Spatial Spillover of a Crime Crackdown Policy in Brazil: the case of the Pacifying Police Units (UPPs)

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Abstract

This paper aims to analyze whether the installation of Pacifying Police Units (UPPs) in some slums (also called *favelas*) in Rio de Janeiro, Brazil, resulted in an overflow of violence to neighboring areas. The key hypothesis is that when a crime crackdown policy is implemented in a community, rather than reducing illicit activity, it merely partially shifts it to other locations with similar characteristics. Using a Spatial Difference-in-Differences (SDID) estimator that allows the modeling of a possible spillover effect, we show that Police Districts (PDs) that received UPPs experienced a decrease in drug trade-related crime, including rates of intentional homicide, violent crime, and car thefts. On the other hand, the opposite effect occurred in neighboring PDs that did not receive UPPs.

Keywords: crime crackdown, crime spillover, public policy.

Resumo

Este trabalho tem como objetivo analisar se a instalação de Unidades de Polícia Pacificadora (UPPs) em algumas favelas no Rio de Janeiro, Brasil, resultou em um transbordamento da violência para as áreas vizinhas. A hipótese chave é que, quando uma política de repressão ao crime é implementada em uma comunidade, em vez de reduzir a atividade ilícita, ela é transferida parcialmente para outros locais com características semelhantes. Usando um estimador de Diferenças em Diferenças Espaciais (SDID) que permite modelar um possível efeito de transbordamento, mostramos que os Distritos Policiais (DPs) que receberam UPPs experimentaram uma diminuição no crime relacionado ao tráfico de drogas, incluindo taxas de homicídio doloso, letalidade violenta e roubo de carros. Por outro lado, o efeito oposto ocorreu em DPs vizinhos que não receberam UPPs.

Palavras-chave: repressão ao crime, transbordamento de crime, políticas públicas.

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1 Introduction

Some Brazilian cities are internationally recognized for their natural and urban beauty, attracting thousands of tourists annually. This is true of Rio de Janeiro, known as "the wonderful city". Despite its abundant attractions, Rio de Janeiro faces high rates of violence and crime according to United Nations (UN) criteria[1], particularly associated with drug trafficking, gang and militia activity. With 6.5 million people, the city witnessed more than 4,000 homicides ($\sim$ 3.7 murders per day) between 2016 and 2018. The situation in the capital was even worse in the early 1990s through 2000 with more than 2,900 murders per year, reflected in homicide rate of 45 deaths per 100,000 inhabitants.

Since 2000, several crime crackdown policies were tested, and one was implemented most prominently: Pacifying Police Units (UPPs). In 2008, Rio de Janeiro was preparing to compete to host the 2016 Olympics and the 2014 FIFA World Cup. Hence, it became urgent to reduce rates of violence before these events. The UPPs were intended to permanently reclaim areas previously dominated by drug trafficking and to pacify these areas (CARDOSO *et al.*, 2016). As previous policies had failed to mitigate this problem (CANO; BORGES; RIBEIRO, 2012), the UPPs were met with distrust by the people of Rio de Janeiro. However, the number of violent crimes, particularly in those slums that received the UPPs, began to decrease.

Some literature has investigated the effectiveness of UPPs. In regions covered by UPPs, there have been short-term positive impacts, including reductions in violent and property crime (BUTELLI, 2015), lethal police violence (MAGALONI; FRANCO; MELO, 2015), conflicts among drug dealers and between police and criminals (VAZ, 2014), and conflicts between gangs (MONTEIRO; ROCHA, 2017).

However, these studies address the effects in regions that received such units, while possible spillover to other regions has been neglected.[2] It remains unclear whether crime reductions in localities covered by UPPs have been accompanied by increased crime rates in neighboring regions. Analysis of this topic is the main contribution of this paper, which seeks to verify if the policy of UPP implementation has resulted in a spillover of crime to neighboring regions within Rio de Janeiro using a spatial difference-in-differences (SDID) methodology.

This article is structured into five sections, including this introduction. Section 2 includes a literature review and presents the study's theoretical background, discussing causes of spillover and empirical analyses of this theme. In section 3, we describe the characteristics of the UPP program in Rio de Janeiro. Section 4 presents the empirical dataset and strategies used in the analysis. In section 5, we show the results obtained through the estimation of the traditional model, difference-in-differences, and spatial difference-in-differences. The final section presents concluding remarks.

2 Spatial Concentration and Spillover of Crime

According to Becker (1968), there are two markets: one consists of legal activities, and the other is

[1] The UN considers homicide rate to be at an epidemic level when it is greater than 10 homicides per 100,000 inhabitants. See <https://www.unodc.org/documents/gsh/pdfs/2014_GLOBAL_HOMICIDE_BOOK_web.pdf>

[2] The exception is Tealde (2015) that consider crime displacement from pacified to non-pacified *favelas*.

based on criminal activities. Acting rationally, an agent will commit a crime if the expected (usually, monetary) utility associated with the criminal act's discounted cost (eg, monetary fines or disutility from being incarcerated) exceeds the utility they would obtain using their time and other resources in legal activities.

Thus, the interaction of three factors can serve to reduce crime: a) increased moral cost of criminal activity; b) increased probability that an individual will be arrested through sentence enhancements and investments in police manpower, policing intensity, and prisons; c) reduced economic incentives to engage in criminal activity through greater opportunities in the labor market (low unemployment rate and/or relevant market wage). Becker's seminal work served as a guide for the empirical literature on crime, which has largely analyzed how crime rates respond to the expected costs and benefits of illegal activity activity (EHRLICH, 1973; EHRLICH, 1996; SJOQUIST, 1973).

In this section, we illustrate this idea through reference to several papers that aim to model the spillover effect. According to this literature, beyond analyzing the expected costs and benefits of crime, it is possible to identify factors responsible for the occurrence of crime in one particular region and not in others. Suppose that there are only two neighborhoods (A and B), as shown in Figure 1. These regions can be considered similar in location, policing, demographics, and wealth. Overall, these regions are equally attractive as crime targets *ex ante* (DEUTSCH; HAKIM; WEINBLATT, 1984; HELSLEY; STRANGE, 1999).

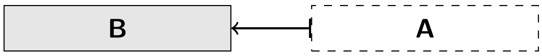

Figure 1 – Simplified Migration Scheme

Consider that crimes in these communities are generally related to drug trafficking. Therefore, in addition to the drug trafficking itself, crimes related to this activity (such as murder, assault, and robbery) are the most frequent in these regions. A potential criminal decides where to operate (A or B). If there is perfect mobility of crime between these neighboring regions, the decision to commit crime in each of these locations will be made by comparing the crime return in each region (SANTOS; FILHO, 2011).[3]

Following Freeman, Grogger and Sonstelie (1996), suppose that the probability of arrest is a function of the police resources (or even police activity), m_i, and the number crimes in the neighborhood $i \in \{A, B\}$, n_i. The probability of arrest increases if police resources increase and the number of observed crimes in that region decreases (because the greater the crime in an area, the smaller the chance, holding police resources constant, that a criminal will be identified as committing a single crime and therefore be arrested).[4]

To calculate the return on a crime, note that the wealth obtained from illegitimate pursuits (z) is limited by the total resources of the victim (in our case, drug users). The higher the number of competing drug traffickers in a locality, the lower the return on drug sales, holding demand constant.

