Spatial Correlation Between Drugs Traffic and Violence in Brazil: Evidence from Urban Neighborhoods

Filipe Padilla de Miranda – Depto. de Economia/UFPE
Filipe Matheus Silva Cavalcanti - Depto. de Economia/UFPE
Raul Silveira Neto – Depto. de Economia, PIMES/UFPE
Diego Firmino – Depto. de Economia, PADR/UFRPE

Resumo
Apesar da reconhecida associação entre tráficos de drogas e violência urbana no Brasil, há muito pouca evidência confiável sobre tal relação e quase nenhuma quando se considera as vizinhanças das cidades. A partir de um banco de informações para os bairros da Região Metropolitana do Recife e modelos econométricos que consideram explicitamente a dependência especial, o trabalho apresenta evidências que sugerem que o maior tráfico de drogas afeta positivamente a ocorrência de homicídios nos bairros analisados (elasticidade em torno de 0.34%). Tal evidência é obtida mesmo depois de considerar a influência de um grande conjunto de variáveis, incluindo condicionantes socieconômicos tradicionais da violência e novos controles, como o percentual de domicílios dos bairros que pertencem a favelas e a densidade de empregos em bares e restaurantes. Os resultados do trabalho também indicam que uma parcela (15%) do efeito estimado decorre de spillovers do tráfico de drogas de bairros vizinhos sobre a taxa de homicídio de cada localidade.

Palavras-chaves: tráfico de drogas, homicídios, violência urbana.

Abstract
Although it is amply recognized that part important of urban Brazilian violence is associated with drugs traffic, formal and academic investigation is rare and almost inexistent when the focus are urban neighborhoods. Using a unique data set of 261 Recife Metropolitan Region neighborhoods and spatial econometric models, the paper presents evidence about the spatial correlation between drugs traffic and homicide rates. The main evidence indicates a positive and robust association between homicide and drugs traffic (homicide rate elasticity related to drugs traffic rate around 0.34%). This result is obtained even after controlling for the influence of a large set of cofactors, including not only traditional socioeconomic local conditionings of violence, but also the presence of slums and bar and restaurants activities in the neighborhoods. Additional evidence also indicates that around 15% of the drugs traffic influence on local violence arises from the influence of neighbors, i.e., it comes from spillovers effects (indirect impacts).

Key-words: drugs traffic, homicide, urban violence.

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1. Introduction

Presenting a homicide rate around 48 homicides per 100.000 inhabitants in 2016, much higher the homicide rate observed for the Brazil as all and for the mean homicide rate for Brazilian capitals (respectively, around 30 and 42 homicides per 100.000 inhabitants), Recife Metropolitan Region violence situation appears to resemble the high urban violence of Brazilian big urban centers. Although certainly there are multiple causes for this situation, data from the Social Defense Secretary of the State of Pernambuco, Brazil, call the attention for the fact of almost 70% of homicides that occurred in the Metropolitan Region of Recife in this year was motivated or presented some relationship with drugs traffic or consume. Thus, this initial information suggests that part important of violence in the RMR can be explained by drugs traffic or use.

Curiously, although very suggestive, the role of drugs traffic or use for explaining the urban violence is not yet much studied in applied empirical investigations. In fact, different researches have been studying the determinants of homicide rates in Brazil (De Mello, 2007; Cerqueira, 2003, 2014; Silva, 2014; Melo et al. 2016) and there are specific works on the conditionings of homicide rates in the city of Recife (Menezes et al. 2013; Pereira et al. 2017), but the set of investigation focus mainly the role of socioeconomic determinants of the urban violence. De Mello (2015) is one of the few exceptions. Considering a panel of municipalities of the State of São Paulo, the author provides evidence of a causal effect of crack traffic on homicides rate of the municipalities, but found no role for drugs consume. More recently, Ratton et al. (2017) have analyzed the drugs market in the city of Recife and called the attention that violence associated to the functioning of this market is intrinsically associated with the urban violence verified in the city. The authors, however, do not provide any empirical systematic support for this link.

The objective of this paper is to provide empirical evidence of the spatial association between drugs traffic and homicide rate in the Recife Metropolitan Region. Using data from 261 neighborhoods of 9 municipalities of the RMR (including Recife) and considering a large set of covariates, including not only traditional socioeconomic ones (income, inequality, unemployment, etc.), but also information about the presence of slums and bar and restaurant employment level in the neighborhoods, the research considers different econometric models to estimate a reliable relationship between drugs traffic and homicide rate. The contribution of the paper is threefold. First, it provides empirical evidence about the association between drugs traffic and urban violence in an important Brazilian Metropolitan Region, something still rare, considering a unique set of control variables. Second, it considers this association using neighborhoods information, a more appropriated spatial unity since drugs traffic and homicide are very collocate within cities. Finally, we are able to measure spillovers effects from traffic drugs of neighbor localities on the homicide rate of the neighborhoods.

The results obtained indicate that a 1% increase of the drugs traffic rate is associated with a 0.34% increase of the homicide rate of a neighborhood in RMR, evidence generated after controlling for large set of covariates conditioning the local environment. We also found that around 15% of this effect is due to spatial spillovers from neighbors localities, in other words, due to traffic drugs in these neighborhoods.

The paper is organized as follows. In section 2, we present theoretical arguments for the existence of a link between drugs traffic and urban violence, together with empirical evidence about this links. In section 3, we present our empirical strategy and the data set. Section 4 presents and discusses the results of the investigation. Final remarks are presented in section 5.

2. Drugs and urban violence

As highlighted by Goldstein (1985), different possible channels can be present behind the association relation between drugs and urban violence. According to this author, there is a possible pharmacological relationship between drugs and violence explained by the change of behavior of drugs users, who can become more socially aggressive and violent.

