. In Section 4, Brazil is presented as the case study and in Section 5, the database and method, which comprises of the empirical strategies and model specification, were presented. The results are reported in Section 6 and discussed against related previous studies in Section 7. Section 8 concludes the study, states the limitations of this study and provides suggestions for future research.

## 2. THEORETICAL BACKGROUND: DEPRIVATION AND CRIME

This study adopts a mixed theoretical framework of neoclassical economic and sociological theories, whereby both the importance of economic and social factors that influence crime levels are acknowledged since, according to Danziger and Wheeler (1975), neither is self-sufficient.

Danziger and Wheeler (1975) extended the economic theory of crime from Becker (1968) by highlighting the role of social interdependence on crime decisions irrespective of the cost and benefit of committing them and how income redistribution may reduce overall crime levels. In this framework, an individual's utility is not only derived by the comparison of his/her possible income from legal and illegal activities, as in Becker (1968), but also how his/her income compares to his social group and the overall economic structure of the society, represented by the relative income distribution. Therefore, *ceteris paribus*, people commit crimes due to the frustration caused by the perceived economic distance between themselves and their reference group. The negative externality of malevolent interdependence, i.e. crime, is even more likely if social institutions are weak or discriminating against a specific population group and the attempts of self-improvement through education or occupation mobility are unsuccessful.

The assumption that income inequality creates a general feeling of malevolence, resentment, and hostility that stimulate aggressive impulses which are expressed as violent crimes is the centerpiece of the anomie and general strain theories that provide a sociological explanation of the causes of deviant behavior (MESSNER and TARDIFF, 1986). Different from the general strain theory which focuses on individual characteristics, the anomie theory is a macro level framework rooted in the works of Emile Durkheim, extended and fitted to the American social structure by Merton (1938), and further narrowed by Messner and Rosenfeld (2012) to the cultural role of the "American Dream" philosophy on crime levels in the United States. Similar to Danziger and Wheeler (1975), these authors agree that unequal opportunities among individuals in society cause strain and, consequently, more criminal offending. Messner and Rosenfeld (2012) added that the predatory mood caused by the inequality of economic opportunities can be mitigated by noneconomic institutions such as family, education, religion, and politics, and, consequently, crimes can be reduced.

Theories presented here suggested income as the measure for both absolute and relative deprivation. However, the authors clarify that the theoretical link between income inequality and homicide does not mean that the poor only attack the rich, but that the overall level of inequality causes a "mood" or "feeling" of malevolence which may stimulate criminal activities against the most "available" property or person (DANZIGER and WHEELER, 1975). Messner and Tardiff (1986) added that such a theoretical link is only valid if individuals perceive themselves as disadvantaged compared to people with whom they are comparable, i.e., high inequality may not affect their criminal choices if not manifested in their reference or social group. Even when inequality is perceived, Blau and Blau (1982) asserted that extreme inequality may incapacitate the lower-income strata to resort to violence. Such an ambiguous association of income inequality has been further discussed regarding property crime through the criminal opportunity theory by Hannon (2002) who found that economic deprivation provokes offending but it may also reduce the access of offenders to potential victims if inequality is very high.

The link between unemployment and crime is commonly rooted in time allocation theories such as that developed by Grogger (1998) and extended by Raphael and Winter-Ebmer (2001). Grounded in the assumption that individuals respond to incentives, these authors theoretically showed that unemployment increases crime since there is available time and criminal activities generate income. However, as shown by Cloward and Ohlin (1960), disposable time and income from illegal activities are not sufficient conditions for individuals to engage in crime since they need crime opportunity and the know-how. Danziger and Wheeler (1975) also showed that people's innate beliefs and allegiance to social norms influence their decisions regarding crime through the "social contract". Nevertheless, holding all else equal, Raphael and Winter-Ebmer (2001) argue that, in the aggregate level, "the relationship between unemployment and crime rates should be unambiguously positive", but may be weak or unclear regarding violent crimes in specific.

## 2.2 PREVIOUS RESEARCH ON HOMICIDES AND DEPRIVATION IN BRAZIL

The high levels of homicides in Brazil have been linked to deprivation as in inequality and economic disadvantage (CARDIA and SHIFFER, 2002; SANTOS and KASSOUF, 2008; SZWARCWALD *et al.*, 1999). Such association, classified as structural violence by Minayo and Souza (1993), is common in the international literature and has been empirically tested concerning Brazil (BARATA *et al.,* 1998; FERNANDEZ and LOBO, 2005; OLIVEIRA, 2005).

The measures commonly used as a proxy for absolute and relative deprivation are poverty and income inequality (measured using the GINI index), respectively. Similarly, as concluded by Pridemore (2011) regarding the international literature, there have been mixed results regarding the effect of these deprivation measures in Brazil. As to the effect of income inequality on homicide, most studies found evidence of a direct association (ANDRADE and BARROS-LISBOA, 2001; BEATO and Reis, (2001); CERQUEIRA, 2014; CERQUEIRA and LOBÃO, 2003; FAJNZYLBER and ARAUJO, 2001; MENDONÇA, 2002; OLIVEIRA, 2005;

RESENDE and ANDRADE, 2011). However, Cano and Santos (2001) and found no evidence of this association, and Ribeiro and Cano (2016) concluded that low income, i.e. poverty, and not inequality is associated with lethal violence. In contrast, a few studies have also found an ambiguous or non-significant effect of poverty on homicides (OLIVEIRA, 2005; RESENDE and ANDRADE, 2011). Specifically, Oliveira (2005) concluded that the increase of the income of the rich population increases crime whereas the increase of the income of the poor population reduces crime. Apart from the ambiguous effect on crime, income is highly correlated with many socioeconomic variables such as education, unemployment, and income inequality and, therefore, may pose serious methodological challenges in isolating the effect of absolute deprivation (RESENDE and ANDRADE, 2011).

Sachsida *et al.* (2007) upholds the evidence of the positive effect of inequality on homicide rates but found no effect of poverty. Nonetheless, these authors and Ribeiro and Cano (2016) found evidence indicating that unemployment is positively associated with homicides. This evidence regarding the direct effect of unemployment on homicide rates is supported by Justus *et al* (2018) but is rejected by Pezzin and Macedo (1986), Beato and Reis (2001), and Sapori and Wanderlei (2001).

Apart from deprivation, other factors that have been frequently identified as determinants of homicides in Brazil are, for example, urbanization, education, demographic composition such as young male population, drug markets, and the availability of firearms (CECCATO *et al.*, 2007; SACHSIDA *et al*., 2007; JUSTUS *et al.*, 2018; OLIVEIRA, 2005). In addition, Goertzel and Kahn (2009) and Goertzel *et al*. (2013) observed that the growth dynamics of homicide are not always determined by social and economic problems but rather by police activity and better law enforcement.

As observed in this section, the evidence concerning the effect of relative and absolute deprivation on crime is widespread in the Brazilian and international literature but little is known about the combined effect of both at different levels. In this study, various contexts of deprivation and homicide levels from Brazil are explored to provide a more comprehensive insight to the literature.

## 3. CONCEPTUAL FRAMEWORK AND HYPOTHESES

High levels of absolute deprivation such as poverty and unemployment and relative deprivation such as inequality and social exclusion result in a high level of crime (DANZIGER and WHEELER, 1975; MERTON, 1938; MESSNER and ROSENFELD, 2012). In the case of violence, Burraston *et al.* (2018; 2019) provided evidence regarding the association of homicide rates with absolute and relative deprivation in U.S. counties. In that case, the effect of both deprivations on homicide is dependent on the levels of one another, i.e. an interactive effect on homicide.

The homicides rate of Global South a country is many times that of the U.S. (UNODC, 2019) likewise other socioeconomic indicators on deprivation (UNDP, 2018). Accordingly, the evidence provided in Burraston *et al.* (2018; 2019) may be limited regarding the effects of deprivation, especially at extremely high levels. Bearing on a similar theoretical background and model specification, this study put forward the following hypotheses regarding Brazil as a model of the Global South perspective

H1: unemployment (as a measure for absolute deprivation) and income inequality (as a measure of relative deprivation) have a positive effect on homicide levels (see Lee *et al.*, 2014), and;

H2: unemployment and income inequality have an interactive or multiplicative effect on homicide levels when combined (see e.g. Burraston *et al.* (2018; 2019).

## 4. FRAMING THE CASE STUDY

Brazil is a country of the Southern hemisphere situated in Latin America. This country has about 210 million populations spread across 8.511 million km² of territory, which is divided into 26 states and one federal district that altogether comprises 5570 municipalities in the year 2019 as illustrated in Figure 1 (IBGE, 2019a).

The country faces pressing safety issues that are reflected in its exceptionally high homicide counts – 65.602 deaths in the year 2017, giving the rate of 31.6 per 100 thousand populations and placing Brazil in a leading position in the global ranking of lethal violence (CERQUEIRA et al., 2019).

Although heterogeneously distributed, homicide rates are expressively higher in urban and metropolitan areas in Brazil (CERQUEIRA et al., 2019). However, Waiselfisz (2011) and Andrade and Diniz (2013) showed that homicide rates are steadily increasing in the rural and inland regions. Cerqueira et al. (2019) recently reported that the distribution of homicide rates is biased as to demographic composition since about 94.4% of the registered victims in the year 2017 are male youths. This report also pointed out the race/ethnic bias whereby 75.5% of homicide victims in the same year were Afro-descendants. It is also noteworthy to mention that homicide against females (i.e. femicide) and LGBTI population is steadily increasing in the North and Northeast regions. It was advised that such a trend may be due to the increased awareness and report of crimes against these specific groups.

Brazil is a highly polarized country in terms of social access and conditions (NERI and SOARES, 2002), politics (LINDQVIST and ÖSTLING, 2010), and economy (CLEMENTI and SCHETTINO, 2013), although Hoffmann (2017) argued that economic polarization has expressively reduced over time but is still at high levels compared to other countries. This polarization is reflected by the significantly high income inequality, social exclusion, and economic disadvantage. Although poverty has reduced in Brazil (MEDEIROS *et al.*, 2019), unemployment is high and steadily increasing over time (POCHMANN, 2015).

# 5. METHOD

## 5.1 SOURCE OFDATA

Data from all 5565 Brazilian municipalities from the year 2000 and 2010 were used since there is limited recent data for most socioeconomic variables at this geographical unit. Nonetheless, this study is more interested in associations and not necessarily the recent socioeconomic scenario. It is worth mentioning that from the year 2011 to 2019, the number of municipalities in Brazil increased from 5565 to 5570.

Homicide count, which is the dependent variable, is defined as the number of deaths caused by external causes through aggression (groupX85–Y09 of the International Classification ofIllness, CID10) and this data was obtained from the Information System about Mortality. The data on deaths caused by legal interventions, especially during police activities and military operations, are not included in the dependent variable to focus on lethal aggression *per se*, which is the focus of the criminological theories that explain crime through social structures.

Data on all there gressors were obtained from the2000 and 2010 censuses available in the IBGE data base.

## 5.2 ESTIMATION PROCEDURES

Deprivation is indicated in the criminological literature as a cause of crime but the mixed results from the empirical investigation of its association with crime show the need for methodological innovations (PRIDEMORE, 2011).

It is common to investigate the determinants of violent crimes by estimating linear models of the logarithm mized rate of homicide per 100 thous and population. However, in line with Burraston *et al.* (2019), count models of homicide are estimated. The first motivation for this methodological approach is that homicide data follow the "law of rare events" characterized in Cameron and Trivedi (2001) and, thus, are natural lyskewe dright, i.e., there are many cases off ewor zero homicide count and few cases of high homicide count (Figure 2). The same skewed distribution is observed even when population size is accounted for, i.e., homicide rate. Secondly, O'hara and Kotze (2010) showed that the log-transformation of count data makes models perform poorly and illogical predictions may be observed such as negative homicide rates. Even though the distribution of homicide rates can be normalize dusing logarithm, the linear parameters estimated by OLS may mask informative non-linear attributes of regressors, which is expected for the interaction effect between relative and abso lute deprivation. In such acase, heteroskedasticity may persist since the variance of residuals will not be constant over distribution (Cameron andTrivedi,2005).

Homicide counts ($homicide_i$) is the dependent variable that has a Passion-like distribution and is regressed against a set of independent variables, $\mathbf{x}_i$, through an exponential functional form representedas

$$homicide_i = e^{x_i'\beta + \varepsilon_i} \quad (1)$$

$$\ln(homicide_i) = x_i'\beta + \varepsilon_i \quad (2)$$

where by the municipalities, $i$, are assumed not to have the same population exposure to homicide, therefore, population size($population_i$) is controlled as the exposure variable as shown below

$$\ln\left(\frac{homicide_i}{population_i}\right) = x_i'\beta + \varepsilon_i (3)$$

$$\ln(homicide_i) = ln\,(population_i) + x_i'\beta + \varepsilon_i \quad (4)$$

The coefficient of the exposure variable is constrained to 1, so the dependent variable of the model is homicide rates – homicides per unit of exposure. It is also assumed *ex-ante* that the distribution of $homicide_i$is over dispersed, i.e., the condition alvariance($\omega$) is not equalto the condition almean($\mu$)assupposed in the classic Poisson model. Specifically, $\omega = \mu + \alpha\mu^2$, where the $\alpha$ is the dispersion multiplier which is Gamma distributed. In other words, $homicide_i$ has a Poisson meananda Gamma distributed variance. Note that the model is a regular Poissonif $\alpha$=0,i.e., the Poission-Gamma model, which is also known as the negative binomial model, is more general.

For the interpretation of coefficients, the incidence-rate ratio (IRR) that is given by $e^{\beta i}$ is calculated. Therefore, values above one are positive and those below are negative. The percentage effect of coefficient sob tained thusly, $(1-IRR)\times 100$.

## 5.3 MODEL SPECIFICATION

The specification of the empirical model is guided by the theoretical and empirical literature presented in Section 2, and based on similar previous studies by Burraston *et al.* (2018; 2019) to enable the comparison of results. The variables of interest of the empirical model are:

a) Unemployment: unlike in most related studies that use poverty, the rate of unemployment is used as a *proxy* measure for absolute deprivation. This is because poverty is, by construct, nested in the lower tail of the distribution of incoming quality (GINIindex) which is a common proxy measure for relative deprivation. The un employment rate was transformed into $z$-scoresto center the data and have a meaningful interpretation of the interaction effect;

b) Incoming quality: is measured by the GINI index to control for relative deprivation .Similarlytoun employment, this in dexwas transformed into $z$-scores for analytical reasons. As already mentioned, most related studies use this measure as a *proxy* for relative de privation;

c) Interaction between unemployment and GINI: the interaction between unemployment and inequality controls for the combined effect of absolute and relative deprivation on homicides. The coefficient obtained from this interaction variable will indicate if the effect of absolute deprivation varies at different levels of relative deprivation, and vice versa. This control has been tested by Burraston *etal.*(2018;2019) for U.S. counties.

Interaction effects should always be interpreted cautiously since the isolated or joint coefficient of the interacted variables become conditional on one another (GREENE, 2003). Given that the variables for unemployment and inequality are centered using $z$-scores, their individual effects show the association with homicide at average values ($z$-score=0). The coefficient for the interaction variable shows how the independent effects of unemployment and inequality are affected by their combined effect and, the refore, should not be interpreted independently. A positive (negative) sign of the interaction variable indicates that the marginal effect of unemployment on homicide increases (decreases) as inequality reduces, and vice versa. For more information and examples on the interpretation of interaction variables, see Greene (2003, p. 123) and Burraston*etal.*(2018).

Apart from the interest variables, few additional regressors were included to control for other socioeconomic, demographic, and geographical factors that correlate with homicide, namely

a) Education: is the average years of schooling to capture the average education attainment of the population;

b) Level of urbanization: is a categorical variable for three levels of urbanization – *Urban* (reference) for municipalities that are predominantly urbanized, *Suburban* for municipalities with an intermediary level of urbanization and, Rural for predominantly rural municipalities. The methodology for the creation of these typologies can be found in IBGE (2017) and Table 3 presented in the appendix.

c) Household income: is the average household income per capita in the Brazilian currency(Reais–R$);

d) Racial/ethnicity heterogeneity: following Blau (1977), aheterogeneity measure for ethnicity is calculated by subtracting one from the squared proportion of each race/ethnic group. This measure varies between zero and one, being that one is complete heterogeneity. The race/ethnic groups contained in the measure are Black, White, Mulatto, Indigenous, and Asian;

e) Young men: given the demography of crime in Brazil, the population of young men between the age of 20 and 29 is included in the model. Since the coefficient for the population (exposure variable) is constrained to 1, the control for young men can be interpreted as the proportion of young men;

f) Dummies for states: is a set of 26 dummy variables to control for the fixed effect or heterogeneity of the 27 Brazilian states.

## 5.4 DESCRIPTIVEANALYSIS

The summary statistics of the dependent and independent variables of the empirical model are presented in Table 1.

The average count of homicides in municipalities is around 8 and 9 in the year 2000 and 2010, respectively. Note that these average counts are low due to the number of municipalities with zero homicide. The average rate of unemployment reduced expressively over the period from about 11% to 7% but the reduction of income inequality was modest from about 0.55 to 0.49. Note that the z-normalized values of these variables have zero mean and 1 standard deviation, whereby the values below average are negative and those above are positive. Therefore, the coefficients observed for these variables in the empirical model are centered around the mean.

The statistics regarding other control variables are also provided in Table 1 for consultation.

# 6 RESULT

## 6.1 DEPRIVATION AND HOMICIDE LEVELS

Table 2 presents the results, whereby separate models were estimated for both years to show the stability of the estimated associations over time. For analysis, the exponentiated coefficients also known as the Incident Rate Ratio (IRR) are calculated and interpreted as rates thusly, $(1-IRR)\times 100$.

The models show robust evidence concerning the positive association between unemployment and homicide in both years. Specifically, a unit increase in the unemployment rate is expected to increase homicide rates in about 14 and 17% in the year 2000 and 2010, respectively. The effect of income inequality appears to be expressively lesser compared to unemployment, although also positive in both years. A unit increase of the income inequality index increases homicide count in about 7 and 5% in the year 2000 and 2010, respectively.

The interaction variable between unemployment and income inequality has a significant and negative value, which implies that the marginal effect (the slope of the effect curve) of one reduces in about 6% and 9% for every unit increase in the other in both years. This interaction effect is better illustrated in Figure 2 that presents the predicted marginal incident rate of homicide across levels of unemployment and income inequality. Note that the predicted values are rates per unit of exposure, i.e., population, hence the low values. Five levels were specified for both variables: very low (10th percentile), low (25th percentile), average (50th percentile), high (75th percentile), and very high (90th percentile). Note that all the predicted margins plotted are statistically significant at 1%.

Graphs (a) and (b) in Figure 3 show that the association between homicide and unemployment is positive, irrespective of the levels of income inequality. However, the negative interactive effect has a multiplicative influence on the isolated effect of unemployment as inequality increases. Specifically, the positive effect of unemployment on homicide is exacerbated as income inequality increases but the marginal effect of unemployment is reduced. Nonetheless, the associations illustrated in graphs (a) and (b) indicate that municipalities with high unemployment and high income inequality will have higher rates of homicide compared to those with low unemployment and low inequality, and even compared to those with high inequality but low unemployment. There were very few municipalities in the context of very high unemployment and very low income inequality (49 in the year 2000 and 10 in the year 2010), thus, the predicted margins for this context should be considered carefully.

Graphs (c) and (d), also in Figure 3 present an analogous exercise for income inequality. As expected, income inequality is positively associated with homicide but with a diminishing marginal effect as the unemployment rate increases to the point at which the magnitude of the effect is inverted. Therefore, an increase in inequality correlates with an increase of homicides to a point at which the association begins to diminish, although still positive. Therefore, from graphs (a) and (b) it is observed that the positive associative effect of unemployment on homicide is continuously, although diminishingly, intensified as inequality increases. However, from graphs (c) and (d) it is observed that, as unemployment increases, the positive associative effect of income inequality on homicide is intensified up to a point from which this effect diminishes. The scenario of a diminishing effect of inequality on homicide when unemployment is very high may be the case of regions with high income polarization where there is a huge gap between the poor and rich population. Curiously, a similar result (especially to graph (d)) was observed by Burraston *et al.*(2019) regarding U.S. counties with very high economic disadvantage. However, the negative slope observed by these authors was less pronounced.

Regarding socioeconomic control variables, average household income has a very modest positive or zero effect on homicide in both years. Education has a negative effect on homicide. Specifically, a unit increase in the average years of education reduces homicide in about 4% and 7% in the year 2000 and 2010, respectively.

Turning to demographic factors, not only the size of the population is a relevant control (as the exposure variable) but also it's racial and gender composition. The coefficient for the young male population indicates a positive association with homicide and ethnic/racial heterogeneity is the strongest predictor of homicide levels. A unit increase in the indicator for ethnic heterogeneity predicts a staggering increase in homicide rate in about 663% in the year 2000, but this effect reduced expressively to 426% in the year 2010.

As for regional control, homicide is lower in municipalities that are predominantly suburban compared to those that are predominantly urban and lowest in predominantly rural municipalities in both years.

The significance of the dispersion multiplier, α, indicates that the distribution of homicide counts is over-dispersed, i.e., the negative binomial model estimated provides a better fit compared to the regular Poisson. The average VIF value shows that the level of multi co linearity of the independent variables is low and the models are stable when state binaries are controlled. To further emphasize the stability of the results, Table 4 (in the annex) presents separate models by levels of urbanization for both years. In short, the results are reliable.

## 7 DISCUSSION OF RESULTS

This study provides further evidence on the association between absolute deprivation (measured by unemployment), relative deprivation (measured by income inequality) and homicides. As an innovation compared to previous studies, unemployment was used as a measure of absolute deprivation instead of poverty because poverty is, by construct, confounded in the lower tail of the distribution of income inequality measures and unemployment is a state which does not directly relate individuals, hence absolute. Besides, this study provides evidence regarding the interactive effect of relative and absolute deprivation and, consequently, explored distinct contexts of the effect of deprivation on homicide.

The main results show that deprivation is a risk factor for homicide as suggested in the theoretical study of Merton (1938) and, in response to Messner (1982), the effect of absolute deprivation on homicide is significantly higher compared to relative deprivation. Such a positive association between deprivation and crime has been observed by Messner *et al.* (2002) and Lee *et al.* (2014) in the international literature and by Fajnzylber and Araujo Jr (2001), Cerqueira and Lobão (2003), and Oliveira (2005) regarding Brazil. The predominance of the effect of absolute deprivation (unemployment in this study) goes in line with that from Burraston *et al.*(2019) regarding U.S. counties and it seems reasonable since it is a form of deprivation that is perceived directly by the unemployed compared to inequality, which according to Messner and Tardiff (1986) may or may not be perceived depending on the characteristics of the individual's reference group. The implication of this result, as hinted by

Oliveira (2005), is that public policies directed towards reducing absolute deprivation (particularly, unemployment) will be effective in reducing homicide.

The results show that the combination of income inequality and unemployment exacerbates the overall effect of deprivation on homicide; however, the marginal effect reduces as any of both measures increases. This result is similar to that found by Burraston *et al.*(2018; 2019), which is the only evidence found in the literature regarding such interactive effect and is regarding U.S. counties. Nonetheless, this effect is not very surprising if considered through sociological theoretical perspectives because according to the anomie and general strain theories the effect of deprivation become even more relevant if individuals perceive high inequality in the society and do not have legitimate means (for example, employment) to reach their pre-established goals or achieve social mobility (DANZIGER and WHEELER, 1975; MERTON, 1938; MESSNER and ROSENFELD, 2012). The results provide additional evidence to support Burraston *et al.*(2019) and emphasize that regions in the context of high unemployment and high inequality should be prioritized by public safety policies that seek to reduce homicides.

The interactive effect of unemployment and inequality on homicide shows that the positive association of unemployment is continuously, although diminishingly, potentialized as inequality increases, whereas, as unemployment increases, the positive association of inequality is potentialized up to a point from which it weakens, i.e. nonlinearity as theoretically suggested by Hannon (2002). This was also observed by Burraston *et al.*(2019) for U.S. counties and we believe it requires more investigation. Nevertheless, such association has been hinted by Blau and Blau (1982) and Messnerand Tardiff (1986) in that very high income inequality may not affect crime if not perceived by deprived individuals as a result of high segregation or, even when perceived, may incapacitate them of resorting to violence.

Different from the result observed in Burraston *et al.* (2018) and Burraston *et al.* (2019), this study shows that racial heterogeneity is the strongest predictor (not cause) of homicide in Brazil. This result supports the evidence from Petee and Kowalski (1993) and Markowitz *et al.* (2001) concerning how racial heterogeneity increases disorder as predicted by social disorganization theories. Specifically, in Brazil, Cerqueira et al.(2019) highlighted the crucial role of population composition in terms of race/ethnicity by reporting that about 75,5% of the victims of homicide in the year 2017 were either Blacks or Mulattos and that the discrepancy between this race group and others is steadily increasing over time. Therefore, policies directed to reduce homicide in Brazil should prioritize the improvement of the socioeconomic condition of this particular group in such a manner that the effect of absolute and relative deprivation may be mitigated. As suggested by Danziger and Wheeler (1975) and Savolainen (2000), redistribution of income and the existence of stronger noneconomic institutions may be more effective ways of reducing crime. Moreover, the reduction of homicide rates, especially in this particular racial group, would significantly increase life expectancy not only of this group but of society as a whole (REDELINGS *et al.*, 2010).

# 8 CONCLUSION

The objective of this study is to provide further evidence on the effect of absolute deprivation (measured using unemployment) and relative deprivation (measured using income inequality) on homicide levels. The interaction between unemployment and income inequality was tested to verify how homicide levels react to different combinations of the degree of both deprivation measures.

Apart from upholding the positive association of homicide levels with unemployment and income inequality, this study shows that the former measure of deprivation has a higher predictive strength on homicide levels. This implies that the increasing unemployment rate and other indicators of deprivation being experienced in Brazil as reported by IBGE (2019b) may be followed by an increase in homicide levels. Besides, this study shows that the effect of deprivation on homicide levels is further potential zed when both deprivation measures coexist at high levels. Therefore, municipalities with high rates of unemployment combined with high levels of income inequality are very likely to be high-risk locations in terms of homicide.

As to the implications for the criminological and economic theory on crime, these findings support the anomie theory in that inequality (of income in this case) and the lack of the means to improve the deprived situation (due to unemployment in this case) increases crime (homicides in this case). The higher impact found for unemployment compared to inequality suggests that the means of improving a disadvantaged situation is more crucial than the perceived gap among individuals in society. The significantly high effect of ethnic heterogeneity on homicides is also supportive of the social disorganization theory.