[3] Although this flow of crime is free, Deutsch, Hakim and Weinblatt (1984) point out that criminals prefer to commit crimes in places close to their home. In the case of drug trafficking, this relationship seems to be even stronger.

[4] As the probability of arrest and the occurrence of crime are inversely correlated, it should be noted that the occurrence of crime decreases with an increase in police resources.

Therefore, a decreasing value of z should decrease the number of crimes. Thus, the expected return from criminal activity in the i locality is:

$$v(m_i, n_i) = (1 - p(m_i, n_i))z(n_i) \tag{1}$$

If the number of crimes is held constant (n_i), and a crime crackdown is observed in region A (i.e., increased police activity), it will be less attractive to engage in illicit activities in that region compared to its neighbor, region B. Crime could be transferred to and intensified in region B if police activity remained unchanged in that region, holding everything else constant. Therefore, given the crime crackdown in region A, crime may increase in region B for two reasons. First, the chances of arrest have relatively decreased in region B, leading to increased crime there. Given this increase in illicit activity, the chances of arrest comparatively fall even more, as the likelihood of criminals being identified decreases. Second, the increase in drug dealers in a place where demand is constant reduces the utility of crime, which generates conflicts between the criminals. Thus, by generating incentives for migration and conflicts in other areas, the crime crackdown in region A imposes the negative externalities inherent in criminal activities on the residents of region B.

This spillover (or non-complete migration, as defined by Cano, Borges and Ribeiro (2012)), could be less severe than the crimes originally committed. However, the authors emphasize that failure to consider the spillover effect in evaluations of the impact of a crime crackdown program results in overestimation of the program impact. Some authors have addressed this problem. For instance, Dell (2015) analyzed how a policy of drug trafficking repression may have shifted illicit activities to other Mexican regions. She analyzed how the election of a conservative party in Mexico, which implemented policies to crack down on trafficking in certain regions, may have diverted the route of trafficking and increased violence along alternative routes.

Crime spillover or displacement is not exclusive to drug-related crimes. Cerezo (2013), who analyzed the effects of the installation of cameras on certain streets of Malaga, Spain, on property crime (robberies and burglaries) and crimes against people, found a significant decrease in these crimes. Nevertheless, nearby streets with similar characteristics presented an increase in property crimes. Another crime displacement case was observed in Gonzalez-Navarro (2013). The introduction of a technology that inhibits car theft in some Mexican states has been effective in reducing theft of these vehicles. However, the author also found evidence that car theft risk had been geographically displaced to neighboring states in which these technologies were not present.

Two articles in particular have employed the same Spatial Difference-in-Differences methodology proposed in this paper. Canavire-Bacarreza *et al.* (2016) analyzed the effects of the Metrocable transit innovation in Medellín, Colombia, on crime through two mechanisms: reducing travel costs and increasing the probability of apprehension. The authors verified a positive spillover effect (reduced violence) of this new system in the vicinity of the stations. Verbitsky-Savitz and Raudenbush (2012) evaluated the effects of Chicago's community policing program on neighborhood crime rates using a generalized three-level linear hierarchical model, finding a negative externality of the policy.

The hypotheses adopted in this paper, therefore, is that after a crackdown program, drug dealers in Rio de Janeiro may have adopted new strategies, such as reorganization and installation in other neighborhoods, including Baixada Fluminense and Nova Iguaçu (MAGALONI; FRANCO; MELO, 2015; DELL, 2015). When this illicit activity moves to neighboring regions, local violence skyrockets due to gang conflicts, increasing individuals' safety concerns and threats in the conflict's location (MONTEIRO; ROCHA, 2017).

3 Pacifying Police Units (UPPs) Program

The Pacifying Police Units (UPPs) program was introduced in 2008 and, since then, more than USD 1 billion has been invested in it (through construction of police stations and conservation of UPP areas). This program was intended to allow the state to recover control of territories previously dominated by drug traffickers and to pacify those regions (CARDOSO *et al.*, 2016). In addition, as important sporting events hosted by the city of Rio de Janeiro including the 2014 FIFA World Cup and the 2016 Olympic Games were approaching, the authorities were pledged to demonstrating their commitment and ability to rapidly reduce the existing violence.

Thus, the UPP implementation policy was presented as a way, at least in the short term, to reduce violence levels in Rio de Janeiro, especially in *favelas* (slums) dominated by drug trafficking. The policy aimed to guarantee security for the city's population and tourists, both those who regularly visited the region and those that would come as a result of the sporting events. The program was inaugurated on December 19, 2008 with the UPP in Santa Marta, a small and relatively peaceful community in the South Zone of the city (MAGALONI; FRANCO; MELO, 2015). Over more than 10 years of the program, 38 UPPs were installed. After a *favela's* occupation by Special Operation Forces (BOPE) or the army, which confronted and drove out traffickers and criminal organizations, a permanent police unit would be installed, insuring an intense local police presence. Thereafter, a UPP Social program would be organized, which aimed to guarantee access to basic social elements, such as transportation, education, and healthcare.

Figure 2 presents a map of Rio de Janeiro State, where we can see the area controlled by each UPP and the units' installation order. The selection of communities that would receive the first units is discussed in Magaloni, Franco and Melo (2015). The authors mention that unlike other approaches, such as hot-spot policing, the UPP interventions were not initially based on the high incidence of violence in these communities. The first *favelas* to receive this program were located in the southern zone of the capital, a relatively peaceful and wealthy place compared to other regions. For example, as noted by Monteiro and Rocha (2017), in 2009, the southern zone registered a homicide rate of 6.6 per 100,00 inhabitants, while the northern zone of the city experienced 60.3 deaths per 100,000 inhabitants. Nonetheless, the southern region received most of the first ten UPPs installed.

Cano, Borges and Ribeiro (2012) mention that the first UPPs installed in Rio were prioritized as follows: i) the South Zone, a tourist area composed of upper-middle-class neighborhoods; ii) downtown, with intense commercial activity and services and a high transient population; and iii) a specific region in the North Zone, called *Cinturão da Tijuca*, surrounding the Maracanã Stadium, host to the 2014 FIFA World Cup. In November 2010, the northern region, mainly the *Complexo do Alemão* and *Complexo da Penha*, headquarters of the most violent criminal faction (the Red

Command) in Rio de Janeiro, became the target of large-scale UPP occupations.

