The crime rate and income inequality in Brazil: a nonlinear ARDL approach

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Abstract: This paper explores the relationship between the crime rate and income inequality for Brazil using a nonlinear autoregressive distributed lag (NARDL) model. Our result suggests that the crime rate and income inequality are significantly cointegrated. Besides, the NARDL model affirms the presence of asymmetric behaviour between the crime rate and income inequality. More specifically, in the long run, reduced income inequality will lead to a decrease in the crime rate with a greater deviation, whereas an increase in income inequality tends to lead to an increase in the crime rate with a lower deviation. Therefore, the crime rate responds more to negative changes than to positive changes in the level of income inequality.

Keywords: crime rate; income inequality; nonlinear autoregressive distributed lag; NARDL.

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1 Introduction

The general strain theory states that noxious stimuli could promote aggression as a way to escape or avoid negative stimuli, terminate negative stimuli or seek revenge against negative stimuli (Agnew, 1992). The theory, thus, suggests that there is a possible correlation between income inequality and the crime rate, as a way to seek revenge against negative stimuli. Besides, crime and violence are developmental issues for most nations. High rates of crime and violence have both short and long-term effects on human welfare, economic growth and social development (UNODC, 2007). Many researchers in the fields of criminology and economics have suggested that income distribution disparities can incite criminal activity (Kelly, 2000; Brush, 2007; Enamorado et al., 2016).

As indicated by the World Health Organization's database on the mortality rate (WHO, 2018), Brazil has recorded high rates of mortality caused by assaults. A rate of 26.6 (per 100,000 inhabitants) was recorded in Brazil for 2015, placing Brazil in the top 5 countries for mortalities caused by assault. Based on the latest report by the United Nations Office on Drugs and Crime (UNODC) (2019), Brazil has the highest total number of murders in any country. The murder rate in Brazil in 2018 and 2017 was reported at 29.2 and 24.7 of murders per year, per 100,000 of the population, respectively. On the other hand, Brazil's income inequality level is the second-highest (after Columbia) in the South American region (World Bank, 2018). As reported by Oxfam (2019), although the Brazilian government has lifted approximately 28 million people out of poverty in the last 15 years, the rich in Brazil have remained dominant and benefit the most, where the wealthiest 10% accounted for 61% of economic growth between 2001 and 2015.

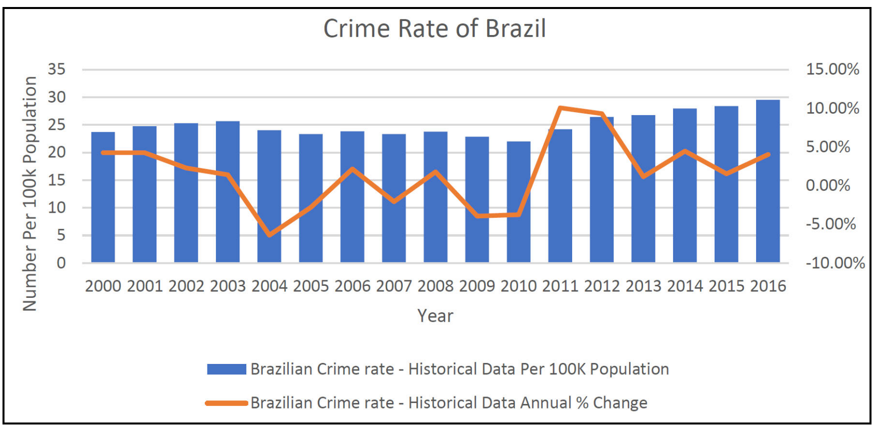
Additionally, although the level of income inequality fluctuates across time, most of the existing literature has assumed that the relationship between income inequality and the crime rate is symmetrical. We argue that if income inequality does indeed lead to the development of negative stimuli in individuals which promotes aggression, then, the magnitude of the increase in negative stimuli, due to the increase in income inequality, may not be the same as the reduction in negative stimuli resulting from the improve distribution parities. Based on a clinical report by a group of neurologists (Schuyler et al., 2014), amygdala, which are a set of neurons located in the brain, tend to recover differently from negative stimuli, rather than from positive stimuli. Thus, the integration between the crime rate and income inequality should not be symmetrical. Based on the significance of the crime rate and the possible asymmetric cointegration standpoints, a study on the asymmetric integration between the crime rate and income inequality in Brazil is required. Therefore, this study adopts the nonlinear autoregressive distributed lag (NARDL) model, proposed by Shin et al. (2014), to highlight the potential long-run asymmetries in the crime rate-income inequality nexus. The remainder of this paper is structured as follows. The next section provides a summary of the crime rate in Brazil, followed by a review of previous literature. Section 3 outlines the methodology; the data and the empirical results are discussed in Section 4. Lastly, Section 5 offers policy implications, concluding remarks and suggestions for further study.