In the same way, the nexus can be justified by economic motivation; the violence associated with drugs would occur due the necessity of habits sustentation. In this way, drugs consume would motivate different kinds of crimes, such robbery and homicide associated with it. Finally, there would be a systematic channel associated with the general illegality character of the drugs use and traffic; because there is no legal or institutional instances for conflicts intermediation, they tend to be solved through violent confronts[1].

Note that these different channels are related to both drugs use (pharmacological relationship and economic channels) and traffic (systematic channel). Based on the available set of empirical evidence about them, however, the knowledge about the operation of the channels tends to present clear variation. Johson, Golup, and Dunlap (2000) summarize the empirical results for US literature indicating that, while the pharmacological channel appears less important, the economic one appears substantive. On the other hand, according to the authors, much less is known about the systematic channel, the one more directly involving drugs traffic. Corman and Mocan (2000) presented evidence indicating weak relationship between drugs consume and property crime.

As for Brazilian case, although the high level of urban violence and its potential association with drugs use and traffic, most of the studies focus on the determinants of homicide rates use municipal or state information and do not directly consider the role of drugs use or traffic (Cerqueira e Lobão, 2003; De Mello, 2007; Carvalho and Lavor, 2009; Scorzafave and Soares, 2009; Cerqueira, 2014). Furthermore, only recently more researches have considered within cities crimes variation. Menezes et al. (2013) and Pereira et al. (2015) both considered the determinants of homicide rates in the city of Recife using neighborhoods or census tracts. Similarly, Oliveira et al. (2017) have studied the determinants of homicide rate in the city of Fortaleza using neighborhoods as unity of analysis. Generally motivated on Becker (1968) approach for crime and sociological Theories of Social Disorganization and Collective Efficacy (Shaw and Mackay, 1942; Sampson and Raudenbush, 1999), these works have considered traditional socio-economic determinants of violence, such as income, inequality, urban density and unemployment. None of these previous studies, however, have considered the local association between drugs traffic or use and urban violence, which tend to be mainly present at neighborhood or local level. Thus, it is much possible that the obtained correlations in these previous three works just reflect the worst social conditions caused by the presence of drugs traffic or particular characteristics of the neighborhoods associated with drugs traffic.

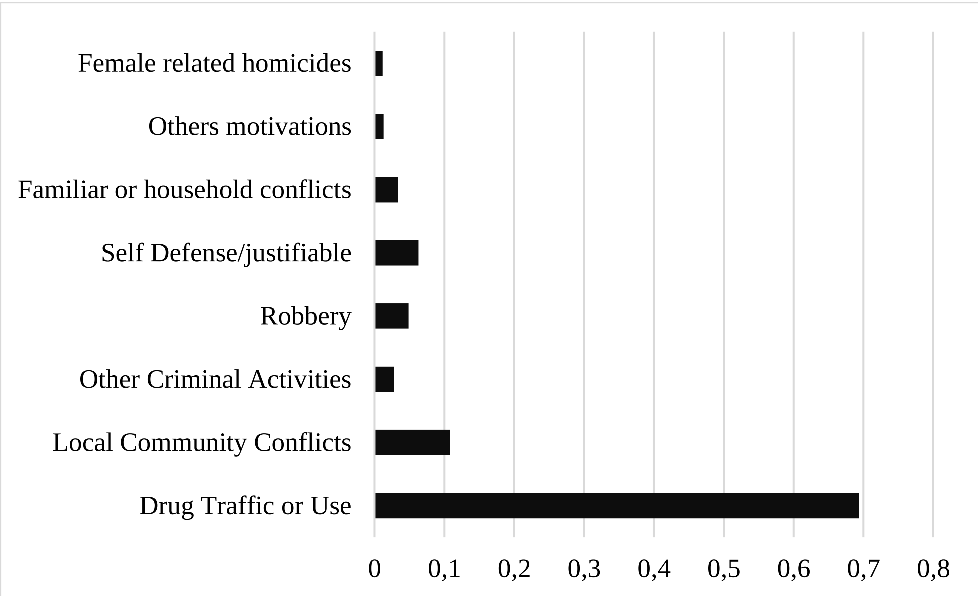
The most convincing evidence of association between drugs traffic and violence in Brazil was provided by De Mello (2015) using information for municipalities of São Paulo state. Using a panel of municipalities, the author obtained evidence about a positive and causal association between crack traffic and homicide rates. The results of this work also indicate that this kind of causality is not present when considering crack use and homicide rates, supporting the idea that the association between drugs and violence in theses municipalities is associated with the systematic channel. More recently, using a national survey, Abdalla et al. (2018) presented statistics associating cocaine use and alcohol disorder with higher chance of being a violent aggressor. These new evidence for all the country are totally in line with De Mello (2015) evidence for São Paulo's municipalities. Nevertheless, both evidence are not obtained considering local within cities characteristics or social environment, thus, the results are quite general and do not account to the fact that the relationship between drugs traffic and urban violence tend be strongly spatial concentrated within cities locations.

[1] De Mello (2015) also provides a good discussion about these channels.

The specificities of the drugs market in Recife have been study recently by Ratton *et al* (2017). The authors empathize the difference between closed and open drug markets and the different associated implications to urban violence. While in the closed markets the transaction are effective by mutual knowledge between the parts and tend to happen in private environments, in the open markets the transactions tend to happen in public environments and the dealers have much less knowledge about the each other. Accordingly, because conflict solutions are difficult and there is less information, there would be a stronger association between drugs traffic and urban violence in the second market. Note that the argument support the idea that the association between drugs and violence in Recife present a clear systematic channel and is consistent with the results obtained by De Mello (2015) for São Paulo municipalities.

Recent information about the association between drugs apprehension and violence provided by Social Defense Secretary of the State of Pernambuco suggest a very strong association between drugs traffic and homicide in Recife Metropolitan Region (RMR). According the official information and based on state law regulating crimes occurrence, around 69% of homicides in RMR during the year of 2017 could be attributed to drugs traffic or use, a percentage higher than the one observed for the year of 2010 (less than 50%). The following Graphic 1 presents the distribution of homicides among different categories of motivations according to this official source. These associations, of course, do not consider any simultaneous events and local characteristics and, thus, can not be taken as reliable indicators[2].

