Bigmouth Strikes Again: Electoral Impact of Reckless Speech during a Pandemic

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Abstract

We investigate how voters react to reckless denialism in light of a global pandemic by looking at the impact of cumulative COVID-19 mortality rate on the electoral performance of the Brazilian incumbent president Bolsonaro in the national elections right after the end of the pandemic. We devise a novel instrument from epidemiological analysis of viral spread to show that the COVID-19 municipal death toll led to large electoral costs for the incumbent presidential candidate, even if geography, not Bolsonaro, was responsible for these deaths. We attribute this result to emotional triggers activated by his denialist speeches, as the vote share of other right-wing candidates was not impacted by the pandemic.

Keywords: COVID-19, Mortality, Elections, Emotions, Grief, Mobility

JEL Codes: D72, D91, H12, I18, J61

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1 Introduction

During the Coronavirus pandemic, some leaders in democratic countries did not enact strict sanitary measures hoping that voters would not hold them responsible for the expected burdens of inevitable economic downturns.[1] The incumbent Brazilian president, Jair Bolsonaro, not only did not display much concern for the disease, but adopted a rhetoric repeatedly minimizing the risks posed by COVID-19, and encouraging the population to engage in unsanitary activities (Ajzenman, Cavalcanti, and Da Mata 2023). Although in line with other Far-Right populists (Castanho Silva, Fuks, and Tamaki 2022; Guriev and Papaioannou 2022), his strong stances against sanitary measures were broadly interpreted as reckless (Lancet 2020), even leading to investigations of criminal negligence (BBC 2021; Guedes 2021).

In this paper, we examine whether the total number of COVID-19 deaths impacted the votes received by president Bolsonaro in the 2022 national elections, using exogenous variation at the municipality level. We devise a novel instrument drawing from epidemiological analyses of the Coronavirus' spread in Brazil and exogenous commuting costs (Monte, Redding, and Rossi-Hansberg 2018) to investigate whether voters associated Bolsonaro with, and thus punished him for, the severity of the pandemic the country faced. We start from the stylized fact that, early in 2020, the Coronavirus was primarily situated in large urban centers, but rapidly disseminated through highways and roads to the country's innards (Candido et al. 2020; Castro et al. 2021; Do Carmo et al. 2020; Nicolelis et al. 2021). Commuting, acting as a vector of dissemination across municipalities (Valsecchi and Durante 2021), makes integration between municipalities' labor markets the core relevant mechanism of infection. Since commuting is costly, municipalities further away from viral-spreading hubs are comparatively more sheltered from the disease initially, following neoclassical gravity models. Our identifying assumption is that, by using COVID-19 deaths resultant of distance to large urban centers, varying according to municipality's size, we can identify the impact of increases in municipal COVID-19 mortality rates on the incumbent president's vote loss.

We present robust evidence showing that COVID-19 deaths drew a large share of voters

1. For cross-national analyses describing the phenomena, see Chiplunkar and Das (2021) and Pulejo and Querubín (2021). To understand the origin of these beliefs, see Oliver (2020).

away from Bolsonaro's platform, ensuring his opponent's victory. We estimate that each Coronavirus death per thousand inhabitants results on vote share variations between negative 1 and 2 percentage points. In the average municipality, we estimate each death to have costed between seven and ten votes; and the pandemic as a whole resulted in 46.2 thousand votes lost per municipality in the first round on average, or 6.55 million votes in total. We argue that, had Bolsonaro kept quiet, his vote share would have grown by up to two and a half percentage points between the 2018 and 2022 elections first round, rather than diminishing by nearly three pp. As a result, he would have nearly been re-elected president in the first round, and easily won in the second.

These results are robust across different specifications and assumptions regarding viral spread throughout the country. Placebo tests show that distance and size are not related to total mortality before the Coronavirus pandemic, and that COVID-19 deaths are not related to previous election results. Since no other candidate or set of candidates faced similar results, we conclude stating Bolsonaro's approach to the pandemic was uniquely impactful on voters' behavior.

Our research contributes to several salient topics in the political economy literature. Immediately, it deals with unanswered questions regarding the electoral impacts of COVID-19 in Brazil. Given the severity of the pandemic in the country, which acted as a continental hub of viral dissemination (Lancet 2021), despite its globally recognized universal healthcare system focused on preemptive care (Castro et al. 2019), existing literature on the topic emphasize the political determinants of outbreak severity (Galhardi et al. 2022), and identify a robust correlation between the electoral support for the president in 2018 and the likelihood of more severe complications due to the disease (Figueira and Moreno-Louzada 2023; Xavier et al. 2022).

Particularly relevant for our analysis is Ajzenman, Cavalcanti, and Da Mata (2023), which suggests ideological affinity with the president made voters more likely to engage in unsanitary behavior immediately after his national broadcasts publicly dismissing COVID-19's severity, especially in regions with greater media presence. In this paper, we deal in the converse relation, showing that voters perception of Bolsonaro's responsibility regarding COVID-19 deaths led to his defeat in the 2022 national elections, even if deaths were not caused by Bolsonaro himself.

