The Harmful Effects of Denial: When Political Polarization meets COVID-19 Social Distancing

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This work uses anonymized geolocation data from 60 million mobile phone users in Brazil to quantify the impact of coronavirus lockdown measures on social distancing. The results confirm that the current share of the population staying home is lower than the target set by the public authorities to combat the spread of COVID-19. Using difference-in-difference and panel data regression to evaluate the determinants of social distancing, this paper confirms a statistically significant association between political support for Bolsonaro and social distancing. Since the Brazilian president is urging the population to ignore the COVID-19 "hysteria" and get back to a normal routine, the impact of social distancing rules on the circulation of people is lower at a statistically significant level in municipalities with a higher share of Bolsonaro voters.

Keywords: COVID-19, social distancing, behavioral change, geolocation data, Brazil

Este trabajo utiliza datos anonimizados de geolocalización de 60 millones de usuarios de teléfonos móviles en Brasil para cuantificar el impacto de las medidas estatales de confinamiento (*lockdown*) por el coronavirus en el distanciamiento social. Los resultados confirman que la proporción actual de la población que permanece en el hogar es inferior al objetivo fijado por las autoridades públicas para combatir la propagación del COVID-19. Utilizando los métodos de diferencia-en-diferencia y de regresión de los datos de panel para evaluar los determinantes del distanciamiento social, este estudio confirma una asociación estadísticamente significativa entre el apoyo político a Bolsonaro y el distanciamiento social. Dado que el presidente brasileño está instando a la población a ignorar la "histeria" alrededor del COVID-19 y a volver a la rutina normal, el impacto de las reglas de distanciamiento social en la circulación de las personas es menor y estadísticamente significativo en los municipios con una mayor proporción de votantes por Bolsonaro.

Palabras clave: COVID-19, distanciamiento social, cambio de comportamiento, datos de geolocalización, Brasil

Introduction and Literature Review

Since the initial outbreak of COVID-19 in Wuhan, China, the coronavirus has spread rapidly across the world, with the World Health Organization (WHO) declaring the disease a global pandemic on March 11, 2020 (Cucinotta and Vanelli 2020). In the absence of any vaccine to protect against COVID-19, the WHO has recommended the implementation of nonpharmaceutical interventions (NPIs) to slow the spread of infection and reduce the intensity of the epidemic, thus reducing the risk of overwhelming health systems (Singh and Adhikari 2020; Kissler et al. 2020). Among the diverse forms of NPIs, mathematical modeling of transmission has indicated that social distancing practiced by the population as a whole is the most effective way to combat the spread of the coronavirus (see, e.g., Koo et al. 2020; Ferguson et al. 2020).

For this reason, public officials around the world are urging the people to stay home and maintain a minimum social distance from one another of approximately two meters. In many countries, governments have implemented strict lockdown policies in response to the COVID-19 outbreak. Interventions such as shutting down schools, facilitating working from home and canceling large events have become common and are communicated as temporary, but necessary, measures to "flatten the curve" (Ioannidis 2020). However, the impact of these social distancing measures depends critically on how people respond to their introduction, which is highly likely to vary across time, from country to country, and even from community to community (Briscese et al. 2020).

Although stay-at-home orders become a part of everyday life around the world, very little is known about the effectiveness of these measures in Latin America, given the methodological difficulties in quantifying precisely the circulation of the population outside their residences. However, a key metric for the success of the curve-flattening strategies is continuous monitoring. Having real-time insight into the flow of people may yield useful information for the local authorities to manage their social distancing interventions.

Therefore, many technology companies (Google, Apple, and Facebook) have applied the geolocation data from their users to produce information on mobility and economic trends during the coronavirus pandemic (Ghader et al. 2020). Consequently, mobile device data became popular for empirical investigations of human behavior during the lockdown measures. Karim and Chan (2020), for example, use the Facebook mobility data, which tracks the location of the users with the mobile version of the application, to estimate the effect of political party affiliation of municipal mayors on regional movement of people in Brazil. To investigate the risk attitudes and human mobility in the US, Chan et al. (2020) apply mobility measures on country and regional levels from the Google Community Mobility Reports, which record the visits and lengths of stay of Google users in six different categories of places (e.g., grocery stores, parks, train stations). Meanwhile, Hadjidemetriou et al. (2020) apply the Apple Mobility Trends Reports containing real-time data on driving, walking, and transit use to investigate the impact of government control measures on human mobility reduction in the UK.

Since the mobility data provided by these technology companies focuses the mobility measures on specific categories of locations (e.g., transit stations and grocery stores in the Google Community Mobility Reports) or different types of activities (e.g., driving and walking in the Apple Mobility Trends Reports), and are limited to the users of the respective companies, researchers have begun to utilize geospatial information from data companies for the analysis of social distancing (Delen et al. 2020). Companies such as SafeGrap, Unacast and VenPath in the US and In Loco in Brazil manage anonymized geolocation data of users of mobile application services and have made their datasets freely available to researchers during the coronavirus pandemic, creating the fundamental cornerstone for a whole range of studies concerning social distancing (see, for the US, e.g., Brzezinski et al. 2020; Chiou and Tucker 2020; Coven and Gupta 2020; Farboodi, Jarosch, and Shimer 2020; Painter and Qiu 2020; Villas-Boas, Sears, and Villas-Boas 2020; and for Brazil, e.g., Ajzenman, Cavalcanti, and Da Mata 2020; Fernandes et al. 2020; Mariani, Gagete-Miranda, and Retti 2020; Peixoto et al. 2020).

In line with this trend, this paper applies anonymized mobile phone data from approximately 60 million users in Brazil to identify the main driving forces behind social distancing and is broadly divided into two parts: the first presents the results of social distancing since the introduction of lockdown rules, while the second investigates whether the chances people will stay home are associated with the political orientation of the area in which they live.

This research is motivated by the contradictory policy responses to the COVID-19 pandemic in Brazil. While public authorities from subnational governments have urged the people to stay home and applied social distancing measures for the wider population, President Jair Bolsonaro has repeatedly attacked these restrictions and advocated for the immediate return to previous daily routines to mitigate the inevitable economic impact of the lockdown. The main hypothesis of this work is that municipalities with a higher proportion of Bolsonaro supporters perform less physical distancing because the president's supporters are following his recommendations that undermine social distancing guidelines.