One of the policy implications of the findings of this study is that unemployment can be tackled to mitigate absolute deprivation and, consequently, reduce homicides. Absolute deprivation can, in the short term, be relieved through government welfare programs centered on reducing poverty such as, for example, the *Bolsa Família* conditional cash transfer in Brazil. In the short run, it is also important to enhance situational prevention by enacting more effective policing with civil society collaborations at neighborhood levels. Stricter regulations on civilian possession of firearms and the control of the use of psychoactive substances can be applied by law enforcement in the short run to reduce aggression and lethal violence. In the long term, homicides can be reduced through public and private initiatives driven towards increasing young people's life chances through employment opportunities and education access, especially for young males (mostly the victims of homicides). These short and long-term policies, as implied by the findings of this study, should be prioritized for locations with high absolute and relative deprivation (e.g. unemployment and income inequality, respectively). Moreover, locations with high ethnical heterogeneity should be given special attention by national and regional public safety and police departments when planning. Given the racial bias of homicide rates against the Black and Mulatto population in Brazil (CERQUEIRA et al., 2019), the reduction of deprivation among this particular group may contribute to improve the life chances of people and by that helping reduce homicide rates in Brazil. These policy measures strongly align with the development recommendations of the United Nations as to being key to reaching the goal of a peaceful society as expressed by the current 2030's Sustainable Development Goals.

The association between deprivation and crime has been a long-established debate in literature given that some studies do not find evidence of a link. Nevertheless, apart from being consistent with the majority of previous theoretical and empirical studies, the results reported are stable, informative, and suggestive of the existing associations between some social structural factors and homicide. Another limitation is that the data used was unavailable to test the forwarded hypotheses for recent periods since most socioeconomic data are only available in the last censuses, which were conducted in the year 2000 and 2010. Data permitting, future research could also further explore the association between ethnic heterogeneity and homicide, which the results show to be crucial. Social structural factors such as poverty, unemployment, inequality measures (social or economic) could be interacted with ethnical heterogeneity to further disentangle its association with homicide rate or level. Future studies should devote time in assessing specific situational characteristics of the actual victims of lethal violence, exploring spectrums of gender, ethnicity, age, etc. in order to unravel the intersection of vulnerabilities that makes a certain group more at the target than others. Nonetheless, this study offers further empirical evidence in promoting a better understanding of the nature of deprivation and its relationship with lethal violence and in a country of the Global South.

Lastly, the COVD-19 global pandemic that started in the late 2019 bears challenges not only to public health but also to the social and economic conditions of many countries around the world, especially affecting the forms of social interaction, employment, income, and magnifying existent patterns of socio-economic inequality. The results of this study may give an insight into what may happen in the near future. Given that the pandemic has dilapidated the economy, increased unemployment, and has disproportionally affected the health and income of the underprivileged population, this study hypothesizes that homicide rates may increase expressively in the close future. This effect may, however, be overrepresented among the deprived and specific ethnic groups of the population were already underprivileged before the pandemic.


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## REFERENCES


ANDRADE, L. T., and DINIZ, A. M. A.. A reorganização espacial dos homicídios no Brasil e a tese da interiorização. *Revista Brasileira de Estudos de População*, *30/1,* 171–191. 2013.

ANDRADE, M. and BARROS-LISBOA, M.. Desesperança de vida: homicídio em Minas Gerais, Rio de Janeiro e São Paulo: 1981 a 1997. *In: Anais do IX Seminário sobre a Economia Mineira [Proceedings of the 9th Seminar on the Economy of Minas Gerais].* Cedeplar, Universidade Federal de Minas Gerais. p. 775-808. 2000.

BARATA, R. B., de ALMEIDA, M. C. S., da Silva, M. B. L., and de Moraes, J. C.. Intra-urban differentials in death rates from homicide in the city of São Paulo, Brazil, 1988–1994. *Social Science & Medicine*, *47*(1), 19–23. 1998.

BECKER, G. S.. Crime and punishment: An economic approach. In *The economic dimensions of crime* (pp. 13-68). Palgrave Macmillan, London. 1968.

BLAU, P. M.. *Inequality and heterogeneity: A primitive theory of social structure*, Volume 7. Free Press New York. 1977.

BLAU, J. R. and P. M. BLAU. The cost of inequality: Metropolitan structure and violent crime. *American sociological review, 47* (1), 114–129. 1982.

BURRASTON, B., J.C. Mc Cutcheon, and S.J. WATTS. Relative and absolute deprivation's relationship with violent crime in the United States: Testing an interaction effect between income inequality and disadvantage. *Crime & Delinquency, 64* (4), 542–560. 2018.

BURRASTON, B., S. J. Watts, J. C. McCutcheon, and K. PROVINCE. Relative deprivation, absolute deprivation, and homicide: Testing an interaction between income in equality and disadvantage. *Homicide Studies 23* (1), 3–19. 2019.

CAMERON, A. C. and P. K. TRIVEDI. Essentials of count data regression. *A companion to theoretical econometrics*. 2001.

CAMERON, A. C. and P. K. TRIVEDI. *Microeconometrics: methods and applications*. Cambridge university press. 2005.

CANO, I. and SANTOS, N. *Violência letal, renda e desigualdade no Brasil*. Rio de Janeiro: 7. Letras, 2001.

CARDIA, N., and SCHIFFER, S.. Violência e desigualdade social. *Ciência e Cultura*, *54*(1), 25–31. 2002.

CECCATO, V., Haining, R., and KAHN, T. The geography of homicide in São Paulo, Brazil. *Environment and Planning A*, *39*(7), 1632–1653. 2007.

CECCATO, V.. The geographic, socioeconomic, and cultural determinants of violence. *Oxford textbook of violence prevention: Epidemiology, evidence, and policy*, 77–86. 2014.

CERQUEIRA, D., and LOBÃO, W.. *Condicionantes sociais, poder de polícia e o setor de produção criminal (Discussion Paper 957).* Instituto de Pesquisa Econômica Aplicada (IPEA). 2003.

CERQUEIRA, D. R. C. de Castro. *Causas e consequências do crime no Brasil.* Banco Nacional de Desenvolvimento Econômico e Social. 2014.

CERQUEIRA, D. R. C. et al. *Atlas da violência 2018.* Instituto de Pesquisa Econômica Aplicada (IPEA) e Fórum Brasileiro de Segurança Pública (FBSP). 2018.

CERQUEIRA, D. R. C. et al. *Atlas da violência 2019*. Instituto de Pesquisa Econômica Aplicada (IPEA) e Fórum Brasileiro de Segurança Pública (FBSP). 2019.

CLEMENTI, F., and SCHETTINO, F.. Income polarization in Brazil, 2001-2011: a distributional analysis using PNAD data. *Economics Bulletin*, *33*(3), 1796–1815. 2013.

CLOWARD, R. A., and OHLIN, L. E.. *Delinquency and opportunity: A study of delinquent gangs*. Routledge. 1960.

DANZIGER, S., and WHEELER, D.. The economics of crime: Punishment or income redistribution. *Review of social economy*, *33*(2), 113–131. 1975.

FAJNZYLBER, P., and ARAUJO JR, A.. Violência e criminalidade. *Microeconomia e sociedade no Brasil*, 333–394. 2001.

FERNANDEZ, J. C., and LOBO, L. F.. A Criminalidade na região metropolitana de Salvador. *Análise Econômica*, *23*(44), 31–65. 2005.

GOERTZEL, T. and KAHN, T.. The great São Paulo homicide drop. *Homicide Studies*, *13*(4), p. 398-410. 2009.

GOERTZEL, T., Shohat, E., Kahn, T., Zanetic, A., and BOGOYAVLENSKIY, D.. Homicide booms and busts: A small-n comparative historical study. *Homicide studies*, *17*(1), 59-74. 2013.

GREENE, W. H.. *Econometric analysis*. Pearson Education India. 2003.

GROGGER, J.. Market wages and youth crime. *Journal of labor Economics*, *16*(4), 756-791. 1998.

HANNON, L.. Criminal opportunity theory and the relationship between poverty and property crime. *Sociological Spectrum*, *22*(3), 363-381. 2002.

HOFFMANN, R.. Medidas de polarização da distribuição da renda e sua evolução no Brasil de 1995 a 2013. *Economia e Sociedade*, *26*(1), 165-187. 2017.

IBGE. *Caracterização dos espaços rurais e urbanos do brasil–uma primeira aproximação* . Technical report, Instituto Brasileiro de Geografia e Estatística. 2017.

IBGE. *Estimativas da população residente no brasil e unidades da federação com data de referência em 1º de julho de 2019.* Instituto Brasileiro de Geografia e Estatística. (2019a)

IBGE. *Síntese de indicadores sociais: uma análise das condições de vida da população brasileira. Instituto Brasileiro de Geografia e Estatística. Coordenação de População, & Indicadores Sociais.* (No. 40). (2019b).

JUSTUS, M., de Castro Cerqueira, D. R., Kahn, T., and MOREIRA, G. C.. The "São Paulo Mystery": The role of the criminal organization PCC in reducing the homicide in 2000s. *EconomiA*, *19*(2), 201–218. 2018.

LEE, B. X., Marotta, P. L., Blay-Tofey, M., Wang, W., and de BOURMONT, S.. *Economic correlates of violent death rates in forty countries, 1962–2008: a cross-typological analysis*. Aggression and violent behavior, 19(6), 729–737. 2014.

LINDQVIST, E., and ÖSTLING, R.. Political polarization and the size of government. *American Political Science Review*, 104(3), 543–565. 2010.

MARKOWITZ, FE, Bellair, PE, Liska, AE, and LIU, J.. Extending social disorganization theory: Modeling the relationships between cohesion, disorder, and fear. *Criminology*, *39* (2), 293–319. 2001.

MEDEIROS, M., Barbosa, R. J., and CARVALHAES, F.. Educação, desigualdade e redução da pobreza no Brasil. Instituto de Pesquisa Econômica Aplicada (Ipea). 2019.

MENDONÇA, M. J. C.. Criminalidade e violência no Brasil: uma abordagem teórica e empírica. *Revista Brasileira de Economia de Empresas*, *2*(1), 33–49. 2002.

MERTON, R. K.. Social structure and anomie. *American sociological review, 3*(5), 672–682. 1938.

MESSNER, S. F.. Poverty, inequality, and the urban homicide rate: Some unexpected findings. *Criminology, 20*(1), 103–114. 1982.

MESSNER,S.F.,L.E.Raffalovich,andP.Shrock. .Reassessing the cross-national relationship between income in equality and homicide rates: Implications of data quality control in the measurement of income distribution. *Journal of Quantitative Criminology, 18*(4), 377–395. 2002.

MESSNER, S. F. and R. Rosenfeld. *Crime and the American dream* (5th ed. ed.). Cengage Learning. 2012.

MESSNER, S.F.and K.Tardiff. Economic in equality and levels of homicide: An analys is of urban neighborhoods. *Criminology, 24*(2), 297–316. 1986.

MINAYO, M. C. D. S. and SOUZA, E. R. D.. Violência para todos. *Cadernos de Saúde Pública*, *9*(1), 65–78. 1993.

NERI, M., and SOARES, W.. Social inequality and health in Brazil. *Cadernos de saúde pública*, *18(1)*, S77–S87. 2002.

O'HARA, Robert B.; KOTZE, D. Johan. Do not log-transform count data. *Methods in ecology and Evolution,1*( 2), 118–122. 2010.

OLIVEIRA, C. A.. Criminalidade e o tamanho das cidades brasileiras: um enfoque da economia do crime. In *Anais do XXXIII Encontro Nacional de Economia- ANPEC* (No. 152). 2005.

PETEE, T. A., and Kowalski, G. S.. Modeling rural violent crime rates: A test of social disorganization theory. *Sociological Focus*, *26*(1), 87–89. 1993.

PEZZIN, L. E. and Macedo, R.. *Criminalidade urbana e crise econômica: o caso de São Paulo.* São Paulo: IPE/USP. 1986.

PRIDEMORE, W. A.. Poverty matters: A reassessment of the inequality–homicide relationship in cross-national studies. *The British Journal of Criminology 51* (5), 739–772. 2011.

POCHMANN, M.. Ajuste econômico e desemprego recente no Brasil metropolitano. *Estudos Avançados*, 29(85), 7–19. 2015.

RIBEIRO, E. and CANO, I.. Vitimização letal e desigualdade no Brasil: evidências em nível municipal. *Civitas-Revista de Ciências Sociais*, *16*(2), 285-305. 2016.

RAPHAEL, S., and WINTER-EBMER, R.. Identifying the effect of unemployment on crime. *The Journal of Law and Economics*, *44*(1), 259–283. 2001.

REIS, I. A. and BEATO, C. D.. Desigualdade, desenvolvimento socioeconômico e crime. In Ricardo Henriques (Org.) Desigualdade e pobreza no Brasil. Instituto de Pesquisa Econômica Aplicada (IPEA). 2000.

REDELINGS, M., Lieb, L., and SORVILLO, F.. Years off your life? The effects of homicide on life expectancy by neighborhood and race/ethnicity in Los Angeles County. *Journal of Urban Health*, *87*(4), 670-676. 2010.

RESENDE, J. P. D., and ANDRADE, M. V.. Crime social, castigo social: desigualdade de renda e taxas de criminalidade nos grandes municípios brasileiros. *Estudos Econômicos (São Paulo)*, *41*(1), 173–195. 2011.

SACHSIDA, A., de Mendonça, M. J. C., Loureiro, P. R., and GUTIERREZ, M. B. S.. Inequality and criminality revisited: further evidence from Brazil. *Empirical Economics*, *39*(1), 93–109. 2010.

SANTOS, M. J., and Kassouf, A. L.. Estudos econômicos das causas da criminalidade no Brasil: evidências e controvérsias. *Revista EconomiA*, *9*(2), 343–372. 2008.

SAPORI, L. F. and Wanderley, C. B.. A relação entre desemprego e violência na sociedade brasileira: entre o mito e a realidade. A violência do cotidiano. *Cadernos Adenauer. São Paulo: Fundação Kinrad Adenauer*, 42-73. 2001.

SAVOLAINEN, J.. Inequality, welfare state, and homicide: Further support for the institutional anomie theory. *Criminology, 38*(4), 1021–1042. 2000.

SZWARCWALD, C. L., Bastos, F. I., Esteves, M. A. P., Andrade, C. L. T. D., Paez, M. S., Medici, E. V., and Derrico, M.. Desigualdade de renda e situação de saúde: o caso do Rio de Janeiro. *Cadernos de Saúde Pública*, *15*(1), 15-28. 1999.

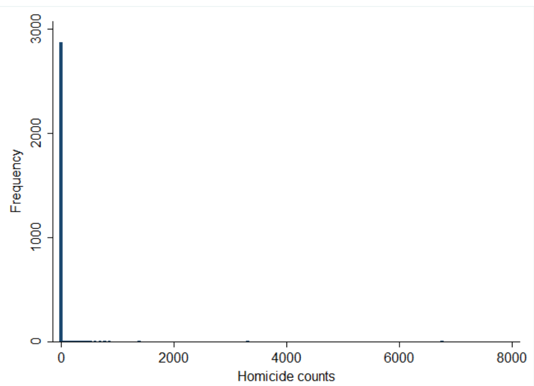
UNDP. Human Development Indices and Indicators: Statistical Update. *United Nations Development Programme*. 2018.

UNODC. Global Study on Homicide: Homicide, development and the Sustainable Development Goals. *United Nations Office on Drugs and Crime*. 2019.

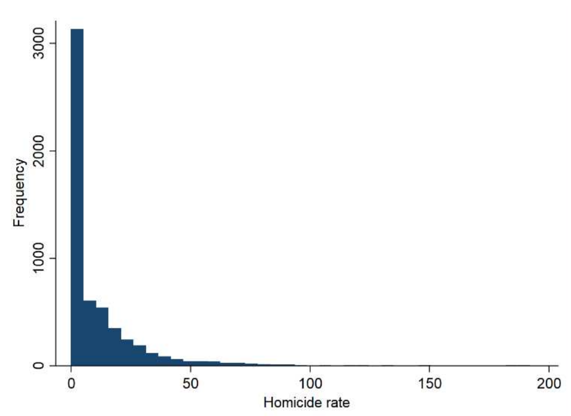
WAISELFISZ, J. J..  Mapa da violência 2010 – os novos padrões da violência homicida no Brasil. Technical report, Instituto Sangari. 2011.

**Figure 1: The geography of Brazil divided in states and municipalities.**

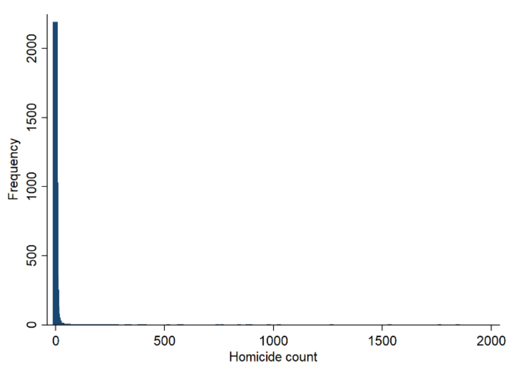

**Figure 2: Histogram of homicide counts and rates, 2000 and 2010, Brazil.**



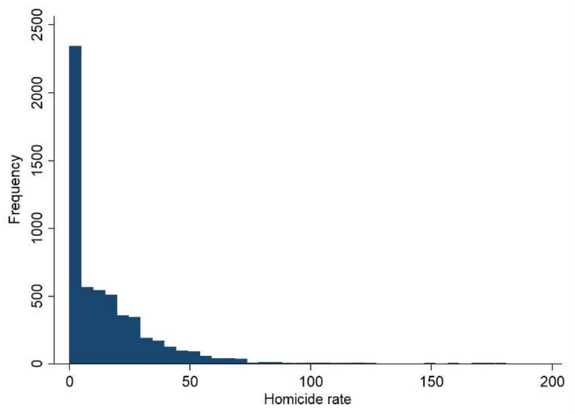

Homicide count; 2000




Homicide rates; 2000




Homicide count; 2010




Homicide rates; 2010

Source: Prepared by authors using the 2000 and 2010 Census data

**Table 1: Statistics of variables**

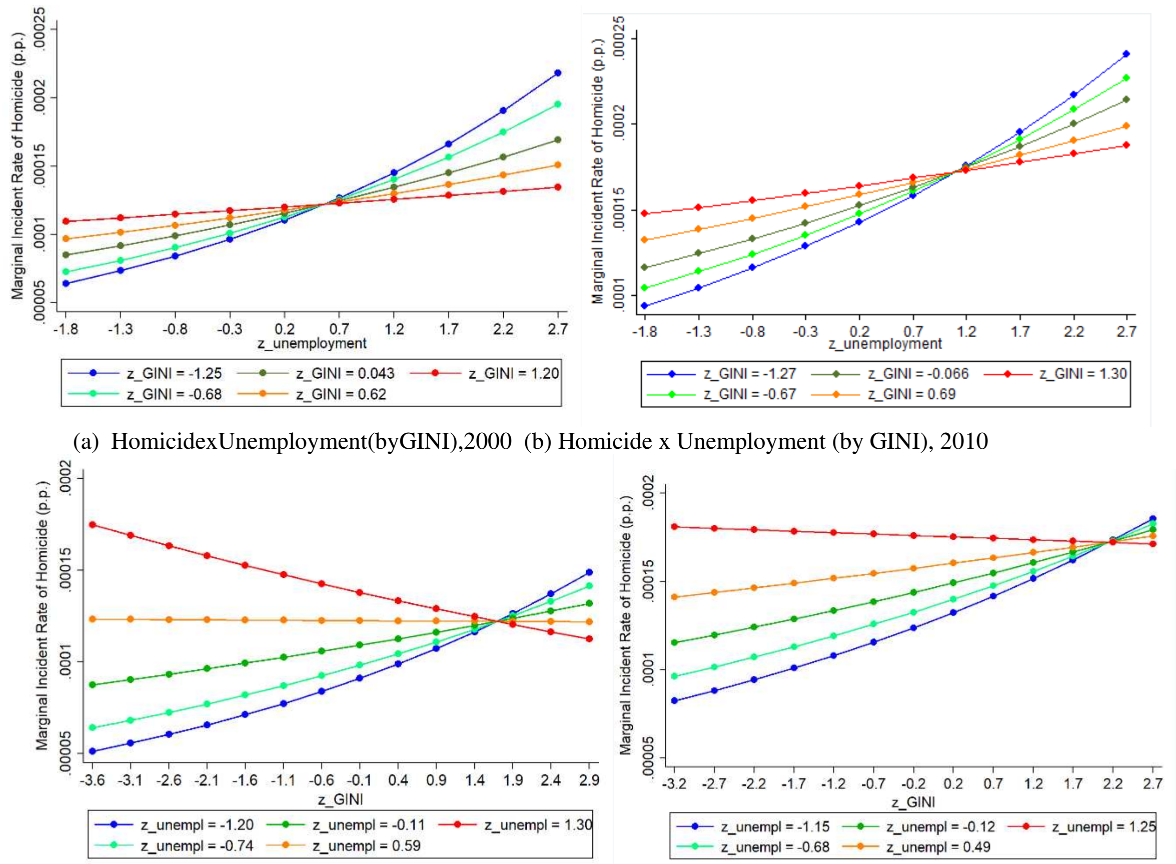
| Variable | Description | 2000 Mean | 2000 s.d. | 2010 Mean | 2010 s.d. |
|---|---|---|---|---|---|
| Homicide | Homicide count | 8.15 | 108.81 | 9.392 | 61.353 |
| Unemployment | Unemployment rate (%) | 11.02 | 6.22 | 6.74 | 3.83 |
| z_Unemployment | z-score of unemployment rate | 0 | 1 | 0 | 1 |
| GINI | Inequality index | 0.547 | 0.069 | 0.494 | 0.066 |
| z_GINI | z-score of inequality index | 0 | 1 | 0 | 1 |
| Household income | Average family income per capita (R$) | 338.58 | 192.44 | 493.65 | 243.267 |
| Education | Average years of schooling (years) | 8.33 | 1.797 | 9.464 | 1.098 |
| Population | Total population | 30516 | 185689 | 34282 | 203131 |
| Young men | Total population of young men between age 20 to 29 | 2671 | 16747 | 3071 | 18190 |
| Ethnicity | Indicator of race or ethnicity heterogeneity (range from 0 to 1) | 0.435 | 0.144 | 0.464 | 0.119 |
| Urban | Percentage of municipalities classified as predominantly urban (%) | 21.2 | 40.9 | 25.4 | 43.6 |
| Intermediary | Percentage of municipalities classified as suburban (%) | 15.5 | 36.2 | 18.6 | 38.9 |
| Rural | Percentage of municipalities classified as predominantly rural (%) | 63.3 | 48.2 | 56.0 | 49.6 |

**Table 2: Result of the estimation of negative binomial models of municipality homicide** counts.

| Dep. variable: Homicide | 2000 $\beta$ | 2000 IRR | 2010 $\beta$ | 2010 IRR |
|---|---|---|---|---|
| Unemployment | 0.132*** | 1.141*** | 0.157*** | 1.170*** |
| | (0.018) | (0.020) | (0.021) | (0.025) |
| GINI | 0.0661*** | 1.068*** | 0.0527** | 1.054** |
| | (0.018) | (0.020) | (0.021) | (0.022) |
| Unemployment X GINI | -0.0602*** | 0.942*** | -0.0927*** | 0.911*** |
| | (0.015) | (0.014) | (0.017) | (0.015) |
| Householdincome | 0.000151 | 1.000 | 0.000986*** | 1.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Education | -0.105*** | 0.900*** | -0.118*** | 0.889*** |
| | (0.019) | (0.017) | (0.019) | (0.017) |
| Young men | 0.00000402*** | 1.000*** | 0.00000568*** | 1.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Ethnicity | 2.045*** | 7.726*** | 1.660*** | 5.260*** |
| | (0.208) | (1.607) | (0.213) | (1.118) |
| Suburban | -0.336*** | 0.714*** | -0.306*** | 0.737*** |
| | (0.040) | (0.028) | (0.051) | (0.038) |
| Rural | -0.575*** | 0.563*** | -0.359*** | 0.698*** |
| | (0.039) | (0.022) | (0.050) | (0.035) |
| Constant | -8.697*** | 0.000167*** | -9.452*** | 0.0000785*** |
| | (0.267) | (0.000) | (0.305) | (0.000) |
| Dispersionmultiplier($\alpha$) | 0.464*** | 0.464*** | 0.377*** | 0.377*** |
| | (0.023) | (0.023) | (0.016) | (0.016) |

| | | | | |
|---|---|---|---|---|
| Population | 1 | 1 | 1 | 1 |
| Dummy for states | Yes | Yes | Yes | Yes |
| N | 5565 | 5565 | 5565 | 5565 |
| pseudo $R^2$ | 0.075 | 0.075 | 0.105 | 0.105 |
| VIF (without state binary) | 1.56 | 1.56 | 1.70 | 1.70 |
| VIF (with state binary) | 8.31 | 8.31 | 8.25 | 8.25 |
| *AIC* | 20261.5 | 20261.5 | 16400.0 | 16400.0 |

Note: *, **, and *** denote significance at 10%, 5%, and 1%, respectively; IRR is the exponentiated coefficients, i.e., incidence-rate ratio; AIC is the Akaike information criterion, respectively; *population* is controlled as the exposure variable, therefore, the coefficients are analyzed as rates, and; unemployment and GINI are both *z* scores and the Pearson correlation value between both are 0.1336 and 0.2776 for the year 2000 and 2010, respectively.




(a) HomicidexUnemployment(byGINI),2000 (b) Homicide x Unemployment (by GINI), 2010

(c) HomicidexGINI(byUnemployment),2000 (d)Homicide x GINI (by Unemployment),2010

Figure 3: Interaction effect between unemployment and income inequality (GINI).
Note: All the marginal effect points plotted here are statistically significant at the level of 1%.