Another pertinent study is Campante, Depetris-Chauvin, and Durante (2024), which identify three key locations where the Ebola virus was detected in the United States, and use distance to these locations and timing of viral appearance as a source of exogenous variation for concern regarding the virus. In a similar design to ours, they find that proximity to the virus is a strong predictor of increased Republican support in the 2014 elections. Although both studies show the strength of emotions as driving factors in elections, their findings report public anxiety being captured by candidates reinforcing preconceived stereotypes, while our paper evinces shifts in general perception due to direct association between the anxiety inducing phenomena and the target of discontent.

Our paper also contributes to the vast body of research exploring informational aspects of electoral decisions, emotionally driven changes in voting patterns, and broad incentive-based political strategies, specially the branch of literature dealing with populism, crises, and their unintended effects regarding private electoral harm or lack of public goods provision.[2] We contribute to this literature by introducing a context where negative emotions and punishment befall on one key figure that is representative of the issue at large, harming their electoral prospects, despite the apparent tacit support of voters (Oliver 2020), and relative inelasticity in political preferences (Guriev and Papaioannou 2022).

Our setup differ from existing research by investigating a scenario in which the negative emotions are the product of a deliberate electoral strategy employed by the incumbent at hand. By examining the electoral cost of COVID-19 deaths, we complement research on the electoral cost of job losses (Wu and Huber 2021) and the existing tradeoff between sanitary measures and employment (Auray and Eyquem 2020; Coibion, Gorodnichenko, and Weber 2020; Graham and Ozbilgin 2021; Hoehn-Velasco, Silverio-Murillo, and Balmori de la Miyar 2021; Marino and Menezes-Filho 2023), useful to understanding electorally optimal policy during a pandemic. Moreover, our research relates to Bursztyn et al. (2022) by exploring the political consequences of inviting blame through reckless statements, highlighting one's

2. See, respectively, Ferraz and Finan (2008), Garz and Martin (2021), and Gentzkow (2006); Bauer et al. (2023), Brader (2005), and Campante, Depetris-Chauvin, and Durante (2024); Besley and Case (1995) and Ferraz and Finan (2011); Ajzenman, Cavalcanti, and Da Mata (2023), Guriev and Papaioannou (2022), and Hernández and Kriesi (2016); Firoozi (2024), Lindgren and Vernby (2016), and Lindvall (2014); Ogeda, Ornelas, and Soares (2024); and Bursztyn (2016).

own administration's failure in avoiding deaths, rather than the expected scenario where incumbents would shift blame on to others in order not to suffer the sanctions resulting from unsuccessful policies.

Finally, our paper adapts the well-established compartmental model of viral outbreaks to a practical framework that can be easily used in future economic analyses. Since we fundamentally rely on commute-spreading of the Coronavirus, we follow in a similar idea to Valsecchi and Durante (2021), who use mobility data during 2020 to suggest that, in Italy, provinces with stronger migratory network links to provinces where the initial Coronavirus outbreak happened experienced substantial increases in deaths compared to previous years, despite the reductions in mobility reflecting increasing concerns regarding the virus. Their argument is that internal migrants act as virus carriers, increasing non-migrants' odds of getting infected and dying due to complications from the disease. Since commuting can be correlated to unobserved variables that impact electoral preferences, we use the distance between municipalities as source of exogenous spatial transmission for COVID-19 outbreaks, rather than mobility data, exploiting the fact that the Coronavirus was initially located disproportionately in large metropolitan centers (Castro et al. 2021; Nicolelis et al. 2021).

We start from the gravity model of trade and commuting developed by Monte, Redding, and Rossi-Hansberg (2018), tying it to conventional dynamic compartmental models in epidemiology. Although the epidemiological literature has explored differences in outbreak severity related to initial population parameters and differently spaced clusters of individuals (Keeling et al. 2001), and also the impact of a commuting workforce in the COVID-19 spread (Kondo 2021), the topic is still fresh among economic analysis and, to the best of our knowledge, void of economic theory.

The rest of the paper is structured as follows: Section 2 describes the various datasets used. Section 3 describes the identification strategy and baseline econometric model. Section 4 presents COVID-19's impact on the 2022 presidential election in Brazil. Section 5 offer explanation for the results shown. Section 6 concludes.

2 Data

2.1 COVID-19 mortality rates

We use Mortality Information System's (SIM) set of yearly death reports, gathered from the Brazilian Unified Health System's Department of Information (DATASUS), to build municipal cumulative COVID-19 mortality rates, and daily municipal-level data compiled by the Ministry of Health (MS) jointly with individual State Health Departments to identify Coronavirus detected cases on municipalities. The former provides thoroughly detailed information for each deceased person in Brazil, including their municipality of residence and basic cause of death, and is generally considered the most reliable source of information on the subject (Guedes et al. 2023); we aggregate every COVID-19 death (basic cause of death registered as ICD-10 code B34.2, MS 2021) up to the day prior to the Brazilian presidential election first round (October 1, 2022) by municipality of residence, thus creating a municipal-level death toll variable, and obtain the cumulative death rate by 100,000 inhabitants by dividing it by the municipal population count from 2022 Demographic Census.[3]

Attesting the severity of the pandemic in Brazil, only eight out of the 5,570 municipalities did not report any deaths by COVID-19 by the day of the 2022 general election, but all of them were infected at some point; see Table A1. The average municipality faced approximately 343 deaths and 17 thousand confirmed cases per hundred thousand inhabitants. Smaller municipalities were less impacted. Municipalities with less than 50,000 inhabitants had 268 deaths per hundred thousand inhabitants on average, as compared to 377 in the municipalities with more than 50,000 inhabitants. Moreover, larger municipalities were first hit by the virus and faced higher mortality rates.