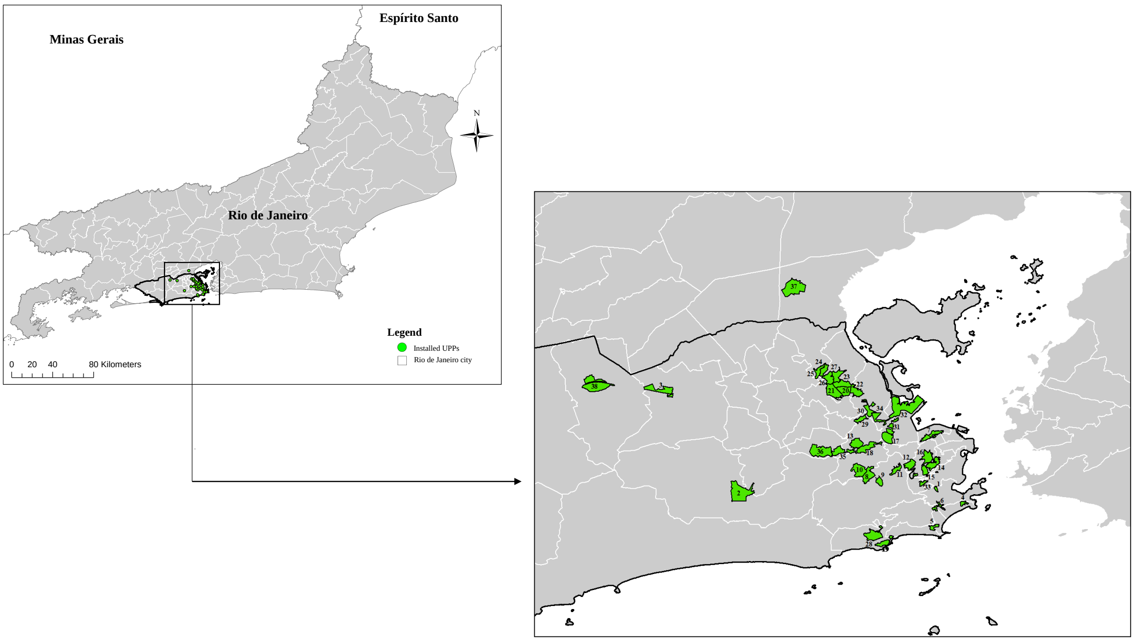

Figure 2 – Map of Rio de Janeiro's Police Districts and UPPs installed in the State
Source – Own elaboration.

Note – The UPP installations were ordered based on the inaugural date provided by ISP-RJ.

Favelas dominated by this faction, which focused on crimes such as drug trafficking, bank robberies, and terrorist activities (BARBASSA, 2015), were disproportionately targeted by the UPP program. Other criminal organizations such as the "Friends of Friends" and "Third Command" also lost control over some areas. Magaloni, Franco and Melo (2015) described two reasons that the Red Command was the main target of the UPP policy: the organization should be weakened since it was notably violent in its demonstrations of power and many of the *favelas* located in the South Zone were under its control. Therefore, the criminals who left the *favelas* occupied by the UPPs were largely members of one of the most belligerent of the drug factions.

Finally, as noted in other studies[5], the UPPs were not randomly assigned to *favelas* or Police Districts (PDs), especially in the beginning, when the focus was on the *favelas* in the richest PDs. Still, poorer regions in the northern part of the city were eventually treated in subsequent stages. However, to avoid any problem of selection bias in estimating the causal effect, we account for population characteristics in each subnormal sector, as described in detail below.

4 Methodology

4.1 Dataset

To reach the proposed objective, datasets were drawn from two sources: the Institute of Public Security of Rio de Janeiro (ISP-RJ) and the Brazilian Institute of Geography and Statistics (IBGE).

[5] See, for example, Canavire-Bacarreza *et al.* (2016) and Verbitsky-Savitz and Raudenbush (2012).

The first presents information about different crimes (physical crimes, drug trafficking, property crimes, etc.) computed monthly by PDs in the State of Rio de Janeiro. To avoid zero inflation regarding crime occurrences, we chose to present the data in quarterly periods, beginning our analysis period in the first quarter of 2005 and ending in the last quarter of 2015. In this dataset, it is also possible to obtain the population of each PD in the analysis period.

We considered three criminal occurrences (two against people's lives and one against property) for each PD: i) intentional homicide; ii) violent lethality[6]; and iii) car theft. These crimes were chosen because they are generally linked to drug trafficking in Rio de Janeiro, and they have a low under-reporting rate. In addition, one non-criminal occurrence related to traffic accidents (road traffic deaths) is used like a placebo to assure the robustness of our identification strategy. It is expected that this kind of occurrence will not be affected by the UPP policy because it is generally not directly linked to crime.

During the analysis period, eight new PDs were created, emerging from the division of other PDs. Occurrences in these new districts, created in 2005 and onward, were merged with the criminal and non-criminal occurrences in the original PDs. For this reason, the maps and regression analysis presented here reflect the number and division of PDs in 2005, before this division.[7]

The second dataset used in this research was the 2010 Census, conducted by the Brazilian Institute of Geography and Statistics (IBGE). The census provides information about households and individuals at the precinct level, or the "subnormal sector".[8] This dataset provides information normally considered in papers analyzing the determinants of criminality[9], including education (adult literacy adult rate, i.e. for those aged 15 and above), race, percentage of youth population (percent of people aged 15 to 24), per capita income, and number of residents per household.

With these two datasets, the control variables used in estimating the impact of UPPs on crime are described in the Table 1. To construct the variable "percentage of people living in the subnormal sector of each PD", as population data was available for smaller subsections of these areas, it was necessary to aggregate them for each PD using the ArcGIS spatial join tool. Having determined the total resident population in the subnormal sectors of each PD in 2010, we determined changes in the population within each PD in each year, using data provided by the ISP-RJ, to determine the patterns of evolution of similar populations.

The two other variables concern changes occurring in PDs and in a broader area, called AISP, in the period. These changes may involve police resources or activity and could have ultimately impacted crime rates. The dates of these changes were provided by the ISP-RJ and are represented using dummy variables.

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6 The following crimes, considered collectively: intentional homicide, bodily injury followed by death, felony murder, and homicide resulting from opposition to police intervention.

7 For example, occurrences observed at PD 130, created on March 6, 2010, were classified within PD 123, since 130 originated from 123. The same procedure was conducted for PDs 11, 42, 45, 67, 70, 132 and 148, created after 2005. Crimes computed in these PDs were classified within 15, 16, 22, 65, 71, 126 and 143, respectively.

8 These are regions, including *favelas*, that lack essential public services (such as garbage collection, sewage systems, water supply networks, electricity, and public lighting).

9 See Canavire-Bacarreza *et al.* (2016), Verbitsky-Savitz and Raudenbush (2012), and Dell (2015).

Table 1 – Controls variables

Variables	Description	Source
People living in subnormal sector	% of people living in subnormal sectors in each PD and each year	IBGE/ISP-RJ
PD division	= 1 after PD was divided, = 0, c. c.	ISP-RJ
AISP change	= 1 if PD changed its Integrated Public Security Areas (AISP), = 0, c. c.	ISP-RJ

Note – Time and individual fixed effects are also included in the regressions.