**Table 3: Conceptual matrix for the rural-urban municipal typology.**

| | Percentage distribution of population in densely populated areas | | | |
|---|---|---|---|---|
| Total population ranges in dense occupation areas | More than 75% | 50% to 75% | 25% to 50% | Less than 25% |
| Population Units with more than 50,000 inhabitants in dense occupation area | Predominantly urban | | | |

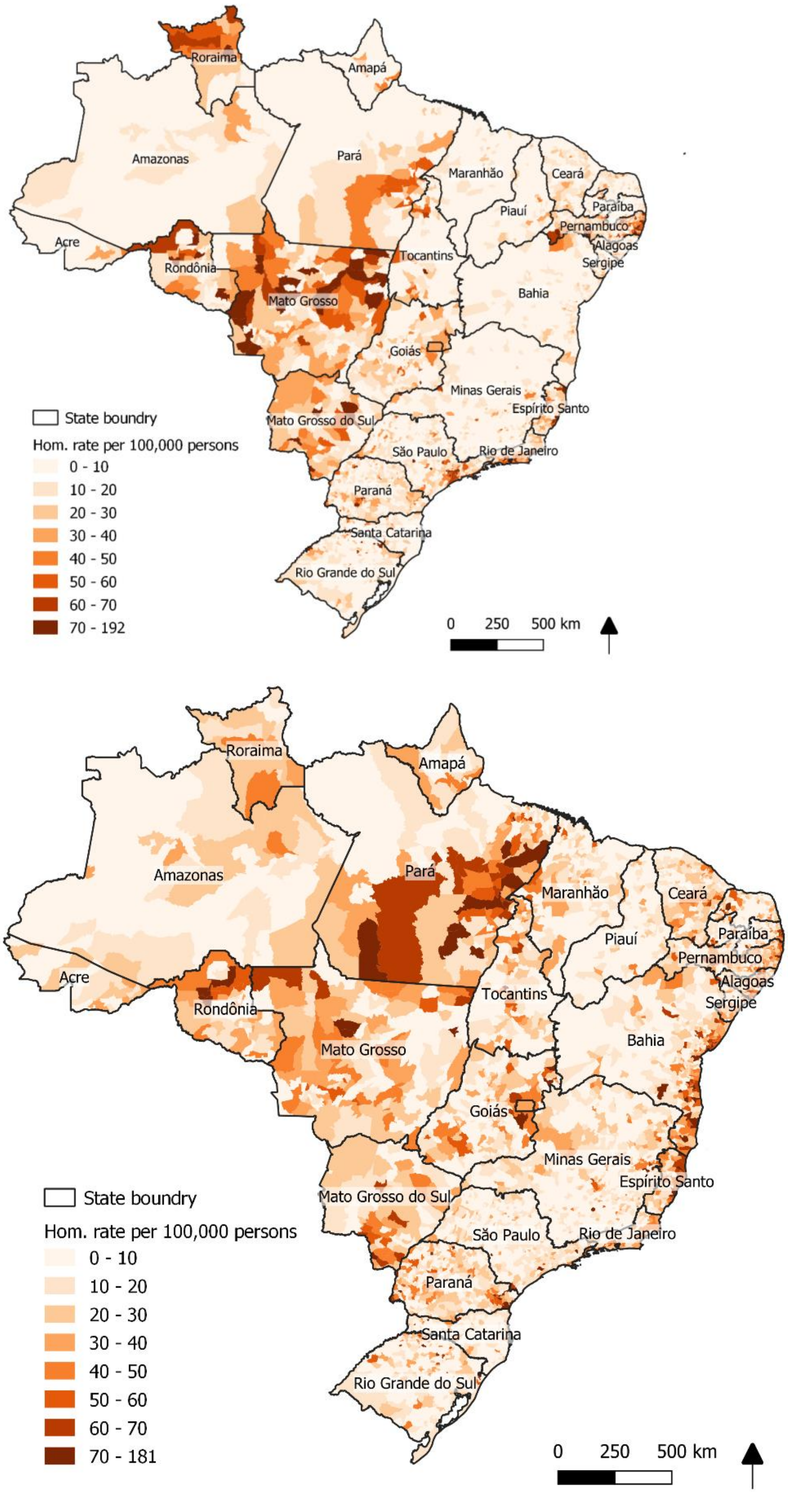
| | | | | |
|---|---|---|---|---|
| Population Units that have between 25,000 and 50,000 inhabitants in dense occupation area | Predominantly urban | Predominantly urban | Suburban | Predominantly rural |
| Population Units that have between 10,000 and 25,000 inhabitants in dense occupation area | Predominantly urban | Suburban | Predominantly rural | Predominantly rural |
| Population Units that have between 3,000 and 10,000 inhabitants in dense occupation area | Suburban | Predominantly rural | Predominantly rural | Predominantly rural |
| Population Units with less than 3,000 inhabitants in dense occupation area | Predominantly rural | | | |

Source: Adapted from IBGE (2017).

**Table 4: Result of the estimation of negative binomial models of municipality homicide by levels of urbanization**

| Dep. variable: Homicide | Brazil 2000 | Urban 2000 | Suburban 2000 | Rural 2000 | Brazil 2010 | Urban 2010 | Suburban 2010 | Rural 2010 |
|---|---|---|---|---|---|---|---|---|
| Unemployment | 0.157*** | 0.344*** | 0.129** | 0.0132 | 0.132*** | 0.236*** | 0.100** | 0.0696** |
| | (0.021) | (0.036) | (0.051) | (0.035) | (0.018) | (0.030) | (0.043) | (0.029) |
| GINI | 0.0527** | 0.0290 | -0.00643 | 0.0489 | 0.0661*** | 0.00473 | 0.0287 | 0.0868*** |
| | (0.021) | (0.046) | (0.053) | (0.031) | (0.018) | (0.030) | (0.043) | (0.031) |
| Unemployment X GINI | -0.0927*** | -0.0718** | -0.0707 | -0.0750*** | -0.0602*** | -0.0656*** | -0.0394 | -0.0649*** |
| | (0.017) | (0.036) | (0.052) | (0.027) | (0.015) | (0.025) | (0.040) | (0.022) |
| Householdincome | 0.000986*** | 0.00160*** | 0.00135*** | 0.000706** | 0.000151 | 0.000574*** | -0.000194 | -0.000384 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Education | -0.118*** | -0.210*** | -0.176*** | -0.101*** | -0.105*** | -0.112*** | -0.171*** | -0.0913*** |
| | (0.019) | (0.037) | (0.051) | (0.029) | (0.019) | (0.033) | (0.045) | (0.030) |
| Young men | 0.00000568*** | 0.00000211** | 0.0000241 | 0.000107*** | 0.00000402*** | 0.00000193** | 0.0000956*** | 0.0000805*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Ethnicity | 1.660*** | 2.460*** | 0.902* | 1.203*** | 2.045*** | 2.492*** | 2.374*** | 1.198*** |
| | (0.213) | (0.360) | (0.509) | (0.311) | (0.208) | (0.332) | (0.523) | (0.311) |
| Suburban | -0.306*** | | | | -0.336*** | | | |
| | (0.051) | | | | (0.040) | | | |
| Rural | -0.359*** | | | | -0.575*** | | | |
| | (0.050) | | | | (0.039) | | | |
| Constant | -9.452*** | -8.962*** | -9.168*** | -9.970*** | -8.697*** | -8.942*** | -8.759*** | -8.928*** |
| | (0.305) | (0.553) | (1.030) | (0.429) | (0.267) | (0.468) | (0.563) | (0.424) |
| Dispersion | -0.767*** | -1.037*** | -0.975*** | -0.463*** | -0.976*** | -1.200*** | -1.067*** | -0.793*** |
| multiplier($\alpha$) | (0.049) | (0.063) | (0.147) | (0.091) | (0.043) | (0.056) | (0.108) | (0.086) |
| Population | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Dummy for states | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 5565 | 1182 | 861 | 3522 | 5565 | 1417 | 1033 | 3115 |
| pseudo $R^2$ | 0.105 | 0.098 | 0.104 | 0.090 | 0.075 | 0.081 | 0.090 | 0.049 |
| VIF (without state binary) | 1.7 | 1.78 | 1.65 | 1.54 | 1.56 | 1.42 | 1.45 | 1.52 |
| VIF (with state binary) | 8.25 | 17.62 | 26.52 | 6.85 | 8.31 | 14.54 | 5.93 | 9.16 |
| *AIC* | 16401.9 | 6893.0 | 2593.7 | 6848.9 | 20261.4 | 8855.9 | 3638.0 | 7662.9 |

**Figure 3: Homicide rates by municipality, 2000 and 2010, Brazil.**




(a) 2000
(b) 2010

Source: Prepared by authors using the 2000 and 2010 Census data

# 3 A MULTIVARIATE TIME SERIES ANALYSIS ON CARGO THEFT

**Temidayo James Aransiola [1]**
**Marcelo Justus[2]**
**Vania Ceccato[3]**

## ABSTRACT

The objective of this study is to contribute to the growing literature on cargo theft by empirically testing four specific hypotheses of its causes – the space-time dynamics hypothesis, the economic attractiveness hypothesis, the social structure hypothesis, and the deterrence hypothesis. This study investigates the case of the economic core of one of the most severe regions regarding cargo theft worldwide – São Paulo state. As a novelty in crime studies, we estimate Autor regressive Distributed Lag models (ARDL). We found that the number of cargo thefts of a geographic area can be predicted by itself and that of neighboring areas. This is unprecedented empirical evidence that cargo theft time series are autoregressive and co integrated. Regarding economic attractiveness and social structure, the results are inconclusive. However, police activity reduces cargo theft in the large metropolitan area and inland municipalities of São Paulo state.

***Keywords*:** Cargo. Theft. Economic. Opportunity. Trade.

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# 1. INTRODUCTION

Cargo theft is one of the major concerns of logistics systems worldwide in that it is costly to businesses and economies either directly through shrinkage (BAILEY, 2006) or indirectly through the cost of prevention measures and/or insurance (ALSTETE, 2006), which may be swift in crippling small and medium businesses.

In the year 2019 alone, the median value of economic losses due to cargo theft ranges from \$100,000 in South America to about \$11,000 in Asia (BSI, 2020). Such cost is internalized by businesses and compensated in the price paid by final consumers in the legal market, thus, distorting market conditions – reduced supply of goods due to shrinkage; increased cost due to crime prevention measures, and, consequently; higher price to final consumers in the legal market, whereas different prices are practiced in the black market (BAILEY, 2006; BURGES, 2012; GUTHRIE and GUTHRIE, 2006; JOHNS and HAYES, 2003). Besides direct economic costs, cargo theft also spawns indirect costs which are often many times higher compared to the direct costs (U.S. General Accounting Office, 1980). Moreover, in certain regions, cargo thefts are very lethal crimes committed by fierce criminal organizations that resort to the use of heavy weapons, violence and, occasionally, the kidnap or death of innocent truck drivers (OLIVEIRA and MARTINS, 2014; JUSTUS *et al.*, 2018; BSI, 2018).

There is unanimous evidence in the literature that the supply chain of cargos transported by trucks is the most disrupted compared to other freights worldwide and that a majority of these crimes happen in-transit (BURGES, 2012; EKWALL and LANTZ, 2015; SCIC, 2018, BSI, 2020). The literature is also in consensus that cargo theft is essentially economically motivated since the target is mostly products that are stolen from trucks, distributed, and sold through illegal channels to transform them into money (BURGES, 2012). These products are defined as hot products because they are CRAVED – concealable, removable, available, enjoyable, and disposable – especially in the black market (BURGES, 2012; CLARKE and WEBB, 1999). In some cases, stolen products return to the legal market through flea markets, pawnshops, or second-hand stores (Johns and Hayes, 2003). Apart from economic attractiveness, which is the major cause of cargo theft, the criminological literature suggests that locational opportunities are crucial to cargo thefts, whereby locations with a higher circulation of cargos tend to have higher cargo thefts and theft locations tend not to be randomly distributed (TOBLER, 1970; COHEN and FELSON, 1979). The situational approach also suggests that social flaws and structures such as, for example, unemployment and inequality create potential criminals (MERTON, 1938) who can be deterred by proper guardianship or policing (BECKER, 1968; COHEN and FELSON, 1979).

The main objective of this study is to provide empirical evidence on some causes of cargo theft, addressing geographical, economic, social structure, and deterrence factors. Specifically, the space-time dynamic of cargo theft is identified; the role of economic attractiveness on cargo theft is investigated using market factors such as sales and prices; the role of the unemployment rate (a proxy for social flaw and structure) on cargo theft is assessed, and, last but not least important; the effect of policing (a proxy for deterrence) on cargo theft is identified. The hypotheses put forward regarding these objectives are

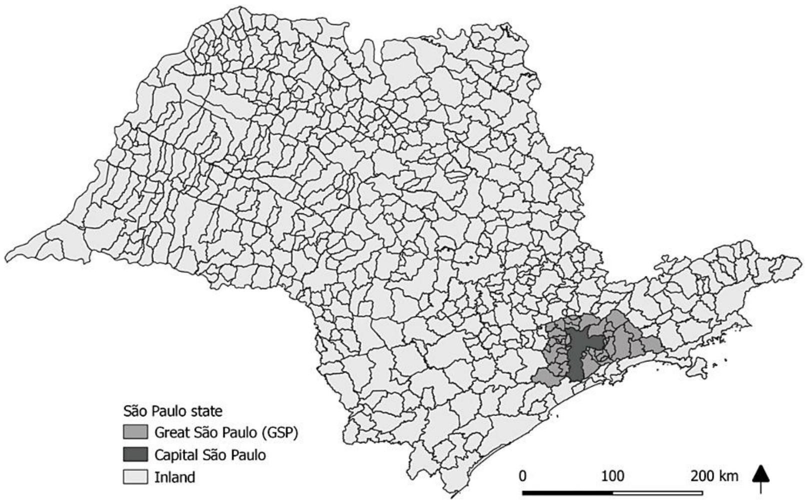
*H1*: space-time dynamics hypothesis – cargo thefts are intertwined across locations and proximity influences spatial links;
*H2*: economic attractiveness hypothesis –higher sales and prices in the legal market increases cargo theft;
*H3*: social structure hypothesis – a higher unemployment rate increases cargo theft, and;
*H4*: deterrence hypothesis – a greater presence of police on the streets reduces cargo theft.

These hypotheses have been tested regarding other crimes such as robbery, theft, and homicide rates but the empirical evidence regarding cargo theft is still modest in the literature. This study resorts to the Brazilian context to test these hypotheses because this modality of crime is most severe in South America (BSI, 2018; SCIC, 2018), whereby Brazil takes the lead with about 22.200 incidences in the year 2018 alone, incurring a loss of about 1.47 billion reais (R$) to the economy (NTC & Logistics, 2019). About 85% of these occurrences were registered in the Southeast of the country, where the states of São Paulo and Rio de Janeiro were responsible for about 39% and 41%, respectively. This position and the reliability and completeness of the database on cargo theft in São Paulo make this state a relevant case to the national and international literature on the topic.

São Paulo is the richest Brazilian state and has the largest commercial and industrial center in South America. This state is responsible for about one-third of the Brazilian GDP and is leading in terms of the consumer market, infrastructure, human capital, population size, etc (IBGE, 2018). Apart from the exceptional road quality, this state also bears locational advantage to businesses for having the largest and most modern port (Harbor of Santos) and the largest cargo terminal which receives and dispatches international cargo (Justus *et al.*, 2018). The economic and geographic relevance of São Paulo state is what makes it an attractive location for cargo theft and also a relevant case study to the literature on the topic.

The geography of São Paulo state is divided into 645 municipalities, which is classified into three groups in this study following Justus *et al.* (2018), namely, the capital São Paulo, the great São Paulo (GSP), i.e., the large metropolitan area excluding the capital, and the inland municipalities that are the non-metropolitan areas (Fig. 1).

**Figure 1 – The geography of São Paulo state.**




Source: Elaborated by the authors.

Cargo theft is expected to naturally correlate in geographic space following the flow of cargos from one location to another. This technically implies that cargo theft series of a location is expected to cointe grate with that of other locations, respecting Tobler's first law of geography – "everything is related to everything else, but near things are more related than distant things." (Tobler, 1970). Judging by the geography of São Paulo state (Fig. 1), cargo theft of the Capital is expected to be more correlated with that of the GSP, and this should be more correlated with that of inland municipalities.

Given the understanding that cargo theft is essentially economically motivated, the inflation and sales indexes are tested as economic predictors of the rate of cargo theft. The price indicator (inflation index) is considered a potential predictor of cargo theft since it is directly reflected in the value of the transported products and, consequently, the perceived reward by cargo thieves. Cargos are stolen, especially, to be transformed into money through sales (Burges, 2012). Therefore, the demand for products in the trade sector is a potential predictor of how "hot" products are both in the legal and illegal market. For this reason, indexes for the volume and revenue from sales of the trade sector are included in the empirical model. Since some cargos are, in many cases, stolen together with trucks (CECCATO, 2015; JUSTUS *et al.*, 2018) this control was further specified by including indexes for the volume and revenue from the sales of vehicles and automobile parts.

The rate of unemployment is tested as a social structural determinant of crime as suggested by Merton (1938) and as a seasonal predictor of property crimes as suggested by Falk (1952). Besides, unemployment is also a proxy indicator of the level of deprivation in the state.

Police activity is the major law enforcement measure adopted in fighting crime. Justus and Kassouf (2013) used the quarterly data on searches or identification of persons as an indirect measure of police activity. However, unlike homicide rates and robbery aggravated by death that have quarterly data since the mids 1990s, quarterly data on cargo theft are only available from the year 2005 and, consequently, the sample size is not as desirable for time series analysis. Therefore, this study resorts to another police activity measure that reflects the indirect activity of the police and also the outcome – police apprehension in the act. This measure combines the number of offenders pursued by the police or caught practicing any criminal offense with or without violence or serious threat.

This study is structured into seven sections. Following this introductory section, Section 2 presents the theoretical background and Section 3 presents the structure of the model and empirical tests and specifications. The results obtained from the models are presented in Section 4 and discussed in Section 5 and Section 6 concludes the study.

## 2. THEORETICAL BACKGROUND

The causes of cargo theft, like other thefts, are mostly explained by using the modern versions of the classical criminological theories: rationality, deterrence, and criminological economics theories as classified by Rasche (1998). From the perspective of these theories, cargo theft happens due to human rational choices which could be persuaded either by changing the decision-making factors or consequences of the crime in terms of punishment.

Rational choice is the essence of the criminological economic theory proposed by Becker (1968), whereby crime becomes attractive if the reward from an offense exceeds the cost of committing it and the rewards from alternative sources. Also drawing from the rational choice perspective, the routine activity theory proposed by Cohen and Felson (1979) explains that crime is an aftermath of the intersection of a motivated offender, a motivated target (e.g., cargo), and the absence of a capable guardian. Both the criminological economic and routine activity theories acknowledge the possibility of crime prevention by increasing the probability of crime failure and deterrence measures. Sharing the rationality perspective, the situational crime prevention approach proposed by Clark (1983) is widely adopted to reduce crime opportunities and deter offenders by using strategies such as, for example, guardianship (or policing), target hardening, surveillance, and access control. This prevention approach is practical against cargo theft since the responsibility of prevention is not entirely on the police but also on private entities such as transport and insurance companies.

The importance of location, which is critical to cargo theft, is explicit in the routine activity and situational crime prevention perspectives. Cargo theft is a mobile crime since both the motivated offenders and the target are in movement. This implies weak geographical boundaries and, consequently, complexity in the explanation of the geography of cargo theft. Crime mobility is the core of the theory of crime displacement which states that crime prevention in an area may have an unintended effect on the crime level of other areas (REPPETTO, 1976). This framework is rooted in the assumption that, apart from being rational, opportunistic criminals are more elastic to prevention measures while professional criminals are less elastic (REPPETTO, 1976). Besides, perpetrators have mobility, although limited, in terms of time, place, method, and type of offense (REPPETTO, 1976; HESSELING, 1994). According to Ekwall (2009b), “crime displacement is one probable explanation as to why the criminal pattern changes in a certain system”.

Deprivation measures are also theoretically identified as causes of crime in social structural theories, whereby crime is not a rational choice but a response to societal flaws such as poverty, unemployment, inequality, etc (MERTON, 1938). Falk (1952) discussed two theories that explain the seasonality of violent crimes (aggression) and property crimes. This author explained that aggressions follow weather temperatures and that the peak is observed in midsummer and drop in winter. Conversely, property crimes are high during fall and winter and often follow trends of seasonal unemployment and poverty. The crime motivations and seasonal patterns suggested by Falk (1952) for both types of crimes were upheld by Gorr *et al.* (2003).

Bearing on the social disorganization theory of crime, cargo theft has also been explained by the level of internal and external management quality of transport companies, whereby companies with weak management experience more theft (SMITH *et al.*, 2000). In this approach, motivated offenders take logistics infrastructure into account to determine their probability of crime success. Internal management flaws of companies occur especially through information leakage to external perpetrators concerning the transported cargo (EKWALL, 2009a).

This study also bears on the fundamental concept of geography endorsed by Tobler (1970) that “everything is related to everything else, but near things are more related than distant things”. Therefore, given the importance of location for cargo theft, spatial correlation and dependence are naturally expected to surface in the empirical model of this study.

# 3. METHOD

The hypotheses of this study are tested using time series methods. The first step is the presentation of the basic vector auto regression model (VAR), which lags structure is specified using statistic methods and regressors chosen based on the literature. The data for all the regressors are plotted to identify trends, seasonal patterns, and outliers. Outliers are removed and replaced by mean values as described in Wilcox (2010) and regressors with seasonal trends are deseasonalized using the X-13-Arima-seats procedure detailed in (SAX and EDDELBUETTEL, 2018). Both the dependent and dependent variables are transformed by applying logarithm, following the Box-Cox procedure (BOX and COX, 1964) to obtain the elasticities of regressors and to reduce data discrepancies.

Prior to these data treatments, the Augmented Dick-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests are performed on all variables to ensure that they are stationary and suitable for time series analysis (Dickey-Fuller, 1979; Kwiatkowski *et al.*, 1992). Given that some of the variables are found to be stationary while others are not, the Bounded Autoregressive-Distributed Lag (ARLD-bound) estimation approach proposed by Pesaran *et al.* (2001) is used to test for station arity and cointegration, and the long and short-run associations are obtained using this method as an alternative to the usual vector autoregressive (VAR) and vector error correction (VEC) estimation approaches that require either station arity or non-stationarity of the regressors. The results obtained from the ARDL models are tested for serial correlation, heteroskedasticity, normality, and misspecification using the Breusch-Godfrey/Box-Ljung test, Breusch-Pagan test, Shapiro-Wilk, and Ramsey RESET test, respectively. Lastly, the stability of the long-run estimates is verified using the cumulative recursive residuals (CUSUM) and its square (CUSUMSQ).

Details regarding the tests, transformations, and estimation procedures and methods are provided in Sections 3.2 and 3.3.

## 3.1. MODEL STRUCTURE

Based on the principles of the routine activity theory (COHEN and FELSON, 1979) and the organized characteristic of cargo theft (TARNEF, 2013), it is reasonable to expect that cargo thefts are serially correlated. Therefore, the starting point of the analysis of cargo theft time series is the estimation of an auto regression vector model (VAR), which consists of a set of K endogenous variables $\boldsymbol{y}_t = (y_{1t}, \ldots, y_{kt}, \ldots, y_{Kt})$. The basic VAR ($p$) process is represented as

$$\boldsymbol{y_t} = \boldsymbol{A}_1\boldsymbol{y}_{t-1} + \cdots + \boldsymbol{A}_p\boldsymbol{y}_{t-p} + \boldsymbol{u}_t, \tag{1}$$

where $\boldsymbol{A}_i$ are the $(K \times K)$ coefficient matrices for $i = 1, \ldots, p$ and $\boldsymbol{u}_i$is a $K$-dimensional process with $E(\boldsymbol{u}_i) = 0$ and time-invariant positive definite covariance matrix $E(\boldsymbol{u}_i, \boldsymbol{u}_t') = \sum_u$. This basic model will be developed based on the course of statistical tests and extended to contain regressors.

The station arty of time series, which is required to estimate the vector autoregressive model presented in Eq. 1, is violated if its mean, variance, and autocorrelation structure vary over time. Time-dependent variance, however, can be stabilized by transforming the data. This study resorts to the Box-Cox transformation procedure (BOX and COX, 1964) which consists of the estimation of parameter $\lambda$ that represents a family of transformations calculated using the maximum likelihood method, whereby the transformed data is expressed as $y^* = (y^\lambda - 1)\lambda$ if $\lambda \neq 0$ and $y^* = \log(y_t)$ if $\lambda = 0$, $t = 1, \ldots, T$. Assuming that data are not i.i.d., the Box-Cox analysis shows that the natural logarithm can be applied to all the series to stabilize data variance. An additional advantage of logarithm transformation is that the estimated coefficients represent elasticities. Therefore, this transformation is performed on all the series before testing for unit root, i.e., station arty.

In addition to the logarithm transformation, all the variables are seasonally adjusted using the X-13arima-seats procedure (SAX and EDDELBUETTEL, 2018) to filter time-specific effects and to isolate the relationship between the variables.

Table 1 presents the regressors specified in the model alongside their sources and Fig. 2-5 show the evolution of these series alongside a Lowess smoothing line to enable easy detection of time trends as suggested by Cleveland (1981).

**Table 1 – Definition and sources of time series (in logarithm), São Paulo, January/2005 –**

**December/2018.**

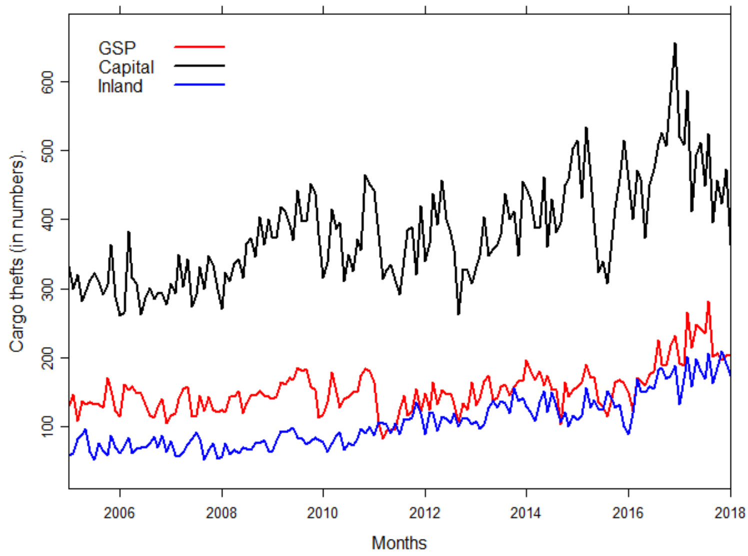
| Series | Definition | Source |
|---|---|---|
| ***H1* – space-time dynamics hypothesis** | | |
| *gsp* | The number of cargo theft in the Great São Paulo | Public Security Department of São Paulo (SSP-SP) |
| *capital* | The number of cargo theft in the São Paulo city | |
| *inland* | The number of cargo theft in the non-metropolitan municipalities | |
| ***H2*: economic attractiveness hypothesis** | | |
| *inflation* | Consumer price index in São Paulo state | Institute of Economic Research Foundation (FIPE) |
| *vehicles.v* | Index of the volume of sales of vehicles and parts in São Paulo state (base year = 2014) | Monthly Trade Survey published by the IBGE (PMC/IBGE) |
| *vehicles.r* | Index of the revenue from the sales of vehicles and parts in São Paulo state (base year = 2014) | |
| *trade.v* | Index of the volume of sales of the trade sector in São Paulo state (base year = 2014) | |
| *trade.r* | Index of the revenue from the sales of the trade sector in São Paulo state (base year = 2014) | |
| ***H3*: social structure hypothesis** | | |
| *unemployment* | Unemployment rate (%) | Statewise System for Data Analysis Foundation (PED/Feade). |
| ***H4*: deterrence hypothesis** | | |
| *police* | The number of offenders apprehended and arrested in the act of committing an offense in São Paulo state | Public Security Department of São Paulo (SSP-SP) |
| Other controls | | |
| *trucks* | Index of the flow of truck in São Paulo state (base year = 1999) | Brazilian Association of Highway Concessionaires |
| *population* | population size of São Paulo state (in numbers) | Brazilian Institute for Geography and Statistics |

Note: the number of observations is 168 (months)

The average number of cargo theft is higher in the São Paulo city (*capital*) compared to the greater metropolitan area of São Paulo (*gsp*) and non-metropolitan areas (*inland*). The temporal trajectory of cargo theft in the *gsp* was relatively stable around an average value until around the year 2016 but reached higher average levels in subsequent years. A similar trajectory was observed in the *capital* city, except that the number of incidences plunged significantly after the increase observed around the year 2016. The average number of cargo theft in the non-metropolitan areas (*inland*) was stable roughly from the year 2005 to 2008 but, thence, continuously increased until around the year 2018. Such a trend may engender non-stationarity to series and has been suspected by Justus *et al.* (2018) to have expressively reduced the cargo theft gap between non-metropolitan areas and the Great São Paulo. As shown in Justus *et al.* (2018), the number of cargo theft in the non-metropolitan areas reached similar levels of the *gsp* around the years 2017 and 2018, indicating possible convergence.

