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Abstract

How does territorial control by organized crime groups affect the enforcement of public policies? We answer this question by studying the enforcement of social distancing policies in Rio de Janeiro during the COVID-19 crisis. Two criminal groups with distinct governance have *de facto* control over several areas of the city: drug trafficking organizations (DTOs) and paramilitary groups (PGs). While the former funds itself mainly through the drug business, where their consumer base lives outside their turfs, the second obtains most of its profits from extortion and illegal commerce of public services to citizens within their territories. This induces different responses to policies that reduce economic activity, such as those enacted in the pandemic. To answer our main question, we estimate difference-in-differences specifications that compare social distancing before and after the outbreak in areas with and without territorial control by these groups. We document that in areas controlled by PGs, distancing was smaller than in government-ruled areas. On the other hand, DTOs' turfs had similar social distancing to places controlled by the government. Our results suggest that the effect of organized crime on the enforcement of public policies depends on their form of criminal governance.

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1 Introduction

Hundreds of millions of individuals worldwide, in both developed and developing countries, currently live under the rule of organized criminal groups (OCGs) (Blattman et al., 2021). They are considered a major problem not only because of their violent practices and illegal activities, but also because of their capacity to disrupt governments' monopoly of violence, compromising the enforcement of public policies that may affect their political and economic interests (Acemoglu et al., 2019; Reuter, 2014). Therefore, understanding whether and how OCGs influence the enforcement of government actions is critical for designing effective public policies where non-state actors have some *de facto* power.

One situation where governments had to take actions that could endanger the revenues of OCGs was the COVID-19 pandemic. This crisis has been particularly intense in countries such as Brazil and Mexico, where millions live under criminal governance according to recent estimates (Lessing, 2021).[1] To control the spread of the virus, governments implemented several non-pharmaceutical interventions (NPIs), ranging from voluntary shelter-in-place measures to the closure of non-essential businesses. Reports that OCGs influence government responses to the pandemic have received intense press coverage since its outbreak (Economist, 2020; Harris, 2021).Understanding their impact on NPIs' enforcement is of first-order importance not only to learn the impact these of interventions in fighting the pandemic but also to understand the delivery of public services and the rule of law where governments lack the monopoly of violence.

Despite growing evidence documenting the economic consequences of OCGs on development (Acemoglu et al., 2019; Melnikov et al., 2019; Fenizia et al., 2020; Slutzky and Zeume, 2020), less is known about how they influence the enforcement of public policies. Likewise, while a growing literature has investigated how socioeconomic and political factors influence social distancing choices[2], there is minimal evidence about the impact of criminal governance on NPIs' enforcement. This paper aims to fill these gaps by answering the following question: how does the territorial control by OCGs affect the enforcement of public policies in times of crisis? More specifically, we investigate how territorial control by drug trafficking organizations (DTOs) and paramilitary groups (PGs) impacts the enforcement of social distancing measures during the first wave of COVID-19 in Rio de Janeiro.

[1] As in Lessing (2021), we understand criminal governance as "the imposition of rules or restriction on behavior by a criminal organization".

[2] See Brodeur et al. (2020) for a survey.

Rio de Janeiro is the perfect testing ground to answer this question. First, a significant share of its population lives in areas with the presence of OCGs (Grandin et al., 2018). Second, there are two forms of organized crime with contrasting governance. DTOs are composed of slum dwellers who fund themselves mostly by selling drugs to consumers outside their territories and usually engage in cooperative relations with local communities to generate social consensus on their territorial control (Magaloni et al., 2020). PGs, in contrast, are composed mainly of active and retired policemen who, in exchange of offering protection to the community, fund themselves mostly by charging taxes for protection and illegally commercializing services within their domains (Cano and Duarte, 2012).

Identifying the causal effect of these OCGs on social distancing is challenging for two main reasons. First, their existence and spatial distribution depend on socioeconomic and political conditions, which in turn may explain enforcement of NPIs (Pinotti, 2020). Second, mapping accurately areas controlled by DTOs and PGs is not straightforward. To deal with this second issue, we use geolocated information on criminal reports and define an area as controlled by a given group if the share of the population exposed to that group is above the third quartile of the distribution, as in Le Moglie and Sorrenti (2020). To deal with the potential imbalance between treatment and control units, we estimate a model that produces a comparable control group using neighborhood and group fixed-effects for a set of variables relevant to moderate the impact of NPIs on social distancing, as in Goodman-Bacon and Cunningham (2019). We then combine the treatment variables with weekly social distancing data from weeks before and after the start of NPIs and implement a difference-in-differences (DiD) approach.

We document two main findings. First, areas controlled by PGs had 0.9 p.p. less social distancing than those from controlled by the government following the decrees establishing NPIs, which corresponds to 7.2 percent of the average increase in social distancing observed after the decrees. Second, in contrast, areas controlled by DTOs had a similar social distancing to those without their presence after the decrees. Our findings are robust to the inclusion of several observable covariates that may affect our result, the inclusion of different levels of geographical fixed-effects, and alternative specifications.

Rationalizing these results requires understanding the governance adopted by each OCG. While both groups evaluate the trade-off between the marginal costs and benefits caused by NPIs (economic impacts versus health effects), the nature of their costs and benefits is very different. Since PGs' profits depend relatively more on the economic activity within their turfs, we can expect NPIs to be costly for them. The same cannot be said for DTOs, as their profits are relatively less dependent on the economic activity within their domains. Unless the marginal benefits of NPIs are high enough to compensate for their costs, we can expect areas controlled by PGs to have less social distancing than those controlled by the government. In contrast, all else equal, areas controlled by DTOs should have a similar degree of social distancing as those controlled by the government.

Several facts support the causal interpretation of our findings. First, we estimate the effect of OCGs using temporal variation of social distancing restricted to groups of hexagons comparable in terms of several observable characteristics. Second, social distancing in areas controlled by OCGs and those controlled by the government followed parallel trends in the weeks before the first NPIs. Third, in line with the mechanism suggested in the previous paragraph, PGs' effect only becomes negative and significant after the 13^{th} week of the year, when the municipal government ordered the closure of all non-essential businesses. Fourth, the magnitude of PGs' effect is stronger and more precise in areas with a larger share of formal businesses per capita, i.e., in areas where the costs for allowing adherence to NPIs are higher.

Our findings contribute to multiple strands of literature. First, we add to the literature studying the economic and social consequences of organized crime. The presence of mafia in Italy (Acemoglu et al., 2019; Pinotti, 2015; Daniele and Geys, 2015) and drug gangs in Latin America (Melnikov et al., 2019; Sviatschi, 2019) have been shown to have negative impacts on economic and political outcomes. In contrast, Le Moglie and Sorrenti (2020) shows that mafia's presence is related to better results during a crisis, and Murphy and Rossi (2020) shows that drug-lords historical presence has led to higher economic development in Mexico. We complement this literature showing that OCGs' effect on compliance with a public policy depends on their criminal governance. More specifically, we find that groups who rely less on local economic activity may be more receptive to health measures that reduce them and vice-versa.

Second, we contribute to the recent literature investigating which economic factors determine social distancing choices during the COVID-19 pandemic. Despite the high volume of research done since the outbreak of this crisis, whether and how territorial control by OCGs affects the enforcement of policies that could potentially save lives remains an overlooked question. Breslawski (2021) provides a descriptive analysis of the actions taken by non-state armed groups in many different countries during the pandemic. Closely related to our work, Blattman et al. (2020) shows that gang rule during the pandemic was limited compared to the governmental response. We complement this literature by showing that, as documented in Medellin, DTOs' territorial control does not affect social distancing, but, in contrast, PGs' control significantly decreases it. This highlights the importance of developing a deeper understanding of the governance of different OCGs..

Finally, we also contribute to the growing literature investigating the interplay between the governance of state and non-state actors with *de facto* over territories and its influence on state capacity. This literature has documented heterogeneous results across different contexts. In Pakistan, Acemoglu et al. (2020) shows that providing information about better public services increases trust in state institutions and move people away from non-state actors. In Congo, Henn (2020) shows that state capacity decreases governance from traditional authorities when the constitution does not recognize them. In contrast, in Colombia, Blattman et al. (2021) find that experimentally increasing state governance in the form of more local city services did not affect gang rule but, in contrast, decade-long increases in access to city services caused by redistricting increased gang rule. We complement such literature by showing that non-state actors' influence on the government's capacity to enforce public policies depends on how they fund their activities.

2 Institutional context

NPIs in Rio de Janeiro. Non-pharmaceutical interventions (NPIs) are actions that can reduce the spread of infectious diseases apart from vaccination and prescription of medicines. The two main NPIs used to curb the spread of COVID-19 are the mandatory use of face masks and measures to promote social distancing. NPIs that promote social distancing may vary significantly across countries, ranging from the closure of non-essential business, shelter in place orders, to full-scale curfews.

Figure A1 displays a timeline of the relevant events and NPIs affecting Rio de Janeiro. The pandemic officially started in the city on March 5, 2020 - in the tenth epidemiological week. On March 16, in the twelfth epidemiological week, the state government recommended the closure of non-essential businesses.[3] The enforcement of this decree took place on March 23, in the thirteenth epidemiological week, when Rio's municipal administration limited the opening hours of several kinds of businesses.[4] After that, both state and city governments initiated plans to gradually reopen the local economy starting June 1, 2020.

[3]Source: State decree 46973 from March 16, 2021 *(in Portuguese)*
[4]Source: Municipal decree 47285 from March 23, 2021 *(in Portuguese)*

Nevertheless, the enforcement of an NPI is constrained by the *de facto* political power of authorities. Citizens in Rio live under a constant tension between the formal *de jure* power of official authorities and the *de facto* power that OCGs exert in their neighborhoods. One remarkable feature of the city is the heterogeneity of its criminal organizations, which have two distinct forms: DTOs, the *tráfico*, PGs, the *milícias*.