4.2 Empirical Strategy

This paper explores the potential breakdown of the "stable value of the treatment unit assumption" (SUTVA). According to this hypothesis, the treatment to which a unit is exposed does not impact other non-treated units that are geographically close to the treated units (RUBIN, 1978). Therefore, this section presents our empirical strategy to identify not only the impact of the UPPs on the PDs in which they were implemented, but also on the PDs located in the vicinity of the treated regions.

4.2.1 The difference-in-differences model (DID)

Delgado and Florax (2015) stated that one of the primary methods used in policy evaluation literature to identify causal effects when participant selection for a study is not random is the difference-in-differences (DID) approach. According to Canavire-Bacarreza *et al.* (2016), this model's chief advantage is that it allows the estimation of the impact of an intervention when unobservable factors are constant over time, or at least during the pre-treatment and post-treatment period. The effect of the treatment, or policy implemented, is obtained by identifying the difference between two potential results, where such results are function of the treatment status.

$$y_i = D_i y^1 + (1 - D_i) y^0 = \begin{cases} y^1 & se \quad D = 1 \\ y^0 & se \quad D = 0 \end{cases} \tag{2}$$

where D is characterized as a binary variable indicating the treatment status of an individual, region, or institution. More specifically, if a unit receives an intervention, the binary variable assumes a value of 1, and for units not impacted by the program, the variable assumes 0. The variable y is the potential result of the variable of interest for region i. Equation 3 shows the basic DID model, without the inclusion of spatial effects, where $i = (1, 2, \ldots, 130)$ PDs that were observed in at least two periods $T \in \{0, 1\}$. Using this model, the difference in violence rates before and after the installation of UPPs for treated and untreated PDs was calculated:

$$y_{i,t} = \alpha + \phi + \tau + \beta X_{i,t} + \delta D_{i,t} + \varepsilon_{i,t} \tag{3}$$

where $y_{i,t}$, the dependent variable, is the crime rate per 100,000 inhabitants of PD i at time t. $X_{i,t}$ is a vector with independent variables, ϕ and τ are the fixed effects of PD and time, respectively.

$D_{i,t}$ is a binary variable that takes a value of 1 after the installation of the UPPs for the PDs that received the UPPs and 0, otherwise. Finally, $\varepsilon_{i,t}$ is the error term with mean 0.

To identify the causal impact of an intervention, it is assumed that there are no overlooked variables that change concurrently with or after the installations of UPPs that directly influence the occurrence of crime. More specifically, by utilizing PDs and time effects this procedure will control for: i) observed and unobserved characteristics common to all treated places during a particular period of time; and ii) observed and unobserved characteristics for every treated territory that are constant over time.

However, according to Verbitsky-Savitz and Raudenbush (2012), the SUTVA hypothesis, which is necessary to ensure consistency within the traditional DID method and to ensure causal identification, is violated in several areas, including crime, education, and epidemiology. Specifically, regarding crime, the authors stated that when a crime crackdown program is implemented in one area, delinquency in that area may be reduced as a result of a spillover of criminal activity to neighboring regions where the program has not been implemented. This hypothesis is formalized as the "diversion hypothesis" by Dell (2015).

Even so, some research on this subject have sought to model these potential violations of the SUTVA hypothesis.[10] Usually the authors disregard the possible spillover, diffusion, and displacement effects or only mention that regions neighboring those who received interventions are not good controls (comparison regions) because they may be affected by these interventions. However, while this latter group mitigates the problem to some extent, but does not completely circumvent it, since the net effect of the policy is not obtained. Such issues characterize most studies that have analyzed the effects of UPP policies on the *favelas* of Rio de Janeiro. To overcome the identification problem of the DID method, authors such as Dubé *et al.* (2014), Delgado and Florax (2015) and Gennaro, Pellegrini *et al.* (2016) developed models that considered possible spatial interactions between treated groups and controls called "spatial difference-in-differences" (SDID) models.

4.2.2 The spatial difference-in-differences model (SDID)

Even though the traditional difference-in-differences method shown in equation 3 adequately controls for latent spatial components in time, it omits the presence of spillover and interference among treated and not treated agents. When considering the possible effects of spillovers, the spatial difference-in-differences model presents a larger methodological gain, allowing us to decompose the average treatment effect into both the average direct effect and the average indirect effect (DUBÉ *et al.*, 2014; BARDAKA; DELGADO; FLORAX, 2018).[11] This approach relaxes the SUTVA hypothesis such that its violation does not preclude the identification of a causal effect, as it would in the traditional DID model (DELGADO; FLORAX, 2015).

Thus, as proposed by Delgado and Florax (2015) and drawing on evidence of spillovers caused by crackdown policies, SDID is applied an extension of the traditional DID method that allows spatial

[10] Cabral (2016) in Brazil and Verbitsky-Savitz and Raudenbush (2012) in the United States are some researchers who have sought to model this problem.

[11] A common approach is to identify all treatment and control groups and apply a difference-in-difference-indifference method. However, as pointed out byDelgado and Florax (2015), there are disadvantages to using this approach. For example, the estimator becomes inefficient in small samples.

interactions. To consider a case where a crime crackdown in one place affects nearby regions, one must consider not only the treatment status of the PD that received the UPP but also the PDs nearby. Thus, the term $W_{i,j}D_{i,t}$, obtained by applying a spatial lag to the treatment variable, can be added to equation 3:

$$y_{i,t} = \alpha + \phi + \tau + \beta X_{i,t} + \delta D_{i,t} + \rho W_{i,j} D_{i,t} + \varepsilon_{i,t} \tag{4}$$

This new term captures the neighborhood relationship between PD i and PD j. In this study, two types of spatial matrices were tested: a) queen contiguity-based spatial weights: $W_{i,j}$ assumes a value of 1 if i is bordered by j and a value of 0, otherwise; and b) nearest k-neighbors: $W_{i,j}$ assumes a value of 1 if j is the closest k-neighbor of i and a value of 0, otherwise. Using this new specification, it is possible to simultaneously estimate two different impacts: the direct causal effects, δ, and indirect effects, ρ.