1.1 Background of the study

1.1.1 The crime rate in Brazil

Over the past decade, the crime rate recorded in Brazil has remained significant. Based on the data obtained from the UNODC (2019), the crime rate in Brazil increased by 1.16% in 2013, 4.47% in 2014, 1.53% in 2015 and 4.03% in 2016. Besides, the rate of crime of 29.53 per 100,000 of the population recorded in 2016 was the fifth-highest crime rate per 100,000 of the population attained by any country in the world. From observation, this positive growth in the crime rate commenced in 2010, signifying that a remedy to reduce the crime rate is urgently needed by policymakers.

Figure 1 Crime rate of Brazil (see online version for colours)



2 Literature review

This section summarises previous research which focuses on assessing the impact of income inequality on the crime rate. While a positive correlation between income inequality and the crime rate is well founded, the literature on the asymmetric cointegration of income inequality and the crime rate remains limited.

Doyle et al. (1999), examined the relationship between the role of labour markets, income distribution, and demographics on property crime in the USA. They pointed out that although wages were significantly correlated with both property and violent crime, income inequality was found to be insignificant. Also, Baharom and Habibullah (2009) examined the causality between income inequality and crime in Malaysia from 1973 to 2003 and concluded that income inequality had no meaningful relationship with any of the crime categories selected in their study. Menezes et al. (2013) analysed the correlation between the homicide rate (crime) and income inequality in Brazil from 2008 to 2010. Using a spatial model and OLS regression in their estimations, the authors suggested that the homicide rate increased in areas with higher income inequality.

Also, Kelly (2000) investigated the relationship between income inequality and crime using data from urban counties and concluded that income had no effect on property crime but had a strong and robust impact on violent crime. Utilising Geocoded Uniform Crime Report data from the Indianapolis, USA, police department together with economic and demographic characteristics from the sampled population derived from the American Community Survey for 2005–2009, Stucky et al. (2016) found that lower levels of income and income inequality were associated with a higher number of uniform crime reports regarding violent and property crimes. Lastly, Coccia (2018) highlighted that the intentional homicides (per 100,000 people) could be explained by high levels of income inequality, both in hot tropical areas and in temperate regions of the globe. Where socioeconomic inequality was one of the factors that contributed to the high rates of intentional homicides in society.

Szwarcwald et al. (1999) conducted an ecological study at two geographical levels, namely; municipalities in the state of Rio de Janeiro, Brazil and administrative regions in the municipality of Rio de Janeiro and concluded that higher homicide rates were found in the city, as it had the greatest concentration of slum residents and the highest degree of income inequality. Enamorado et al. (2016) exploited a dataset containing income inequality and crime statistics on more than 2000 Mexican municipalities over 20 years. Their results indicated that a one-point increment in the Gini coefficient between 2007 and 2010 translated into an increase of more than 36% in the number of drug-related homicides per 100,000 inhabitants. Cheong and Wu (2014) examined the impact of intra-provincial regional inequality on crime rates in China. They concluded that the crime rate was positively correlated with intra-provincial regional inequality, thus, suggesting that income inequality is an important determinant of the crime rate in China.