Drug trafficking organizations. Territorial control by DTOs in Rio de Janeiro started with the foundation of the faction *Comando Vermelho* (CV) in the early 1980s (Dowdney, 2003). In the late 1980s, CV dissidents created the *Terceiro Comando* (TC). In the early 1990s, CV and TC dissidents started two more gangs: *Amigos dos Amigos* (ADA) and *Terceiro Comando Puro* (TCP). The DTOs expanded quickly between 1990 and 2008, reaching all areas of the city.[5] Despite the fragmented market, CV is the most relevant DTO by far, controlling most of the slums in the town (GENI-UFF, 2020).

DTOs' primary funding source is the lucrative cocaine commerce to upper-classes of Rio. These groups also engage in other crimes like bank robberies and car thefts, but on a minor scale. They operate primarily within slums, which are perfect for drug commerce because of their proximity to middle and upper-class consumers and a natural shelter against police incursions. Composed of young slum dwellers (Carvalho and Soares, 2016), DTOs often develop close ties and adopt a cooperative relationship with the communities to generate social consensus on their presence (Magaloni et al., 2020).

During the pandemic, authorities seized large amounts of cocaine in the state of Rio de Janeiro, which suggests that DTOs' main source of revenue was not severely affected by the crisis (Zuazo, 2020). Media coverage on the actions of DTOs during the pandemic indicates that in many areas, they actively enforced NPIs within turfs, such as curfews, mandatory use of masks and prohibition of gatherings (Moraes et al., 2020; Eisele, 2020). According to local newspaper *O Dia*, at the beginning of the pandemic drug dealers from the *Jacarézinho* slum used a Twitter account dedicated to promoting events in their neighborhood to threaten sellers of hand sanitizers who were supposedly engaging in price-gouging (Dia, 2020).[6]

Paramilitary groups. Popularly known in Rio as *milícias*, PGs started operating in the city during the 1980s when a group of policemen expelled drug dealers from *Rio das*

[5] A law enforcement program expelled DTOs from 120 slums from 2008 to 2014 (Manoel, 2019). However, DTOs are regaining territories after the end of the program.

[6] Transcripts of media reports on the actions of OCGs during the pandemic are available in Appendix B1.

Pedras, a slum in the western zone of the city (Manso, 2020). Initially restricted to this area, PGs recently spread to all the city, taking control of neighborhoods where DTOs lost ground and places without OCGs (Cano and Duarte, 2012). In 2019, PGs were present in 41 neighborhoods in Rio, the home of around 2.1 million people according to GENI-UFF (2020).

PGs are usually composed of corrupt policemen, firefighters, military and retired members of these forces (Imbusch et al., 2011). They have adopted a predatory form of governance in their territories (Magaloni et al., 2020). Their profits mainly come from activities that depend on the level of economic activity inside their turfs, such as charging taxes from households and firms, and monopolizing the commerce of cooking gas and illegal cable TV (Hidalgo and Lessing, 2019; Freixo, 2008). Instead of militarily occupying their domains, PGs exert territorial control by using intimidation and selective murders to enforce tax payments (Cano and Iooty, 2008). Because of their close ties with the state, PGs can rule their territories with little interference from the authorities, as reported in Hirata et al. (2021).

Several reports indicate that PGs pressured local businesses to stay open during the 2020 health crisis, consistent with their form of criminal governance. The media also reported that PGs monitored the flow of emergency relief transfers to individuals in their areas and took advantage of reduced government presence to expand their illegal construction activities (Fantti, 2020; Altino, 2020). All these accounts fit the description done by Magaloni et al. (2020) that *milícias* are characterized by predatory and violent practices towards the local population.

3 Data

Social distancing. To measure social distancing, we use an index developed by *Incognia*, a Brazilian start-up that collects anonymized location data to reduce fraud and deliver context-aware services. Their technology allows real-time tracking of devices' locations with a three-meter precision. Just before the pandemic arrived in Brazil, the company started calculating a social distancing index for different cities in Brazil, including Rio de Janeiro. This index represents the percentage of devices that remained within a radius of 450 meters from the location marked as their home for a given area. We use the most granular geographical unit for which this index is calculated: 450-meter radius non-overlapping hexagons that cover Rio's inhabited territory.[7]

[7]This data was also used by Brotherhood et al. (2019) in their analysis of how population density affected the dynamics of the pandemic in Brazil.

Demographics, NGOs, elections. Neighborhoods in Rio are noticeably different concerning their demographic and urban characteristics. To account for this, we use data from IBGE's 2010 Brazilian Population Census[8] to construct covariates at the enumeration area level, the smallest unit of observation from the Brazilian census. These include information on the population itself (e.g. gender, race, literacy), the residencies (e.g. access to water) and their surroundings (e.g. street lights). We also use data at the voter section level to account for political preferences. This is done using the vote share in Bolsonaro in the second round of the 2018 election, which is highly correlated with adherence to NPIs (Ajzenman et al., 2020). Since NGOs play a large role in filling the gaps in public service provision in less privileged areas, we also account for their presence using geolocated data from IPEA. Finally, we use data from *CNPJ Aberto* to obtain the number of commercial establishments per capita. This is relevant since NPIs directly affect the revenues of some OCGs through the closure or reduction in profits from these places.

Criminal organizations. In order to map the presence of OCGs in Rio, we use a dataset assembled by a consortium comprised of multiple scholars and NGOs.[9] The data was released in October 2020, and provides a bird's eye view of the turfs controlled by each criminal faction by the end of 2019, just before the start of the pandemic. In order to do this, the participating organizations analyzed almost 38 thousand reports and transcribed emergency calls to *Disque Denúncia*, a toll-free crime report hotline, similar to United States' Crime Stoppers, and classified them using a dictionary of terms that reflected some measure of territorial control, social control or economic activity from criminal groups using natural processing language techniques. These geolocated reports were then assigned to polygons provided by Pista News, an organization that maps the control of armed groups in Rio's favelas and housing complexes in real time (but not with historical perspicacity). According to the consortium, the dataset generated after combining these two sources is intended to provide an approximate measure of the territorial presence of armed groups in Rio. For the purposes of this paper, this data allows us to match the territories controlled by the factions to hexagons, the unit of observation of our outcome variables.

Our measure differs from the ones used in Dipoppa (2021) and Sobrino (2019), which rely on news from media outlets in order to measure criminal presence in Italy and Mexico, respectively. Unlike media organizations, *Disque Denúncia* focuses exclu-

[8]IBGE (*Instituto Brasileiro de Geografia e Estatística*) is Brazil's official statistical bureau.

[9]The organizations are Disque Denúncia, Fogo Cruzado, Pista News, GENI-UFF and NEV-USP.

sively on taking anonymous calls from citizens, making it comparatively more reliable than direct reports to news outlets or potentially corrupt authorities. Moreover, data from *Disque Denúncia* has previously been used in other research studying criminal activity in Rio, such as Monteiro and Rocha (2017) and Ferraz et al. (2020).

We validate our dataset with Grandin et al. (2018), which used official intelligence information from the state police and judiciary branches as a source to map the presence of PGs in 2018 (one year prior to ours). Overall, our data matches theirs in classifying enumeration areas as with or without PG presence in 83.4% of the cases. This is close to the value obtained by Dipoppa (2021) when comparing her measure of mafia presence with official sources.[10]

An abridged description of all the variables used in our analyses can be found in Table A1. We also provide a detailed explanation on how we aggregate information from enumeration areas and crime turfs into hexagons in Appendix C1.

4 Empirical strategy

Main specification. Estimating the causal effects of OCGs on social distancing is challenging for two main reasons. First, areas controlled by OCGs can be different from those controlled by the government in characteristics that may moderate the effect of social distancing measures during the pandemic. Second, the definition of the treatment group itself imposes a challenge since improperly classifying units as treated can lead to contamination in the control group and compromise the identification.

In response to this potential imbalance between treatment and control units, we implement an approach similar to Goodman-Bacon and Cunningham (2019). More specifically, we estimate a model that produces a comparable control group using neighborhood and group fixed-effects for a set of variables relevant to predicting the main outcome of interest. These variables, which define the groups, are income per capita, percentage of illiterate population, urbanization, and President Bolsonaro's vote share in the 2018 election. The first two variables are relevant predictors of social distancing since economic conditions are one of the main predictors of adherence to NPIs (Weill et al., 2020; Lou et al., 2020). Urbanization, in turn, is one of the main drivers of the geographic variation in health outcomes during the pandemic (Allcott et al., 2020). Finally, Bolsonaro's popularity, proxied by his vote-share in the 2018 elec-

[10]The dataset from Grandin et al. (2018) does not provide information on DTOs. Nevertheless, given Rio's spatial structure and the fact that DTOs are mostly settled in hills and geographically well defined areas, the odds of wrongly classifying an hexagon as a DTO are smaller.

tion, was found in previous research to be a key predictor of social distancing behavior and, consequently, the spread of COVID-19 in Brazil (Ajzenman et al., 2020; Mariani et al., 2020).

By taking this approach, we compare the evolution of the outcome variable over time among hexagons that are similar in characteristics that are key in moderating the effect of the treatment. In Figure 1 we show that treatment and control hexagons become balanced on a set of over twenty baseline variables when we take this approach, suggesting that treatment and control groups become comparable in non-observables.