Therefore, this paper enters the broader discussion about the role of political attitudes in determining physical distancing responses. Recent investigations carried out during the corona crisis have demonstrated that this association does matter. Using GPS data from smartphone users, several studies indicate a lower social distancing effectiveness in US regions with higher Republican vote shares (see, e.g., Allcott et al. 2020; Gadarian, Goodman, and Pepinsky 2020; Grossman et al. 2020; Painter and Qiu 2020). Similarly, Cornelson and Miloucheva (2020) demonstrate using an MTurk survey that the willingness to comply with social distancing measures is lower in more polarized US states. The influence of political attitudes on social distancing behavior has also been examined for Brazil (see, e.g., Ajzenman, Cavalcanti, and Da Mata 2020; Calvo and Ventura 2020; Fernandes et al. 2020; Karim and Chan 2020; Mariani, Gagete-Miranda, and Retti 2020).

The empirical analyses of Ajzenman, Cavalcanti, and Da Mata (2020), Karim and Chan (2020), Fernandes et al. (2020), and Mariani, Gagete-Miranda, and Retti (2020) are excellent companions to this paper. Karim and Chan (2020) applied the Facebook mobility data to estimate the effect of political party affiliation of municipal mayors on social distancing of the population. According to the

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authors, the residents of Bolsonaro-affiliated municipalities had a 60-percent smaller reduction in regional movement than the residents of the control municipalities. As I do in this paper, Ajzenman, Cavalcanti, and Da Mata (2020), Fernandes et al. (2020) and Mariani, Gagete-Miranda, and Retti (2020) combined the electoral results of Bolsonaro in 2018 with the In Loco geolocalized mobile phone data. While Ajzenman, Cavalcanti, and Da Mata (2020) and Mariani, Gagete-Miranda, and Retti (2020) found that social distancing decreased after Bolsonaro's public statements against social isolation policies in those municipalities where he received the majority of votes in the 2018 election, the results of Fernandes et al. (2020) indicate that the higher the proportion of votes for Bolsonaro in any given municipality in 2018, the higher the number of COVID-19 deaths there, corresponding to higher transmission rates caused by a lower rate of effective social isolation.

Compared with the studies mentioned above, this paper presents some methodological differences: First, I focus the empirical investigation on physical distancing during the pandemic, applying the Social Distancing Index (SDI) based on geolocalized mobile phone data as a dependent variable in the empirical analysis, and not as an instrumental variable to investigate the COVID-19 outputs—measured in terms of the number of deaths, confirmed cases, and mortality rate—as in Fernandes et al. (2020). Second, this paper seeks to develop a novel approach, with the goal of expanding the empirical investigation to the municipalities where Bolsonaro had low political support. While Ajzenman, Cavalcanti, and Da Mata (2020) and Mariani, Gagete-Miranda, and Retti (2020) assume as their treatment group only the municipalities in which the president achieved more than 50 percent of the votes in 2018, this work integrates all the municipalities, presenting a linear relationship between Bolsonaro's support and social distancing. In addition, I expand the investigation to a period of 103 days (February 1, 2020 – May 14, 2020) in contrast to the 17 days of Mariani, Gagete-Miranda, and Retti (2020) and the 20 days of Ajzenman, Cavalcanti, and Da Mata (2020).

Brazilian policy responses to the COVID-19 pandemic provide the basis for an extremely promising area of research. To date, Brazil has imposed no nationwide lockdown rules, in contrast to many other countries around the world. Instead, the states and municipalities are free to impose their own restriction measures by means of executive decree. Starting with Distrito Federal on March 14, 2020, all Brazilian states have since implemented government interventions to prevent the spread of COVID-19.

Figure 1: Lockdown Measures by State
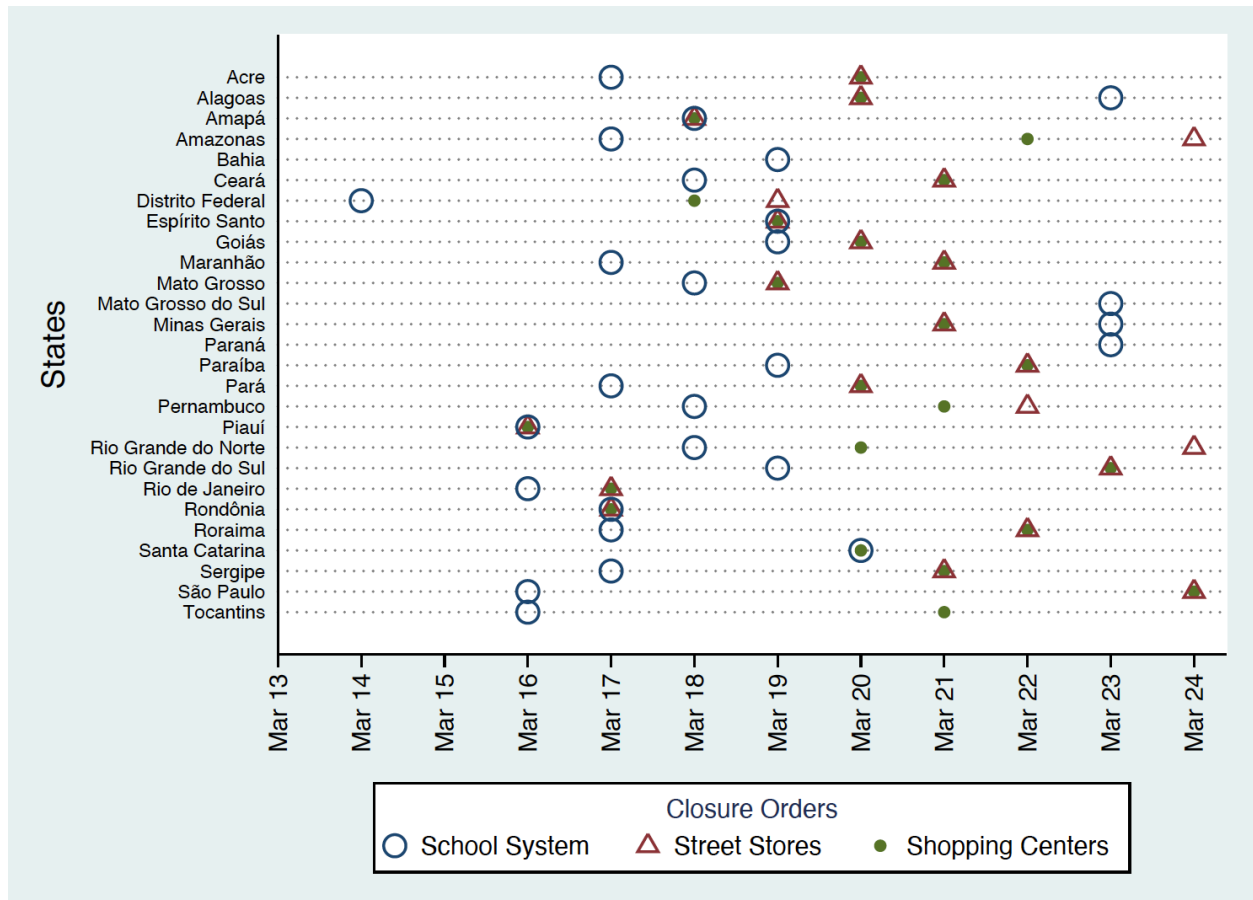
Notes: Lockdown measures refer to the decrees issued by state governments mandating the temporary closing of establishments. Bahia, Mato Grosso do Sul and Paraná have no decree to close stores or shopping centers. Santa Catarina and Tocantins have no decree to close stores.

