City of God Redux: Inequality, Migration, and Violent Crime in Brazil between 1980 and 2000

Revisitando Cidade de Deus: Desigualdade Salarial, Migrações e Crime Violento no Brasil entre 1980 e 2000

Tiago Freire
tiago@tiagofreire.com
Faculty of Business, Government and Law, University of Canberra

Abstract/ Resumo

There is a long-held belief that inequality is a major determinant of violent crime, particularly homicides. Some previous studies suggest that these results hold in the short term only. This could result from measurement error in income inequality.

This study addresses the issue of measurement error in inequality by using the relationship between migration and inequality. Using rainfall shocks and changes in transport costs as exogenous sources of out-migration from rural areas in Brazil between 1980 and 2000, the study shows how migration from rural areas affects income inequality in urban areas. It finds that not only is there a negative and statistically significant relationship between inequality and crime in Brazil, and that the effects are much larger than previously thought, but also that this relationship holds in the long term.

Keywords: Crime; Inequality; Rural–Urban Migration; Brazil.

JEL Codes: J61, J15, K42, R10

Muitas pessoas acreditam que desigualdade é um determinante do crime violento. Estudos anteriores sugerem que este relação existe apenas no curto prazo. Esta conclusão é o resultado de erros de medição da desigualdade de rendimento.

O presente estudo procura resolver o problema de erros de medição da desigualdade, utilizando a relação entre migração e desigualdade. Utilizando precipitação e alterações nos custos de transporte como choques exogenous e fontes de migração de zonas rurais no Brasil entre 1980 e 2000, este estudo mostra como migração de zonas rurais afecta desigualdade de rendimento em zonas urbanas. Este estudo mostra, não só que existe uma relação negativa e estatisticamente significativa entre desigualdade e crime no Brasil, mas também que esta é uma relação de longo prazo.

Palavras-chave: Crime; Desigualdade; Migração Rura-Urbana; Brasil

Código-JEL: J61, J15, K42, R10

1. INTRODUCTION

According to the World Bank's World Development Indicators for 2013, Brazil had a Gini index of 55, making it the country with the 14th largest income inequality in the world between 1993 and 2012. According to homicide statistics for 2013 from the United Nations Office on Drugs and Crime (UNODC), Brazil had the 27th largest homicide rate in the world in 2013, with 21.8 homicides per 100,000 people, down from 30.2 in 2002. While the relationship between crime—particularly homicides—and inequality has been studied extensively, the results have been mixed; some authors find evidence of a short-term relationship only. This article examines whether there was a long-term relationship between violent crime (i.e., homicides) and inequality in Brazil between 1980 and 2000.

To understand why a relationship exists between homicides and income inequality, violent crime should be viewed as an activity complementary to other crimes with economic motivation (i.e., property or drug-related crime), as proposed by Grogger (2000). Paulo Lins' award-winning book from 1997, *Cidade de Deus* (City of God), on which a movie by the same name is based, provides a good description of the relationship between violent crime and inequality in Brazilian cities using interviews with residents in a *favela* (shanty town) of Rio de Janeiro. Brazilians living in the *favela* join gangs to sell drugs to make a living. To expand their market and control distribution in an area, gang members often resort to fatal gun-related violence.

While the literature on income inequality and crime records clear evidence of correlation between property crime and inequality, evidence of correlation for violent crime, particularly homicide, is mixed. For instance, Fajnzylber et al. (2002a, 2002b) found a positive and statistically significant impact of income inequality (using the Gini index) on homicide and robbery rates using a panel of 34–45 countries between 1965 and 1995. Similarly, Scorzafave and Soares (2009) and Sachsida et al. (2010) found a positive and statistically significant correlation between homicide rates and inequality across Brazilian states between 1981 and 1995.

Conversely, Kelly (2000) used data on violent crime (including murder) and property crimes across counties in the US in 1991 and found that while income inequality (measured by the difference between mean and median household incomes) has a positive and statistically significant impact on property crimes, there is no impact on violent crime, in particular murder. Choe (2008) confirmed this result using a panel of US states between 1995 and 2004. Wu and Wu (2012) found a negative and statistically significant relationship between murder and income inequality for the UK.

This study finds a negative and statistically significant relationship between homicides and income inequality in Brazil using data for 1980–2000, a period for which there is consistent data. Consistent with the findings of Scorzafave and Soares (2009) and Sachsida et al. (2010), the results of this study show that the marginal effect of a change in the ratio of low skill wage on the number of homicides in Brazil's urban areas is 0.7 increase in crime.

Furthermore, with the exception of Choe (2008), few authors have controlled for time fixed effects; thus, they might have identified only short-term and not long-term effects. In fact, Saridakis (2004) found no evidence of a long-run relationship between violent crime (including murder) and income inequality (measured by the Gini index) using time series data for the US between 1960 and 2000, although a negative short-run relationship exists. Similarly, Brush (2007) employed US census data for 1990–2000, and while he found a positive relationship between inequality and crime in the cross-sectional analysis, the relationship was negative or zero with first differenced data. Similar inconsistent results between inequality and crime were found by Neumayer (2005) for a panel of countries similar to that used by Fajnzylber et al. (2002a, 2002b).

Measurement error in the inequality variable may be one reason for these differences. In particular, Bound and Krueger (1991) and Bound et al. (1994) showed that measurement error could worsen with the inclusion of fixed effects. This problem can be solved using an Instrumental Variable (IV) approach. Fajnzyber et al. (2002a, b) and Scorzafave and Soares (2009) used the dynamic panel data methods proposed by Arellano and Bond (1991) and Blundell and Bond (1998) to achieve identification. These methods use lagged variables as instruments. However, lagged variables may not solve the measurement error problems if measurement error is correlated over time correlated over time (Chen et al., 2008; Biørn, 2012; Meijer et al., 2013).

This study shows a long-term relationship between homicide and income inequality. It uses migration as an IV to address the measurement error problem. Using rainfall shocks, changes in transport costs in rural areas and distance as exogenous shocks to rural migration flows into urban areas of Brazil between 1980 and 2000, the problem of measurement error is addressed even if it is correlated over time. The results show that migration is strongly correlated with inequality while being uncorrelated with the error term. Not only is there a positive and statistically significant relationship between inequality and homicides in Brazilian cities between 1980 and 2000, but the result is larger than previously thought. This holds in both the short and long run and is robust even with assumptions about the distribution of the probability of criminal behavior, different samples, and an inequality proxy.

Finally, the study shows that there is no direct long-term relationship between migration and homicide in Brazil. To control for all mechanisms through which migration affects homicides, the study follows Bianchi et al. (2012) and Spenkuch (2014) and includes the migration rate directly in regressions. Like these studies, we find that migration has a positive impact on homicides. However, once the IVs on the migration rate into cities and income inequality are used, the results show that migration has only an indirect effect on homicides through changes in inequality, which is consistent with previous studies.

This article is structured as follows. The empirical strategy is developed in Section 2. A simple model of criminal behavior is constructed for the relationship between crime and inequality. Next, estimation issues are examined and the relationship between inequality and migration is analyzed. Section 3 describes the data. Section 4 presents the results and develops the IV approach. Section 5 concludes.

2. EMPIRICAL STRATEGY

The basic economic model of crime is based on the work of Becker (1968) and Ehrlich (1973). An individual will commit a crime if his indirect utility from the criminal activity is higher than that from working, net of the expected cost of being caught. Therefore, the decision to commit a crime is given by

$$Crime^{*}_{irt} = 1\left[\ln Y^{crime}_{irt} - \ln Y^{work}_{irt} - \ln C_{irt} + \eta_{irt} > 0\right] \quad (1)$$

where Y^{crime}_{irt} and Y^{work}_{irt} are the returns to committing crime and legal work, respectively, for individual i in city r at time t, and C_{irt} measures the expected cost of committing a crime, such as the likelihood of being caught and sent to jail. η_{irt} is the error term. 1[.] is an indicator function, which takes the value one if the value inside the brackets is positive, and zero otherwise.

To test this theory, a survey is needed of the overall population, including the incomes of individuals who committed crimes (usually incarcerated individuals). However, we are unaware of any survey that meets this requirement for Brazil. Most studies on crime rely on the area approach, in which estimates are obtained by comparing crime rates across regions (and potentially across time). Then, the crime rate in a particular city r for a particular year t is $E[Crime^{*}_{irt}] = (Crime\ rate)_{rt}$.

As noted by Stoker (2008) and Durlauf et al. (2010), to obtain the expected value of crime across regions we need to assume a distribution for the probability to commit a crime. A common assumption is to use a Poisson distribution (Kelly, 2000; Osgood, 2000). Accordingly, Equation 2 can be estimated by the Generalized Method of Moments (GMM):

$$\ln(Crime_{rt}) = \alpha + \gamma\left[\ln \overline{Y^{crime}_{rt}} - \ln \overline{Y^{work}_{rt}}\right] + \beta \ln \bar{C} + \varepsilon_{rt} \quad (2)$$

Thus, for city r at time t, $Crime_{rt}$ is the number of crimes per capita, and $\ln \overline{Y^{work}_{rt}}$ is the average log income from work; $\ln \overline{Y^{crime}_{rt}}$ is the average log income from crime; while $\ln \bar{C}$ is the average of the log of the cost of committing a crime. α is a constant.

