When the State steps down: evidence from Police Strikes in Brazil.

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Abstract

Drastic shifts in police affect criminals and civilians through channels arguably different than a marginal change in the number of police officers. Therefore, extreme events such as police strikes or the deployment of police officers following terrorist attacks may capture a very particular effect of shifts in police and may not be interpreted as an instrument of the overall effect of police on crime. The socio-economic context where abrupt shifts in police occur may affect the magnitude of crime outcomes, especially if organized criminal groups are strong and the state hardly holds the monopoly on the use of force. More specifically, criminal gangs have a central role in escalating violent crimes after an abrupt shift in the police. In this paper, I show that criminal gangs exploit Police strikes to attack rival groups. In the first days of a police strike, homicides of suspected gang members account for 70% of the deaths in neighborhoods disputed by Brazilian criminal groups. Facing the state's absence, a reduction in the probability of police intervention led criminal gangs to intensify conflicts in contested turfs.

Keywords: Economics of Crime, Criminal Gangs, Police Strikes

1. Introduction

In contexts of criminal gang conflicts, natural experiments using shifts in the police may not be interpreted as an instrument for the overall effect of police on crime. The existing literature uses the deployment of police officers following terrorist attacks and the drastic reduction in surveillance in police strikes as a source of exogenous variation to break the classical reverse causality problem. However, when criminal groups are powerful, and the state hardly holds the monopoly on the use of force, abrupt shifts in police patrols affect the cost of attacking the rival gang. Therefore, it is crucial to clarify how criminals respond to shocks in the number of police officers to interpret the causal effect of policing on crime.

There is little evidence about how the presence of organized criminal groups may affect crime outcomes when relevant shifts in police happen. Arguably, the effect of abrupt changes in policing may differ from one very stable and developed society to another, presenting significant levels of poverty and criminality. This fact is even more critical when organized criminal groups dispute a hegemonic position in drug trafficking. More precisely, natural experiments exploiting shifts in policing must disentangle the mechanisms driving the increase in violent outcomes to capture the effect of the police on crime accurately in contexts where extreme poverty and gang conflicts are prevalent.

To shed light on the mechanisms leading to an escalation in violent crimes following shocks in policing, this paper exploits unique data to perform a case study and analyze how different areas within a municipality respond to a drastic reduction in police patrols, especially in a context of criminal gang conflicts. First, I use police strikes as a natural experiment to assess the effect of a sudden decrease in the number of police officers on violent crimes. Police strikes are rare since most countries present legal restrictions that veto the right to strike. Police officers provide an essential service, and reducing police patrols and surveillance would expose civilians to dangerous situations. Hence, the identification strategy using these events relies on the hypothesis that the particular outbreak day of a police strike is exogenous to crime dynamics, representing a natural experiment that eliminates the simultaneity between crime and policing. I use daily data on Brazilian deaths from 2000 to 2020 regarding homicides, especially those caused by firearms in public spaces such as streets and avenues. I combine this data with information regarding police strikes registered in the same period. A differences-in-differences analysis that compares violent deaths in states affected by a sudden decrease in police patrols to states not affected provides an estimate of the aggregate effect of police strikes on homicides.

Overall, a police strike significantly increases violent crimes: homicides in states affected by Military Police strikes are 45% higher than the average, and deaths caused by firearms in public spaces drive this result. Additionally, I find no evidence of increases in other types of death, such as individuals killed in car accidents, which rules out the possibility of a generalized increase in all types of deaths during these events. To enhance the credibility that my results are the causal effect of reducing police on violent deaths, I present a placebo test in which strikes occur one month before the actual dates. The results validate my exercise and do not show increased homicides in the states affected by police strikes during these pseudo periods. Furthermore, I present a daily event study that did not show a previous upward trend in homicides before the outbreak of police strikes.

The drastic reduction in police patrols during a strike can increase homicides basically in three ways: (a) criminal gangs can exploit the decrease in policing to attack rivals, (b) criminals can become more willing to use violence when committing property crimes, and (c) civilians can use greater violence both in protecting their property and settling personal disputes. To support the research strategy, I present a model where criminals choose to attack a rival gang in a police strike because of an increase in the expected payoff of confrontation and a commitment issue prevalent in criminal bargaining. Both gangs benefit from an abrupt reduction in policing that reduces (possible) confrontation losses and increases the expected payoff of a criminal gang war. A commitment problem makes both choose to fight instead of being accommodating, given the expected payoff to starting a war. I show that this mechanism explains most of the increase in violent deaths following police strikes.

In a case study, I show that most of the victims in a police strike are suspected gang members, and districts disputed by criminal groups were disproportionately affected within a municipality, which supports my theoretical model of criminal gang conflicts. I use homicide data at the district level to analyze violent deaths before and after the Military Police strike occurred in 2020 in the municipality of Fortaleza. In this city, two criminal groups dispute the control of drug trafficking. I exploit a unique data set that allows identifying criminal records of individuals killed from 2014 to 2020. I combine this information with socio-economic data to determine districts with a high probability of criminal gang conflicts. Districts disputed by criminal groups present 56% more violent deaths on average. During a police strike, the deaths of suspected gang members represent about 70% of the increase in homicides in these areas. These results are consistent with my model of gang conflicts. They show that a sudden reduction in police surveillance increases the expected payoff in a war, leading criminal groups to intensify territorial disputes instead of accommodating.

This paper is directly related to the literature on the effect of policing on crime. The seminal work of Becker (1968) presents a theoretical basis for evaluating the effect of police presence on crime. Becker defines *crime* as a rational decision in which an individual would compare the costs and benefits of a criminal action. The most relevant conclusion for this paper is the deterrent effect of policing, i.e., a more significant police presence would reduce crime by reducing the expected utility of criminals and increasing the probability of conviction. Ehrlich (1981) exploits the fact that the police also affect crime by removing criminals from circulation through arrest and incarceration, which is the incapacitation effect of police. However, drastic reductions in police as strikes may capture a specific effect of police on crime since these events are rare and can affect crime through other channels compared to the standards deterrence and incapacitation effects of policing. My findings provide evidence of the effect of police in a context of high violence and the significant presence of organized criminal groups. The first relevant contribution is using very granular daily data at the district level to assess the effect of a substantial reduction in police patrols. Police strikes in Brazil are opportunities to exploit the effect of policing in the opposite direction from most works, which usually exploit the increase in police allocation. Brazilian municipalities present considerable district heterogeneity, wildly contrasting wealthy neighborhoods to peripheral locations occupied by criminal gangs. Thus, I disentangle at the district level which homicides are arguably related to criminal gang conflicts from the total increase in homicides by assessing previous criminal records of individuals killed during police strikes. To my knowledge, there is no work studying the effect of police on crime with such granular data in a setting where criminal gangs are prevalent and disentangling the mechanisms driving the increase in violence caused by a sharp reduction in policing.

Most papers about the effect of police on crime use instrumental variables (Levitt, 1995, 2002, McCrary, 2002) or terrorist attack-related events (Di Tella and Schargrodsky, 2004, Klick and Tabarrok, 2005, Draca et al., 2011) as identification strategies. Although these works find some evidence supporting the effect of police presence in reducing property and violent crimes, none of them address the role of organized criminal groups following abrupt shifts in police patrols. Furthermore, following a terrorist attack, the deployment of police officers is concentrated in public buildings, subway stations, and main avenues. Suppose these places do not present significant criminal outcomes before the event. In that case, the increase in the police may not affect some types of crime[1], and thus can not be interpreted as an overall effect of police on crime. Although the shift in policing after terrorist attacks can be considered exogenous to crime dynamics, these papers do not exploit significant confounding factors to the effect of police on crime in this context (e.g., gang conflicts and the interplay between state and criminals). My findings represent rigorous empirical evidence to interpret the effect of police on crime following abrupt shifts in surveillance and police patrols in contexts of gang conflicts.

Last, my findings also contribute to the literature on police strikes. Sherman and Eck (2003) presents a literature review pointing out to an increase in both violent and property crime on police strikes (Takala (1979) and Andenaes (1974)). Nevertheless,

[1] Klick and Tabarrok (2005) exploit the exogenous variation in the Washington DC police presence using terrorist attack alerts issued by the US Department of Homeland Security. The authors find a significant drop in crimes typically committed on the streets, such as robbery and theft, in areas that have received police reinforcements. However, they do not find a significant reduction in homicides in these locations. Analogously Di Tella and Schargrodsky (2004) show the effect of police on auto theft after a terrorist attack on Jewish community buildings in Buenos Aires. After the event, the Argentine government increased police patrols in mosques and synagogues.

these results must be viewed with caution since the papers reviewed do not present a counterfactual scenario or robustness tests to verify if the crime would have increased in the absence of the strike. Piza and Chillar (2021) try to address this question by exploiting a 13% decrease in police officers given a mass layoff executed by the Newark Police Department of New Jersey in November 2010. Although they do not disentangle the mechanisms driving such an increase in violence (e.g., the profile of victims, cause of death, etc.), the authors find a significant increase in the number of offenses registered by Newark police after the layoff compared to the Jersey City Police Department, which does not suffer the same budgetary reduction. Cardoso and Resende (2018) exploits the effect of strikes by military police officers in Brazil from 2010 to 2014 and finds a 16% increase in monthly homicides when evaluating 13 events in different states. Although they use the same identification strategy as this paper, the authors do not tackle many questions as the issue of considering monthly data to measure the effect of events lasting a couple of days and a robust approach to the mechanisms driving such a boost in the number of homicides. More precisely, these papers do not answer who suffers the consequences of a sudden decrease in police officers, i.e., if the violence arises from criminals attacking civilians, gangs fighting for territories, or conflicts between civilians. The fear and social tension caused by a sudden decrease in police patrols may affect the behavior of criminals and potential victims, changing their mobility on the streets during the strike. White (1988) show that confounding factors such as the social tension between the upper and working class contributed to the increased violence during the Boston police strike in 1919. Without addressing changes in civilians' and criminals' behavior, estimates of the effect of policing on crime are inaccurate. In this paper, I try to close this gap in the literature by presenting a framework that allows disentangling the mechanisms by which police strikes affect violent crime conditional to the socio-economic context and the presence of criminal gangs.

The remainder of this paper is organized as follows. Section 2 presents an overview of police forces in Brazil. I introduce the data and describe the empirical strategy in Section 3. Section 4 presents the main results, such as sensitivity and robustness analyses. Section 5 present a case study of a police strike in context of significant criminal gangs conflicts and Section 6 concludes.

2. Police Forces and Public Security in Brazil

2.1. Conceptual Framework

Police forces in Brazil are part of a complex public security system[2] commanded by the Federal Government, States, and Municipalities. The Federal Government manages: (i) the Federal Police, entitled to investigate criminal acts against institutional order, border surveillance, and exerting the role of the State Union's judicial police, (ii) the Federal Highway Police, and (iii) the Federal Railway Police, responsible for patrolling highways and railways respectively. State police forces are responsible for patrolling streets and investigating crimes. While the Military Police manage surveillance and repression of criminal acts, the Civil Police conduct the investigation procedure. Finally, in municipalities with more than 500 thousand inhabitants, Municipality Guards also use lethal weapons to exert a complementary role to the Military Police in surveillance and patrolling tasks.

According to the Federal Constitution (1988), Armed Forces and Military Police members cannot go on strike. This prohibition was extended to the Federal Police and Civil Police by a Supreme Court decision in 2017. The legal understanding is that police forces perform an essential service to society that cannot be interrupted at the risk of exposing civilians to danger. However, even under this legal restriction, there have been around 30 strikes of military police officers and 200 strikes of civil police officers in different Brazilian states since 2000. They generally demand improved wages, social benefits, and working conditions. Strikers can pass through administrative prosecution and answer for military crimes. However, most are forgiven as part of the agreements to end the strike and the difficulty of identifying which police officers joined the movement.

The Brazilian Public Security System's complexity contrasts with high criminality. The Brazilian Yearbook of Public Security[3] registered more than 50 thousand intentional violent deaths in Brazil in 2020, an average rate of 23.6 homicides per 100 thousand inhabitants. Some Brazilian cities are among the most violent places in the world in terms of homicides per 100 thousand people, such as Caucaia/CE (89.6), Feira de Santana/BA (89.9), and Cabo de Santo Agostinho/PE (90.0). Lima et al. (2016) discuss the inefficiency of this institutional arrangement and how law improvements could create synergies between police forces to reach better public security outcomes.