Using a simple theoretical model and panel data from seven Columbian cities, from 1986 to 1998, Bourguignon et al. (2003) suggested that the majority of crimes in Columbian cities were committed by individuals whose income per capita was below 80% of the mean of the population. Hojman (2002) examined the role of income inequality and unemployment on the crime rate in Buenos Aires, Argentina, from 1985 to 1997. Utilising multiple regression analysis techniques, the author concluded that income inequality helped to explain changes in the crime rate. However, unemployment was not a significant determinant of the crime rate. In Sao Paolo, Brazil, income inequality had a positive effect on pecuniary crime (Scorzafave and Soares, 2009). As highlighted in their empirical results, a percentage point change in income inequality was likely to increase the pecuniary crime rate of Sao Paolo by 1.46%, hence, suggesting that a more effective legal system was needed.

3 Methodology

The empirical objective of this study is to investigate the impact of income inequality on Brazil's crime rate through the asymmetric cointegration approach, as suggested by Shin et al. (2014). This approach uses the nonlinear autoregressive distributed lag (NARDL) approach to capture the long-run asymmetry between income inequality and the crime rate, where the income inequality variable is decomposed into two partial sum processes, cumulating in positive changes and negative changes. Besides, from the existing literature, the urban population growth rate and economic growth [proxied by the real gross domestic product per capita (RGDPC)] are often associated with the crime rate (Lobonţ et al., 2017; Hayman and Brack, 2002), hence, both the urban population growth rate and the RGDPC are included as control variables in the following model.

The asymmetric long-run equation of the crime rate is as follows:

$$CR_t = \alpha_0 + \alpha_1 IE_t^+ + \alpha_2 IE_t^- + \alpha_3 UBR_t + \alpha_4 RGDPC_t + \varepsilon_t \tag{1}$$

where *CR* is the crime rate, *IE* is income inequality, *UBR* is the urban population growth rate, and *RGDPC* represents the real gross domestic product per capita. α_0, α_1, α_2, α_3, α_4 are the vectors of the long-run parameters to be estimated. Whereas IE_t^+ and IE_t^- are the partial sums of the positive and negative changes in IE,

$$IE_t^+ = \sum\nolimits_{i=1}^{t} \Delta IE_t^+ = \sum\nolimits_{i=1}^{t} \max\left(\Delta IE_i, 0\right) \tag{2}$$

and

$$IE_t^- = \sum\nolimits_{i=1}^{t} \Delta IE_t^- = \sum\nolimits_{i=1}^{t} \max\left(\Delta IE_i, 0\right) \tag{3}$$

where

$$IE_t = IE_0 + IE_t^- + IE_t^-$$

Based on equation (1), the long-run association between the crime rate and income inequality is captured by α_1 and α_2. Where α_1 highlights the long-run relationship between the crime rate and the rising income inequality level and α_2 the relationship between the crime rate and the subsiding income inequality level. Equation (4) indicates that the current value of the income inequality level (IE) variable is given by the sum of its initial value together with the positive and negative partial sums.

In the empirical implementation, we frame the long-run equation, equation (1) in an autoregressive distributed lag (ARDL) setting, as proposed by Shin et al. (2014), as follows:

$$\begin{aligned}\Delta CR_t = {} & \beta_0 + \beta_1 CR_{t-1} + \beta_2 IE_{t-1}^+ + \beta_3 IE_{t-1}^- + \beta_4 UBR_{t-1} + \beta_5 RGDPC_{t-1} \\ & + \sum\nolimits_{i=1}^{p} \varphi_i \Delta CR_{t-i} + \sum\nolimits_{i=0}^{q} \left(\theta_i^+ IE_{t-i}^+ + \theta_i^- IE_{t-i}^-\right) + \sum\nolimits_{i=0}^{r} \gamma_i \Delta UBR_{t-i} \\ & + \sum\nolimits_{i=0}^{p} \delta_i \Delta RGDPC_{t-i}\end{aligned} \tag{5}$$