The variable we are interested in is the potential gains from crime, $\ln \overline{Y^{crime}_{rt}}$. We will use the ratio of high to low skill wage, $\frac{w_{Hrt}}{w_{Lrt}}$, as a proxy for potential gains from crime, a measure of inequality similar to the one used by Ehrlich (1973) and Kelly (2000). Therefore, $\ln \overline{Y^{crime}_{rt}} = \frac{w_{Hrt}}{w_{Lrt}} - u_{rt}$, where u_{rt} is a general term for measurement error, which has expected value of zero and is uncorrelated with other observable variables.

Regarding the other variables in Equation 2, it is common to use using average city income for low skill male individuals and unemployment rate as a measure of labor income, $\ln \overline{Y_{rt}^{work}}$, and the size of the police force in city as measure of the cost of committing a crime, $\ln \bar{C}$ [1]. Let us denote these variables as $\bar{X}_{rt}$.

Most studies estimate an equation similar to the following:

$$\ln(Crime_{rt}) = \gamma_1 + \gamma_2 \frac{w_{Hrt}}{w_{Lrt}} + \gamma_3 \bar{X}_{rt} + (\varepsilon_{rt} - \gamma_2 u_{rt}) \quad (3)$$

To see how the use of a proxy variable affects estimates of γ_2, consider a simpler version in Equation 3.

$$\ln(Crime_{rt}) = \gamma_2 \ln \overline{Y_{rt}^{crime}} + \varepsilon_{rt} \Leftrightarrow$$
$$\ln(Crime_{rt}) = \gamma_2 \frac{w_{Hrt}}{w_{Lrt}} + (\varepsilon_{rt} - \gamma_2 u_{rt}) \quad (4)$$

Then, the estimate of γ_2 will be

$$\begin{aligned} \hat{\gamma}_2 &= \frac{cov\left(\frac{w_{Hrt}}{w_{Lrt}}; \ln(Crime_{rt})\right)}{var\left(\frac{w_{Hrt}}{w_{Lrt}}\right)} \\ &= \frac{cov\left(\ln \overline{Y_{rt}^{crime}} + u_{rt}; \gamma_2 \ln \overline{Y_{rt}^{crime}} + \varepsilon_{rt}\right)}{var\left(\ln \overline{Y_{rt}^{crime}} + u_{rt}\right)} \\ &= \gamma_2 \frac{\sigma_{\ln \overline{Y_{rt}^{crime}}}}{\sigma_{\ln \overline{Y_{rt}^{crime}}} + \sigma_{u_{rt}}} \end{aligned} \quad (5)$$

where σ_m is the standard error of *m*. The estimates of γ_2 will be biased towards zero. Furthermore, as pointed out by Griliches and Hausman (1986) and Pischke (2007), standard errors will be biased upward, leading to lower *t*-statistics.

The inclusion of fixed effects, such as city fixed effects, can worsen measurement errors if these are correlated across time. Suppose that ρ is the autocorrelation of potential gain from criminal activity, $\ln(Crime_{rt})$, and r is the autocorrelation of the measurement error term u_{rt}. Similar to Bound and Krueger (1991) Bound et al. (1994), and Pischke (2007), considers the case of estimating Equation 4 with city fixed effects, γ_r.

$$\ln(Crime_{rt}) = \gamma_r + \gamma_2 \frac{w_{Hrt}}{w_{Lrt}} + (\varepsilon_{rt} - \gamma_2 u_{rt}) \quad (6)$$

Taking the first difference of the data gives a similar regression model to before.

$$\Delta \ln(Crime_{rt}) = \gamma_2 \Delta\left(\frac{w_{Hrt}}{w_{Lrt}}\right) + (\Delta\varepsilon_{rt} - \gamma_2 \Delta u_{rt}) \quad (7)$$

The estimate of γ_2 will be biased as follows.

$$\begin{aligned} \hat{\gamma}_2 &= \gamma_2 \frac{\sigma_{\Delta \ln \overline{Y_{rt}^{crime}}}}{\sigma_{\Delta \ln \overline{Y_{rt}^{crime}}} + \sigma_{\Delta u_{rt}}} \\ &= \gamma_2 \frac{\sigma_{\ln \overline{Y_{rt}^{crime}}}(1-\rho)}{\sigma_{\ln \overline{Y_{rt}^{crime}}}(1-\rho) + \sigma_{u_{rt}}(1-r)} \\ &= \gamma_2 \frac{1}{1 + \frac{\sigma_{u_{rt}}(1-r)}{\sigma_{\ln \overline{Y_{rt}^{crime}}}(1-\rho)}} \end{aligned} \quad (8)$$

It is easy to see that when the measurement error is not correlated over time, $\rho \approx 0$, and when $\ln \overline{Y_{rt}^{crime}}$ is highly correlated over time, $r \approx 1$; adding fixed efects increases the bias.

A possible solution is to find an instrument, Z_{rt}, that is uncorrelated with the measurement error $cov(\Delta u_{rt}; Z_{rt}) = 0$ but is correlated with changes in the maximum potential gain from criminal activity, $cov\left(\Delta \ln \overline{Y_{rt}^{crime}}; Z_{rt}\right) \neq 0$. Thus, the estimate of γ_2 is given by

$$\begin{aligned} \hat{\gamma}_2 &= \frac{cov(Z_{rt}; \Delta\ln(Crime_{rt}))}{cov\left(Z_{rt}; \Delta\left(\frac{w_{Hrt}}{w_{Lrt}}\right)\right)} \\ &= \frac{cov\left(Z_{rt}; \gamma_2 \Delta \ln \overline{Y_{rt}^{crime}} + \Delta\varepsilon_{rt}\right)}{cov\left(Z_{rt}; \Delta \ln \overline{Y_{rt}^{crime}} + \Delta u_{rt}\right)} \\ &= \frac{\gamma_2 cov\left(Z_{rt}; \Delta\ln \overline{Y_{rt}^{crime}}\right)}{cov\left(Z_{rt}; \Delta \ln \overline{Y_{rt}^{crime}}\right)} = \gamma_2 \end{aligned} \quad (9)$$

Which is an unbiased estimate of γ_2.

The standard instrument used in the literature is the second lag of the level of income inequality, as suggested by Bound et al. (1994), Arellano and Bover (1995), and Bond (2002). However, this method will provide unbiased estimates of γ_2 only if the error term in Equation 7, $(\Delta\varepsilon_{rt} - \gamma_2 \Delta u_{rt})$, is not serially correlated. As Durlauf et al. (2010) noted, there is no reason to assume that this is true, since individuals may be forward looking and the nature of individual- and city-specific heterogeneity is unknown. In fact, Chen et al. (2008) and Biørn (2012) use Montecarlo simulations to show that under a general structure for the measurement error term u_{rt}, Bound et al.'s (1994) and Arellano and Bover's (1995) method will still provide biased estimates of γ_2.

We use as an instrument rainfall shocks, changes in transportation costs in rural areas as distance between rural and urban areas, $f(Rain_{rural,t}; Trans_{rural,t-5}, Distance_{rural,urban})$, that explain the (predicted) move of low skill migrants, $\left(\widehat{\Delta N_{Lrt}}\right)^{mig}$, and the ratio of high to low skill migrants from rural areas to cities, $\frac{\left(\widehat{\Delta N_{Hrt}}\right)^{mig}}{\left(\widehat{\Delta N_{Lrt}}\right)^{mig}}$. We showed in Freire (2010) that

[1] These could also be sources of measurement error. We will show in our regression results that this is not a problem with our data.

the inflow of rural migrants to urban areas affects inequality as measured by the ratio of high to low skill wage, $\frac{w_{Hrt}}{w_{Lrt}}$, which is our proxy for the the potential gains from crime, $\ln \overline{Y_{rt}^{crime}}$.

As we pointed out in Freire (2010), we cannot use the actual flow of rural to urban migrants, as city characteristics that determine crime also determine the flow of migrants into cities. Instead we use the predicted inflow of rural-urban migrants that is driven by rainfall shocks, changes in transportation costs in rural areas and distance between rural and urban areas, which are orthogonal to urban characteristics. We need to predict the number of rural-urban migrants by skill level as a way to weight the impact of exogenous rainfall shocks and changes in transportation costs in each rural municipality (over 3000) on each city (123 urban areas).

