EconomiA 22 (2021) 147–163

Contents lists available at ScienceDirect

EconomiA

journal homepage: www.elsevier.com/locate/econa

How do Covid-19 stay-at-home restrictions affect crime? Evidence from Rio de Janeiro, Brazil[☆☆,☆]

Jessie Bullock[a,*,1], Ana Paula Pellegrino[b,2]

[a] Department of Government, Harvard University, United States
[b] Department of Government, Georgetown University, United States

ARTICLE INFO

Article history:
Received 15 July 2021
Received in revised form 29 October 2021
Accepted 8 November 2021
Available online 1 January 2022

Keywords:
Crime
Violence
Extortion
Organized crime
Covid-19

ABSTRACT

How do changes in mobility impact crime? Using police precinct-level daily crime statistics and shootings data from the state of Rio de Janeiro, Brazil, we estimate that extortion, theft, and robberies decrease by at least 41.6% following COVID-19 mandated stay-at-home orders and changes in mobility in March 2020. Conversely, we find no change in violent crimes, despite fewer people being on the streets. To address the relationship between crime and mobility, we use cellphone data and split the precincts into subgroups by pre-Covid-19-related restrictions mobility quintiles. We estimate a similar average decrease in extortion regardless of a precinct's previous activity level, but find that the decrease in theft and robberies is substantially higher for the more mobile precincts while it disappears for the least mobile precincts. Using daily cellphone mobility data aggregated at the police precinct level, we find that changes in mobility while the stay-at-home order is in place only have a meaningful effect on robberies, which increase in likelihood when a precinct's mobility ranking is higher than the previous day. Together, these results suggest that the stay-at-home order and associated decline in mobility strongly affected extortion and property crimes while not interfering with the dynamics of violent crime. These findings support the hypothesis that violent and property crime follow different dynamics, particularly where there is a bigger impact of organized criminal groups.

☆☆ Production and hosting by National Association of Postgraduate Centers in Economics, ANPEC.
☆ We thank the UNDP Policy Response Research Team and GRANDATA for providing access to the mobility data and for their inclusion in the 'Exploring the impact of COVID-19 and the policy response in LAC through mobility data' project." We thank the Harvard Political Economy of Development workshop for helpful comments. All errors are our own.
* Corresponding author.
E-mail address: jbullock@g.harvard.edu (J. Bullock).
[1] ORCID :0000-0003-2486-4439
[2] ORCID :0000-0001-6058-0594

https://doi.org/10.1016/j.econ.2021.11.002
1517-7580/

1. Introduction

Immediately following COVID-19 mobility restrictions, commonly referred to as "lockdowns,"[3] crime changed around the world as those who could stayed off streets and in their homes. Initial reports showed plummeting violent and non-violent crime rates while domestic violence rose. Across the Global South and particularly in Latin America, international observers predict that the pandemic strengthened the power of organized crime as they watched gangs provide social welfare for community residents and, at times, enforced harsher mobility restrictions than the government (McDermott and Dudley, 2020). In contexts where the government is wholly focused on managing the state's response to the pandemic, it is possible that a pandemic could be an opportunity for criminal groups.

We study the relationship between mobility and crime in the State of Rio de Janeiro, a quintessential case where criminal groups and state wield overlapping influence. We first ask the question, how did stay-at-home restrictions impact both violent and nonviolent crime? We study the impact of a mandatory stay-at-home order in Rio de Janeiro, Brazil on several types of violent and nonviolent crime, as well as police killings. We then consider whether variation in quarantine compliance affected violent and nonviolent crime differently.

We first compare crime levels in the 30 days before and after COVID-19 mobility restrictions were issued, exploiting detailed daily police precinct-level data on shootings, lethal violence - including homicides and police killings – extortion, theft, and robberies. We estimate this using an interrupted time series, also called a regression discontinuity in time (RDiT) design (Hausman and Rapson, 2018). We then leverage granular data on mobility at the daily level, which we use to estimate variation in levels of quarantine compliance, also at the police precinct level. We use this panel data to estimate the effect of changes in mobility on crime levels once the stay-at-home order had already been enacted.

There are two main sets of results. First, regardless of model specification, bandwidth, or sample, we find that violent crime did not change following the mandated restrictions, despite large reductions in mobility. This is inconsistent with many findings from elsewhere around the world where violent crime plummeted following quarantine restrictions. It is also inconsistent with early journalistic evidence, claiming that criminal groups halted violence in order to lock down and protect their communities (Dalby, 2020; GloboNews, 2020).

If true, criminal groups merely halted *increases* in violence, as our results show there was no meaningful decrease in shootings, homicides, or other forms of lethal violence. We find that police killings decreased slightly following the stay-at-home order, but this effect dissipates over time and the correlation disappears when we consider mobility level of the precinct. These results suggest that COVID-19 restrictions did not noticeably disrupt the dynamics of violence in Rio de Janeiro. We interpret this as evidence that incentives and norms governing violent crime – predominately, thought not exclusively related to organized crime – suffered little impact from mobility restrictions. They support the need for further investigation into the relationship between mobility and incentives to engage in violent criminal behavior.

Second, we find that extortion and property crimes plummeted following mobility restrictions. In our preferred regression discontinuity specification, we find that extortion decreased by 45.9%, theft by 69.4%, and robbery by 41.6% following the mandate. This could be due to social distancing measures and fewer people on the streets (mechanically making it more difficult to steal, rob, or extort from people), or could be due to criminal behavioral changes in the areas most likely for property crimes to happen (which also happen to be the most mobile areas, or the areas at greatest risk for spreading COVID-19).

We take two strategies to address the possibility that the underlying mobility level was related to decreases in property crime rates and extortion. We conduct a subgroup analysis using our preferred regression discontinuity specification, splitting all police precincts in the state into quintiles that correspond to their pre-pandemic mobility level. The coefficient is similar in magnitude across all five quintiles for extortion, indicating that extortion decreased following the stay-at-home order, but was not very elastic to mobility levels.

On the other hand, there was no perceptible decrease in robberies and thefts among lower mobility police precincts, while more mobile precincts registered decreases in robberies and thefts of a maximum of 38% and 37% in the upper quintiles, respectively. Though this finding is partially indicative of the nature of the crimes, it suggests that the decreases in thefts and robberies was mostly driven by the highest trafficked areas that locked down, whereas the decreases in extortion occurred across all police precincts, from high to low mobility levels.

We then consider whether within-lockdown changes in mobility impacted crime levels, and if relative day-over-day changes in mobility was related to crime. All correlations disappear except for that on robberies when our parameter of interest becomes the relative change in precinct daily mobility levels. We find a positive but small relationship between robberies and increases in mobility vis-a-vis the previous day.

Our paper is related to the broader literature on COVID-19 and the impact of mobility restrictions. First, it is closest to the growing body of work on COVID-19, crime, and mobility (Ashby, 2020; Bullinger et al., 2021; Campedelli et al., 2020; Estevez-Soto, 2020; Halford et al., 2020; Bullinger et al., 2021) in a variety of national and criminal contexts. Second, it speaks to others that have studied the specific case of Rio de Janeiro's response to COVID-19 and crime, including Bruce et al., 2021; Bullock,

[3] The extent of "lockdowns" varied widely across and within countries. For a time series of within-country variation in the nature of lockdown restrictions in this paper's case, Brazil, see Brazil's COVID-19 Policy Response from Oxford Blavatnik School's COVID-19 Government Response Tracker. For a comparison with measures adopted by other countries, see the comparative Stringency Index's containment and closure policy indicators. We will refer to the mobility restrictions throughout the paper as lockdowns, keeping with local vocabulary.

2022 and Monteiro (2020). These works consider in greater detail how criminal groups may have reacted to the pandemic. Our findings are broadly consistent with those of Bruce et al., 2021), who argue that criminal groups known for extortion (in Portuguese, *milícias* began forcing residents to reopen commercial establishments during the lockdown. If it is the case that these groups suffered extortion rent losses, as our findings show, our stories are consistent with each other. Finally, we also contribute to the literature on spatial dynamics of crime and its incentive structures (Weisburd et al., 2004; Tita and Griffiths, 2005; Bernasco and Block, 2009; Guerette and Bowers, 2009).

Section 2 introduces the context of crime in Rio de Janeiro and the government's response to COVID-19. Section 3 introduces our empirical strategies. We present results in Section 4, and conclude in Section 5.

2. Context

2.1. Crime in the state of Rio de Janeiro

A tragic feature of contemporary Rio de Janeiro is its high rate of crime and lethal violence. The homicide rate was 37.6 per 100,000 people in 2018 (Cerqueira et al., 2020), on par with the national rate for Honduras, Belize, or Venezuela, which rank among the most murderous countries in the world. Property crimes are also high and have been rising in recent years, with 10,599 incidents of cargo robberies, 125,646 incidents of street robberies, and 54,366 incidents of vehicle robbery in 2017 alone (Rolim, 2020). Lastly, the state of Rio de Janeiro ranks amongst the worst places in the world for police killings. Police kill someone approximately every 10 hours oursin Rio de Janeiro (News, 2020) and are known for their brutal tactics that, in some cases, provoke more violence (Magaloni et al., 2020).

Organized criminal groups play an important role in the spread of crime and violence throughout the state. In Rio de Janeiro, there are several competing criminal groups that fight for territorial and market control – of both illegal and legal nature - as well as control over voters and informal influence over police and elected officials. These frequent disputes have created a constant state of turf wars, reputational disputes, or firefights with the police. Of the criminal groups present in Rio de Janeiro, three major gangs concentrate their illegal drug trafficking and other criminal operations in informal settlements scattered across the state. There are also several vigilante militia groups, who operate extensive protection rackets in the settlements they dominate, extorting residents and local businesses for everything from weekly "security provision" to car parking spaces to gas, cable, and electric utilities. While these groups originally formed to combat gangs and their illegal drug operations, they have since entered this illegal market as well. Many violent crimes and extortion incidents are related to these groups, and nearly all police killings are indirectly related to these groups (Magaloni et al., 2020). Even when an innocent bystander is assassinated by the police, it usually happens during a targeted raid to arrest drug traffickers or when police are pursuing a member of a criminal group (Andreoni et al., 2020). Specific groups are also involved in theft and robberies.