In order to define our treatment groups for DTOs and PGs we take an approach similar to Le Moglie and Sorrenti (2020) and define a hexagon as controlled by an OCG if the share of the population exposed to that group is above the third quartile. On the one hand, we are likely contaminating the control group, since areas with some presence of this OCG are included in it. On the other hand, this ensures that only areas where OCGs are very influential are in the treatment group. Besides, to avoid units with two treatments with different prior effects, we drop contested hexagons.[11]

Finally, we combine our treatment variables with weekly social distancing data from 2020 epidemiological weeks 6 to 31 - February 2nd to August 1st - and estimate the following difference in differences (DiD) model:

$$
\begin{aligned}
Distancing_{hnt} = \;& \alpha_h + \phi_{nt} + \beta^{DTO} \cdot DTO_h \cdot PostNPI_t + \\
& \beta^{PG} \cdot PG_h \cdot PostNPI_t + \mathbf{G}_h \cdot \gamma_t + \epsilon_{hnt}
\end{aligned} \tag{1}
$$

$Distancing_{ht}$ is the measure of social index in hexagon h in neighborhood n in week t. The terms α_h and ϕ_{nt} capture, respectively, hexagon fixed-effects and neighborhood-week fixed-effects. DTO_h and PG_h are indicator variables equal to one when, respectively, a DTO or a PG controls hexagon h. $PostNPI_t = \mathbb{1}(t > 12)$ is an indicator variable that equals one after week 12 of 2020, the first with NPI enforcement. Finally, $\mathbf{G}_h \cdot \gamma_t$ are the group fixed-effects – constructed from the four variables as previously described – interacted with week-specific slopes to flexibly control for the influence of omitted characteristics on the dynamics of social distancing behaviors after the enforcement of NPIs. We cluster standard errors at the hexagon level, our treatments' level of variation.

[11]We consider contested hexagons under control of a PG (DTO) - i.e., above the last quartile of the distribution of criminal presence - but with a positive fraction of the population exposed to a DTO (PG). Therefore, we retain in our analysis only hexagons with a single form of criminal governance or hexagons without any OCG. Overall, we have 27 contested hexagons (3% of the total).

Since $Distancing_{ht} \in [0, 1]$, β measures the change in percentage points in social distancing caused by criminal organizations' territorial control relative to the weeks without NPIs. Its causal interpretation relies on the hypothesis that the social distancing of hexagons with and without OCGs' control would follow parallel trends in the absence of NPIs. To assess the plausibility of this hypothesis and to understand the dynamics of our estimated effect, we also estimate a dynamic DiD specification using the epidemiological week 12, from March 8th to March 14th, the last week before the enforcement of NPIs, as the reference period.

We present visually the estimating sample in Figure A2. Hexagons in red are those where $DTO_h = 1$, in blue are those where $PG_h = 1$. Contested hexagons, in dark yellow, are left out of our analysis since it's not clear which criminal governance regime is in place in them. Finally, hexagons in grey, where $DTO_h = PG_h = 0$ are part of our control group.

5 Results

Balance check. To ensure that hexagons controlled by PGs and DTOs are comparable to government areas, we use neighborhood and group fixed-effects of a set of four variables, selected according to their relevance in predicting the primary outcome of interest, namely income per capita, percentage of illiterate population, urbanization, and Bolsonaro's vote share in the 2018 election.

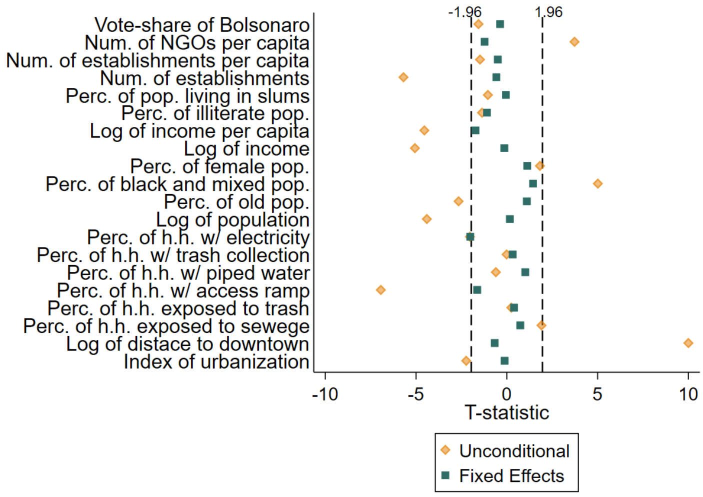
Figure 1 reports t-statistics for the estimated mean difference between treatment and control units for a set of baseline variables.[12] In Panel (a), we compare hexagons controlled by PGs to government areas. Areas controlled by PGs are different from government areas among several characteristics. In particular, on average, they have a higher number of NGOs per capita, a higher number of black and mixed population, and are located further from the city center. On the other hand, they have fewer establishments, lower income, are less populated, and have less presence of urban infrastructure. Once we condition on neighborhoods and groups fixed-effects, all differences discussed here become statistically non-significant. In Panel (b) we make a similar analysis comparing hexagons controlled by DTOs to government areas. As with PGs, once we condition on neighborhoods and groups fixed-effects, differences become non-significant, showing that, after conditioning on neighborhoods and groups

[12] Tables A2 and A3 in the Appendix show detailed figures for the difference between treatment and control units. Figure A3 displays the standard mean differences between treatment and control groups for each OCG.

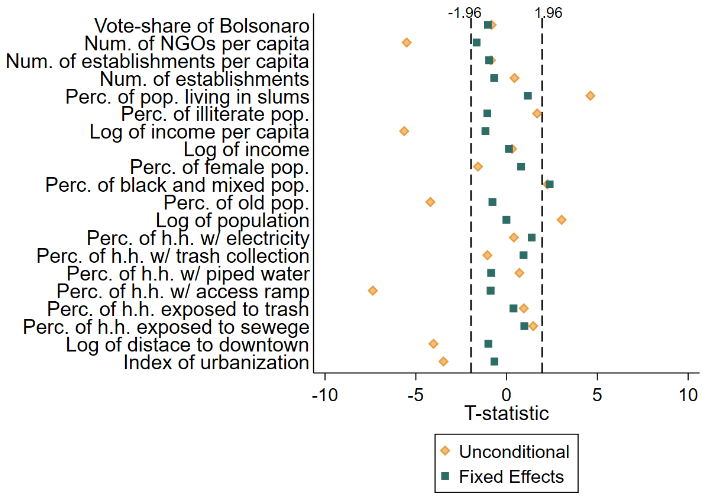
fixed-effects, treatment and control units become comparable so we can use temporal variation in social distancing indexes to estimate the impact of territorial control.

Figure 1: Checking balance on covariates:
Areas with and without OCG are comparable within groups and neighborhoods

(a) Balance check, PGs



(b) Balance check, DTOs



Notes: This figure reports statistics that check whether treatment and control groups become similar after restricting comparisons to hexagons within the same neighborhood and groups defined according to quintiles of four variables. The four variables defining groups are the index of urbanization, percentage of illiterate population, household per capita income, and Jair Bolsonaro's vote share in the 2018 election. Panel **(a)** reports t-statistics comparing hexagons controlled by PGs and the government. Panel **(b)** reports the same statistic but comparing hexagons controlled by DTOs with those controlled by the government. We plot the t-statistic of the statistical hypothesis $H_0 : \mu_x(T = 1) = \mu_x(T = 0)$, where x is one of our baseline controls, $T \in \{DTO_h, PG_h\}$ is one of our treatments, and μ_x is the mean of x. We estimate the t-statistic associated with such test by regressing each baseline covariate x on our treatment indicators PG_h and DTO_h using robust standard errors. We plot vertical bars on -1.96 and 1.96 to highlight the differences in observables that are not significant at 5%.

Main results. In Table 1 we present estimates from Equation 1, that allow us to compare social distancing before and after the adoption of NPIs in Rio between treated and control hexagons. We begin by describing the results for PGs. Column (1) displays a difference-in-differences specification controlling only for week fixed-effects and shows a strong and negative relationship between the PGs' control and social distancing. In Column (2), we include group-week fixed-effects, making treatment and control groups more comparable but not yet mirroring the specification used in the balance exercises. The coefficients drop more than three times but still remain negative and significant. In Columns (3) and (4), we sequentially add hexagon fixed-effects and zone-week fixed-effects, allowing each city-zone to have a specific trend in the social index over time. The coefficient hardly changes when compared to estimates from Column (2). Finally, in Column (5), we have our preferred specification, in which we allow each neighborhood to have a specific trend in the social distancing index over time, mirroring the specification used in Figure 1 that generates a balance between control and treatment groups. According to this specification, the presence of PGs decreases social distancing by approximately 0.9 percentage points, which corresponds to a decrease of 2% percent in the outcome, considering the average social distancing index in the control group.

Coefficients for DTOs are reported just below the ones for PGs. The specification in the first Column also shows a strong and negative relationship between the presence of DTOs and social distancing. After including group-week fixed-effects, in Column (2), that make treatment and control groups more comparable, the coefficient drops and becomes insignificantly different from zero. Following the structure previously mentioned, in Columns (3)-(5), we include sequentially hexagon, zone-week, and neighborhood-week fixed-effects. The coefficient in all these specifications remain non-significant, showing that the presence of DTOs does not affect social distancing measures after the adoption of NPIs.

Table 1: Baseline specification with group-week and neigbourhood-week FEs
Control by PGs decreases compliance to NPIs, but control by DTOs does not affect it.