Source: Official gazette of the respective states; author's own elaboration.

However, since the beginning of the coronavirus crisis, the reaction of President Bolsonaro was characterized by denial (see, e.g., *New York Times* 2020; *The Conversation* 2020). On several different occasions, the leader of the sixth-most populous country in the world has systematically ignored WHO recommendations for combating the coronavirus pandemic (see table A1). According to Brazil's president, social distancing measures must be limited to those at the highest risk for becoming very ill or dying from COVID-19.[1] Against this backdrop, the present paper will apply an econometric approach to identify whether municipalities with more Bolsonaro supporters present lower levels of social distancing.

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[1] See Ricard and Medeiros (2020) for an extensive discussion on Bolsonaro's actions to minimize the severity of the coronavirus, discredit social isolation measures intended to mitigate the course of the disease's spread, and increase the distrust of public data.

The empirical results of this study show that the lockdown measures have not produced the expected results. While public authorities have stipulated a social distancing target of 70 percent, I show that after April on average only one in two people stayed at home on weekdays, and as time went on, this share decreased even more. In addition, this paper confirms a statistically significant association between political support for Bolsonaro and social distancing, suggesting that the positive impacts of stay-at-home orders are higher in municipalities with a lower share of Bolsonaro voters.

Data

This study combines four different datasets in the empirical investigation. The COVID-19 data are compiled daily by the Brazilian Health Ministry and contain the diagnosed cases of, and deaths due to, coronavirus. The data on election results are from the Superior Electoral Court (TSE) and refer to the first-round election held on October 7, 2018. The information on Gross Domestic Product (GDP) and population comes from the Brazilian Institute of Geography and Statistics (IBGE). Finally, the data on social distancing are provided by In Loco, a Brazilian technology company headquartered in the city of Recife and with operational centers in São Paulo, New York, and Santa Clara, California.

In Loco uses large-scale geolocation data collected via the Global Positioning System (GPS) from 60 million smartphone users in Brazil. Thanks to the built-in GPS chip, modern mobile devices can access satellite data to calculate the exact position of the users and provide a whole range of functions, such as satellite navigation, geolocation-based social networking, personal sports performance tracking, and so on (Sansurooah and Keane 2015). Consequently, an increasing number of private and public companies are utilizing GPS technology to provide services through mobile applications, also called apps.

Seeing the resultant potential market, several start-up companies began to use this huge geolocation database for commercial purposes. This is the background of the database used in this paper. Founded in 2010, In Loco specializes in ubiquitous computing and has developed a software module to collect data from mobile devices through a Software Development Kit (SDK) installed in partner applications, allowing the company to track the geolocation data of approximately 60 million smartphone users.[2]

The recording software was designed to run in the background of the apps, uploading recorded data automatically. For this to happen, the apps are required to inform the users that geolocation data might be collected by the SDK, and only after the users accept In Loco's privacy policy will the software start collecting data. For privacy reasons, the company does not collect unique static identifiers from mobile devices (IMEI and MAC), associated accounts (email address and telephone number), civil identification data, or sensitive data (ethnicity, religion, political opinion, etc.). In addition, the mobile advertising IDs are stripped out and encrypted to ensure data protection standards. Therefore, the resulting data become strictly anonymized and do not enable any inference with the

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[2] The concept of "ubiquitous computing" is used in software engineering to describe the technology to integrate computing into all everyday activities of the users (see, e.g., Weiser 1999).

user's personal data, thus fulfilling the requirements set out in Brazilian law for data processing (Data Protection Law and Civil Rights Framework for the Internet).

Since the COVID-19 outbreak in Brazil, In Loco has been making use of this geolocation database to create technological tools to support the public authorities and research bodies in combating the spread of the coronavirus.[3] Within this framework, four main projects related to the COVID-19 pandemic are currently in progress: (i) direct communication with the population through push notifications on government apps; (ii) an accounting system to avoid overcrowding of hospitals and other essential services; (iii) mapping of the nonessential services that are not complying with the isolation rules; and (iv) the creation of population-mobility indexes, which will be presented later in these research notes.

As of now, 22 of the 27 Brazilian states have direct agreements with In Loco to use the geolocation database in the fight against COVID-19. With the Social Distancing Index (SDI) the company provides a visualization of the regions with high levels of individuals leaving their residences, allowing the government authorities to take immediate actions in order to increase the effectiveness of the lockdown measures. The mailing of push notifications through government apps or the sending of cars equipped with loudspeakers to highlight the importance of the lockdown rules are only some examples of measures that have already been employed in areas with low levels of social distancing.

The study database was supplemented by COVID-19 data obtained from the Brazilian Health Ministry (MS). Since the eruption of the coronavirus crisis, the MS has made available on its website a daily updated source of the most important data on COVID-19 in Brazil, containing the number of confirmed cases, deaths, recoveries, and suspected cases divided into municipalities and days. This information is reported electronically by the municipal secretariats of health through the Notification System of the Health Ministry (e-SUS VE) and the Electronic System for the Monitoring of Epidemiological Surveillance (SIVEP Gripe). While the former registers all the cases of flu, the latter contains the cases of Severe Acute Respiratory Syndrome (SARS).

The information about the political support for Bolsonaro stems from the Electoral Data Repository of the TSE, which contains detailed results of all Brazilian elections since 1945. In this paper, I use the microdata from the first-round presidential election of October 7, 2018, including the votes received by each candidate/party and total votes cast at the constituency level. Finally, for the GDP on a municipal level, I apply the database Gross Domestic Product of Municipalities of IBGE from 2017. These data present the gross value added, at current prices, of the three major sectors of the economy—Agriculture, Industry and Services—as well as taxes, net of taxes, GDP, and GDP per capita from 2010 to 2014.