2.2. Rio de Janeiro's response to COVID-19

The response to COVID-19 in Brazil was decentralized and poorly coordinated at the city and the state level.[4] Across the country, state governors and mayors enacted a series of closure and COVID-19 containment measures that were soon to be contested by the federal government – the disagreement ended up in the Supreme Court, that decided in favor of governors and mayors. Rio de Janeiro State's governor was one of the first in the country to close schools and suspend public events in early March 2020. The city's then mayor was initially reluctant to follow suit but ultimately also adhered to social distancing policies. The timeline for COVID-19 mobility restrictions in Rio de Janeiro is as follows:

- March 5: First Covid-19 case confirmed in the state, closure of state public schools.
- March 13: Municipal[5] public school closure and state-mandated stay-at-home order.
- March 27: Closure of all non-essential businesses by the Governor.
- June 06: Governor relaxes Covid-19 non-essential business restrictions.

Only in early June, 12 weeks after the state-level stay-at-home order was enacted, did the governor begin to gradually relax quarantine restrictions. Though there was variation in citizen compliance with the restrictions, overall trends show that mobility decreased suddenly after the March 13 order, as shown in Fig. 1. Using GRANDATA mobility data (described below in Section 3.2), we see that mobility plummeted in the city of Rio de Janeiro in mid-March, and gradually increased in the coming weeks, though never quite to pre-pandemic levels. This pattern can be found throughout Brazil, regardless of specific dates when public authorities issued orders. While the issuance and compliance to stay-at-home orders was irregular throughout the country and often contradictory at the different levels of government, empirical data shows a clear change in mobility dynamics following March 13, be it the result of personal restrictions or adherence to edicts.

[4] See the Blavatnik School's Brazil's Covid-19 Policy Response project for more detailed information on measures and their variation between subnational governments.
[5] "Municipal" only refers to schools in the capital city of Rio de Janeiro. Other cities closed schools in different timelines.

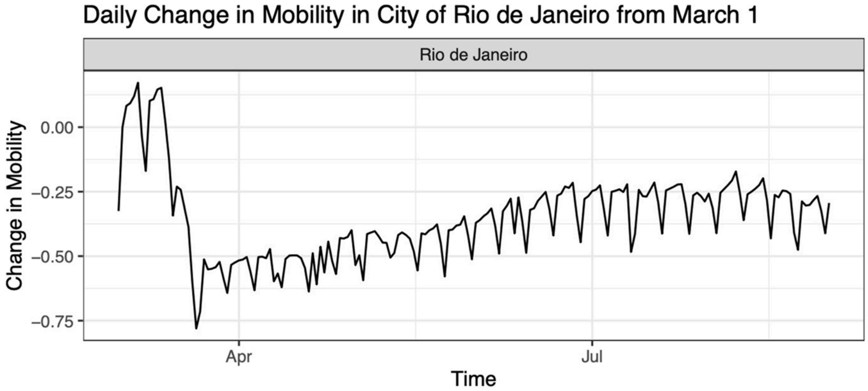


Fig. 1. Change in mobility following stay-at-home order. Note: This figure plots the daily average mobility level for the capital city of Rio de Janeiro vis-a-vis the first day in the data set, March 1. A value of 0 implies that citywide out-of-home mobility was the same as March 1; a negative value means that out-of-home mobility was lower. The stay-at-home order coincides with the large drop in early March. The minimum value occurred on March 19, one week after the announcement of the stay-at-home order. Other municipalities in Rio de Janeiro state show similar trends. Source: GRANDATA.

3. Empirical strategy

We use two strategies to estimate the impact of COVID-19 restrictions on crime. First, we estimate the initial effect of the mobility restrictions and how quarantine changed crime. Second, we estimate how changes in mobility – once restrictions were already put in place – may have been related to fluctuations in crime levels.

To begin, we estimate an interrupted time series model (also called a regression discontinuity in time) (Hausman and Rapson, 2018) to estimate the effect of COVID-19 restrictions on crime and violence. These designs are growing increasingly common in studies in the economics of crime field (Mummolo, 2017; Carr and Packham, 2020; Zoorob, 2020; Jassal, 2020; Ouss, 2020) and have been shown to be similar to experimental benchmarks (St. Clair et al., 2014). The specification is as follows, for police precinct i and day t:

$$Crime_{it} = \alpha + \beta_1 Lockdown_t + f(days_t) + \beta_2(days_t \times Lockdown_t) + \lambda_d + \pi_i + u_{it} \quad (1)$$

where Y_{it} represents the count of a particular crime or shooting registered in the precinct for a certain day (described in greater detail below). The coefficient of interest is β_1. $Lockdown_t$ is a dummy equal to one on after March 13 and $f(days_t)$ represents linear, quadratic, and cubic functions that model time trends on either side of the treatment threshold in days, which is the running variable. To account for the seasonality of crime, we include day of the week fixed effects (λ_d), as well as police precinct-level fixed effects (π_i). Standard errors are clustered at the police precinct level.

To alleviate concerns about unequal compliance with quarantine restrictions or unequal risks of the spread of COVID-19 when comparing high-traffic areas to low-traffic areas, we conduct a subgroup analysis for each crime by mobility level (described in greater detail in Section 3.2) of each police precinct. We subset the sample of police precincts into the five mobility quintiles shown in Figs. 2 and 3 and run the same regression above to examine within-mobility level changes before and after mobility restrictions.

Our second estimation strategy is focused on looking at day-to-day changes in crime. We are interested in how the day-to-day changes in compliance with restrictions within a precinct affect crime and violence. We analyze how the day-to-day change in mobility level of a police precinct is related to crime. We estimate the below panel fixed effects model:

$$Crime_{it} = \alpha + \beta_1 \Delta Mobility_{i,t-1} + \lambda_d + \pi_i + u_{it} \quad (2)$$

In this model, we estimate regressions of the change in mobility from the prior day's level ($\Delta Mobility_{i,t-1}$) on each type of crime. The coefficient of interest is again β_1 and the unit of analysis is the police precinct. We include day of the week fixed effects (λ_d), police precinct-level fixed effects (π_i), and cluster standard errors at the police precinct level.

3.1. Crime and violence data

We measure the impact of quarantine restrictions on crime and violence using two primary sources of crime data. The first contains official police reports, drawn from the Public Safety Institute (ISP) database. We obtained the daily police precinct-level reports for all crimes in the state of Rio de Janeiro. There are 137 police precincts in the state. The second source is Fogo Cruzado, a civic tech and data collection nonprofit that collects citizen-, media-, and government-reported data on shootings in the greater Rio de Janeiro metropolitan area, verifies them, and publishes a georeferenced database of the shootings.

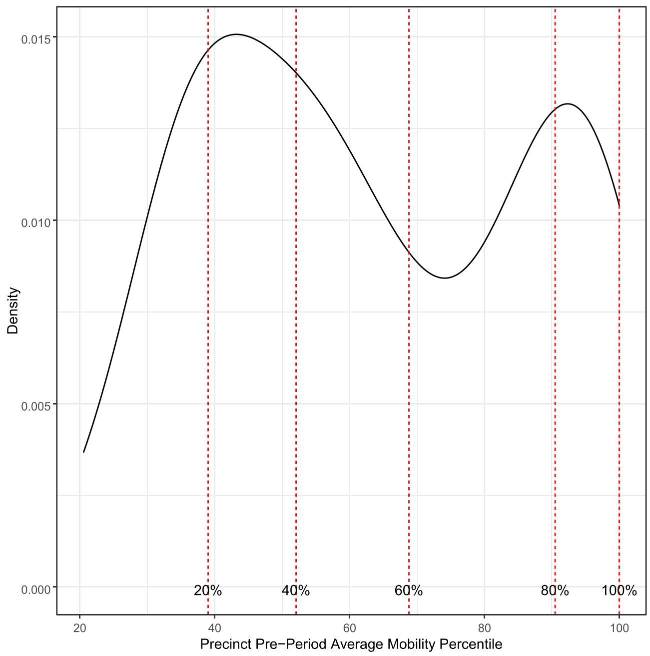


Fig. 2. Average police precinct mobility quintiles. Note: This figure shows the distribution of average mobility level for precincts during the two-week period before the pandemic began. As an example to aid in interpretation, the top 20% most active precincts, between the 80% and 100% dotted lines crossing the x-axis, had average mobility levels of 90.5 or higher, calculated from the underlying hex-level mobility scores. The most active precincts were uniformly high mobility, whereas the middling and lower mobile precincts included a mixture of high- and low- mobility hex cells. Source: GRANDATA and ISP.

Our analysis considers six crimes or types of crimes taken from the ISP database. We first look at a set of three variables to measure how lethal violence changed in response to the COVID-19 restrictions. For this, we analyze reported homicides, police killings, and the ISP omnibus indicator of "lethal violence," which sums the daily totals of homicides, robbery followed by death, and injury followed by death. We then look at three variables to measure how nonlethal violence and property crimes changed in response to mobility restrictions. The first of these is a variable we constructed for extortion, summing the individual police reports for both extortion and threats. The second variable we constructed is the total number of robberies, summing all of the categories of robbery in the ISP database.[6] The third variable we constructed is the total number of thefts, summing all categories of theft in the ISP database.[7]

We use the Fogo Cruzado data to analyze how shootings changed in response to mobility restrictions. The Fogo Cruzado database captures a different quantity of interest than the ISP data, which all draws from police reports. Shootings are reported by citizens, local leaders, or journalists to Fogo Cruzado, who then cross-check the data with verified sources (press, community leaders, and their partners within law enforcement agencies) before eventually publishing and pushing them to their public geocoded API (Perguntas Frequentes, 2019). Anyone that wants to report to Fogo Cruzado can do so anonymously on the cell phone app, online, or via phone. Shootings are published once they are verified by the Fogo Cruzado team. Though there may be some overlap in ISP and Fogo Cruzado data – especially if the shooting results in a death or injury, that medical staff are required to report – some shootings will likely never be officially tallied, particularly if there is no subsequent incident to report to the police. Yet shootings indicate that a situation could turn lethal, even if it has not done so already. For this analyses, we calculate daily total shootings per police precinct so as to be comparable to the ISP data at the police precinct unit of analysis.