Finally, as discussed by Chagas, Azzoni and Almeida (2016), the indirect effect of treatment, ρ in equation 4, on treated and untreated units is given in average values. However, the effects in two different regions can vary significantly. Therefore, as a further analysis proposed by the authors, in equation 5 we decomposed the effects on treated ($W_{T,T}$) and non-treated ($W_{NT,T}$) neighbors to verify if the effect found in the neighbors differs due to treatment status.

$$y_{i,t} = \alpha + \phi + \tau + \beta X_{i,t} + \delta D_{i,t} + \rho_1 W_{T,T} D_{i,t} + \rho_2 W_{NT,T} D_{i,t} + \varepsilon_{i,t} \tag{5}$$

This unrestricted model is a special form of the SDID model where $W_{T,NT}D_{i,t}$ and $W_{NT,NT}D_{i,t}$, other elements of the WD matrix decomposition, are suppressed in equation 5 because they are $\mathbf{0}$-vectors.[12]

5 Results

5.1 Descriptive Analysis

To verify the evolution of crime rates in the State of Rio de Janeiro, we considered one crime against life and one crime against property. More specifically, violent lethality and car theft rates were analyzed in two years before the beginning of the program, 2005 and 2008, and in three years after the beginning of UPP activities, 2010, 2012 and 2015. We classified crime rates into five groups, from the lowest crime rate to the highest: 1) low; 2) medium-low; 3) medium; 4) medium-high, and; 5) high.

Figure 3 shows that before the implementation of UPPs, only a few PDs presented criminality rates considered “high” or “medium-high” when considering crimes against life in Rio de Janeiro State. The more violent PDs, represented by brown spots, were located near the city of Rio de Janeiro (the area enclosed within the black border) and in the coastal region of Búzios. In general, however, little difference existed among the lethality rates in PDs in Rio de Janeiro State in the periods prior to UPPs’ installation in 2008.

[12] For more details, see Chagas, Azzoni and Almeida (2016).

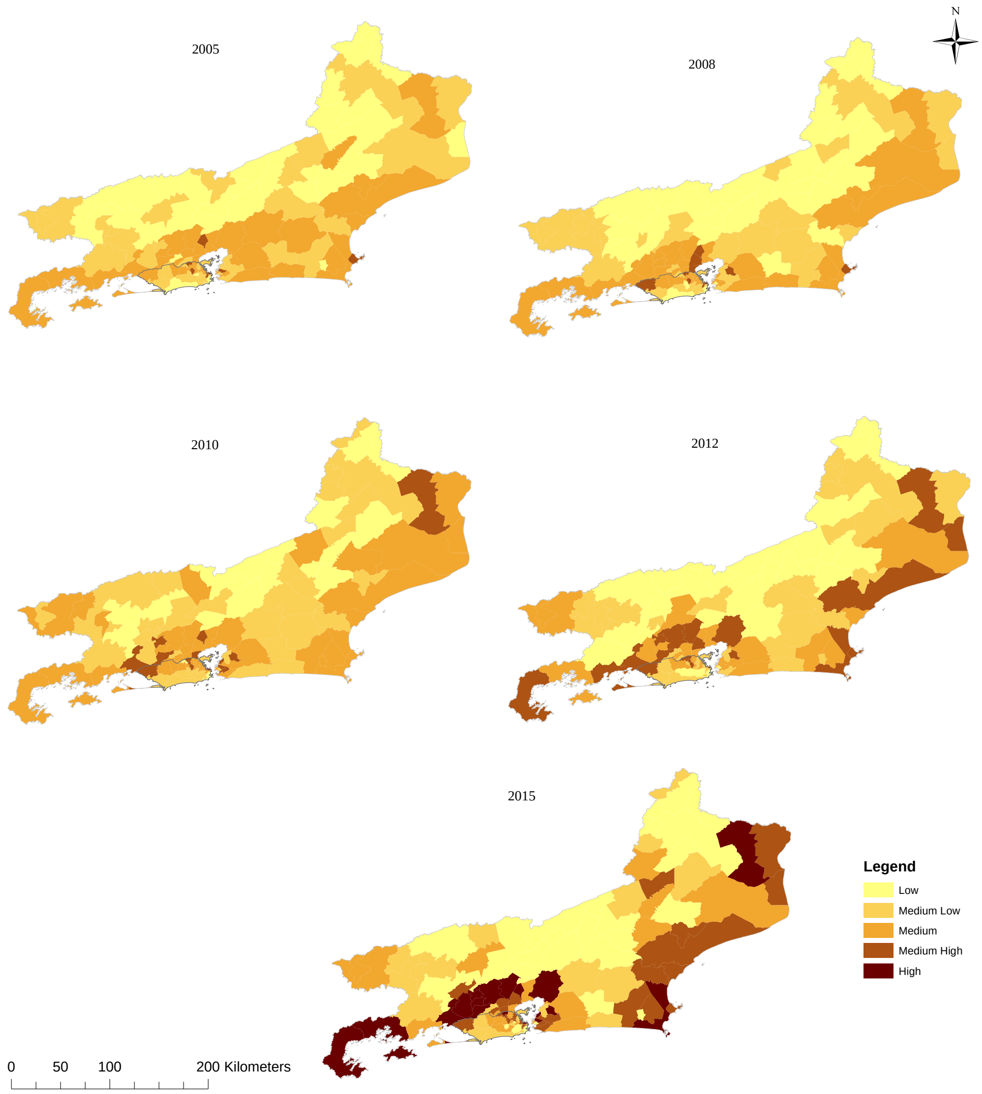

Figure 3 – Evolution of violent lethality rates per 100,000 people, 2005–2015

Source – Authors' calculation.

Note – The Jenks natural breaks method was used to classify each PD in each year into a group, as violent lethality rates varied throughout each year. The average upper-limit rate of the "low" group was 15.93 homicides per 100,000 inhabitants, whereas "medium-low" was 33.82, "medium" was 59.99, "medium-high" was 125.87, and "high" was 363.38.

In 2010, two years after the first implementation and occupation of UPPs in the capital, a greater concentration of PDs are marked with darker colors, mainly around the state capital, indicating an intensification of crimes against life in this region compared to others. In 2012 and 2015, when the UPPs implementation had reached an advanced stage, the figures show even greater differences than between 2005 and 2008. In 2015, 16 out of 130 PDs, particularly those near the state capital and on the coast, began to present lethality rates considered "high" when compared with the rates of other

PDs in the state. This may indicate the proliferation and migration of violence to various regions of the state, especially those regions close to the capital.

Figure 4, which presents property crimes, specifically car theft rates, contributes to a better understanding of violence migration, as this type of crime was once concentrated in the capital area. In 2005, only PDs in the capital were classified as having "medium-high" or "high" car theft rates. However, this type of occurrence spread after the implementation of the UPP program. Other regions, mainly the Baixada Fluminense and Niterói, presented concentrations of PDs with high car theft rates in 2010, 2012, and particularly 2015.