p, *q*, *r* and s are the respective lag orders. The long-run parameters in equation (1) are derivable from (5), i.e., $-\beta_2/\beta_1 = \alpha_1$ and $-\beta_3/\beta_1 = \alpha_2$. Besides, $\sum\nolimits_{i=0}^{q} \theta_i^+$ measures the short-run influences of income inequality increases, while $\sum\nolimits_{i=0}^{q} \theta_i^-$ examines the short-run influences of income inequality reductions on the crime rate.

The implementation of the nonlinear ARDL analysis applied the following steps. First, the augmented Dickey-Fuller (ADF) and Philips-Perron (PP) unit root tests are carried out to test and verify that all of the variables are either I(0) or I(1). Similarly, to the ARDL error correction model, proposed by Pesaran et al. (2001), the NARDL model does not allow I(2) variables, where the presence of I(2) variables will cause the computed F-statistics for the cointegration test to be invalid. Secondly, Equation (5) is estimated using the standard Ordinary Least Squares (OLS) estimation method and is followed by the nonlinear error correction model under the NARDL model using a two-step least squares estimation to obtain the optimum lags of the NARDL model. Subsequently, we utilise the bounds testing approach to identify the presence of cointegrating variables, as suggested by Pesaran et al. (2001) and Shin et al. (2014). Next, we apply the Wald test, under the restriction $-\beta_2/\beta_1 = -\beta_3/\beta_1$ to examine the presence of long-run asymmetric cointegration between income inequality and the crime rate. Finally, we check the robustness of the estimation with serial correlation and stability diagnostic tests.

3.1 The data

Annual data ranging from 1979 to 2015 are employed in the analysis. All of the variables are expressed in natural logarithms. The assault mortality rate (CR) is used to represent the crime rate and the data are taken from the WHO mortality rate database. Income inequality (IE) data are taken from the Standardized World Income Inequality Database (SWIID). The urban population growth rate (UBR) data is taken from the World Development Indicators (WDI). The real gross domestic product per capita is utilised to reflect economic growth and the data is also taken from the WDI.

4 Results and discussion

Similarly to the ARDL error correction model, proposed by Pesaran et al. (2001), the NARDL model does not allow I(2) variables. Hence, we employed both the ADF and PP unit root tests on each of the time-series data to confirm that no I(2) variables are involved in the analysis. The results of the tests are shown in Table 1. As displayed in Table 1, both the ADF and PP unit root tests are in agreement that all of the variables are integrated at order 0 (I(0)), or order 1 (I(1)). Hence, the absence of I(2) variables, allows us to proceed to perform the NARDL model estimation.

Table 1 ADF and PP unit root tests

Variable	*Level*		*First Difference*	
	ADF	*PP*	*ADF*	*PP*
Crime rate (CR)	–3.3719**	–4.8561***	–5.7796***	–6.0145***
Income inequality (IE)	–0.8546	–0.8725	–3.1507**	–3.5923***
UBR	–4.3686***	–3.2925***	–3.0371***	–3.0095***
RGDPC	–0.2961	–0.2775	–5.3887***	–5.4318***

Notes: UBR represents the urban population growth rate, and RGDPC represents the real gross domestic product per capita. The constant and trend terms are included in the test equation, and the SIC is utilised for the optimal lag order in the ADF test equation. ***, ** and * denote the significance at the 1%, 5% and 10% levels.

The cointegration test on the income inequality-crime rate nexus was performed by regressing equation (5) with the OLS estimation method and the nonlinear error correction model (ECM) under the NARDL model through the two-step least squares method to arrive at the model's final specification. The maximum lag order considered is 4. Table 2 reports the results of the model specification and Table 3 highlights the comparison between the F-statistic of the joint null hypothesis of level variables with the critical values of Narayan (2005) for observations less than 100. From the results presented in Table 3, the F-Statistic is 4.587 which is greater than the critical upper bound value at the 5% significance level, thus, rejecting the null of non-cointegration in the long run.