**Figure 2 – The number of cargo thefts (hypothesis 1), São Paulo city, great São Paulo,**

**inland municipalities, from January to December 2018.**



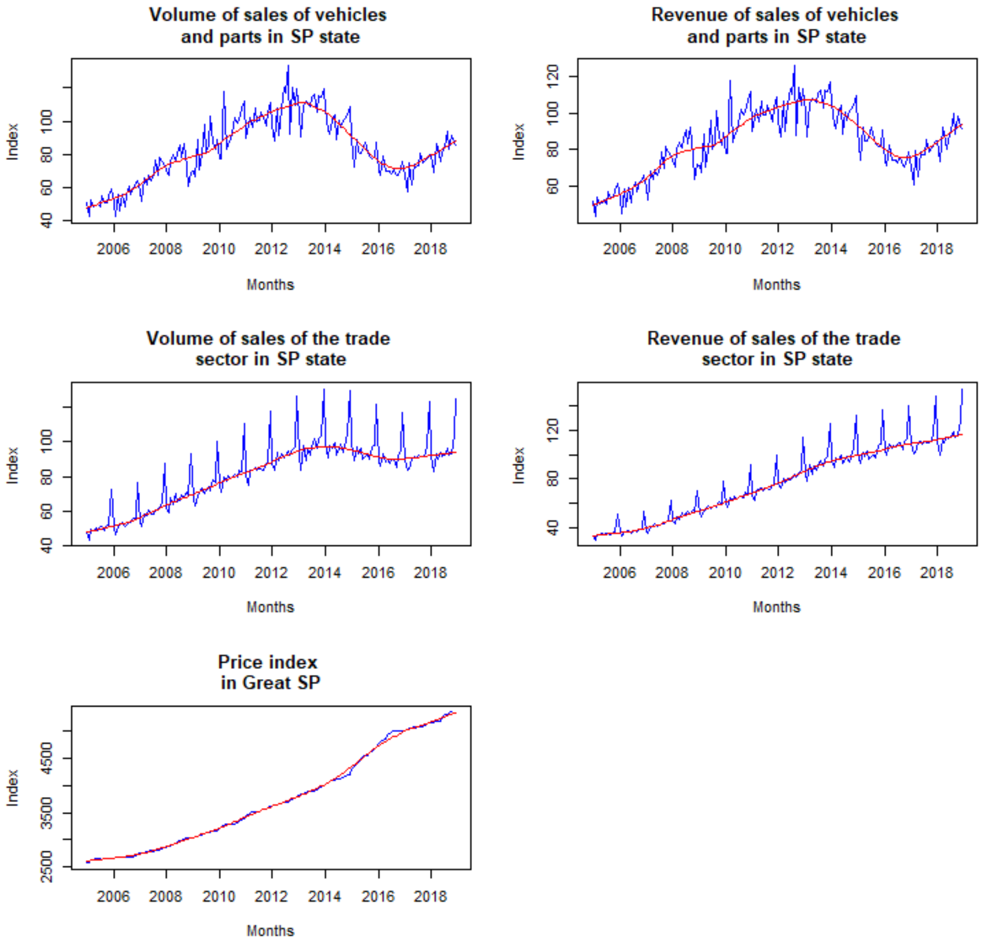

Source: Elaborated by the authors using the data referenced in Table 1.

.

The rate of unemployment reduced significantly from the year 2005 until around the year 2014 but regained a positive trend and increased until the year 2018. The seasonal unemployment discussed by Falk (1952) is noticeable in the time series but there is no apparent association with the trends of cargo theft. Nevertheless, the temporal direction of the rate of unemployment is inversely mirrored by the series of the volume and revenue from the sale of vehicles and automobile parts.

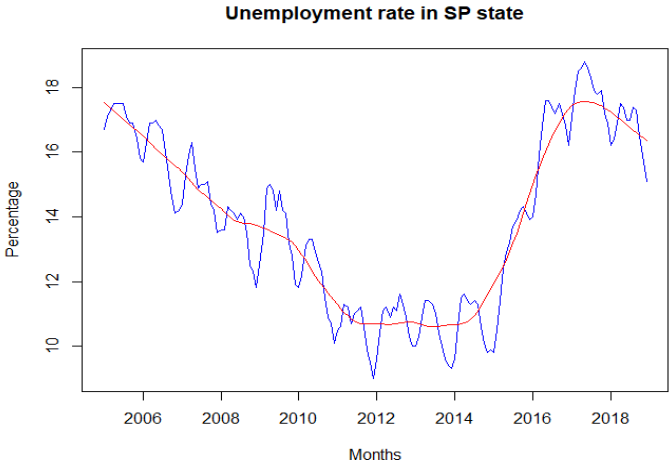
The volume of sales and revenue of the overall trade sector showed a seasonal trend throughout the analysis. However, the volume of sales stabilized in terms of growth around the years 2014 and 2018 but the revenue from the same sector continued increasing. The price index shows that consumer prices were less volatile and increased continuously throughout the period. The police activity measure shows that the rate of apprehension of offenders in the act increased significantly over the period, especially, from the year 2013 to 2014 but plunged from the year 2016 to 2018. It is noteworthy to point out that the series of police activity has a similar trend compared to the cargo theft rate of the *capital* city, especially from the year 2016 to 2018.

**Figure 3 – Economic attractiveness (hypothesis 2), São Paulo state, from January 2005 to December 2018.**



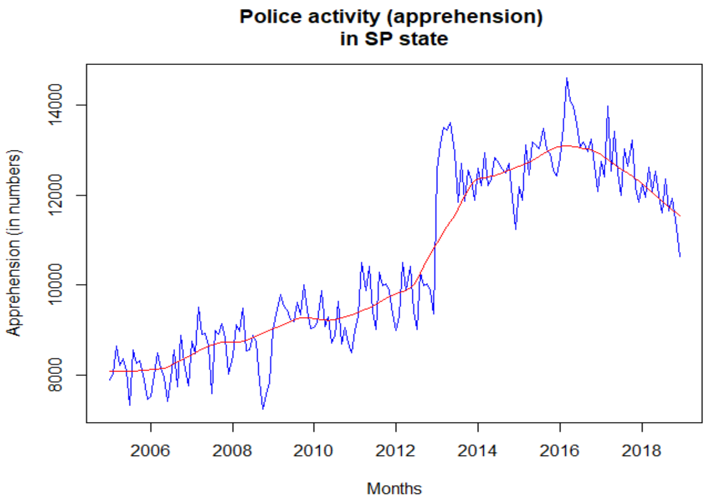

Source: Elaborated by the authors using the data referenced in Table 1.

**Figure 4 – Social structure (hypothesis 3), São Paulo state, from January 2005 to December 2018.**




Source: Elaborated by the authors using the data referenced in Table 1.

**Figure 5 – Deterrence (hypothesis 4), São Paulo state, from January 2005 to December 2018.**




Source: Elaborated by the authors using the data referenced in Table 1.

The periodicity of the cargo theft series prompted the concern of monthly seasonality as observed by Falk (1952) regarding property and violent crimes. Such an attribute invalidates the regular time series tests and estimation if not properly addressed.  For this reason, the Fig. 10 (Annex) illustrates the monthly plot of the cargo theft rate series of the *capital, gsp,* and *inland* to verify the presence of monthly seasonality. This plot shows the evolution and average of cargo theft rate for each month of the year over time. Given that each label on the x-axis represents the months of the year, it is observable that the average rate of cargo theft rate per month is stable in the *capital* throughout the year; slightly increasing from January to December in the *inland*, and; more unstable in the *gsp* from January through December – the month of highest and lowest cargo theft rate in the *gsp* is March and September, respectively. It is important to highlight that the months of high and low cargo theft rates reported by Justus *et al.* (2018) for São Paulo state as a whole coincides with and, therefore mostly attributed to, that observed for the *gsp.* Nonetheless, the monthly plot is convincing that the monthly seasonality of cargo theft across the three locations is subtle. Still, this study opts to transform these series to eliminate possible seasonal patterns in order to better identify and isolate the empirical associations of interest.

## 3.2. UNIT ROOT TEST

The literature is consolidated regarding the temporal pattern of economic time series such as growth, unemployment, etc., but little is known about crime series. There is evidence in the literature regarding the non-stationarity of the time series of violent crimes as in homicide rates (JUSTUS and KASSOUF, 2013; SARIDAKIS, 2011) and property crimes as in burglary, robbery, and property theft (DEADMAN and PYLE, 2004; GORR *et al.*, 2003) but none on crime against trading such as cargo theft. Therefore, an unprecedented contribution of this study is to provide station arity tests of the time series of cargo theft that may guide future empirical studies that use time-series methodologies.

The existence of a unit root, i.e. non-station arity, in the stochastic process that generates the time series data is tested by using the ADF (DICKEY-FULLER, 1979) and KPSS (KWIATKOWSKI *et al.*, 1992) tests. The null hypothesis of a unit root ($H_0: d = 1$) is tested against the alternative hypothesis of no unit root ($H_A: d = 0$) in the ADF test, whereas these hypotheses are inverted in the KPSS test ($H_0: d = 0$ and $H_A: d = 1$).

Bearing on Enders (2008), the ADF and KPSS tests were first performed on models with both constant and trend as deterministic regressors and then reduced to constant-only models if non-station arity is concluded and further reduced to models without constant and trend if the non-station arity conclusion is sustained. Table 2 presents the statistics and critical values of the tests which were analyzed at 5% of significance. The ADF and KPSS confirmed stationarity for the three cargo theft series and non-stationarity for other regressors (see Table 2). Following the steps of Almi (2014) and Dube *et al.* (2018) by performing the ADF and KPSS unit root tests on the differenced series of those that were non-stationary, the series are concluded to be difference-stationary. Therefore, cargo theft series are I(0) but other series are I(1).

**Table 2 – ADF and KPSS unit root tests.**

| | | At level | | | At first difference | | | |
|---|---|---|---|---|---|---|---|---|
| | | Test value | p | Decision | Test value | p | Decision | d |
| *GSP* | ADF | -4.99 | 1 | Stationary | | | | I(0) |
| | KPSS | 0.27 | 4 | | | | | |
| *Capital* | ADF | -3.83 | 1 | Stationary | | | | I(0) |
| | KPSS | 0.13 | 4 | | | | | |
| *Interior* | ADF | -5.19 | 1 | Stationary | | | | I(0) |
| | KPSS | 0.18 | 4 | | | | | |
| *Vehicles.v* | ADF | -1.77 | 2 | Non- Stationary | -12.63 | 1 | Stationary | I(I) |
| | KPSS | 0.77 | 4 | | 0.071 | 4 | | |
| *Vehicles.r* | ADF | -1.95 | 2 | Non- Stationary | -8.77 | 2 | Stationary | I(I) |
| | KPSS | 0.76 | 4 | | 0.063 | 4 | | |
| *Trade.v* | ADF | -0.48 | 1 | Non- Stationary | -10.55 | 1 | Stationary | I(I) |
| | KPSS | 0.84 | 4 | | 0.13 | 4 | | |
| *Trade.r* | ADF | 0.48 | 1 | Non- Stationary | -9.67 | 1 | Stationary | I(I) |
| | KPSS | 0.80 | 4 | | 0.14 | 4 | | |
| *INPC* | ADF | -2.59 | 2 | Non- Stationary | -5.76 | 1 | Stationary | I(I) |
| | KPSS | 0.44 | 4 | | 0.14 | 4 | | |
| *Unemp* | ADF | -1.29 | 3 | Non- Stationary | -3.70 | 3 | Stationary | I(I) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | KPSS | 0.77 | 4 | | 0.11 | 4 | | |
| *Police* | ADF | -2.63 | 1 | Non- Stationary | -8.67 | 3 | Stationary | I(I) |
| | KPSS | 0.27 | 4 | | 0.065 | 4 | | |
| *Trucks* | ADF | -1.22 | 1 | Non- Stationary | -10.82 | 2 | Stationary | I(I) |
| | KPSS | 0.73 | 4 | | 0.053 | 4 | | |
| *Population* | ADF | -3.46 | 1 | Non- Stationary | 3.43 | | Stationary | I(I) |
| | KPSS | 0.46 | 4 | Stationary | 0.10 | 4 | | |

Note: Critical values at 5% of ADF= -3.43 and KPSS = 0.14. p is the order indicated by the Akaike Information Criterion (AIC), and; *d* is the order of integration.

## 3.3. ARDL BOUNDS COINTEGRATION TEST AND MODEL IDENTIFICATION

Cointegration is a broadly applied econometric approach to investigate the short-run dynamics and long-run associations between time series in various academic fields (ALMI, 2014; DUBE *et al.*; 2018; JUSTUS and KASSOUF, 2013) using, especially, the methods developed by Engle and Granger (1987) or Johansen (1988). Although these methods are very effective, they both require that all the series in a model must be integrated in the same order, which is not always the case as shown in Table 2 and observed by Afzal *et al.* (2010), Almi (2014) and Dube *et al.* (2018). This challenge, however, is solved in the bounded Autoregressive Distributed Lag (ARDL) cointegration approach developed by Pesaran *et al.* (2001) which allows series contained in a model to be a mix of level and first-differenced stationary variables, i.e., I(0) and I(1). Therefore, given the results presented in Table 2, this study uses the ARDL Bounds test. This method has been applied by recent studies from diverse areas of research namely, Timilehin *et al*. (2019), Tursoy (2019), and Algaeed (2020). Apart from specification flexibility, the ARDL Bounds test produces unbiased long-run estimates and is also more efficient for small and finite sample (HARRIS and SOLLIS, 2003).

The cointegration exercises performed throughout this study are carried out using the 'dLagM' statistical package developed by Demirhan (2019) for the R software.

Although all the series described in Table 1 could be tested for cointegration, this study focuses only on the ARDL equations for cargo theft, which are represented as follows for the capital city

$$\Delta\, ln\, capital_t = \beta_{01} + \alpha_{11}\, ln\, capital_{t-1-i} + \alpha_{21}\, ln\, gsp_{t-1} + \alpha_{31}\, ln\, inland_{t-1} + \alpha_{41}\, ln\, unemp_{t-1} + \alpha_{51}\, ln\, vehicles.v_{t-1} + \alpha_{61}\, ln\, vehicles.r_{t-1} + \alpha_{71}\, ln\, trade.v_{t-1} + \alpha_{81}\, ln\, trade.r_{t-1} + \alpha_{91}\, ln\, inpc_{t-1} + \alpha_{10,1}\, ln\, police_{t-1} + \alpha_{11,1}\, ln\, trucks_{t-1} + \alpha_{12,1}\, ln\, population_{t-1} + \sum_{i=1}^{p} \beta_{1i}\, \Delta\, ln\, capital_{t-1-i} + \sum_{i=1}^{q} \beta_{2i}\, \Delta\, ln\, gsp_{t-i} + \sum_{i=1}^{q} \beta_{3i} \Delta\, ln\, inland_{t-i} + \sum_{i=1}^{q} \beta_{4i} \Delta\, ln\, unemp_{t-i} + \sum_{i=1}^{q} \beta_{5i} \Delta\, ln\, vehicles.v_{t-i} + \sum_{i=1}^{q} \beta_{6i} \Delta\, ln\, vehicles.r_{t-i} + \sum_{i=1}^{q} \beta_{7i} \Delta\, ln\, trade.v_{t-i} + \sum_{i=1}^{q} \beta_{8i} \Delta\, ln\, trade.r_{t-i} + \sum_{i=1}^{q} \beta_{9i} \Delta\, ln\, inpc_{t-i} + \sum_{i=1}^{q} \beta_{10,i} \Delta\, ln\, police_{t-i} + \sum_{i=1}^{q} \beta_{11,i} \Delta\, ln\, trucks_{t-i} + \sum_{i=1}^{q} \beta_{12,i} \Delta\, ln\, population_{t-i} + \varepsilon_t \qquad (2)$$

for the greater São Paulo thusly

$$\Delta \ln gsp_t = \beta_{02} + \alpha_{12} \ln gsp_{t-1-i} + \alpha_{22} \ln capital_{t-1} + \alpha_{32} \ln inland_{t-1} + \alpha_{42} \ln unemp_{t-1} + \alpha_{52} \ln vehicles.v_{t-1} + \alpha_{62} \ln vehicles.r_{t-1} + \alpha_{72} \ln trade.v_{t-1} + \alpha_{82} \ln trade.r_{t-1} + \alpha_{92} \ln inpc_{t-1} + \alpha_{10,2} \ln police_{t-1} + \alpha_{11,2} \ln trucks_{t-1} + \alpha_{12,2} \ln population_{t-1} + \sum_{i=1}^{p} \beta_{1i} \Delta \ln gsp_{t-1-i} + \sum_{i=1}^{q} \beta_{2i} \Delta \ln capital_{t-i} + \sum_{i=1}^{q} \beta_{3i} \Delta \ln inland_{t-i} + \sum_{i=1}^{q} \beta_{4i} \Delta \ln unemp_{t-i} + \sum_{i=1}^{q} \beta_{5i} \Delta \ln vehicles.v_{t-i} + \sum_{i=1}^{q} \beta_{6i} \Delta \ln vehicles.r_{t-i} + \sum_{i=1}^{q} \beta_{7i} \Delta \ln trade.v_{t-i} + \sum_{i=1}^{q} \beta_{8i} \Delta \ln trade.r_{t-i} + \sum_{i=1}^{q} \beta_{9i} \Delta \ln inpc_{t-i} + \sum_{i=1}^{q} \beta_{10,i} \Delta \ln police_{t-i} + \sum_{i=1}^{q} \beta_{11,i} \Delta\, ln\, trucks_{t-i} + \sum_{i=1}^{q} \beta_{12,i} \Delta\, ln\, population_{t-i} + \varepsilon_t \qquad (3)$$

and, lastly, for the inland municipalities

$$\Delta \ln inland_t = \beta_{03} + \alpha_{13} \ln inland_{t-1-i} + \alpha_{23} \ln capital_{t-1} + \alpha_{33} \ln gsp_{t-1} + \alpha_{43} \ln unemp_{t-1} + \alpha_{53} \ln vehicles.v_{t-1} + \alpha_{63} \ln vehicles.r_{t-1} + \alpha_{73} \ln trade.v_{t-1} + \alpha_{83} \ln trade.r_{t-1} + \alpha_{91} \ln inpc.v_{t-1} + \alpha_{10,3} \ln police_{t-1} + \alpha_{10,3} \ln trucks_{t-1} + \alpha_{10,3} \ln population + \sum_{i=1}^{p} \beta_{1i} \Delta \ln inland_{t-1-i} + \sum_{i=1}^{q} \beta_{2i} \Delta \ln capital_{t-i} + \sum_{i=1}^{q} \beta_{3i} \Delta \ln gsp_{t-i} + \sum_{i=1}^{q} \beta_{4i} \Delta \ln unemp_{t-i} + \sum_{i=1}^{q} \beta_{5i} \Delta \ln vehicles.v_{t-i} + \sum_{i=1}^{q} \beta_{6i} \Delta \ln vehicles.r_{t-i} + \sum_{i=1}^{q} \beta_{7i} \Delta \ln trade.v_{t-i} + \sum_{i=1}^{q} \beta_{8i} \Delta \ln trade.r_{t-i} + \sum_{i=1}^{q} \beta_{9i} \Delta \ln inpc_{t-i} + \sum_{i=1}^{q} \beta_{10,i} \Delta \ln police_{t-i} + \sum_{i=1}^{q} \beta_{11,i} \Delta\, ln\, trucks_{t-i} + \sum_{i=1}^{q} \beta_{12,i} \Delta\, ln\, population_{t-i} + \varepsilon_t \qquad (4)$$

where $\ln(.)$ is the logarithmic transformation discussed in Section 4.3.1, $\Delta$ is the first difference and $\varepsilon_t$ are the error terms. Note that Eq. 2-4 are general representations of the ARDL models which contain the short and long-run associations that are represented in differences and levels, respectively (PESARAN *et al.*, 2001).

The long-run association between the series (henceforth, co-integration) is confirmed if the null hypothesis of the F-test, which states that the lagged series in level are jointly equal to zero (i.e. $H_0$: $\alpha_{1i} = \alpha_{2i} = \alpha_{3i} = \alpha_{4i} = \alpha_{5i} = \alpha_{6i} = \alpha_{7i} = \alpha_{8i} = \alpha_{9i}$), is rejected. Two critical values were provided by Pesaran *et al.* (2001) for the F-test; one for level-stationarity (lower bound, F(0)) and another for first-difference stationarity (upper bound, F(1)). The F-test result is only conclusive if cointegration is confirmed for both bounds, i.e., F-test > F(0) and F(1). The optimal lag order of the ARDL equations that are chosen based on the Akaike Information Criterion (AIC), F-statistics, and critical values are presented in Table 3. The test values show that three cargo theft series are cointegrated within the ARDL bounds.

**Table 3 – ARDL bounds test results for Cointegration**

| Equation | F-statistics | Decision | lag orders $p$and $q$ |
|---|---|---|---|
| $capital$ | 4.10 | Cointegrated | ARDL (2, 2, 1, 1, 2, 2, 2, 1, 1, 2) |
| $gsp$ | 4.97 | Cointegrated | ARDL (2, 2, 2, 3, 1, 1, 2, 1, 2, 1) |
| $inland$ | 6.13 | Cointegrated | ARDL (2, 2, 2, 1, 1, 2, 2, 2, 1, 2) |
| Critical value | at 1% | at 5% | at 10% |
| $F(0)$ | 2.97 | 2.43 | 2.16 |
| $F(1)$ | 4.24 | 3.56 | 3.24 |

Note: the first lag order of the ARDL(.) is $p$ which is the order for the dependent variable and the other lag orders, $q$, are for the regressors in the same sequence they follow in Eq. 2-4 and Table 2.

The models indicated as best fit by the AIC are tested for autocorrelation using Breush-Godfrey and Box-Ljung tests; homoskedasticity using the Breusch-Pagan test; normality using the Shapiro-Wilk test, and; model specification error using the Ramsey RESET test. The test statistics and the $p$-values of these diagnostic measures are presented in Table 5. At 5% level of significance, the calculated values indicate that the three models reject the null hypothesis of autocorrelation, heteroskedasticity, absence of normality of residuals, and misspecification. Therefore, the models chosen based on the AIC can be used for analyses.

**Table 4 – Model diagnostics**

| | Test statistics (p-value) | | |
|---|---|---|---|
| **Tests** | *capital* | *gsp* | *inland* |
| Autocorrelation in residuals | | | |
| Breusch-Godfrey test | 0.48 (0.49) | 0.81 (0.37) | 0.39 (0.53) |
| Box-Ljung test | 0.077 (0.78) | 0.11 (0.742) | 0.067 (0.79) |
| Homoskedasticity of residuals | | | |
| Breusch-Pagan test | 20.56 (0.76) | 29.99 (0.31) | 22.71 (0.70) |
| Normality of residuals | | | |
| Shapiro-Wilk test | 0.98 (0.051) | 0.98 (0.10) | 0.99 (0.85) |
| Model specification error | | | |
| Ramsey RESET test | 2.81 (0.063) | 0.14 (0.86) | 3.058 (0.050) |

The stability of the long-run estimates obtained from the best fit models is tested using the cumulative sum of recursive residuals (CUSUM) and its square (CUSUMSQ) as suggested by Pesaran and Pesaran (1997). The plots of the CUSUM and CUSUMSQ illustrated in Fig 11 shows that the residuals are within stable ranges at the level of significance of 5%, i.e., the long-run estimates are stable.

## 4. RESULTS

The lag orders indicated by the AIC are used to specify the long-run models for cargo theft in the capital city of São Paulo (*capital*), Great São Paulo (*gsp*), and non-metropolitan municipalities of São Paulo state (*inland*) as presented in Eq. 2-4, respectively. The coefficients obtained for these models are presented in Table 4, focusing on the coefficients that indicate significant long-run Granger causality.

The significance of ln $capital_{t-1}$ in the equation for *capital* shows evidence of long-run Granger causality of cargo theft in São Paulo city by the preceding rates of the same city. Similar evidence is observed in the models for the *gsp* and *inland.* This implies that cargo theft is serially correlated in the three geographic units of São Paulo state and that the present and future rates of cargo theft can be predicted by previous ones. The negative sign of this autoregressive parameter indicates that the increase of cargo theft in a particular period is followed by a reduction in subsequent periods.

Apart from the temporal association, the models also show evidence of the geographical association of cargo thefts. The models for the three geographic locations show that cargo theft in the *gsp* has a positive Granger-effect on that of the *capital* and *inland* cities, i.e., an increase in cargo theft in the *gsp* in a particular period increases cargo theft in the *capital* and *inland* in the subsequent period. The model for *gsp* shows that an increase in the cargo theft of the capital also increases that of the *gsp*, i.e., the long-run causality between cargo theft in the *gsp* and *capital* is bi-lateral. The effect of the *gsp* on both the *capital* and *inland* indicates the relevance of *gsp* as the middle ground of the geography of cargo theft. This is reasonable given the geography of the three locations as shown in Fig 1.