3.2. Mobility data

The second data source is related to mobility during COVID-19. We use mobility data taken from cell phone records to construct estimates of how much out-of-home activity occurred before and after the stay-at-home restriction *in each police precinct*. The cell phone mobility data was provided by GRANDATA, a private firm that calculated out-of-home estimates at granular, sub-municipal levels.[8] Limitations of cellphone mobility data and comparison to other widely used datasets are reported in the Appendix A.1.

[6] These include cell phone robbery, bike robbery, cargo truck robbery, robbery of a business, car robbery, home robbery, robbery at an ATM or financial institution, robbery while driving the victim to an ATM or financial institution, robbery of an ATM, bank robbery, robbery while on the street, and robbery while in a bus.

[7] These include bike theft, vehicle theft, cell phone theft, and theft while on the street or while on a bus.

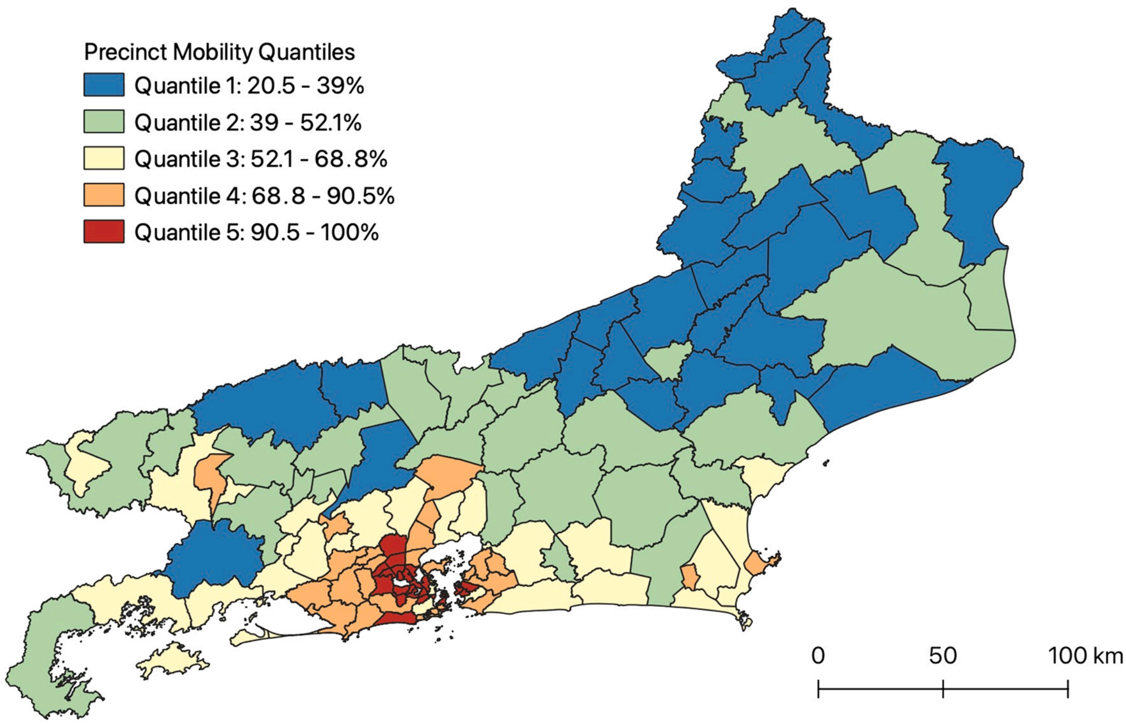


Fig. 3. Geographic distribution of pre-lockdown mobility levels, by police precinct. Note: This figure shows all 137 police precincts in the state of Rio de Janeiro, Brazil. Precincts are colored according to their average mobility level from March 1–12 before the stay-at-home order was mandated, where mobility is measured as an average of the percentile rank of GRANDATA H3 hex cells within each precinct. Source: GRANDATA and ISP.

The smallest unit of analysis that GRANDATA reports is the H3 hex cell at the 8th level, (0.72 km^2), which includes a few city blocks in an urban setting. For each day, hex cells are ranked by percentile (0–100) of out-of-home mobility across the entire state of Rio de Janeiro, where 0 indicates least mobile and 100 indicates most mobile. If a cell phone registered the same location for more than eight consecutive hours, this was tagged as "home" and all home observations were dropped from the dataset. Users with less than 10 events a day were also dropped from the dataset. Only out-of-home locations were used to calculate mobility level. Hex cells with more out-of-home registries were ranked as higher, those with fewer, as lower. There are 16,745 city-day observation in the dataset for the state of Rio de Janeiro, spanning from March 1 to August 31st 2020.

We calculate the pre-pandemic mobility levels of the police precincts in the following way. First, we subset the data to just March 1–12, the days before the stay-at-home order was issued. Second, for each hex cell, we calculate an average percentile ranking. This is important because mobility may be quite different on a weekday versus weekend in some communities, and one day's percentile ranking may not reflect how active a few blocks are. Third, we categorize all hex cells for which police precinct they are in or not. On average, there were 34 hexes per precinct. For hex cells that were on the boundary of two precinct, we included them in both groups. Lastly, we calculated an average mobility level per precinct for the entire pre-period by averaging the individual hex averages within each precinct.

Fig. 2 shows the distribution of pre-period averages per precinct. The first quintile with the lowest out-of-home mobility levels included all precincts that had an average percentile ranking of 39 or lower. The second lowest quintile included all those from 39 to 52, third from 52 to 68, fourth from 68 to 90, and the highest quintile included all from 90 to the maximum value of 100. Fig. 3 then shows the geographic distribution of the police precincts, colored by quintile. The red and orange colors correspond to the most active police precincts, those in quintiles four and five, that registered the highest average number of out-of-home pings per hex cell. Most of these correspond to the capital city (where police precincts are smaller in land mass because they cover a denser population) and the city's suburbs, although there is some within-city variation on which precincts are the highest traffic. The yellow color mostly corresponds to precincts that cover medium-size cities, whereas the green and blue correspond to smaller or rural cities further away from the capital.

We believe the pre-lockdown mobility levels can be useful for analysis because it captures a quantity of interest that population density or population size does not. Not all people or cell phone users will live in a hex cell they pass through, but

[8] The authors were selected as part of an open call for research by the United Nations Development Program (UNDP), acting in partnership with GRANDATA during the COVID-19 pandemic. For more information on the collaboration, see their joint press release.