We follow Freire (2010) and obtain the predicted migration flows by skill level i, from all rural municipalities to each city r, at time t, or $\left(\widehat{\Delta N_{irt}}\right)^{mig}$, using the following equation:

$$\left(\widehat{\Delta N_{irt}}\right)^{mig} = \sum_{j=t-5}^{t} \sum_{rural} \left(\frac{\widehat{Migrants_{i,rural,r}}}{\sum_r Migrants_{i,rural,r}}\right) \widehat{Migrants_{i,rural,j}} \quad (10)$$

Where $\left(\frac{\widehat{Migrants_{i,rural,r}}}{\sum_r Migrants_{i,rural,r}}\right)$ is the predicted share of rural migrants with skill i, from municipality $rural$, to urban area r, and $\widehat{Migrants_{i,rural,j}}$ is the predicted number of migrants of skill i, who leave the rural area *rural*, at time *j*.

In essence we are dividing the decision to migrate to urban areas into two. First is the decision of where to go, or which city do migrants in rural areas decide to go, as measured by the share of rural migrants who decide to move to an urban area. As shown on Freire (2010), this decision depends on the distance between origin and destination. Therefore, we estimate the following equation:

$$\frac{Migrants_{i,rural,r}}{\sum_r Migrants_{i,rural,r}} = \eta_0 + \eta_1 Distance_{rural,urban} + \eta_2 W_{i,rural,urban} + \varpi_{i,rural,urban} \quad (11)$$

Where $Distance_{rural,urban}$ is the great-circle distance between the geographical centers of the rural municipality of origin and the destination city, a measure of transportation costs, and $W_{i,rural,urban}$ are controls for different characteristics of rural and urban areas, including fixed effects.

Second, is the decision to leave the rural areas, as measured by the number of migrants who leave each rural area. As shown in Freire (2010), this decision depends on the number of rainfall shocks in each rural area and changes in transportation costs from rach rural area to urban areas. Therefore, we estimate the following equation:

$$\ln \text{Migrants}_{i,rural,t} = \delta_0 + \delta_1 \ln \text{N}_{i,rural,t-10} + \delta_2 \text{Rain}_{rural,t} + \delta_3 \ln \text{Transp}_{rural,t-5} + \delta_4 \text{W}_i + \upsilon_{i,rural,t} \quad (12)$$

Where $N_{i,rural,t-10}$ is the (lagged) number of people by skill *i*, living in a rural area, *rural*, in the previous census year, *t*−10; $Rain_{rural,t}$ is the (log) average of monthly rainfall (mm) in *rural* in year *t* (since the timing of the drought and its impact is uncertain, lagged rainfall is also included)[2]; and $\ln Transp_{rural,t-5}$ is the (log) index of the transport cost to São Paulo from *rural* in 1986 and 1995, or *t*−5. W_i is a set of controls depicting the characteristics of the rural area of origin (including the log of agricultural area, year dummies, and municipality fixed effects).

In summary, we use rainfall shocks, changes in transportation costs and distance as exogenous instruments for changes in the potential gains from criminal behavior. We do so by estimating Equation 11 and 12 for each skill group, and obtain the predicted value of the fraction of migrants from each rural area that goes to each city and the predicted number of rural migrants that leave rural areas. We combine these using Equation 10 to construct the predicted number of migrants of each skill level *i*, arriving at each city *r*, at time *t*. We use this to obtain the predicted value of the ratio of high to low skill migrants, $\frac{\left(\widehat{\Delta N_{Hrt}}\right)^{mig}}{\left(\widehat{\Delta N_{Lrt}}\right)^{mig}}$, and the number of low skill migrants, $\left(\widehat{\Delta N_{Lrt}}\right)^{mig}$, arriving at each city, our instrumental variables, Z_{rt}. These instrumental variables combines rainfall shocks in rural areas, changes in transportation costs in each rural municipality and distance, into exogenous shocks in urban areas, which are correlated with the potential gain from criminal activity, $\ln \overline{Y_{rt}^{crime}}$, but uncorrelated with the measurement error, u_{rt}. We should note that this instrumental variable approach also addresses other problem that exist

[2] A quadratic term was initially included in our specifications, but was later dropped, as it was statistically insignificant.

in estimating γ_2 in Equation 3, such as the fact that the potential gains from criminal activity are endogenous. However, endogeneity does not explain why the inclusion of time fixed effects would lead to different results in the literature.

3. CRIME, INCOME INEQUALITY, AND RURAL–URBAN MIGRATION IN BRAZIL

The three sources of crime statistics for Brazil include data on homicides from the public health database, police records for some states, and data from victimization surveys (Santos and Kassouf, 2008). Data on victims are very limited; there is only one nationally representative survey, and the existing panel data are limited to four states (World Bank, 2006). Police records prior to 2002 do not exist at the national level (World Bank, 2006). According to the 2002 police records, the public health database (DATASUS) over reports the number of homicides (World Bank, 2006); while public health records count homicide deaths resulting from legal interventions (killings by police and public security forces), war, and declared homicides. Regardless of the data source, Brazil has one of the highest homicide rates in the world, according to UNODC (2009), and it has been increasing over time (World Bank, 2006).

Given these data limitations, following Scorzafave and Soares (2009) and Sachsida et al. (2010), this study uses homicides reported in DATASUS as a proxy for criminal activity and are an upper bound of the effect of income inequality on homicides. As explained in Section 2, this study assumes that homicides are committed in relation to property and drug-related crimes, and therefore, they can be studied with an economic model of crime, which is consistent with the findings of Fajnzylber et al. (2002a, 2002b). This study assumes that the homicide rate is a measure of the number of crimes committed, and therefore, follows a Poisson distribution with multiplicative errors. The regressions measure the response to changes in income inequality at the intensive and extensive margins of criminal behavior. However, as noted in Section 4, the conclusions hold if a uniform distribution is assumed and the crime rate measures the number of criminals in a city, the extensive rate.

The data are restricted to the census years 1980, 1991, and 2000, since a definition of "city" is required that allows for a comparison of city characteristics over time. This study uses the 123 urban agglomerations (also referred to as "cities" or "urban areas") defined by Mata et al. (2007) as the metropolitan statistical areas of the US, allowing city-level comparisons between 1980 and 2000. There is no such definition of "city" that allows for the inclusion of the 2010 census data. The basic statistics appear in Table 1. The results are consistent with the current literature: the number of homicides in these 123 cities increased 73% during this time period (23.5 per 100,000 people in 1980 to 40.59 per 100,000 in 2000).

According to the National Penitentiary Department Database of the Ministry of Justice (Infopen, 2008), most incarcerated people are males under the age of 45 years (Table 2), and most incarcerated males have had a high school education or less (Table 3). These characteristics are also assumed to be the characteristics of criminals committing homicides, assuming that the Brazilian justice system is as efficient in catching and convicting murderers as individuals committing other crimes. Therefore, Table 1 also reports the number of homicides per 100,000 committed by young men (between 15 and 45 years) with low skill (less than 12 years of education).

According to Cerqueira (2010), between 1980 and 1991, more police officers were employed in response to the increasing number of homicides. Using data of the 1980, 1991, and 2000 Brazilian population censuses, the number of people working in public security (police and military police) is calculated. The number of police officers in urban areas reported in the censuses increased 31% from 375.78 per 100,000 in 1980 to 492.91 per 100,000 in 1991 (Table 1). Cerqueira (2010) notes that this did not curb crime due to increasing inefficiency in investigating and convicting criminals. Between 1990 and 2000, although government spending on public safety increased, Cerqueira (2010) notes a 41.7% decrease in the size of the police force in urban areas (Table 1). This period also saw a significant increase in the size of the private security industry, usually staffed with workers from the public security sector (which creates an obvious incentive incompatibility problem).

The period 1980 to 2000 saw other changes in the Brazilian economy, which may have affected criminal behavior patterns. In response to the country's balance of payments crisis, wages decreased between 1980 and 1991 for both high skill (high school graduates or higher) and low skill (high school dropouts or lower) workers (Table 1).

Driven in part by government budget deficits, unemployment increased slightly between 1980 and 1991.[3] However, due to the reforms of the Real Plan, the number of unemployed men aged 15–45 years increased significantly. In particular, Table 1 shows that the percentage of young and low skill men outside the labor force increased during this period.

Income inequality increased between 1980 and 1991, with hourly wages dropping more for low skill workers than high skill workers. Between 1991 and 2000, hourly wages rebounded, with wages for low skill workers increasing more than those for high skill workers, leading to a decrease in income inequality (Table 1). The relationship between homicide rates and the ratio of high to low skill wages across cities appears in Fig. 1. As predicted by my model, there is a positive relationship between changes in income inequality and changes in the homicide rate. However, as before, there is large variation across cities, consistent with the possibility of measurement error.

As explained in Section 2, changes in the relative supply of high and low skill workers in cities, driven by rural migration, affects urban income inequality. Therefore, it is not surprising that there is a positive relationship between migration and income inequality (Fig. 2) and between migration and the homicide rate (Fig. 3).