Finally, there is strong evidence showing that most of the homicides in Brazil are

[2] As described in article 144 of the Federal Constitution link

[3] Brazilian Yearbook of Public Security - 2021

related to criminal gangs. Public security policies aimed at combating these groups are incredibly challenging. In some cases, deploying police forces to gang turfs can intensify conflicts between criminal groups (Dell (2015)). Magaloni et al. (2020) exploit this complexity by analyzing the effects of the Pacifying Police Units (UPP) in Rio de Janeiro. They show heterogeneous effects of policing conditional to the presence of criminal gangs and their interplay with the community.

2.2. Strikes of Police Forces in Brazil (2000-2020)

Police strikes are rare since the Brazilian Federal Constitution vetoes the right to strike to police officers and fire brigades. These drastic shifts in police officers may affect the number of crimes through two main mechanisms according to the model presented by Becker (1968): (a) a decrease in the deterrence effect due to fewer police officers on the streets and (b) a decrease in the incapacitation effect due to fewer arrests in this period. Regarding violent deaths, police strikes can affect criminal violence and domestic disputes involving civilians. Given the lower probability of arrest and conviction, criminals can intensify reckoning and conflicts for territories or become less cautious during robberies. These facts would increase criminal gangs' conflicts and homicides following property crimes. On the other hand, the sharp decrease in policing can also affect civilians' behavior, increasing the probability that domestic arguments end up in homicides.

Thus, to assess the effects of the police on violent crimes, this paper focuses on three channels: (a) criminal gangs may use the period to reckoning and dispute turfs, (b) criminals may become more prone to commit crimes and adopt violent measures, and (c) civilians may use greater violence to protect their assets or domestic arguments. Despite the inherent difficulties of identifying the causes of homicides and types of crimes, I will exploit how these channels operate in a police strike in the following sections.

3. Data and Empirical Strategy

3.1. Data

I exploit the quasi-experiment of police strikes between 2000 and 2019 to investigate the effect of a sharp reduction in policing on violent crime. I use daily homicide panel data based on records from 5.568 Brazilian municipalities in 26 Brazilian states and the federal district.

As my focus is on violent deaths, I use the International Statistical Classification of Diseases and Related Health Problems (ICD-10) for aggression (X85-Y09) and legal intervention (Y35-Y36). Homicide data comes from the Ministry of Health

- Mortality Information System (SIM-DataSUS). Table A.1 shows that the average number of homicides during a strike by the Military Police is higher than the average number of homicides from 2000 to 2019. On the other hand, the average number of deaths during Civil Police strikes is not distinguishable from the average in the entire sample.

About the indicator of police force strikes, I use data from the Interunion Department of Statistics and Socioeconomic Studies (DIEESE)[4]. The data show the timing of strikes according to what was reported by the media, labor unions, and class associations. The table A.2 shows the number of events, average duration, and standard deviation in days of civil and military police strikes. Civil Police strikes are often longer than the Military Police, which partially reflects that only in 2017 did the Supreme Court extend the strike veto to Civil Police. About Military Police strikes, for which we expect a more significant effect on violent crimes through a decrease in surveillance and patrols, most events last less than seven days, as shown in figure A.3.

3.2. Empirical Strategy

I use SIM-DATASUS daily homicide records from January 1, 2000, to December 31, 2019. The reduction in policing that I analyze comes from 29 Military Police strikes, 194 Civil Police strikes registered by DIEESE since 2000 in different Brazilian states, and daily homicide observations at the state level. Some states do not show Military or Civil Police strikes during this period. The identification comes from the variation in homicides: (a) across states affected and not affected by a police force strike and (b) before and after a strike in states affected.

Given the panel data structure, it is possible to control for non-observable time and location fixed effects, which can be correlated with the occurrence of a strike, eliminating a potential source of endogeneity. About the possibility that strikes occur precisely in states with a previous violence trend, I address this issue in an Event Study using a variable indicating days before and after the event. In this approach, I assess the dynamic effect of police strikes to identify if there is a previous trend in homicides before the particular day of a sudden decrease in police patrolling. Moreover, working with daily data allows identifying the exact date of the strike outbreak, which reinforces the identification strategy since the precise outbreak day of a strike can be considered exogenous to other confounding factors that affect

[4]The report "Balanço das Greves" is available here. For this paper, I request to DIEESE detailed records of all Civil and Military Police strikes between 2000 and 2020.

criminality over time (e.g. increase in unemployment, budgetary reductions at the state level, etc.).

3.3. Model

States that registered police force strikes are the target group, while those that have not suffered this shock are the non-target group. I include a series of time-fixed effects so that all common shocks in the evolution of homicides across states are absorbed. I also include state-fixed effects to control for unobservable crime determinants invariant at the state level. The difference-in-differences estimator of the police effect on homicide using the following model is:

$$homicides_{it} = \alpha_i + \beta_1 * PM_{strike_{it}} + \beta_2 * PC_{strike_{it}} + \phi_t + \mu_{it} \tag{1}$$

Where the subscripts i and t respectively denote state and date; $PM_{strike_{it}}$ and $PC_{strike_{it}}$ are dummies equal to one during the military and civil police strike days in the State i; ϕ is a set of time-fixed effects that includes the year, month, and weekday dummies; α are state-fixed effects. The dependent variable *homicides* indicates the number of daily homicides in a given state. SIM-DATASUS provides information on gender, age, and cause of death that allows exploring the heterogeneous effect of police strikes on different specifications of the dependent variable in the equation 1.

A possible inference concern is the potential serial correlation in the dependent variable over time in this setting. The standard solution is to estimate standard errors allowing for within-cluster auto-correlation. However, Cameron and Miller (2015) show that the validity of robust cluster estimators depends on the number of clusters, and settings with few clusters generally lead to biased estimators. In this context, Angrist and Pischke (2008) suggest that standard clustering provides a good approximation when working with more than 42 clusters. Since police strikes in Brazil occur at the state level, I estimate a baseline regression using 27 states[5] as clustering units. Therefore, as my quasi-experimental setting shows few clusters, I estimate cluster bootstrap standard errors to overcome a potential auto-correlation. Cameron and Miller (2015) shows that this resampling-based approach is efficient even in cases of few clusters.

The identification strategy comes from two key assumptions. The first is that the particular day of a police strike outbreak in a state is exogenous to the evolution of homicides, i.e., the decision of police officers to go on strike that day is not related to confounding factors that can affect criminal activity. In this case, the strike

[5] I consider the Federal District in this amount.

represents a quasi-experiment that breaks the simultaneity between crime and police presence. The second crucial hypothesis is that the increase in homicides during strike days is exclusively due to the sudden reduction of police officers in the streets and not other confounding factors.

4. The Effect of Police on Violent Crime

4.1. Results

Table A.3 report the results from the estimation of Equation 1 using Total Homicides and Homicides by Gender as dependent variables of interest. I highlight the differences-in-differences point estimates for Military Police (β_1) and Civil Police (β_2) strikes. I display the 95% confidence intervals obtained using the baseline specification and bootstrap cluster-robust standard errors. The results show that a sharp decrease in police patrols causes a significant increase in total homicides, especially in men deaths. Outcomes are only significant to Military Police strikes which suggests that the surveillance and regular street patrols of Military Police are essential mechanisms for the deterrence effect of policing on crime. The β_1 coefficient represents a 45% increase in daily homicides compared to the average from 2000 to 2020[6].

I also exploit the leading cause of death in Table A.4, and I find that firearms primarily drive the increase in homicides. Furthermore, Table A.5 shows that Hospitals and Public Spaces (streets and avenues) are the most common places where deaths occur during a police strike. Last, I show in Table A.6 that people from 15 to 45 years old are the primary victims; however, this result must be analyzed with caution since the data provided by SIM-DataSUS have a lot of missing information about age.

The quasi-experiment in this paper exploits a sudden decrease in police patrols (police strike) that makes the criminal activity less costly (deterrence effect) and also results in fewer offenders captured (incapacitation effect). Since I only find significant results on violent crime to Military Police Strikes, which last on average eight days, I believe that my results capture mainly the deterrence effect of police on homicides. In this short period, such a significant increase in violent deaths seems to be caused by criminals when there are few police officers to interfere, given the significant effect of individuals killed by firearms in public spaces.

My results are larger than the estimates of 16% increase in homicides of Cardoso and Resende (2018), which probably indicates a more precise identification using daily records and focusing only on the actual days of the strike rather than an

[6]The ratio between the coefficient $\beta_1 = 2.934$ over the 6.442 average daily homicides by state.

entire month. Furthermore, my findings add to the evidence found by Evans and Owens (2007) and Levitt (2002) that show a positive effect of police on violent crime. However, I present evidence in the opposite direction, i.e., an adverse effect of decreasing police on homicides.

4.2. Robustness and alternative specification

In this section, I present additional evidence to assure the validity of my results by exploiting previous trends and alternative specifications.

4.2.1. Placebos and previous trend

My baseline results indicate that homicides increase significantly more during military police strikes than the average on non-strike days. One possible threat to the research design is a shift in unobservable factors that could increase the number of homicides in the states affected. In such a case, the estimates would capture a spurious correlation. To overcome that, I perform a placebo test and an event study to assess the robustness of my results.

First, I check whether the target group (states affected by strikes) shows an upward trend in violent outcomes one month before the event (pseudo-treatment period). I run Equation 1 as if strikes had occurred in each treated unit in the previous month. Table A.7 shows the pseudo-treatment coefficients with their 95% confidence intervals and the baseline estimates. The results confirm that there is a particular change in the dynamic of homicides after the precise outbreak day of a police strike.

As a second placebo test, I exploit homicides unrelated to criminal activities during the days of police strikes. If the decrease in police patrols drives the results, I do not expect a significant increase in deaths that are not directly related to the deterrence effect of police on crime. Hence, I re-estimate Equation 1 using traffic accidents that killed pedestrians, cyclists, or bikers as a dependent variable. I display the estimates of this exercise in Table A.8. The outcomes do not show a significant increase in deaths caused by car accidents during strikes in Brazil. These results reveal that police strikes do not affect other types of deaths related to people on the streets, reinforcing the interplay between decreased police patrols and deaths caused by criminals.

Furthermore, I investigate if there was a previous increase in homicides just before the public announcement of a Military Police strike. If the Military Police decide to go on a strike precisely during a period of growing violence, my results would capture a previous trend of violence rather than a causal impact of police on crime. To check the previous trend in the target group, I perform an Event-Study using the specification presented in Clarke and Tapia-Schythe (2021):

$$homicides_{it} = \alpha_i + \sum_{j=2}^{J} \beta_j (Lag_j)_{it} + \sum_{k=1}^{K} \gamma_k (Lead_k)_{it} + \phi_t + \mu_{it} \tag{2}$$

Where lags and leads to the beginning of a Military Police strike are defined as follows:

$$\begin{aligned}
(Lag_J)_{it} &= 1[t \leq Strike_i - J] \\
(Lag_j)_{it} &= 1[t = Strike_i - j] \ for \ j \in (1, ..., J-1) \\
(Lag_k)_{it} &= 1[t = Strike_i + k] \ for \ j \in (1, ..., K-1) \\
(Lag_K)_{it} &= 1[t \geq Strike_i + K]
\end{aligned}$$

The specification uses the lag one as a baseline to capture the difference between states and days where strikes do and do not occur. Lags and Leads capture the difference between treated and control states compared to the prevailing difference in the omitted baseline. This event study tests if states affected by strikes show different homicide dynamics than non-affected states. I display at the Figure A.8 the results of the Equation 2. I find no evidence of a previous trend in homicides before a Military Police strike. The effect of the decrease in police patrols on days 2 and 3 is equivalent to 65% more deaths compared to the average level of homicides. These outcomes validate my exercise and show no previous trend in states affected by Military Police strikes.

Last, I perform an exercise to assess the heterogeneous effect of military police strikes where I exploit the difference in the duration of these events. Arguably short police strikes must have a different impact on homicides than longer events. I aggregate military police strikes in three groups: small events (less than seven days), medium events (7 to 11 days), and large events (greater than 11 days). I show the results in Figure A.4. There is no clear evidence of a previous trend in homicides in all groups. Regarding strikes that last more than 11 days, I find a more persistent increase in homicides than shorter events. The decrease in surveillance and police patrols caused a significant increase in violent deaths in states affected by police strikes. This effect seems more prominent when criminals realize that it will take a long time for the government and military police to agree to re-establish the state's monopoly of using force.