Graphic 1 – Distribution of homicides by attributed motivations – Recife Metropolitan Region



Source: Authors' calculus based on data from the Social Defense Secretary of the state of Pernambuco (SDS/PE). The data do not consider events with motivation not specified.

3. Empirical strategy

3.1 Model specification

Although there are significant different levels of urban violence across cities, across neighborhoods within cities criminality differences can be even more significant (Sampson, 2012).

[2] Drugs traffic or use attributions as causes of homicide by the official records are based on the official norm nº 357 of 2010 of GACE/PE (Gerência de Analise Estatística Criminal/PE). According to this norm, the association between drugs and homicide is established when the victim was a drug dealer or drug consumer or was involved in crime related to drugs activities.

Additionally, within areas or urban neighborhoods' social characteristics or circumstances are much better measured by traditional social indicators than when such indicators are used for representing cities as all. Thus, we use the neighborhoods of the municipalities of RMR as analytic spatial unity for obtaining a confident measure of association between drugs traffic and homicide rate and consider regressing drugs traffic on homicide rate. Traditional endogeneity problems and spatial dependence in the variables remains challenges to be dealt with.

To deal with the last question, we incorporate the possibility of spatial dependence among the variables by considering initially the following general spatial model (Lesage and Pace, 2009; Elhorst, 2014):

$$H = \alpha + \rho WH + X\beta + \theta WX + \varepsilon \quad (1)$$

$$\varepsilon = \lambda W\varepsilon + \mu \quad (2)$$

where, H is the homicide rate (matrix 261 x 1); X is a set of explicative variables (discussed in the following lines), including drugs traffic (matrix 261 x k); W is a spatial weighting matrix (matrix 261 x 261); $\alpha, \rho, \beta, \theta,$ and λ are parameters; and μ is a normally distributed random term. Note that the specification captures three different kinds of spatial influence: the effect from the spatial endogenous variable (*lag spatial* of *H*), the influence from the neighborhoods' explicative variable (*WX*), and the possibility of spatial correlation in the residues ($W\varepsilon$).

As shown, for example, by Elhorst (2014), different specific models can be obtained assuming different hypothesis about the spatial parameters (ρ, β, λ). Note, particularly, that SDEM (Spatial Durbin Error Model), SDM (Spatial Durbin Model), and SAC (Spatial Auto-Regressive Combined Model) are obtained assuming, respectively, $\rho = 0, \lambda = 0,$ and $\theta = 0.$ We use LM and Wald tests for choosing the appropriated model specification.

Maximum-likelihood or Instrumental Variable estimations can be used to estimate parameters for the above models, dealing appropriately with possible endogeneity arising from spatial dependence (in the case of specifications presenting a spatial lag endogenous variable as regressor). However, these strategies are not enough for dealing tradition endogeneities problems (reverse causality and omitted variable problems). Although we recognize they are possible not enough, we believe that the two additional strategies we adopt strongly attenuate the problem. First, we avoid much of reverse causality considering explicative variables measured in the year of 2010, while the dependent variable (homicide rate) is measured for the years of 2013-2015. Second, we included in the variables *X* a great set of potential determinants of homicide rate, part of them still not applied in Brazilian empirical works.

As for the set of variables in *X*, following previous empirical works, such as Kelly (2000), Cook (2009), Scorzafave and Soares (2009), and Menezes et al. (2013), we include traditional socioeconomic and environmental conditionings of urban violence, all measured at neighborhoods levels. More specifically, this set of variables includes per capita income, the Gini index for per capita income, population, density, percentage of female as household-head, percentage of young people, percentage of non-occupied household heads, and distance to Recife's CBD.

Motivated by broken-windows theory and using google images, He et al. (2017) recently showed that local physical aspects are strongly associated with urban violence. Thus, similarly to Oliveira et al. (2017), we also use the new information of 2010 Demographic Census to build a neighborhood infrastructure index based on the % of residences in streets with regular garbage collection, % of residences with street with culvert, % of residence in streets with public illumination, % of residences with paved street, and % of residences in streets with sidewalk. We use Component Principal Approach (PCA) to sum up these information and use the first and most important component to obtain an index of around neighborhood infrastructure indicating the quality of local public environment. In the appendix, we present eigenvalues, autovectors, and the expression used for obtaining this index.

Finally, three more conditionings still not explored in Brazilian literature are considered. To control for the degree of local guardianship, we also use the percentage of rented residences in the neighborhoods as an additional regressor; according to Homevoter Hypothesis by Fischel (2005), given the possibilities of capital losses, houses owners tend to be more worry about local environmental occurrences and, thus, more involved in public guardianship than house renters. Second, because there is the possibility of drugs traffic be concentrated in some specific poor neighborhoods, we also consider the percentage of residences of the neighborhoods located in slums. This conditioning is important if the presence of slums is both associated with homicide and drugs traffic.

Third, using geocoding techniques applied to the address information of all formal sector firms of the RMR, we built an additional variable measuring the density of employment in Bar and Restaurant (number of occupations/area) for each neighborhood of the RMR[3]. As suggested by Gruenewald (2007), in order to differentiate from the others establishments and to avoid stronger competition in places with higher density of bars, some of them implement strategies favorable to heavy drinkers and people with more risk for problems. Leidenfrost et al (2017) present some researches supporting this idea. Since this density can be both associated with homicide and drugs traffic, to get a credible estimative for the association between these occurrences, this influence must be controlled for.

3.2 Data

The RMR is composed by Recife (capital of the state of Pernambuco) plus 13 others municipalities. Because of inexistence of data for neighborhoods of 5 municipalities, we consider only the others 9 municipalities: Abreu e Lima, Camaragibe, Cabo de Santo Agostinho, Igarassu, Itapissuma, Jaboatão dos Guararapes, Olinda, Paulista e Recife[4]. For these municipalities, we collect and build information for 261 neighborhoods.