4. Results

We estimate the following equation using GMM with clustered-robust standard errors.

$$\Delta \ln(Crime_{rt}) = \gamma_t + \gamma_2 \Delta\left(\frac{w_{Hrt}}{w_{Lrt}}\right) + \gamma_3 \Delta\bar{X}_{rt} + \Delta e_{rt} \quad (13)$$

where the coefficient of interest γ_2 measures the impact of the the ratio of high to low skill hourly wages, $\frac{w_{Hrt}}{w_{Lrt}}$, on the crime rate. $\bar{X}_{rt}$ is a set of city characteristics that measure the benefits of work and the cost of commiting a crime. These characteristics include unemployment rate, hourly wage and the size of the police force. In some specifications, variables that are standard in migration- and crime-related literature are added, namely, city size and the fraction of recent migrants as a percentage of lagged city size. To measure city size, this study uses the lagged size of the resident population, which includes only individuals who were living in the city in the five years prior to the previous Census, and therefore, it is predetermined and uncorrelated with current or lagged city characteristics in the error term. γ_t denotes a set of year dummies. Two versions of the model are estimated, one without year dummies (similar to the specification standard in the literature) and the other with year dummies (to capture the long-run effects of income inequality on the crime rate).

Individual characteristics such as gender, education, and age are also important determinants of the crime rate. However, including a control for these individual characteristics is likely to bias our estimates (Stoker, 2008 and Durlauf et al., 2010). Therefore, we restrict the measures of the crime rate, unemployment, and income to a sample of young men, as they are more likely to commit crimes as we showed in Section 3. In Section 4.3, we show that our results remain unchanged when we extend our sample to all men and women between the ages of 15 and 65.

4.1 Basic regression

The model in Equation 1 is estimated by including only changes in the ratio of high to low skill wages (inequality), changes in the average log hourly wage for young and low skill men, changes in the young and low skill male unemployment rate, and growth of the police force; the specification is similar to that used by Scorzafave and Soares (2009) and Sachsida et al. (2010) for Brazil.

The results appear in columns 1 and 2 of Table 4. Like the work of Sachsida et al. (2010) for Brazil, the model shown in column 1 does not control for changes across time (no constant or time dummies). In this specifica-

[3] While the 1980 and 1991 Brazilian population censuses queried if individuals were employed, looking for a job, or outside the labour force, this information was not collected in the 2000 census. Therefore, this study measures unemployment as those individuals without jobs (1 − the labour force participation rate). This value could be affected by the number of young people who decide to continue studying but has remained relatively stable over the given period.

tion, which is consistent with Sachsida et al. (2010), inequality has a positive and statistically significant impact on the growth rate of homicides. In particular, the marginal effect of the change in the ratio of high to low skill wages is a statistically significant 0.21 increase in the number of homicides. Also consistent with Sachsida et al. (2010), an increase in unemployment leads to a positive and statistically significant increase in the number of homicides, an increase in wages leads to a decrease in the number of homicides, while the number of police officers has no impact on crime. Column 2 includes time dummies. These results are comparable with studies of the long-term impact of inequality on crime, such as Saridakis (2004) and Neumayer (2005). While inequality has a positive impact on the number of homicides, it is not statistically significant; this is consistent with the idea that the impact of inequality on crime is only a short-term relationship. Furthermore, the point estimates for changes in the high to low skill wage ratio are smaller than those presented in column 1, which is consistent with the possibility of measurement error being worse when year fixed effects are included.

In columns 3 and 4 of Table 4 we include migration and city size as controls as in Bianchi et al. (2012). Migration can affect crime through several indirect channels. For instance, in line with the migration literature (LaLonde and Topel, 1991; Ottaviano and Peri, 2012), Bianchi et al. (2012) argue that migrants might face different earnings potential from legal work and crime. Borjas et al. (2010) argue that migration affects crime rates through the labor market conditions of local residents, namely wages and unemployment, which is also consistent with the migration literature (Borjas, 2003). Finally, Bianchi et al. (2012) and Bell et al. (2013) observe the possibility that migrants have a different propensity to commit crimes than local residents, and therefore, migration captures changes in the population composition. Therefore, we add migration directly to control for all mechanisms through which migration may affect crime, including income, unemployment, and changes in the population composition. It also includes a control for city size, which is standard in the migration literature. The results in columns 3 and 4 of Table 4 are consistent with those of Bianchi et al. (2012). In particular, regardless of whether we include controls for changes over time (time dummies), the change in the ratio of high to low skill wages (inequality) has a positive but statistically insignificant impact on the number of homicides. Furthermore, other controls, such as unemployment and wages, as well as city size growth and growth of the police force, are not statistically significant in either model. Consistent with Bianchi et al. (2012), only the coefficient for the fraction of recent young and low skill migrants is positive and statistically significant in both models.

Finally, in columns 5 and 6 of Table 4, this study estimates a reduced model with only change in the ratio of high to low skill wages (inequality), fraction of migrants and control for city size, in order to remove any potential bias from the other control variables. The impact of change in the ratio of high to low skill wages is still positive but not statistically significant, while the impact of migration remains positive and statistically significant, consistent with our results in columns 3 and 4.

As argued in Section 2, the fact that change in the ratio of high to low skill wages (inequality) has a statistically significant impact in column 1 but not in column 2 could be driven by measurement error. It is possible that these variables are endogenous. Both these problems can be solved using an IV approach as we described in Section 2.

4.2 Instrumental variables

As we discussed in Section 2, we use exogenous rainfall shocks, changes in transportations costs and distance to construct an instrumental variable for change in the ratio of high to low skill wages (inequality), as in Freire (2010). To do so, we will first estimate Equation 12, or how many people decide to leave rural areas as a result of rainfall shocks and changes intransportation costs in rural areas. Then, we will estimate Equation 11, or how distance determines where migrants decide to go. We then use the predicted values from Equation 12 and 11 to construct the predicted number of rural migrants arriving in each city by skill level, using Equation 10. We do this in order to aggregate these exogenous shocks in rural areas into exogenous shock to urban areas. We can then use these predicted values of the number of low skill migrants, $\left(\widehat{\Delta N_{Lrt}}\right)^{mig}$, and the ratio of high to low skill migrants from rural areas to cities, $\frac{(\Delta\widehat{N_{Hrt}})^{mig}}{(\Delta\widehat{N_{Lrt}})^{mig}}$ as instruments for changes in ratio of high to low skill wages and migration.

4.2.1 How many people decide to leave rural areas.

In this section we estimate Equation 12. Table 5 shows the characteristics of rural areas. The average number of people leaving a rural area decreased by 2.3% between 1991 and 2000 (not shown in the table), but the composition changed, with more high skill workers leaving in 2000 than in 1991. We observe the opposite pattern for low skill workers.

From the distribution of workers across sectors (Table 5), we see that in 1991, 43.62% of low skill men worked in farming, dropping to 30.45% in 2000. Therefore, it is likely that individuals in rural areas working in agriculture (or businesses complementary to agriculture) would respond to rainfall shocks (droughts or floods), which are likely to affect income from agricultural production.

The number of high skill people increased by 43% between 1991 and 2000, much faster than the number of low skill people living in rural areas (12%; Table 5), but the percentage of high skill people migrating remained the same at 48%. Furthermore, we notice that the average cost of moving, as measured by the index of transport cost from rural municipalities to São Paulo, as constructed by Castro (2002), dropped by 14% between 1991 and 2000.[4] Therefore, as noted by Vidal (1998), Docquier and Rapoport (2004), and Beine et al. (2008), the possibility of migration (due to reduced transport costs) leads to more investment in education, and thus, increased out-migration of high skill people from rural areas. Furthermore, it is unlikely that more high skilled people are leaving rural areas in search of higher levels of education as the number of people with a college degree remained largely unchanged during this period (Souza, 2001).

Since there are a considerable number of rural municipalities with zero out-migration (Table 6; around 70% for high skill migration) and fixed effects are included, we use Honore (1992), to obtain unbiased estimates of our coefficients from a Tobit model with fixed effects.

Table 6 presents the results for high and low skill men by group. Since rural municipalities' fixed effects are included, our coefficients are interpreted as responses to shocks (deviations from the average over the period). As in Freire (2010), the study finds that reductions in transport costs cause increased out-migration of high skill people, for men only, a 10% decrease in transport costs increases the number of high skill migrants by 3%. Furthermore, rainfall shocks affect migration of low skill people only, in particular, a 1 SD decrease in rainfall leads to an increase of 5% in migration. These results do not hold for all of Brazil. In the drought-prone area in the northeast, the impact of drought differs. As noted by Baer (2008), this region receives government aid, which is often misused, in years of drought. Therefore, during years of plenty rainfall (when there are no government transfers), out-migration decreases for both low and high skill people. Finally, the instruments seem to be relevant for explaining out-migration, passing the non-linear version of an *F*-test on all coefficients equal to zero.

4.2.2 Where migrants go.

In this section we estimate Equation 11. Distance between the destination and origin is used to explain the historical migrant settlement pattern. The 1991 Brazil population census asks the question: "Where were you living 10 years ago?" Along with information on "When did you move to your current municipality," this study uses the migrant settlement pattern between 1981 and 1985 as an historical pattern of migrant settlement across cities. Furthermore, distance between the origin and destination is used as a proxy for moving cost; therefore, it is orthogonal to changes in conditions in urban areas between 1985 and 1999.