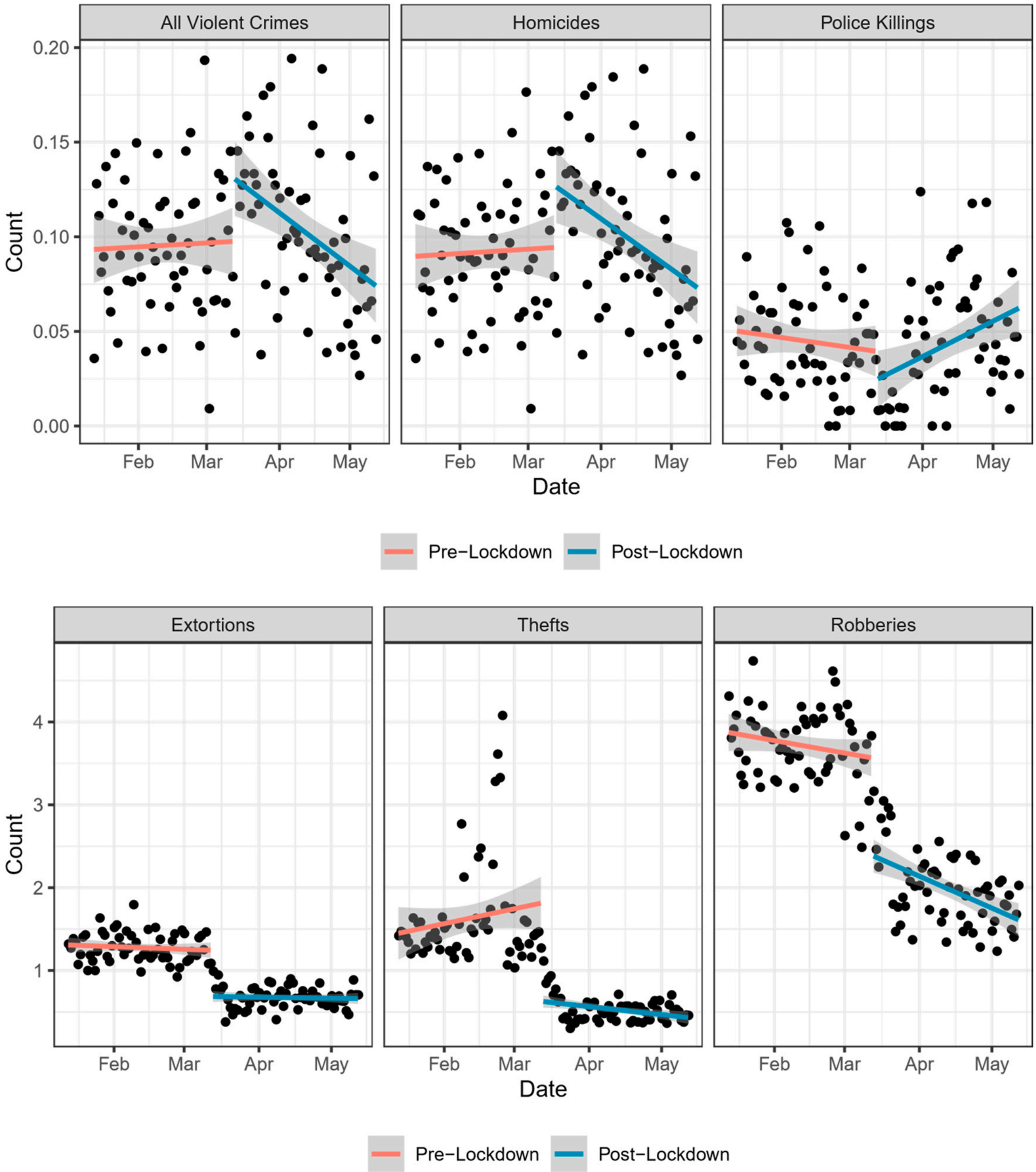


Fig. 4. Violent and property crimes after the stay-at-home restrictions. This figure represents the daily average per precinct for each type of crime reported by the Institute for Public Safety (ISP), starting on January 1, 2020. The top series of plots shows all violent crimes, homicides, and police killings, while the bottom panel shows extortions, thefts, and robberies. The lines are generated by an ordinarly least squares (OLS) regression without covariate adjustment on either side of the March 13, 2020 date. The plots are aggregated at the precinct-day average across the entire state to aid in visualization, but in the following analyses the unit of analysis is the police precinct-day, of which there are 137 observations for each day.

their cell phone will register a ping if they pass through an area they work, commute, run errands, etc. Some of these areas, such as a downtown bus station or central business district, may not have a high density of residences but may be risky areas for spreading COVID-19 due to the high level of activity in the area. The mobility data captures this trend, while residential population data does not. The limitations of this data is in its format: by measuring all daily mobility levels by daily percentile rank vis-a-vis the other hexes, rather than as a fixed value, it makes comparisons for each hex over time difficult. For this reason, we averaged mobility levels over several days to leverage the data and create this pre-lockdown benchmark for each police precinct.

Table 1
Effect of lockdown on crime and violence.

	Dependent variable:						
	Shootings	Violent Crimes *Lethal Violence*	*Homicides*	*Police Killings*	Property Crimes *Extortion*	*Theft*	*Robbery*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	30 Day Bandwidth						
Lockdown	-0.043	0.019	0.020	-0.025 **	-0.591 ***	-0.682 ***	-0.948 ***
	(0.031)	(0.018)	(0.017)	(0.011)	(0.057)	(0.082)	(0.115)
Source	Fogo	ISP	ISP	ISP	ISP	ISP	ISP
N	4453	6989	6989	6989	6989	6989	6989
R^2	0.226	0.094	0.088	0.080	0.300	0.243	0.646
	60 Day Bandwidth						
Lockdown	-0.010	0.024 *	0.023 *	-0.018 **	-0.614 ***	-1.305 ***	-1.457 ***
	(0.021)	(0.012)	(0.012)	(0.008)	(0.040)	(0.087)	(0.090)
Source	Fogo	ISP	ISP	ISP	ISP	ISP	ISP
N	8833	13,904	13,904	13,904	13,904	13,904	13,904
R^2	0.221	0.081	0.078	0.069	0.298	0.224	0.677

Note: All models estimate the effect of the stay-at-home restriction on daily precinct-level crimes from the Public Safety Institute (ISP) official crime statistics or Fogo Cruzado's shootings database. Models use either a 30- or 60-day bandwidth, a linear estimator, and control for police precinct and day of week. Clustered standard errors at the police precinct level are shown in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

4. Results

4.1. Effect of mobility restrictions on crime

Fig. 4 shows the our results graphically for six different types of crimes reported to the Public Safety Institute (ISP): the omnibus lethal violence variable, homicides, police killings, extortion, theft, and robberies. Each plot shows the daily registries for each type of crime across all police precincts in the state of Rio de Janeiro. The visual evidence for the crimes shown on the top panel (lethal violence, homicides, police killings) is not indicative of large changes following the stay-at-home order. Both lethal violence and homicides look like they may have increased slightly following mobility restrictions, though not at a level that is statistically distinguishable from random noise. Police killings, also appear to have fallen, especially in the days immediately following restrictions. Yet none of the violent crimes appear to have decreased at the magnitude or for the duration at which those in the bottom panel have decreased. The bottom panel subplots representing extortion, thefts, and robberies indicate a precipitous decline in property crimes committed following the March 13 restrictions.

Table 1 shows our core specification (Eq. (1)) in the top panel, regressing a variety of violent and non-violent crimes on the interrupted time series estimator *Lockdown*. Our preferred model is a linear estimator that uses a bandwidth of 30 days before and after the restrictions were announced (March 13), but we estimate models for a wider bandwidth at 60 days as well, shown in the bottom panel. Given that the observations are at the granular day-police precinct level, we prefer the narrower sample that just includes the days in the month before or after the restrictions began. Though there is no substantive difference between the estimates in the 30-day and 60-day models in Table 1, we prefer the 30-day bandwidth to eliminate doubt that changes in crime could be driven by something else.[9] All reported models include police precinct and day-of-week fixed effects. We also report quadratic and cubic specifications of the functional form for both the 30- and 60-day bandwidths in Appendix Tables A1 and A2, respectively.

The upper panel of Table 1 columns (1)–(3) shows that violent crime changes very little in the 30 days following COVID-19 restrictions. This is consistent with the lack of visual evidence in Fig. 4. Regardless of whether violent crimes were reported by the police (homicides and other lethal crimes included in the "lethal violence" variable) or were monitored independently (shootings are reported by CrossFire, independent of police), violent crime did not appear to change following quarantine restrictions. Models with the 60-day bandwidth reflect the lack of change in violent crime post-lockdown, although there is weak evidence that homicide and other lethal violence may have actually slightly increased in the 60 day bandwidth.

We take this as evidence supporting the view that violent conflict between criminal groups did not cease just because restrictions were put in place. It is possible that criminal groups continued defending their territories or using force against rivals, despite that stay-at-home order. Though there is no way to know from this data if reported homicide and lethal violence are perpetrated by criminal groups, it is widely known that Rio de Janeiro's criminal groups are the drivers of much of the city's lethal violence, whether they are fighting each other or fighting the police. For this reason, we are cautious about interpreting the coefficient as a causal estimate of criminal violence, but we interpret it as suggestive evidence that restrictions alone did not disrupt the dynamics of violence in a meaningful way.

[9] In the pre-period, Rio de Janeiro's summer, especially the Carnaval period, often registers higher rates of violent crime than the rest of the year. In the post-period, several other important political events happened (a police killing that mobilized the Brazilian version of *Black Lives Matter* protests, impeachment proceedings of the then-Governor of Rio de Janeiro that led to social unrest, etc.

Police killings, shown in column (4), did appear to decrease slightly following the quarantine restrictions. When considering just 30 days before and after the quarantine mandate began, our coefficient estimate of −0.025 for police killings translates into 3.4 fewer police killings per day in the entire state. The drop-off in police killings is especially acute around the cutoff point, which is visible in Fig. 4. This decrease dissipates when considering a 60-day bandwidth. Though still statistically significant and negative, the coefficient estimate for police killings of −0.018 translates to a decrease of 2.46 killings per day across the state.

There are a few possible explanations for why police killings decreased in Rio de Janeiro following mobility restrictions. First, police themselves were infected early and at a high rate with Covid-19: around 8–10% of the police force contracted Covid-19 early in March and each precinct was operating with limited human resources (ISTOE, 2020). Reports show that one in three police officers for the state of Rio de Janeiro had to be placed on sick leave at some point throughout 2020, and 65 officers died due to Covid-19 (G1, 2021). The shortage of police officers may have affected their ability to conduct police raids, which require a lot of manpower and are where most police killings occur (Magaloni et al., 2020; Andreoni et al., 2020). Second, police were required to perform different tasks that were pandemic-related, such as limiting entry to public spaces, conducting traffic stops, and monitoring occupancy at testing centers (ISTOE, 2020). The average officer may have spent less time doing crime control (where they are more likely to use force) and more time doing public safety and enforcement duties. Finally, if there were fewer people on the streets – including people committing acts of violence – then this may have lowered the likelihood that police would encounter someone and use force.[10]

Extortion, theft, and robbery all fell dramatically following the Covid-19 lockdown, as shown in columns (5)–(7). The coefficient estimates translate into a decrease of 80.3 reported incidents of extortion, 92.8 fewer reported thefts, and 128.9 fewer robberies across the entire state. The estimates from the 60-day model show that the second month of quarantine exacerbates these differences as extortion, theft, and robberies decrease even further. The coefficients for theft and robbery lose their significance when modeling with a quadratic specification (Table A.1) and robbery loses significance when modeling with a cubic specification (Table A.2). The decrease in registered extortion is robust to model specification or bandwidth.

One natural explanation for why extortion, theft, and robberies decreased so suddenly following COVID-19 restrictions is that fewer people were out in public and businesses were closed during this time. When people began staying home, it decreased opportunities for thieves and robbers to steal cell phones, cars, or other valuables when away from home, and increased the risk of breaking and entering a home because it was likely to be occupied. More complex robbery schemes – such as bank robberies or cargo robberies – could be more exposed to police, in banks where they were not controlling adherence to COVID-19 restrictions, or more visible, since there was less transit. Overall, there was a change in the opportunity structure for this type of criminal behavior. Similarly, criminal specialists in extortion may have had a harder time collecting extortion payments when non-essential businesses temporarily closed their doors or when people stopped using services. Journalists and other scholars noted these as potential reasons for why extortion and property crime decreased during the pandemic (Monteiro, 2020; Bruce et al., 2021). Finally, there is no reason to believe this decrease is due to changes in reporting by the population or processing capacity on behalf of police. While under reporting is an issue in all these categories, thefts and robberies can be reported online and police stations were kept open during lockdown. We expect changes in mobility to have no impact on incentives to report crimes.