	(1)	(2)	(3)	(4)	(5)
PG $\times$ Post NPI	-1.933	-0.653	-0.641	-0.587	-0.924
	[0.342]***	[0.246]***	[0.244]***	[0.244]**	[0.340]***
DTO $\times$ Post NPI	-1.017	-0.057	0.004	0.036	-0.106
	[0.340]***	[0.267]	[0.259]	[0.293]	[0.380]
Observations	20814	20814	20814	20814	20814
Num. of hexagons	822	822	822	822	822
R-squared	0.742	0.850	0.908	0.910	0.925
Outcome mean	42.838	42.838	42.838	42.838	42.838
Outcome standard deviation	8.727	8.727	8.727	8.727	8.727
Outcome post-pre treat. variation	12.829	12.829	12.829	12.829	12.829
Week FEs	Yes	Yes	Yes	Yes	Yes
Group-Week FEs	No	Yes	Yes	Yes	Yes
Hexagon FEs	No	No	Yes	Yes	Yes
Zone-Week FEs	No	No	No	Yes	No
Neighbourhood-Week FEs	No	No	No	No	Yes

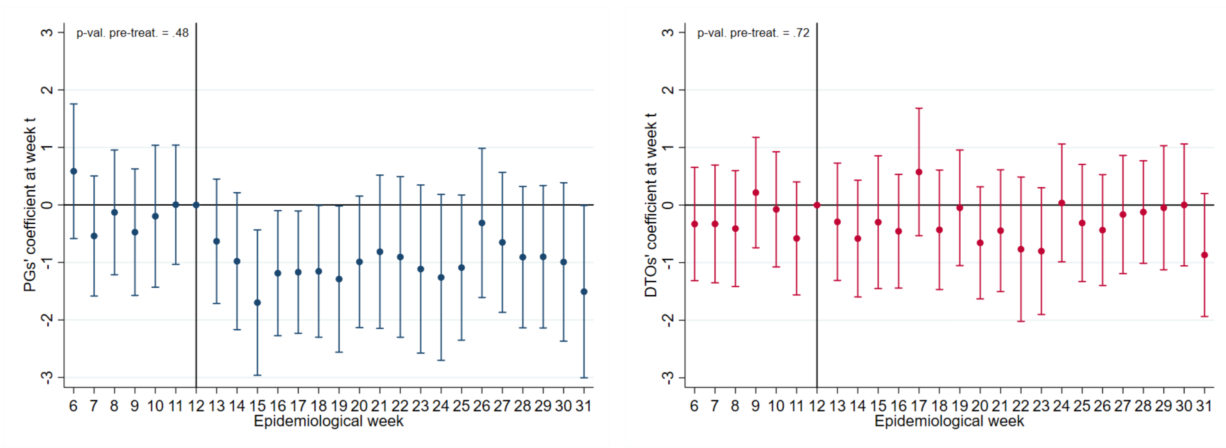
Note: This table displays estimates of the effect of territorial control by drug trafficking organizations (DTOs) and paramilitary groups (PGs) on social distancing estimated by a difference-in-differences (DiD) specification using weekly data from weeks 6 to 31 of 2020. The DiD regression model reported in column (5) has the form $Distancing_{hnt} = \alpha_h + \phi_{nt} + \beta^{DTO} \cdot DTO_h \cdot Post\_NPI_t + \beta^{PG} \cdot PG_h \cdot POST\_NPI_t + \gamma_t \cdot \mathbf{G}_h + \epsilon_{hnt}$ where h denotes and hexagon, n neighbourhood, and t week. α_h captures hexagon fixed effects and α_{nt} neighbourhood-week fixed effects. DTO_h is an indicator variable equal to one when a drug trafficking organization controls the hexagon h. PG_h is an indicator variable equal to one when a paramilitary group controls the hexagon h. $Post\_NPI_t = \mathbb{1}(t > 12)$ is an indicator variable that equals one after week 12 of 2020, the first one before the enforcement of NPIs in Rio de Janeiro. $\mathbf{G}_h$ capture a set of group fixed effects defined according to the quintiles of four variables: index of urbanization, percentage of illiterate population, household per capita income, and Jair Bolsonaro's vote share in the 2018 election. $\gamma_t \cdot \mathbf{G}_h$ are group-week fixed effects that control non-parametrically for the influence of hexagons' characteristics on the change on social distancing behaviours after the enforcement of NPIs. Column (1) display the classic DID specification only with week fixed effects. Column (2) adds group-week fixed effects to the specification in column (2). Column (3) adds hexagon fixed effects to the specification in column (2). Column (4) adds zone-week fixed effects to the specification in column (3). Column (5) adds neighbourhood-week fixed effects to the specification in column (4). We display clustered standard errors at the hexagon level between squared brackets. Coefficients significantly different from zero at 99% (***), 95% (**), and 90% (*) confidence levels.

Dynamic effects. In Figure 2 we present the estimates comparing the change in social distancing in hexagons dominated by OCGs relative to control hexagons with respect to the last week without NPIs. In Panels (a) and (b), we present, respectively, results for PGs and DTOs.

Panel (a) shows that after adopting NPIs, areas controlled by PGs presented less social distancing than government areas, relatively to the reference week. This difference increased until the fifteenth week, when it reached 1.8 percentage points, coinciding with the period when Rio registered the higher figures in social isolation during

Figure 2: Baseline specification with group-week and neighborhood-week FEs
Control by PGs decreases compliance to NPIs, but control by DTOs does not affect it.

(a) Event study, PGs **(b)** Event study, DTOs



Notes: This figure displays two graphs reporting the effect of territorial control by drug trafficking organizations (DTOs) and paramilitary groups (PGs) on social distancing across the weeks 6 to 31 of 2020 with its 90% confidence interval. Treatment effects across years are estimated using the DiD regression model: $Distancing_{hnt} = \alpha_h + \phi_{nt} + \sum_{k\neq 12} \beta_k \cdot DTO_h + \sum_{k\neq 12} \beta_k \cdot PG_h + \gamma_t \cdot \mathbf{G}_h + \epsilon_{hnt}$, where h denotes and hexagon, n neighborhood, and t week. α_h captures hexagon fixed effects and ϕ_{nt} neighborhood-week fixed effects. DTO_h is an indicator variable equal to one when a drug trafficking organization controls the hexagon h. PG_h is an indicator variable equal to one when a paramilitary group controls the hexagon h. $\mathbf{G}_h$ capture a set of group fixed effects defined according to the quintiles of four variables: index of urbanization, percentage of illiterate population, household per capita income, and Jair Bolsonaro's vote share in the 2018 election. $\gamma_t \cdot \mathbf{G}_h$ are group-week fixed effects that control non-parametrically for the influence of hexagons' characteristics on the change on social distancing behaviours after the enforcement of NPIs. We normalize treatment effects concerning week 12 of 2020, the last one before the enforcement of NPIs in Rio de Janeiro. We cluster standard errors at the hexagon level.

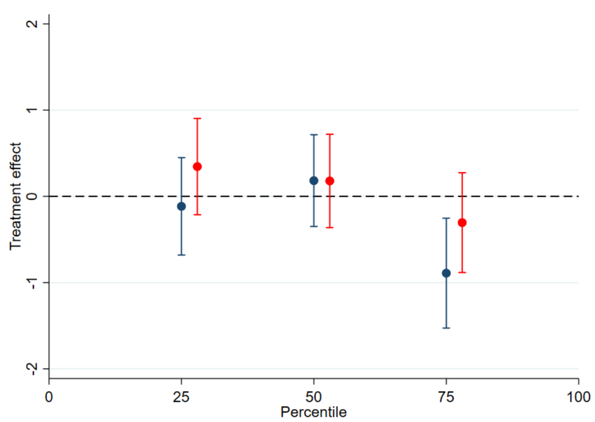
the first wave of the COVID-19 pandemic[13]. After the fifteenth week, the difference decreased. Point estimates become negative for the entire period analyzed, but the difference becomes statistically equal to zero after the twentieth week, coinciding with the beginning of the flexibilization of the social distancing measures. In Panel (b), we present results of the estimates for DTOs. Following the results reported in Table 1, the estimated coefficients are statistically equal to zero. Finally, both figures report p-values above critical levels for a joint significance test of coefficients prior to the enforcement of NPIs, suggesting that the parallel trends hypothesis is valid in our case.

Falsification. In defining our two treatment variables, we took an approach similar to Le Moglie and Sorrenti (2020). We defined a hexagon as controlled if the share of the population under the control of a given group is above the third quartile of the dominated population distribution. We opt for quartiles of the distribution to obtain

[13] According to data from *Incognia*, Rio reached the peak of social isolation between weeks 13 and 15

a clearer contrast between the group of hexagons under and not under OCG's control. However, as there is no univocal way to define OCG's control, we conduct a falsification analysis in which we vary treated hexagons' definition and compare different quartiles of the dominated population distribution. The results presented in Figure 3 show that increases in the presence of OCGs across the first three quartiles of the distribution do not influence distancing in a significant way, validating the choice of combining the first three quartiles of the OCG-exposed population distribution as the control group of the baseline analysis. We present details of the analysis in the figure notes.

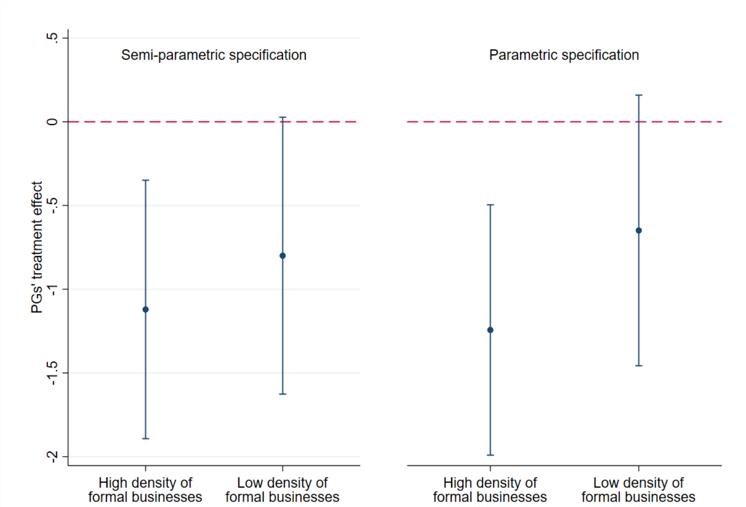
Figure 3: Falsification exercise comparing different quartiles



Note: This figure shows the effect of territorial control by drug trafficking organizations (DTOs) and paramilitary groups (PGs) on social distancing from week 6 to 31 of 2020 using different definitions of territorial control. We opt for the use of quartiles of the controled population distribution to obtain a clearer contrast between the group of hexagons under and not under OCGs control, as in Le Moglie and Sorrenti (2020). Since there is no unique way to define territorial control, this figure reports a falsification analysis using defining territorial control according to different percentiles. For each percentile *pctle* of the share of the dominated population distribution we define $PG_h^{pctle} = \mathbb{1}(share\_PG_h > share\_PG_h^{pctle})$ and $DTO_h^s = \mathbb{1}(share\_DTO_h > share\_DTO_h^{pctle})$. Therefore, PG_h^{pctle} and DTO_h^{pctle} are indicator variables that take value 1 when the share of population dominated by a PG or a DTO is above the percentile *pctle* in hexagon h. Each pair of coefficients reported in the graph represents a regression with different thresholds *pctle* for territorial control with the corresponding 90% confidence interval. Importantly, for each regression we drop hexagons with a share of population exposed to the presence of an OCG that falls into the next quartile. For instance, when $pctle = 25$, we define an hexagon as treated when the share of dominated population is between the 25th and 50th percentile. Control hexagons are those that have a share of dominated population bellow the 25th percentile.