4.2.2. Alternative specification

Since the number of homicides is a count data, i.e., discrete data with non-negative integer values, one can argue that Poisson regression models would be more appropriate to estimate the causal effect of police on crime. Moreover, even in a context of considerable violence, homicides are rare compared to other types of offenses. Therefore, as a robustness test, I run a Poisson regression model with fixed effects and robust standard errors clustered at the state level. The coefficients represent the effect of a 1-strike day on the logarithm of the expected incidence of daily homicides and show the percentage effect of strikes of police forces on daily homicides. My estimates of the impact of police force strikes on homicides remain significant. Table A.9 presents the Poisson estimates together with my baseline results. The Poisson coefficients show an increase of 42% in daily homicides during Military Police strikes, consistent with the estimates of my baseline specification.

5. Case Study: how abrupt police reductions can trigger violent gang conflicts.

5.1. Introduction

This case study exploits how gang conflicts affect violent crimes, especially during a police strike. I use the disruption in the no confrontation agreement between the most prominent criminal gangs (PCC and CV) in 2016 as a quasi-experiment to identify which districts within the city of Fortaleza/Ceará were significantly affected by the increase in gang conflicts and violent crimes. The identification hypothesis relies on the spatial dynamic of violent deaths within the municipality, which changed abruptly after these gangs disrupted the non-compete agreement. I argue that the increased gang competition intensified conflicts and violent deaths in turfs disputed by these groups. Consistent with this argument, I show that in these disputed turfs, deaths of suspected criminals drive homicides following a police strike. The abrupt reduction in police caused by the strike increased the expected payoff of confrontation, creating incentives to attack the rival.

In the first part of this paper, I show that Military Police strikes cause a large and significant increase in homicides, and most of the victims are young men killed by firearms in public spaces. These findings are robust, but they do not disentangle which mechanisms drive this massive increase in violent deaths (e.g., criminal gang disputes, deaths related to property crimes, or conflicts between civilians). To address this question, I exploit a Military Police strike that occurred in 2020 in the state of Ceará. The Secretary of Public Security in Ceará has provided very detailed data on homicides at the district level since 2014. I use this information to check previous criminal records of victims at the State Judiciary. Most of the cases display individuals' names, ages, and gender, which allows using personal identification to assess other public databases. Therefore, these features provide a unique opportunity to disentangle the deaths of individuals investigated or convicted in civilian and criminal courts from the total homicides registered during a police strike at the district level.

A relevant confounding factor affecting the crime dynamic of Ceará is the escalation of criminal gang conflicts. Although there are several regional gangs in Brazil, two criminal groups exert a dominant position in the drug market: *"Primeiro Comando da Capital"* (PCC), from the State of São Paulo, and *"Comando Vermelho"* (CV) from Rio de Janeiro. For an extended period, these criminals had a non-compete agreement that assured no confrontation, especially over turfs where one had a monopolistic position. In the North and Northeast region, these groups keep strategic alliances with local gangs as *"Família do Norte"* (FDN) and *"Guardiões do Estado"* (GDE), respectively CV and PCC allies. These arrangements generally provide drug and firearms supply, financial support, and protection in penitentiaries.

I use daily data on deaths at the district level from 2014 to 2020 to identify shifts in the spatial dynamic of homicides before and after the disruption between PCC and CV. To determine the districts where the disruption caused violent disputes (criminal gangs turfs), I use homicides of individuals with previous criminal records, which have a higher probability of being a gang member. I exploit the fact that gang conflicts disproportionately affect areas within a municipality. I combine the gender and age information of the victims with socio-economic data at the district level to assess the heterogeneous effect of my estimates. A differences-in-differences analysis comparing deaths in disputed turfs to non-target ones estimates the aggregate impact of gangs' war on homicides.

To disentangle which mechanisms drive my results, I present a model that characterizes how commitment problems create conflicts when there is a rapid shift in the expected payoff of a gang war. The disruption in the no-confrontation agreement between CV and PCC arguably increased investments in weapons and the recruitment of soldiers that improved criminal gangs' capabilities. Thus, the inability to commit of these gangs increased the probability of a war to control drug trafficking routes. I use this model to analyze how a police strike intensified conflicts. Reductions in police patrols decrease confrontation's cost and increase the expected payoff in a gang war. If a criminal group chooses to accommodate instead of fighting, the rival can use the opportunity to attack first. In this context, the inability to commit makes both gangs choose to fight rather than be accommodating. Consistent with my model of gang conflicts, I show that the disruption between PCC and CV had a large and significant impact on violent crimes. After 2016 target districts show a 32% increase in homicides, which goes to 88% during a police strike. Moreover, I find that the gang conflicts also affected other crimes (robbery and gun apprehensions), supportive evidence of collateral damages to residents of these districts.

To assess the validity of my findings, I perform a placebo test choosing a random specification of criminal turfs. The outcomes of this exercise do not show a significant increase in homicides in pseudo gang turfs. Secondly, I used a Military Police strike in 2011 before disrupting the non-confrontation agreement between PCC and CV to assess the effect of a police strike on homicides when a single criminal gang exerts a hegemonic position in drug trafficking. My results show a more significant increase in violent deaths in police strikes when there are two gangs disputing territories in Ceará. Thus, criminal gang competition plays a crucial role in the increase in homicides following abrupt shifts in the police. Last, I test the parallel trend assumption by comparing the previous trend of homicides in target and non-target districts before 2016. I find no evidence of a different dynamic in homicides.

Brazil is one of the most violent countries in the world, and it is also a top supplier of cocaine to Europe, an illegal market valued at more than USD 10 billion in 2020[7]. States closer to the Amazon region as Ceará are strategic to criminals as routes to receive and export drugs produced at Colômbia, Peru, and Bolivia. Moreover, the United Nations Office on Drugs and Crime (UNODC) estimates that drug production in South America doubled from 2013 to 2017. This considerable increase in supply may result in falling prices that potentially attract more consumers worldwide. Hence this paper presents compelling evidence of the crucial role of criminal gang conflicts on violent outcomes in a strategic drug trafficking route, providing valuable guidance to public policies aiming to alleviate the terrible consequences of violent crimes.

Controlling drug trafficking routes is essential to any criminal gang (Calderón et al. (2015), Lessing (2017)). Rarely more than one gang exploit the same drug route because of the difficulties of assigning property rights and enforcing agreements in illegal markets. Problems of commitment and an inability to prevent new entrants make the use of violence the main alternative to keep and expand control over drug trafficking routes (Schelling (1971), Buchanan (1973)). However, assuming that criminal gang conflicts are costly to both sides, it is puzzling why many gangs engage in prolonged conflicts rather than settling a cooperation agreement. Levitt and Venkatesh (2000) discuss the costs associated with gang conflicts in the United States, and they present evidence of these enormous costs in terms of lost lives and

[7]Source: Reuters Magazine (link)

lost profits[8]. On the other hand, the authors also argue that the efficiency gains obtained through the monopoly of a drug trafficking route can offset such costs, which partially explains the employment of violence as a strategy for shifting the control of drug trafficking turfs. Similarly, Trejo and Ley (2020) argues that using large-scale violence is expensive for gangs and exposes criminals to police intervention. They show that changes in Mexico's political system threatened the domain of criminal gangs leading to an arms race and considerable investments in private militias to defend their turf. Gangs in Mexico focused on recruiting and training young men from peripheral areas to join their private armies as soldiers in the cartel's turf war. Gang conflicts became increasingly lethal and even more complex after the federal government started a War on Drugs in 2007, focusing on dismantling criminal cartels. Last, some works exploit an additional factor that can lead to gang conflicts, the interplay between criminals, state, and police forces. Trejo and Ley (2020) and Arias (2006) show that some level of state support protecting gangs from repression is essential to the success of a criminal organization. In this sense, military police interventions can elevate violence since criminal groups will have to fight against the state repression rather than focus only on drug trafficking and manage their turfs (Dell (2015)). Thus a police intervention can exacerbate violence in gangs' contested territories (Magaloni et al. (2020)).

My findings contribute to the literature about police and organized crime organizations providing evidence that gang conflicts have a crucial role in violent outcomes during a drastic reduction in policing. Some police strikes in Brazil occurred in contexts of significant criminal gang competition. Hence, criminals can exploit the decrease in surveillance as an opportunity to attack the rival without the credible threat of police intervention. The intensification of disputes over drug trafficking routes by these gangs can be a relevant mechanism explaining higher levels of violence following military police strikes. Hence, when criminal gangs are powerful, drastic shifts in police are not directly comparable to marginal changes in policing over criminality. I also contribute to the literature about the effect of organized criminal groups by measuring the magnitude of the impact of gangs' war on violent deaths in a country with a high homicide rate.

The remainder of this section is organized to discuss the context of organized criminal groups in Brazil, the disruption between the most relevant gangs, PCC and CV, the rise of GDE in Ceará, and lastly, I present data, empirical strategy, and the results found in this case study.

[8]They show that wars are associated with dramatic declines in price, quantity, profit, and drug revenue.

5.2. The rise of "Guardiões do Estado" (GDE) at Ceará

A group of prisoners decided to break the hegemonic position occupied by "*Comando Vermelho*"(CV) and "*Primeiro Comando da Capital*"(PCC) in penitentiaries of Ceará. They have created the gang "*Guardiões do Estado*" (GDE)[9] motivated by issues as the expensive fees and high bureaucracy to receive assistance and financial support from these major groups. The GDE founders also announced the new gang as an opportunity to create an entity with local identity and legitimacy to represent the prisoners of Ceará.

Documents intercepted in an investigation conducted by the State Secretary of Penitentiaries show that the foundation of GDE occurred on January 1, 2016, and it estimates that almost 20 thousand prisoners joined the criminal organization (about 70% of the prisoners of Ceará) in a process called "batismo" (baptism). Even as an independent group, the gang leadership has settled an agreement to have PCC as an ally and drug supplier. The investigation also revealed details of the GDE's organizational structure. At the top of the hierarchy, there are three councils composed each of 13 members:

- Final Council - entitled to strategic and complex decisions such as organizing attacks against authorities;
- General Council - responsible for the financial management and organizing incursions against rival groups; this council also has a judiciary role judging cases not solved by the first council;
- Legendary Council - it is the first council to judge and punish members who are not complying with internal rules and monthly fees to support the group.

Furthermore, GDE has smaller structures that handle the daily operations such as recruitment of new members, coordination between district leaders, management of property crimes, punishment, execution, and other tasks. The final statement of the document that consolidates the foundation of GDE focuses on the mission of the group, and it says:

Finally, what motivates the organization will always be to expand and propagate the union and equality of the favelas in communion with the prison population. We will fight for peace inside and outside the system, constantly adding and never splitting or diminishing. To establish that the right prevails in crime and the wrong will be

[9]Based on the information provided by the State Secretary of Penitentiaries in Ceará. (link)

charged and punished because we will fight for collective ideals and better days restlessly, under the protection of God, who will always bless this family that rises.
– the last article of GDE by-law

The gang has started a movement to consolidate its presence in the metropolitan region of Fortaleza, where CV controlled strategic zones to receive drugs from Amazon, supply the local market, and export cocaine to Europe through the Port of Ceará. They have recruited many members inside and outside prisons to dispute the region's control, which triggered intense violence in the following years, especially after a broader disruption between CV and PCC (GDE ally) at the national level.

5.3. Gangs at War (Brazil, 2016-2020)

For decades the two major Brazilian criminal groups had a non-compete agreement. Geographically, PCC and CV keep a significant position on crime in their original states, São Paulo and Rio de Janeiro, respectively. However, these gangs also act at the national level, especially in states that are strategic routes to receive drugs from South American countries, such as Paraguay, Colombia, Bolivia, and Peru.

PCC started an expansionary movement in mid-2016 when the gang decided to take control of territories on the border Brazil-Paraguay. Previously in this region, both groups had agreements with the local producers to obtain drugs, especially cocaine. This fact has ended the non-aggression agreement and triggered a series of violent conflicts between PCC and CV in the entire Brazilian territory.

These conflicts occurred particularly in the North and Northeast regions of Brazil, where both gangs intensified the process of recruitment inside prisons through partnerships with local gangs as "*Guardiões do Estado*" and "*Família do Nordeste*." Between 2016 to 2017, there were four big rebellions in penitentiaries, causing more than 100 hundred deaths of prisoners in the states of Ceará, Rondônia, Roraima, and Amazonas, territories disputed by PCC and CV. The use of violence also increased outside the penitentiaries. The number of violent deaths[10] in North and Northeast regions increased 16.3% in these years, above the national index (9.6%). Only in 2017, 35 thousand people were murdered in the region, 55% of Brazil's total number of homicides.