4.2. Effect of lockdown on crime, by pre-pandemic mobility level

We break down our results for each type of crime by mobility level to analyze differences in high activity areas compared to low activity areas. For each police precinct, we use the pre-pandemic period (March 1–12) average mobility level for each precinct, shown in Fig. 3. This is to account for within-crime variation in responses to the mobility restrictions. For instance, it is possible that the most active of precincts (precincts that register the highest mobility levels pre-pandemic) locked down more severely – and therefore changed daily life in a more noticeable way – than less active precincts, altering the likelihood of different crimes being committed. In other words, we expect the change in mobility in a mostly non-essential commercial area to be different than in police precincts of a more residential or rural makeup. If we expect a relationship between mobility and the opportunity structure for violent and property crime, the impact of lockdown should vary between quintiles.

Table 2 breaks down the results for each type of crime by mobility quintile. The top panel shows the bottom 20% of precincts that registered the fewest number of out-of-home cell phone pings in the pre-period, or what we call the “least mobile" quintile. The bottom panel shows the top 20% of precincts that registered the highest density of out-of-home pings in the pre-period, what we call the “most mobile" quintile.

The results for violent crime are consistent with those found in Table 1, providing more supporting evidence that violent crime did not change following quarantine restrictions even when conditioning on previous mobility level of a precinct. Columns (1)–(3) show that shootings, all incidents of lethal violence, and homicides did not change following COVID-19 restrictions regardless of mobility quintile. Fig. 5 illustrates this graphically. Panel A of Fig. 5 shows that the change in shootings by quintile is indiscernible after lockdown for all precincts in the sample (The Fogo Cruzado database did not register any shootings for the precincts in the lowest mobility quintile). This panel provides visual evidence that the near-zero coefficient on shootings

[10] This explanation doesn't apply to police raids, where police seek out suspects to arrest and often execute them. Stray bullet victims are often victimized in their homes.

Table 2
Effect of lockdown on crime and violence, by mobility quintile.

	Dependent variable:						
	Shootings	Violent Crimes *Lethal Violence*	*Homicides*	*Police Killings*	Property Crimes *Extortion*	*Theft*	*Robbery*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Quintile 1: *Least Mobile*						
Lockdown	–	-0.004	-0.004	–	-0.449 ***	-0.070	-0.020
		(0.028)	(0.028)		(0.112)	(0.050)	(0.031)
	Quintile 2						
Lockdown	-0.006	0.037	0.041	-0.006	-0.549 ***	-0.475 ***	-0.348 ***
	(0.064)	(0.048)	(0.047)	(0.010)	(0.121)	(0.094)	(0.121)
	Quintile 3						
Lockdown	-0.049	0.010	0.011	0.001	-0.813 ***	-0.384 ***	-0.658 ***
	(0.034)	(0.034)	(0.034)	(0.012)	(0.128)	(0.101)	(0.169)
	Quintile 4						
Lockdown	-0.098	0.051	0.044	-0.062 *	-0.749 ***	-0.862 ***	-1.097 ***
	(0.065)	(0.043)	(0.043)	(0.036)	(0.151)	(0.171)	(0.273)
	Quintile 5: *Most Mobile*						
Lockdown	0.022	-0.022	-0.016	-0.041	-0.452 ***	-1.245 ***	-1.608 ***
	(0.056)	(0.036)	(0.036)	(0.034)	(0.121)	(0.289)	(0.362)
Source	Fogo	ISP	ISP	ISP	ISP	ISP	ISP
N	1565	1565	1565	1565	1565	1565	1565

Note: All models estimate the effect of the stay-at-home restriction on daily precinct-level crimes from the Public Safety Institute (ISP) official crime statistics or Fogo Cruzado's shootings database. Each panel estimates linear models for all six crimes reported (or shootings) within that mobility quintile using the 30-day bandwidth. In Panel 1, there is no coefficient estimate for shootings or police killings because there were zero in both the pre- and post-lockdown period. Clustered standard errors at the police precinct level are shown in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

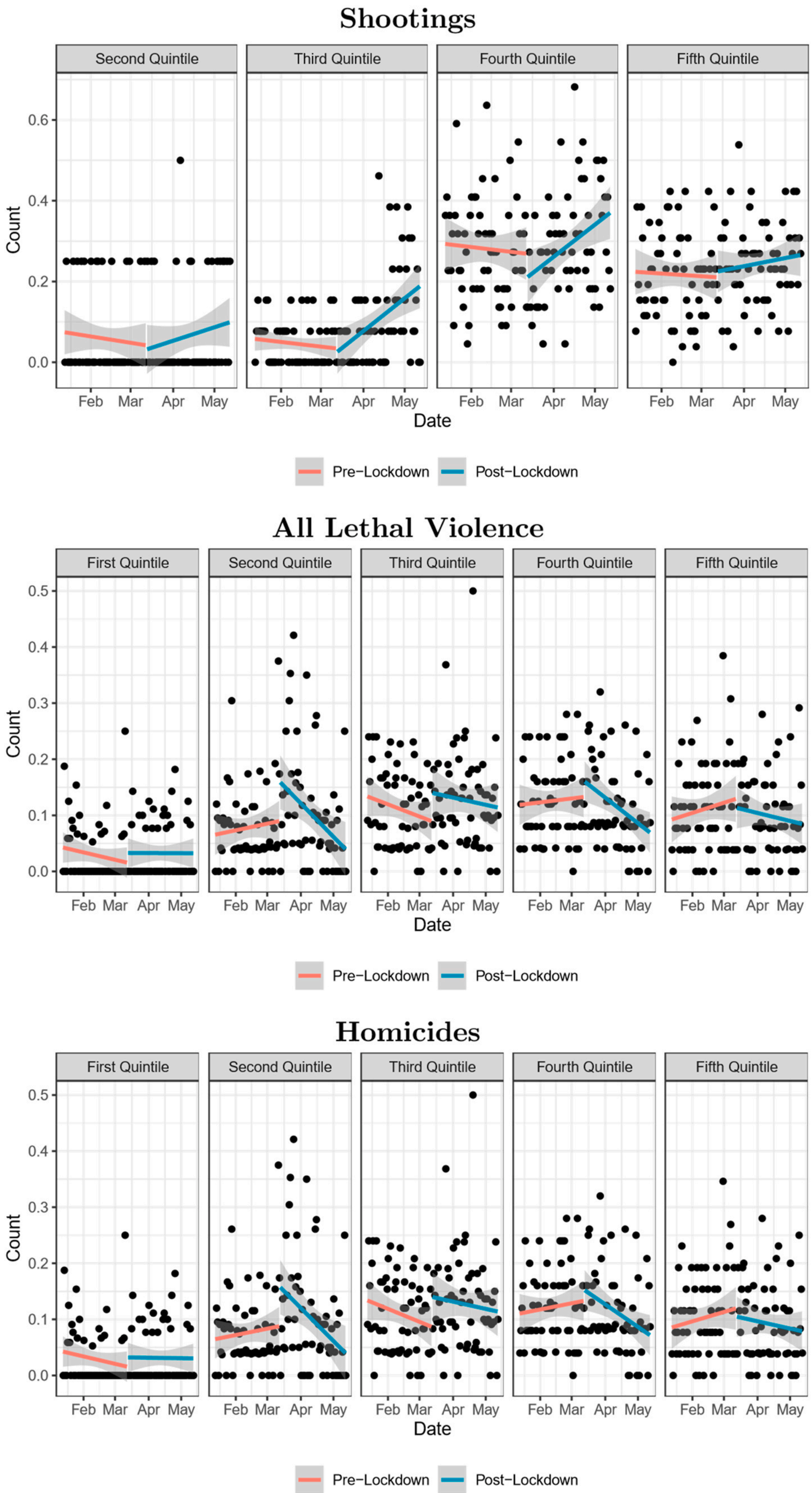
from Table 2 applies across mobility levels and isn't driven solely by one particular type of precinct. Panels B and C show that the null effect on lethal violence and homicides is not driven by one particular type of precinct.

The (lack of) change across quintiles from the pre-pandemic period to post-lockdown period is constant, even though lethal violence and homicides are slightly more frequent in the more mobile quintiles. Together, all three panels in Fig. 5 show that COVID-19 restrictions and their impact on mobility – even in densely populated areas where the pandemic posed a greater threat – did not change the incidence of violent crime. This can be interpreted as strong evidence that changes to mobility did not alter the incentive or opportunity structure for violence.

In Column (4) of Table 2, we show our results for police killings by mobility quintile. These results add nuance to the findings from Table 1, which suggested that police killings decreased slightly following COVID-19 restrictions. Though many of the coefficients are also negative in Column (3), the only one that is statistically significant (and only at the $p < 0.1$ level) is that for the police precincts in the 60–80% range of pre-pandemic mobility. According to Fig. 3, many of these precincts are not in the capital, but are in the suburbs or surrounding cities in the capital. Fig. 6 shows that there is little to no change in police killings after mobility restrictions in the bottom three quintiles (where police killings are rare in the first place), and the decreases in police killings in the more mobile fourth and fifth quintiles appear modest and temporary. These results suggest that police killings slightly decreased following the implementation of COVID-19 restrictions, but that these decreases were more noticeable in the suburbs of the capital city.

Column (5) shows results for extortion and shows marked decreases in extortion rates across all mobility quintiles. The coefficients range from a low of −0.449 to a high of −0.813, but all are highly statistically significant and visually noticeable in Fig. 7. These results are similar in magnitude to the coefficients from Table 1, which indicates that the decrease in extortion was of a similar magnitude across mobility quintiles. Even though extortion levels are lower in the least mobile quintile, they showed an expressive decrease after restrictions, indicating that extortion decreased even in areas with lower population density and lower out-of-home foot traffic. We believe this may be due to the commercial closings put in place with the restrictions, making it more difficult for extortionists to demand rents from establishments that were temporarily closed. The constant relationship across all quintiles indicates that relationship between extorted and the extorters does not depend on mobility.