2.2 Election results

To gather electoral support for a candidate, we aggregate district results, publicly available by the Superior Electoral Court system, into municipality-year-round observations for every general and midterm election from 2008 up to 2022, then create valid vote share variables for

3. We use the 2022 population count, rather than 2019 estimates like official data, due to the nearly 7 million inhabitants excess present in the latter (Carrança 2023).

the set of relevant candidates. Elections in Brazil happen every two years, in which midterm elections, when voters elect municipal representatives, happen in leap years in a winner-takes-all format in municipalities with less than 200,000 voters (98.3% of municipalities), and in a two-round runoff otherwise (in which case, we consider solely results in the first round); general elections, when voters elect state and federal representatives, happen in non-leap years in a two-round runoff format. Changes in electoral support are, therefore, measured merely by the difference between a candidate/party valid vote share and said candidate/party valid vote share four years prior, in the same round. Our baseline estimates use valid vote share variation for Bolsonaro between the first round of the 2022 and 2018 elections since the literature regards it as more "sincere", in opposition to "strategic", than second round vote share (Piketty 2000).

2.3 Intermunicipal geographic relation

We use the Brazilian Institute of Geography and Statistics (IBGE) territorial network data to identify coordinates for municipalities' centroids, then use the haversine formula to calculate a 5,700 by 5,700 origin-destination matrix of Brazilian municipalities' pairwise distance. This yields an approximate measure for communication between municipalities that rely on a few simplifying assumptions: all of municipalities' economic activity is located in one point in space (in particular, the centroid), and that distance homogeneously obstructs intermunicipal communication.

We use data from the 2022 Demographic Census to identify the total population of each municipality, finding that approximately 75% of municipalities in Brazil have less than 25,000 inhabitants, 90% have less than 50,000 inhabitants, and 95% have less than 100,000 inhabitants. These population thresholds heavily relate to the construction of the instrument, which we detail in section 3.1. Moreover, the Brazilian population is heterogeneously spread across the country; in Table 1 we show how, despite the uneven distribution of population across municipalities, the distribution of municipalities surpassing the threshold is roughly reflective of the overall sample. Although nearly 40% of large municipalities in the sample are located in the Southeast, the region also harbors 30% of all Brazilian municipalities, and its share of large municipalities is just 30% larger than the national average (15.8 vs.

11.8 pp.). Similarly, distance to large municipalities is generally much larger in the Northern and Mid-Western regions than the national average (108.9 and 74.7 kilometers, versus 41.4, respectively), which we circumvent by employing a large set of municipal and regional controls.

Table 1: Regional distribution of Brazilian municipalities

Region	Municipalities	Large municipalities	Share of large municipalities	Distance to nearest large municipality
North	450	71	15.78%	108.9
	[8.1%]	[10.8%]		(111.2)
Northeast	1,794	175	9.75%	40.28
	[32.2%]	[26.6%]		(32.41)
Southeast	1,668	275	16.49%	24.52
	[29.9%]	[39.1%]		(24.26)
South	1,191	110	9.24%	33.69
	[21.4%]	[16.7%]		(22.68)
Mid-West	467	44	9.42%	74.69
	[8.4%]	[6.7%]		(59.88)
Total	5,570	657	11.80%	41.35
	[100%]	[100%]		(50.52)

Notes: The table divides Brazil in its five regions and reports (per region and in total): total municipalities and large municipalities, percentage regarding to total across regions in brackets; share of municipalities which are large (defined by a population surpassing 50,000 inhabitants); and population-weighted average distance to NLM in kilometers, standard deviations in parentheses.

2.4 Municipal characteristics

This section briefly describes the full set of municipal controls necessary to ensure exogeneity of the instrument, and their sources. Summary statistics of all variables are reported in Table A1D, alongside a detailed description of them provided in Appendix B. The main source of information for municipality characteristics is IBGE's decennial Demographic Census. Due to delays in publication in its thirteenth release, the most recent data available for most variables refers to 2010 values, but two pertinent characteristics for this study are available with 2022 values: the population per municipality, which is used in its natural logarithm to account for large inter-municipal discrepancies, and the average population density of each municipality, measured by total inhabitants per squared kilometers.