In this scenario of growing violence, the state of Ceará was one of the most affected by criminal gang conflicts. GDE and CV have started an intense dispute regarding the control of territories, especially by drug trafficking routes and peripheral areas

[10]Source: *Brazilian Yearbook of Public Security.* (link)

of Fortaleza, the state capital. Ceará is strategic in exporting cocaine given its proximity to Europe, an additional element that has intensified the battle between these gangs by a monopolistic position in the state. Criminals exert authority over the local population by regulating traffic hours within districts, removing people from their houses, and punishing civilians related to rival gangs or suspected of being legal authorities informants. The state weakness in the periphery of Fortaleza is so huge that each district has signs indicating which gang is in charge of the turf. Last, the poverty in the state contributed significantly to these criminal groups recruiting young men from *"favelas"* to this war.

5.4. Model of Gang Conflicts

Controlling drug trafficking routes is crucial to organized criminal groups. When more than one gang decides to exploit the same turf, it is possible that the bargaining by the flow of traffic rents leads to violent outcomes. However, why does an abrupt reduction in policing intensify conflicts? Levitt and Venkatesh (2000) show that the bargaining problem faced by criminal groups is challenging due to the absence of property rights and legally binding contracts. However, the inability of two criminal groups to keep a collusive equilibrium is somehow puzzling, since wars destroy resources and are costly for both sides. Fearon (1995) presents three approaches to this conflict puzzle: (i) informational problems, (ii) bargaining indivisibilities, and (iii) the inability to commit. I argue that the primary mechanism that triggers violent conflicts between organized criminal groups is a problem of commitment.

To illustrate how shifts in policing can trigger a criminal gang war, I use the model of conflicts presented by Powell (2006). The author shows that some groups choose fighting if the expected outcome of attacking is larger than accommodating, even in scenarios of complete information. Moreover, even if gangs turfs were indivisible units, there are still agreements that both sides would prefer to engage in a costly war. Hence, to Powell (2006) (i) informational problems and (ii) bargaining indivisibilities are secondary motivations of wars, and the main obstacle to gangs reaching an agreement is (iii) the inability to commit.

First, I argue that asymmetric information does not provide an accurate answer to prolonged conflicts since both sides accurately assess the rival capabilities after years of war. Even conflicts following the entry of a new gang can not be explained by asymmetric information since some criminal groups can decide to contest a drug trafficking turf no matter the level of information about the rival. In many cases, these groups have a good understanding of both sides' capabilities because they have been fighting for years. Thus, I argue that informational problems do not cause most gang conflicts, especially those following abrupt shifts in police strikes. Second, even if a disputed turf were indivisible, the fact that a war is costly would lead both sides to bargain and reach an agreement instead of fighting. Therefore the real issue leading to gang conflicts seems to be the inability to commit rather than bargain indivisibilities.

The main difference in my framework compared to Powell (2006) is the introduction of the Military Police in the model as an actor capable of interfering in criminal gang battles. I include police in the game as a player who imposes additional losses on criminal groups. Assuming that commitment issues cause conflicts, I show that the mechanism leading to a war in police strikes is an increase in the expected payoff in a conflict that undermines a possibility of an agreement.

5.4.1. The conflict condition

Although there are substantial differences regarding state, civil and criminal gangs war, these cases share the same commitment problem. In this case study, two criminal groups bargain by the flow of drug trafficking benefits in a setting where:

1. gangs cannot commit to comply with the agreement in the future
2. gangs can use violence to break the original agreement and expand their turf
3. the use of violence is costly, and it destroys resources
4. the distribution of power between gangs shifts over time
5. State can use the Military Police to repress criminal disputes

I add the last assumption in the model presented by Powell (2006) to reflect the particular institutional setting of criminal gang conflicts in Brazil and how police forces can interfere in a gang war. Leadership changes, new entrants, and the arrest of gang members can rapidly break down in this setting, making agreements between criminal groups fragile.

To illustrate the mechanism that leads to inefficient bargaining, suppose that gangs A and B bargain by the flow of drug trafficking benefits (*"a pie"*) equal to V. A player C represents the Military Police that interferes if there is an outbreak of violent conflicts. The increase in drug trafficking rents of a criminal group necessarily harms the benefits of the rival. Suppose that initially gangs A and B keep a *status quo* division of the pie equal to Q_A and Q_B such as $Q_A + Q_B = V$, respectively, i.e., a *Pareto* improvement is not possible. In each period, gangs $g = A \ or \ B$ can choose to use violence to lock in a payoff $D_g(t)$ but doing so is costly, and it destroys some of the gang resources (e.g., weapons, soldiers, and supplies).

Gangs keep an extremely fragile equilibrium in this framework since there are no property rights and legally binding contracts to enforce the territorial division over time. Suppose gangs face an opportunity to increase drug trafficking rents by expanding over rival territories. In that case, they have significant incentives to break the *status quo* and start a war to settle territorial disputes. In the limit, each gang prefers to keep the monopoly of drug trafficking rents instead of bargaining with a competitor able to use violence at any time to break an agreement. If in time t a gang decides to break the original status quo division and use violence to fight for a monopolistic position it obtains:

$$\begin{aligned} D_g(t) &= (p_g * V - L_g) + (1 - p_g) * 0 - p_C * L_C \\ &= (p_g * V - L_g) - p_C * L_C \end{aligned} \tag{3}$$

Where p_g is the probability that a gang $g = A \text{ } or \text{ } B$ conquers the monopoly of the disputed turf after spending the resources L_g in the war. If A chooses to run after the beginning of a war, the gang reduces the confrontation damages, but it also loses the future flow of drug trafficking benefits. To simplify this scenario, I assume a zero payoff when gang g decides to fight but it is defeated with probability[11] $(1 - p_g)$. Last, I consider a probability p_C of police intervention that causes additional losses in criminal conflicts. Hence, gang g can obtain at least $D_g(t)$ if it decides to fight for the control of a drug trafficking turf, which is the minimum payoff in any equilibrium. Therefore, a criminal gang decides to start a war when the expected payoff of a conflict is larger than the current status quo division of the *pie*, i.e.:

$$D_g(t) > Q_g(t) \tag{4}$$

5.4.2. Police strikes

Now consider a shift in the probability of police intervention p_C. Strikes in municipalities disputed by criminal gang decrease the threat of police intervention represented by p_C and thus reduces losses in criminal gang conflicts. Combining equation 3 and 4, it is possible to assess how changes in the probability of police intervention p_C can trigger violent conflicts:

$$\begin{aligned} (p_g * V - L_g) - p_C * L_C > Q_g \\ p_g * \frac{V}{L_C} - \frac{(L_g + Q_g)}{L_C} > p_C \end{aligned} \tag{5}$$

Equation 5 characterizes which values of p_C make a gang start a war given the probability of victory (p_g), conflict losses (L_g, L_C) and the share of the pie (Q_g).

[11] By the sake of simplicity I assume $p_A + p_B = 1$

Figure A.16 shows how the probability of police intervention affects the decision to a gang $g = A \ or \ B$ start a war given the the equation 5. Holding other variables constant, to a certain probability of intervention $\bar{p}_C$, a criminal gang decides to start a war if the probability of victory is greater than $\bar{p}_g$. The first proposition of the model is:

Proposition 1. To some $(\bar{p}_C, L_g, Q_g)$, if a criminal gang with probability of victory $\bar{p}_g$ chooses to start a war, any gang with $p_g > \bar{p}_g$ also chooses to start a war.

Proposition 1 states that when A and B share the territory equally $(Q_A = Q_B)$ and have the same expected conflict losses $(L_A = L_B)$, the gang with a higher probability of victory is more prone to start a war at a certain level of police intervention. In summary, the shaded area in Figure A.16 shows when a gang with probability p_g decides to start a war given the probability of police intervention.

Proposition 2. Suppose that a police strike decreases the probability of police intervention from $\bar{p}_C$ to p_S. To the same set of parameters (L_g, Q_g), criminal gangs with a lower probability of victory will choose to start a war.

A police strike increases the probability of a criminal gang starting a war. Figure A.16 shows that a decrease in the probability of police intervention to p_S reduces the minimum probability of victory required for which a gang decides to start a war. In other words, gangs under the standard level of police intervention $\bar{p}_C$ would not choose by war now decided by the conflict following a police strike.

Propositions 1 and 2 shed some light on the mechanisms leading to increased conflicts after abrupt shifts in the police. A police strike increases the expected payoff of a conflict and creates incentives for a gang to start a war even when the territory is equally divided with the rival. Furthermore, assuming that criminal groups have similar losses in conflicts, if the decrease in the probability of police intervention is large enough, even gangs with a small probability of victory will decide to start a war.

5.4.3. Some Comparative Statistics

Now I show some comparative statics exercises. I consider only the case of interior solution, that is, when $(p_c, p_g, L_g, Q_g, V) > 0$. First, I present the effect of a shift in losses and turf control on the decision of a gang to start a war (**Proposition 3**) and second, the decision to start a war when the distribution of power between gangs is unequal (**Proposition 4**).

Proposition 3. Suppose that there is an increase in the cost of conflict or the size of the turf controlled by a Gang g, that is, $\Delta(L_g + Q_g) > 0$, which increases potential losses faced by a Gang in a war. Then, the higher the conflict costs fewer the combinations of p_c and p_g that trigger a conflict.

Figure A.17 show the result of Proposition 3. Initially, in t_0, a gang g with a probability of victory $\bar{p}_g$ will start a war if the probability of police intervention falls below $\bar{p}_c$. An increase $\Delta(L_g + Q_g)$ in conflict costs shifts the curve to the right in t_1. In this case, the same combination of $\bar{p}_g$ and $\bar{p}_c$ do not trigger a war. Therefore, Proposition 3 states that, holding the probability of victory constant, a rise in potential losses in confrontation or the share of drug turf under control make conflicts more difficult following police strikes. For instance, in the case of Figure A.17, the shift $\Delta(L_g+Q_g)$ is so significant that there is no reduction in police intervention that makes a gang with a probability of victory $\bar{p}_g$ choose to start a war. Thus, when conflicts become too costly, reductions in police intervention can not be enough to start a war between criminal gangs.

Proposition 4.A. Suppose that power and turf control are unequal; that is, gang A is more powerful than gang B, which means a higher probability of victory ($p_a > p_b$) and a larger share of the disputed turf ($Q_a > Q_b$). Assuming equal losses in confrontation, i.e., $L_a = L_b$ the distribution of p_a and p_b defines which gang will start a war following shifts in the probability of police intervention $\bar{p}_C$.

Figure A.18 presents four possible scenarios of confrontation depending on the probability of victory of gangs A and B. The blue shaded area shows when the gang B starts a war, and the red shaded area is similar to gang A. Assuming a probability of police intervention equal to $\bar{p}_C$, there are some values (p_A^1, p_B^1) for which no shift in police intervention makes both gangs decide to start a war (**scenario 1**). When the probabilities are (p_A^2, p_B^2), Gang B decides to start a war (**scenario 2**) whereas to (p_A^3, p_B^3) both gangs will choose the confrontation (**scenario 3**). Last, when the probabilities of victory are (p_A^4, p_B^4), gang A will decide to start a war (**scenario 2**).

Proposition 4.B. To any set of parameters $(p_c, p_g, L_g, Q_g, V) > 0$, a decrease in the probability of police intervention increases the number of combinations that lead to war.

It is easy to see in Figure A.18 that a decrease in the probability of police intervention from $\bar{p}_C$ to p_S increases the number of combinations that the decision to start a war is binding to both gangs. Thus, when the probability of confrontation with police decreases abruptly in police strikes, even gangs with few chances of victory and small turf control will decide to start a war. Proposition 4.B is the more significant result of the model that reveals why police strikes trigger violent conflicts between criminal gangs.

5.5. Data and Empirical Strategy

5.5.1. Data

I exploit the entry of a contestant criminal group (GDE) in the metropolitan area of Fortaleza, a region previously controlled by another gang (CV). I use a daily panel of homicides registered in 13 districts covering the metropolitan area of Ceará State. Homicide data comes from the Secretary of Public Safety of Ceará (SSPDS-CE) from 2014 to 2020. The registers of SSPDS-CE are very detailed and display personal identification and the district where each violent death occurred. Using this data, I assess richer information compared to the data provided by the Ministry of Health - Mortality Information System (SIM-DataSUS).

Furthermore, I use the personal identification of victims to track previous engagement in illegal activities. The State Judiciary of Ceará has an online tool to assess public records of criminal cases filled in the court. The system provides criminal public records by individual name or process number. I have 27.307 records with personal identification. After consulting each register in the Judiciary system, I built a database with the information collected at the public case level. I observe each record's start and termination date and one or more tags on the discussed subjects. The defendant(s) and plaintiff(s) are identified by their full name.