We then turn to the property crimes of theft and robbery, shown in Columns (6) and (7). There are two clear observations from the regression coefficients by quintile in Table 2. First, the post-lockdown decrease in incidence of crime grows in magnitude as the quintiles move from least active to most. In the least mobile quintile, the coefficient for both theft and robbery is small and statistically insignificant. It is negative and significant for the 20–40% quintile, and increases in magnitude for each subsequent quintile of activity level. Second, this is partially due to variation in pre-pandemic levels of theft and robbery in each quintile. The higher mobility, more densely populated areas had higher baseline levels of theft and robbery to begin with, as shown in Fig. 8. These two observations suggest that higher mobility areas were greater hotspots of theft and robbery before COVID-19 restrictions, but that other, less mobile areas experienced significant decreases in theft or robbery relative to baseline levels. For example, theft and robbery decreased by an average of 32% and 19% in the fifth quintile, respectively, while they decreased by a larger 36% and 21% in the fourth or 37% and 38% in the third quintiles, respectively. The view that mobility



(caption on next page)

Fig. 5. Violent crimes after the stay-at-home restrictions, by mobility quintile. Note: Each data point and curve shown in this figure is as described in Fig. 4. Each quintile is a subset of the entire dataset corresponding to pre-lockdown mobility level. In the top panel, there were no shootings registered in the Fogo Cruzado database before of after lockdown in the lowest mobility quintile precincts, therefore, only four plots are shown.

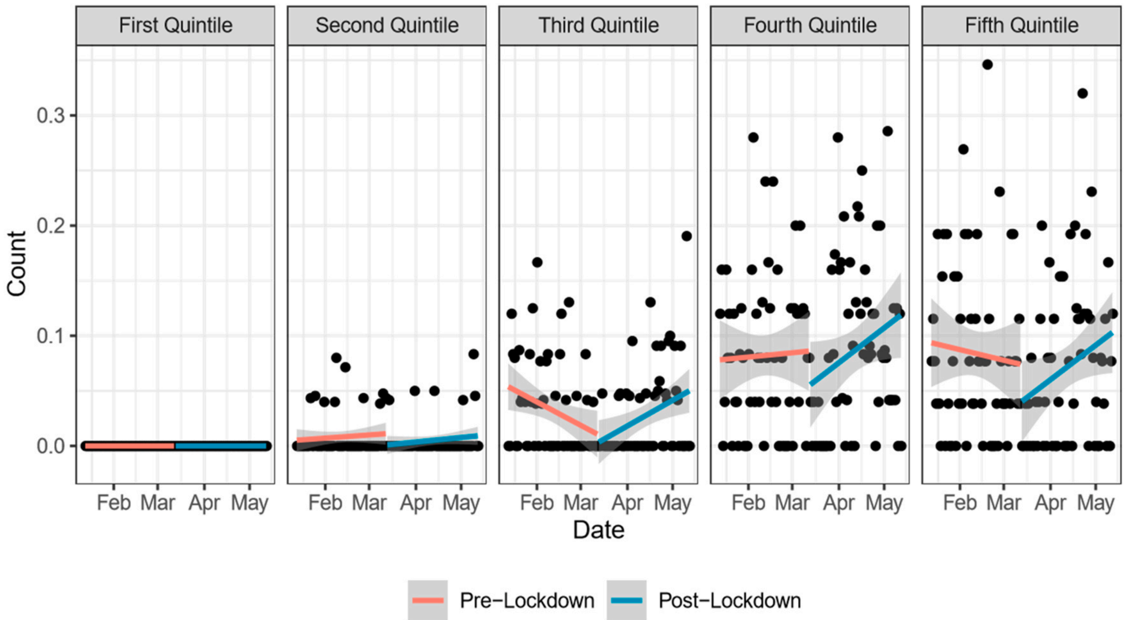


Fig. 6. Police killings after the stay-at-home restrictions, by mobility quintile. Note: Each data point and curve shown in this figure is as described in Fig. 4. Each quintile is a subset of the entire dataset corresponding to pre-lockdown mobility level. The leftmost panel indicates that there were no police killings in any of the precincts in the lowest mobility quintile.

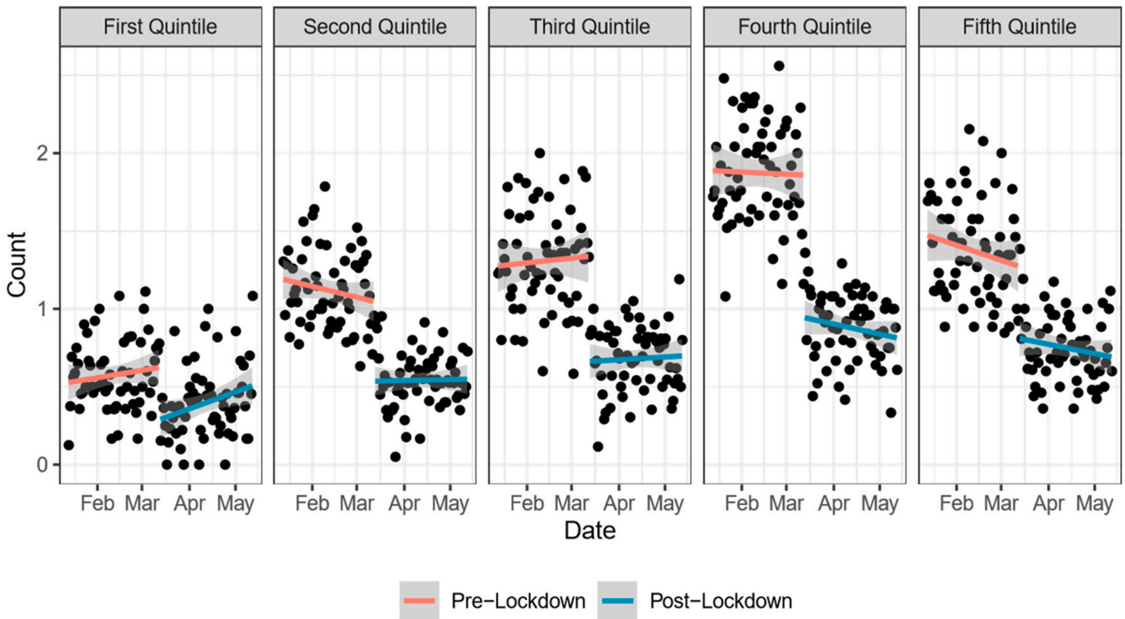


Fig. 7. Extortion after the stay-at-home restrictions, by mobility quintile. Note: Each data point and curve shown in this figure is as described in Fig. 4. Each quintile is a subset of the entire dataset corresponding to pre-lockdown mobility level.

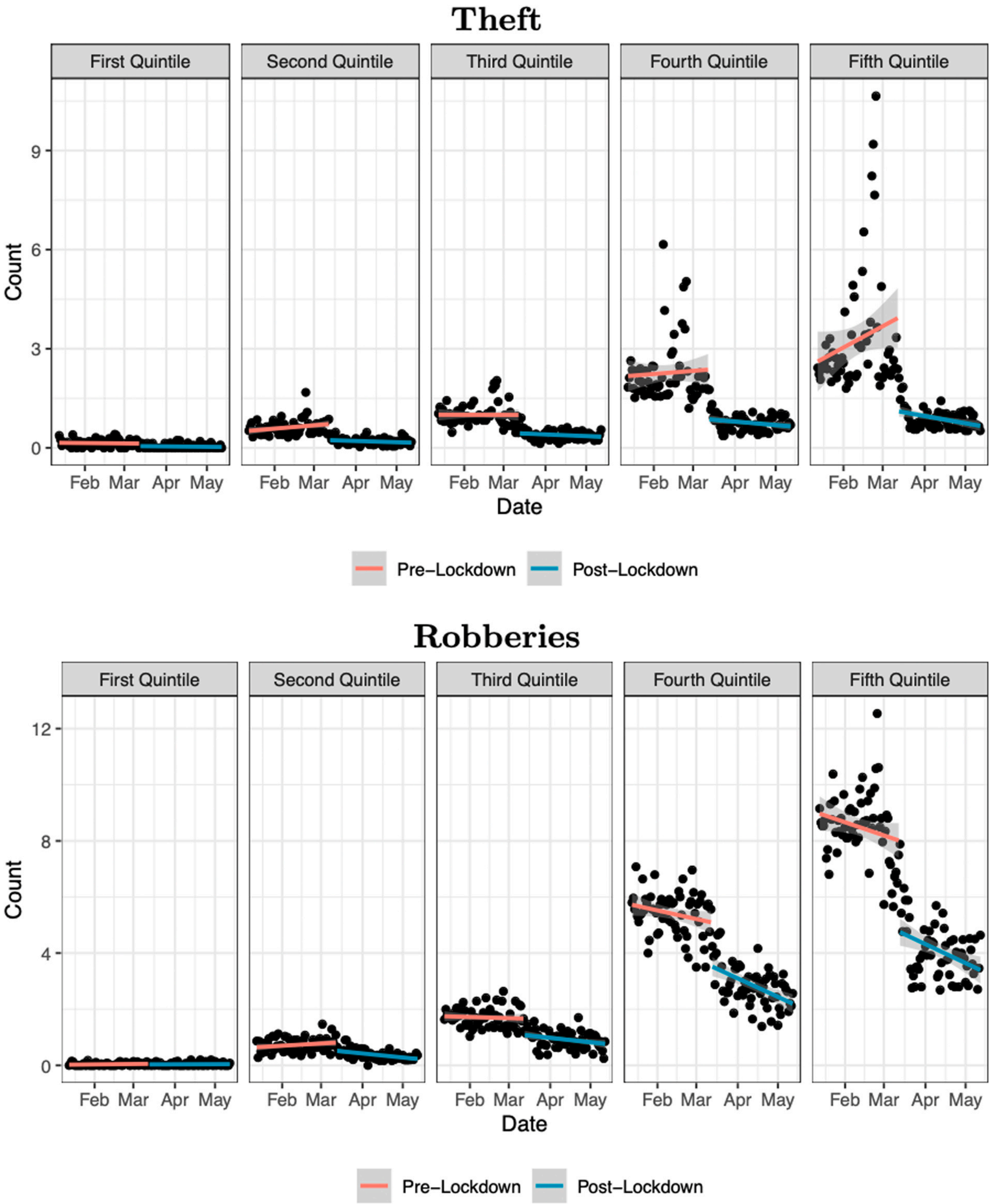


Fig. 8. Property crimes after the stay-at-home restrictions, by mobility quintile. Note: Each data point and curve shown in this figure is as described in Fig. 4. Each quintile is a subset of the entire dataset corresponding to pre-lockdown mobility level.

restrictions had a significant impact on theft and robberies across mobility levels (except for areas with lowest baseline activity levels) is tenable, given these results. This indicates that mobility has a big impact on the incentive structure for property crime, as documented in criminology literature on trajectories of crime (Weisburd et al., 2004; Bernasco and Block, 2009).