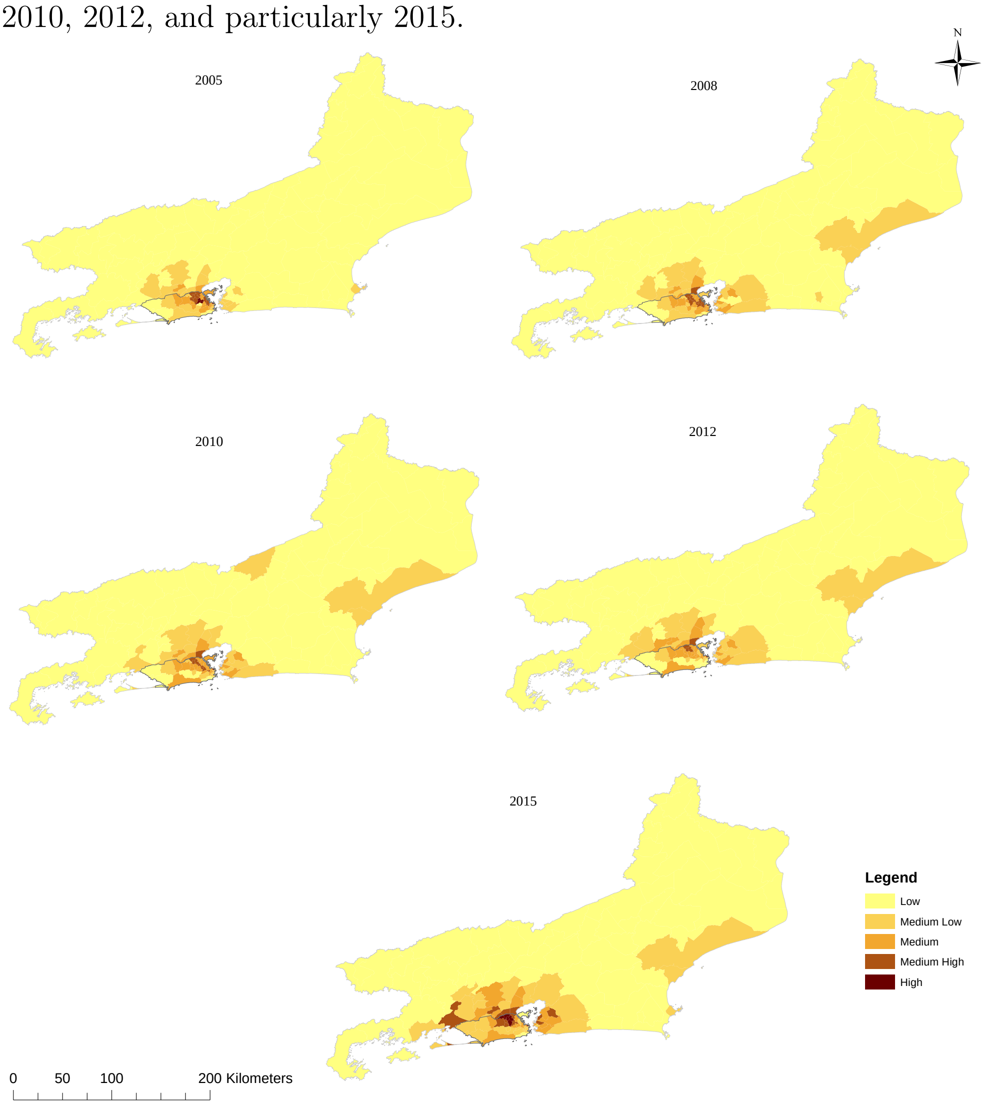

Figure 4 – Evolution of car theft rates per 100,000 people, 2005–2015
Source – Authors' calculation.

Note – The Jenks natural breaks method was used to classify each PD in each year into a group, as car theft rates varied throughout each year. The average upper-limit rate of the "low" group was 67.62 homicides per 100,000 inhabitants, whereas "medium-low" was 190.22, "medium" was 385.39, "medium-high" was 662.72, and "high" was 1,506.96.

The new pattern observed in the state may be related to the installation of UPPs, which may have reduced the violence rates in PDs which received them, especially in the state capital, but contributed to the movement of violence into other regions, increasing the heterogeneity of violence in the state. This will be the topic of the next subsection of this article.

5.2 UPP Effects

Tables 2 and 3 present the results of both the traditional difference-in-differences (DID) model and the spatial difference-in-differences (SDID) model. Two specifications for each methodology are presented. In columns 1 and 3, there are no control variables. In columns 2 and 4, the control variables explained in Table 1 are included. We also controlled for time effects and PD fixed effects in both specifications. In Table 2, we consider the UPPs' implementation date as the beginning of the policy. Furthermore, only the coefficients of interest, δ for traditional DID, and ρ for spatial DID, are displayed in each regression. Comparing the DID and SDID models, it is notable that the UPP policy decreased crime in the areas that receive the units and increased crime in neighboring areas.

Table 2 – DID and SDID estimations of UPP effects (after UPP installation date)

	(1) DID	(2) DID	(3) SDID	(4) SDID
Intentional homicide	–17.03***	–16.97***	–18.80***	–19.08***
	(–7.13)	(–6.84)	(–6.87)	(–6.32)
W(intentional homicide)			7.75*	7.84*
			(2.38)	(2.11)
Violent lethality	–22.55***	–22.31***	–24.79***	–24.92***
	(–7.87)	(–7.56)	(–7.75)	(–7.13)
W(violent lethality)			9.80**	9.70*
			(2.69)	(2.34)
Car theft	–10.95***	–7.60	–120.90***	–116.95***
	(–1.50)	(–1.05)	(–8.82)	(–8.17)
W(car theft)			70.02***	63.43***
			(6.61)	(5.28)
Placebo				
road traffic deaths	–1.56	–2.42	–2.67	–4.17
	(–0.70)	(–1.04)	(–0.97)	(–1.39)
W(road traffic deaths)			4.86	6.55
			(1.47)	(1.79)
Time Fixed Effect	Yes	Yes	Yes	Yes
Unit Fixed Effect	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Spatial Effect	No	No	Yes	Yes
Observations	4,290	4,290	4,290	4,290

Note – $^{***}p < 0.001, ^{**}p < 0.01, ^{*}p < 0.05$. T-stats are shown in parentheses, and we use robust standard errors. In these specifications we used queen contiguity and quarterly data for each PD. The covariates used in each specification are described in Table 1. The coefficients in columns 1 and 2, correspond to δ (traditional DID model), equation 3. The coefficients in columns 3 and 4, correspond to δ and ρ (spatial DID model), equation 4.

Source – Authors' calculation.

For example, in the last column of Table 2, our results show that the effect of the program on homicide rates in the analyzed region would be reduced by 19.08 homicides per 100,000 people in a region that presented 41 homicides per 100,000 inhabitants in 2007, a year prior to UPP implementation. However, this reduction was accompanied by a statistically significant increase of 7.84 homicides per 100,000 inhabitants in the region's immediate neighbors, when controls are considered.

This effect was also observed regarding property crimes. Car thefts were reduced by 116.95 occurrences per 100,000 inhabitants in the PDs that received UPPs but increased by 65.43 in neighboring areas. Therefore, despite generally reducing crime, the UPP policy seems to exercise an opposite effect in PDs neighboring those in which UPPs were installed. This phenomenon was valid both for crimes against life and property crimes.