Therefore, to build an indicator of engagement in illegal activities, I create three specifications for suspected criminals using tags presented in Table A.10. I use tags on case subjects to track drug trafficking, violent crimes, and civil prosecution. At least 53% of the individuals identified in the homicide data show previous criminal records. When I restrict only violent and gang-related crimes, there are still 43% of suspected criminals identified in the data. To avoid over-identification, I exclude any case of repeated names, even when deaths occurred on different dates or locations. Last, since not all individuals engaged in illegal activities present crime registers in the Judiciary System, it is reasonable assuming these measures as a lower bound of the total number of suspected criminals killed in Ceará.

Table A.11 presents the mean and standard error of daily homicides by the district of Fortaleza to the entire sample and the reduced sample with only suspected criminals before and after the GDE foundation. There is relevant district heterogeneity since some present a considerable decrease in homicides after the entry of GDE (e.g., 17% and -18% in the Full Sample and the Reduced Sample, respectively, to District 5). In contrast, others go opposite (e.g., +16% and +22% to District 13). This heterogeneity allows us to identify where potential conflicts of gangs increased in the metropolitan region of Fortaleza and define these areas as criminal gang turfs.

5.5.2. Spatial Heterogeneity and Criminal Gang Turfs

I exploit the change in the distribution of homicides before and after entering GDE, contesting the dominant position of the established gang CV. Suppose that both gangs decided to split drug trafficking rents peacefully. In that case, violent deaths at the district level would not show significant changes after controlling for other factors that can also affect violence. On the other hand, if we note a different pattern in deaths at the district level after the entry of a gang, it can be a result of a turf war to control strategic drug trafficking routes.

To disentangle violent deaths that are arguably related to gang conflicts to those of innocent individuals that are victims of criminals, I use the deaths of individuals investigated or convicted of violent and drug-related crimes. Hence I define as *criminal gang turfs* the districts that show a significant increase in the homicides of individuals previously convicted of violent and drug-related crimes. Figure A.10 shows the results of a t-test at 95% confidence level comparing monthly homicides before and after the entry of GDE and the beginning of gang turf war in the metropolitan region of Fortaleza.

Districts 6, 11, 12, and 13 present a significant increase in homicides of suspected criminals. Most of the remaining districts show a large and significant decrease in deaths, indicating a possible reallocation of criminals and conflicts to territories disputed by GDE and CV. Moreover, we see in Table A.12 that districts 11, 12, and 13 present some of the lowest income levels and the most significant homicides rates in Ceará, according to data provided by the Brazilian Bureau of Statistics (IBGE, CENSO-2010) and the State Secretary of Public Safety (SSPDS-CE). Last, anecdotal evidence points out that these districts at the border of Fortaleza are strategic drug trafficking routes from Amazon region to the port of Ceará.

Therefore I assume districts 6, 11, 12 and 13 as *criminal gangs turfs* and the remainder as *non-target districts* in the metropolitan area of Fortaleza. Figure A.9

shows these districts in red on a map that points out their location in peripheral areas crossed by roads to reach the city center of Fortaleza, such as the main Port of Ceará State. The identification comes from the variation in deaths of suspected criminals: (a) across gang turfs and non-target districts in the metropolitan region and (b) before and after the entry of GDE contesting the monopolistic position of CV. Given the panel data structure, it is possible to control non-observable time and location fixed effects, which can correlate with the start and end of the conflicts between criminal groups, eliminating a possible source of endogeneity.

5.5.3. Model

I use a difference-in-differences model to estimate the causal effect of criminal gang conflicts on homicides. I include a series of time-fixed effects to absorb all common shocks in the evolution of homicides across districts. I also include district-fixed effects to control unobservable crime determinants invariant at the district level. Criminal gangs turfs that have suffered a sudden increase in deaths of suspected criminals after the entry of GDE are in this setting the "treatment group" while the remainder is the "control group". I obtain the difference-in-differences estimator of the effect of a contestant criminal group on homicide using the following model:

$$\begin{aligned} homicides_{jt} = \alpha_j + \beta_1 * (post * Area_j) + \beta_2 * PM_{strike_t} \\ + \beta_3 * (PM_{strike_t} * Area_j) + \phi_t + \mu_{jt} \end{aligned} \tag{6}$$

Where the subscripts j and t respectively denote districts and date; *post* is a dummy variable equal to one since the entry of GDE in 2016 contesting the monopoly of CV in the metropolitan region of Fortaleza; $Area_j$ is a dummy equal to one if the district is in the treated group specified in the previous section; PM_{strike_t} is a dummy equal to one during the military police strike days (18feb2020 to 01mar2020); ϕ is a set of time-fixed effects that includes the year, month, and weekday dummies; α are district-fixed effects[12].

The dependent variable *homicides* indicates the number of daily homicides in a given district. SSPDS-CE data provides information on gender, age, name, and cause of death that allows evaluating the heterogeneous effect of police strikes on different specifications of the dependent variable in Equation 6.

A possible concern in this setting is that standard inference methods may not perform well in difference-in-difference models with few treated units. Since gang conflicts occur at the district level, my baseline estimates use 13 clustering units and

[12]The dummy indicator *post* and the interaction term ($PM_{strike_t} * Area_j * post$) were dropped because of collinearity with time fixed-effect.

four treated districts. I estimate bootstrap cluster-robust standard errors to calculate the confidence intervals to alleviate this concern. Cameron and Miller (2015) shows that this resampling-based approach is efficient even in cases of few clusters.

The identification strategy comes from two key assumptions. The first is that target and non-target districts of Fortaleza present parallel trends in violent deaths before the foundation of GDE and the disruption in the non-compete agreement between the most prominent Brazilian criminal gangs in 2016. In this case, the coefficient β_1 represents the change in homicides between treated and control regions after the entry of GDE and β_3 the increase in violent deaths caused by a Police Stike in criminal gang turfs. Figure A.11 shows the evolution of homicides over time in treated and control districts where the red line indicates the entry of GDE. I exploit the variation pre and post-this event to test the parallel trend assumption. The second crucial hypothesis is that the increase in homicides after the entry of a contestant gang is exclusively due to conflicts in criminal gangs turfs to reach a hegemonic position and not due to other confounding factors.

5.6. Results

Table A.13 report the results from the estimation of Equation 6 using Total Homicides and Homicides by Gender as dependent variable. I highlight the differences-in-differences point estimates to the GDE effect (β_1) and the Military Police Strike (β_3) in treated districts. I display the 95% confidence intervals obtained using the baseline specification and bootstrap cluster-robust standard errors.

The results show that the entry of a contestant criminal group causes a significant increase in daily homicides, especially among men. Outcomes from the Military Police strike are much more prominent in magnitude, suggesting that the reduction in police patrols led to violent conflicts in gang turfs. Therefore, disputes between organized criminal groups have a crucial role in explaining the violence increase in the metropolitan region of Fortaleza. The sudden decrease in policing in March of 2020 had a two times larger impact on violent deaths compared to the effect estimated to the entry of a contestant gang. The β_1 and β_3 coefficients represent a 32% and 56% increase in daily homicides in the gang turfs, respectively, compared to the average from 2014 to 2020[13]. Therefore, in districts 6, 11, 12, and 13, I find an average 88% increase in deaths during the Military Police strike.

Consistent with my identification strategy, I find that deaths of suspected criminals drive the increase in homicides. Using the three specifications mentioned in Table A.10 as a dependent variable, I show in Table A.18 that deaths of suspected

[13]Ratio between the coefficients and the 1.588 average daily homicides in the criminal gang turfs.

criminals account for 55% of homicides in criminal gang turfs after the entry of GDE and 69% of violent deaths during the Military Police strike[14]. I also show in Table A.14 the effect by age group, and I find that the entry of GDE affected particularly violent deaths of people from 15 to 45 years old, and these results go in the same direction during the Military Police.

5.7. Robustness

My findings show that criminal gang conflicts play a crucial role in the escalating violence following police strikes. My model of gang conflicts indicates that criminal groups exploit the decrease in the probability of police intervention to attack the rival gang. The deaths caused by these conflicts are the main driver of the increase in homicides during a military police strike. However, what happens when a police strike occurs in a context of a single hegemonic gang? If a gang holds the monopoly of drug trafficking routes in a state, rapid and transitory shifts in the probability of police intervention will not trigger conflicts in my conceptual framework. Therefore, in contexts of a single hegemonic criminal group, an increase in violent deaths during police strikes is not explained by gang conflicts. To test how changes in gang competition affect homicides in military police strikes, I perform a robustness test using a police strike in a context of a single hegemonic criminal gang.

In 2011 (29dec2011 to 07jan2012), the state of Ceará had another episode of a military police strike. At that time, the CV had a hegemonic position in drug trafficking in the state. Therefore, it is possible to compare violent deaths in the 2011 and 2020 strikes to assess how different scenarios of gang competition affect homicides during these events. Although I don't have detailed data about the identification of victims at the district level before 2014, I run a regression comparing the effect of police strikes on homicides across municipalities inside and outside the metropolitan area of Ceará[15] to both police strikes using data from SIM-DataSUS. Figure A.12 shows the results of my estimates controlling by location and time fixed effects. The increase in violent deaths in the 2020 Military Police Strike is more significant than in the previous strike, especially in the metropolitan area of Ceará. These findings indicate that the police strike triggers more violence in contexts of gang conflicts than in a scenario of hegemonic control of drug trafficking by a single group. The entry of GDE in 2016 created considerable tension by controlling strategic routes and territories in Ceará, which explains the larger magnitude of the increase in deaths in

[14]Ratio between the coefficients of *Suspected Criminals* and *Total Homicides*.

[15]The metropolitan area considers the following cities: Fortaleza, Caucaia, Maracanaú, Aquiraz, Cascavel, Eusébio, Pindoterama, Guaiúba, Pacatuba, Horizonte, Itaitinga e Pacajus

the metropolitan area compared to a strike before 2016. These results are consistent with my model of gang conflicts and shed some light on the mechanism driving the increase in homicides following abrupt shifts in police in contexts of gang competition.

My results show that the increased competition by controlling drug trafficking routes after the entry of GDE caused significantly more deaths in target districts during a police strike. Nevertheless, I cannot rule out that the more significant number of deaths is driven by previous confounding factors, which I am not accounting for in target and non-target control districts. The parallel trend assumption would be violated in this case, and my estimates would capture a spurious correlation. To alleviate this concern, I perform previous trend analyses.

To check whether criminal gangs turfs and non-target districts show different homicide dynamics before 2016, I test the parallel trend assumption in this period. Figure A.13 shows the homicide dynamic in both groups before the entry of GDE. Controlling for the year, month, and district fixed effects, I show in Figure A.14 that there are no significant differences in the variation of deaths over time from 2014 to 2016 comparing target and non-target districts. These results confirm that the particular dynamic in homicides affecting criminal gang turfs is specific to the period of increased competition between organized criminal groups in Fortaleza.

A second concern is the specification of target and non-target groups in this differences-in-differences framework. Suppose criminal groups are fighting in other regions. In that case, my results will capture the violence increase caused by other factors unrelated to the entry of GDE and large competition by drug trafficking routes in Fortaleza. To address this issue, I perform randomization of criminal gang turfs, keeping the number of 4 selected districts constant. As shown in Tables A.16 and A.17 I don't find a significant effect in homicides when the treated group is randomly assigned. Therefore outcomes validate my assumption of using changes in deaths of suspected criminals to identify criminal gangs turfs. Figure A.15 also show the dynamic in homicides in this falsification test. This evidence supports my choice of criminal gang turfs to perform the differences-in-differences approach.

5.8. Discussion

I show a significant increase in homicides following the increased competition by the drug trafficking control in Ceará. These findings indicate that districts disputed by criminal groups are the most affected by the total increase in homicides in the metropolitan region of Fortaleza over the years. Moreover, consistent with my model of gang conflicts, this sudden decrease in police patrols increases the expected payoff of fighting, which leads to conflicts between organized criminal groups, causing more violent deaths in criminal gangs turfs.

Nevertheless, other crimes should also be affected, given the significant presence of criminals in these districts. If property crime also increases, increasing drug trafficking competition may reveal a broader effect on crime outcomes. Criminal groups can exploit robbery and theft as a source to fund their operations, buy weapons and pay soldiers to attack the rival group. Table A.15 show the estimates of the GDE effect to other type of crimes using the baseline specification of 6. My results show a significant increase in robbery (about 90% compared to the average) in criminal gang turfs after the outbreak of conflicts between GDE and CV. I also find a significant increase in the apprehension of guns in these areas, additional evidence of the criminal presence in these districts. On the other hand, the effect over other crimes during the police strike is not significant or much smaller, indicating that criminal gangs focus on attacking the rival group following an abrupt reduction in policing.