**Table 5 – Estimates for the long-run Granger causality.**

| | *capital* | | *gsp* | | *inland* | |
|---|---|---|---|---|---|---|
| Variables | $\alpha$ | $s.e.$ | $\alpha$ | $s.e.$ | $\alpha$ | $s.e.$ |
| ***H1* – space-time dynamics hypothesis** | | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| $\ln capital_{t-1}$ | -0.711*** | 0.091 | 0.308** | 0.152 | -0.062 | 0.132 |
| $\ln gsp_{t-1}$ | 0.394*** | 0.071 | -0.744*** | 0.111 | 0.259* | 0.116 |
| $\ln inland_{t-1}$ | 0.021 | 0.072 | 0.072 | 0.097 | -0.655*** | 0.091 |
| *H2*: economic attractiveness hypothesis | | | | | | |
| $\ln vehicle.r_{t-1}$ | 0.791 | 0.538 | -0.873 | 0.693 | -2.161*** | 0.643 |
| $\ln vehicle.v_{t-1}$ | -0.864* | 0.495 | 0.728 | 0.638 | 2.114*** | 0.596 |
| $\ln trade.r_{t-1}$ | 3.464*** | 0.993 | 0.476 | 1.313 | 0.630 | 1.222 |
| $\ln trade.v_{t-1}$ | -2.511** | 1.094 | 0.193 | 1.440 | -1.896 | 1.318 |
| $\ln inpc_{t-1}$ | -1.403 | 1.161 | -2.794* | 1.465 | 0.155 | 0.182 |
| ***H3*: social structure hypothesis** | | | | | | |
| $\ln unemp_{t-1}$ | -0.254 | 0.183 | 0.892*** | 0.271 | -0.526 | 0.232 |
| ***H4*: deterrence hypothesis** | | | | | | |
| $\ln police_{t-1}$ | 0.249* | 0.139 | -0.406** | 0.177 | 1.175 | 1.369 |
| Other controls | | | | | | |
| $\ln trucks_{t-1}$ | -0.192 | 0.293 | 0.496 | 0.468 | 0.050 | 0.362 |
| $\ln population_{t-1}$ | -3.064** | 1.185 | 2.690 | 1.654 | -0.930 | 1.589 |
| $Constant$ | 64.029** | 26.342 | -26.732 | 35.927 | 14.258 | 33.835 |

Note: $\alpha$ $are$ estimates of the long-run parameter of Eq. 2-4 presented in Section 3.3; *s.e* are the standard errors; *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

The effect of the economic (*vehicle*, *trade*, *inpc*) and socioeconomic (*unemp*) conditions vary significantly between the *capital*, *gsp,* and the *inland*, indicating the differences in the economic, and socioeconomic dynamics of these locations. The rate of unemployment only Granger-causes cargo theft in the *gsp*, whereby its effect is positive. It is, however, important to recall that the unemployment rate available and used in this study is that of the metropolitan area of São Paulo that includes both the *gsp* and *capital*. Therefore, in the long run, a higher unemployment rate in the metropolitan are increases cargo theft in the *gsp.* The long-run Granger-effect of revenue from the sales of vehicles and automobile parts is negative in the *inland*. The volume of sales of vehicles and automobile parts, however, has a negative and significant Granger-effect on the cargo theft series in the *capital* but the effect is positive and significant in the *inland.*

The long-run Granger-effect of the overall trade sector is only significant in the equation for capital, whereby the effect of revenue and volume of sales is positive and negative, respectively. The Granger-effect of the price index (a proxy for inflation) on cargo theft is negative in the *gsp.* The *police* activity variable has a positive Granger-effect in the *capital* city in the long run but a negative effect in the *gsp*. The control for the circulation of *trucks* showed no impact on cargo theft in any of the locations and the control for population size is only significant in the equation for the *capital* city.

The residuals obtained from the long-run cointegration models in Eq. 2-4 are used to correct the short-run associations between the variables which are represented by the lagged differences of the equations (PESARAN *et al.*, 2001). The models estimated from such a correction is called the Vector Error Correction Model (VECM) and the results are presented in Table 6.

The relationship between the incidences of cargo thefts across locations in São Paulo state is also observed in the short-run models. Similarly to the long run, the spatial link between the *gsp* and *capital* is positive and bi-lateral, and the effect from the *capital* to the *gsp* is both from contemporary and lagged cargo thefts. Cargo thefts from the *inland* did not affect that of the *gsp* and *capital*. However, contrary to the sign observed for the long run, a higher number of cargo thefts in the *gsp* reduce cargo thefts in the *inlands* in the short run. The comparison of the models for the three locations indicates a bilateral relationship of cargo thefts between the *gsp* and the *capital*, and the *inland* locations are crime receivers both in the short and long run.

Similarly to the result for the long-run associations, the short-run models show that the effects of economic and socioeconomic conditions on cargo theft very expressively across locations in the state of São Paulo.

A positive and significant effect of unemployment on cargo theft is observed in the *gsp* in the short run, i.e., a higher unemployment rate causes an increase in the cargo theft rate of the *gsp*. The lagged variations of the volume and revenue from the sales of vehicles and automobiles affect the cargo theft rate in the *capital* city, whereby an increase in the revenue from these sales reduces cargo theft, and an increase in the volume of sales increases cargo theft. The volume of sales of the overall trade sector also has a positive lagged effect on cargo theft in the *capital*. None of the sales variables have a significant effect on cargo theft in the *gsp.* As for the *inland*, a contemporary increase in the revenue from the sales of vehicles and automobile parts reduces cargo theft, and a contemporary increase in the volume of these sales increases cargo theft, although this latter effect is mitigated by lagged shocks.

There was no significant effect of inflation shocks on cargo theft rate in any of the locations in the short run.

The *police* variable, which is a control for the presence of law enforcement, reduces cargo theft rate in the *gsp* and *inland* in the short run. This implies that an increase in the rate of apprehension of offenders in the act reduces cargo theft in both locations. The significant effect of the *police* on cargo theft rate in the *gsp* is contemporary, whereas the effect is only observed in the inland for lagged shocks.

The contemporary effect of the circulation of *trucks* on cargo theft is positive in the *inland* but its lagged effect is negative in the *gsp*.

**Table 6 – Estimates of the Vector Error Correction Model (VECM) for short-run associations.**

| Variables | *capital* $\beta$ | *capital* $s.e.$ | *gsp* $\beta$ | *gsp* $s.e.$ | *inland* $\beta$ | *inland* $s.e.$ |
|---|---|---|---|---|---|---|
| ***H1* – space-time dynamics hypothesis** | | | | | | |
| $\Delta \ln gsp_t$ | 0.249*** | 0.048 | 0.008 | 0.078 | 0.020 | 0.064 |
| $\Delta \ln gsp_{t-1}$ | | | | 0.000 | -0.200*** | 0.065 |
| $\Delta \ln capital_t$ | | | 0.471*** | 0.088 | 0.109 | 0.080 |
| $\Delta \ln capital_{t-1}$ | -0.089 | 0.068 | 0.241*** | 0.089 | | |
| $\Delta \ln inland_t$ | 0.046 | 0.052 | 0.038 | 0.070 | 0.053 | 0.075 |
| ***H2*: economic attractiveness hypothesis** | | | | | | |
| $\Delta \ln vehicle.r_t$ | -0.112 | 1.369 | 2.129 | 1.833 | -3.408** | 1.699 |
| $\Delta \ln vehicle.r_{t-1}$ | -2.476* | 1.355 | | | | |
| $\Delta \ln vehicle.v_t$ | 0.234 | 1.322 | -1.994 | 1.772 | 3.323** | 1.641 |
| $\Delta \ln vehicle.v_{t-1}$ | 2.509* | 1.315 | | | -0.216* | 0.130 |
| $\Delta \ln trade.r_t$ | 1.412 | 0.923 | -1.324 | 1.134 | -0.525 | 1.059 |
| $\Delta \ln trade.r_{t-1}$ | -1.524 | 0.954 | | | | |
| $\Delta \ln trade.v_t$ | -0.522 | 0.984 | 0.126 | 1.261 | -1.351 | 1.191 |
| $\Delta \ln trade.v_{t-1}$ | 2.481** | 1.016 | | | 1.288 | 0.820 |
| $\Delta \ln inpc_t$ | -1.902 | 2.073 | -0.204 | 2.529 | 2.406 | 2.376 |
| $\Delta \ln inpc_{t-1}$ | 3.241 | 2.001 | | | | |
| ***H3*: social structure hypothesis** | | | | | | |
| $\Delta \ln unemp_t$ | -0.474 | 0.309 | 1.541*** | 0.424 | -0.566 | 0.376 |
| $\Delta \ln unemp_{t-1}$ | 0.346 | 0.313 | -0.641 | 0.428 | | |
| $\Delta \ln unemp_{t-2}$ | | | -0.684 | 0.425 | | |
| ***H4*: deterrence hypothesis** | | | | | | |
| $\Delta\, ln\, police_t$ | 0.266 | 0.17 | -0.657*** | 0.221 | -0.191 | 0.214 |
| $\Delta\, ln\, police_{t-1}$ | | | | | -0.455** | 0.215 |
| Other controls | | | | | | |
| $\Delta \ln trucks_t$ | -0.039 | 0.181 | -0.007 | 0.283 | 0.775*** | 0.220 |
| $\Delta \ln trucks_{t-1}$ | | | -1.025*** | 0.313 | | |
| $\Delta \ln trucks_{t-2}$ | | | -0.544** | 0.268 | | |
| $\Delta \ln population_t$ | -17.73*** | 5.784 | 9.190 | 7.193 | -2.942 | 6.839 |
| $trend_t$ | -0.009*** | 0.001 | 0.008*** | 0.001 | 0.001*** | 0.000 |
| $ECM_{t-1}$ | -0.711*** | 0.077 | -0.744*** | 0.092 | -0.655*** | 0.083 |
| $Constant$ | 64.03*** | 6.915 | -26.732*** | 3.288 | 14.258*** | 1.812 |

Note: $\beta$ $are$ estimates of the long-run parameter of Eq. 2-4 presented in Section 3.3; *s.e* are the standard
errors; *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

## 5. DISCUSSIONS

The empirical results indicate that the short and long-run dynamics of cargo theft rate are strongly determined by temporal and spatial associations. The effect of socioeconomic and economic conditions varies across locations and that of law enforcement is more emphasized in the short run.

The temporal dependency indicated by the results implies that the current rates of cargo theft depend on past ones, thus, enabling predictability over time rather than the seasonality suggested by Falk (1952) – higher frequency of property crimes during fall and winter. This temporal dependency is observed for all locations in the São Paulo state in the long run, implying that cargo theft may be more opportunistic in the short run as suggested by Repetto (1976).

Although the seasonal variation of cargo theft is higher in the Great São Paulo, there was no overt sign of monthly seasonality comparable to that overtly observed in previous studies for days of the week, hours of the day, and specific months of the year (BURGES, 2012; CECCATO, 2015; EKWALL and LANTZ, 2015; JUSTUS *et al.*, 2018). Specifically, Justus *et al.* (2018) reported that cargo thefts are more frequent between March to May and between October and December in São Paulo state. The results presented here add that the seasonality reported by these authors is mostly linked to the greater São Paulo rather than other regions.

The evidence of the interdependence of cargo theft rates between locations in São Paulo state supports the evidence from Justus *et al.* (2018) that cargo thefts follow a spatial clustering pattern as observed for the state of Minas Gerais by Queiroz *et al.* (2009) and the state of Rio de Janeiro by Ruediger *et al.* (2018). Apart from being clustered in big cities and around main highways of São Paulo state, Justus *et al.* (2018) observed that the clustering pattern also follows urbanization rate and the level of economic activities of the region, especially of port and other freight operations that are also strategically clustered in space. Apart from the cluster of the economic opportunity, the spatial dependence of cargo theft, according to Repetto (1976) and Ekwall (2009b), may be caused by the inherent mobility of cargo thefts and by the displacement provoked by crime prevention measures. Not surprisingly, stronger correlations were observed between locations in the short run compared to the long run. The results showed the importance of location proximity on the spatial correlation as highlighted by Hesseling (1994). This study showed that, in the short and long run, the greater São Paulo acts as the bridge between the capital city and inland cities. Moreover, the spatial link between the great São Paulo and the Capital is positive and bi-directional, whereas the link between the great São

Paulo and inland municipalities is positive in the long run, negative in the short run, and uni-directional– from the former to the latter.

The effect of the economic (inflation and trade variables) and socioeconomic (unemployment) conditions on cargo theft rates vary and were barely significant across the models. Therefore, the results regarding these variables should be interpreted with caution. According to Justus and Kassouf (2018), the non-significance of economic conditions in time series' models of crime has been discussed in the literature and is mostly attributed to the time necessary for individuals to adjust their decisions to economic and socioeconomic conditions in the short run. The results show that the unemployment rate significantly explains the cargo theft rate both in the short and long run in the great São Paulo. Specifically, the immediate effect of a higher unemployment rate is the increase in cargo theft rate as observed by Falk (1952).

Based on the results from Burges (2012), it was expected that a higher revenue and volume of sales in the trade sector will increase cargo thefts since the economic attractiveness and the opportunity is increased, respectively. However, the results for the short run indicate that the revenue from sales in the legal market reduces cargo theft rates while the volume of sales increases cargo theft rates, especially in the capital. This result may be plausible since the higher revenue from sales in the legal market implies lesser disruption of the supply chain by theft or lesser competition with the illegal market. However, the positive effect of the volume of trade on cargo theft is expected since it implies that more goods are in circulation and, therefore, more crime opportunities as suggested by the routine activity theory (COHEN and FELSON, 1979). Nonetheless, the relationship between the legal trade sector and cargo theft requires more investigation.

Similarly to revenue, inflation is expected to increase the economic attractiveness of cargo theft as indicated by John and Hayes (2003). However, the results show no evidence of association both in the short and long-run.

Goertzel and Kahn (2009) and Goertzel *et al*. (2013) observed that the growth dynamics of crime are not always determined by social and economic problems but rather by police activity and better law enforcement. The results found here show that police activity as in presence in the streets is effective in reducing cargo theft in the great São Paulo and inland areas. This result supports that found by Justus and Kassouf (2013) regarding the effect of arrests on lethal crimes in São Paulo city.

## 7. CONCLUSIONS

This study tests the hypotheses of the effect of geographic dependence, economic attractiveness, social structure or flaw, and deterrence on cargo theft. This objective is achieved by using the bounded Autoregressive Distributed Lag modeling approach (ARDL bounds) and resorting to one of the most severe context of cargo theft worldwide in terms of the number of incidences – São Paulo, Brazil. Significant results are found regarding the temporal and geographic dynamics of cargo theft rates, but economic and socioeconomic conditions struggled in explaining cargo theft rates in São Paulo. Such a challenge has been reported by previous studies that investigate crime in São Paulo using a similar method at the aggregate level.

Regarding the first specific objective of this study – the space-time dynamics hypothesis, the empirical results do not reject the hypothesis that cargo theft are intertwined across locations and that proximity plays a crucial role in the strength of this link.

Cargo theft rates are autoregressive in the capital city, inland, and the large metropolitan area, i.e., current and future rates are influenced by preceding rates. This autoregressive characteristic is observed for all locations in the São Paulo state in the long run but not in the short run. This may be indicative that cargo thefts are opportunistic in the short run in São Paulo state. Therefore, police patrol, surveillance, and other situational prevention measures that indicate the active presence of law enforcement along distribution channels on highways and roads may go a long way in reducing cargo theft in São Paulo state.

The high concentration of cargo theft in the capital city of São Paulo makes spatial spills to neighboring locations inevitable. The cargo theft rates of the capital city only affect that of the great São Paulo in the short and long run, emphasizing the role of proximity. This effect is positive and bi-directional between the capital and the greater São Paulo. Still, on the geographic spill, higher incidences of cargo theft in the greater São Paulo cause increase in the number of incidences in inland municipalities. Therefore, in the short and long run, the greater São Paulo acts as the bridge of cargo theft between the capital and inland areas. These spatial links imply that the cargo theft rate of a location can be predicted using the rates of neighboring locations. The political implication of this finding is that cargo theft prevention measures such as, for example, road and transport policing, should not be concentrated in specific locations and designed with too rigid borders to control crime displacement.

As to the second specific objective – the economic attractiveness hypothesis, the empirical evidence found varies across locations and, therefore, there is not enough evidence to sustain the hypothesis that higher sales and prices in the legal market increase cargo theft. These economic conditions do not appear to have the same effect on cargo thefts in the capital, large metropolitan area, and inland areas of São Paulo state. Therefore, the associations found in this study for these variables are inconclusive and should not be generalized.

The results indicate that, in the short run, higher revenue from sales in the legal market reflects fewer incidences of cargo theft, whereas a higher volume of trade increases cargo theft opportunity, especially in the capital. This implies that the circulation of higher volumes of goods should be followed by more crime prevention measures. On one hand, this could be achieved by private logistics companies by increasing providing security escorts, more surveillance, and tracking system for a higher volume of goods. On the other hand, more policing could be allocated during seasons of higher circulation of goods such as, for example, the Christmas season.

The empirical evidence of this study permits to sustain the third hypothesis regarding the effect of social structure on cargo theft only for the greater São Paulo, i.e., a higher unemployment rate increases cargo theft in the greater São Paulo both in the short and long run, but there is no evidence of this effect in the capital or inland municipalities. This implies that economic growth and development policies designed to reduce unemployment will have a mitigating effect on cargo theft in the greater São Paulo in the short and long run.

Regarding the fourth hypothesis – the deterrence hypothesis, the empirical findings sustain the hypothesis that a greater presence of the police on the streets reduces cargo theft in the greater São Paulo and in the inland municipalities. No evidence is found regarding this effect in the capital city.

Cargo theft is a complex crime to investigate due to mobility, whereby both the economic target and the offender are in movement. Despite the coherent results obtained regarding the space-temporal dynamics of cargo theft, the results regarding the economic determinants are not as stable and consistent as desired. This may be due to the vast economic and socioeconomic differences among the geographic units considered or the modifiable area unit problem. Therefore, future studies on cargo theft in Brazil should consider investigating the determinants of cargo theft at smaller geographic units such as the municipality. Moreover, the spatial correlation hinted in this study could be further investigated by identifying the clusters of cargo theft in São Paulo. As to the international literature, this study recommends the test of the hypotheses put forward here in contexts of less severe cargo theft since the Brazilian is extreme compared to many other countries and may be more linked to national-specific factors or criminal organizations.

This study only considered the frequency of cargo theft and not the value of the goods *per se*. This may be misleading since, for example, the theft of a few cargos carrying medications may engender higher economic loss compared to the theft of many cargos of food items.

Despite these limitations, this study expands the evidence in the literature regarding the space-temporal dynamics of cargo theft in São Paulo state.

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**REFERENCES**


AFZAL, M., Farooq, M. S., Ahmad, H. K., Begum, I., and QUDDUS, M. A.. Relationship between school education and economic growth in Pakistan: ARDL bounds testing approach to cointegration. *Pakistan Economic and Social Review*, *48*(1), 39-60. 2010.

ALGAEED, A. H.. Symmetric oil price shocks and government expenditure-real exchange rate nexus: ARDL and SVAR models for an oil-based economy, 1970–2018. *Cogent Economics & Finance*, *8*(1), 1-18. 2020.

ALIMI, R. S.. ARDL bounds testing approach to Cointegration: A re-examination of augmented fisher hypothesis in an open economy. *Asian Journal of Economic Modelling*, *2*(2), 103-114. 2014.

ALSTETE, J.. "Inside advice on educating managers for preventing employee theft", *International Journal of Retail & Distribution Management*, *34*(11), pp. 833-844. 2006.

BAILEY, A. A.. Retail employee theft: A theory of planned behavior perspective. *International Journal of Retail & Distribution Management*, *34*(11), 802-816. 2006.

BECKER, G. S.. Crime and punishment: An economic approach. In: The *economic dimensions of crime* (pp. 13-68). Palgrave Macmillan, London. 1968.

BOX, G. E., and COX, D. R.. An analysis of transformations. *Journal of the Royal Statistical Society: Series B (Methodological)*, *26*(2), 211-243. 1964.

BURGES, D.. *Cargo theft, loss prevention, and supply chain security*. Butterworth-Heinemann. 2012.

BSI - British Standards Institutions. *BSI & TT Club Cargo Theft Annual Report*. Retrieved from <https://www.ttclub.com/loss-prevention/publications/tt-club-bsi-cargo-theft-report-2018/> 2018.

BSI - British Standards Institutions. BSI & TT Club Cargo Theft Report 2020. Retrieved from <https://www.ttclub.com/-/media/files/tt-club/bsi-tt-club-cargo-theft-report/bsi-and-tt-club-cargo-theft-report-2020.pdf/> 2020.

CECCATO, V.. *Theft of Goods Transport in Sweden*. Washington, DC: Annual Conference of American Society of Criminology, Washington. 2015.

CLARKE, R. V.. Situational crime prevention: Its theoretical basis and practical scope. *Crime and justice*, *4*, 225-256. 1983.

CLARKE, R. V. G., & Webb, B.. *Hot products: Understanding, anticipating and reducing demand for stolen goods*. London: Home Office, Policing and Reducing Crime Unit, Research, Development and Statistics Directorate (Vol. 112). 1999.

CLEVELAND, W. S.. LOWESS: A program for smoothing scatterplots by robust locally weighted regression. *American Statistician*, *35*(1), p.54. 1981.

COHEN, L. E., and FELSON, M.. Social change and crime rate trends: A routine activity approach. *American sociological review*, *4*(44), 588-608. 1979

DEADMAN, D., and PYLE, D.. Crime and the business cycle in post-war Britain. *The British Journal of Criminology*, *34*(3), 339-357. 1994.

DEMIRHAN, H.. dLagM: *Time Series Regression Models with Distributed Lag Models.* R package version 1.0.19. 2019.

DICKEY, D. A., and FULLER, W. A.. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*(366a), 427-431. 1979.

DUBE, A., Ozkan, B., and GOVINDASAMY, R.. Analyzing the Export Performance of the Horticultural Sub-Sector in Ethiopia: ARDL Bound Test Cointegration Analysis. *Horticulturae*, *34*(4), 1-18. 2018.

EKWALL, D. *Managing the Risk for Antagonistic Threats against the Transport network.* Division of Logistics and Transportation, Chalmers university of technology, Göteborg. . (2009a).

EKWALL, D.. The displacement effect in cargo theft. *International Journal of Physical Distribution & Logistics Management*, *39*(1), 47-62. (2009b).

EKWALL, D., and LANTZ, B.. Cargo theft at non-secure parking locations. International *Journal of Retail & Distribution Management*, 43(3), 204-220. 2015.

ENDERS, W.. *Applied econometric time series*. John Wiley & Sons. 2008.

ENGLE, R. F., & Granger, C. W.. Co-integration and error correction: representation, estimation, and testing. *Econometrica: journal of the Econometric Society*, *55*(2), 251-276.

1987.

FALK, G. J.. The influence of the seasons on the crime rate. *Journal of Criminal Law, Criminology & Police Science*, 2(*43*), 199-213. 1952.

GORR, W., Olligschlaeger, A., and THOMPSON, Y.. Short-term forecasting of Crime. *International Journal of Forecasting*, 19(4), 579-594. 2003.

GOERTZEL, T. and Kahn, T.. The great São Paulo homicide drop. *Homicide Studies*, *13*(4), p. 398-410. 2009.

GOERTZEL, T., Shohat, E., Kahn, T., Zanetic, A., and Bogoyavlenskiy, D.. Homicide booms and busts: A small-n comparative historical study. *Homicide studies*, *17*(1), 59-74. 2013.

GUTHRIE, J., and Guthrie, A.. A research agenda for loss prevention. *International Journal of Retail & Distribution Management,34*(11), 873–878. 2006.

HARRIS, R., and Sollis, R.. Applied time series modelling and forecasting. Wiley, West Sussex. 2003.

HESSELING, R.. Displacement: A review of the empirical literature. *Crime prevention studies*, *3*(1), 97-230. 1994.

IBGE . *Sistema de Contas Regionais: Brasil 2016*. Instituto Brasileiro de Geografia e Estatística. 2018.

JOHANSEN, S.. Statistical analysis of cointegration vectors. *Journal of economic dynamics and control*, 12(2-3), 231-254. 1988.

JOHNS, T., and HAYES, R.. Behind the fence: Buying and selling stolen merchandise. *Security journal*, *16*(4), 29-44. 2003.

JUSTUS, M., and KASSOUF, A. L.. A cointegration analysis of crime, economic activity, and police performance in São Paulo city. *Journal of applied statistics*, 40(10), 2087-2109. 2013.

JUSTUS, M., Ceccato, V., Moreira, G. C., & Kahn, T.. Crime against trading: The case of cargo theft in Sao Paulo. In *Retail Crime* (pp. 297-323). Palgrave Macmillan, Cham. 2018.

KWIATKOWSKI, D., Phillips, P. C., Schmidt, P., and Shin, Y.. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?. *Journal of econometrics*, *54*(1-3), 159-178. 1992.

MERTON, R. K.. Social structure and anomie. *American sociological review 3* (5), 672–682. 1938.

NTC & Logistics - Associação Nacional do Transporte de Cargas e Logística. *Roubo de Cargas: panorama nacional*. Retrieved from <https://www.portalntc.org.br/images/jce/Apresentacao-Roubo-de-Cargas-2018.pdf>. 2019.

OLIVEIRA, E. N., and Martins, J. H.. Globalização e mercados transnacionais ilícitos na América Latina. *Conexão Política*, *3*(2), 11-26. 2014.

PESARAN, M. H. and B. Pesaran. *Working with Microfit 4.0: Interactive Econometric Analysis*. Oxford: Oxford University Press. 1997.

PESARAN, M. H., Shin, Y., and SMITH, R. J.. Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics*, *16*(3), 289-326. 2001.

QUEIROZ, M. P., SILVA, F. D., and ARAUJO, C. E. F.. Análise espacial exploratória de roubos de cargas em rodovias federais no Estado de Minas Gerais. *Revista Brasileira de Risco e Seguro, Rio de Janeiro*, *4*(8), 129-144. 2008.

RUEDIGER, M. A., Azevedo, A. L., Sanches, D., Contarato, A. D. S., and Oliveira, W.. Roubo de carga: panorama no estado do Rio de Janeiro. FGV DAPP: Rio de Janeiro. 2018.

RASCHE, C. E.. Theorizing About Homicide: A Presentation on Theories Explaining Homicide and Other Crimes. In *The Nature of Homicide: Trends and Changes*. Proceedings the Homicide Research Working Group. pp. 23-35. 1998.

REPPETTO, T. A.. Crime prevention and the displacement phenomenon. *Crime & Delinquency*, *22*(2), 166-177. 1976.

SARIDAKIS, G.. Violent crime and incentives in the long-run: evidence from England and Wales. *Journal of Applied Statistics*, *38*(4), 647-660. 2011.

SAX, C., and Eddelbuettel, D.. Seasonal adjustment by x-13arima-seats in R. *Journal of Statistical Software*, *87*(11), 1-17. 2018.

SCIC - Supply Chain Intelligent Center. *Avaliação Global de Risco de Roubo de Carga*. Retrieved from <https://www.bibliotecadeseguranca.com.br/livros/avaliacao-global-de-risco-

de-roubo-de-carga-2018/>. 2018

SMITH, W. R., Frazee, S. G., and Davison, E. L.. Furthering the integration of routine activity and social disorganization theories: Small units of analysis and the study of street robbery as a diffusion process. *Criminology*, *38*(2), 489-524. 2000.

TARNEF, B.. Organized criminal groups. In D, Burges (Ed.), *Cargo Theft, Loss Prevention, and Supply Chain Security* (pp.45-59). Butterworth-Heineman. 2013.

TIMILEHIN, J. O., Adeniyi, A. M., Adeyemi, K. K., Motunrayo, A. S., Ibitoye, J., Kowe, B., Onifade, E. O.. The Saint-Louis Equation Rebirth: Re-Accessing Fiscal and Monetary Policy Mix in Nigeria. *Acta Universitatis Danubius. Oeconomica*, *15*(1), 240-252. 2019.