Heterogeneity. As discussed in Section 2, PGs adopt a predatory form of criminal governance in their territories, with profits coming mainly from charging taxes and from the commerce of cooking gas and illegal cable TV, sources of revenue that rely heavily on local economic activity. To test if this is the primary mechanism explaining our results, we check if the effect of PGs is stronger in areas more likely to be economically affected by the adoption of NPIs. More specifically, we estimate Equation 1 splitting the sample according to the density of businesses in each hexagon. If territorial control by PGs prevents individuals and firms from following NPIs, then we should expect the effect to be stronger in areas with a high density of formal businesses. We define an hexagon as having a high (low) businesses density if it is above (below) the median of the number of formal businesses per capita, as described in Table A1. Results are presented in Figure 4. The left panel shows results from the semi-parametric specification in Equation 1. The right panel presents results using the parametric specification used in Table A4. In both specifications, point estimates associated with the presence of PGs are larger in the high-density sample. More importantly, the coefficients are statistically significant only in that sub-sample.

Figure 4: Heterogeneous effects
The effect of PGs has is stronger in areas with a high density of formal businesses



Note: This figure displays two graphs reporting the effect of territorial control by paramilitary groups (PGs) splitting the sample according to the variables *high density of formal businesses* and *low density of formal businesses*. We define a hexagon as having a high (low) density of formal businesses if it is above (below) the median of the variable *number of establishments per capita* described in table A1. In panel (a), we add interactions between the treatments variables and indicators for high and low density of businesses to the specification in equation 1. In panel (b), we repeat the procedure done in panel (a) using the parametric specification described in the robustness exercise reported in Table A4.

Robustness. Although we adopt a strategy that produces comparable treatment and control groups, one may be concerned that our effects are partially explained by differences in other relevant characteristics that affect social distancing behavior during the pandemic. In order to rule out this hypothesis, we estimate a parametric specification, including our entire set of control variables interacted with week fixed-effects. The results are reported in Table A4 and Figure A4 and show that our findings are robust and, more importantly, do not reflect any unbalance in predetermined characteristics that may affect social distancing.

Discussion. Since the attitude of OCGs towards NPIs depends on how they trade-off their marginal economic costs and marginal health benefits, one can learn about their preferences by observing $\widehat{\beta}^{PG}$ and $\widehat{\beta}^{DTO}$. On the one hand, a negative and significant $\widehat{\beta}^{PG}$ implies that, relatively to the control group, the marginal cost of NPI for PGs outweigh their marginal benefits, which is consistent with findings showing that social distancing measures more impacted more PG's revenues (Bullock and Pellegrino, 2020; MP-RJ, 2020). A small and non-significant $\widehat{\beta}^{DTO}$, on the other hand, implies that marginal costs and benefits of NPIs should be similar for this group relative to the control group.

Our estimates also provide some clues about the mechanism. The dynamics of the effect of PGs and the more substantial magnitudes in areas with more formal businesses are consistent with weaker enforcement of businesses closures being the primary mechanism explaining $\widehat{\beta}^{PG}$. As suggested by the reports presented in Section 2, such weaker enforcement is likely caused by PGs continuing to charge taxes during business closures and, in extreme cases, violently opposing them.

Overall, our favorite specification reveals that territorial control by PGs had a moderate effect on social distancing. More precisely, $\beta^{PG} = 0.9$ corresponds to a decrease of 2% of the average social distancing in the control group and 10% of its standard deviation. Besides, it corresponds to 7.2% of the average increase in social distancing observed after the enforcement of NPIs in Rio. The moderate magnitudes we document are not surprising since, according to previous findings, voluntary responses to the pandemic explain most of the variation in social distancing (Gupta et al., 2020). Moreover, although moderate in absolute terms, β^{PG} may represent a considerable fraction of the impact of business closures since, in light of recent evidence, even the strictest NPIs have only limited effects on social distancing (Alexander and Karger, 2021).

Territorial control and COVID-19 cases. Given the association between social distancing and COVID-19 transmission (Kuhbandner and Homburg, 2020), a natural step is testing whether areas dominated by PGs presented more COVID-19 cases. To do so we estimate partial correlations between our treatment variables and COVID-19 cases, as in Brotherhood et al. (2019).[14] The results are reported in Table A5. Consistent with our previous evidence, we find a positive correlation between PGs' control and COVID-19 cases in all months. This correlation is remarkably high in May, the month just after the peak effect of PGs on social distancing. Correlations between DTOs' control and COVID-19 cases, on the other hand, are negative and non-significant in all periods.

6 Conclusion

Our findings suggest important policy implications. First, governments should target more efforts to enforce costly public policies where OCGs are relatively more dependent on extracting rents from communities. Second, governments may have to decrease reliance on non-state actors (e.g., by using information campaigns) or regain the monopoly of violence to enforce policies costly to OCGs. Third, in places where regaining *de facto* control is not viable, crisis management may depend on coordinating with OCGs.

Our findings stimulate future investigations into the influences of OCGs on public policy. First, it would be interesting to study how OCGs impact adherence to other public policies, such as general trash collection, environmental regulations, and safety standards for building construction. Second, it would also be interesting to quantify the effect of OCGs on public spending efficiency. We leave such open questions for future investigations.

[14]We face numerous challenges in estimating this relation, mainly due to data availability, which we detail in the notes of Table A5, in the appendix.

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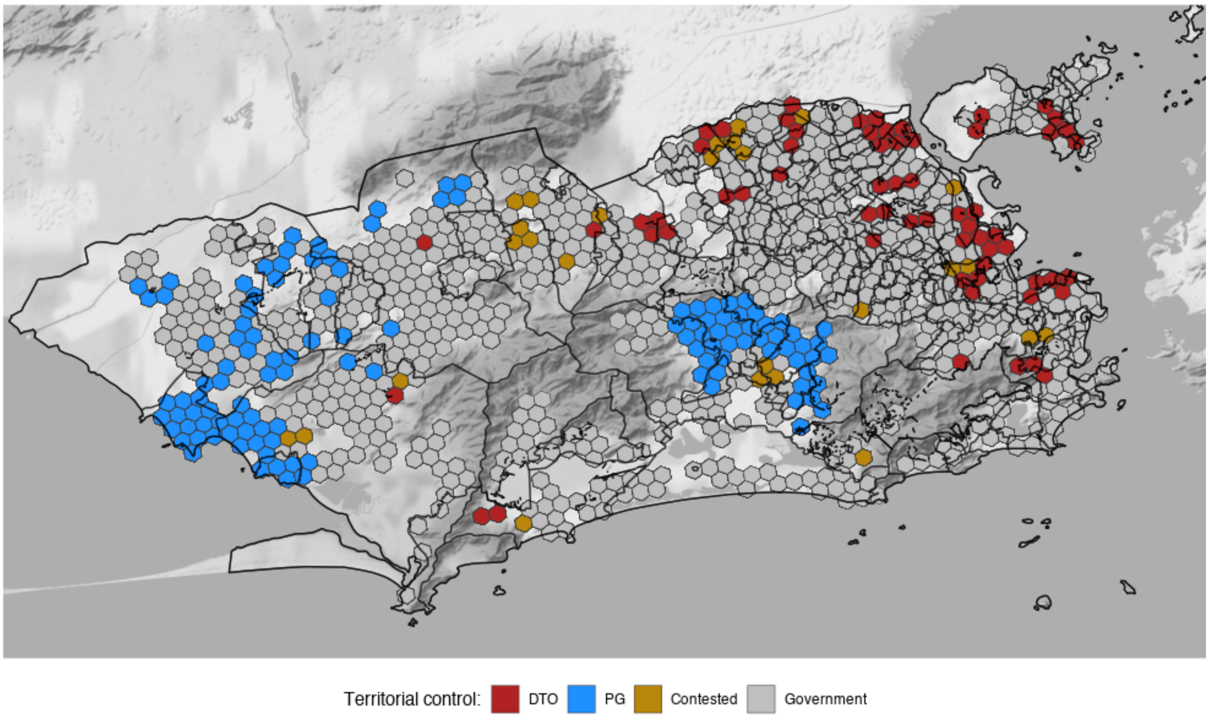
Appendix

A1 Additional Tables and Figures

Figure A1: Timeline of non-pharmacological interventions (NPIs) in Rio de Janeiro

Notes: This Figure shows the chronology of government response to the pandemic in Rio de Janeiro (time in epidemiological weeks). The pandemic officially started in the city on March 5, 2020 - in the tenth epidemiological week. On March 16, in the twelfth epidemiological week, the state government recommended the closure of non-essential businesses. The enforcement of this decree took place on March 23, in the thirteenth epidemiological week, when Rio's municipal administration limited the opening hours of several kinds of businesses. After that, both state and city governments initiated plans to gradually reopen the local economy starting June 1, 2020.