Our results, like Freire (2010), show that migrants are more likely to move to cities closer to their home (rural municipality; column 1 of Table 7). In particular, a city that is 10% closer receives 0.2% more migrants. Column 2 of Table 7 shows that distance matters less for high skill men. In columns 3 and 4, I check whether this result can be attributed to the fact that municipalities nearer cities have a higher supply of high or low skill men, by controlling for how many people live in the rural and ur-

[4] This index is the result of a linear programming exercise using information on the conditions of the roads connecting the rural municipality and São Paulo.

ban areas of origin. Even with this control, distance remains statistically significant.

Next, the predicted valued of these two estimates (how many people migrate from rural areas and where they decide to go) are combined to construct our instruments.

4.2.3 First and second stage result of instrumental variables

We use the predicted values to Equation 12 and Equation 11, estimated in the previous two section to build the predicted value of migrants by skill group, using Equation 10. We use these predicted values as instruments for changes in the ratio of high to low skill wages and the number of migrants in urban areas, as in Freire (2010)[5].

The first-stage results for changes in the ratio of high to low skill wages (inequality) appear in columns 1 (no constant) and 2 (time dummies) of Table 8. The results show that changes in the ratio of high to low skill migrants are correlated with the endogenous variables and changes in high to low skill wages (high *t*-statistics and high *F*-statistics). Moreover, the instruments predict the log of recent migrants. In column 1, an increase in the predicted values of high to low skill young and low skill men decreases high to low skill wages. However, for column 2, the sign of the coefficient for the predicted changes in the high to skill ratio is positive, contrary to expectations, although the sign for the percentage of recent young and low skill male migrants is negative. This is because cities with a higher ratio of high to low skill migrants also received more migrants (Table 7).

The first-stage results for migration are reported in columns 3 (no constant) and 4 (time dummies) of Table 8. In column 3, the coefficient for the predicted log number of recent migrants is positive and statistically significant (the *F*-statistic for both instruments is well above 10). However, when time dummies are included in column 4, only changes in high to low skill young and low skill men have a statistically significant impact. In particular, a decrease in the ratio of high to low skill migrants increases the percentage of recent young and low skill male migrants. However, the *F*-test is less than 10, suggesting the presence of weak instruments. However, the estimated standard errors are only efficient under homoskedasticity. Aggregating individual data leads to heteroskedasticity. Therefore, the second-stage regressions calculate the Stock–Wright Lagrange Multiplier (LM) *S*-statistic for weak instruments, which is robust to heteroskedasticity (Baum et al., 2007).

The second-stage results for the reduced model appear in columns 1 and 2 of Table 9. When a control for changes common to all cities over time (a model with no constant in column 1) is excluded, inequality has a negative but not statistically significant impact on the number of homicides. Migration has a positive and statistically significant impact on the number of homicides. This is likely caused by weak instruments, as the Stock–Wright test is rejected only at the 10% level. However, after including time dummies, the Stock–Wright test is rejected at the 5% level, and the Kleibergen–Paap test for under-identification (weak correlation between the instruments and endogenous variables; see Baum et al., 2007) is rejected at the 1% level. In this case, changes in the high to low skill wage ratio (inequality) have a positive and statistically significant impact on the number of homicides. In particular, the marginal effect of changes in the ratio of high to low skill wages is a 0.63 increase in the number of homicides. This is sixteen times larger than the coefficient found in column 6 of Table 4 and is consistent with the presence of measurement error. This is also consistent with the findings of Bianchi et al. (2012) that migration does not have a statistically significant impact on the number of homicides.

In columns 3 and 4 of Table 9, the model with all other control variables is estimated. Both specifications pass the tests for weak instruments and under-identification. In both columns, changes in the high to low skill wage ratio (inequality) lead to positive and statistically significant increases in the number of homicides. In particular, the marginal effect of changes in the ratio of high to low skill wage is a 0.7 to 0.73 increase in the number of homicides. Migration does not have a statistically significant impact on the number of homicides.

In summary, when both instruments are valid, there is a positive and statistically significant relationship between inequality and homicides.

[5] In order to use predicted migration flows as instruments for changes in high to low skill wages we must also instrument directly for migration into cities, or else our instrumental variable would be biased.

4.3 Robustness checks

In columns 5 and 6 of Table 9, the same regressions with all individuals (men and women) between the ages of 15 and 65 years are run. Therefore, this study's measures of inequality, migration, poverty, and unemployment relate to this sample. The results are consistent with previous results. In particular, the marginal effect of changes in the ratio of high to low skill wage is a statistically significant 0.63 increase in the number of homicides. This result is true only when the instruments are appropriate (i.e., they pass the Stock–Wright test for weak instruments). Migration is never statistically significant.

In addition, the results are robust to different measures of inequality. The ratio of the 75th to 25th wage quantile is used as the measure of inequality in columns 7 and 8 of Table 9. As before, when the instruments are valid (the Stock–Wright *S*-statistic is significant at the 5% level), there is a positive and statistically significant relationship between inequality and homicides, while migration does not have a statistically significant impact on homicides.

Finally, the results are robust to the assumption about the distribution of the probability to commit a crime. The online appendix presents the results for a uniform distribution.

5. CONCLUSION

We began by replicating the findings of previous researchers, who have shown a positive and statistically significant relationship between inequality and homicides in Brazil in the short run. However, previous studies also found no impact in the long run. We explained how these results could be biased downward due to measurement error, a problem that worsens with the inclusion of time dummies. This study showed that this problem cannot be addressed using the standard dynamic panel data models used in the literature. Instead, we used the relationship between inequality and migration to construct an instrument for inequality.

This study showed how rainfall shocks, particularly droughts, in rural areas, changes in transport costs and distance are important determinants of high and low skill migration from rural to urban areas. Furthermore, we argued that the migration flows predicted from these models are orthogonal to the current characteristics of urban areas; therefore, they can be used as instruments. we showed how the instruments are correlated with inequality and the number of recent migrants.

The results for instrumental variables show that inequality has a positive and statistically significant impact on homicides in the long run. In particular, it increases the number of homicides. These results are robust to the model specification, sample, proxy used to measure inequality, and the assumption made about the probability distribution of committing a crime. Furthermore, this study confirms the relationship between migration and crime. Notably, it found no statistically significant relationship between migration and the homicide rate, which is consistent with Bianchi et al. (2012) and Spenkuch (2014).

The award-winning book *Cidade de Deus*, which is based on real events and was ultimately adapted as a movie, gives us an idea of how the mechanism between inequality and homicides may work. In this book, migrants from rural areas who settled in the *favela* deal in drugs as a way to escape poverty. They sell drugs to middle-income people living in the city's center. Rivalries between drug dealers in the *favelas* often result in homicides.

This study's results have important implications for public policy on social programs to reduce criminality in Brazil. In particular, since the impact of inequality on homicides is significantly larger than previously thought, social programs with the potential to reduce inequality, such as *Bolsa Familia*, which started in 2003, are likely to be effective. Furthermore, policies that decrease rural–urban migration may help reduce violent crime in Brazilian cities.

REFERENCES

Arellano, Manuel, and Stephen Bond. 1991. “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations.” *The Review of Economic Studies* 58, no. 2: 277–97.

Arellano, Manuel, and Olympia Bover. 1995 “Another Look at the Instrumental Variable Estimation of Error Components Models.” *Journal of Econometrics* 68, no. 1: 29–51.

Baer, Werner. 2008. *The Brazilian Economy: Growth and Development*, 6th edition. Westport, CT: Lynne Rienner Publishers.

Baum, Christopher F.; Mark E. Schaffer; and Steven Stillman. 2007. “Enhanced Routines for Instrumental Variables/GMM Estimation and Testing.” *The Stata Journal* 7, no. 4: 465–506.

Becker, Gary S. 1968. “Crime and Punishment: An Economic Approach.” *The Journal of Political Economy* 76, no. 2: 169–217.

Beine, Michel; Frederic Docquier; and Hilel Rapoport. 2008. “Brain Drain and Human Capital Formation in Developing Countries: Winners and Losers.” *The Economic Journal* 118, no. 528: 631–652.

Bell, Brian; Francesco Fasani; and Stephen Machin. 2013. “Crime and Immigration: Evidence from Large Immigrant Waves.’ *Review of Economics and Statistics* 21, no. 3: 1278–1290.

Bianchi, Milo; Paulo Buonanno; and Paolo Pinotti. 2012. “Do Immigrants Cause Crime?” *Journal of the European Economic Association* 10, no. 6: 1318–1347.

Biørn, Erik. 2012. The Measurement Error Problem in Dynamic Panel Data Analysis: Modeling and GMM Estimation. Memorandum no. 02/2012. Department of Economics, University of Oslo, Norway.

Blundell, Richard, and Steven Bond. 1998. “Initial Conditions and Moment Restrictions in Dynamic Panel Data Models.” *Journal of Econometrics* 87, no. 1: 115–143.

Bond, Richard. 2002. “Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice.” *Portuguese Economic Journal* 1, no. 2: 141–162.