The disruption between Brazilian organized criminal groups and the increase in the expected payoff of fighting during police strikes led to violent conflicts in drug trafficking turfs. The mechanism driving the increase in violent deaths is consistent with the commitment problem illustrated in the model of gang conflicts. Hence, I shed some light on the mechanisms driving violent crimes in territories disputed by organized criminal groups following an increase in competition by controlling drug trafficking routes and after abrupt reductions in policing.

6. Conclusion

This paper shows that police strikes cause a large and significant increase in violent deaths. However, this natural experiment seems to have a very particular interpretation. Following an abrupt reduction in policing, violent deaths are more significant in territories disputed by organized criminal groups that exploit these periods to attack rival gangs.

My results highlight that the increase in homicides in police strikes differs from marginal changes in policing. Districts disproportionately affected reveal unequal violence outcomes on these extreme events. Moreover, the increase in violent deaths is impressive since the number of homicides was already very high before the strike.

A police strike reduces the cost of confrontation and increases the expected payoff of fighting. The inability to commit with the *status quo* division of a drug trafficking turf leads to conflicts since criminal gangs choose to fight rather than allow the rival to attack first. Consistent with this hypothesis, I provide novel and robust evidence that the increase in homicide during police strikes comes from deaths of suspected criminals in gang turfs in a setting of significant criminal presence.

My work sheds some light on the impact of criminal gang conflicts on evaluating the effect of police on crime. I expect to contribute to public policies targeting violence reduction by presenting these results, especially showing that the interplay between criminal gangs and state authorities is crucial to evaluating the effect of shifts in the police on crime.

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Appendix A. Figures and Tables

Table A.1: Daily Homicides - CID-10 = X85-Y09,Y35-Y36 (2000-2019)

	Mean	Std. Err.	[95% Conf.	Interval]
Full Sample	1.462	0.0016	1.459	1.465
Military Police Strikes	1.757	0.0720	1.615	1.898
Civil Police Strikes	1.455	0.0088	1.437	1.475

Table A.2: Police Forces Strikes (2000-2020)

Police Force	**Events**	**Duration (Mean)**	**Duration (Std. Dev.)**
Military	29	8.52	6.04
Civil	194	20.46	29.85

Table A.3: The effect of Police on crime - Baseline and Gender Results

	Dependent Variable	β_1	**95% Confidence Interval**	
			Lower	Upper
Military Police Strikes	Total Homicides	2.934	0.880	4.988
	Homicides (Men)	2.829	0.825	4.833
	Homicides (Women)	0.104	-0.022	0.230
	Dependent Variable	β_2	**95% Confidence Interval**	
			Lower	Upper
Civil Police Strikes	Total Homicides	0.364	-0.030	0.758
	Homicides (Men)	0.331	-0.053	0.715
	Homicides (Women)	0.032	-0.002	0.066

Notes: Military Police Strikes cause a large and significant increase in homicides while Civil Police Strikes have no effect on violent deaths. The effect is basically driven by deaths of men.

Table A.4: The effect of Police on crime - Cause of Death

	Dependent Variable	β_1	**95% Confidence Interval**	
			Lower	Upper
Military Police Strikes	Firearms	2.776	0.884	4.668
	White arms	0.116	-0.032	0.264
	Body Injuries	0.011	-0.028	0.050
	Car Crash	-0.008	-0.012	-0.003
	Legal Intervention	-0.002	-0.050	0.046

	Dependent Variable	β_2	**95% Confidence Interval**	
			Lower	Upper
Civil Police Strikes	Firearms	0.326	0.038	0.614
	White arms	0.000	-0.039	0.039
	Body Injuries	-0.002	-0.013	0.010
	Car Crash	0.004	-0.004	0.012
	Legal Intervention	0.025	-0.031	0.082

Notes: The increase in homicides is driven by firearms. I find no effect to other types of intentional homicides.

Table A.5: The effect of Police on crime - Place of Death

	Dependent Variable	β_1	**95% Confidence Interval**	
			Lower	Upper
Military Police Strikes	Homicides (Public Spaces)	1.596	0.340	2.852
	Homicides (Home)	0.049	-0.142	0.240
	Homicides (Hospitals)	0.990	0.374	1.606
	Homicides (NA)	0.299	-0.007	0.605

	Dependent Variable	β_2	**95% Confidence Interval**	
			Lower	Upper
Civil Police Strikes	Homicides (Public Spaces)	0.053	-0.124	0.231
	Homicides (Home)	0.031	-0.010	0.072
	Homicides (Hospitals)	0.129	-0.048	0.306
	Homicides (NA)	0.147	0.006	0.288

Notes: During Military Police strikes we find there is a significant increase in deaths at public spaces as roads and streets such as at hospitals.

Table A.6: The effect of Police on crime - Homicides by Age

	Dependent Variable	β_1	**95% Confidence Interval**	
			Lower	Upper
Military Police Strikes	Homicides (<15)	0.116	-0.007	0.239
	Homicides (15 - 25)	0.681	0.055	1.307
	Homicides (26 - 45)	0.671	0.225	1.117
	Homicides (>45)	0.179	0.073	0.285
	Dependent Variable	β_2	**95% Confidence Interval**	
			Lower	Upper
Civil Police Strikes	Homicides (<15)	0.009	-0.012	0.031
	Homicides (15 - 25)	0.141	-0.006	0.288
	Homicides (26 - 45)	0.132	-0.007	0.271
	Homicides (>45)	0.026	-0.014	0.065

Notes: The homicides data provide by SIM-DataSUS have a lot of registers without age identification, which makes difficult measuring the heterogeneity in this category. In Military Police strikes, the increase in homicides concentrated in individuals from 15 to 45 years old.

Table A.7: Placebo Test - One Month Before

	Dependent Variable	β_1	**95% Confidence Interval**	
			Lower	Upper
Military Police Strikes	Homicides (Baseline)	2.934	0.880	4.998
	Homicides (Placebo)	-0.400	-1.144	0.344
	Dependent Variable	β_2	**95% Confidence Interval**	
			Lower	Upper
Civil Police Strikes	Homicides (Baseline)	0.364	-0.030	0.758
	Homicides (Placebo)	0.258	-0.090	0.606

Notes: The pseudo-treatment coefficients are not significant at 95% confidence level, which indicates a specific dynamic of homicides at the month of a police force strike.

Table A.8: Placebo Test - Deaths in Car Accidents

	Dependent Variable	β_1	**95% Confidence Interval**	
			Lower	Upper
Military Police Strikes	Pedestrians Deaths	0.099	-0.039	0.238
	Cyclists Deaths	0.018	-0.031	0.067
	Bikers Deaths	-0.007	-0.111	0.096

	Dependent Variable	β_2	**95% Confidence Interval**	
			Lower	Upper
Civil Police Strikes	Pedestrians Deaths	0.024	-0.031	0.078
	Cyclists Deaths	0.001	-0.015	0.016
	Bikers Deaths	-0.002	-0.065	0.060

Notes: There are no evidence of increase in deaths in car accidents during strikes of police forces since none of the coefficients are significant at 95% confidence level.

Table A.9: Poisson Estimates

	OLS	**Poisson**
Military Police Strikes (β_1)	2.934**	0.420***
	(2.73)	(6.14)
Civil Police Strikes (β_2)	0.364	0.050*
	(1.84)	(2.43)

Notes: t statistics in parentehses. *p<0.05,**p<0.01,***p<0.001

Table A.10: Identification of Suspected Criminals

Suspected Criminals (1) n = 14.423	Robbery, Theft, Drug Traffic, Criminal Gang Member, Illegal Gun Possession, Domestic Violence, Falsification, Fraud, Traffic Tansgression and Stolen Goods.
Suspected Criminals (2) n = 12.694	Robbery, Theft, Drug Traffic, Criminal Gang Member, Illegal Gun Possession, Domestic Violence and Stolen Goods.
Suspected Criminals (3) n = 11.879	Robbery, Theft, Drug Traffic, Criminal Gang Member and Illegal Gun Possession.

Notes: In the full sample we have 27.307 registers with personal identification. After consulting thes individuals at the State Judiciary System we find that at least 14.423 (53%) of them present a previous criminal record using the tags above.

Table A.11: Homicides by District - Full Sample and Suspected Criminals (3)

		Homicides (Full Sample)		**Homicides (Susp. Criminals)**	
		Pre	Post	Pre	Post
District 1	Mean	1.673	1.366	0.775	0.611
	Std. Err.	(0.041)	(0.040)	(0.035)	(0.035)
District 2	Mean	1.806	1.505	0.770	0.620
	Std. Err.	(0.045)	(0.032)	(0.035)	(0.024)
District 3	Mean	1.383	1.377	0.718	0.609
	Std. Err.	(0.044)	(0.035)	(0.039)	(0.030)
District 4	Mean	1.669	1.244	0.757	0.562
	Std. Err.	(0.048)	(0.030)	(0.033)	(0.031)
District 5	Mean	1.671	1.391	0.745	0.611
	Std. Err.	(0.046)	(0.038)	(0.036)	(0.029)
District 6	Mean	1.093	1.345	0.500	0.572
	Std. Err.	(0.037)	(0.037)	(0.066)	(0.030)
District 7	Mean	1.414	1.389	0.540	0.570
	Std. Err.	(0.036)	(0.037)	(0.034)	(0.024)
District 8	Mean	1.592	1.486	0.679	0.672
	Std. Err.	(0.042)	(0.034)	(0.035)	(0.028)
District 9	Mean	1.475	1.345	0.566	0.585
	Std. Err.	(0.042)	(0.026)	(0.036)	(0.022)
District 10	Mean	1.517	1.254	0.523	0.501
	Std. Err.	(0.045)	(0.028)	(0.033)	(0.028)
District 11	Mean	1.528	1.666	0.593	0.684
	Std. Err.	(0.041)	(0.033)	(0.035)	(0.022)
District 12	Mean	1.366	1.692	0.546	0.731
	Std. Err.	(0.035)	(0.035)	(0.033)	(0.024)
District 13	Mean	1.338	1.559	0.537	0.655
	Std. Err.	(0.041)	(0.036)	(0.039)	(0.024)

Notes: Comparing total homicides and deaths of suspected criminals we note significant differences before and after the foundation entry of GDE in 2016.

Table A.12: Socioeconomic Variables by District

District	Population	% Non White	% Men	Avg. Hous. Income	Hom.'000 people (avg. 2017-20)
District 1	173,761.00	47.3%	45.7%	R$ 6,341.36	37.84
District 2	214,388.00	70.0%	49.0%	R$ 1,149.90	86.06
District 3	205,137.00	68.6%	48.6%	R$ 1,454.04	69.10
District 4	164,268.00	60.3%	46.5%	R$ 2,455.80	47.03
District 5	313,642.00	58.0%	46.8%	R$ 2,461.27	35.07
District 6	362,681.00	62.3%	47.4%	R$ 1,863.39	36.33
District 7	265,925.00	62.9%	48.2%	R$ 2,639.19	48.42
District 8	236,970.00	68.2%	48.1%	R$ 1,334.49	44.20
District 9	233,811.00	66.7%	48.5%	R$ 1,449.47	65.44
District 10	176,767.00	50.5%	46.1%	R$ 4,797.70	30.83
District 11	405,347.00	69.5%	48.4%	R$ 1,162.96	92.45
District 12	453,354.00	71.0%	48.8%	R$ 981.37	86.85
District 13	436,962.00	70.1%	49.9%	R$ 1,447.73	68.77

Notes: Districts of the metropolitan region of Fortaleza are very heterogeneous. In special Districts 2, 11 and 12 show a combination of low income and high level of homicides.

Table A.13: District Level Results - Total and Gender

	Dependent Variable	β_1	95% Confidence Interval	
			Lower	Upper
GDE effect	Total Homicides	0.510	0.379	0.641
	Homicides (Men)	0.475	0.328	0.622
	Homicides (Women)	0.035	-0.011	0.080

	Dependent Variable	β_3	95% Confidence Interval	
			Lower	Upper
Military Police Strike	Total Homicides	0.878	0.118	1.638
	Homicides (Men)	0.752	0.154	1.350
	Homicides (Women)	0.126	-0.155	0.406

Notes: Treated districts present larger violence levels after the entry of a contestants criminal group and also during the Military Police strike in 2020. The increase in homicides is driven by death of men.