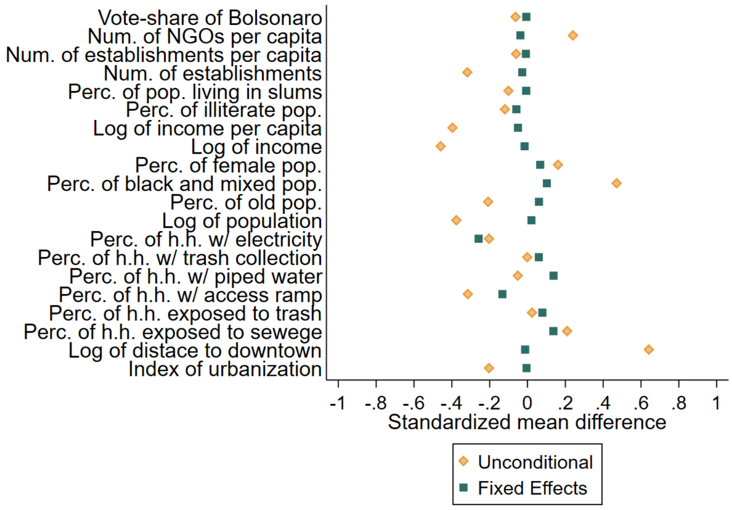
Figure A2: Crime control in the hexagon level



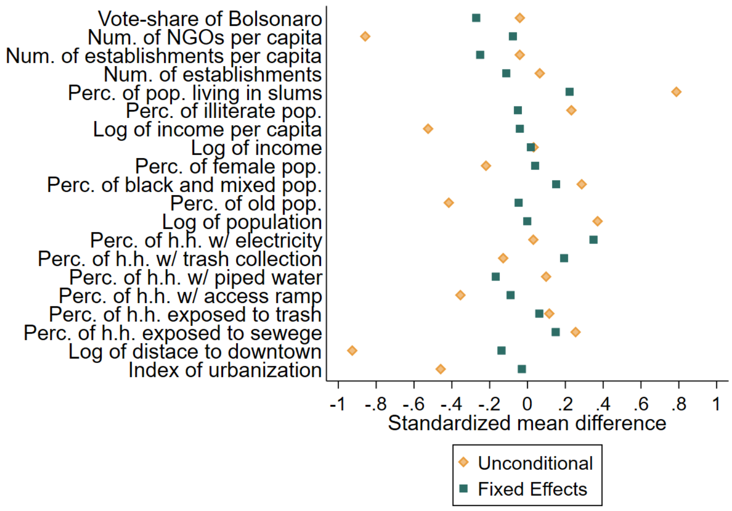
Notes: This Figures presents visually the estimating sample used in the main analysis. Hexagons in red are those where $DTO_h = 1$, in blue are those where $PG_h = 1$. Contested hexagons, in dark yellow, are left out of our analysis since it's not clear which criminal governance regime is in place in them. Hexagons in grey, where $DTO_h = PG_h = 0$ are part of our control group.

Figure A3: Checking balance on covariates:
The magnitude of the differences between areas w/ and w/out organized crime decreases substantially within groups and neighborhoods

(a) Balance check, PGs



(b) Balance check, DTOs



Notes: This figure reports statistics that check whether treatment and control groups become similar after restricting comparisons to hexagons within the same neighborhood and groups defined according to quintiles of four variables. The four variables defining groups are the index of urbanization, percentage of illiterate population, household per capita income, and Jair Bolsonaro's vote share in the 2018 election. Panel **(a)** reports standardized mean difference estimates comparing hexagons controlled by PGs and the government. Panel **(b)** reports the same statistic but comparing hexagons controlled by DTOs with those controlled by the government. We estimate each Δ_x by regressing each standardized baseline covariate $\frac{x}{\hat{\sigma}_x}$ on our treatment indicators PG_h and DTO_h.

Table A1: Data Description: Baseline Covariates

Variable	Description	Source
Panel A: Outcomes and treaments		
Social distancing	Social distancing index.	Incognia[1]
Governed by a drug trafficking	Indicator variable equal to one when a drug trafficking organization (DTO) controls the hexagon.	Pista News[2]
Governed by a paramilitary group	Indicator variable equal to one when a paramilitary group (PG) controls the hexagon.	Pista News
Panel B: Demographic controls		
Log. of population	Total population (in logarithmic scale).	IBGE 2010 Census[3]
Perc. of old pop.	Share of the total population with more than 60 years.	IBGE 2010 Census
Perc. of black and mixed pop	Share of the total population self-declared black or mixed race.	IBGE 2010 Census
Perc. of female pop.	Share of the total population from the female gender.	IBGE 2010 Census
Panel C: Socioeconomic controls		
Log. of income	Total household income (in logarithmic scale).	IBGE 2010 Census
Log. of income per capita	Total household per capita income (in logarithmic scale).	IBGE 2010 Census
Perc. of illiterate pop.	Share of the total population that is illiterate.	IBGE 2010 Census
Perc. of pop. living in slums	Share of the total population living in enumeration areas (EAs) classified as a subnormal agglomerate.[4]	IBGE 2010 Census
Num. of establishments	Total number of commercial establishments.	CNPJ Aberto[5]
Num. of establishments per capita	Total number of commercial establishments per capita.	CNPJ Aberto
Panel D: Urban controls		
Index of urbanization	First principal component of the share of households with access to seven different urban services.[6]	IBGE 2010 Census
Log of distace to downtown	Distance from the hexagon's centroid to downtown (in logarithmic scale).	Incognia
Perc. of h.h. exposed to sewege	Share of households in enumeration areas exposed to open air sewage.	IBGE 2010 Census
Perc. of h.h. exposed to trash	Share of households in enumeration areas exposed to open air trash.	IBGE 2010 Census
Perc. of h.h. w/ access ramp	Share of households in enumeration areas without access ramp.	IBGE 2010 Census
Perc. of h.h. w/ piped water	Share of households with piped water.	IBGE 2010 Census
Perc. of h.h. w/ trash collection	Share of households with trash collection.	IBGE 2010 Census
Perc. of h.h. w/ electricity	Share of households with electricity.	IBGE 2010 Census
Panel E: Other controls		
Vote-share of Bolsonaro	Vote share of president Jair Bolsonaro in the second round of the 2018 election.[7]	TSE[8]
Num. of NGOs per capita	Number of NGOs per inhabitant.[9]	Mapa das OSCS (IPEA)[10]

Notes: All variables are aggregated at the hexagon level.
[1] Incognia provides data on social isolation at the H3 (Hexagonal Hierarchical Spatial Index) level.
[2] *Mapa dos Grupos Armados* is project in which civil society organizations *Disque Denúncia*, *Fogo Cruzado* and *Pista News* and research groups NEV-USP and GENI-UFF participated. They used reports from official records, emergency calls and information from citizens in areas under dispute or control of criminal groups in order to map their presence in Rio de Janeiro.
[3] IBGE's demographic census in 2010. It is the most recent available country-covering census in Brazil.
[4] "Subnormal agglomerates" is the official name given to slums by IBGE.
[5] *CNPJ Aberto* provides the zipcode for every registered commercial establishment in Brazil.
[6] Services: official address number, public lighting, street paving, sidewalk, curb, manhole, and tree coverage.
[7] We extrapolate geocoded data at the polling place level by defining a tesselation of Voronoi cells over the municipality based on these points.
[8] *Tribunal Superior Eleitoral* (Brazilian Electoral Court), the Brazilian electoral authority.
[9] We collapse geocoded data on NGOs at the hexagon level after spatially joining from points to polygons. Data from IPEA's Mapa das Organizações Sociais.
[10] *Mapa das OSCS* provides geolocated information on every civil society organization in Brazil.

Table A2: Baseline check: PGs *vs* GAs
Areas controlled by PGs are different from those controlled by the government.

Variable	PGs (treatment 1) Mean	Std. dev.	GAs (control) Mean	Std. dev.	p-value
Panel A: Outcomes and treaments					
Social distancing index	41.454	7.913	43.198	8.930	0.000
Governed by a drug trafficking organiz.	0.000	0.000	0.000	0.000	
Governed by a paramilitary group	1.000	0.000	0.000	0.000	
Panel B: Demographic controls					
Log of population	8.146	1.058	8.584	1.302	0.000
Perc. of old pop.	10.750	4.704	12.314	6.711	0.008
Perc. of black and mixed pop.	49.147	17.310	39.952	18.419	0.000
Perc. of female pop.	47.299	12.313	45.284	14.434	0.069
Panel C: Socioeconomic controls					
Log of income	14.410	1.304	15.074	1.488	0.000
Log of income per capita	6.446	0.569	6.742	0.686	0.000
Perc. of illiterate pop.	20.037	21.051	22.480	25.192	0.172
Perc. of pop. living in slums	11.326	19.215	11.934	18.750	0.297
Num. of establishments	459.590	532.649	851.288	1317.443	0.000
Num. of establishments per capita	0.100	0.103	0.690	10.458	0.140
Panel D: Urban controls					
Index of urbanization	-0.463	2.149	0.124	2.415	0.025
Log of distace to downtown	3.439	0.507	2.929	0.798	0.000
Perc. of h.h. exposed to sewege	8.205	12.214	5.677	10.116	0.057
Perc. of h.h. exposed to trash	4.511	7.927	4.233	8.294	0.806
Perc. of h.h. w/ access ramp	0.882	2.909	5.293	14.153	0.000
Perc. of h.h. w/ piped water	94.547	10.683	95.102	13.345	0.545
Perc. of h.h. w/ trash collection	99.149	1.969	99.174	1.899	0.989
Perc. of h.h. w/ electricity	99.810	0.474	99.905	0.485	0.043
Panel E: Other controls					
Vote-share of Bolsonaro	35.206	2.018	34.607	3.687	0.000
Num. of NGOs per capita	0.004	0.003	0.022	0.309	0.119
Number of hexagons	117		642		759

Note: This table displays descriptive statistics of the outcome, treatments, and baseline controls at the hexagon level. More precisely, we report statistics that check whether our hexagons controlled by paramilitary groups (PGs) - treatment group 1 - and the government (GAs) - control group - have similar characteristics. The second and third columns report the mean and standard deviation for the sub-sample of hexagons controlled by PGs for each variable described in the first column. The third and fourth columns repeat the but restricting the sample to hexagons controlled by the government. In the last column, we plot the p-value associated with the statistical hypothesis $H_0 : \mu_x(PG_h = 1) = \mu_x(GA_h = 1)$, where x is one of our baseline controls and μ_x is the mean of x. Tables A2 and A3 have the same control group. We computed the p-value of each mean difference test by regressing each x_h on PG_h and DTO_h using robust standard errors.