Borjas, George. 2003. “The Labor Demand Curve is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market.” *Quarterly Journal of Economics*, 118, no. 4: 1335–1374.

Borjas, George. 2006. “Native Internal Migration and the Labor Market Impact of Immigration.” *The Journal of Human Resources* 41, no. 2: 221–58.

Borjas, George J.; Jeffrey Grogger; and Gordon H. Hanson. 2010. “Immigration and the Economic Status of African-American men.” *Economica* 77, no. 306: 255–282.

Bound, John, and Alan B. Krueger. 1991. “The Extent of Measurement Error in Longitudinal Earnings Data: Do Two Wrongs Make a Right?” *Journal of Labor Economics* 9, no. 1: 1–24.

Bound, John; Charles Brown; Greg Duncan; and Wilard Rodgers. 1994. “Evidence on the Validity of Cross-Sectional and Longitudinal Labor Market Data.” *Journal of Labour Economics* 12, no. 3: 345–368.

Brush, Jesse. 2007. “Does Income Inequality Lead to More Crime? A Comparison of Cross-Sectional and Time-Series Analyses of United States Counties.” *Economic Letters* 96, no. 2: 264–68.

Card, David. 2009. “How Immigration Affects US Cities.” In *Making Cities Work: Prospects and Policies for Urban America*, ed. Robert P. Inman. Princeton: Princeton University Press, 158–200.

Castro, Newton. 2002. “Custos De Transporte E Produção Agrícola No Brasil, 1970–1996.” *Agricultura em São Paulo* 49, no. 2: 87–109.

Cerqueira, Daniel R.C. (2010) “*Causas e Consequencias do Crime do Brasil*,” PhD diss., Pontifica Universidade Catolica do Rio de Janeiro.

Chen, Jie; Shawn Ni; and Michael Podgursky. 2008. “Estimating Dynamic Panel Data Models with Measurement Errors with an Application to School Evaluation based on Student Test Scores,” Proceedings of the 2008 meeting of the American Statistical Association, pp. 951–957.

Choe, Jongmook. 2008. “Income Inequality and Crime in the United States.” *Economics Letters* 101, no. 1: 31–3.

Docquier, Frederic, and Hilel Rapoport. 2004. *Skilled Migration: The Perspective of Developing Countries.* World Bank Policy Research Working Paper no. 3382, New York.

Durlauf, Steven; Salvador Navarro; and David Rivers. 2010. “Understanding Aggregate Crime Regressions." *Journal of Econometrics* 158, no. 2: 306–317.

Ehrlich, Isaac. 1973. "Participation in Illegitimate Activities: A Theoretical and Empirical Investigation." *Journal of Political Economy* 81, no. 3: 521–565.

Fajnzylber, Pablo; Daniel Lederman; and Norman Loayza. 2002a. "Inequality and Violent Crime." *The Journal of Law and Economics* 45, no. 1: 1–40.

Fajnzylber, Pablo; Daniel Lederman; and Norman Loayza. 2002b. "What Causes Violent Crime?" *European Economic Review* 46, no. 7: 1323–1357.

Freire, Tiago, (2010) "Essays in Applied Economics." PhD diss., Brown University, Providence.

Griliches, Zvi, and Jerry A. Hausman. 1986. "Errors in Variables in Panel Data." *Journal of Econometrics* 31, no. 1: 93–118.

Grogger, Jeff. 2000. "An Economic Model of Recent Trends in Violence." In *The Crime Drop in America.* Cambridge, UK: Cambridge University Press, pp. 266–287.

Honore, Bo E. 1992. "Trimmed Lad and Least Squares Estimation of Truncated and Censored Regression Models with Fixed Effects." *Econometrica* 60, no. 3: 533–565.

Infopen. 2008. *Infopen – Informacoes Penitenciarias*. www.infopen.gov.br (accessed November 5, 2013).

Kelly, Morgan. 2000. "Inequality and Crime." *The Review of Economics and Statistics* 82, no. 4: 530–539.

LaLonde, Robert J., and Robert H. Topel. 1991. "Immigrants in the American Labor Market: Quality, Assimilation, and Distributional Effects." *American Economic Review* 81, no. 2: 297–302.

Mata, Daniel; Uwe Deichmann; John Vernon Henderson; Somik Lall; and Hyoung Wang. 2007. "The Determinants of City Growth in Brazil." *Journal of Urban Economics* 62, no. 2: 252–272.

Meijer, Erik; Laura Spierdijk; and Tom Wansbeek. 2013. "Measurement Error in the Linear Dynamic Panel Data Model." In *ISS–2012 Proceedings Volume On Longitudinal Data Analysis Subject to Measurement Errors, Missing Values, and/or Outliers*. New York: Springer, pp. 77–92.

Neumayer, Eric. 2005. "Inequality and Violent Crime: Evidence from Data on Robbery and Violent Theft." *Journal of Peace Research* 42, no. 1: 101–112.

Osgood, D. Wayne. 2000. "Poisson-Based Regression Analysis of Aggregate Crime Rates." *Journal of Quantitative Criminology* 16, no. 1: 21–43.

Ottaviano, Gianmarco, and Giovanni Peri. 2012. "Rethinking the Effect of Immigration on Wages." *Journal of the European Economic Association* 10, no. 1: 152–97.

Peri, Giovanni. 2011. "Rethinking the Area Approach: Immigrants and the Labor Market in California." *Journal of International Economics* 84, no.1: 1–14.

Pischke, Steve. 2007. *Lecture Notes on Measurement Error*.econ.lse.ac.uk/staff/spisch k e/ec524/merr.pdf (accessed April 12, 2013).

Sachsida, Adolfo; Mario Jorge Cardoso de Mendonça; Paulo R. A. Loureiro; and Maria Bernadete Sarmiento Gutierrez. 2010. "Inequality and Criminality Revisited: Further Evidence from Brazil." *Empirical Economics* 39, no. 1: 93–109.

Santos, Marcelo Justus, and Ana Lúcia Kassouf. 2008. "Estudos Econômicos das Causas da Criminalidade no Brasil: Evidências e Controvérsias." *Revista Economia* 9, no. 2: 343–372.

Saridakis, George. 2004. "Violent Crime in the United States of America: A Time-Series Analysis between 1960–2000." *European Journal of Law and Economics* 18, no. 2: 203–21.

Scorzafave, Luiz Guilherme, and Milena Karla Soares. 2009. "Income Inequality and Pecuniary Crimes." *Economics Letters* 104, no. 1: 40–42.

Spenkuch, Jorg L. 2014. "Understanding the Impact of Immigration on Crime." *American Law and Economic Review* 16, no. 1: 177–219.

Souza, Paulo Renato. 2001. "Education and Development in Brazil, 1995–2000." *CEPAL Review* 73, no. 1: 65–80.

Stoker, Thomas M. 2008. "Aggregation (Econometrics)." In *The New Palgrave Dictionary of Economics*, 2nd edition, eds. Steven N. Durlauf and Lawrence Blume. New York: Palgrave Macmillan, pp. 1–12.

United Nations Office on Drugs and Crime (UNODC). 2009. *International Homicide Statistics.* New York: United Nations Publication.

Vidal, Jean-Pierre. 1998. "The Effect of Emigration on Human Capital Formation." *Journal of Population Economics* 11, no. 4: 589–600.

World Bank. 2006. *Brazil – Crime, Violence and Economic Development in Brazil: Elements for Effective Public Policy*. Washington DC: World Bank.

Wu, Dongxu, and Zhongmin Wu. 2012. “Crime, Inequality and Unemployment in England and Wales.” *Applied Economics* 44, no. 29: 3765–3775.

A1 – TABLES

Table 1. Basic statistics for 123 cities (agglomerations as defined in Mata et al. (2007)) for 1980, 1991 and 2000)

Basic statistics for 123 agglomerations						
	1980		**1991**		**2000**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Homicides per 100,000 people	23.56	16.990	31.26	23.25	40.59	29.48
Homicides per 100,000 men	48.33	35.91	64.44	48.8	83.6	61.21
Police per 100,000 people	375.78	239.63	492.91	282.49	287.26	169.22
City average of median hourly wage						
High skill men	5.943	1.791	5.480	1.121	5.831	1.168
Low skill men	1.844	0.481	1.234	0.403	1.395	0.345
High skill women	2.71	0.79	2.88	0.78	3.42	0.72
Low skill women	1.03	0.24	0.77	0.25	0.95	0.22
Male unemployment rate (%)	19.14	6.33	18.17	5.19	28.26	5.94
Average city size	271,456	781,434	357,993	943,243	454,041	1,148,864
High skill men	9,894	33,137	14,260	47,149	19,157	59,462
Low skill men	106,045	303,146	146,247	373,477	177,147	430,659
High skill women	9,603	30,874	15,755	48,664	23,534	70,238
Low skill women	110,706	311,532	154,900	391,469	185,110	452,309
Percentage men	49.21	1.7	48.7	1.28	48.73	0.997
Percentage migrants			6.52	2.88	5.1	2.05
Percentage migrants (only men)			6.34	2.8	4.97	2.02
Ratio of high to low skill migrants			0.076	0.049	0.096	0.058

Notes: "High skill" is defined as having 12 years or more of education and "low skill" as less than 12 years of education. "Migrants" are defined as people who moved into an agglomeration in the last five years, as recorded by the 1991 and 2000 Brazilian population censuses. SD stands for standard deviation. Total homicides data are sourced from DATASUS. Numbers for the police denote the total number of people working as members of a security force (excluding the army) from their respective census year. Unemployment is not reported consistently across census years; therefore, the non-participation rate in the labor market is reported as unemployment. City (agglomeration) size excludes recent migrants.