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[3] All partnerships with In Loco are governed by contracts at zero cost to the institutions and involve the transfer exclusively of anonymized data.

Identification Strategy

To identify the effects of political support for Bolsonaro on social distancing, I apply a difference-in-difference (DiD) approach at the municipality level that compares the SDI pre- and post-lockdown. The empirical model is given as:

Equation 1

$$SDI_{i,t} = \pi_0 + \pi_1 \left(Lockdown_s \; X \; Voting_{i,2018}\right) + \pi_2 \, Lockdown_s + \pi_3 \, Voting_{i,2018}$$
$$+ \gamma_1 \, ACCcases_{i,t-1} + \gamma_2 \, ACCdeaths_{i,t-1} + \gamma_3 \, GDPcapita_{i,2017}$$
$$+ \gamma_4 CaseBR + \gamma_5 \, CaseMU_i + \mu_i + \mu_s + \mu_t + \varepsilon_{i,t}$$

where $SDI_{i,t}$ denotes the Social Distancing Index in municipality i and on day t, $Lockdown_s$ is a dummy taking a value of 1 for each day after the stay-at-home order enacted by the respective state s, and $Voting_{i,2018}$ is the proportion of valid votes received by candidate Jair Bolsonaro in the first-round election on October 7, 2018.[4] The variables $ACCcases$ and $ACCdeaths$ are lagged values of the accumulated confirmed cases and deaths due to COVID-19, and $GDPcapita_{i,2017}$ denotes the GDP per capita in 2017.[5] $CaseBR$ and $CaseMU_i$ are dummies indicating whether any COVID-19 case had already been registered in Brazil and in the municipality i, respectively, on that day.[6] The model also includes municipality-fixed effects (μ_i), time-fixed effects (μ_t) and a random component $\mu_{i,t}$, assumed to be distributed as $N(0, \sigma^2)$. Finally, the estimations are weighted by the respective population sizes in 2019, and the standard errors are robust and clustered at the municipality level.

The SDI ranges from 0 to 100 and is calculated as follows: First, In Loco uses the geolocation data from the smartphones to identify the residential addresses of users, and each of these locations becomes the center of a small circular region with a radius of 40 meters. If the mobile device visits a location outside this circle, the software recognizes that as a home leave.[7] Then, the SDI is calculated initially within microregions, which are formed by regular polygons with six sides and a circumradius of 450 meters (see figure 2). Consequently, the SDI for the microregion (polygon) corresponds to the proportion of users with residences registered in this area that stayed within the 40-meter radius all day.[8] Finally, to ensure the identification of macrotrends, the results from the polygons are aggregated at different administrative levels (municipal, state, and national) using the weighted average for the mobile devices registered in the respective level.

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[4] Lockdown refers to the closing orders for schools, stores and shopping centers applied by the respective states (see figure 1). Given different dates, the earliest one was used.

[5] To present a linear relationship in the regression outputs, the continuous variables $ACCcases, ACCdeaths$ and $GDPcapita$ are standardized to mean 0 and standard deviation 1.

[6] Table A2 reports the descriptive statistics for the variables.

[7] Movements within the 40-meter radius are not assumed to be breaching the lockdown rules, as they are necessary to carry out essential daily activities, such as going to the supermarket, bakery, or pharmacy.
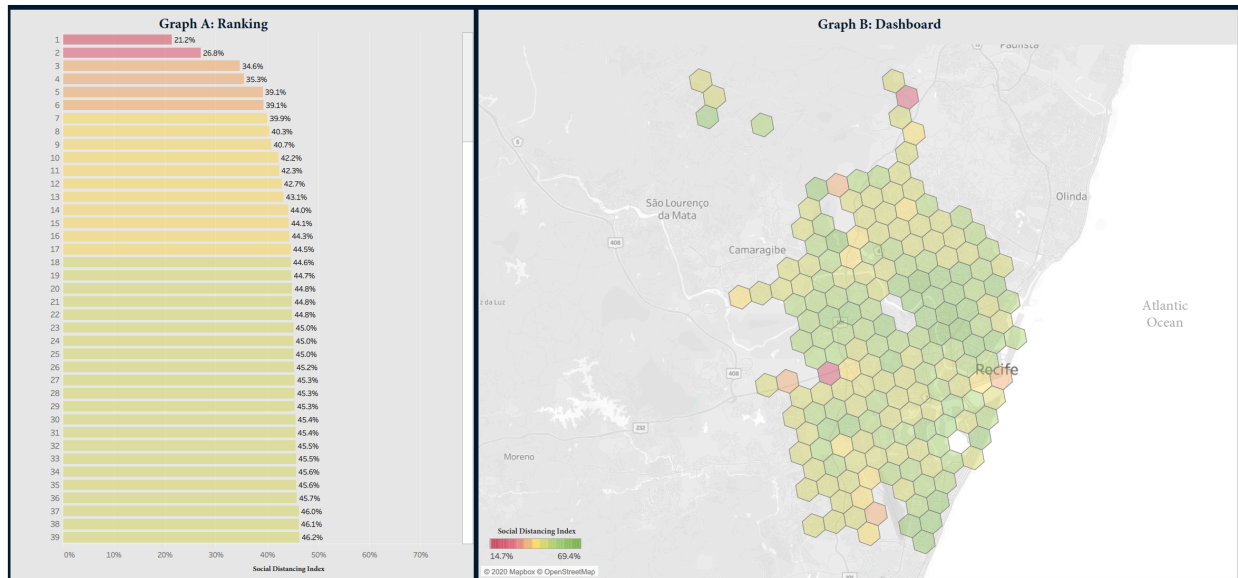
[8] Due to data protection and privacy issues, the SDI is calculated only for microregions with more than 20 mobile devices.