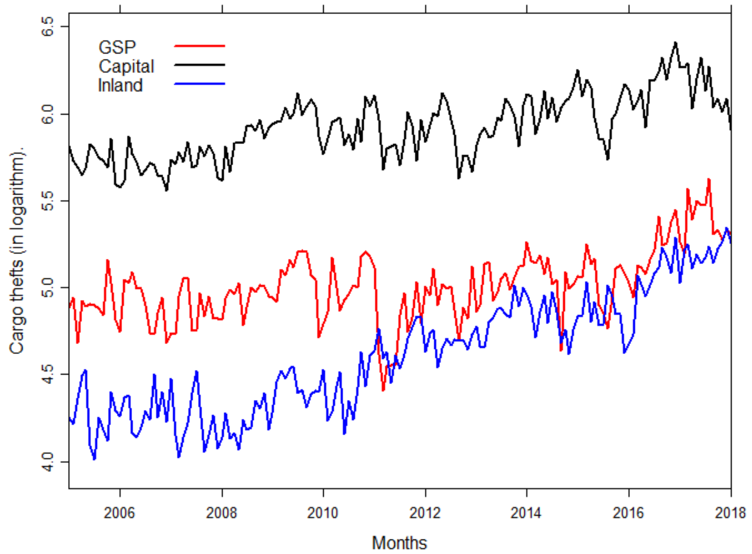
TOBLER, W. R.. A computer movie simulating urban growth in the Detroit region. *Economic geography*, *46*(1), 234-240. 1970.

TURSOY, T.. The interaction between stock prices and interest rates in Turkey: empirical evidence from ARDL bounds test cointegration. *Financial Innovation*, *5*(1), 1-12. 2019.

U.S. General Accounting Office. *Report by the Comptroller General of the United States: Promotion of Cargo Security Receives Limited Support*. US General Accounting Office, Washington DC. 1980.

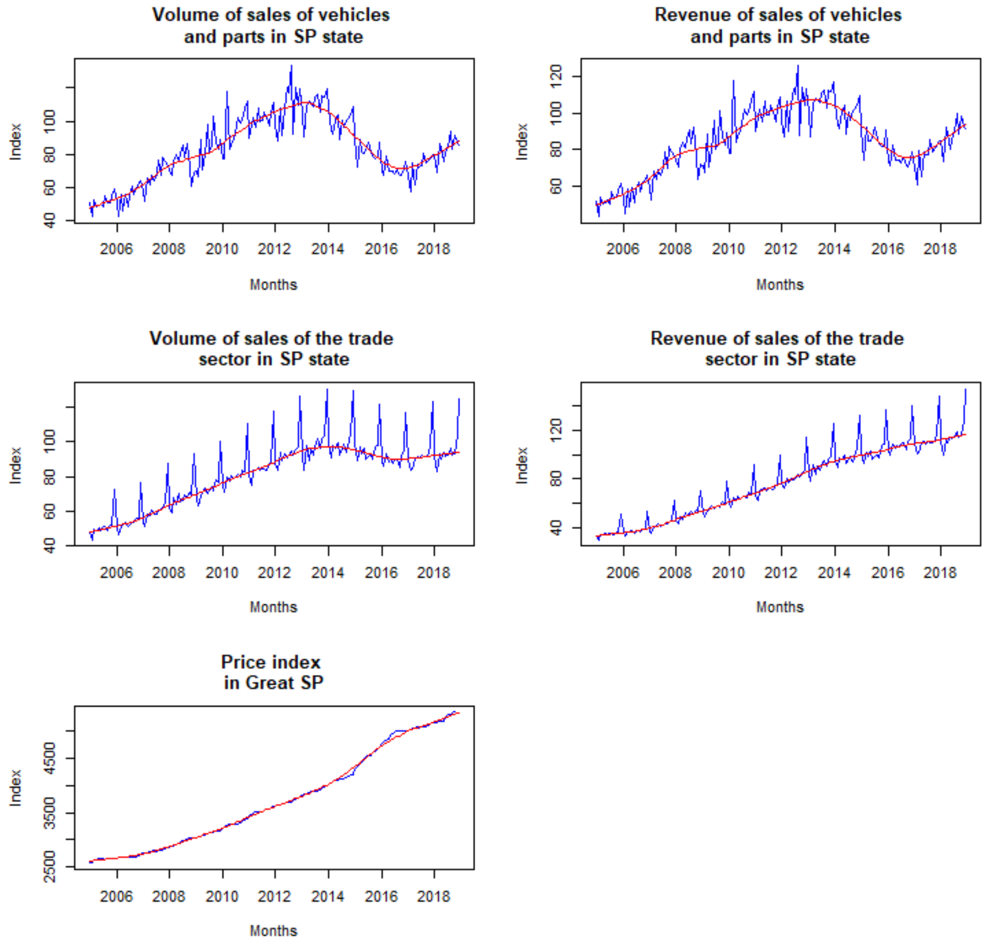
WILCOX, R. R.. *Fundamentals of modern statistical methods: Substantially improving power and accuracy*. Springer (2nd edition), pages 31-35. 2010.

**Figure 6 – Logarithm and deseasonalized series of cargo thefts (hypothesis 1), São Paulo city, great São Paulo, inland municipalities, from January to December 2018.**



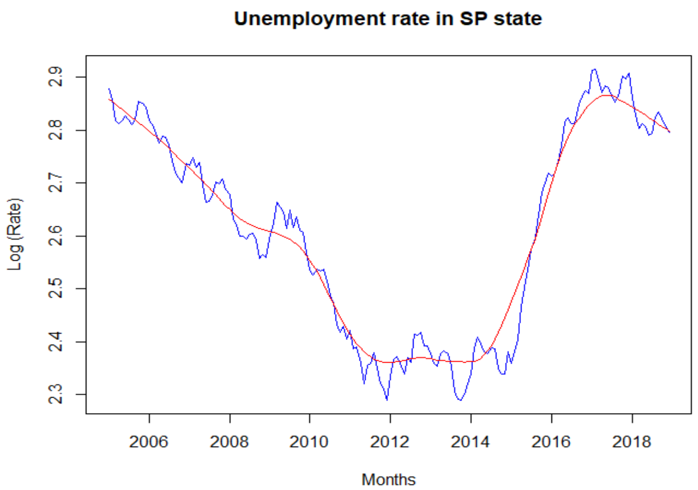

Source: Elaborated by the authors using the data referenced in Table 1.

**Figure 7 – Logarithm and deseasonalized series for economic attractiveness (hypothesis 2), São Paulo state, from January 2005 to December 2018.**



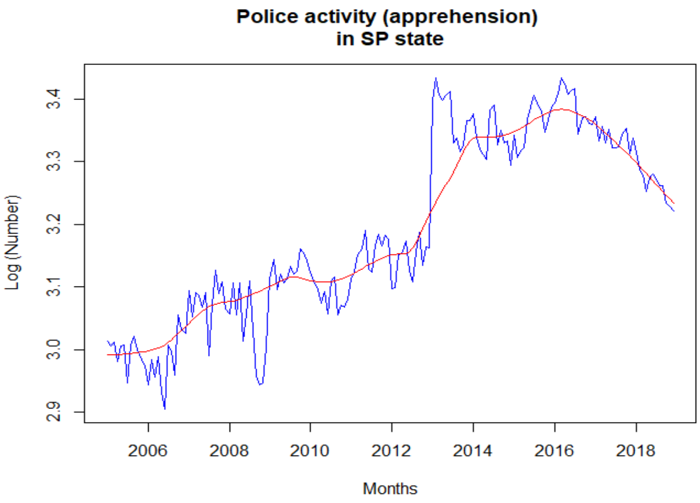

Source: Elaborated by the authors using the data referenced in Table 1.

**Figure 8 – Logarithm and deseasonalized series for social structure (hypothesis 3), São Paulo state, from January 2005 to December 2018.**



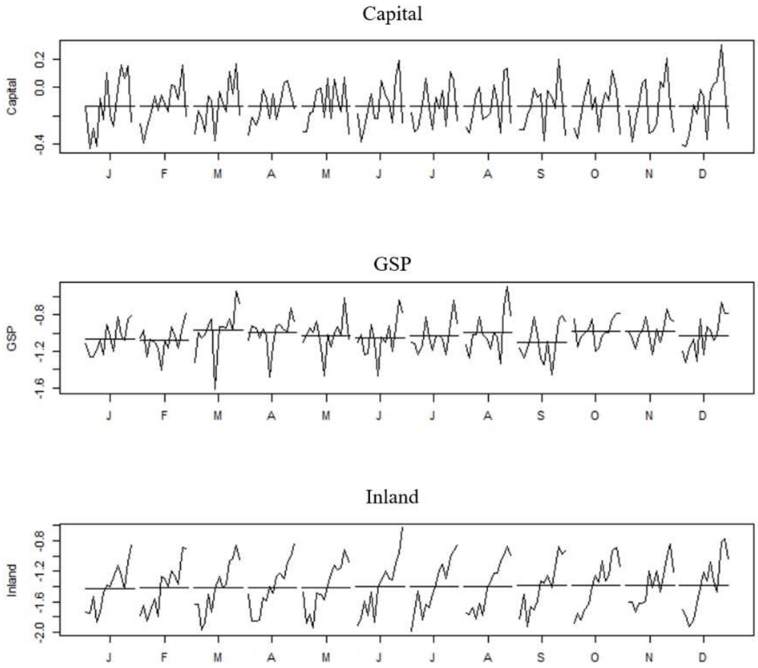

Source: Elaborated by the authors using the data referenced in Table 1.

**Figure 9 – Logarithm and deseasonalized series for deterrence (hypothesis 4), São Paulo state, from January 2005 to December 2018.**



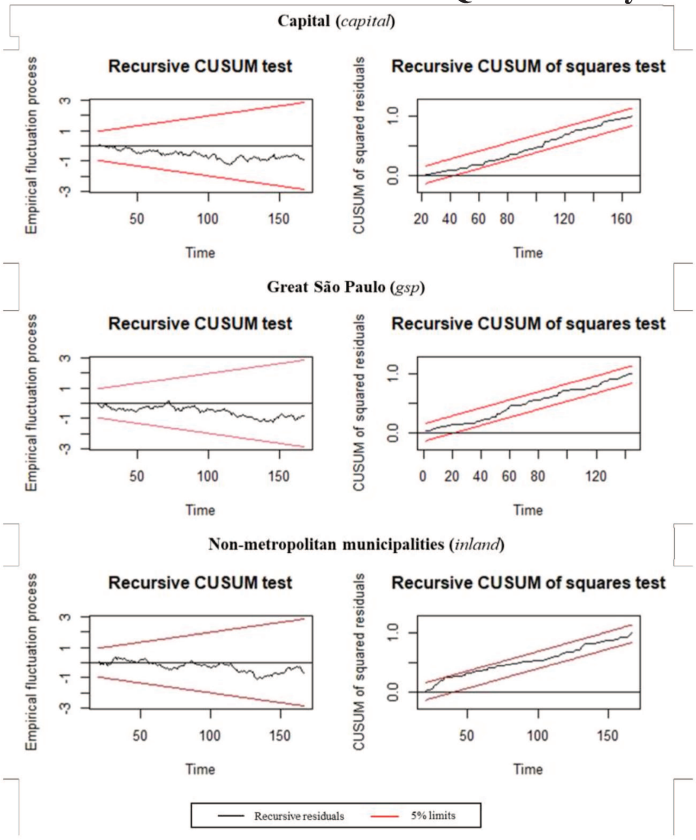

Source: Elaborated by the authors using the data referenced in Table 1.

**Figure 10 – Average cargo theft rates per month for the Capital, GSP, and Inland locations**.




Source: Elaborated by the authors.
Note: The letters on the x-axis are initials of the months of the year.

**Figure 11 – Plot of the CUSUM and CUSUMSQ for stability check of Eq. 2-4.**



# 4 ECONOMIC GROWTH, INCOME INEQUALITY, AND LETHAL VIOLENCE IN DEVELOPED COUNTRIES

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## ABSTRACT

This study investigates the effect of economic conditions on lethal crimes by testing the hypotheses that the relationship between GDP and homicide rates is non-linear and influenced by levels of income inequality. The OECD panel data from the year 2000 to 2018 is used to estimate GMM models for testing these hypotheses. The results confirm the existence of a non-linear relationship between GDP and homicide rates, indicating a dual effect of the former on the latter. Besides having a predominant effect on homicide rates, income inequality condition the effect of GDP on homicide rates. This study concludes that GDP growth is most efficient in reducing crime in contexts of high inequality since there is room for more improvements.

***Keywords*:** Growth. Development. Violence. Property. Crime.

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# 1. INTRODUCTION

Increasing values of the overall wealth, i.e., economic growth, of a nation is good news for everyone only in the context of equal income distribution. Economic growth in the context of structural income inequality heightens or gives rise to other social flaws such as crime (DANZIGER and WHEELER, 1975).

Economic expansions and recessions have an impact on the well-being of individuals in society. From an economic perspective, all other things constant, expansion is characterized by low unemployment, higher income, and better living conditions, and crime is lower (BECKER, 1968). That is, in this perspective, the association between GDP and crime is inverse. However, in the scenario of income inequality, economic expansion heightens the feeling of frustration of the deprived groups who may resort to crime or violence (DANZIGER and WHEELER, 1975), hence the possibility of non-linearity. Therefore, the role of income distribution is crucial in determining the effect of economic expansion on crime. This study uses homicide rates as a proxy for lethal violence to investigate the relationship between crime, economic growth, and income inequality since the data concerning homicide rates are more reliable and complete compared to other crimes that are more susceptible to underreporting (FAJNZYLBER *et al.*, 2002; PARKER, 1985).

The main objective of this study is to fill some gaps in the literature regarding the association between economic conditions, measured in GDP, and homicide rate. In specific, firstly, the effect of GDP growth on crime is investigated, and the hypothesis of non-linearity (U-shape) is tested. Also, this study tests the interaction between GDP and income inequality and investigates its effect on the association between the former and homicide rates. The hypothesis regarding this interaction is that the effect of GDP on homicide rate varies based on levels of income inequality and, consequently, various scenarios of effect may appear. Furthermore, the effect of government expenditure on public safety, income inequality, alcohol consumption, and the percentage of youths Not in Education, Employment, or Training (NEET) on homicide rates is assessed and discussed.

Regarding the main objectives, the hypotheses (*H1* and *H2*) put forward are

*H1* - homicide rates reduce as GDP increases (the economic hypothesis) but the opposite effect may occur as GDP increases in contexts of income inequality (the social structure hypothesis), consequently;

*H2* - there is an interaction effect between GDP and income inequality on the homicide rate, whereby the effect of GDP on homicide rates is conditioned to levels of income inequality.

Regarding other determinants, the hypotheses are that income inequality, NEET population, and alcohol consumption are directly associated with crime. The association between government expenditure on public safety and crime is conceptually expected to be inverse. However, in practice, this association can be ambiguous due to endogeneity since the government spends more on public safety when crime rates are high. Such ambiguity is addressed by using fitting modeling methods and specification strategies.

A higher rate of criminality is not only more prevalent in developing countries compared to developed ones but it also coexists with many other socioeconomic flaws. This is even more so regarding violent or lethal crimes, thus, making it even more challenging to isolate the causal effect of economic conditions on these crimes. Therefore, this study resorts to the context of developed countries to identify the relationship between economic growth, inequality, and crime, whereby other socioeconomic conditions such as poverty, unemployment, low education attainment, etc. are less pronounced.

Accordingly, data from member countries of the Organization for Economic Co-operation and Development (OECD) are used to test the hypotheses put forward due to the reliability and completeness of the database. The Organization for Economic Co-operation and Development (OECD) is a group of 36 countries (as of the year 2019) with the common goal of stimulating economic progress and trade, alongside sharing policy experiences and identifying good practices that can be employed to solve problems of member countries. The OECD member countries are considered developed countries due to their high GDP and high human development index. Similarly, crime rates are significantly lower in OECD member countries compared to other countries of the world. In the year 2018, the average homicide rate of the OECD was around 2.25 per 100,000 populations, which is many times that of developing countries such as, for example, Brazil (31.6 in the same year according to CERQUEIRA *et al.*, 2019).

The OECD member countries are namely, Australia, Austria, Belgium, Canada, Chile, Czech, Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, South Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, and the United States. Brazil is not yet a member country, although it is on the list of potential countries that may join the OECD.

Although these countries share common development goals, the OECD member countries differ in terms of culture, institutions, and geography, which may also influence criminal behavior. Moreover, these countries have very diverse levels of lethal crimes, whereby, on the one hand, there are countries with expressively high homicide rates such as Mexico, Estonia, Latvia, and the United States, and, on the other hand, those with very low rates such as Norway, Denmark, Luxembourg, Austria, and Iceland. This heterogeneity, combined with panel data availability and reliability makes the OECD group an attractive case to test the hypotheses of this study. The empirical strategy adopted in this study permits to explore the diverse contexts of crime, GDP, and inequality levels of the OECD, making the contribution of this study extendable to a wide range of international contexts.

This study is structured into five sections. The next section presents the related literature that further details the links between economic conditions and crime. The data source, empirical modeling, and procedures are detailed in Section 3. The results are reported and discussed in Section 4. Section 5 concludes the study.

## 2. RELATED LITERATURE

The relationship between economic conditions and crime is formally established in Becker (1968) and extended by Danziger and Wheeler (1975) to address the effect of income inequality on this relationship and crime itself.

The classical school of criminology advocates that crime decisions are rational, intelligent, hedonistic, and self-determining (BECCARIA, 1764). In this approach, which is core in the economic theory of crime proposed by Becker (1968), crime is a product of the conscious choice made based on the costs and benefits of committing it, whereby a crime is committed only when the benefit from it exceeds the cost of committing it and the benefit from legal means of income. This theory has been applied and extended to understand the economic motivations of criminal behaviors at the individual level (DANZIGER and WHEELER, 1975; SULIVAN, 1973) and has also been sustained at the aggregate or macro-level, whereby crime levels are explained by economic structures and performance (FAJNZYLBER et al., 2002). In the classical economic theory of crime, *ceteris paribus*, economic expansion implies higher income and employment which, in turn, would reduce crime levels since the benefit from legitimate sources would exceed that from illegitimate means.

Danziger and Wheeler (1975), drawing on the social structure explanation of crime by Merton (1938), theoretically demonstrated and empirically confirmed that an increase in the aggregate level of income results in more crime in the scenario of constant distribution of income or high income inequality. This occurs because, in this framework, the utility or satisfaction of individuals depends on their reference group, the average income of this group, his/her income, and his/her taste for equality. Therefore, despite in times of overall economic expansion, victims of structural inequality who encounter frustrated attempts to increase their income or wellbeing (through education, longer working hours, etc.) to a similar level to their reference group may abandon the legitimate means and strike out at the system by resorting to illegal means. This author presented the example of racial discrimination against the black population and the levels of crime within this group in the United States. Danziger and Wheeler (1975), acknowledged the possibility of ambiguous effects of macro-level income on crime in contexts of income inequality but did not explicitly present the hypothesis of non-linearity.

The theoretical associations suggested in Becker (1968) and Danziger and Wheeler (1975) regarding the effect of economic expansion on crime is connected by Hemley and McPheters (1975) who suggested the existence of two opposing hypothesis that explains this association – the "environmentalist" and "technocratic" hypotheses. According to this author, the environmentalist hypothesis suggests that "economic growth disrupts the stability of the human environment and contribute to crime and other anti-social action". The technocratic hypothesis suggests that "increased production, output, and income actually act to prevent crime, mainly since the production process provides income and employment to persons who might otherwise turn to crime" (HEMLEY and MCPHETERS, 1975). This association between economic performance and crime is described by Hemley and McPheters (1975) as a U-shaped relationship, whereby an increase in the aggregate income reduces crime to a point where the association is inverted.

In sum, the theoretical foundation of this study is built on the contributions of Becker (1968), Danziger and Wheeler (1975), and Hemley and McPheters (1975). The U-shaped association between macro-level income and crime is inspired by Hemley and McPheters (1975), whereby the inverse association is rooted in the explanation provided by the economic theory from Becker (1968) and the possibility of a positive association is rooted in the social structure theory from Danziger and Wheeler (1975).

As to crime deterrence or prevention at the macro-level, the economic approach (Becker, 1968), on one hand, advocates measures that increase punishments and the cost of committing crimes in a way that makes the benefit of crime unattractive. In practice, this implies government expenditure on public safety on, for example, policing and the justice system. The social structure approach (DANZIGER and WHEELER, 1975), on the other hand, advocate measures that mitigate the effect of social flaws on individuals such as, for example, reducing inequality and deprivation.

The theoretical link between crime and economic conditions detailed thus far has been empirically tested in the literature. However, most of the empirical studies that investigate the relationship between economic growth and crime focus on the impact of the latter on the former, i.e., the effect of crime on growth. However, conversely, alongside with few studies, this study asserts that the economic condition of a nation plays an important role as a determinant of its crime rates.

Table 5 (in the annex) provides details concerning objectives, data, methodology, and conclusions of some empirical studies that investigated the relationship between economic growth and crime. A general overview of this table shows the preeminence of studies interested in the effect of crime on economic growth (DETOTTO and OTRANTO, 2010; ENAMORADO *et al*., 2014; GOULAS and ZERVOYIANNI, 2013, 2015; NEANIDIS and PAPADOPOULOU, 2013; TORRES-PRECIADO *et al*., 2015; YEARWOOD and KOINIS, 2011), compared to those that study the opposite direction of effect (Fajnzylber *et al*., 2002; Hemley and McPheters, 1975). Note that the existence of empirical studies regarding both directions of effect indicates endogeneity between economic performance and crime. Nonetheless, the focus here is on the effect of the former on the latter and not otherwise.

The effect of economic conditions on individuals' decisions concerning crime is not a recent topic. Hemley and McPheters (1975) examined the external diseconomies, as in crime, which economic growth may provoke posing two opposing hypotheses that are in line with the non-linearity that will be tested in this study. First is that economic growth disrupts the stability of the human environment and, thus, leads to an increase in crime rates. Second, that increased production, output, and income may prevent crime since individuals are employed and earn income. The results found by these authors confirmed the first hypothesis, pointing that economic growth, characterized by higher production and income levels, contribute to increasing crime. Conversely, Fajnzylber et al. (2002) concluded that economic expansion, measured by higher GDP growth, reduces crime rates of intentional homicide and robbery.

Detotto and Otranto (2012) acknowledged that the link between economic growth and crime is quite puzzling and, thus, avoided seeking a causal relationship but only co-movements between both variables. The results found by these authors affirmed a strong relationship between business cycles and various types of crime. Specifically, the conclusion was drawn that a rise in economic performance is associated with a decrease in crime rates. Moreover, Detotto and Otranto (2012) identified the lagging behavior of crime series, thus, suggesting the use of dynamic models.

Despite the differences regarding the direction of effect investigated, Table 5 indicates consensus regarding data type and methodology, whereby the use of panel data of regions or countries to estimate General Method of Moment models (GMMs) is frequent. This is, especially, because these models allow controlling for regional heterogeneity and time dynamics across locations, and also address endogeneity, which is suspected to exist between economic growth and crime rates.

Apart from economic performance, factors regarding social welfare are also crucial for understanding crime rates (DANZIGER and WHEELER, 1975). Some studies have shown that absolute deprivation as in poverty and unemployment are significant determinants of crime rates (BATATA *et* al., CECCATO, 2017; LEE *et al.*, 2014; MESSNER and TARDIFF, 1986; 1998). Although acknowledging the role of absolute deprivation on crime, other studies argue that the effect of relative deprivation as in income inequality has a more crucial role in explaining crime rates (CANACHE, 1996; BURRATSON *et al.*, 2018).

The demography and social welfare of youths, especially men, have been frequently raised in the literature as a predictor of lethal violence (SHAW and MCKAY, 1942; Justus, *et al.*, 2018). Nardi *et al.* (2013) found that adolescents and youths who are not employed in education or training (NEET) are more involved in property crimes and less involved in crimes against persons. The consumption of psychoactive substances such as drugs and alcohol has also been linked to crimes (VALDEZ *et al.*, 2007). The role of law enforcement has been highlighted in the theoretical and empirical literature as crucial in fighting crimes (Becker, 1968). Economic studies on crime have shown that government expenditure on policing, prisons, courts, and the overall public safety infrastructure creates crime deterrence, the overall feeling of safety, and efficient policing and the judicial system (BRAND and PRICE, 2000; MAYHEW, 2003).

## 3. METHOD

### 3.1. DATA AND SAMPLE

This study uses a panel data of 36 OECD member countries from the year 2000 to 2018 (total of nineteen years), which is available in the organization’s database. In a balanced panel structure, the data would have 684 observations (36 countries multiplied by 19 years). However, this is not the case due to the unavailability of data regarding some countries for some years, i.e., the panel data is unbalanced.

## 3.2. EMPIRICAL MODELING

The empirical method used to achieve the objectives of this paper is that of dynamic panel data models fitted by the General Method of Moments estimators (GMM). Aside from being most adequate for cross-national analyses, this method enables to explore the variations over time and among countries, thus providing more precise estimates. Besides, these models account for the unobserved country-specific fixed effect, time dynamics, and endogeneity of variables, which are potential limitations that cross-sectional or time-series analyses encounter.

The general dynamic panel model of order $p$ for homicide rates is represented as

$$\boldsymbol{homicide}_{it} = \gamma_1 \boldsymbol{homicide}_{i,t-1} + \cdots + \gamma_p \boldsymbol{homicide}_{i,t-p} + \boldsymbol{x}_{it}^{j}\beta + \boldsymbol{\alpha}_i + \boldsymbol{\varepsilon}_{it}, \quad t = p+1, \dots, T \qquad (1)$$

where $\boldsymbol{homicide}_{it}$is the homicide rate for 100.000 population of country $i$ at time $t$, $\boldsymbol{\alpha}_i$ represents the country-specific effect, $\boldsymbol{x}_{it}$ is a matrix of regressors which are initially assumed to be uncorrelated with the error term, $\boldsymbol{\varepsilon}_{it}$. According to Cameron and Trivedi (2010), the main reasons for the correlation of $\boldsymbol{homicide}_{it}$over time are: i) true state dependence, which refers to the direct natural relation of y in preceding periods; ii) observed heterogeneity through direct relation with $\boldsymbol{x}_{it}$ and; iii) unobserved heterogeneity through time-invariant country-specific effects, $\boldsymbol{\alpha}_i$, which in our case may be political institutions or regimes, constitutional laws, ethnic structures, etc. Aside from providing consistent estimates for $\gamma_1$ , ..., $\gamma_p$ and $\beta$, the Arellano-Bond estimator deals with endogeneity by including internal instruments derived from lagged values of the endogenous regressors.

In the equation, the set of regressors, $\boldsymbol{x}_{it}$, are

a) $GDP$: is the control for Gross Domestic Product (in constant values of the year 2015), which is the regressor of major interest of this study. The values used are in constant or real prices, i.e., inflation has been deducted. To test the non-linear hypothesis, the square of GDP is also included in the model. Natural logarithm was applied to both the level and square values of the GDP to reduce the expressive variation of the GDP across the OECD member countries;
b) *NEET*: is the control for youths between age 15 and 29 who are neither in employment,

education nor training. This control is measured in the proportion of the total population;

c) $GINI$: is the GINI index that controls for income inequality;

d) $pubsafety$: is the control for government expenditure on public safety. This control is measured in the proportion of the total annual government expenditure;

e) $alcohol$: is the control for the consumption of psychoactive substances. This control is measured in liters per capita of alcohol consumed by individuals above age 15;

f) $Binary\ for\ years$ and $trend$: are both time controls for year-specific shocks (in binaries) and the linear trend of crime.

g) $Binary\ for\ continents$: a categorical variable is included as a control for the four continents in which the OECD member countries are contained, namely, North America, Europe, Asia, and Australia.