Table 2. Number of individuals incarcerated in Brazil in December 2008 by gender and age (Infopen, 2008)

Incarcerated population by age group and gender (2008)			
Age group (years)	Male	Female	Total
18–24	113,635	5,686	119,321
25–29	96,058	5,160	101,218
30–34	63,475	3,903	67,378
35–45	53,924	4,135	58,059
46–60	20,800	1,729	22,529
More than 60	3,174	154	3,328
No information	12,869	510	13,379
Total	371,884	21,604	393,488

Table 3. Number of individuals incarcerated in Brazil in December 2008 by gender and educational level (Infopen, 2008)

Incarcerated population by educational attainment and gender (2008)			
Educational attainment	Male	Female	Total
Illiterate	27,192	1,24	28,432
Literate	44,582	2,422	47,004
Incomplete basic education	163,518	9,408	172,926
Basic education completed	46,476	2,786	49
High school dropout	39,212	2,489	41,701
High school completed	26,578	294	28,972
Some university education	3,301	417	4
Bachelor's degree	1,493	212	1,705
Post-graduate degree	61	7	68
No information	19,366	625	19,991
Total	371,884	21,604	393,488

Table 4. Estimates of impact inequality (measured by the ratio of high to low skill wages) on homicides, assuming a Poisson distribution for the probability of committing a crime

GMM regression on homicides						
	Change in log number of homicides					
	(1)	(2)	(3)	(4)	(5)	(6)
Change in high to low skill wage ratio	0.216*** (0.074)	0.078 (0.084)	0.074 (0.079)	0.049 (0.081)	0.102 (0.074)	0.039 (0.832)
Change in young and low skill males' average log hourly wage	-1.288*** (0.376)	0.487 (0.654)	-0.275 (0.423)	0.343 (0.637)		
Growth rate of young and low skill males' unemployment rate	1.397*** (0.265)	0.087 (0.389)	0.174 (0.302)	0.095 (0.399)		
Growth rate of police force	0.1997 (0.134)	0.121 (0.152)	0.074 (0.128)	0.023 (0.137)		
Growth rate of city population			0.281 (0.702)	0.235 (0.678)	0.421 (0.647)	0.213 (0.668)
Percentage of recent young low skill migrants			8.169*** (2.936)	6.317** (3.259)	8.243*** (2.935)	6.509** (3.241)
Year dummies Observations	No 228	Yes 228	No 228	Yes 228	No 228	Yes 228

Notes: The model is in first difference, controlling for characteristics of cities, which do not change over time. Marginal effects reported. Cluster-robust standard errors are in parentheses. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table 5. Percentage of high and low skill male and female workers in 3,214 rural municipalities working in different occupations between 1970 and 2000

Occupational distribution of workers in rural areas in 1991 and 2000				
	1991		2000	
	Low skill	High skill	Low skill	High skill
Number of rural out-migrants	168.34 (551.06)	26.2 (174.87)	164.1 (557.71)	29.58 (179.71)
Number of rural non-migrants	5,757.37 (25,534.48)	250.48 (5,654.9)	6,588.44 (28,125.04)	329.42 (6,114.44)
Occupations				
Administrative (%)	*8.17*	*34.46*	*6.69*	*29.16*
Technical or scientific (%)	*1.87*	*36.76*	*2.95*	*39.37*
Farming (%)	*43.62*	*2.75*	*30.45*	*2.44*
Mining (%)	*1.43*	*0.18*	*0.60*	*0.08*
Industry (%)	*20.67*	*5.16*	*25.49*	*5.48*
Commerce and trade (%)	*7.99*	*7.19*	*9.87*	*8.99*
Transport (%)	*5.50*	*1.96*	*6.69*	*2.49*
Services (%)	*0.48*	*0.06*	*0.81*	*0.05*
Domestic services (%)	*3.36*	*2.40*	*5.24*	*3.06*
Security and defense (%)	*1.87*	*5.02*	*2.22*	*5.62*
Other (%)	*5.05*	*4.06*	*8.98*	*3.28*
Average rainfall (monthly average in cm)	11.27 (4.19)		11.14 (4.34)	
Transport costs to São Paulo	1,811 (1,437)		1,549 (1,126)	
Agricultural area (km^2)	1,074 (4,716)		963 (4,537)	
Area (km^2)	2,237 (13,093)			

Source: 1991 and 2000 Brazilian population censuses.
Notes: The average and standard deviation (SD), in parentheses, of the number of migrants leaving rural areas appear for each year for the four years before the census, conditional on the municipality having rural out-migrants. The average rainfall and SD are monthly averages in centimeters for all months between 1986 and 1990, and between 1995 and 1999. Transport costs to São Paulo comprise an index centered around 1,000 and based on linear programming calculations by Castro (2002). The average agricultural (farming) area is for 1985 and 1995, sourced from the respective agricultural censuses. The area of the municipality is sourced from the 1970 census and is constant over time (the municipalities are comparable over time).

Table 6. Estimates of the impact of rainfall shocks and changes in transport costs from rural municipalities to São Paulo on out-migration from rural areas by group for 1986–1990 and 1995–1999

Estimate of the impact of rainfall shocks and change in transport costs on rural out-migration		
	Log migrants	
	Low skill	High skill
Log lag natives	0.7896*** (0.069)	0.108 (0.063)
Log agricultural area (ha)	-0.046 (0.032)	-0.172** (0.081)
Transport costs to São Paulo	0.079 (0.095)	-0.849** (0.3496)
Average monthly rainfall (mm)	-0.0052** (0.0024)	-0.016 (0.011)
Previous year's average monthly rainfall	-0.0052** (0.0024)	-0.016 (0.011)
Average monthly rainfall in semi-arid area	0.0201*** (0.0055)	0.1301*** (0.037)
Previous year's average monthly rainfall in semi-arid area	0.032*** (0.0061)	0.097** (0.037)
Observations	25 712	22 338
Fraction of observations censured (%)	2.57	72.01
Municipality fixed effects	Yes	Yes
Year dummy variables	Yes	Yes
Number of municipalities	3,214	3,21
χ-squared test on parameters (*p*-value)	44.79 (0)	26.43 (0)

Notes: Cluster-robust standard errors are in parentheses. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table 7. Estimates of the importance of distance between the origin (3,214 municipalities) and destination (123 cities) in the choice of destination, pooling each group

Estimates for distance as an explanation for migration location decision				
	Percent rural–urban migrants			
	(1)	(2)	(3)	(4)
Log distance	-0.017** (0.00018)	-0.021** (0.00025)	-0.022** (0.00027)	-0.022** (0.00026)
Log distance (for high skill)		0.0101** (0.00034)	0.013** (0.00043)	0.011** (0.0004003)
(Log) People living in rural area *X* (Log) People living in urban area			0.00103** (0.000011)	0.0014** (0.000024)
Log number of people				-0.0082**
living in rural area				(0.00024)
Log number of people living in urban area				-0.0011** (0.00014)
Dummy for high skill	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes
Observations	787,815	787,815	787,815	787,815
Number of rural municipalities	3,214	3,214	3,214	3,214
R-squared	0.04	0.05	0.07	0.07

Notes: Cluster-robust standard errors are in parentheses. * Significant at 10%, ** significant at 5%, *** and significant at 1%.