The data set of the investigation is based on three different sources of information. The information about crimes was obtained from the Defense Secretary of the State of Pernambuco. The information includes occurrence of homicides and drugs traffic registries for each neighborhoods for the years 2013-2015. In order to avoid extreme volatility when registering occurrence at the neighborhood level, we consider the average of homicide and drugs traffic registry rates (occurrence/100.000) in this period. The logarithm of the average of the homicide rates is our dependent variable[5].

As for the other explicative variables, most of them are built using information from 2010 Demographic Census (per capita income, Gini index, population, density, % of female as household-head, % of young people, % of non-occupied household heads, % of residences in streets with garbage collection, % of residences with street with culvert, % of residence in streets with public illumination, % of residences with paved street, and % of residences in streets with sidewalk, % of rented residences, and % of residences of the neighborhoods located in slums). The values of these variables for the neighborhoods were obtained aggregating the information from census tracks. From RAIS and Minister of Finance, we use the information necessary (firms location and employment) to obtain the density of employment in Bar and Restaurant in each neighborhood.

Table 1 and Table 2 present, respectively, description and descriptive statistics of the variables and the coefficients of correlation between the variables. We perceive none very high correlation coefficient between any pairs of variables, which indicates that multicollinearity is not an important concern in our estimative.

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[3] The geocoding uses the QGis soft and information from RAIS (Relação Anual de Informações Sociais) database provided by Minister of Labor and Employmen and data from Minister of Finance.

[4] The excluded municipalities are São Lourenço da Mata, Araçoiaba, Moreno, Vitória de Santo Antão, and Ipojuca. These municipalities and are more peripheral (more distant from Recife) and less urban ones.

[5] Because some few neighborhoods present no occurrences during the period, in order to use logarithms, we added 1 to the values of the crime rates.

Table 1 – Descriptive Statistics – RMR's Neighborhoods

Variable	Description	Mean	Std. Desv.
Homicide rate	Homicides/100.000	44.5	63.3
Drugs Traffic	Occurrences/100.000	137.0	623.8
Gini	Gini index	0.4911	0.0963
Income	Household per capita income (R$)	588.93	616.25
Population	Inhabitants	12,591.43	14.881.47
Female H-H	% of female household heads	43.88	7.83
Unemployment	% of non-occupied household heads	14.06	6.14
Density	Population/km^2	0.0133	0.0622
Young	% of people of 15-25 years old	18.24	1.73
Rented proprieties	% of rented proprieties	19.03	6.74
Bar and R. Emp.	Number of employment in Bar and Restaurants/Km^2	88.15	241.89
Infrastructure	Index of urban infrastructure (PC analysis)	0.753	0.198
Slums	% of residences located in slums	20.54	27.20
Distance to CBD	Km of distance from Recife's CBD	13.27	8.04

Source: Generated by the authors using data from 2010 Demographic Census, RAIS (Relatório Anual de Informações Sociais) provided by Minister of Labor and Employment, and Social Defense Sate Secretary of State of Pernambuco (SDS/PE). Bar and Rest. Employment Density variable was built using QGis soft for geocoding firms based on their address. The Index of Infrastructure was obtained by Component Principal technique.

Table 2 – Paired correlations of the variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Homicide rate	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-
(2) Drugs traffic	0.40	1.00	-	-	-	-	-	-	-	-	-	-	-	-
(3) Gini	-0.03	0.19	1.00	-	-	-	-	-	-	-	-	-	-	-
(4) Income	-0.18	0.21	0.37	1.00	-	-	-	-	-	-	-	-	-	-
(5) Population	0.29	0.34	0.09	0.03	1.00	-	-	-	-	-	-	-	-	-
(6) Female H-H	0.16	0.33	0.20	0.05	0.23	1.00	-	-	-	-	-	-	-	-
(7) Unemploy.	0.15	-0.14	0.12	-0.53	0.12	0.20	1.00	-	-	-	-	-	-	-
(8) Density	-0.04	0.25	0.05	-0.01	0.54	0.31	-0.02	1.00	-	-	-	-	-	-
(9) Young	0.11	-0.11	-0.19	-0.27	0.03	0.01	0.30	-0.09	1.00	-	-	-	-	-
(10) Rented prop.	0.04	0.31	-0.02	0.27	0.33	0.14	-0.22	0.36	-0.13	1.00	-	-	-	-
(11) Bar, R. Emp.	0.01	0.32	0.21	0.55	0.23	0.23	-0.47	0.27	-0.26	0.37	1.00	-	-	-
(12) Infrastruct.	-0.06	0.25	0.02	0.36	0.15	0.01	-0.43	0.20	-0.30	0.43	0.40	1.00	-	-
(13) Slums	0.33	0.23	-0.02	-0.23	0.43	0.20	0.35	0.20	0.29	0.01	-0.06	-0.15	1.00	-
(14) Dist. to CBD	0.01	-0.43	0.19	0.40	-0.14	-0.44	0.35	-0.38	0.17	-0.32	-0.56	-0.26	-0.56	1.00

Source: Calculated by the authors using data from 2010 Demographic Census, RAIS (Relatório Anual de Informações Sociais) provided by Minister of Labor and Employment, and Social Defense Sate Secretary of State of Pernambuco (SDS/PE). All variables are in logarithms. "Infrastructure" refers to Principal Component Index.

4. Results

4.1 Spatial distribution of drugs traffic and violence

In the following Figure 1, we present the spatial distributions of drugs traffic and homicide rates across the 261 neighborhoods of the RMR. We first note that both types are quite unequally distributed across neighborhoods; for homicide rate, for example, we notice that some neighborhoods present a value higher than 700 homicides per 100.000 habitants and others presenting less than 2 homicides per 100.000 habitants. Thus, there is a great urban variation in violence conditions among neighborhoods for both kinds of occurrences. Additionally, the two maps of Figure 1 suggest spatial association or dependence for both kinds of crimes; in general, higher (lower) rates in a neighborhood tend to happen together with its neighbors.