These are important characteristics as they heavily correlate with the study of Coronavirus' spread, as denser and more populous cities have differing sanitary conditions that impact COVID-19's severity disproportionately, and increase radial contamination, at least in the beginning of the pandemic (Nicolelis et al. 2021). Other than those, from the 2010 persons sample we build municipal measures of urbanity, age, race, origin, religion, education, reliance on welfare programs, employment, income, and behavioral patterns. From the 2010 households sample we build municipal measures of household compositions, living conditions, and access to public and private goods and services.

We complement this set of municipal characteristics using several other datasets. We use National Civil Aviation Agency's and IBGE's Coastal Municipalities data to gather non-road connections, which might weaken distance's impact on Coronavirus' spreading. This manner of municipal contact is, in fact, a core element epidemiologists use to model the spread of viral infections, including the Coronavirus pandemic (De Souza et al. 2021; Grais, Hugh Ellis, and Glass 2003). From the Unified Health System's (SUS) National Registry of Health Service Providers and Primary Care Information and Management Services datasets, we gather municipal supply and coverage of publicly and privately managed healthcare services, since they are core determinants of municipal capacity to deal with the pandemic. We address people's desire for law-and-order oriented politics using the 2017 homicide rate available from the Institute of Applied Economic Research's Violence Atlas, since this is the latest year with data available for all municipalities in supplement tables, allowing for the identification of 9 additional observations that would otherwise be excluded from the sample.

To address the prevalence of clientelistic practices in local politics, influence of lobbyists vouching for farmers' and rural landowners' interests, and unaccounted poverty and reliance on government's assistance we use the IBGE's estimates of municipal GDP composition and data on *Programa Bolsa Família* (PBF), one of the largest social welfare and poverty alleviation programs in the world and most important welfare program in Brazil (Chitolina, Foguel, and Menezes-Filho 2016; Gerard, Naritomi, and Silva 2021). Finally, from IBGE's territorial network data we also collect some geographic characteristics that might reflect lasting patterns in municipality's development: these are the latitude-longitude ordered pair, a state capital dummy, municipal connections with the municipality we assume is the source of municipality's contagion, and a vector of 133 dummy variables, one for each region.[4]

3 Identification strategy

3.1 Empirical framework

We address endogeneity concerns in COVID-19's severity by leveraging exogenous geographic variation to construct measures of municipalities' relative isolation from spreading hubs as a source of quasi-random assortment of Coronavirus outbreaks, and use it as an instrument to estimate the impact of COVID-19 deaths on support for the incumbent Brazilian president, Jair Bolsonaro. The idea behind this approach it to employ only COVID-19 deaths stemming from municipal isolation as identification to consistently estimate their impacts on Bolsonaro's electoral prospects.

In our setup, this will work if municipal location relative to other municipalities is uncorrelated with shifts in electoral preferences, once we address the various manners in which isolated municipalities differ from non-isolated municipalities. We pursue this by employing a large vector of control variables, composed of 70 municipal characteristics (X, see Appendix B) and a set of 133 regional dummies (Λ), such that municipal isolation $Z \perp\!\!\!\perp \varepsilon \mid (X, \Lambda)$; where ε refers to all unobserved shifts in electoral outcomes. Since the exogeneity assumption might seem strong, despite our usage of intercity distance to calculate isolation and the various controls used, we shed light on its plausibility by running a battery of placebo tests, ultimately showing that under our specification municipal COVID-19 mortality rates are not estimated to have had any significative impact on elections that happened prior to the pandemic, and that our instrument is not an adequate predictor of mortality rates stemming from alternative causes of death.

Out identification assumption also requires that COVID-19 deaths are correlated to location after we account for the set of controls. This assumption rests upon the particular process of the pandemic's interiorization throughout the Brazilian territory. During the first

4. Intermediary geographic regions or meso-regions, simply called regions, are composed of municipalities broadly sharing a single urban reference point of regional relevance, which act as a trading hub among neighboring local markets for goods and factors. (IBGE 2017).

quarter of 2020, COVID-19 confirmed cases and deaths were primarily located in a few clusters of municipalities, most of them capital cities and metropolitan regions in the most populous and interconnected states. As the pandemic evolved, the virus disseminated from these focal regions onto neighboring regions, and then onto their neighboring regions and so on, in a cascading effect guided primarily by road networks (Castro et al. 2021; Nicolelis et al. 2021).

Since the municipality's size is strongly correlated with how early it were first exposed to the virus, municipal position in space might offer insights on the dynamics of viral diffusion. In particular, traveling is costly and distance to large municipalities holds a robust negative correlation with migration and commuting flows (Monte, Redding, and Rossi-Hansberg 2018), which decreases the odds of commuters acting as virus-carriers to their home municipalities, plausibly delaying municipality's first contact with the virus. Importantly, local authorities who faced the virus later, in turn, had more time to prepare for adequate preemptive and palliative measures, and had vaccines delivered later in their epidemic curve. If the described delayed-contact mechanism from isolation measures has a lasting impact on municipal cumulative mortality rates, our first-stage holds. Evidence shows that reduced communication, distance, and mobility between infected and uninfected populations reduce spread of the virus (Keeling et al. 2001; Kondo 2021). First-stage regressions can show whether distance is indeed reflective of isolation, as the theory suggests (Monte, Redding, and Rossi-Hansberg 2018), and whether isolation has a lasting impact on municipal mortality rates.