Table 2 Nonlinear ADRL estimation results

Independent variable	*Income inequality*	
	Coefficient	*P-value*
Intercept	–36.3111***	0.0027
CR(–1)	–1.3635***	0.0040
IE_POS(–1)	3.4340*	0.0590
IE_NEG(–1)	12.9385***	0.0047
UBR(–1)	–1.1586**	0.0231
RGDPC(–1)	4.4969***	0.0023
ΔCR(–1)	0.7290*	0.0796
ΔIE-POS	–6.6267	0.5414
ΔIE_POS(–1)	3.5732	0.6963
ΔIE_POS(–2)	–20.1053**	0.0144
ΔIE_NEG	9.7034**	0.0120
ΔIE_NEG(–1)	–3.4627	0.2992
ΔIE_NEG(–2)	–0.4112	0.9279
ΔIE_NEG(–3)	11.2863**	0.0469
ΔUBR	–0.4799*	0.0557
ΔUBR(–1)	0.5309	0.1211
ΔUBR(–2)	–0.3092	0.2903
ΔUBR(–3)	0.4829*	0.0993
ΔRGDPC	1.9633***	0.0015
ΔRGDPC(–1)	–2.6755***	0.0093
ΔRGDPC(–2)	–1.3846*	0.0932
ΔRGDPC(–3)	–1.8021***	0.0099

Notes: CR refers to the crime rate, where IE represents income inequality. UBR represents the urban population growth rate, and RGDPC refers to the real GDP per capita. *, ** and *** denote the significance at the 10%, 5% and 1% levels.

Table 3 Asymmetric cointegration test

	F-statistic	*95% lower bound*	*95% upper bound*	*Conclusion*
Brazil	4.587	3.058	4.223	Cointegration

Note: The critical values are from Narayan (2005) critical value case III.

The results presented in Table 2 are not the long-run coefficients, to obtain the long-run coefficients; we divided the negative coefficient of each of the explanatory variables by the coefficient of the CR (-1). For instance, the long-run coefficient of IE_POS (–1) is –3.4340/–1.3635 ($-\beta_2/\beta_1 = \alpha_1$) = 2.5186 and the long-run coefficient of IE_NEG (–1) is –12.9386/–1.3635 ($-\beta_3/\beta_1 = \alpha_2$) = 9.4895. Hence, the long-run cointegrating equation can be written as follows:

Long-run equation:

$$\begin{aligned}\text{Crime rate} = {} & -26.6317 + 2.5186\,\text{IE\_POS} + 9.4895\,\text{IE\_NEG} - 0.8498\,\text{UBR} \\ & + 3.2982\,\text{RGDPC}\end{aligned} \tag{6}$$

Both positive and negative changes in income inequality have long-run positive effects on the crime rate. Equation (6) indicates that a 1% increase in the rate of income inequality leads to a 2.5186% increase in the crime rate (positive relation), and a 1% decrease in the rate of income inequality leads to a 9.4895% decrease in the crime rate (positive relation as well). Therefore, Brazil's crime rate responds more to negative changes rather than to positive changes in the level of income inequality. Additionally, the urban population growth rate tends to decrease the crime rate, while the real GDP per capita is positively associated with Brazil's crime rate. This suggests that urbanisation is one remedy to combat the crime rate in Brazil. Where better job opportunities and security in urban areas act to discourage crime. Surprisingly, the real GDP per capita is positively associated with the crime rate, suggesting that economic growth does not have a mediating impact on Brazil's crime rate.

Table 4 reports the long-run asymmetry of the positive and negative changes in income inequality. The null hypothesis of income equality is rejected, as the p-value is less than 0.05, which indicates that there is an asymmetry in the long-run impact of income inequality on the crime rate of Brazil. The asymmetric long-run impact of income inequality on Brazil's crime rate can also be observed from the NARDL Multiplier Graph (Figure 2).