From the Figure 1, we also observe that homicide rates are spatially spreader across neighborhoods than drugs traffic rates. Specifically, while drugs traffic are clearly located in some neighborhoods of the RMR around the CBD of Recife and in the north part of it, higher homicide rates are found both around Recife's CBD and in the neighborhoods in different peripheries of the RMR. Interestingly and important for our next exercises, from the two maps of Figure 1, we note that, although there many neighborhoods presenting both higher drugs traffic and homicide rates, we also found others neighborhoods presenting lower drugs traffic and higher homicide rates. This specific evidence suggests that the registration of the drugs traffic occurrences is not driven by the possible more frequent presence of police force in neighborhoods with higher homicide rates and, thus, brings more confident for our regression results.

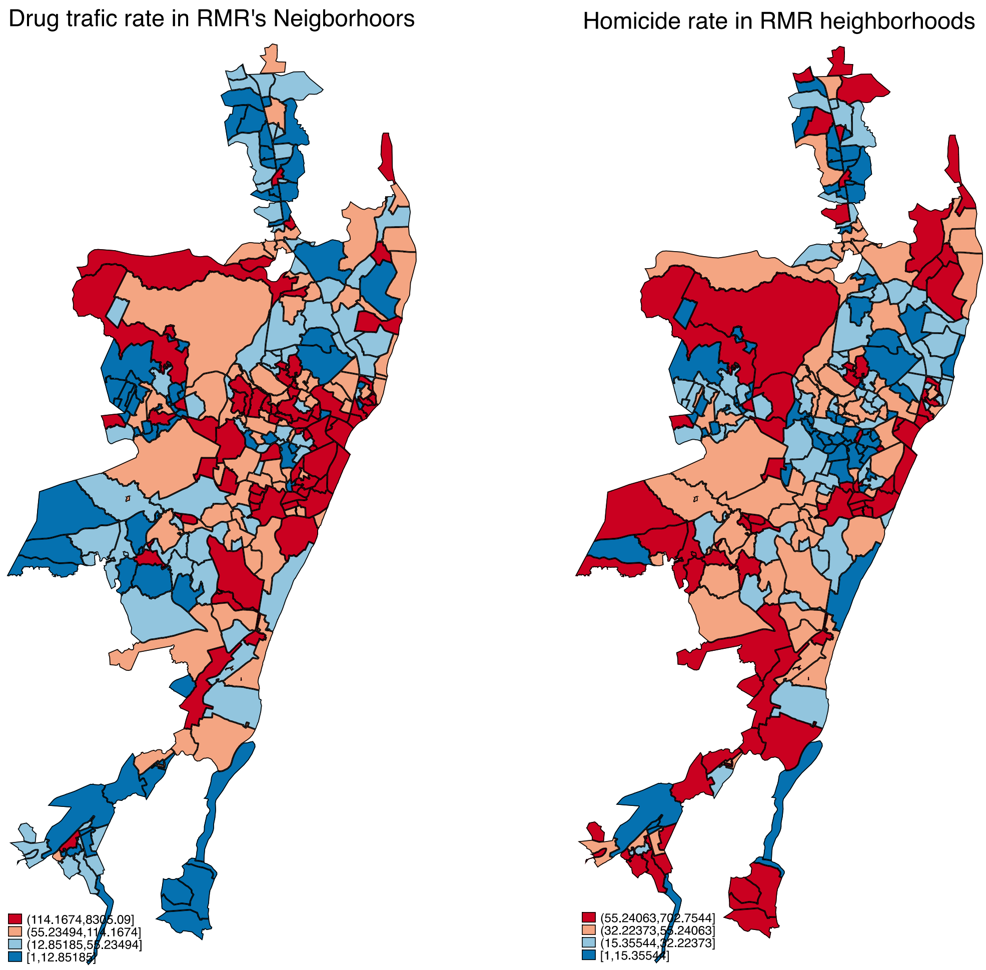

Figure 1: Drugs traffic and homicide rates and in the neighborhoods of the RMR.

Nonetheless, as the evidence from Figure 2 shows, there is a clear positive association between the kinds of crimes[6]. This positive association, of course, can arise from many different factors affecting both kinds of crimes and, in order to get an credible measure of the influence of drugs traffic on homicide rate, we try to eliminate them in our regression exercises.

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[6] We use the logarithms in order to deals with the big difference between the numbers of registry between the two kinds of crimes. Because some few neighborhoods present zero registry, we add the value 1 for all neighborhoods' registry. Positive association is also found using levels.