3.2 The Isolation Measure

We begin by describing the construction of the municipal isolation instrument. Since municipal population is a determinant of viral outbreak, we set 50,000 inhabitants as the baseline arbitrary threshold characterizing a municipality as sufficiently populous to be considered a Coronavirus radial spreader onto nearby municipalities, but different thresholds do not change of main results. From the origin-destination matrix described in Section 2.3, we identify the *nearest large municipality* (NLM) as the non-m municipality with more than fifty thousand inhabitants which minimizes the set of haversine-distances between municipalities' centroids to that of municipality m. Municipality m's Distance to NLM variable is then defined as:

$$distance_m = \min_{n \neq m} \{hav_{m,n} : population_n > 50{,}000\}, \tag{1}$$

where $population_n$ stands for municipality n's total population count according to IBGE's 2022 Census data, and $hav_{m,n}$ is the haversine distance between municipalities m and n.[5]

To differentiate arguably exogenous factors driving municipal exposition to the virus (namely, proximity to its NLM) from endogenous factors driving exposition (municipality's overall size and relevance to the national economy), we solely use distance to the nearest *distinct* municipality that surpasses the population threshold, municipalities with more inhabitants than the pre-established threshold have the closest municipality that also surpasses the threshold as their NLM; which in turn requires explicit modeling of the interaction between municipalities' size and distance. This approach, in opposition to setting large municipalities' distance to zero for instance, allows for a clearer distinction between differently-sized municipalities, since municipalities' capacity to disseminate the Coronavirus is not only dependent of the spreader-municipality's size, but also the recipient-municipality's size.

Following Nicolelis et al. (2021), consider a small subset of large cities were first importers of the virus from abroad, through air connections. While neighboring municipalities might be exposed to the virus via the road network, far away municipalities might still be exposed to the same virus if more people travel between it and the original infection hub. This is expected to be the case the larger the yet-uninfected municipality is, following usual neoclassical gravity models (Monte, Redding, and Rossi-Hansberg 2018). In particular, the first international importers have their Coronavirus outbreaks completely orthogonal to municipal isolation to a large urban center, acting only as spreaders but not recipients of the virus. Results that the link between distance, as calculated in Equation 1, and the COVID-19 severity in a municipality must be weakening according to municipality's own population.

5. The haversine distance, in turn, is calculated as

$$hav_{m,n} = 2r \sin^{-1} \left[\sqrt{\sin^2\left(\frac{\text{lat}_m - \text{lat}_n}{2}\right) + \cos(\text{lat}_m)\cos(\text{lat}_n)\sin^2\left(\frac{\text{lon}_m - \text{lon}_n}{2}\right)} \right],$$

where $(\text{lat}_i, \text{lon}_i)$ represents the latitude-longitude ordered pair for municipality $i = m, n$'s centroid and $r \approx 6{,}371$ stands for the Earth's radius in kilometers.

We build the instrument, therefore, as the random vector

$$Z_{mr} = \begin{bmatrix} \ln distance_{mr} \\ \ln distance_{mr} \times \ln population_{mr} \end{bmatrix}, \tag{2}$$

where $\ln distance_{mr}$ is the natural logarithm of the distance municipality m in region r has to its NLM, and $\ln population_{mr}$ is the natural logarithm of municipality m's population. The non-linear correlation between the estimated instrument and its components is reported in Figure 1.