Table A.14: District Level Results - Total and Age

	Dependent Variable	β_1	**95% Confidence Interval**	
			Lower	Upper
GDE effect	Total Homicides	0.510	0.379	0.641
	Homicides (<15)	0.014	-0.005	0.033
	Homicides (15-45)	0.476	0.333	0.619
	Homicides (>45)	0.020	-0.033	0.073

	Dependent Variable	β_3	**95% Confidence Interval**	
			Lower	Upper
Military Police Strike	Total Homicides	0.878	0.118	1.638
	Homicides (<15)	0.023	-0.114	0.161
	Homicides (15-45)	0.672	0.078	1.266
	Homicides (>45)	0.183	-0.031	0.397

Notes: The entry of GDE affected specially deaths of adults in treated districts. The same occurs during the Military Police Strike.

Table A.15: District Level Results - Other crimes

	Dependent Variable	β_1	**95% Confidence Interval**	
			Lower	Upper
GDE effect	Robbery	236.1	118.8	353.4
	Theft	115.6	-5.8	237.0
	Drugs	5.52	-0.01	11.05
	Guns	5.92	1.41	10.44

	Dependent Variable	β_3	**95% Confidence Interval**	
			Lower	Upper
Military Police Strike	Robbery	90.1	14.4	165.9
	Theft	22.7	-22.1	67.4
	Drugs	1.47	-11.20	14.13
	Guns	0.43	-8.84	9.70
	Rape	2.73	-3.22	8.68

Notes: The entry of GDE increased robbery and apprehensions of guns in the treated districts. In the Military Police strike there is also a significant increase in robbery but in smaller magnitude.

Table A.16: District Level Results - Falsification Test (Gangs)

	Dependent Variable	β_1	**95% Confidence Interval**	
			Lower	Upper
GDE effect (placebo)	Total Homicides	-0.012	-0.082	0.058
	Homicides (Men)	-0.114	-0.183	0.045
	Homicides (Women)	0.005	-0.023	0.033
	Dependent Variable	β_1	**95% Confidence Interval**	
			Lower	Upper
GDE effect (placebo)	Homicides (<15)	-0.005	-0.025	0.014
	Homicides (15-45)	-0.143	-0.214	-0.072
	Homicides (>45)	0.030	-0.009	0.068

Notes: When I randomly assign which districts are treated, I don't find any significant increase in homicides after the entry of GDE.

Table A.17: District Level Results - Falsification Test (Strikes)

	Dependent Variable	β_3	**95% Confidence Interval**	
			Lower	**Upper**
Strike Effect (placebo)	Total Homicides	-0.022	-0.414	0.370
	Homicides (Men)	0.090	-0.298	0.478
	Homicides (Women)	-0.112	-0.271	0.047
	Dependent Variable	β_3	**95% Confidence Interval**	
			Lower	**Upper**
Strike Effect (placebo)	Homicides (<15)	0.043	-0.068	0.155
	Homicides (15-45)	-0.191	-0.587	0.205
	Homicides (>45)	0.126	-0.090	0.342

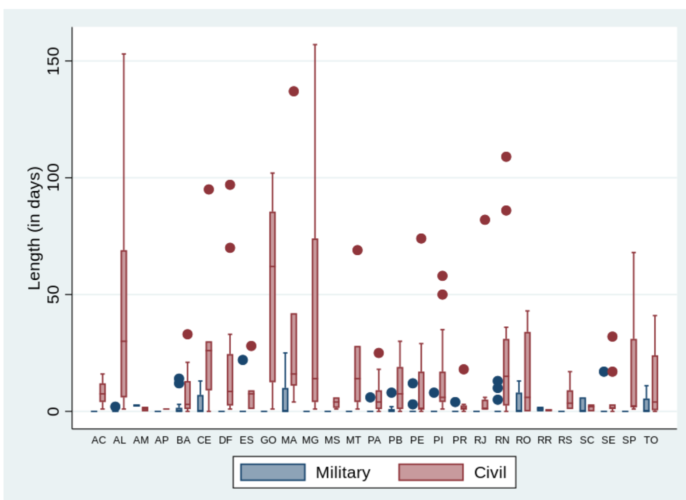
Notes: When I randomly assign which districts are treated, I don't find any significant increase in homicides during the police strike.

Table A.18: District Level Results - Suspected Criminals Deaths

Variables	**Total Homicides**	**Suspected Criminals (1)**	**Suspected Criminals (2)**	**Suspected Criminals (3)**
GDE Effect	0.510***	0.281***	0.243***	0.222***
Military Police Strike	0.878**	0.610***	0.547***	0.444***

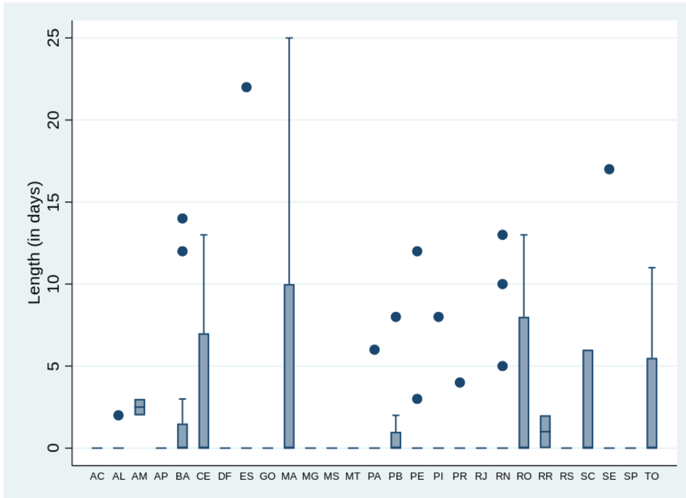
Notes: *p<0.05,**p<0.01,***p<0.001. Deaths of suspected criminals account for up to 55% of the increase in homicides in treated districts after the entry of GDE in 2016 and up to 69% of the deaths during a police strike.

Figure A.1: Police Forces Strikes - Boxplot by State (2000-2020)



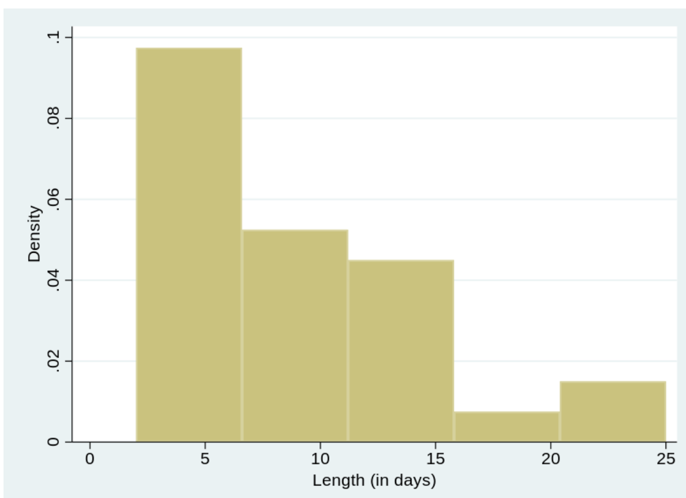
Notes: Civil Police strikes are longer and more frequent than Military. This pattern is probably due the fact that only in 2017 the Brazilian Supreme Court extended to Civil Police the prohibition to go on strike.

Figure A.2: Military Police Strikes - Boxplot by State (2000-2020)



Notes: Military Police strikes did not occur in all states in the period.

Figure A.3: Military Police Stikes - Histogram (2000-2020)



Notes: Most of the strikes last less than seven days. We explore this distribution to assess heterogeneous effects of the event by length.

Figure A.4: Heterogeneous Effect by strike duration

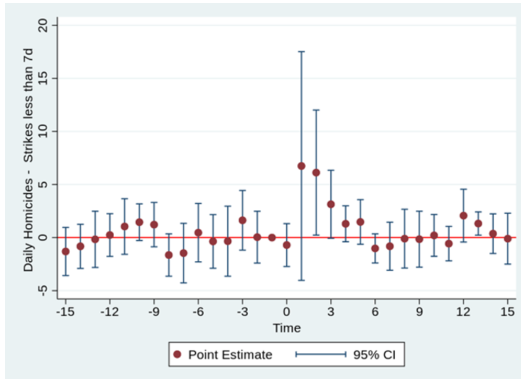


Figure A.5: Small Events

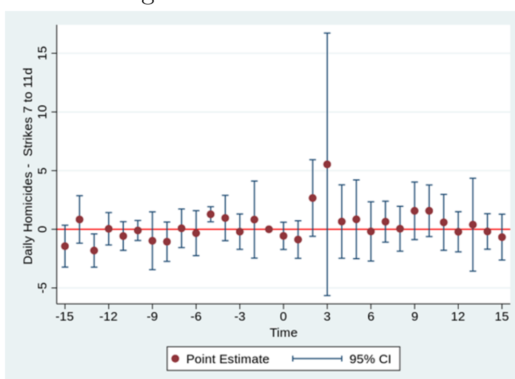


Figure A.6: Medium Events

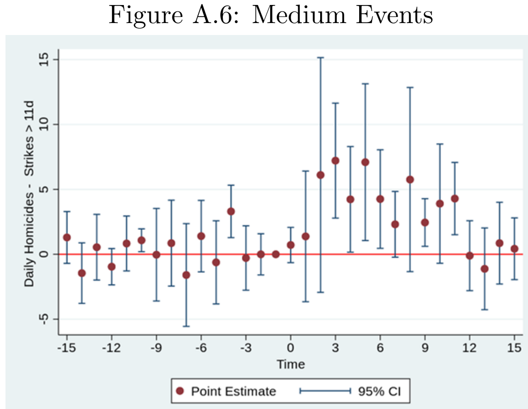
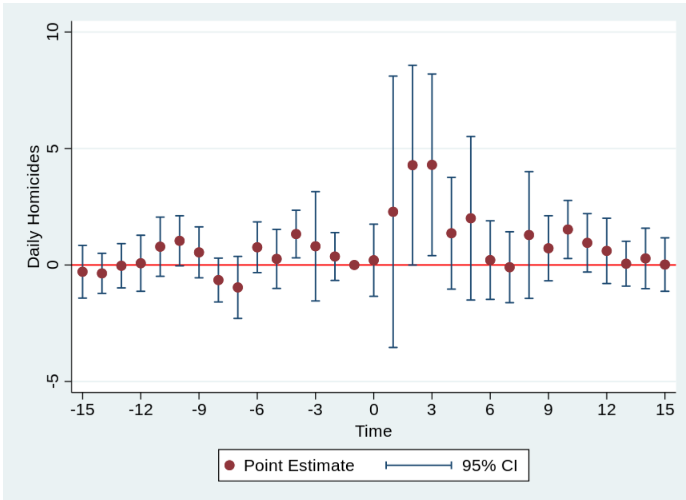


Figure A.7: Large Events

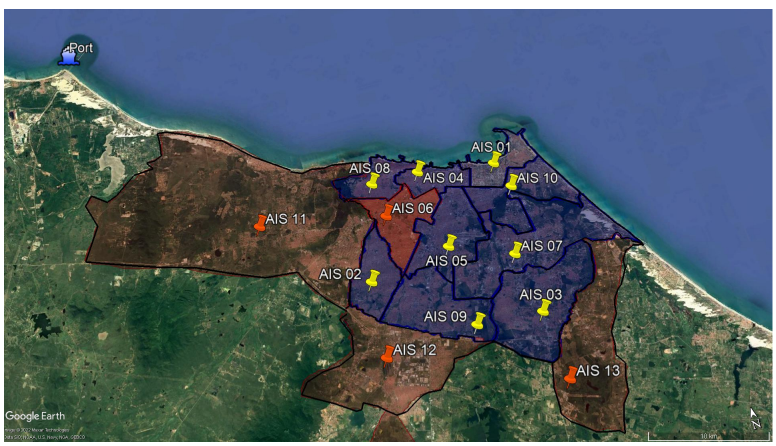
Notes: There is no clear evidence of a previous trend in homicides before the beginning of a Military Police Strike. Events longer than 11 days seem to be resilient affecting homicides.

Figure A.8: Event Study - Military Police Strikes



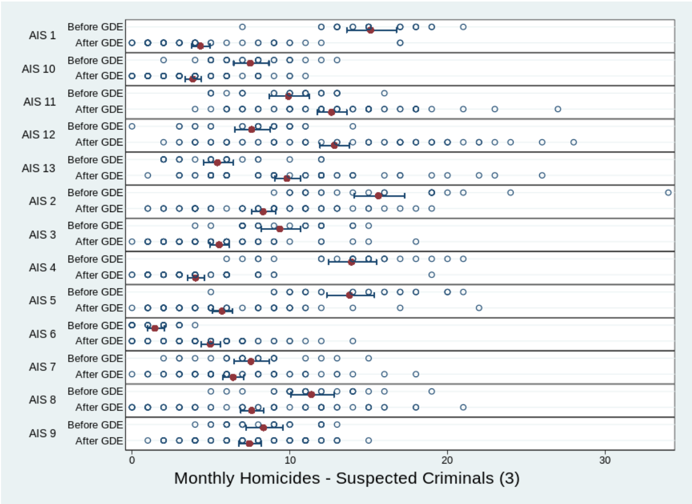
Notes: There is no clear evidence of a previous trend in homicides before the beginning of a Military Police Strike. The impact in homicides is huge and it lasts for days.