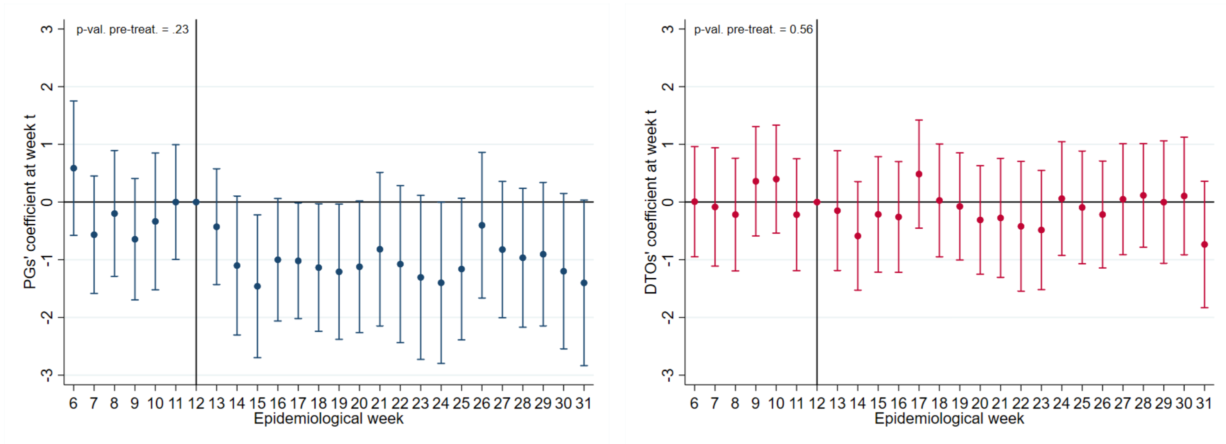
Table A3: Baseline check: DTOs *vs* GAs
Areas controlled by DTOs are different from those controlled by the government.

	DTOs (treatment 2)		GAs (control)		
Variable	Mean	Std. dev.	Mean	Std. dev.	p-value
Panel A: Outcomes and treaments					
Social distancing index	41.816	7.735	43.198	8.930	0.000
Governed by a drug trafficking organiz.	1.000	0.000	0.000	0.000	
Governed by a paramilitary group	0.000	0.000	0.000	0.000	
Panel B: Demographic controls					
Log of population	9.057	1.177	8.584	1.302	0.000
Perc. of old pop.	9.664	4.580	12.314	6.711	0.000
Perc. of black and mixed pop.	45.254	17.852	39.952	18.419	0.096
Perc. of female pop.	42.156	15.190	45.284	14.434	0.081
Panel C: Socioeconomic controls					
Log of income	15.122	1.150	15.074	1.488	0.330
Log of income per capita	6.391	0.447	6.742	0.686	0.000
Perc. of illiterate pop.	28.223	26.057	22.480	25.192	0.071
Perc. of pop. living in slums	27.624	26.494	11.934	18.750	0.000
Num. of establishments	932.556	1439.303	851.288	1317.443	0.446
Num. of establishments per capita	0.312	1.216	0.690	10.458	0.451
Panel D: Urban controls					
Index of urbanization	-0.978	2.414	0.124	2.415	0.001
Log of distace to downtown	2.083	1.659	2.929	0.798	0.000
Perc. of h.h. exposed to sewege	8.445	14.755	5.677	10.116	0.208
Perc. of h.h. exposed to trash	5.173	7.493	4.233	8.294	0.362
Perc. of h.h. w/ access ramp	0.789	1.974	5.293	14.153	0.000
Perc. of h.h. w/ piped water	96.381	13.872	95.102	13.345	0.448
Perc. of h.h. w/ trash collection	98.930	1.744	99.174	1.899	0.294
Perc. of h.h. w/ electricity	99.919	0.241	99.905	0.485	0.407
Panel E: Other controls					
Vote-share of Bolsonaro	31.462	4.416	34.607	3.687	0.000
Num. of NGOs per capita	0.011	0.045	0.022	0.309	0.483
Number of hexagons	63		642		705

Note: This table displays descriptive statistics of the outcome, treatments, and baseline controls at the hexagon level. More precisely, we report statistics that check whether our hexagons controlled by paramilitary groups (DTOs) - treatment group 2 - and the government (GAs) - control group - have similar characteristics. The second and third columns report the mean and standard deviation for the sub-sample of hexagons controlled by DTOs for each variable described in the first column. The third and fourth columns repeat the but restricting the sample to hexagons controlled by the government. In the last column, we plot the p-value associated with the statistical hypothesis $H_0 : \mu_x(DTO_h = 1) = \mu_x(GA_h = 1)$, where x is one of our baseline controls and μ_x is the mean of x. Tables A2 and A3 have the same control group. We computed the p-value of each mean difference test by regressing each x_h on PG_h and DTO_h using robust standard errors.

Figure A4: Complementary specification with all controls interacted with week FEs
Control by PGs decreases compliance to NPIs, but control by DTOs does not affect it.

(a) Event study, PGs　　**(b)** Event study, DTOs



Notes: This figure displays two graphs reporting the effect of territorial control by drug trafficking organizations (DTOs) and paramilitary groups (PGs) on social distancing across the weeks 6 to 31 of 2020 with its 90% confidence interval. Treatment effects across years are estimated using a difference-in-differences regression model:$Distancing_{hnt} = \alpha_h + \phi_{nt} + \sum_{k \neq 12} \beta_k \cdot DTO_h + \sum_{k \neq 12} \beta_k \cdot PG_h + \gamma_t \cdot \mathbf{X}_h + \epsilon_{hnt}$, where h denotes and hexagon, n neighborhood, and t week. α_h captures hexagon fixed effects and ϕ_{nt} neighborhood-week fixed effects. DTO_h is an indicator variable equal to one when a drug trafficking organization controls the hexagon h. PG_h is an indicator variable equal to one when a paramilitary group controls the hexagon h. $\mathbf{X}_h$ is a vector with our twenty baseline controls. $\gamma_t \cdot \mathbf{X}_h$ are week-specific slopes controlling for the influence of hexagons' characteristics on change on social distancing behaviours after the enforcement of NPIs. We normalize treatment effects concerning week 12 of 2020, the last one before the enforcement of NPIs in Rio de Janeiro. We cluster standard errors at the hexagon level.

Table A4: Baseline specification with parametric controls and neigbourhood-week FEs
Control by PGs decreases compliance to NPIs, but control by DTOs does not affect it.

	(1)	(2)	(3)	(4)	(5)
PG × Post NPI	-1.048	-1.108	-1.018	-0.931	-0.875
	[0.378]***	[0.346]***	[0.342]***	[0.328]***	[0.334]***
DTO × Post NPI	-1.474	-0.568	-0.144	-0.084	-0.188
	[0.409]***	[0.359]	[0.343]	[0.346]	[0.320]
Observations	20814	20814	20814	20814	20814
Num. of hexagons	822	822	822	822	822
R-squared	0.918	0.922	0.924	0.927	0.928
Outcome mean	42.838	42.838	42.838	42.838	42.838
Outcome standard deviation	8.727	8.727	8.727	8.727	8.727
Outcome post-pre treat. variation	12.829	12.829	12.829	12.829	12.829
Week FEs	Yes	Yes	Yes	Yes	Yes
Hexagon FEs	Yes	Yes	Yes	Yes	Yes
Neighbourhood-Week FEs	Yes	Yes	Yes	Yes	Yes
Urban controls × Week	No	Yes	Yes	Yes	Yes
Demographic controls × Week	No	No	Yes	Yes	Yes
Socioeconomic controls × Week	No	No	No	Yes	Yes
Other controls × Week	No	No	No	No	Yes

Note: This table displays estimates of the effect of territorial control by DTOs and PGs on social distancing estimated by a difference-in-differences (DiD) specification using weekly data from weeks 6 to 31 of 2020. The DiD regression model reported in Column (5) has the form $Distancing_{hnt} = \alpha_h + \alpha_{nt} + \beta^{DTO} \cdot DTO_h \cdot Post\_NPI_t + \beta^{PG} \cdot PG_h \cdot Post\_NPI_t + \gamma_t \cdot \mathbf{X}_h + \epsilon_{hnt}$ where h denotes and hexagon, n neighborhood, and t week. α_h captures hexagon fixed effects and $\alpha_{n,t}$ neighbourhood-week fixed effects. DTO_h is an indicator variable equal to one when a drug trafficking organization controls the hexagon h. PG_h is an indicator variable equal to one when a paramilitary group controls the hexagon h. $Post\_NPI_t = \mathbb{1}(t > 12)$ is an indicator variable that equals one after week 12 of 2020, the first one before Rio de Janeiro's governor enforced NPIs. $\mathbf{X}_h$ is a vector with our 19 baseline controls. $\gamma_t \cdot \mathbf{X}_h$ are week-specific slopes controlling for the influence of hexagons' characteristics on change on social distancing behaviors after the enforcement of NPIs. In the first column, we present the results of a DiD specification with hexagon and neighborhood-time fixed-effects, which is similar to the specification reported in Column (5) of Table 1, except we omit group fixed-effects. In Columns (2)-(5), respectively, we sequentially add urban, socioeconomic, demographic, and political controls interacted with week fixed-effects to the specification in Column (1). In the most restrictive specification, in Column (5), we include all our twenty baseline variables interacted with week fixed-effects, allowing the social distancing index to vary every week according to the baseline level of observable variables. The results indicate that our findings are robust to different specifications and, more importantly, do not reflect any unbalance in predetermined characteristics that may affect social distancing. Clustered standard errors are displayed at the hexagon level between squared brackets. Coefficients significantly different from zero at 99% (***), 95% (**), and 90% (*) confidence levels.