Furthermore, as expected, traffic accident deaths were not statistically affected by UPP policies in PDs that received them or in their neighbors. As already mentioned, this type of occurrence is not linked to drug trafficking activity in Rio de Janeiro. Considering that the UPPs installation date typically occurred after an occupation by police forces, the effects of the UPP program can be perceived even before the units' installation. To test this "pre-installation effect", a second analysis is presented in Table 3, which considers the program to have started on the occupation date provided by the ISP-RJ.

Table 3 – DID and SDID estimations of UPP effects (after UPP occupation date)

	(1) DID	(2) DID	(3) SDID	(4) SDID
intentional homicide	–11.28***	–10.78***	–13.47***	–12.96***
	(–7.19)	(–6.75)	(–6.57)	(–6.19)
W(intentional homicide)			8.52**	8.54*
			(2.59)	(2.29)
violent lethality	–13.90***	–13.54***	–16.61***	–16.19***
	(–6.95)	(–6.74)	(–6.63)	(–6.36)
W(violent lethality)			10.54**	10.35*
			(2.88)	(2.50)
car theft	–42.92***	–46.45***	–61.12***	–62.87***
	(–3.58)	(–4.01)	(–4.44)	(–4.61)
W(car theft)			70.77***	64.19***
			(6.56)	(5.25)
Placebo				
road traffic deaths	–1.56	–2.42	–2.67	–4.17
	(–0.70)	(–1.04)	(–0.97)	(–1.39)
W(road traffic deaths)			4.86	6.55
			(1.47)	(1.79)
Time Fixed Effect	Yes	Yes	Yes	Yes
Unit Fixed Effect	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Spatial Effect	No	No	Yes	Yes
Observations	4,290	4,290	4,290	4,290

Note – $^{***}p < 0.001, ^{**}p < 0.01, ^{*}p < 0.05$. T-stats are shown in parentheses, and we use robust standard errors. In these specifications we used queen contiguity and quarterly data for each PD. The covariates used in each specification are described in Table 1. The coefficients in columns 1 and 2, correspond to δ (traditional DID model), equation 3. The coefficients in columns 3 and 4, correspond to δ and ρ (spatial DID model), equation 4.

Source – Authors' calculation.

In this new formulation, it is notable that the overestimation of the impact is even greater when we consider only the traditional DID method. The net effect of the UPP policy on intentional homicide rates in the State of Rio de Janeiro would be an approximate reduction of 5 homicides per 100,000 inhabitants rather than around 11, as found in the first traditional DID formulation. Further, specifically regarding property crimes, a greater increase in neighboring regions' crime rates can be attributed to the UPPs' occupation than the reduction noticed in the locations that received the UPPs. A possible reason for this beyond proportional increase in crime within neighboring regions may involve changes in the activity of criminals coming from the PDs occupied by the UPPs. To maintain the profits previously obtained through drug trafficking, these criminals, who initially lack control of territories and thus cannot control drug traffic, might focus on property crimes in these neighborhoods.

Again, even considering the date of occupation as the beginning of the policy, there were no statistically significant results for occurrences not related to drug trafficking, such as deaths caused by traffic accidents. The results found in this section corroborate the study's hypothesis that at least part of the reduced violence in the areas addressed by the UPP policy may actually reflect the movement of criminals to neighboring regions. It is important to verify, however, the crime spillover pattern. This objective requires a deeper analysis and is developed below.

5.3 Spillover to Treated and Non-treated Neighbors

Using Chagas, Azzoni and Almeida (2016) approach, we tested if the statistically significant indirect effect found in the previous analysis differed between non-treated and treated PDs. That is, we investigated if the migration of criminals to other areas differed if these other areas had UPPs. Drawing on Becker (1968), it is expected that after a UPP program began, criminals would not migrate to other regions with UPPs since these regions were already intensely policed, especially in the *favelas*. This analysis will again compare the installation and occupation dates.

In the Table 4, first we find that the policy's indirect effect of increasing crime in neighboring PDs is largely confined those PDs that never received the intervention, represented as WNT. The indirect effects on the treated neighbors, WTT, were not statistically significant for any kind of crime, indicating that if criminals migrated, they chose to target places without UPPs. This finding was valid when considering both the installation date and the occupation date, demonstrating the robustness of the results.

Secondly, when we consider the magnitude of the coefficients, changing the start dates of the policy yields different results. Regarding the installation date, the UPP policy still had the net effect of reducing both crimes against life and property in the State of Rio de Janeiro during the analysis period. If the occupation date was considered in the investigation of the policy's effect on crimes against life, the policy's indirect effect on untreated PDs slightly exceeded the direct effect of the policy on the treated PDs. This effect of the policy becomes even more negative when property crimes are analyzed, as seen in car theft rates. Even though the final net effect was not robust, our results clearly imply that measuring the impact of the UPPs using traditional DID methodology will overestimate effects. It seems clear that the policy had some adverse effects, mainly in neighboring regions not served by UPPs. This indirect effect could be of the same magnitude, but in the reverse direction.

Table 4 – SDID estimations of UPP effects separated for installation and occupation date

	Inauguration		Occupation	
	(1)	(2)	(3)	(4)
Intentional homicide	–16.39***	–16.68***	–10.44***	–9.95***
	(–7.45)	(–7.08)	(–6.82)	(–6.17)
WTT(intentional homicide)	0.70	0.73	–0.05	–0.02
	(0.46)	(0.45)	(–0.03)	(–0.01)
WNT(intentional homicide)	9.92*	10.25*	11.17**	11.45*
	(2.38)	(2.14)	(2.65)	(2.37)
Violent lethality	–21.77***	–21.99***	–12.78***	–12.42***
	(–8.23)	(–7.84)	(–6.41)	(–6.05)
WTT(violent lethality)	0.95	0.98	–0.34	–0.34
	(0.50)	(0.50)	(–0.18)	(–0.18)
WNT(violent lethality)	12.51**	12.65*	13.91**	13.99**
	(2.70)	(2.37)	(2.97)	(2.62)
Car theft	–93.38***	–92.91***	–29.95*	–34.54**
	(–7.51)	(–7.38)	(–2.38)	(–2.82)
WTT(car theft)	–10.65	–7.98	–17.76	–16.17
	(–0.96)	(–0.70)	(–1.57)	(–1.39)
WNT(car theft)	94.80***	87.58***	98.12***	91.51***
	(7.19)	(5.77)	(7.42)	(6.01)
	Placebo		Placebo	
road traffic deaths	–0.45	–1.53	–0.84	0.19
	(–0.21)	(–0.66)	(–0.69)	(0.14)
WTT(road traffic deaths)	–1.62	–1.30	–1.44	–0.99
	(–1.48)	(–1.09)	(–1.41)	(–0.88)
WNT(road traffic deaths)	6.85	9.20	7.63	9.85*
	(1.62)	(1.94)	(1.70)	(1.97)
Time Fixed Effect	Yes	Yes	Yes	Yes
Unit Fixed Effect	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	4,290	4,290	4,290	4,290

Note – $^{***}p < 0.001, ^{**}p < 0.01, ^{*}p < 0.05$. T-stats are shown in parentheses, and we use robust standard errors. In these specifications we used queen contiguity and quarterly data for each PD. The covariates used in each specification are described in Table 1. The coefficients in each of the specifications correspond to δ, ρ_1 and ρ_2 for equation 5. WTT = Treated Neighbors; WNT = Non-treated Neighbors.