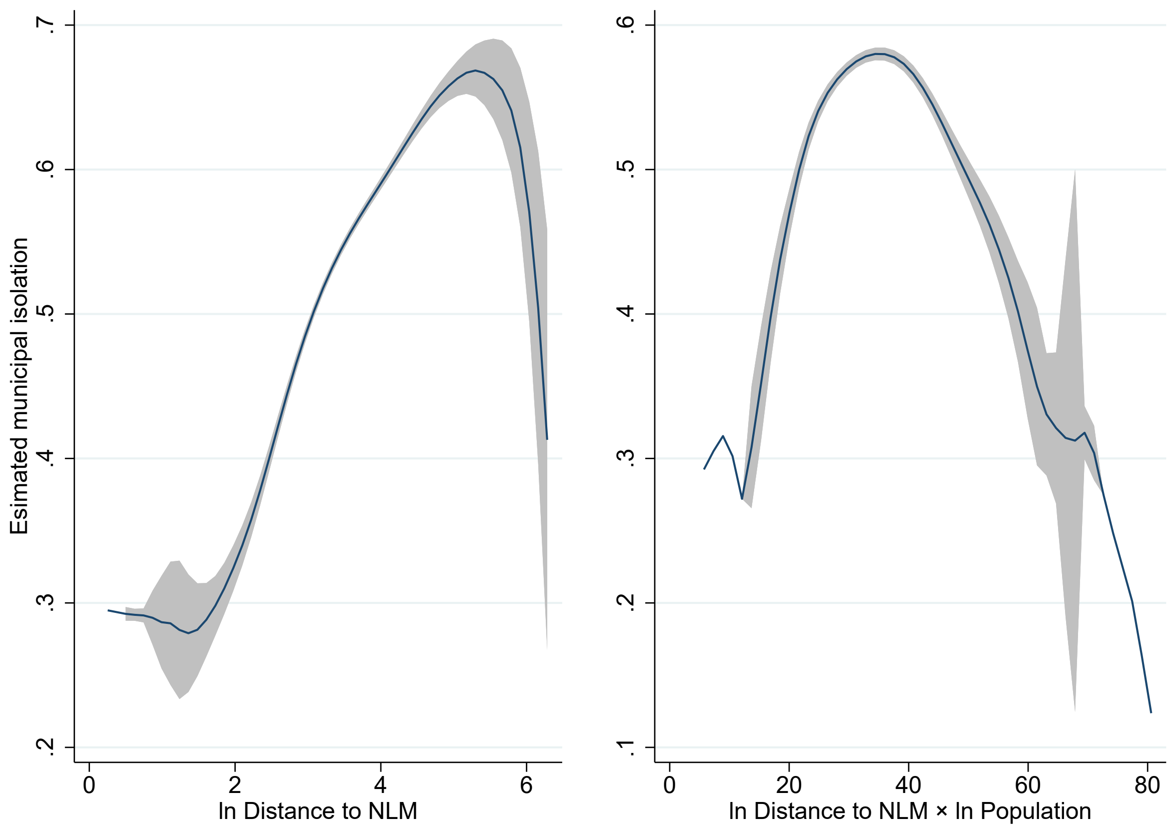

Figure 1: Municipal isolation by its building components

Notes: The figure reports the non-parametric correlation between estimated municipal isolation $Z'_m\hat{\Pi}$ (re-centered and normalized) and its building components, the distance to *nearest large municipality* (defined by a population surpassing 50,000 inhabitants) and its interaction with municipal population (all in logs). Optimal kernel and bandwidths calculated according to Cox (2021). 95% confidence interval in gray.

This decomposition is useful since, with it, we can model Coronavirus severity in a municipality directly as a function of the distance to NLM variable. As a result, we can test the strength of the correlation between COVID-19 mortality and the proposed instrument through the First-Stage regression equation

$$covid_{mr} = \eta + Z'_{mr}\Pi + X'_{mr}\psi + \Lambda_r + \upsilon_{mr}, \tag{3}$$

where $covid_{mr}$ is the cumulative COVID-19 mortality rate per hundred thousand inhabitants in municipality m, in region r; $\Pi = (\pi_1, \pi_2)$ is the column-vector of weight-parameters for each of the instrument's components; X_{mr} is the vector of municipal-level controls listed in Appendix B; Λ_r is the vector of regional intercepts; and υ_{mr} is the heteroskedastic random error term, clustered at the regional level.

If distance to large municipalities' impact on date of first infection has lasting consequences on cumulative mortality rates, π_1 and π_2 are jointly statistically different than zero and the Inclusion Restriction holds. We build municipal isolation measures from the aforementioned estimates, and report the non-linear relation between estimated isolation and how early the virus reaches municipalities and their cumulative death rate in Figure 2.

We then use the arguably exogenous components of municipal isolation $Z'_{mr}\hat{\Pi}$ as an instrument for the cumulative COVID-19 mortality rate up to election day in the following structural model:

$$\Delta voteshare_{mr} = \alpha + \beta covid_{mr} + X'_{mr}\gamma + \Lambda_r + \varepsilon_{mr}, \tag{4}$$

where $\Delta voteshare_{mr}$ is the valid vote share variation for a candidate/party in municipality m, region r, between two consecutive elections of the same type, in the same round; and ε_{mr} is the heteroskedastic random error term, clustered at the regional level. All regressions of the structural model are weighted by municipalities' population.