Empirical Findings

Social Distancing Index

Figure 2 presents the first level of analysis and refers to the values of SDI in Recife on May 5, 2020.[9]

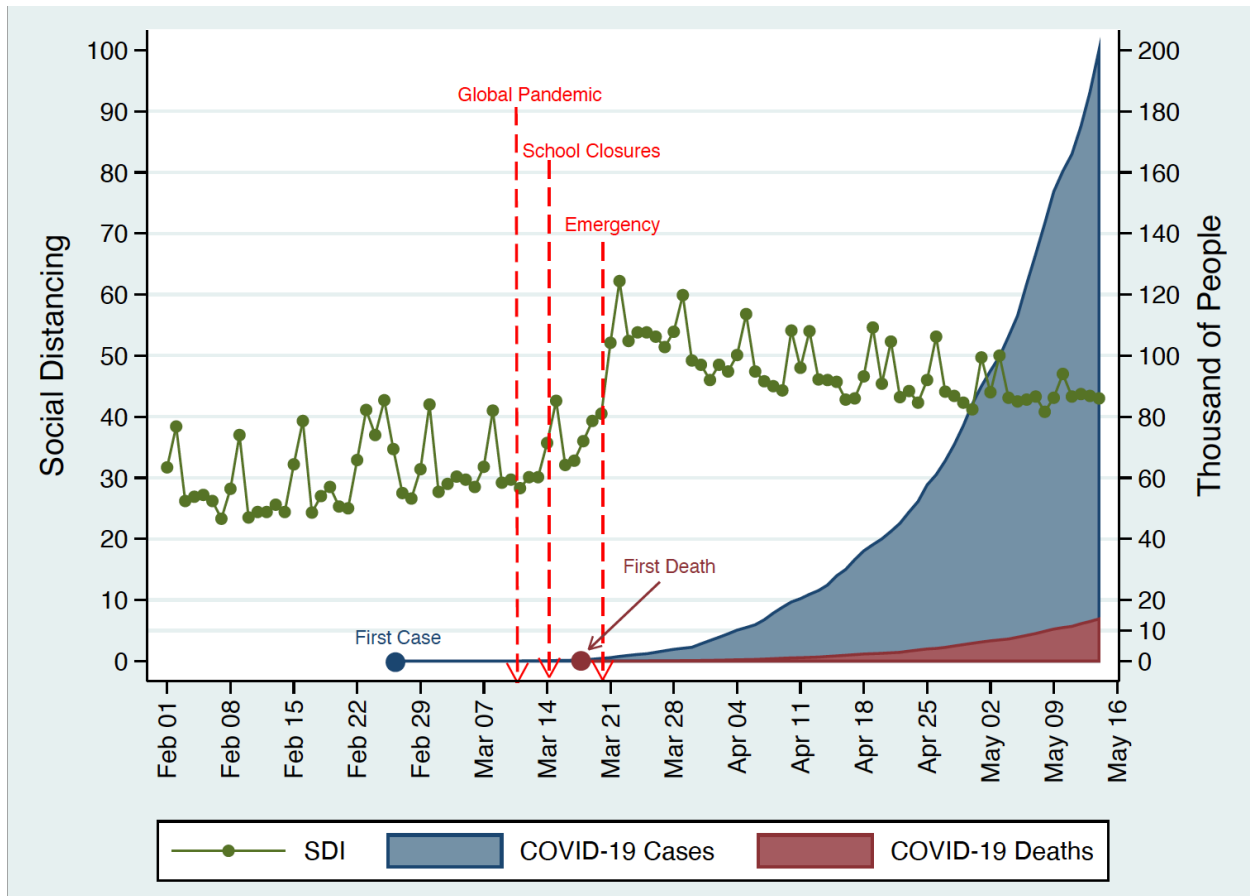### Figure 2: Social Distancing at the Micro Level

Notes: Social distancing represents the share of the population that stayed at home. Data are from May 5, 2020, and not representative of the whole population. Graphs refer to the microregions (polygons) located in the municipality of Recife. The regular polygons have six equal sides and a circumradius of 450 meters. The color scale ranges from the minimum (in dark red) to the maximum (in dark green) values of the Social Distancing Index (SDI) reported in the figure. SDI is calculated only for microregions with more than 20 mobile devices.

Source: In Loco database; author's own elaboration.

In the dashboard the microregions (regular polygons) are illustrated independently on the right side and sorted in ascending order with their respective index in the left graphic. The color scale ranges from the minimum (in dark red) to the maximum (in dark green) values of the SDI reported in the figure. The lower the value, the lower the share of the population that have stayed at home. Note that on May 5, 2020, the SDI in Recife ranged from 21.2 to 62.3 percent, achieving an average value of 49.9 percent with a standard deviation of 5.5 percentage points.

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[9] The choice of Recife for the figure was random.

Figure 3 expands the investigation of social distancing to the state level. To that end, I average the values of all (single) polygons located within the municipalities of Pernambuco, allowing for the comparison of the SDI over time and between the municipalities.

Figure 3: Social Distancing at the Municipal Level

Notes: Social distancing represents the share of the population that stayed at home. Data are not representative of the whole population. Graph A ranks the 185 municipalities in Pernambuco according to the Social Distancing Index (SDI) of May 5, 2020, and graph B presents the same data in a heat map. Graph C lists the daily SDI for all the municipalities since February 1, 2020. Graph D illustrates the average value of SDI for the period from April 13, 2020, through May 10, 2020, for the municipality of Recife (bar chart) and the state of Pernambuco (line chart). The color scale ranges between the minimum (in dark red) and the maximum (in dark green) values of the SDI reported in the figure.

Source: In Loco database; author's own elaboration.

As described in the introduction, the first objective of this work was to present the values of social distancing since the introduction of the lockdown rules. Figure 4 plots the results of this exercise, reporting the evolution of the SDI over time for the whole country and integrating into the investigation the number of cases and deaths due to COVID-19. To combat the transmission of the coronavirus, the responsible authorities in Brazil have set a goal of keeping 70 percent of the population social distancing (São Paulo 2020), but as shown in figure 4 this target was achieved on only one day during the period from February 26 to May 14, 2020.

Figure 4: Evolution of Social Distancing Index

Notes: Social distancing represents the share of the population that stayed at home. Data are not representative of the whole population. The WHO declared COVID-19 a global pandemic on March 11, 2020. On March 14, 2020, Distrito Federal was the first state to suspend schools and Paraná the last on March 23, 2020. The state of emergency was declared by the federal government on March 20, 2020.

Source: In Loco and Ministry of Health databases; author's own elaboration.

Impact of Support for Bolsonaro on Social Distancing

Table 1 reports the empirical findings from equation (1) applying OLS and FE models. While OLS assumes that each observation is independent of any other, the FE identifies the two dimensions of the data, following the same municipalities i over time t.