Table 3
Effect of lockdown on crime and violence.

	Dependent variable:						
	Shootings	Violent Crimes			Property Crimes		
		Lethal Violence	*Homicides*	*Police Killings*	*Extortion*	*Theft*	*Robbery*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta Mobility$	0.002	-0.001	-0.001	0.0005	0.0002	0.002	0.010 ***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Source	Fogo	ISP	ISP	ISP	ISP	ISP	ISP
N	3965	8277	8277	8277	8277	8277	8277

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

To summarize, in Tables 1 and 2, COVID-19 restrictions appear to be reliably correlated with decreases in extortion, theft, and robberies. The effect of the stay-at-home order on extortion is not sensitive to the pre-pandemic activity level in a precinct, and decreases across all precinct types. Decreases in theft and robbery are largest in higher-activity precincts. When breaking down by activity level, we see that the decreases in theft and robbery post-lockdown are large in magnitude for all types of precincts except those with the lowest activity levels. Violent crimes, however, do not appear to have reacted to the stay-at-home order as strongly as nonviolent crimes. Across model specifications, bandwidths, and subsets by mobility level, we find no evidence that shootings, lethal violence, or homicides changed following the implementation of quarantine measures. There is slight evidence that police killings decreased, especially in the days immediately following restrictions, but these decreases dissipate over time. When looking at the effect of these measures on police killings by mobility quintile, the relationship is weak or non-existent, especially in the densely populated capital city where most of the police killings happen.

4.3. Relationship between changes in mobility and crime

We now turn to our panel results looking at how changes in mobility over time were related to changes in crime. We estimate Eq. (2) in Table 3, restricting our sample to just looking at within-precinct variation in mobility and crime once COVID-19 restrictions were put in place. The sample shown in this table begins on March 13, when the stay-at-home mandate was issued, and ends 60 days after.[11] The coefficient β_1 for the change in mobility is reported for precinct-level shootings, as well as the violent crimes and property crimes.

The way day-to-day mobility is calculated in our data is a relative measure, changes in Δ*Mobility* do not just indicate changes in mobility, they indicate changes in mobility relative to the surrounding precincts. For example, if a high traffic area that ranks in the 95th percentile of activity in the days prior to the stay-at-home restrictions and dramatically reduces their mobility following the lockdown order but at the same rate as all other areas, it is possible the area would still rank in the 95th percentile, even though their mobility fell.

A change in relative mobility across time can measure of how responsive the incentive structure of a precinct is to such change and how mobile the opportunity for crime – be it by changes to the trajectory of victims or of the perpetrator. In other words, when it comes to mobility changes, we can expect some crimes to be more “sticky" than others. There are no significant results for most reported crimes. Thus we may infer that violent crime and extortion are stickier in relation to territory in face of changes in mobility.

The only noticeable relationship between a day-to-day change in mobility and crime is for robberies. An increase in a precinct’s daily average mobility level by one percentile rank from the previous day corresponds to 0.01 more robberies. We interpret this as evidence that higher trafficked areas facilitate robberies. Robbers and thieves have fewer targets when people are not on the streets, or conversely, are under closer scrutiny when people are in their homes or businesses that are target locations. This effect is most notable when mobility increases from one day to the next, bringing people onto the streets and lowering the bar for a robber to commit a crime.

Yet we would expect a similar effect to appear for theft, which we do not see in the data. The main difference between the two categories is that a robbery involves the use of violence. A closer analysis of the data could reveal if there is a relationship between the level of violence employed in the robbery – the use of a handgun, for example, is a possible indicator of link to an organized criminal group – and the stickyness of such crime. It may be the case that robberies that involve lower levels of violence present the same relationship to relative changes in mobility as thefts. This merits further investigation.

[11] We also extend the sample to the earliest date available before the stay-at-home mandate (March 1) and subset the sample even further to just 30 days after the mandate. In either case, coefficients do not change in sign or substantive interpretation.

5. Conclusion

In this paper, we used daily variation in mobility and crime to estimate how stay-at-home mandates and subsequent changes in mobility affected crime. Our estimates focus on the state of Rio de Janeiro, which not only is a high-crime state in Brazil, but is so because of the presence of multiple contesting criminal organizations.

We suggest that the presence of criminal organizations is why we saw the large decrease in extortion and property-related crimes that are predicated on people being out of home or at work, yet observed no effect on violent crimes. Our estimates show that extortion, theft, and robbery decreased sharply following mobility restriction orders, ranging from 41.6% to 69.4% decreases, yet violent crimes did not change and police killings only slightly fell, though that effect was temporary. The decreases in extortion were nearly uniform across mobility levels, while the decreases in theft and robberies were more elastic to changes in mobility. Only robberies appeared sensitive to day-over-day changes in mobility during the lockdown, increasing slightly when a day's mobility was higher than the prior.

These results tell a consistent story. Our findings suggest that the impact of mobility restrictions affected the number of people on the street during commercial hours, the number of businesses open, and subsequently, the opportunities to rob, steal, or extort for potential criminals. The way that potential victims of theft, robbery, or extortion move about the world was restricted with the stay-at-home orders, and, therefore, these crimes decreased. Shootings, homicide, other lethal violence, and police killings, however, are less random and are usually not predicated on the availability of extortion or theft targets or people being "in the streets." We show that this is particularly salient in the case of robberies, which are sensitive to day-over-day relative change during the lockdown. With no evidence that violent crime is as sensitive to mobility and the availability of potential targets, we have no reason to suggest that COVID-19 restrictions would have a large, negative impact on violent crime rates.

These results could indicate that lethal violence is more latent to territorial and spatial dynamics of organized criminal groups rather than to overall mobility levels in the population. Yet we would need further testing in order to confirm this hypothesis. While current data reported by ISP nor Fogo Cruzado report gang or *militia* involvement, a possible test of this theory is to compare the impact of COVID-19 restrictions on different types of crime across hexes under the control of different groups. Indeed, we could expect violent confrontations to decrease if the pandemic triggered a ceasefire between the state's criminal groups or slowed the rate of turf wars, but anecdotal and journalistic evidence indicates that neither of these occurred. Such findings will advance our understanding of how the presence of criminal groups changes the baseline level of violence in territory, distinguishing them from other urban criminal dynamics.

Conflict of interest statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Acknowledgments

We thank the UNDP Policy Response Research Team and GRANDATA for providing access to the mobility data and for their inclusion in the "Exploring the impact of COVID-19 and the policy response in LAC through mobility data" project. We thank the Harvard Political Economy of Development workshop for helpful comments. All errors are our own.

Appendix A

A.1. Mobility data

Using cellphone data to measure mobility, especially amidst Covid-19 restrictions, has grown increasingly common. We leverage a novel dataset, GRANDATA, that uses extremely disaggregated mobility data at the hexagon level, the smallest of which is less than one square kilometer. To validate the GRANDATA measure, we compare it to one of the more well-known datasets in Brazil that measures mobility at the municipality level. The comparison dataset, *In Loco*, uses a similar measurement tactic to GRANDATA, based off of cell phone location pings. It also used pre-pandemic mobility data to estimate the home base of each cellphone and from there calculated whenever the device left such area.

There are two important features that distinguish GRANDATA from the *In Loco* data. First, the dataset begins on February 1st for *In Loco*, and only on March 1st for GRANDATA. Second, *In Loco* measures the level of "isolation", not a change in mobility.In the GRANDATA dataset, a positive value indicates an increase in mobility relative to the reference date (March 1st) and a negative value a decrease in mobility. The opposite is true for the *In Loco* data: a positive value indicates increases in isolation, and vice versa. We inverted the *In Loco* index in Fig. A.1 to allow for easier comparison, using GRANDATA's reported change in mobility level at the municipality-level and comparing that with *In Loco*'s municipality-level social isolation index. The direct comparison shows that GRANDATA is more sensitive to increases in mobility in the city of Rio de Janeiro, both in the pre-pandemic weeks and post-lockdown measures that lasted for months. Yet the overall trends during the critical lockdown period, are quite similar, giving us confidence that the GRANDATA dataset is capturing underlying changes in mobility. The difference between the two measures is related to how cellphone signals are interpreted.

The limitations of using such datasets are well-known. First, they are aggregated indexes and the actual number of observations is unknown for each hex-day. The commercial nature of data-collection also means researchers are unable to ascertain the continuity of methodology, since improvement rollouts are not necessarily reported. Additionally, each dataset has their own limitation. In spite of these, there is no reason to believe in systematic bias in data collection when comparing cities in Rio de Janeiro, where cellphone coverage and usage is more uniform among the population. In fact, the two datasets are closely correlated. We were not able to access the sub-municipal level data from *In Loco* in order to run our analysis on this dataset.