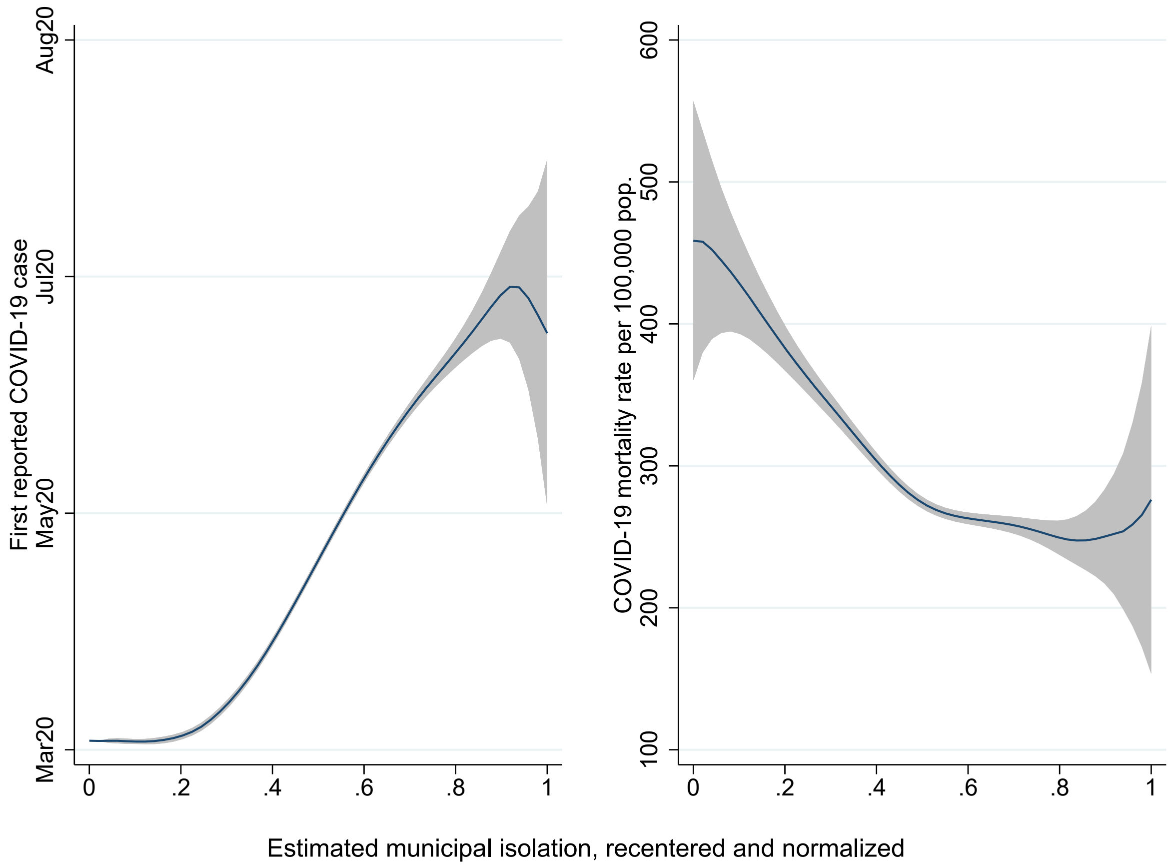

Figure 2: COVID-19 first case and mortality rate by estimated municipal isolation

Notes: The figure reports the non-parametric correlation between estimated municipal isolation $Z_m'\hat{\Pi}$, as measured by the (recentered and normalized) linear combination between the distance to *nearest large municipality* (defined by a population surpassing 50,000 inhabitants) and its interaction with municipal population (all in logs), and date of COVID-19 first appearance and cumulative death toll up to Oct. 1, 2022, in the municipality. Optimal kernel and bandwidths calculated according to Cox (2021). 95% confidence interval in gray.

4 Results

4.1 Municipal isolation and severity of the COVID-19 outbreak

We begin by analyzing the systematic relation between cumulative COVID-19 municipal mortality rate up to October 1, 2022 (the day prior to the presidential election), and the arguably exogenous components of our measure of how sheltered a municipality is: municipality's distance to the *nearest large municipality* (NLM, identified by having more than 50,000 total inhabitants in 2022) and its interaction with municipality's population count (in logs), once we address for population count and various other manners in which municipalities differ. OLS estimates of Equation 3 are reported in Table 2.

Table 2: COVID-19 mortality rates and municipal isolation (First-Stage)

	COVID-19 mortality rate (Oct. 1, 2022)					
	(1)	(2)	(3)	(4)	(5)	(6)
Distance to NLM (logs)	-33.52	-74.19***	-141.1**	-109.8	-119.0***	-110.8***
	(33.40)	(20.11)	(63.82)	(68.67)	(28.64)	(20.69)
Distance × Population (logs)	0.532	7.440***	11.07**	8.985	9.887***	9.163***
	(3.113)	(1.960)	(5.430)	(6.161)	(2.754)	(2.092)
Mean value dep. var.	273.2	273.2	342.9	342.9	342.9	342.9
Joint F-stat (2, 132 df.)	9.544***	7.207***	3.943**	3.204**	10.60***	20.27***
Total population (logs)	Yes	Yes	Yes	Yes	Yes	Yes
Regional intercepts	No	Yes	No	Yes	No	Yes
Municipal controls	No	Yes	No	No	Yes	Yes
Population weights	No	No	Yes	Yes	Yes	Yes
Observations	5,570	5,563	5,570	5,570	5,563	5,563
R-squared	0.042	0.557	0.268	0.697	0.687	0.802
N. clusters (regions)	133	133	133	133	133	133

Notes: The table reports correlation between COVID-19 municipal mortality rate and the natural logarithm of distance to *nearest large municipality* (defined by a population surpassing 50,000 inhabitants), the natural logarithm of municipality's population, and their interaction; mortality rate is measured per 100,000 inhabitants, cumulatively up until Oct. 1, 2022. Columns 1 and 2 reports the aforementioned correlation without weighting for municipality's population; columns 3 to 6 employ municipality's population as analytical weight; columns 1 and 3 employs no additional controls, except for an omitted constant; column 4 employs regional intercepts; column 5 employs the vector of municipal control variables listed in Table A1D, and an omitted constant; columns 2 and 6 employ regional intercepts and the vector of municipal controls. Heteroskedasticity-robust standard errors clustered at the regional level reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