The hypothesis of an interaction between GDP and income inequality (GINI) is tested by including the product of both variables as a regressor in the model. The statistical significance of this new variable indicates that both variables interact such that the slope of the effect of one changes as the value of the other increases, and vice versa. Note that the individual effect of GDP and GINI should not be interpreted independently after the inclusion of the interaction term since these values are only valid if one of both is equal to zero, which is not realistic in this case. In a model with an interaction term, the individual effect of any of the interacted variable is obtained by combining the individual effect of the variable of interest with the interactive effect.

In the empirical model, the regressors $\boldsymbol{x}_{it}$can be exogenous, weakly endogenous, or contemporary endogenous. Specifically, this study assumes, based on the theoretical model of Becker (1968), that the variable for government expenditure on public safety is potentially endogenous. The reason for this is that crime decisions depend on the conceived probability of apprehension, conviction, and effective punishment by offenders, which are directly influenced by the government through investment in public safety. Moreover, as detailed in the literature review, economic growth is likely endogenous since studies found evidence that crime rates affect growth and vice versa. These variables suspected to be endogenous will be addressed in the GMM method by using internal instruments – lagged values of the variables in level. Therefore, this method deals with endogeneity by controlling it rather than solving it although still providing consistent estimates. Nonetheless, Arellano and Bover (1995) showed that this procedure controls for endogeneity efficiently.

To obtain a consistent estimation of the empirical model, the Arellano-Bond estimator assumes that $\varepsilon_{it}$ must be serially uncorrelated. Specifically, the first-differenced errors, $\Delta\varepsilon_{it}$, are correlated in the AR (1) but not in subsequent orders. The statistics test that verifies this assumption is the Arellano-Bond test. The null hypothesis of this test is that there is no autocorrelation in the first-differenced errors. The test used to verify if the dynamic panel model is missing specified is the Sagan test of over identifying restrictions. It is important to note that this test assumes that model errors are independent and identically distributed (i.i.d), thus the Sargan test cannot be performed on the heteroskedastic-robust errors.

In posterior publications Arellano and Bover (1995) and Blundell and Bond (1998) suggested to consider an additional moment condition, $E(\Delta homicide_{1,t-1}, \varepsilon_{it}) = 0$, in order to enable the inclusion of levels as in Equation 1 and use $\Delta y_{1,t-1}$ as an additional internal instrument to address endogeneity. This latter version of the GMM estimator called the System Dynamic Panel-Data Estimator (abbreviated, GMM-SYS) satisfies the moment conditions stipulated in previous paragraphs. The GMM-SYS presents more consistent estimates in the sense that it controls for individual fixed effects, $\boldsymbol{\alpha}_i$, intertemporal dynamics of dependent and independent variables, endogeneity, and heteroskedasticity can be accounted for by using robust standard errors. For this reason, the GMM-SYS is used for the analysis of this study.

## 3.3. PRELIMINARY ECONOMETRIC PROCEDURES

Table 1 presents the preliminary statistics for the dependent and independent variables specified in the empirical model.

Although the OECD member countries share similar development goals and policies, they are heterogeneous in terms of institutional, judicial, and social structures. This is reflected by the standard deviations (s.d.), whereby the overall deviation shows the average variability of the data; the between deviations show how the data vary across countries, and; the within deviations show how data vary over time. A higher between deviations for most of the variables emphasizes the differences among OECD member countries, emphasizing the necessity of a method such as the GMM-SYS that addresses country-specific effects, i.e., heterogeneity.

Table 1: Definition and descriptive statistics

| Variable | Definition | | Mean | s.d. | N, $i$, T |
|---|---|---|---|---|---|
| $homicide$ | Intentional Homicide Rate (homicides for 100 000 population) | overall | 2.33 | 3.15 | N = 586 |
| | | between | | 2.76 | $i$ = 35 |
| | | within | | 1.37 | $\overline{T}$= 16.7 |
| | Gross Domestic Product | overall | 1,197,265 | 2,729,203 | N = 684 |

| | | | | | |
|---|---|---|---|---|---|
| $GDP$ | (in million US$, constant prices of the year 2015) | between | | 2,747,202 | $i$ = 36 |
| | | within | | 290,928 | T = 19 |
| $NEET$ | The proportion of young people between age 15 and 29 who are neither in employment, education nor training (%) | overall | 14.85 | 6.51 | N = 592 |
| | | between | | 5.91 | $i$ = 35 |
| | | within | | 2.71 | $\overline{T}$ = 16.9 |
| $GINI$ | Gini (disposable income, post taxes and transfers) | overall | 0.31 | 0.05 | N = 291 |
| | | between | | 0.06 | $i$ = 34 |
| | | within | | 0.01 | $\overline{T}$ = 8.6 |
| $pubsafety$ | Public safety investment (% of GDP) | overall | 3.97 | 1.24 | N = 564 |
| | | between | | 1.34 | $i$ = 32 |
| | | within | | 0.38 | $\overline{T}$= 17.6 |
| $alcohol$ | Alcohol consumption – liters per capita (age 15+) | overall | 9.41 | 2.84 | N = 636 |
| | | between | | 2.74 | $i$ = 36 |
| | | within | | 0.84 | $\overline{T}$= 17.7 |

Note: s.d. is the standard deviation; N is the number of observations; $i$ represents units (countries), and; T is time (number of years) and $\overline{T}$is the average of T in cases where data is unavailable for specific years.

The modeling exercise begins with the estimation of the base model using various panel data methods, whereby all the regressors are included. Before estimating models using the GMM method, the classic pooled linear, Random, and Fixed Effect models (abbreviated as OLS, RE, and FE, respectively) are estimated to ensure that the GMM is the most appropriate method.

The results and test values obtained are in Table 2. The heteroskedasticity, collinearity, and residual normality are tested using the linear model estimated by the OLS method. The test values indicate that the residuals of the base model are normally distributed at a 5% level of significance but not at 1%. Not with standing, the comparison of the residual distribution to the conceptual normal distribution shows that the distribution of the calculated residuals is close to normal. Therefore, normality is assumed. The Breush-Pagan test for heteroskedasticity indicates that the residuals do not have constant variance. Given the size of the database ($N$ = 205) and the number of regressors that are controlled (total of 23, including time and continental binaries), robust standard errors are not calculated. Nevertheless, the distribution of the residuals is decently distributed around the zero average. Therefore, we assume homoskedasticity. The empirical models with robust standard errors are provided in Table 4 in the annex section for consultation.

The F, Breush-Pagan, and Hausman tests used to identify the best fit model between the classic linear, RE, and FE models show that the FE model is most appropriate. The flaw of these three models is that they are biased in the presence of serial correlation of the dependent variable or the presence of an endogenous regressor in the model, which is likely to be the case of the control for public safety expenditure, $pubsafety$. These issues are addressed by the GMM estimators, which builds on the FE models.

The Arellano-Bond test for serial correlation rejects the null hypothesis of zero correlation in the first-differenced errors only at order 1. Therefore, the moment conditions used by GMM estimator are satisfied and the GMM method can be used for analysis. The Sargan test is performed on the GMM-SYS I (the base model) to verify the model specification and the validity of instruments. The test value for a one-step GMM-SYS model rejects the null hypothesis that the over identifying restrictions are valid, i.e., the model and instruments need to be reviewed. It is, however, important to recall that the Sargan test over rejects in the presence of heteroskedasticity, which seems to be the case as indicated in the linear model estimated using the OLS method. For further assessment, the same GMM-SYS model is estimated using a two-step procedure as suggested by Arellano and Bond (1991). The Sargan test result for the two-step model does not reject the null hypothesis that the over identifying restrictions are valid.

The statistical procedures performed here indicates that the GMM-SYS yields better estimates compared to other panel data models assessed. Therefore, this model is henceforth referred to as the base model, and all the empirical analysis of this study is focused exclusively on models estimated using this method.

**Table 2: Estimation procedures and statistic tests.**

| | OLS | RE | FE | GMM-SYS |
|---|---|---|---|---|
| $\log(GDP)$ | $-7.157^{***}$ | $-4.522^{***}$ | -3.754 | $-3.134^{**}$ |
| | (0.601) | (1.509) | (3.483) | (1.540) |
| $\log(GDP)^2$ | $0.277^{***}$ | $0.172^{***}$ | 0.0621 | $0.118^{*}$ |
| | (0.023) | (0.059) | (0.137) | (0.063) |
| $NEET$ | 0.0295 | 0.0278 | 0.00256 | $0.0359^{**}$ |
| | (0.018) | (0.018) | (0.022) | (0.018) |
| $GINI$ | 2.562 | -2.844 | -4.162 | 3.038 |
| | (2.341) | (3.097) | (3.341) | (3.762) |
| $pubsafety$ | $28.42^{***}$ | $72.01^{***}$ | $73.00^{***}$ | $53.83^{***}$ |
| | (7.271) | (9.966) | (11.107) | (11.087) |
| $alcohol$ | $0.110^{***}$ | $0.146^{***}$ | $0.148^{***}$ | $0.206^{***}$ |
| | (0.034) | (0.049) | (0.054) | (0.063) |
| $homicide_{t-1}$ | | | | $0.418^{***}$ |
| | | | | (0.056) |
| $constant$ | $44.13^{***}$ | $27.39^{***}$ | 36.56 | 15.87 |
| | (4.120) | (9.846) | (22.401) | (9.757) |
| $N$ | 217 | 217 | 217 | 205 |
| $R^2$ | 0.621 | | 0.361 | |

**Statistic tests**

| Test | Value |
|---|---|
| Heteroskedasticity: Breush-Pagan | $\chi^2 = 21.09$; $p$-value$= 0.000$ |
| Collinearity: Variance Inflation factor | mean VIF$= 1.41$ |
| Normality: Shapiro-wilk | $w = 0.9837$;$p$-value$= 0.0132$ |
| Pooled vs. FE: F-test | $F = 36.69$;$p$-value$= 0.000$ |
| Pooled vs. RE: Breusch and Pagan test | $\bar{\chi}^2 = 489.48$;$p$-value$= 0.000$ |
| FE vs. RE: Hausmann test | $\chi^2 = 31.73$; $p$-value$= 0.000$ |
| Autocorrelation: Arellano-bond | |
| order 1 | $z = -2.83$;$p$-value$= 0.0066$ |

| | |
|---|---|
| order 2 | $z = -1.41$;$p$-value= 0.1626 |
| Over-Identification: Sargan (one-step) | $\chi^2 = 139.04$; $p$-value= 0.001 |
| Over-Identification: Sargan (two-step) | $\chi^2 = 13.99$; $p$-value= 1.000 |

Note: ***, **, and * denote significance at 1%, 5%, and 10%, respectively; OLS is the classic linear regression, FE is the Fixed Effect model; RE is the Random Effect model; GMM-SYS is the System Generalized of Moments Method.

Three specification exercises were performed building on the base model estimated using the GMM-SYS method and presented in Table 3 that is analyzed in the next section. In the first variation, GMM-SYS I, the endogeneity of the GDP and governmental expenditure on public safety is controlled using internal instruments as described in the methodology section. In the model GMM-SYS II, controls are included for continental and time-specific effects, and the interaction between GDP and income inequality (GINI) is tested in model GMM-SYS III. Note that changes in the model specifications did not severely affect the results, i.e., the estimates are relatively stable across models, especially for the main variables of interest, i.e., GDP and GINI. The magnitude of the $G$DP and $GINI$ coefficients vary significantly in GMM-SYS III compared to other models due to the effect of the interaction on the average values.

## 4. RESULTS AND DISCUSSION

The classic economic theories of crime (BECKER, 1968) center mostly on the effect of economic conditions on crime, but criminological and recent economic theories have emphasized the need to seek beyond economics to explain crime, especially when it comes to crimes against persons such as aggression and lethal violence (FAJNZYLBER, 2002; DANZIGER and WHEELER, 1975; MERTON, 1938;). In this latter framework, social structures that include, for example, income distribution and crime culture are also important factors that explain crime. This study combines the contributions from these frameworks to expand the literature on the determinants of homicide rates (a proxy for lethal violence).

The relationship between economic conditions and crime is not as straightforward as it seems (Pridemore, 2011) because higher income levels may reflect better living condition, whereby crime is unnecessary, or unattractive to criminals. On one hand, theoretical and empirical studies show that the growth of the overall income reduces crime (DAZINGER and WHEELER, 1975), and, on the other and, other theoretical and empirical studies show the opposite (BECKER, 1968; HEMLEY and MCPHETERS, 1975). In line with Hemley and McPheters (1975), this study acknowledges this complexity and hypothesize that the relationship between absolute income (GDP) and crime (homicide rate in this case) is non-linear – negative at first then positive (U-shaped). This is confirmed in all the estimation exercises performed in this study, indicating that GDP has a significant effect on homicide rates and this effect is non-linear (U-shaped), i.e., the effect of GDP on homicide rate (a proxy for lethal violence) in OECD member countries with lower GDP is inverse and the effect is positive in those with a higher GDP. On one hand, other things constant, an increasing GDP, i.e., economic expansion is particularly influential in reducing homicide rates in OECD member countries with lower GDP, and the opposite is true for those with a higher GDP. It is also important to highlight that coefficient for both directions of effect show that the mitigating effect of GDP on homicide rates is, on average, dominant.

**Table 3: The empirical specifications and result for homicide rates**

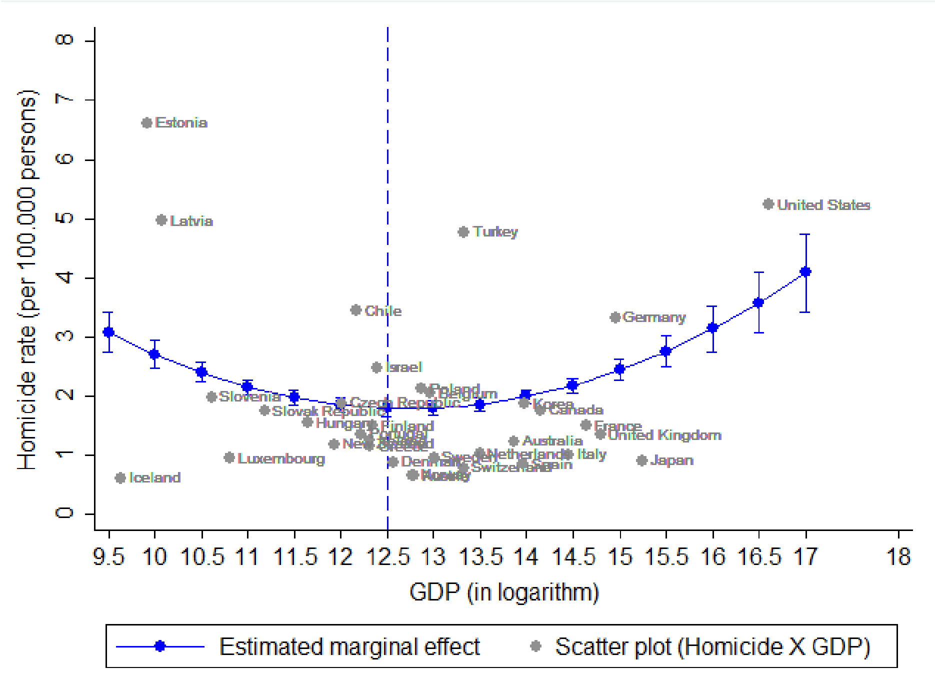
| | GMM-SYS I | GMM-SYS II | GMM-SYS III |
|---|---|---|---|
| $Intercept$ | 16.11$^{***}$ | 18.13$^{***}$ | 9.928$^{***}$ |
| | (3.117) | (3.314) | (3.179) |
| $\boldsymbol{Homicide_{t-1}}$ | 0.532$^{***}$ | 0.532$^{***}$ | 0.459$^{***}$ |
| | (0.036) | (0.036) | (0.038) |
| **Interest variables** | | | |
| $\log(GDP)$ | -2.830$^{***}$ | -3.187$^{***}$ | -3.163$^{***}$ |
| | (0.461) | (0.505) | (0.468) |
| $\log(GDP)^2$ | 0.109$^{***}$ | 0.125$^{***}$ | 0.189$^{***}$ |
| | -2.830$^{***}$ | -3.187$^{***}$ | -3.163$^{***}$ |
| $GINI$ | 4.982$^{***}$ | 5.268$^{***}$ | 66.34$^{***}$ |
| | (1.494) | (1.453) | (9.498) |
| $GINI \times \log(GDP)$ | | | -5.390$^{***}$ |
| | | | (0.810) |
| **Control variables** | | | |
| $alcohol$ | 0.0764$^{***}$ | 0.0896$^{***}$ | 0.0421 |
| | (0.026) | (0.032) | (0.030) |
| $NEET$ | -0.0118 | -0.0139 | -0.00734 |
| | (0.011) | (0.011) | (0.011) |
| $pubsafety$ | 38.71$^{***}$ | 43.27$^{***}$ | 43.65$^{***}$ |
| | (8.159) | (8.202) | (7.877) |
| $pubsafety_{t-1}$ | -21.51$^{**}$ | -22.56$^{***}$ | -23.95$^{***}$ |
| | (8.442) | (8.529) | (8.192) |
| Continent-fixed effects | No | Yes | Yes |
| Time-fixed effects | No | Yes | Yes |
| **Tests** | | | |
| Autocorrelation test: Arellano-bond: $z$ ($p$-value) | | | |
| order 1 | -2.3 (0.023) | -2.2 (0.030) | -2.5 (0.012) |
| order 2 | -1.6 (0.11) | -1.6 (0.11) | -1.35 (0.18) |
| Over-Identification test: Sargan $\chi^2$ ($p$-value) | | | |
| one-step | 213.5 (0.098) | 176.5 (0.45) | 180.01 (0.36) |
| two-step | 19.9 (1.00) | 3.4 (1.00) | 3.4 (1.00) |
| Normality test: Shapiro-wilk $w$ ($p$-value) | | | |
| | 0.98 (0.082) | 0.98 (0.098) | 0.98 (0.082) |

Note: GMM-SYS I is the base model with control for the endogeneity of GDP and governmental expenditure on public safety and its lagged effect, and control for binaries for continents; GMM-SYS II includes time shock controls to model GMM-SYS I; GMM-SYS III adds the control for the interaction between GDP and GINI; the number of observations for the four models is 205; ***, ** and * denote significance at 1%, 5%, and 10%, respectively.

The graphical illustration of the non-linear relationship between GDP and homicide rate (Fig. 1) shows the lowest point of the parabola, identifying the countries that fall in both segments of the curve – before and after the lowest point with negative and positive signs, respectively. Countries that fall under the category of a negative sign are: Iceland, Estonia, Latvia, Lithuania, Slovenia, Luxembourg, Slovak Republic, Hungary, New Zealand, Czech Republic, Chile, Portugal, Ireland, Greece, Finland, and Israel. Those that fall under the category of a positive sign are: Denmark, Norway, Austria, Poland, Belgium, Sweden, Switzerland, Turkey, Netherlands, Mexico, Canada, Italy, France, United Kingdom, Germany, Japan, and the United States.

In Fig 1, it is perceptible that, on one hand, Estonia and Latvia (neighboring countries of Northern Europe) are at the lowest extreme of the curve where GDP is lowest and crime is highest. On the other hand, the United States is single-handedly responsible for the highest extreme of the curve, where crime and GDP are both highest. Mexico, which is not included in the figure for being an outlier, had the highest rate of homicide rates during the period (average of 15.8) combined with an average level of GDP (about 13.8). At this point, it is clear that the effect of the economic growth of a country on its crime levels depends on the pre-existing economic conditions of the same – GDP growth reduces homicide rates in the context of a pre-existing low income, but GDP growth increases homicide rates in the context of a pre-existing high income.

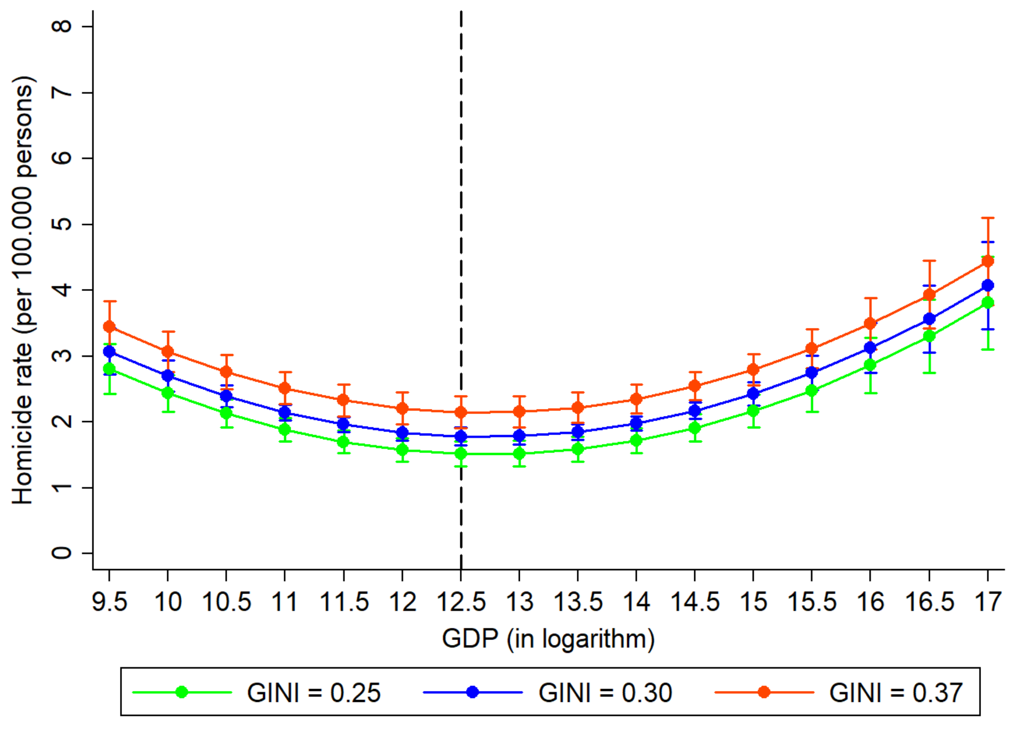
**Figure 1 – The non-linear marginal effect of Gross Domestic Product (GDP) on homicide rates.**




Note: Elaborated by the author using results from model GMM-SYS II. The broken vertical line indicates the lowest point of the U curve and the bars around the marginal effects are confidence intervals. All the marginal effects plotted are statistically significant at 1%. Mexico is excluded in the figure to avoid the distortion of the data illustration due to the exceptionally high rates of lethal crimes. The scatter plot is calculated using the average values between the year 2000 and 2018.

It is reasonable to acknowledge that an increasing absolute income is insufficient to infer the economic welfare of a country's population since this expressively depends on the way the income is distributed. The coefficient observed for GINI that measures income inequality is positive and significant across all models, indicating that an increase in the level of income inequality provokes an increase in homicide rates. Inferring by the coefficient's magnitude, income inequality is the second most influential factor on homicide rates and this effect is about twice the mitigating effect of GDP growth. In other words, i.e., *ceteris paribus,* an equal and simultaneous increase in both GDP and GINI would result in higher levels of crime. Note that without considering the interactive effect between GDP and GINI (models GMM-SYS I or GMM-SYS II), Fig 2 shows that a higher level of GINI increases homicide rates, irrespective of GDP levels, causing parallel dislocation of the curves. It is also important to note that the effect of GINI on homicide rate is portrayed as linear and constant in models GMM-SYS I and II (shown by the gaps between the GINI lines), whereby the same effect of inequality is observed across all levels of GDP.

**Figure 2 – The non-linear marginal effect of Gross Domestic Product (GDP) on homicide rates.**



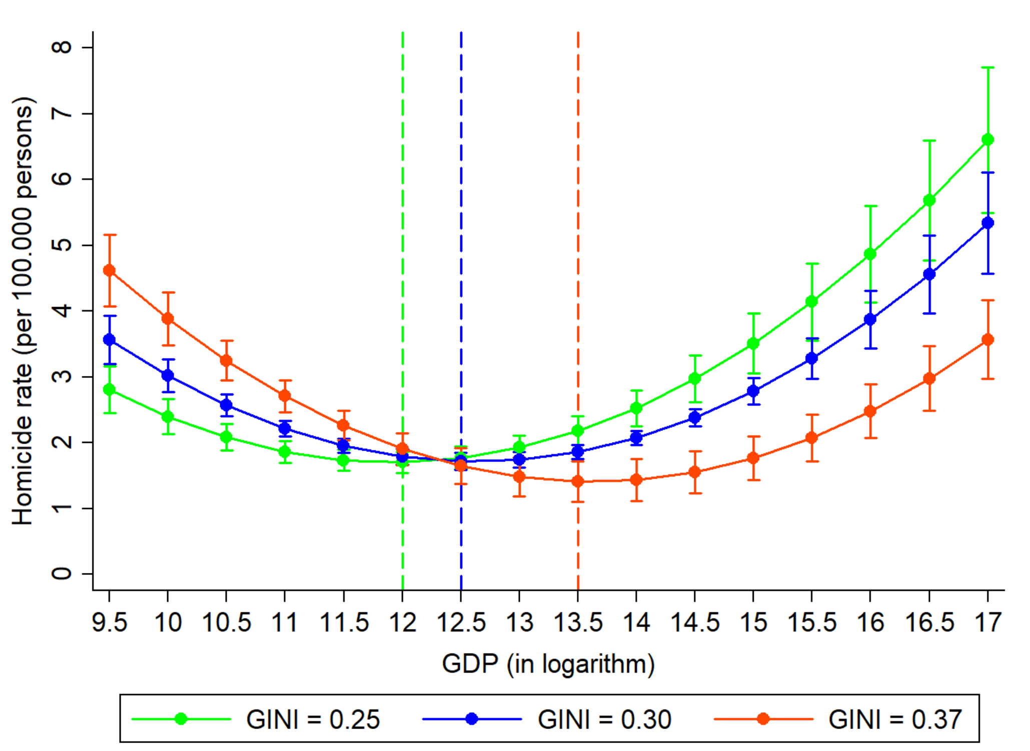

Note: Elaborated by the author using results from model GMM-SYS II. The broken vertical line indicates the lowest point of the U curve and the bars around the marginal effects are confidence intervals.

According to Fajnzylber (2002), economic growth and income inequality are the most robust and significant determinants of crimes. This author, although without an explicit empirical test, describes that the effect of poverty alleviation on crime rates is a product of the joint effect of income inequality and economic growth. The hypothesis of this joint effect has been long forwarded by Danziger and Wheeler (1975), whereby these authors theoretically and empirically showed that "a greater degree of inequality in the distribution of income and increases in the absolute level of income when the distribution is constant are both accompanied by more crime". In other words, the magnitude of the effect of income growth is conditioned to the level of income inequality and, therefore, the GDP and GINI variables are expected to naturally interact since the former measures the absolute level of income and the latter measures its distribution among the population.

Specifically, the interaction effect between GDP and GINI hypothesized in this study is that the effect of GDP on homicide rate varies across different levels or contexts of income inequality. This hypothesis is confirmed by the significant negative sign observed for the interaction term in model GMM-SYS III. This implies that the overall effect of GDP on homicide rates is dependent on the level of inequality. Note that the effect of the interaction effect is directly on the slope of the curve, i.e., the marginal effects.