In the first step, I estimate the models using data for the 5,570 Brazilian municipalities and the 103 investigated days (February 1, 2020 – May 14, 2020).[10] Next, since the coronavirus pandemic is strongly concentrated in Brazil's largest cities, I run the empirical models with the same time period as before, but using only the 1,000 and 100 municipalities with the greatest number of recorded COVID-19 cases (top 1000 and top 100).[11] This limitation of the investigation to the municipalities with a real COVID-19 outbreak is extremely important from a theoretical perspective to exclude the effects of self-selection (see, e.g., Fernandes et al. 2020). Our key hypothesis is that Bolsonaro's supporters are persuaded by the president to take the risk of being infected and break the rules of social distancing. In places with no registered cases of coronavirus there is practically no risk of infection, therefore the decision to leave home will be less dependent on one's individual political orientation.

The response for the main research question of this paper—namely whether the effectiveness of social distancing measures is associated with the political orientation of the population—can be found in table 1. The main coefficient of interest is the interaction term between the dummy for lockdown measures and the continuous variable presenting the proportion of valid votes received by Bolsonaro in the first-round election of 2018, because it indicates whether the SDI changes according to the share of Bolsonaro supporters in the municipality. As hypothesized from the beginning, this coefficient is negative and significant for the models using the worst-hit cities by COVID-19, which implies that—in the presence of a concrete risk of infection—the municipalities with a higher percentage of Bolsonaro voters are likely to present lower shares of individuals staying at home.

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[10] For 952 (small-sized) municipalities the SDI could not be calculated, as the number of mobile devices within the microregions (polygons) was lower than 20. The total population living in these municipalities in 2019 was 3,736,497, which corresponded to 1.78 percent of the country's population.
[11] On May 14, 2020, these 1,000 (100) municipalities accounted for approximately 70 (36) percent of the country's population, but 96 (75) percent of its COVID-19 infections.

Table 1: Empirical Results

	All		Top 1000		Top 100	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	FE	OLS	FE	OLS	FE
Lockdown X Voting	0.025***	0,009	-0,003	-0,014	-0.086***	-0.073***
	(3.021)	(1.293)	(-0.249)	(-1.329)	(-4.139)	(-4.398)
Lockdown Measures	11.976***	-0,213	15.495***	0,880	21.297***	4.441***
	(28.851)	(-0.573)	(23.707)	(1.623)	(19.307)	(5.746)
Voting for Bolsonaro	0.024***	0,000	0.020***	0,000	0,022	0,000
	(5.471)	(.)	(3.304)	(.)	(1.274)	(.)
Lagged COVID-19 Cases	0.347**	0.226*	0.261**	0.176*	0	0,033
	(2.371)	(2.234)	(2.107)	(2.022)	(-0.005)	(0.730)
Lagged COVID-19 Deaths	-0.299*	-0,172	-0.224*	-0,130	-0,001	-0,013
	(-1.938)	(-1.639)	(-1.710)	(-1.439)	(-0.006)	(-0.285)
GDP per capita	0.284**	0,000	0,183	0,000	-0,048	0,000
	(2.235)	(.)	(1.420)	(.)	(-0.244)	(.)
COVID-19 in Brazil	2.514***	2.081***	2.510***	-7.904***	2.504***	-13.645***
	(44.541)	(5.257)	(31.031)	(-41.430)	(16.807)	(-53.244)
COVID-19 in Municipality	0,33	3.694***	-0.913***	3.454***	-0,156	3.773***
	(1.455)	(17.611)	(-3.143)	(13.765)	(-0.255)	(4.646)
Number of Observations	414.167	414.167	101.152	101.152	10.300	10.300
Number of Groups	-	4.514	-	1.000	-	100
R-square	0,569	0,9	0,619	0,938	0,687	0,969
Weighted by Population	Yes	Yes	Yes	Yes	Yes	Yes
Municipality Fixed Effect	No	Yes	No	Yes	No	Yes
State Fixed Effect	No	Yes	No	Yes	No	Yes
Time Fixed Effect	No	Yes	No	Yes	No	Yes

Notes: Dependent variable is social distancing index. Top 1000 (100) focuses on the 1,000 (100) municipalities with the greatest number of COVID-19 cases on May 14, 2020. Lagged COVID-19 cases, lagged COVID-19 deaths and GDP per capita are standardized to mean 0 and standard deviation 1. Data are not nested within municipalities. Standard errors in parentheses are robust to heteroskedasticity and clustered at the municipality level.

Source: In Loco, TSE, IBGE and Ministry of Health databases, author's own estimates.

To show how social distancing correlates to political support for Bolsonaro, I compute the marginal effects from equation (1) for the top 100 municipalities and plot the adjusted predictions in figure 5.

Figure 5: Adjusted Predictions of Lockdown
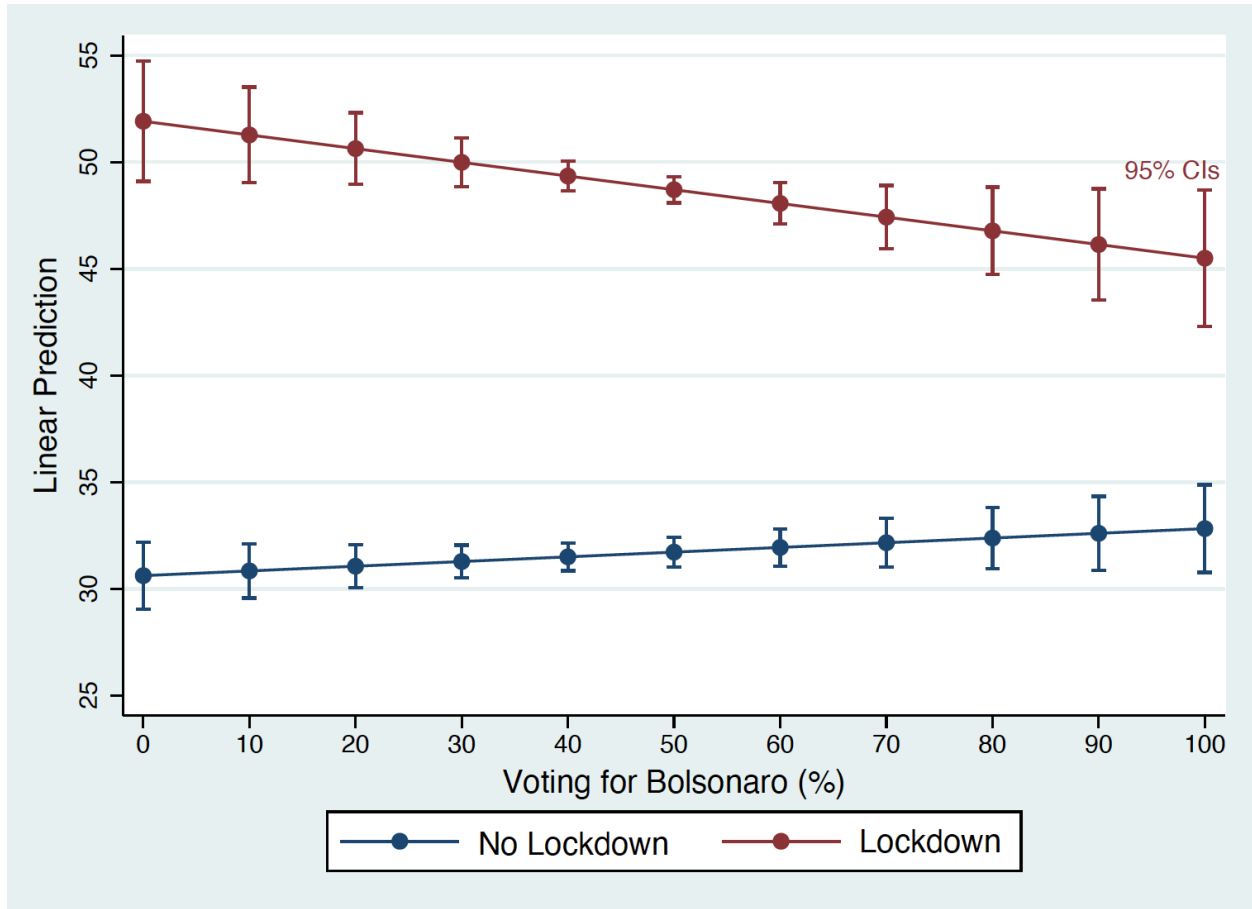
Notes: The figure plots the predicted effects of political support for Bolsonaro on social distancing using model 3 from table 1. Investigation is limited to the 100 municipalities with the greatest number of COVID-19 cases on May 14, 2020. Social distancing represents the share of population that stayed at home. Voting for Bolsonaro refers to the valid votes he obtained in the presidential election of October 7, 2018. Solid points illustrate the linear prediction, with 95 percent confidence intervals, of social distancing by changes in the percentage of votes for Bolsonaro given two different scenarios (with and without lockdown measures). Data are not representative of the whole population.