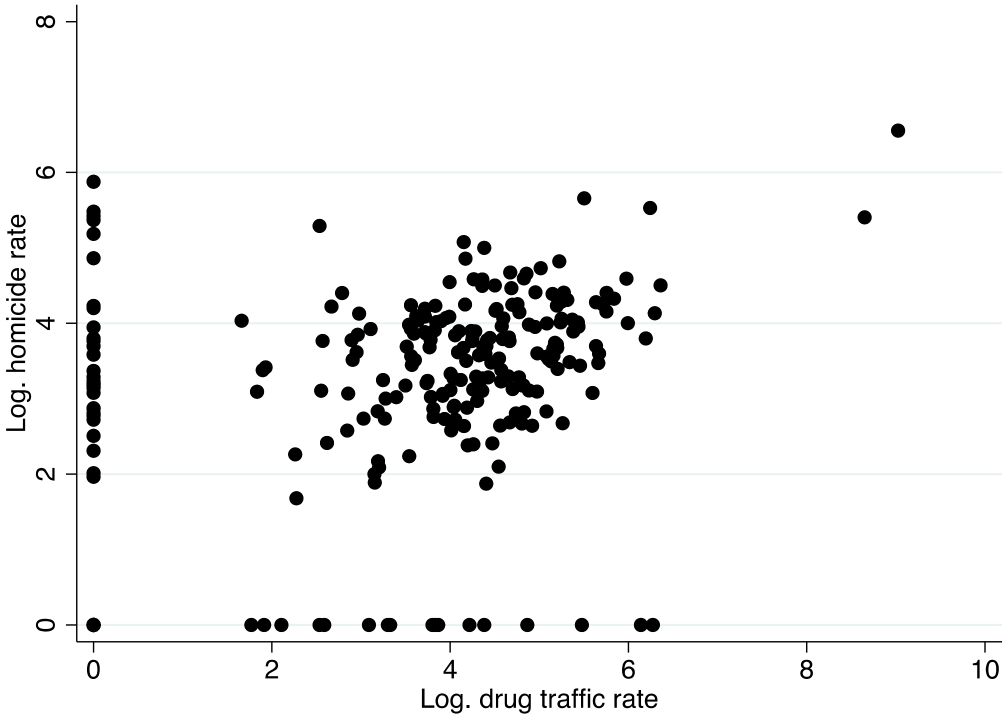

Figure 2: Association between drugs traffic and homicide rate in RMR's neighborhoods.

Furthermore, as the numbers of Table 3 show, there is another difficult for our next empirical investigation, the spatial dependence of homicide rates among neighborhoods. Using two traditional measure of spatial correlation (Moran's I and Geray's C) and different kinds of spatial weighting matrix, the evidence form Table 3 indicates that we must strongly reject the hypothesis of no spatial dependence among neighborhoods' homicide rates. This indicates that, even eliminating more traditional problems of endogeneity, in order to guarantee unbiased estimative, we have to adequately with this spatial association (Anselin, 1988).

Table 3 – Spatial dependence tests – Homicide rate in RMR's Neighborhoods

Matrix W	Moran's I	Geary's C
Contiguity (Queen)	0,155	0,790
	(0,000)	(0,000)
5 Nearest Neighbors	0,214	0,785
	(0,000)	(0,000)
Inverse of Distance	0,051	0,938
	(0,000)	(0,000)

Obs.: *P-value* in parenthesis. Similar results are obtained using *Rook* contiguity matrix.

4.2 Drugs traffic affecting homicide in RMR

In the Table 4, we present estimative of the coefficient of our econometric models we used to get a credible association between drugs traffic and homicide rates in the RMR. As advanced, we start by running a traditional OLS estimation considering a great number of different sets of controls; then, we use statistical tests and information for comparing and choosing appropriated spatial econometric model.

The estimative of Table 4 corresponding to OLS estimative indicates that, after taking in account the influence of different variable that potentially affect neighborhood homicide rates, there is a positive association between drugs traffic and homicide in RMR's neighborhoods: a 1% increase of drugs traffic is associated with a 0.3% increase of homicide rate. The neighborhoods' homicide rate appears also positively associated with population and the presence of slums and negatively associated with the neighborhoods' per capita income and demographic density.

In order to consider spatial information and models, we need to consider a spatial weighting of neighborhoods. After running spatial models for contiguity and 1-10 nearest neighbors' matrices, we have chosen the 5 nearest neighbors matrix because it presents the highest value of the Log-Likelihood function[7]. Thus, we use the 5 nearest neighbors matrix for testing for spatial dependence and for deciding about spatial models.

From the OLS column of Table 4, we note that LM tests for spatial dependence (Anselin, 1988; Anselin et al. 1996) do not reject the hypothesis of no spatial dependence when OLS is compared with a Spatial Error Model (SEM), but they indicate rejection of the hypothesis in favor of a Spatial Auto-Regressive Model (SAR). When considering the same tests applied to a XLS model (a model incorporating spatially lag of explicative variables), they indicate that we cannot reject the hypothesis of no spatial dependence in favor of either SE or SAR models (XLS columns of Table 4). Nevertheless, using a LR test for choosing between XLS and OLS models, we get a statistic with value of 18.94 and a p-value of 0.09, what favors OLS model. In addition, a Wald test for the coefficients of WX of the XLS model generates a statistics of 1.47 and a *p-value* 0.135, providing more evidence in favor of the OLS specification.

Given this initial evidence favoring the SAR model, we also consider more general models including the spatial endogenous variable (SDM and SAC models) and additional tests for choosing the appropriated spatial econometric specification. The evidences are presented in Table 5 and correspond to LR and Wald statistics for testing SDM and SAC models against alternative models. According to the numbers of Table 5, both for LR or Wald statics tests, it not possible to reject the hypothesis that alternative models (XLS, SAR or SEM) are preferable to the SDM. On the other hand, the bottom part of Table 5 indicates that SAC is preferable to SEM, but not to the SAR model. Taking together, these two additional evidences indicate that the SAR model is the most appropriated way for modeling the spatial dependence present in the data. Thus, in the last column of Table 4, we present coefficient estimative for the SAR model, including the one for the coefficient for the spatial lag of the endogenous variable[8].

Table 4 – Drugs traffic and homicide rates in the RMR. Dependent variable is the logarithm of homicide rate of RMR's Neighborhoods.

	OLS	XLS		SAR
	$\hat{\beta}$	$\hat{\beta}$	$\hat{\theta}$	$\hat{\beta}$
Drugs Traff.	0.303***	0,266***	0,175*	0.289***
	(0.059)	(0,058)	(0.097)	(0,045)
Gini Index	0.183	0.152	-1.047	0.111
	(0.526)	(0.625)	(1.267)	(0.537)
Income	-0.580***	-0.499***	-0.321	-0.546***
	(0.141)	(0.150)	(0.305)	(0.141)
Population	0.357***	0.349***	-0.078	0.341***
	(0.099)	(0.109)	(0.162)	(0.085)
Female H-H	0.595	0.536	2.949**	0.515
	(0.868)	(0.838)	(1.093)	(0.522)
Unemployment	-0.194	-0.185	-0.670	-0.161
	(0.341)	(0.328)	(0.521)	(0.261)

[7] This number also corresponds to the average number of neighbors in the contiguty (Queen) Matrix.
[8] The set of estimative for SDM and SAC models can be immediately provided by the authors upon request.