Table 8. First stage of instrumental variables regression for changes in high to low skill wage ratio

OLS first-stage regression for inequality								
	Percentage of recent young and low skill migrants				Change in high to low skill wage ratio			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Predicted changes in the ln of recent migrants	0.00817*** (0.0013)	-0.00431 (0.0096)	0.00793*** (0.0013)	-0.004 (0.00904)	0.175*** (0.038)	-0.859*** (0.141)	0.033 (0.028)	-0.769*** (0.144)
Predicted change in high to low skill migrants	-17.12*** (4.096)	-9.451* (4.83)	-10.24** (4.14)	-8.15* (4.56)	-650.4*** (111.5)	387.3*** (82.52)	216.6** (83.29)	349.6*** (81.39)
Growth rate of city population	0.115*** (0.018)	0.107*** (0.017)	0.112*** (0.017)	0.109*** (0.017)	1.633*** (0.467)	0.56 (0.41)	0.61 (0.459)	0.43 (0.451)
Change in young and low skill males' average log hourly wage			0.0174* (0.0101)	0.033** (0.014)			-3.146*** (0.403)	-2.24*** (0.568)
Growth rate of young and low skill males' unemploy-ment rate			-0.0229* (0.012)	-0.017 (0.015)			-0.581 (0.45)	-0.227 (0.527)
Growth rate of police force			0.0117*** (0.0041)	0.0101** (0.00397)			0.021 (0.153)	-0.07 (0.155)
Year dummies	No	Yes	No	Yes	No	Yes	No	Yes
Observations	228	228	228	228	228	228	228	228
R-squared	0.859	0.362	0.871	0.397	0.374	0.508	0.661	0.541
F-test	21.63	5.445	21.48	4.155	104.7	21.08	9.987	18.33

Notes: As instruments, we use the predicted log number of total recent migrants and the predicted change in high to low skill migrants (see Section 4). Standard errors are in parentheses and are only efficient for homoskedasticity. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

Table 9. Estimates of the impact of inequality (measured by the ratio of high to low skill wages) on homicides, for the Poisson model

Second-stage of IV regression on homicide (GMM)								
	Change in the log number of homicides							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in high to low skill wage ratio	-0.216 (0.262)	0.629** (0.252)	0.701** (0.388)	0.728** (0.285)	0.484 (0.358)	0.634** (0.248)		
Change in 75th percentile wage to 25th percentile wage ratio							10.829 (23.392)	3.642*** (1.243)
Percentage of recent young and low skill migrants	14.229** (6.179)	3.863 (11.303)	4.129 (4.9612)	3.826 (14.264)	5.135 (5.496)	7.548 (14.611)	34.018 (51.861)	5.293 (17.235)
Growth rate of city population	-0.026 (0.877)	0.138 (1.367)	0.194 (0.946)	0.213 (1.763)	0.317 (0.957)	-0.017 (1.748)	0.514 (2.701)	1.589 (2.044)
Change in young and low skill males' average log hourly wage			1.9002 (1.291)	2.151** (1.041)	1.132 (1.159)	1.856** (0.991)	14.948 (33.071)	5.132*** (1.883)
Growth rate of young and low skill males' unemployment rate			0.111 (0.419)	0.186 (0.702)	0.053 (0.389)	0.332 (0.724)	-1.275 (3.167)	-0.757 (0.759)
Growth rate of police force			0.076 (0.161)	0.063 (0.196)	0.046 (0.158)	-0.024 (0.221)	0.094 (0.478)	0.182 (0.228)
Year dummies	No	Yes	No	Yes	No	Yes	No	Yes
Observations	228	228	228	228	227	227	227	227
Kleibergen–Paap rk LM-statistic (*p*-value)	0	0.0018	0.001	0.0079	0.0003	0.0074	0.563	0.0642
Stock–Wright LM *S*-statistic (*p*-value)	0.0521	0.0165	0.0203	0.0111	0.2620	0.0144	0.262	0.0144

Notes: All regressions are estimated using generalized method of moments (GMM). Marginal effects are reported. The sample is restricted to young and low skill men. The model is in the first difference, controlling for characteristics of cities, which do not change over time. In columns (1)–(4) and (7)–(8), the sample includes only young men (15–45 years), while in columns (5)–(6), the sample includes both men and women between the ages of 15 and 65 years.
Cluster-robust standard errors are in parentheses. * Significant at 10%, ** significant at 5%, and *** significant at 1%

A2 - FIGURES

Figure 1. Relationship between the change in the homicide rate by 10,000 young and low skill men in each agglomeration and the change in the ratio of high to low skill wage (a proxy for income inequality).

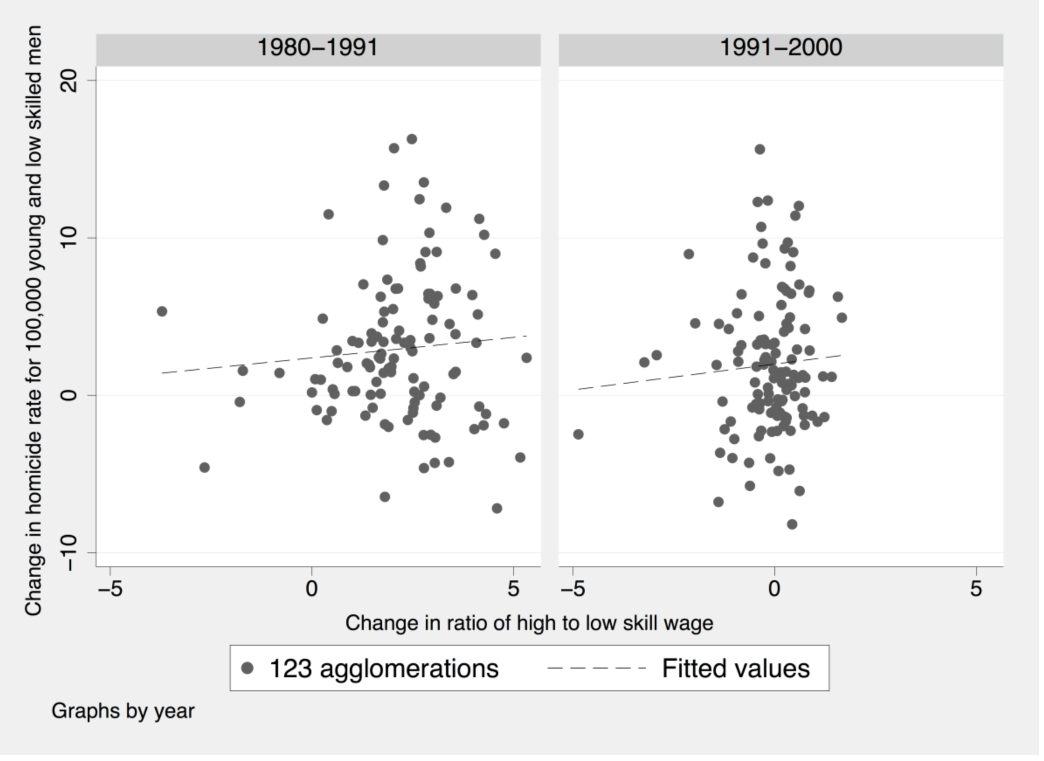

Figure 2. Relationship between change in the ratio of high to low skill wages (a proxy for income inequality) in each agglomeration and the log of recent young and low skill male migrants

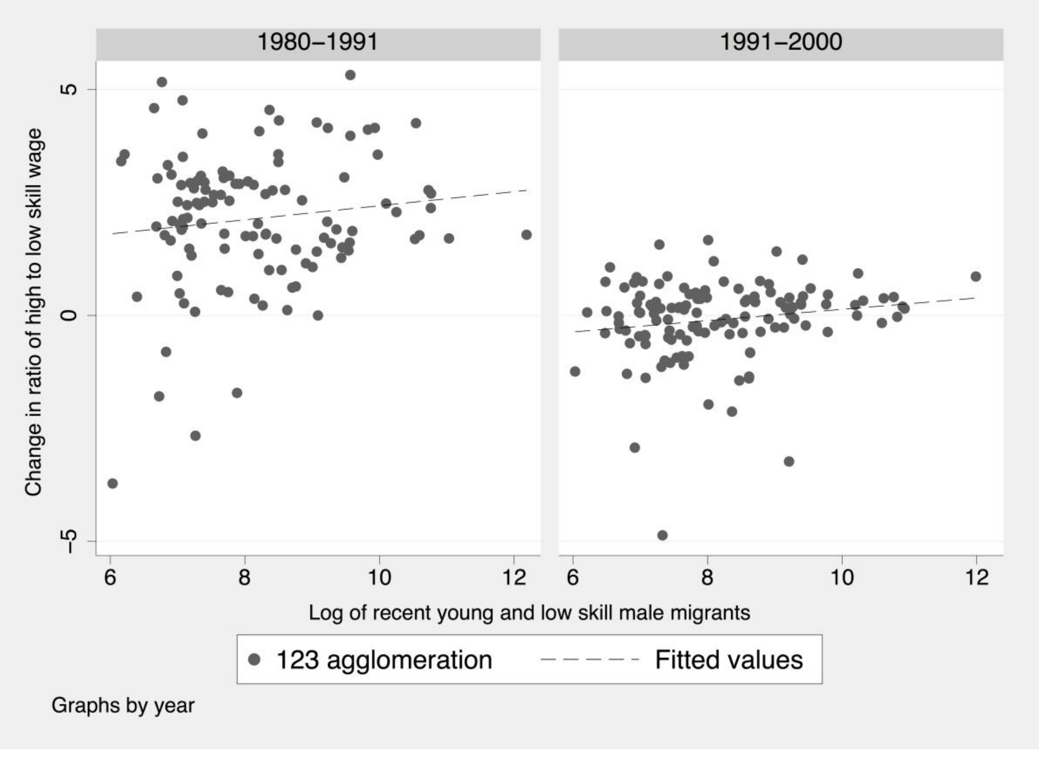

Figure 3. Relationship between the change in the homicide rate by 100,000 young and low skill males in each agglomeration and the log of recent young and low skill male migrants.