Table A5: Correlation between COVID cases and Territorial Control overtime
Areas controlled by PGs present more COVID cases

	(1)	(2)	(3)	(4)	(5)	(6)
	March	April	May	June	July	Aug
PGs	0.433	0.445	0.644	0.375	0.276	0.213
	[0.281]	[0.324]	[0.343]*	[0.302]	[0.333]	[0.338]
DTOs	-0.302	-0.231	-0.095	-0.322	-0.273	-0.340
	[0.319]	[0.285]	[0.283]	[0.275]	[0.269]	[0.227]
Observations	822	822	822	822	822	822
R-squared	0.29	0.18	0.20	0.22	0.21	0.27

Note: This table reports correlations between our treatment variables and COVID-19 cases. To avoid biases caused by differential under-notification of COVID-19 cases, ideally, we would like to use data on the number of notified cases of Severe Acute Respiratory Infection. Since this information is not available at levels that can be matched to our treatment variables, we use the number of COVID-19 hospitalizations available at the zip-code level to circumvent this issue, which we aggregate at the hexagon level. The use of this data imposes some challenges. First, the number of confirmed COVID-19 cases at the hexagon level represents only a fraction of the total number of COVID-19 infections, which reduces outcome variation. Second, the presence of criminal organizations may affect COVID-19 testing, creating a non-classical measurement error problem. Finally, it limits the analysis, not allowing us to conduct an event-study exercise since the number of COVID-19 cases is available only after the beginning of the pandemic. Given these challenges, we estimate and report in this table correlations between our treatment variables and COVID-19 cases, as in Brotherhood et al. (2019). Formally, for each month between March and August, we estimate $Y_{hn} = \alpha + \gamma_n + \beta^{DTO} \cdot DTO_h + \beta^{PG} \cdot PG_h + \epsilon_{hn}$, where Y_{hn} is the logarithm of number of per capita COVID-19 cases for each hexagon h in neighborhood n, and DTO_h and PG_h, respectively, equal to one for hexagons controlled by DTOs or PGs. We include neighborhood fixed-effects γ_n to reduce endogeneity concerns related to differential under-notification of COVID-19 cases.

B1 News Appendix

This appendix provides a few transcripts from local media reports covering OCGs' actions during the COVID-19 pandemic in Rio. We aim to provide evidence on how these groups dealt differently with the health crisis due to their distinct criminal governance. Despite being journalistic and not academic accounts, they are consistent with previous research regarding their governance such as Magaloni et al. (2020), Cano and Duarte (2012) and Arias and Rodrigues (2006).

Drug Trafficking Organizations

> There are several reports on DTOs' activities during the pandemic. Many of them describe cars with loudhailers and messages on social media warning citizens of the consequences of obeying social distancing. These comprise not only medical consequences but also punishments they impose in their territory.
>
> In the report below, the journalists describe gang members actions in the neighborhood of Acari, in the northern zone of Rio de Janeiro:
>
> *Audios and photos about the [pandemic in slums] have circulated on social networks. One of them appears to be a recording of a megaphone in which a man explains the "rules" for circulation in the neighborhood. "Our car will pass by at 7:30 pm. Do not stay on the street walking around. Attention, moms, do not leave your children in the street. We are not on vacation; we're in quarantine. During the day, if you have to go out on the street, wearing a mask is mandatory. Do you want to have a party? Barbecue? It will only be allowed inside the house. Our car will inspect." The audio follows, and the man claims that only people who work with deliveries will be allowed to circulate at night. Even so, the "permission" would only be given to those wearing a mask and gloves. (...) In another audio, another man reports having gone to Acari and that "the drug dealers' car" was passing by with rifles. "The gangs' car stops everyone not wearing a mask", he said.*
> (Excerpt from Martins and Satriano (2020) *(translated from Portuguese).*)

The report below, from another *G1 Piece*, describes cars with armed men warning citizens on the potential consequences of disobeying their orders:

> *According to [messages sent by local drug traffickers], residents are prohibited*

> *from being on the streets after 8 pm. Parties are forbidden, as well as meetings in squares, bars, and shops. Residents of these locations are instructed to buy their products and immediately return to their homes while wearing masks. All messages are accompanied by threats to those who do not follow the orders. (...) Our portal obtained a video made in the Vila Aliança community, in the West Zone of the city. In the images it is possible to see a car with a loudhailer crossing the community and giving a message to the residents. Next to the vehicle, in what appears to be an escort, there are two men on a motorcycle. One of them, on the back, is armed with a rifle.*
> (Excerpt from Leitão and Martins (2020) *(translated from Portuguese)*.)

In another piece, from the local newspaper *A Tribuna*, the journalist describes how DTOs' adopted a curious commercial strategy and started selling in their drug dens a bundle of marijuana and antiseptic gel in some neighborhoods:

> *After starting to impose quarantine rules for residents of various slums throughout Rio (...), in some of them even establishing a curfew, under the threat of "punishment", traffickers are now trying to demonstrate that they are committed to some of the COVID-19 prevention guidelines. (...) In drug dens, traffickers from the Comando Vermelho (CV) faction are offering a "combo", where small bottles of antiseptic gel are sold together with the drugs. The combo is being displayed on social networks. In one of the posts, traffickers in the Jardim Catarina neighborhood, São Gonçalo, say that in the marijuana "special deal", for R$ 10, the buyer receives a small bottle of antiseptic gel.*
> (Excerpt from Tribuna (2020) *(translated from Portuguese)*.)

Paramilitary Groups

The local media also provided accounts of the actions of PGs during the health crisis. An anonymous citizen interviewed by the website *G1* in April 2020 reported the following:

> *"The milicianos from this area keep oppressing us, telling us to keep the bar open, saying that we have to keep making money to pay them so they can bribe the military police."*
> (Excerpt from Prado and Peixoto (2020) *(translated from Portuguese)*.)

In the same report, journalists obtained a quote from another citizen which provides a graphic description of how members of the *milícias* engage with the victims of their extortion activities:

> *"They always go at night, one of them is hooded, one is fatter, another is darker and another is stronger, you know? There are three who went to my house to get R$ 30"*
> (Excerpt from Prado and Peixoto (2020) *(translated from Portuguese)*.)

In a different report from July 2020, a citizen living in one of the oldest *milícia* strongholds, provides yet another description of how extortion by PGs takes place:

> *"On the 15th day of every month, they come and knock on our doors, in a group of three or four armed men, harassing us and asking for their payment. Now, with the pandemic, when everyone is poor and unemployed, we still have to give them money that would be used to buy food instead."* (Excerpt from Prado and Dondossola (2020) *(translated from Portuguese)*.)

In the same piece, another citizen provides a graphic testimony on the intimidation tactic used by *milicianos* to obtain their money from the victims:

> *"We are poor, we cannot pay them every month. We don't know where to run. And they still come with rifles at our door in order to scare us. They keep locking and unlocking their guns to make us afraid so we pay. And we don't have the conditions for that. We are asking for help."*
> (Excerpt from Prado and Dondossola (2020) *(translated from Portuguese)*.)

C1 Data Appendix

From enumeration areas and crime turfs to hexagons. Both criminal presence and socioeconomic characteristics are measured within boundaries that do not exactly match our unit of analysis. Socioeconomic characteristics are measured at the enumeration area level, while criminal presence, since it is reported by citizens, may point to broad or informal urban subdivisions. In order to deal with this, we follow a similar procedure from Brotherhood et al. (2019). First, we classify each enumeration area into different criminal groups according to the largest overlapping area with a turf controlled by a DTO or a PG. This means that an enumeration area is classified as belonging to a DTO if the largest portion of its area intersects with a DTO turf. The same reasoning applies to PGs and areas without criminal presence. Next, we aggregate enumeration areas into hexagons. More specifically, we obtain the weighted average of enumeration areas' observable characteristics, where the weight is given by the area of the intersection between the enumeration area and the hexagon. This provides an approximation of each hexagon's socio-economic profile and the share of the population exposed to criminals. Note that, by doing this, we implicitly assume that individuals are uniformly distributed over hexagons and enumeration areas. Ultimately, this means that the weight reflects both the share of the population from a certain enumeration area which have this tracts' characteristics and the overlapping area with the hexagon. For example: if 30% of enumeration area A with the presence of a DTO overlaps with an hexagon B, 30% of A's population (with its observable characteristics) will belong to B.

Defining treatment. In order to translate the presence of criminal organizations into territorial control at the hexagon level we follow a quantile-based criterion similar to Le Moglie and Sorrenti (2020). We set a high bar on the share of the population subject to the presence of a DTO or a PG in a given hexagon and define it as controlled by a given group if the share of the population under the control of that group is above the third quartile. This enables us to have a more conservative approach and focus on areas that are well within the criminal turfs. Focusing on the share of the population exposed to criminals with different criminal governance is also reasonable since since our main outcome is a proxy for the number of individuals following or not NPIs in each hexagon.