Density	-0.390***	-0.347***	-0.121	-0.378***
	(0.090)	(0.092)	(0.150)	(0.074)
Young	0.347	-0.052	1.156	0.245
	(1.339)	(1.303)	(1.965)	(0.907)
Rented proprieties	0.052	0.078	-0.748	0.031
	(0.288)	(0.280)	(0.590)	(0.181)
Bar and R. Emp.	0.057	0.027	0.001	0.058
	(0.056)	(0.057)	(0.093)	(0.049)
Dist. to CBD	0.127	0.930	-0.623	0.111
	(0.195)	(0.879)	(0.922)	(0.162)
Infrastructure	-0.386	-0.142	0.195	-0.315
	(0.513)	(0.598)	(0.737)	(0.451)
Slum	0.093*	0.050	0.077	0.076
	(0.049)	(0.052)	(0.092)	(0.052)
Constant	-2.700	-12.198	-	-2.582
	(5.149)	(8.552)		(3.514)
ρ	-	-	-	0.156**
				(0.077)
N	261	261		261
R^2	0.3675	0.4150		0.3653
Log. Verossim.	-411.5731	-402.1046		-409.5409
I de Moran	1.549	1.451		
LM Erro	1.048	0.153		
LM Rob. Erro	1.510	0.380		
LM Lag.	4.624**	0.029		
LM Rob. Lag.	5.086**	0.256		

Note: Heterocedastic robust standardized error in parenthesis. * p < 0.10, ** p < 0.05, *** p < 0.01. Variables are defined in Table 1 and are measured in logarithms.

Table 5 – Specification tests for spatial models

SDM *versus*	XLS	SAR	SEM
	$H_0: \rho = 0$	$H_0: \theta = 0$	$H_0: \theta + \rho\beta = 0$
LR	0,12	16,50	19,81
	(0,944)	(0,223)	(0,099)
Wald	0,34	16,95	17,58
	(0,733)	(0,202)	(0,174)
SAC *versus*	SAR	SEM	
	$H_0: \lambda = 0$	$H_0: \rho = 0$	
LR	2,37	5,69	
	(0,123)	(0,017)	
Wald	-1,57	2,82	
	(0,117)	(0,005)	

Obs.: P-value entre parentheses.

While in OLS and XLS models the estimated coefficients indicate marginal effects of the explicative variables, as argued by LeSage and Pace (2009), the presence of the spatial lag of the endogenous variable as a regressor indicates the existence of feedbacks effects arising both from neighborhoods own explicative variables and from neighbors explicative variables. Thus, in the SAR models, the estimated coefficients do not represent the marginal effect of the explicative variables on the homicide rate of the neighborhoods. The marginal effects are obtained by considering a SAR specification of equations (1) and (2) and taking appropriate derivative. More specifically, from the following SAR specification,

$$H = \alpha + \rho WH + X\beta + \mu \ , \tag{3}$$

we obtain the marginal effect of a variable X_j as:

$$\frac{\partial E(H)}{\partial X_j} = (I_n - \rho W)^{-1}\beta_j \ . \tag{4}$$

Note that the right side of equation (4) corresponds to a matrix (261 x 261), where the average of principal diagonal elements measures the direct effect (influence from own explicative variable) and the average of elements off of it corresponds to the indirect effect (influence from neighbors' explicative variable).

We present direct and indirect marginal effects of the variables in the next Table 6. Two general evidences must initially be highlighted. First, although not all estimative are statically significant at standardized levels, except for the case of the percentage of unemployment[9], all the neighborhood level variable present the expected influence on homicide rates. Second, considering the statically significant effects, we note that influences on homicide rates arise mainly from the direct effects, but, in all cases, there are also spillovers effects arising from neighbors' characteristics.

More specifically, we observe a positive effects of the drugs traffic on homicide rate higher than the one once obtained for OLS estimative or indicated by the SAR coefficient estimative (Table 4): a one 1% increase of drugs traffic is associated with a 0.34% increased in the homicide rate, being around 15% of this influence coming from spillovers effect (indirect effect) of neighbors locations. Thus, the results indicate that the homicide rate is not only positively affected by the drugs traffic presence in own neighborhoods, but also by drugs traffic occurrence in their neighbor locations. Thus, our results are in light with these obtained by Mello (2015), for the influence of drugs traffic on homicide rate using cities of São Paulo, and by Abdalla et al. (2018), who highlighted the association between drugs and violence in Brazil using a representative survey. In addition, our set of evidence also indicates the importance of considering spatial dependence when studying urban homicides rates in Brazilian urban space.

Similarly to Oliveira et al. (2017), who studied the determinants of homicide rates for the city of Fortaleza using its neighborhoods, we also found negative effects of neighborhoods' income and density on homicide rate, these evidence are consistent, respectively, with higher opportunity costs of being arrested associated with higher income (Becker, 1968; Bruckner, 2011) and with stronger public guardianship (Sampson, 2012). But differently from the estimative of these authors, our evidence indicates that these influence also come from spillovers from neighbor locations. Thus, in the case of RMR's neighborhoods, important spillover effects arise from richer and denser neighbor locations helping to reduce homicides. The opposite happens for the effect of neighborhoods population influence on homicide rate.