The resulting empirical evidence suggests that the impact of the lockdown is stronger in locations with a lower share of Bolsonaro voters. Note that given lockdown measures, social distancing decreases as political support for Bolsonaro rises (red line).

Figure 6: Contrasts of Predictive Margins of Lockdown
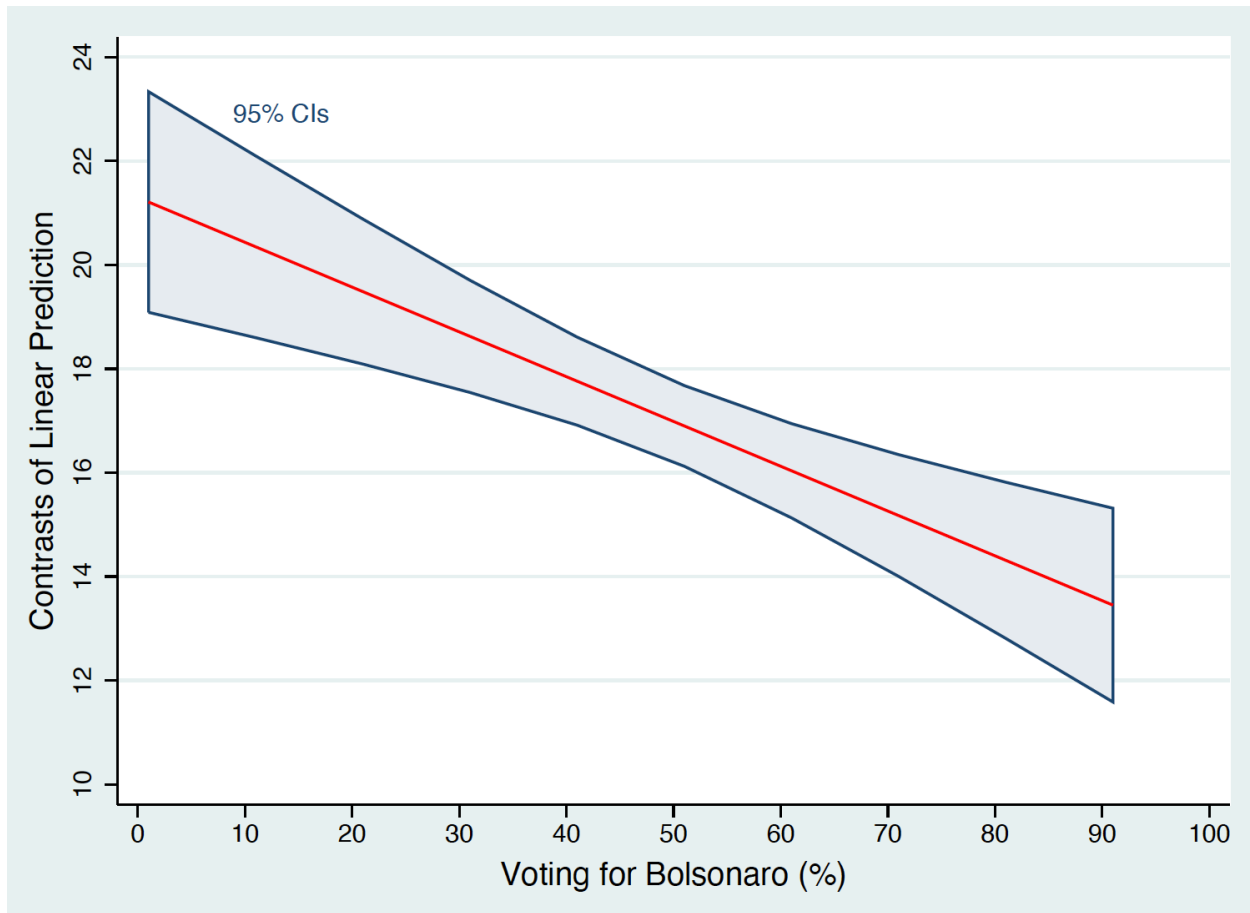
Notes: The figure summarizes the differences in linear prediction margins between lockdown and no lockdown presented in figure 5. Voting for Bolsonaro refers to the valid votes he obtained in the presidential election of October 7, 2018. Data are not representative of the whole population.

Source: In Loco database; author's own elaboration.