Table 4 Long-run asymmetry test

Wald test equation	*Value*	*P-value*
F-statistic	8.424***	0.0158

Note: *** denotes the significance at the 5% level.

Lastly, Table 5 reports the Bruesch-Godfrey serial correlation LM statistics for serial correlation up to lag 2. Besides, in Figure 3, we also graph the CUSUM and CUSUMSQ statistics for testing the structural stability of the model. The estimation results obtained passed all of the diagnostic tests, thus, suggesting that there was no serial correlation and that the parameters were stable.

Table 5 Bruesch-Godfrey serial correlation LM Test (lag (2))

	Value	*P-value*
F-statistic	0.5930	0.5732

Figure 2 NARDL multiplier (see online version for colours)

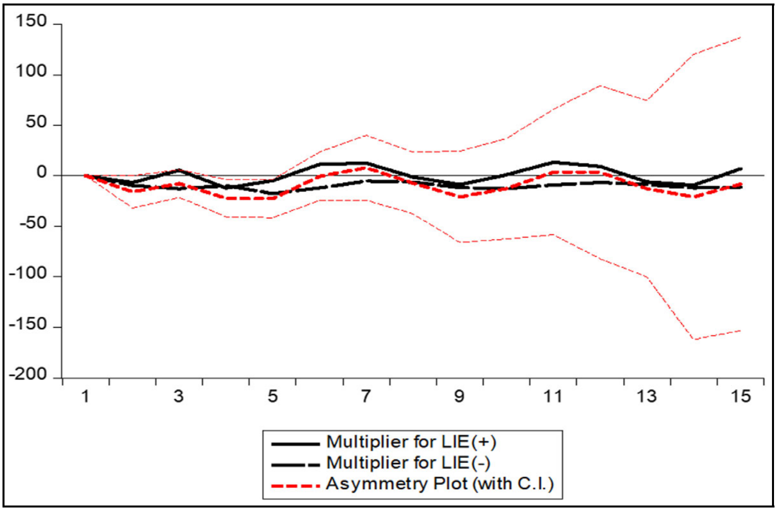
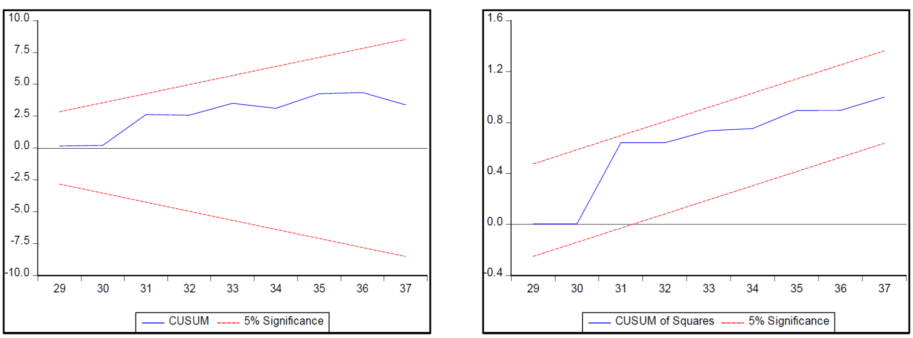


Figure 3 Cusum and cusum of square (see online version for colours)



5 Conclusions

Recognising that variations in the level of income inequality may impact the crime rate, this paper adopts a nonlinear ARDL model, as proposed by Shin et al. (2014), to investigate the presence of asymmetric cointegration between the crime rate and income inequality in Brazil. From the results of the analysis, we find that there is asymmetric behaviour between the crime rate and income inequality. More specifically, in the long run, an increase in income inequality tends to lead to an increase in the crime rate with a lesser deviation, while an income inequality reduction will lead to a decrease in the crime rate with a higher deviation. Therefore, the crime rate responds more to negative changes than to positive changes.