Source – Authors' calculation.

Finally, Figure 5 presents the observed change in average rates of crimes against life from baseline rates observed in the first quarter of 2007, prior to the UPP policy. Coefficients are estimated in the second column (date of installation with controls) of Table 4 for both PDs that received UPPs and PDs neighboring these areas. For example, the average intentional homicide rate in the areas surrounding PDs that would be given UPPs in the first quarter of 2007 was 48.42 homicides per 100,000 inhabitants. With an average estimated increase of 10.25 homicides per 100,000 inhabitants registered after UPP policy, there was a 21.20% increase in this type of crime in such areas, totaling 58.59 homicides per 100,000 inhabitants. Regarding violent lethality and accounting for an estimated increase of 12.65 deaths per 100,000 inhabitants, these neighboring PDs experienced, post policy implementation, a rate of 73.71 deaths per 100,000 inhabitants, representing an increase of 20.71%.

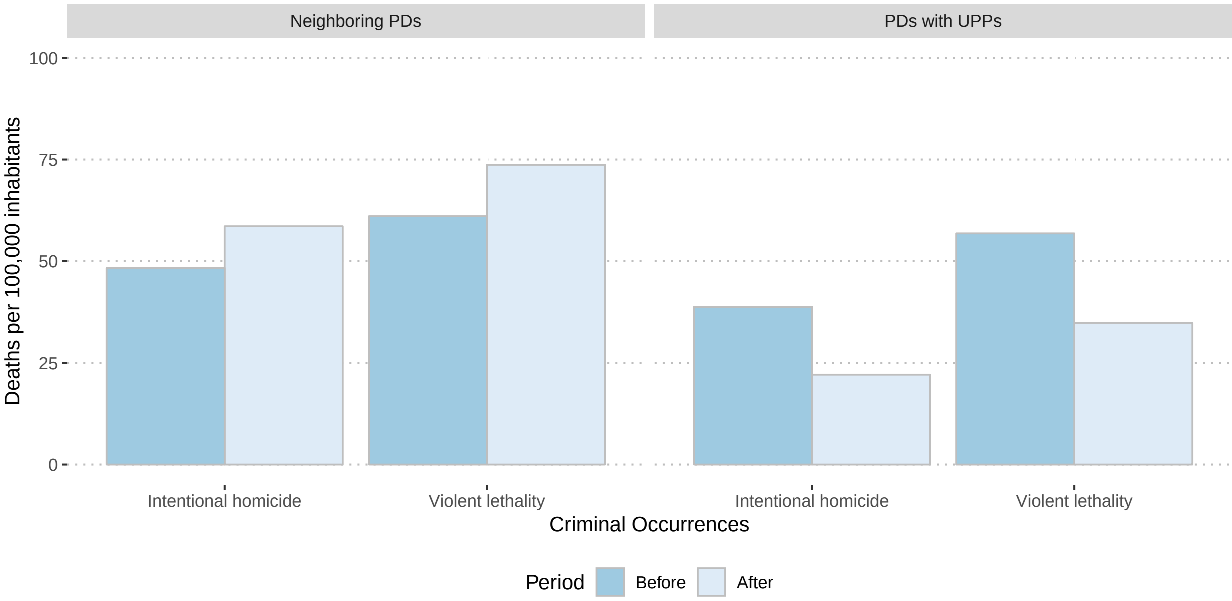

Figure 5 – Intentional homicide and violent lethality average per 100,000 people before and after UPP installation.

Source – Authors' calculation.

Note – We utilized average crime rates in the first quarter of 2007 as a baseline. We considered those PDs bordering PDs with UPPs to be "neighboring PDs" (queen contiguity).

On the other hand, it is possible to verify a 43.01% reduction in the average intentional homicide rates (from 38.78 to 22.10 homicides per 100,000 inhabitants) and a 38.68% reduction in the average rates of violent lethality (from 56.84 to 34.85 deaths per 100,000 inhabitants) in PDs that received the UPPs. Therefore, this result indicates that the UPP policy has resulted in greater crime disparities between regions of Rio de Janeiro, leading to higher crime rates in regions that were, on average, more violent before UPP implementation.

6 Concluding Remarks

This paper aimed to verify possible crime spillover to regions neighboring those that received UPPs in Rio de Janeiro City. To meet this goal, datasets from the ISP-RJ and IBGE containing criminal and population information from 2005 to 2015 were utilized. We employed difference-in-differences methodological approach and its spatial variation, spatial difference-in-differences. Thus, we were not only able to ascertain the direct effects of the UPP policy on PDs in which it was implemented, but also its indirect effects on neighboring PDs, particularly those in which UPPs were not implemented.

Three different categories of crime were investigated. Two were related to crimes against life and one to property crimes. It was observed that failing to account for the UPP policy's effect on neighboring areas leads to an overestimation of the general impact of the UPP policy in Rio de

Janeiro State. We verified that murder rates, for example, significantly decreased in the PDs that received UPPs. However, this decrease was followed, also significantly, by increased murder rates in these regions' immediate neighbors. In some models, the effect of increased crime in neighboring regions surpassed that of the decreased crime rates in PDs that received UPPs.

The literature suggests these results are due to the spillover caused by these kinds of crime crackdown policies. In other words, criminals affected by the policy could migrate to nearby regions that lacked a UPP presence where the cost of crime remained constant. In those locales, criminals would fight for new territories and/or undertake new criminal practices to maintain profits, which could increase crime rates and individuals' safety concerns.

It is clear that the UPP policy did not considered these possible spillovers to neighboring regions. Its focus was to reduce criminal rates in the capital, mainly in the places where would receive a great number of tourists from the international sports events, through the expulsion of criminals from their areas of origin. Therefore, as other regions that received them were less prepared for the fight against these organized gangs, they were significantly and negatively affected by this policy. The policy implication of this paper shows that the short-term effect of the UPP program was lower than observed by the recent literature. Even worst, in some cases the effect could be reversed than expected.

Finally, a possible limitation of this paper stems from its dataset. Socioeconomic factors were not controlled for in our estimates, as this type of information was not available on an annual basis for each PD. Although we control the fixed effects of time and PD, these characteristics may vary over time and within each PD, affecting the violence rates in Rio de Janeiro State and the results of the estimates obtained in this paper. Further research may seek to correct this limitation and, moreover, to estimate medium-term and long-term effects of the policy not only on the regions in which it was implemented but also on neighboring PDs. This could promote an understanding of whether this costly policy has served to improve the well-being of the population of the State of Rio de Janeiro, particularly in the metropolitan region surrounding the capital.

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