Figure 6 summarizes the evolution of the difference between the two lines. In municipalities with low political support for Bolsonaro social distancing increases by 21.2 points after lockdown measures have been implemented, and in locations where Bolsonaro obtained the majority of the votes, this percent is just 13.4.

Conclusion

This work has presented the In Loco database to the academic community. Using geolocation data from nearly 60 million smartphone users, the results show that in Brazil the coronavirus lockdown measures applied by the state governors did not lead to the expected reduction in the circulation of persons. Despite the promising increase in social distancing registered at the beginning of the lockdown, the number of people staying home declined constantly in the subsequent weeks.

In addition, this paper set out to explore the determinants for the strong variation in social distancing across Brazilian municipalities and integrated into the investigation the contradictory policy responses to the COVID-19 pandemic on the part of the Brazilian public authorities. The key assumption—that Bolsonaro's supporters would follow his recommendations and undermine social distancing guidelines—was confirmed. The impact of the state-run social distancing measures on the circulation of people is lower at a statistically significant level in municipalities with a higher share of Bolsonaro voters.

Apart from the results for Brazil, an important contribution of this paper is the dissemination of the technology behind the SDI to the research community. The case reported here—in which geolocation data are compiled and analyzed to support public decisions concerning the confrontation of the COVID-19 crisis—can serve as an example for other countries going through similar situations. Given the low costs involved in the project, several other countries—including low-income developing nations—will be able to incorporate this technology practically.

Last but not least, the empirical findings presented in this study represent the state of the art in science and technology when it comes to monitoring social distancing, and this technology can be used in further research projects related to the coronavirus pandemic. Therefore, this work is only the first step towards a more profound understanding of the health and economic burdens posed by COVID-19. The in-depth insights into the lockdown and the opportunity to track SDI by geographic region should make the database used in this paper attractive to the research community and consequently support the development of numerous studies aiming to assess the economic consequences of the lockdown measures related to COVID-19.

Despite the compelling results presented in this paper, some limitations should be addressed in future studies. The most obvious shortcoming of this work is the absence of controls for important determinants of social distancing, such as the share of population employed in essential activities, urban density, level of education and poverty, and access to and usage of media in any given municipality. These factors might explain a substantial portion of differences in compliance among the population and might be also correlated with voting preferences. If Bolsonaro's supporters are located in areas where social distancing is hard to maintain—because, for example, a high share of the population is employed in essential activities—we may wrongly conclude that they are (intentionally) following the president's political guidelines to ignore the social distancing guidelines recommended by the WHO. Therefore, the use of more accurate and complete data could contribute to improving our understanding of the role of political views on determining physical distancing responses.

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Appendix: Tables

Table A1: Timeline of COVID-19 and policy responses

02/26/2020	First case is diagnosed. Patient lives in São Paulo and was in Italy.
02/28/2020	Federal government launches prevention campaign against COVID-19.
02/29/2020	Second case is diagnosed. Patient lives in São Paulo and was in Italy.
03/04/2020	Third case is diagnosed. Patient lives in São Paulo and was in Italy.
03/05/2020	First domestic transmission of COVID-19.
03/10/2020	Bolsonaro plays down the coronavirus outbreak and dismisses the disease as "fantasy."
03/11/2020	World Health Organization declares COVID-19 a global pandemic.
03/13/2020	Ministry of Health recommends that agglomeration of people must be avoided and regulates the legal framework for COVID-19 isolation.
03/13/2020	State of São Paulo suspends events with more than 500 people.
03/13/2020	Rio de Janeiro is the first state to declare a state of emergency. Public events are suspended, while bars, restaurants and shopping centers remain open but with restrictions.
03/15/2020	Bolsonaro ignores coronavirus warnings from the health ministry and attends a street protest in defense of his own government.
03/16/2020	Bolsonaro urges the population to ignore the COVID-19 "hysteria" and get back to work.
03/17/2020	First COVID-19 death.
03/20/2020	Federal government declares a state of emergency.

03/21/2020	Federal government determines the essential services that cannot be closed during the COVID-19 pandemic.
03/23/2020	Schools close in all Brazilian states.
03/23/2020	Federal government determines entry restrictions for foreign citizens.
03/24/2020	Lockdown in São Paulo. Only essential services can stay open.
03/24/2020	Bolsonaro plays down the coronavirus as "a little flu" and urges mayors and state governors to roll back lockdown measures.
03/28/2020	Ministry of Health calls on people to maintain the "the maximum degree of social isolation."
03/29/2020	Bolsonaro undermines social distancing guidelines and mingles with political supporters on the streets of Brasília.
04/01/2020	Cases of COVID-19 are diagnosed in all 27 Brazilian states.
04/02/2020	Federal government recommends the use of a face mask.
04/10/2020	First death of an indigenous person due to COVID-19.
04/21/2020	Deaths due to COVID-19 are registered in all 27 Brazilian states.
04/30/2020	Brazil surpasses China in number of COVID-19 cases.
05/23/2020	Brazil surges to second place in COVID-19 cases worldwide.

Notes: Declaration of a state of emergency allows the government to free up budgetary resources for the coronavirus crisis. Lockdown is the technical term for restrictive measures that aim to reduce the movement of people and refers to executive decrees to close nonessential services and recommendations that individuals stay at home. Quarantine refers to more rigid rules to limit circulation and, among other things, entails a prohibition on leaving one's residence or accessing certain areas.

Source: Government official gazette and media reports; author's own elaboration.

Table A2: Descriptive Statistics

	Mean	SD	Min	Max	N	n	Tbar
Social Distancing Index	37.799	9.055	7.407	85.455	423,877	4,618	91.788
Voting for Bolsonaro	38.683	19.685	2.531	83.893	424,829	5,570	76.271
COVID-19 Cases	7.066	200.974	0	31,873	423,877	4,618	91.788
COVID-19 Deaths	0.475	16.493	0	2,596	423,877	4,618	91.788
GDP per capita	22,150	21,942	3,285	344,847	424,829	5,570	76.271
Population	49,764	257,812	1,833	12,252,023	424,829	5,570	76.271
Lockdown Measures	0.561	0.496	0	1	424,829	5,570	76.271
COVID-19 in Brazil	0.766	0.424	0	1	424,829	5,570	76.271
COVID-19 in Municipality	0.161	0.368	0	1	424,829	5,570	76.271

Notes: This table provides descriptive statistics for the panel data structure in which each of the 5,570 Brazilian municipalities was accompanied during the 103 days (February 1, 2020 – May 14, 2020). Data are not nested within municipalities.

Source: In Loco, TSE, IBGE and Ministry of Health databases; author's own elaboration.