A.2. Tables

See Table A.1.
See Table A.2.

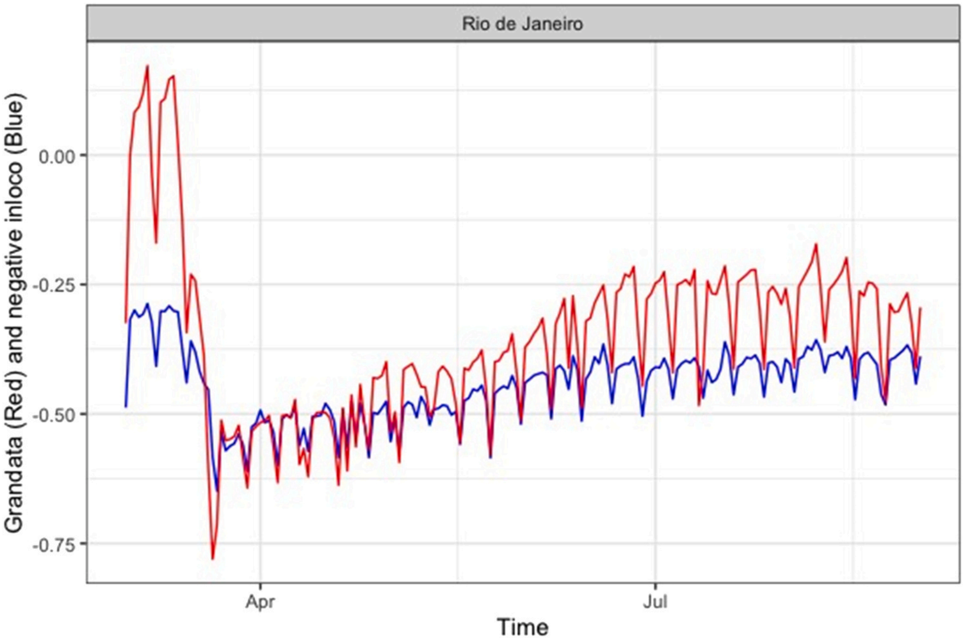


Fig. A.1. Comparison of GRANDATA and *In Loco* mobility data in Rio de Janeiro. Note: This figure plots the mobility level for the city of Rio de Janeiro vis-a-vis the March 1 in the GRANDATA and city-level *In Loco* datasets. A value of 0 implies that citywide out-of-home mobility was the same as March 1 (GRANDATA) or February 1(*In Loco*); a negative value means that out-of-home mobility was lower than the reference date, a positive value means that it was higher. The stay-at-home lockdown order coincides with the large increase in late mid to late March.

Table A.1
Effect of lockdown on crime and violence: quadratic specification.

	Dependent variable:						
	Shootings	Violent Crimes			Property Crimes		
		Lethal Violence	*Homicides*	*Police Killings*	*Extortion*	*Theft*	*Robbery*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	30 Day Bandwidth						
Lockdown	-0.152 ***	0.003	0.003	-0.062 ***	-0.471 ***	0.106	-0.160
	(0.048)	(0.026)	(0.026)	(0.017)	(0.088)	(0.158)	(0.186)
Source	Fogo	ISP	ISP	ISP	ISP	ISP	ISP
N	4453	6989	6989	6989	6989	6989	6989
R^2	0.227	0.093	0.088	0.08	0.297	0.24	0.646
	60 Day Bandwidth						
Lockdown	-0.060 *	0.018	0.018	-0.037 ***	-0.535 ***	-0.730 ***	-0.916 ***
	(0.033)	(0.019)	(0.018)	(0.012)	(0.061)	(0.083)	(0.121)
Source	Fogo	ISP	ISP	ISP	ISP	ISP	ISP
N	8833	13,904	13,904	13,904	13,904	13,904	13,904
R^2	0.222	0.081	0.078	0.07	0.298	0.226	0.678

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Table A.2
Effect of lockdown on crime and violence – cubic specification.

	Dependent variable:						
	Shootings	Violent Crimes			Property Crimes		
		Lethal Violence	*Homicides*	*Police Killings*	*Extortion*	*Theft*	*Robbery*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	30 Day Bandwidth						
Lockdown	-0.075	-0.031	-0.036	-0.022	-0.320 ***	-0.666 ***	0.154
	(0.065)	(0.034)	(0.033)	(0.020)	(0.115)	(0.183)	(0.250)
Source	Fogo	ISP	ISP	ISP	ISP	ISP	ISP
N	4453	6989	6989	6989	6989	6989	6989
R^2	0.228	0.094	0.088	0.081	0.299	0.244	0.647
	60 Day Bandwidth						
Lockdown	-0.098 **	-0.001	-0.001	-0.043 ***	-0.506 ***	0.094	-0.284 *
	(0.045)	(0.024)	(0.024)	(0.015)	(0.081)	(0.119)	(0.165)
Source	Fogo	ISP	ISP	ISP	ISP	ISP	ISP
N	8833	13,904	13,904	13,904	13,904	13,904	13,904
R^2	0.222	0.081	0.078	0.07	0.298	0.229	0.679

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

References

Andreoni, M., Londoño, E., Galdieri, D., 2020. Licença para matar': por trás do ano recorde de homicídios cometidos pela polícia no Rio.The New York Times.
Ashby, M.P.J., 2020. Initial evidence on the relationship between the coronavirus pandemic and crime in the United States. Crime Sci. 9, 6.
Bernasco, W., Block, R., 2009. Where offenders choose to attack: a discrete choice model of robberies in Chicago. Criminology 47, 93–130.
Bruce, R., Cavgias, A., Meloni, L., 2021. Policy Enforcement in the Presence of Organized Crime: Evidence from Rio de Janeiro. SSRN Scholarly Paper ID 3678840. Social Science Research Network.
Bullinger, L.R., Carr, J.B., Packham, A., 2021. COVID-19 and crime: effects of stay-at-home orders on domestic violence. Am. J. Health Econ.
Bullock, J., 2022. Limiting Aggressive Policing Tactics Can Reduce Police and Civilian Violence.
Campedelli, G.M., Aziani, A., Favarin, S., 2020. Exploring the Effects of COVID-19 Containment Policies on Crime: An Empirical Analysis of the Short-term Aftermath in Los Angeles. Preprint. Open Science Framework.
Carr, J.B., Packham, A., 2020. SNAP schedules and domestic violence. J. Policy Anal. Manag. ⟨https://onlinelibrary.wiley.com/doi/pdf/10.1002/pam.22235⟩.
Cerqueira, D., Bueno, S., Alves, P.P., de Lima, R.S., 2020. Atlas de Violência. Technical Report. Instituto de Pesquisa Econômica Aplicada.
Dalby, C., 2020. Six Ways Coronavirus is Impacting Organized Crime in the Americas. Section: Analysis.
Estévez-Soto, P.R., 2020. Crime and COVID-19: Effect of Changes in Routine Activities in Mexico City. Technical Report. SocArXiv.
G1, 2021. Monitor da Violência: RJ é o estado com mais policiais mortos pela Covid no país c Rio de Janeiro c G1. G1.
GloboNews, 2020. Mesmo com quarentena, Brasil tem alta de 6% no número de assassinatos no 1 semestre.
Guerette, R.T., Bowers, K.J., 2009. Assessing the extent of crime displacement and diffusion of benefits: a review of situational crime prevention evaluations. Criminology 47, 1331–1368.
Halford, E., Dixon, A., Farrell, G., Malleson, N., Tilley, N., 2020. Crime and coronavirus: social distancing, lockdown, and the mobility elasticity of crime. Crime Sci. 9, 11.
Hausman, C., Rapson, D.S., 2018. Regression discontinuity in time: considerations for empirical applications. Annu. Rev. Resour. Econ. 533–552.
ISTÓE, 2020. Covid-19 já matou pelo menos oito policiais no Rio – ISTOÉ Independente.
Jassal, N., 2020. Gender, law enforcement, and access to justice: evidence from all-women police stations in India. Am. Polit. Sci. Rev. 1035–1054.
Magaloni, B., Franco-Vivanco, E., Melo, V., 2020. Killing in the slums: social order, criminal governance, and police violence in Rio de Janeiro. Am. Polit. Sci. Rev. 552–572.
McDermott, J., Dudley, S., 2020. GameChangers 2020: Predictions for 2021 – Shaking Off the Virus. Section: Analysis.
Monteiro, J., 2020. O Comportamento dos Indicadores de Segurança Pública durante a Pandemia de Covid-19 no Rio de Janeiro. Working Paper. Ministério Público. Rio de Janeiro.
Mummolo, J., 2017. Modern police tactics, police-citizen interactions, and the prospects for reform. J. Politics 1–15.
News, B., 2020. Rio Violence: Police Killings Reach Record High in 2019 – BBC News.
Ouss, A., 2020. Misaligned incentives and the scale of incarceration in the United States. J. Public Econ. 191, 104285.
Perguntas Frequentes, 2019.
Rolim, L., 2020. Segurança Pública em Números 2020. Technical Report. Instituto de Segurança Pública. Rio de Janeiro, Brazil.
St. Clair, T., Cook, T.D., Hallberg, K., 2014. Examining the internal validity and statistical precision of the comparative interrupted time series design by comparison with a randomized experiment. Am. J. Eval. 311–327.
Tita, G., Griffiths, E., 2005. Traveling to violence: the case for a mobility-based spatial typology of homicide. J. Res. Crime Delinquency 42, 275–308.
Weisburd, D., Bushway, S., Lum, C., Yang, S.M., 2004. Trajectories of crime at plces: a longitudinal study of street segments in the city of Seattle. Criminology 42, 283–322.
Zoorob, M., 2020. Do police brutality stories reduce 911 calls? Reassessing an important criminological finding. Am. Sociol. Rev. 176–183.