The evidence of the response of the crime rate to changes in income inequality in Brazil indicates that income inequality is an important determinant of the crime rate in Brazil. Besides, the crime rate responds more to negative changes in income inequality indicating that the speed of adjustment to income inequality decreases is faster. The first policy implication of our findings is that a reduction in income inequality is a remedy to combat Brazil's crime rate. Thus, policymakers should consider reforming the existing tax brackets in Brazil, where an increase in the tax rate for the top income earning group should be uplifted from the existing rate of 27.5%. For instance, the World Bank suggested to the government of Malaysia recently that the income tax rate for the top income earning group should be increased to 35% from the existing rate of 28% (The Star, 2019). Thus, a revision of the progressive income tax rate is expected to reduce the income gap and, thus, discourage crime.

Additionally, policymakers should adopt hot-spot or focused crime deterrence policies. Such policies include; deploying more enforcement officers to crime hot-spot areas (concentrated crime zones) to reduce the crime rate, retraining enforcement officers and increasing the involvement of the community. Existing empirical studies have highlighted that focused deterrence policies generate noteworthy reductions in violent crime, and should be adopted by policymakers to reduce the crime rate (Braga, 2017). Lastly, policymakers should also consider ways to keep children in schools or to reduce the school dropout rate. Waibei (2011), in her study, concluded that, in Mississippi, USA, a 10% increase in the graduation-rate could prevent 45 murders and 870 aggravated assaults each year. Additionally, raising the male graduation rate by 10% would save Mississippi $133 million in crime-related costs each year, and those graduates would also earn $52 million more each year.

This study identifies the significant impact of income inequality on the crime rate. However, as the determinants of the crime rate are not confined solely to the level of income inequality, perhaps future research could attempt to identify other key indicators that are drivers of the crime rate. Additionally, due to the process of modernisation and our increasing reliance on technology, cyber crimes have become a serious issue for enforcement officers to deal with. Hence, it is recommended that future research prioritises on the investigation of the causes and consequences of digital crimes.

References

Agnew, R. (1992) 'Foundation for a general strain theory of crime and delinquency', *Criminology*, Vol. 30, No. 1, pp.47–87.

Baharom, A.H. and Habibullah, M.S. (2009) 'Crime and income inequality: the case of Malaysia', *Journal of Politics and Law*, Vol. 2, No. 1, pp.55–70.

Bourguignon, F., Nunez, J. and Sanchez, F. (2003) 'A structural model of crime and inequality in Columbia', *Journal of the European Economic Association*, Vol. 1, Nos. 2–3, pp.440–449.

Braga, A.A. (2017) 'Focused deterrence and the reduction of gang homicide', *The Handbook of Homicide*, John Wiley & Sons, Inc., pp.643–658, DOI: 10.1002/9781118924501.ch36.

Brush, J. (2007) 'Does income inequality lead to more crime? A comparison of cross-sectional and time-series analyses of United States counties', *Economic Letters*, Vol. 9, No. 2, pp.264–268.

Cheong, T. and Wu, Y. (2014) 'Crime rates and inequality: a study of crime in contemporary China', *Journal of the Asia Pacific Economy*, Vol. 20, No. 2, DOI: 10.1080/13547860.2014.964961.

Coccia, M. (2018) 'Violent crime driven by income inequality between countries', *Turkish Economic Review*, Vol. 5, No. 1, pp.33–55.

Doyle, J.M., Ahmed, E. and Horn, R.N. (1999) 'The effect of labor markets and income inequality on crime: evidence from panel data', *Southern Economic Journal*, Vol. 65, No. 4, pp.717–738.

Enamorado, T., López-Calva, F.T., Rodríguez-Castelán, C. and Winkler, H. (2016) 'Income inequality and violent crime: evidence from Mexico's drug war', *Journal of Development Economics*, Vol. 120, No. C, pp.128–143.

Hayman, G. and Brack, D. (2002) *International Environmental Crime, the Nature and Control of Environment Black Markets*, Sustainable Development Programme, Royal Institute of International Affairs, UK.