Although presenting some similarities, our results present important differences when compared to those obtained by Menezes et al. (2013), who considered the determinants of homicide rates using exclusively the 94 neighborhoods of the city of Recife (discarding the neighborhoods of contiguous municipalities), 2000 Demographic Census information, and homicide in the period 2008-2010. As these authors, we also found a positive influence of neighborhoods' population on homicide rates when considering small urban areas of almost all RMR's municipalities and this appears consistent with the higher probability of convergence in time and space between victims and potential offenders, as

[9] We do not have a definitive explication for this effect, but we note that unemployment can be correlated with less regular activities and public exposition. Actually, Silveira Neto and Moura (2018) have recently shown that a longer commuting time increases the probability of being victim of robbery in the Brazilian metropolitan regions.

advocated by routine activities theory (Cohen and Felson, 1979; Cohen and Cantor, 1981). Nevertheless, we did not find any evidence for the role of income inequality (Gini index)[10] and, more important, we obtained a positive parameter of the spatial lag endogenous variable (ρ), indicating positive feedback effects of homicide rates from neighbors. Thus, in our case, areas with low crime rates are not surrounded by neighborhoods with high murder rates as defended by those authors, but the opposite. In other words, our evidence indicates that the higher the urban violence in its neighbors' areas, the higher tends to be the violence in the neighborhoods of RMR.

Table 6 – Marginal Effects of the variables on homicide rate – SAR Model.

	Direct Effect	Indirect Effect	Total Effect
Drugs Traffic	0.291***	0.052*	0.343**
	(0.045)	(0.029)	(0.057)
Gini	0.111	0,020	0,131
	(0.539)	(0.097)	(0.635)
Income	-0.550***	-0.099*	-0.649***
	(0,142)	(0.059)	(0.171)
Population	0.343***	0.062*	0.405***
	(0.086)	(0.037)	(0.104)
Female H-H	0.517	0.024	0.611
	(0.523)	(0.093)	(0.616)
Unemployment	-0.162	-0.029	-0.191
	(0.261)	(0.049)	(0.308)
Density	-0.381***	-0.067*	-0.448***
	(0.075)	(0.040)	(0.094)
Young	0.246	0.044	0.290
	(0.910)	(0.165)	(1.074)
Rented proprieties	0,031	0.006	0.037
	(0.182)	(0.033)	(0.215)
Bar and R. Emp.	0.058	0.010	0.068
	(0.049)	(0.010)	(0.059)
Dist. to CBD	0.107	0.019	0.126
	(0.163)	(0.030)	(0.192)
Infrastructure	-0.317	-0.057	-0.374
	(0.453)	(0.085)	(0.534)
Slums	0.073	0.013	0.086
	(0.052)	(0.011)	(0.061)

Obs.: Standardized deviations obtained by Delta-method in parenthesis.

5. Final Remarks

Although drug traffic is commonly associated with the very high level of urban violence in Brazil, few studies have provided convincing evidence that this association does not merely reflect cofactors affecting both circumstances, such as local infrastructure or location of bars or other events. Furthermore, the most reliable available evidence about a potential causal association from drugs traffic and violence was obtained comparing municipalities (De Melo, 2015) and, thus, ignoring the fact that both drug traffic and violence are within cities spatial located events. In this research, we contribute to attenuate both

[10] This specific results is also similar to the one obtained by Oliveira et al. (2017).

limitations by providing evidence of the association between drugs traffic and homicide rate in 261 neighborhoods of RMR.

Using a unique data set from different and complementary sources (2010 Demographic Census, State Secretary of Social Defense, and RAIS), we were able to consider an important and unique set of control variables, including the share of households in slums and density of employment in Bars and Restaurants, and, applying econometric spatial models, we obtain a strong and reliable association between drugs traffic and homicide rate for RMR's neighborhoods. According to our estimative, a 1% increase of the drugs traffic rate is associated with 0.34% increase of the homicide rate, being 15% of this effect generated by neighbor locations (i.e., due to spillovers from neighbors). The evidence, thus, supports the systematic association between drugs and violence proposed by Goldstein (1985) and is in line with the results of De Mello (2015) and the drugs market characteristics in the RMR discussed by Ratton et al. (2017).

Although it is not possible to guarantee that we have obtained a causal relationship between drugs traffic and homicide rate, the quantity and quality of the controls variable used in the investigation and the fact that reverse causality is not apparent in our data make our results at least very suggestive. The investigation could be improved by considering instrumental variables for drugs traffic (for example, the location of residence of consumer of drugs or the share of different cohorts in the neighborhoods in past decades) and by using the share of drugs traffic in the total of official violence registries.

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Appendix: infrastructure index based on PAC

The urban infrastructure index we used in the regressions is based on the results of Principal Component Analysis (PCA) and it is similar to the one used by Oliveira et al. (2017). The vector of variables is composed by the % of residences in streets with regular garbage collection (C1), % of residences with street with culvert (C2), % of residence in streets with public illumination (C3), % of residences with paved street (C4), and % of residences in streets with sidewalk (C5). The following Table A1 presents the principal components (autovectors) and associated eigenvalues.

Table A1 – Contributions of the variables to the Principal Components

	Principal Components - Autovectors				
	PC1	PC2	PC3	PC4	PC5
C1	0.544	0.157	-0.126	-0.750	0.319
C2	0.600	0.011	0.201	0.076	-0.770
C3	0.573	-0.037	0.079	0.620	0.5284
C4	0.001	0.795	-0.557	0.213	-0.112
C5	-0.123	0.585	0.792	-0.051	0.115
Eigenvalues	2.408	1.090	0.937	0.409	0.155

Source: Authors' calculus.

Similar to Oliveira et al. (2017), we also use the PC1 to obtain an urban infrastructure index for each neighborhood j given by:

$$Infrastructure_j = \frac{y_{max} - y_j}{y_{max} - y_{min}} \tag{A1}$$

where y_j is the value of PC1 for the neighborhood j, y_{max} corresponds to the maximum value of y, and y_{min} corresponds to the minimum value of y. Thus, the formula allows obtaining a set of values between 0 and 1 for the 261 neighborhoods of the RMR