Figure A.9: Districts of Fortaleza/CE



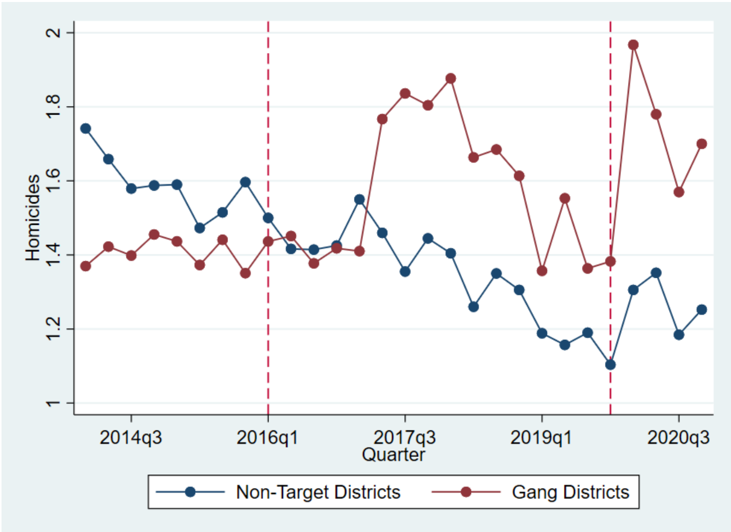
Notes: The map highlight the districts of the metropolitan region of Fortaleza according to the State Secretary of Security.

Figure A.10: Treatment and Control Group specification



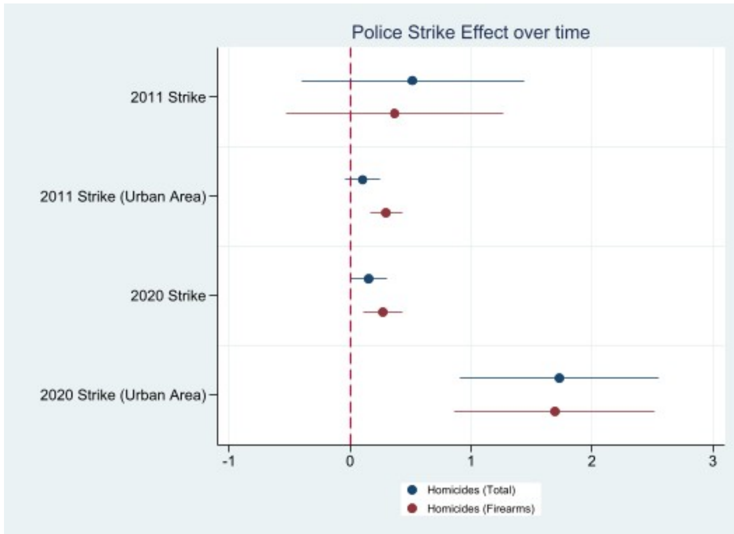
Notes: Using a t-test at a 95% confidence level we see that Districts 6, 11, 12 and 13 present a significant increase in monthly homicides of suspected criminals.

Figure A.11: Treatment and Control Group - Pre and Post Trend



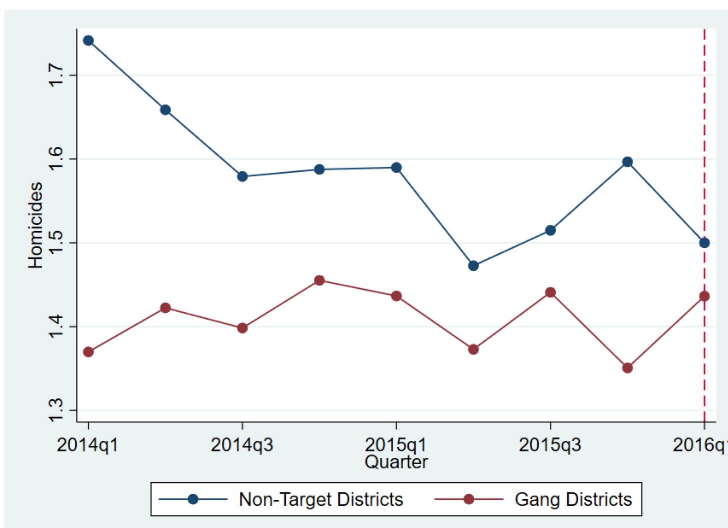
Notes: The first vertical red line indicates the entry of GDE in the first quarter of 2016 and the second a quarter before the Military Police strike.

Figure A.12: Military Police Strike 2011 x 2020



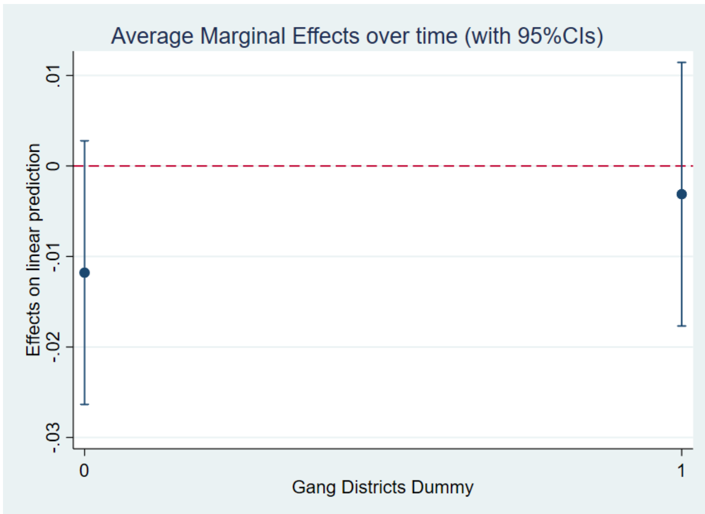
Notes: The increase in violent deaths in the 2020 Police Strike (when GDE and CV are disputing turfs in Ceará) is larger than what happened in the 2011 Police Strike (when CV had a hegemonic position).

Figure A.13: Treatment and Control Group - Previous Trend



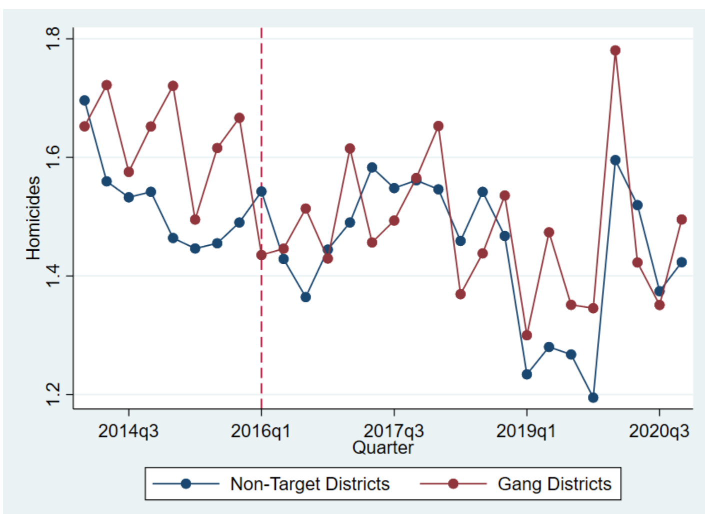
Notes: Treated and Control Group show similar trends before 2016.

Figure A.14: Treatment and Control Group - Previous Trend



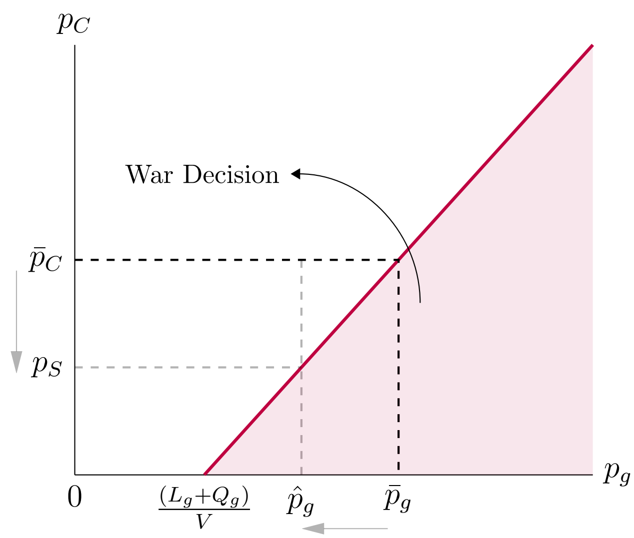
Notes: Treated and Control Group do not show a significant difference in homicide dynamic before 2016.

Figure A.15: Falsification Test - Pre and Post Trend



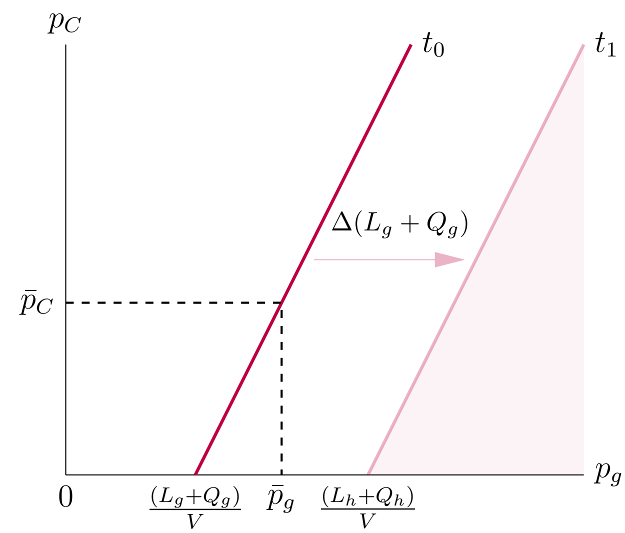
Notes: Exploiting a random assignment of Treated and Control Group I don't find significant difference in homicides dynamic after the entry of GDE.

Figure A.16: A Theoretical Model for Gang Conflicts



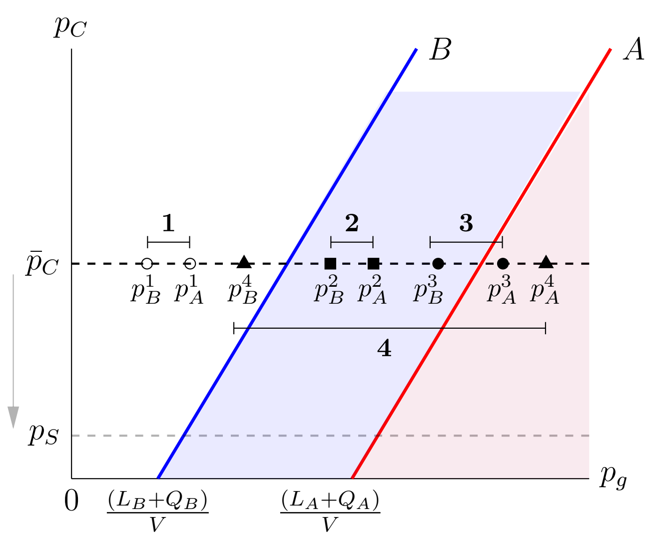
Notes: The dashed area shows when a gang decides to start a war. **(P1.)** To some $(\bar{p}_C, L_g, Q_g)$, if a gang g with probability of victory p_g starts a war, any gang with $p_h > p_g$ also decide by the conflict. **(P2.)** A decrease in the probability of police intervention from $\bar{p}_C$ to p_S reduces the minimum probability of victory for which a gang g decides to start a war.

Figure A.17: Shifts in Conflict Losses and Territory Control



Notes: The dashed area shows when a gang decides to start a war after a positive shift in conflict losses and territory control. **(P3)** The higher the conflict costs fewer the combinations of p_c and p_g that trigger a conflict.

Figure A.18: Distribution of Power and Conflicts



Notes: The blue dashed area shows when gang B decides to start a war and the red shaded area the same to Gang A. **(4.A.)** Assuming the unequal distribution of power between gangs, i.e., $p_A > p_B$ and $Q_A > Q_B$, and the same conflict losses $L_A = L_B$, the distribution of (p_A, p_B) defines which gang will start a war. **(4.B.)** To any set of parameters $(pc, pg, Lg, Qg, V) > 0$, a decrease in the probability of police intervention increases the number of combinations that lead to war.