Hojman, D.E. (2002) 'Explaining crime in Buenos Aires: the roles of inequality, unemployment and structural change', *Bulletin of Latin American Research*, Vol. 21, No. 1, pp.121–128.

Kelly, M. (2000) 'Inequality and crime', *The Review of Economics and Statistics*, Vol. 82, No. 4, pp.530–539.

Lobonţ, O.R., Nicolescu, A.C., Moldovan, N.C. and Kuloğlu, A. (2017) 'The effect of socioeconomic factors on crime rates in Romania: a macro-level analysis', *Economic Research-Ekonomska Istraživanja*, Vol. 30, No. 1, pp.91–111, DOI: 10.1080/1331677X.2017.1305790.

Menezes, T.A.D., Neto, R.S., Monteiro, C. and Ratton, J.L. (2013) 'Spatial correlation between homicide rates and inequality: evidence from urban neighborhoods', *Economics Letter*, Vol. 120, No. 1, pp.97–99.

Narayan, P.K. (2005) 'The saving and investment nexus for China: evidence from cointegration tests', *Applied Economics*, Vol. 37, No. 17, pp.1979–1990.

Oxfam (2019) *Fight Inequality, Beat Poverty* [online] https://www.oxfam.org/en/take-action/campaigns/fight-inequality-beat-poverty (accessed 4 January 2020).

Pesaran, M.H., Shin, Y. and Smith, R.J. (2001) 'Bounds testing approaches to the analysis of level relationships', *Journal of Applied Econometrics*, Vol. 16, pp.289–326.

Schuyler, B.S., Kral, T.R.A., Jacquart, J., Burghy, C.A., Weng, H.Y., Perlman, D.M., Bachhuber, D.R.W., Rosenkranz, M.A., MacCoon, D.G, Reekum, C.M.V., Lutz, A. and Davidson, R.J. (2014) 'Temporal dynamics of emotional responding: amygdala recovery predicts emotional traits', *Social Cognitive Affect Neuroscience*, Vol. 9, No. 2, pp.176–181.

Scorzafave, L.G. and Soares, M.K. (2009) 'Income inequality and pecuniary crimes', *Economics Letters*, Vol. 104, No. 1, pp.40–42.

Shin, Y., Yu, B. and Greenwood-Nimmo, M. (2014) 'Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework', in Sickles, R. and Horrace, W. (Eds.): *Festschrift in Honor of Peter Schmidt*, Springer, New York, NY.

Stucky, T.D., Payton, S.B. and Ottensmann, J.R. (2016) 'Intra- and inter-neighborhood income inequality and crime', *Journal of Crime and Justice*, Vol. 39, No. 3, pp.345–362, DOI: 10.1080/0735648X.2015.1004551.

Szwarcwald, C.L., Bastos, F.I., Viacava, F. and de Andrade, C.L. (1999) 'Income inequality and homicide rates in Rio de Janeiro, Brazil', *Am. J. Public Health*, Vol. 89, No. 6, pp.845–50.

The Star (2019) https://www.thestar.com.my/business/2019/10/14/guan-eng-says-malaysia039s-tax-rate-still-among-the-lowest (accessed 3 January 2020).

United Nations Office on Drugs and Crime (UNODC) (2007) *Crime, Violence, and Development: Trends, Costs, and Policy Options in the Caribbean*, United Nations Office on Drugs and Crime, Vienna, Austria.

United Nations Office on Drugs and Crime (UNODC) (2019) *UN Standards and Norms in Crime Prevention and Criminal Justice*, UNODC.

Waibei, E. (2011) *The Dropout-Crime Connection* [online] https://www.jacksonfreepress.com/news/2011/oct/19/the-dropout-crime-connection/ (accessed 4 January 2019).

WHO (2018) *World Health Statistics*, World Health Organization, Geneva, Switzerland.

World Bank (2018) *Brazil Overview*, World Bank, Washington, DC, USA.