Apart from the dependence between GDP and GINI, the negative sign of the interaction term indicates that the inverse or mitigating effect of GDP is emphasized at higher levels of income inequality and the positive or direct effect is reduced at high levels of income inequality. In other words, the role of GDP in reducing homicide rates is greater in contexts of higher income inequality compared to context with lower income inequality. The illustration of these interaction effects in Fig. 3 prompts three observations. First, the slope of the curves shows that the marginal reduction caused by GDP growth is higher in the context of higher inequality. Second, the shift of the lowest point of the curves to the right as income inequality increases shows that higher values of GDP go a long way in reducing homicide rates in the context of higher inequality compared to that of lower inequality. Third, the positive effect of GDP growth on homicide rate is lower compared in the context of higher inequality compared to that of lower inequality. In sum, the interaction exercise illustrated in Fig. 3 shows that GDP growth is most efficient in reducing crime in the context of high inequality. This is mostly because there is room for more improvements in such contexts.

**Figure 3 – The non-linear marginal effect of Gross Domestic Product (GDP) on homicide rates.**




Note: Elaborated by the author using results from model GMM-SYS II. The broken vertical line indicates the lowest point of the U curve.

The control for $pubsafety$ shows that the government expenditure on public safety in a period reduces homicide rates in the subsequent period. There is consensus in the literature that the role of government investment in public safety factors such as, for example, policing, prisons, and courts is crucial in tackling crime (BECKER, 1968; FAJNZYLBER, 2002). These factors are directly associated with crime deterrence, which is crucial in reducing crime rates (DANZIGER and WHEELER, 1975). The evidence presented here upholds this by showing that government expenditure on law enforcement reduces homicide rates, although with a year of lag. Despite acknowledging the importance of law enforcement, Danziger and Wheeler (1975) suggest that crime reduction could be further achieved in the long run by the reduction of inequality rather than increasing punishment or adjusting other law enforcement factors. This is because the former approach influences a cause of crime and is beneficial to the population at large, whereas the latter approach mostly only affects the offender's probability of getting caught or crime deterrence and is costly to the society at large.

The control for the consumption of psychoactive substances, $alcohol$, indicates that higher consumption of alcohol increases the homicide rates, but this result is only confirmed in two of the three models estimated in this study. Nonetheless, the result presented here upholds that of Rossow (2001) regarding Europe; that of Shaw *et al.* (2006) regarding England and Wales, and; that by Valdez *et al*. (2007) for the United States.

There is not enough evidence to decide regarding the effect of the proportion of disconnected youths, NEET, on homicide rates. This result aligns with that reported by Nardi *et al* (2013) that deviant and criminal behaviors, especially homicides, are not linked to youths who are NEET.

The three variations of the GMM-SYS model present evidence of the inertia of homicide rates over time, i.e., the homicide rate of a specific period is affected by that from the preceding period.

## 5. CONCLUSIONS

This study tests two hypotheses – first, that homicide rates reduce as GDP increases (the economic hypothesis) but the opposite effect may occur as GDP increases in contexts of income inequality (the social structure hypothesis), consequently; second, that there is an interaction effect between GDP and income inequality on the homicide rate, whereby the effect of GDP on homicide rates is conditioned and varies across levels of income inequality.

Regarding the first hypothesis, the relationship between GDP and homicide rates (a proxy for lethal violence) is found to be non-linear. This finding implies that the effect of economic expansion on lethal crimes depends on the pre-existing economic conditions.

Specifically, an increase in GDP reduces homicide rates in the context of pre-existing low GDP, whereas the opposite is observed in contexts of pre-existing high level of GDP.

The group of OECD member countries where an inverse association is found between homicide rates and GDP are namely, Iceland, Estonia, Latvia, Lithuania, Slovenia, Luxembourg, Slovak Republic, Hungary, New Zealand, Czech Republic, Chile, Portugal, Ireland, Greece, Finland, and Israel. And the group of country where a direct association is found are Denmark, Norway, Austria, Poland, Belgium, Sweden, Switzerland, Turkey, Netherlands, Mexico, Canada, Italy, France, United Kingdom, Germany, Japan, and the United States. In other words, economic growth results in the reduction of lethal violence in the first group but results in the opposite in the second group.

Regarding the second hypothesis, it is found that the increase caused by a unit increase in income inequality is about twice the reduction caused by a unit increase in GDP. Besides, income inequality does not only increase homicide rates but also conditions the effect of GDP on homicide rates. Specifically, GDP growth is most efficient in reducing crime in contexts of high inequality since there is room for more improvements. Therefore, the public safety of countries with high inequality will benefit more from economic growth compared to those with low inequality. These results imply that the reduction policies or social programs designed to reduce income inequality go a long way in reducing lethal crimes against persons, especially in the context of high inequality.

The result of government expenditure on policing, courts, prisons, the justice system, etc. in a specific period expressively reduces homicide rates in the subsequent period. A fair balance between the investment in law enforcement and inequality reduction programs or policies appears to be a promising approach towards reducing homicide rates since, on the one hand, the former tackles crime in the short run, and the latter amends the social flaws that lead to crime in the long run.

Many European countries have adopted stricter policies towards the sales of alcoholic beverages and the use of other psychoactive substances in order to reduce crimes. Nonetheless, this continues to be a determinant factor of homicide rates. The studies reviewed here suggest that more efforts could be made in this direction focusing on specific seasons of the year and regions.

Given the dual effect of GDP on homicide studies pointed out in this study, it is suggested that future studies consider estimating a separate models for the two group of countries identified in this studies based on the sign of the effect of GDP on homicide rate to better understand the mechanisms behind the rates of lethal crimes. Moreover, the non-linear effect of income inequality on homicide rates signalized in the empirical analysis is beyond the scope of this study and should be further investigated.

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**REFERENCES**


ARELLANO, M. and BOND, S.. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies*, 58, 277–297. 1991

ARELLANO, M. and BOVER, O.. Another look at the instrumental variable estimation of erro-components model. *Journal of Econometrics*, 68, 29-51. 1995.

BARATA, R. B., de Almeida, M. C. S., da Silva, M. B. L., and de MORAES, J. C.. Intra-urban differentials in death rates from homicide in the city of São Paulo, Brazil, 1988–1994. *Social Science & Medicine*, *47*(1), 19–23. 1998.

BECCARIA, C.. On crimes and punishments. *Criminology Theory: Selected Classic Readings*, 367. 1794.

BECKER, G. S.. Crime and Punishment: An Economic Approach. *The Journal of Political Economy*, *76*(2), 169-217.Blundell, R. and Bond, S. (1998). Inertial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87, 115–143. 1968.

BLUNDELL, R., and BOND, S.. Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, *87*(1), 115-143. 1998.

BRAND, S., and PRICE, R.. The economic and social costs of crime.Economics and Resource Analysis Research, Development and Statistics Directorate, n. 217. 2000.

BURRASTON, B., J.C. Mc Cutcheon, and S.J. Watts. Relative and absolute deprivation's relationship with violent crime in the United States: Testing an interaction effect between income inequality and disadvantage. *Crime & Delinquency, 64* (4), 542–560. 2018.

CANACHE, D.. Looking out my back door: The neighborhood context and perceptions of relative deprivation. *Political Research Quarterly*, *49*(3), 547-571. 1996.

CAMERON, A. C. and TRIVEDI, P. K.. *Microeconometrics using stata*, volume 2. Stata Press College Station, TX. 2010.

CECCATO, V.. Does Poverty Cause Violence?. *The Wiley Handbook of Violence and Aggression*, p1-13. 2017.

CERQUEIRA, D. R. C. et al. Atlas da violência 2019. Instituto de Pesquisa Econômica Aplicada (IPEA) e Fórum Brasileiro de Segurança Pública (FBSP).2019.

DANZIGER, S., and WHEELER, D.. The economics of crime: Punishment or income redistribution. *Review of social economy*, *33*(2), 113-131. 1975.

DETOTTO, C. and OTRANTO, E.. Does crime affect economic growth? *Kyklos*, *63*(3), 330–345. 2010.

DETOTTO, C. and OTRANTO, E.. Cycles in crime and economy: leading, lagging and coincident behaviors. *Journal of Quantitative Criminology*, *28*(2), 295–317. 2012.

ENAMORADO, T., López-Calva, L. F., and Rodríguez-Castelán, C.. Crime and growth convergence: Evidence from Mexico. *Economics Letters*, *125*(1), 9–13. 2014.

FAJNZYLBER, P., Lederman, D., and LOAYZA, N.. What causes violent crime? *European Economic Review*, *46*(7), 1323–1357. 2002

GOULAS, E. and ZERVOYIANNI, A.. Economic growth and crime: does uncertainty matter? *Applied Economics Letters*, *20*(5), 420–427. 2013.

GOULAS, E. and ZERVOYIANNI, A.. Economic growth and crime: Is there an asymmetric relationship? *Economic Modelling*, *49*, 286–295. 2015.

HEMLEY, D. D. and MCPHETERS, L. R.. Crime as an externality of economic growth: an empirical analysis. *The American Economist*, *19*(1), 45–47. 1975.

JUSTUS, M., de Castro Cerqueira, D. R., Kahn, T., and MOREIRA, G. C.. The "São Paulo Mystery": The role of the criminal organization PCC in reducing the homicide in 2000s. *EconomiA*, *19*(2), 201–218. 2018.

LEE, B. X., Marotta, P. L., Blay-Tofey, M., Wang, W., and de BOURMONT, S.. Economic correlates of violent death rates in forty countries, 1962–2008: a cross-typological analysis. Aggression and violent behavior, 19(6), 729-737. 2014.

MAYHEW, P.. Counting the costs of crime in Australia. *Trends & issues in crime and criminal justice*,no. 247. Canberra: Australian Institute of Criminology. 2003.

MERTON, R. K.. Social structure and anomie. *American sociological review 3* (5), 672–682. 1938.

MESSNER, S.F. and K. Tardiff . Economic inequality and levels of homicide: Ananalysis of urban neighborhoods. *Criminology 24* (2), 297–316. 1986.

NARDI, B., ARIMATEA, E., GIUNTO, P., LUCARELLI1, C., NOCELLA, S. and BELLANTUONO, C.. Not Employed in Education or Training (NEET) adolescents with unlawful behaviour: an observational study. *Journal of Psychopathology*, *19*(1), 42-48. 2013.

NEANIDIS, K. C. and PAPADOPOULOU, V.. Crime, fertility, and economic growth: Theory and evidence. *Journal of Economic Behavior & Organization*, 91, 101–121. 2013.

PARKER, R. N.. Aggregation, ratio variables, and measurement problems in criminological research. *Journal of Quantitative Criminology*, *1*(3), 269-280. 1985.

PRIDEMORE, W. A.. Poverty matters: A reassessment of the inequality–homicide relationship in cross-national studies. *The British Journal of Criminology 51* (5), 739–772. 2011.

ROSSOW, I.. Alcohol and homicide: a cross-cultural comparison of the relationship in 14 European countries. *Addiction*, *96*(1s1), 77-92. 2001.

SHAW, J., HUNT, I. M., FLYNN, S., AMOS, T., MEEHAN, J., ROBINSON, J., BICKLEY, H., PARSONS, R., MCCANN, K., BURNS, T., KAPUR, N.ma and APPLEBY, L. & KAPUR, N.. The role of alcohol and drugs in homicides in England and

Wales. *Addiction*, *101*(8), 1117-1124. 2006.

SHAW, C. R., and MCKAY, H. D.. Juvenile delinquency and urban areas. Chicago, IL, US: University of Chicago Press. 1942.

SULLIVAN, R. F.. The Economics of Crime: An Introduction to the Literature. *Crime & Delinquency*, *19*(2):138-149. 1973.

TORRES-PRECIADO, V. H., POLANCO-GAYTÁN, M., and TINOCO-ZERMENÕ, M. A.. Crime and regional economic growth in Mexico: A spatial perspective. *Papers in Regional Science*, *96*(3), 477-494. 2015.

VALDEZ, A., Kaplan, C. D., and CURTIS Jr, R. L.. Aggressive crime, alcohol and drug use, and concentrated poverty in 24 US urban areas. *The American journal of drug and alcohol abuse*, *33*(4), 595-603. 2007.

YEARWOOD, D. L. and KOINIS, G.. Revisiting property crime and economic conditions: An exploratory study to identify predictive indicators beyond unemployment rates. *The Social Science Journal*, *48*(1), 145–158. 2011.

**Table 4: The empirical specifications and result for homicide rates (with robust standard errors)**

| | GMM-SYS I | GMM-SYS II | GMM-SYS III |
|---|---|---|---|
| $Intercept$ | $16.11^{**}$ | $18.13^{**}$ | 9.928 |
| | (7.856) | (9.192) | (6.915) |
| $\boldsymbol{Homicide_{t-1}}$ | $0.532^{***}$ | $0.532^{***}$ | $0.459^{***}$ |
| | (0.151) | (0.148) | (0.133) |
| **Interest variables** | | | |
| $\log(GDP)$ | $-2.830^{**}$ | $-3.187^{**}$ | $-3.163^{***}$ |
| | (1.285) | (1.526) | (1.209) |
| $\log(GDP)^2$ | $0.109^{**}$ | $0.125^{**}$ | $0.189^{***}$ |
| | $-2.830^{**}$ | $-3.187^{**}$ | $-3.163^{***}$ |
| $GINI$ | 4.982 | $5.268^{*}$ | $66.34^{***}$ |
| | (4.228) | (3.263) | (20.520) |
| $GINI \times \log(GDP)$ | | | $-5.390^{***}$ |
| | | | (1.730) |
| **Control variables** | | | |
| $alcohol$ | 0.0764 | 0.0896 | 0.0421 |
| | (0.062) | (0.077) | (0.064) |
| $NEET$ | -0.0118 | -0.0139 | -0.00734 |
| | (0.015) | (0.016) | (0.014) |
| $pubsafety$ | $38.71^{*}$ | $43.27^{**}$ | $43.65^{**}$ |
| | (23.363) | (21.695) | (22.226) |
| $pubsafety_{t-1}$ | -21.51 | -22.56 | -23.95 |
| | (19.349) | (18.697) | (19.109) |
| Continent-fixed effects | No | Yes | Yes |
| Time-fixed effects | No | Yes | Yes |

Note: GMM-SYS I is the base model with control for the endogeneity of GDP and governmental expenditure on public safety and its lagged effect, and control for binaries for continents; GMM-SYS II includes time shock controls to model GMM-SYS I; GMM-SYS III adds the control for the interaction between GDP and GINI; the number of observations for the four models is 205; ***, ** and * denote significance at 1%, 5%, and 10%, respectively.

**Table 5: The literature review on the association between economic growth and crime**

| Author | Objective | Data and Methodology | Conclusions |
|---|---|---|---|
| Hemley and McPheters (1975) | Examine the empirical relationship between crime rate and various measures of economic production and income | OLS, using 1933 -1970 data from the U. S. Department of Justice | Increasing levels of production and income may also generate levels of criminal activity which strain the the ability of society to cope with and deter them. |
| Fajnzylber et al. (2002) | Analyze the determinants of national crime rates both across countries and over time | GMM estimators, using 1970-1994 cross-national panel data | There is a negative effect of GNP growth rate on the rates of intentional homicide and robbery. |
| Detotto and Otranto (2010) | Study the impact of crime on economic performance in Italy | Step-wise regression, using 1977-2007 United States data | Crime acts are like a tax on the entire economy: it discourages domestic and foreign direct investments, reduces the competitiveness of firms, and reallocates resources, creating uncertainty, and inefficiency. |
| Yearwood and Koinis (2011) | Analyze the puzzling links between unemployment and crime rates. Specifically about the effect of crime on economic growth | Theoretical modeling and simulations | An increase in the crime rate among the unemployed has a negative influence on the unemployment rate and growth rate. Nonetheless, an increase in the crime rate among employed workers might help to improve unemployment and promote economic growth. |
| Detotto and Otranto (2010) | Detect some comovements between the business cycle and the cyclical component of some typologies of crime, which could evidence some relationships between these variables | Nonparametric version of dynamic factor model, using 1991-2004 monthly data from Italy National Statistical Institute | A rise in economic performance is associated with a decrease in the total crime rate. |
| Goulas and Zervoyianni (2013) | Explore how the crime-uncertainty interaction impacts on economic growth. | System-GMM, using panel data of 25 countries over the period 1991-2007 | Findings indicate that higher-than-average macroeconomic uncertainty enhances the adverse impact of crime on growth |
| Neanidis and Papadopoulou (2013) | Study the link between crime and fertility and the way by which they jointly impact on economic growth | GMM-difference, using 1970–2008 Cross-national data | There is a negative effect of crime on output Growth |
| Enamorado et al. (2014) | Study the effect of drug-related and non-drug-related crimes on income-growth | OLS and 2SLS estimators, using Mexico's cross-municipality data for the years 2005 and 2010. | Evidence was only found concerning the negative effect of drug-related crimes on income-growth |
| Goulas and Zervoyianni (2015) | Examine the relationship between crime and per-capita output growth | System-GMM, using panel data of 26 countries for 1995-2009 | Crime does not seem to be so harmful to growth when economic conditions are sufficiently satisfactory. But crime negatively affects when there is pessimism, low employment and high government spending on public safety. |
| | Examine the effects of crime on regional | Spatial panel data by states | Crime exerts a negative total effect on economic growth |

| | | | |
|---|---|---|---|
| Torres-Preciado et al. (2015) | economic growth in Mexico | using 1997 and 2011 Mexico's data | across Mexican states |

# 6. DISCUSSION

The literature is vast with empirical researches on the causes of crime and violence but this study is unique in that it innovatively and ingeniously explores empirical techniques combined with the skilful mix of theoretical frameworks from diverse fields, and, by consequence, expands the existing literature.

The need for an interdisciplinary approach for the better understanding of the causes of crime, violence and delinquent behaviours has been overtly flagged in criminological studies (McCARTHY, 2002; ELLIS et al., 2010). According to McCarthy (2002), this is because, on one hand, some economic studies on crime have underestimated the potential theoretical contribution of sociological criminology on the topic. On the other hand, some sociological criminology studies focus on culture, values and social structure neglecting the theoretical frameworks of the rational approach. In line with the suggestion of this author, this study significantly explores the essence of both approaches and, therefore, identifying how the effect of determinant of crime and violence varies across time, place, and contexts.

Deprivation is agreed to be an important predictor of crimes and deviant behaviours. On one hand, there is the general strain and anomie theories (MERTON, 1982; AGNEW, 1999) that explains this, and, on the other hand there is the economic theory (BECKER, 1968) that also explains this. Nonetheless, the empirical evidence regarding the effect of deprivation (and the appropriate measures) on crime is still in datable in the literature (PRIDEMORE, 2011). This study used innovative proxies to navigate the challenges identified in Pridemore (2011) regarding the mixed results found for the effect of deprivation on crime, and consistent results were found. In specific, this study found that unemployment increases homicide rates and cargo theft. It is also found that income inequality significantly increases homicide rate, and that this effect is more pronounced in developed countries such as OECD member countries where absolute income is high compared to underdeveloped countries such as Brazil where absolute income is lower. In Brazil, the results show that the effect of unemployment dominates that of income inequality.

The temporal dynamics of crime is substantially explored in the first and third essay on homicide rates and cargo theft, respectively, whereby in the first the growth convergence of homicide rate is tested and in the second the temporal dependence of cargo theft is modelled and identified. The convergence approach has been similarly applied by on homicide rates by Justus and Santos-Filho (2011) and the time series modelling has also been used by Justus and Kassouf (2013) to explain homicide rates in São Paulo state. The results from this study shows that the growth of lethal violence follow a temporal pattern that stimulates the convergence of homicide rates to similar levels across the national territory. As to cargo theft, it is found that cargo thefts are autoregressive both in the short and long run, i.e., future cargo thefts can be predicted using the patterns of the present and past ones.

Burratson et al. (2018, 2019) inspired the testing of interactive effects of deprivation measures one homicide rates. This was replicated and largely explored in the second and forth paper of this study, whereby unemployment rate and income inequality were interacted in the second paper on Brazil, and GDP and income inequality were interacted in the fourth paper on OECD member countries. These interactions showed that the effects of absolute and relative deprivation on lethal crime are dependent on one another. Specifically, unemployment aggravates the effect of income inequality on homicide levels, and income inequality accentuates the reduction of homicide rates caused by economic growth.

The study also explores the cross-national context of economic development in the fourth paper by testing the non-linear effect of income and economic growth on lethal violence. This test of such a relationship is inspired by the ambiguity suggested by Danziger and Wheeler (1975) regarding the effect of economic expansion on crimes in the context of inequality, and by the empirical verification of this non-linearity by Hemley and McPheters (1975), although from a different perspective. This study upholds the relationship suggested by these authors and confirms that the relationship between GDP and homicide rate is non-linear (U-shaped), whereby countries with lower GDP experience an inverse relationship between GDP and homicide rate, and those with high GDP experience the opposite direction of effect. This suggests that the contrasting results commonly found in the literature regarding income and crime (PRIDEMORE, 2011) may be indicative of the different stages of the relationship between both.

The empirical results provided in the empirical essays developed in this study expands the literature at large and provide new insights regarding the determinants of crime and lethal violence.

# 7. CONCLUSION

This study provided specific discussions regarding some determinants of crime and violence in four empirical essays. The main lesson drawn from this study is that absolute deprivation as in unemployment and/or low income and relative deprivation as in income inequality are crucial determinants of lethal violence, whereas cargo thefts are mostly determined by geographic opportunities. The comparison of the second and for the essays indicates that the roles of absolute and relative deprivation on lethal crime are similar when comparing Brazil to the OECD member countries. However, the magnitude of the effect of absolute deprivation is more emphasized in the Brazilian context. The four essays of this study also pointed out the importance of space, time, and context on the causes of crime and lethal violence.

The first paper confirmed the hypothesis of the convergence of homicide rates in Brazil due to the changing geography of violence – the South and Southeast regions that had high homicide rate have experienced a reduction or stagnancy in the rate of violence from the year 2000 to 2017, whereas the North and Northeast regions that had low homicide rates have experienced increase growth of violence during the same period. This is further emphasized by the cluster analysis that showed that the major hotspots of lethal violence were located in the South and Southeast in the year 2000 but these hotspots are now located in the North and Northeast regions. The empirical results also showed that unemployment played a significant role in the growth of lethal crime in Brazil from the year 2000 to 2017.

The second paper further confirmed that unemployment and income inequality increase lethal violence, and the effect of the former is more pronounced. More importantly, this study confirmed the hypotheses of the interaction between both deprivation measures, whereby the effect of both is exacerbated when combined, i.e., unemployment potentializes the effect of income inequality and vice versa.

The third paper confirmed and identified the geographic pattern of cargo theft in São Paulo state and concluded that deterrence by policing reduces the number of cargo thefts in the state. There was not enough empirical evidence to consistently conclude regarding the effect of economic attractiveness and social structure on cargo theft.

The fourth paper upholds the result found in the second essay (on Brazil) regarding the role of absolute deprivation and relative deprivation for the OECD member countries, i.e., low income (GDP) and high income inequality increases lethal violence. Contrary to the finding for Brazil, the fourth essay indicates that the effect of income inequality on homicide rate is significantly higher in the OECD member countries compared to the effect of absolute income, i.e., GDP. This essay advanced the second in that it identifies the non-linear effect of GDP on homicide rates, whereby countries with low income experience an inverse relationship between GDP and homicide rate, and the opposite direction of effect in high-income countries (hence, the U-shape). Similar to the second essay on Brazil, this fourth essay also confirmed the existence of an interaction effect of income inequality and GDP on homicide rates, whereby the effect of economic growth on homicide rate is more pronounced in the context of high income inequality.

**REFERENCES**

AGNEW, Robert. A general strain theory of community differences in crime rates. *Journal of research in crime and delinquency*, v. 36, n. 2, p. 123-155, 1999.

GUTHRIE, John; TODD, Sarah; ALSTETE, Jeffrey. Inside advice on educating managers for preventing employee theft. *International Journal of Retail & Distribution Management*, v. 34, n. 11, p. 833-844, 2006.

BECKER, Gary. Crime and Punishment: An Economic Approach. *The Journal of Political Economy*, v. 169, p. 176-177, 1968.

BURRASTON, Bert; MCCUTCHEON, James C.; WATTS, Stephen J. Relative and absolute deprivation's relationship with violent crime in the United States: Testing an interaction effect between income inequality and disadvantage. *Crime & Delinquency*, v. 64, n. 4, p. 542-560, 2018.

BURRASTON, Bert et al. Relative deprivation, absolute deprivation, and homicide: testing an interaction between income inequality and disadvantage. *Homicide studies*, v. 23, n. 1, p. 3-19, 2019.

DANZIGER, Sheldon; WHEELER, David. The economics of crime: Punishment or income redistribution. *Review of social economy*, v. 33, n. 2, p. 113-131, 1975.

ELLIS, Lee; HARTLEY, Richard D.; WALSH, Anthony. *Research methods in criminal justice and criminology: An interdisciplinary approach*. Rowman & Littlefield Publishers, 2009.

FAJNZYLBER, Pablo; ARAUJO JR, Ari. Violência e criminalidade. In: LISBOA, M. de B; MENEZES FILHO, N. A [orgs]. *Microeconomia e sociedade no Brasil*. Rio de Janeiro: Contra Capa - FGV/EPGE, p. 333-394, 2001.

HEMLEY, David D.; MCPHETERS, Lee R. Crime as an externality of economic growth: an empirical analysis. *The American Economist*, v. 19, n. 1, p. 45-47, 1975.

CERQUEIRA, Daniel Ricardo de Castro et al. *Atlas da violência* 2018. Instituto de Pesquisa Econômica Aplicada (IPEA) e Fórum Brasileiro de Segurança Pública (FBSP), 2018.

CERQUEIRA, Daniel Ricardo de Castro et al. Atlas da violência 2019. Instituto de Pesquisa Econômica Aplicada (IPEA) e Fórum Brasileiro de Segurança Pública (FBSP). 2019.

JUSTUS, Marcelo; KASSOUF, Ana Lucia. A cointegration analysis of crime, economic activity, and police performance in São Paulo city. *Journal of applied statistics*, v. 40, n. 10, p. 2087-2109, 2013.

JUSTUS, Justus; DOS SANTOS FILHO, Jonas Irineu. Convergência das taxas de crimes no território brasileiro. *Revista EconomiA*, v. 12, n. 1, p. 131-147, 2011.

JUSTUS, Marcelo et al. The "São Paulo Mystery": The role of the criminal organization PCC in reducing the homicide in 2000s**.** *EconomiA*, v. 19, n. 2, p. 201-218, 2018.

MESSNER, Steven F. Poverty, inequality, and the urban homicide rate: Some unexpected findings. *Criminology,* v. 20, n. 1, p. 103-114, 1982.

MCCARTHY, Bill. New economics of sociological criminology. *Annual Review of Sociology*, v. 28, n. 1, p. 417-442, 2002.

PRIDEMORE, William Alex. Poverty matters: A reassessment of the inequality–homicide relationship in cross-national studies. *The British Journal of Criminology*, v. 51, n. 5, p. 739-772, 2011.