Column 1 presents the most pedestrian version of the model relating between municipal isolation and cumulative COVID-19 mortality rates, regressing it on Distance to NLM, Population and their interaction, but no additional controls; column 2 reports estimates for the complete model in Equation 3, columns 3 to 6 use total municipal population as analytical weights, with column 3 employing no additional covariates, column 4 including the vector of regional intercepts, column 5 including the vector of municipal covariates, and column 6 including both vectors of intercepts and municipal covariates. Besides point estimates for the individual components of the instrument, we also report the F-statistic for the joint hypothesis test that $\pi_1 = \pi_2 = 0$. It tests our instrument's strength, reporting the

F-statistic and the probability of instrument's individual components presenting such values under the null hypothesis, suggesting how likely our measure of municipal isolation actually being uncorrelated with COVID-19 mortality.

Although the point estimates for the individual variables are sensitive to the specification employed, testing whether both of them are jointly uncorrelated with deaths consistently have p-values < 0.05. The complete model, with population weights and the entire set of controls in column 6 presents p-value < 0.0001. We conclude the further away a municipality is from its NLM, the more isolated it is facing less deaths as a result, but this correspondence weakens on the totality of municipality's inhabitants. It seems the observed correlation between COVID-19 spread and our proposed instrument is consistent with the epidemiological literature (Keeling et al. 2001; Kondo 2021), economic theory (Monte, Redding, and Rossi-Hansberg 2018), and similar results for economic research of COVID-19 in other countries (Valsecchi and Durante 2021).

To examine whether we are not capturing the impact of the spreading of the Coronavirus described by Castro et al. (2021) and Nicolelis et al. (2021), rather than unobserved municipal characteristics, we also regress the yearly cumulative mortality rate by other causes of death on the same set of variables for each year since 2008 as placebo tests. Estimates reported in Table 3 show that the results are not statistically significant at the usual levels, and are seemingly centered on zero. We conclude that more sheltered municipalities are robustly associated with less COVID-19 deaths per hundred thousand inhabitants, and this is due to delayed and reduced contact with the virus, rather than urban density or differences in lifestyle.

In sum, it seems that municipalities' relative isolation as measured by distance to the nearest population center with more than 50,000 inhabitants delayed municipalities' contact with the virus and, in doing so, reduced mortality rates in them. This phenomena is more pronounced the less relevant a municipality is to the overall national economy, as measured by total inhabitants. Since intercity distance is defined prior to the pandemic, and all other factors relating to both mortality rates and electoral preferences are accounted for, we can use the intercity-distance component of relative municipal isolation as a source of variation to estimate the impacts of COVID-19 on Brazil's 2022 presidential election.

Table 3: Placebo Tests: Municipal isolation and non-COVID mortality over time

	Yearly mortality rate (all other causes of death)														
	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Distance to NLM (logs)	3.577	-3.015	3.368	4.306	-9.771	-12.87	-23.09	-26.90	-19.85	-12.20	-16.63	-31.80*	24.80	3.211	-17.31
	(20.39)	(20.10)	(20.58)	(22.40)	(19.58)	(19.08)	(20.04)	(20.95)	(20.65)	(18.77)	(18.41)	(18.83)	(22.60)	(23.17)	(18.08)
Distance × Population (logs)	-0.651	-0.00366	-0.605	-0.469	0.574	1.097	1.830	2.027	1.456	0.966	1.301	2.404	-2.673	-0.633	1.205
	(1.798)	(1.721)	(1.754)	(1.914)	(1.688)	(1.692)	(1.772)	(1.911)	(1.797)	(1.626)	(1.641)	(1.641)	(2.006)	(2.058)	(1.577)
Mean value dep. var.	528.3	540.9	557.9	574.3	579.6	594.1	602.3	620.8	643.2	644.9	647.0	663.4	660.6	692.2	726.8
Joint F-stat (2, 132 df.)	0.338	0.224	0.317	0.051	0.326	0.228	0.728	1.295	0.571	0.238	0.484	1.793	1.59	0.361	0.800
Total population (logs)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Population weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,563	5,563	5,563	5,563	5,563	5,563	5,563	5,563	5,563	5,563	5,563	5,563	5,563	5,563	5,563
R-squared	0.814	0.821	0.826	0.822	0.823	0.830	0.822	0.822	0.833	0.833	0.832	0.838	0.818	0.824	0.830
N. clusters (regions)	133	133	133	133	133	133	133	133	133	133	133	133	133	133	133

Notes: The table reports lack of correlation between non-COVID-19 municipal mortality rate and the natural logarithm of distance to *nearest large municipality* (defined by a population surpassing 50,000 inhabitants), the natural logarithm of municipality's population, and their interaction; for each column, mortality rate is measured cumulatively from January 1 to December 31 of each indicated year. All columns employ regional intercepts, a vector of municipal control variables, listed in Table A1D, and employ municipality's population as analytical weight. Heteroskedasticity-robust standard errors clustered at the regional level are reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

4.2 COVID-19 and presidential support

We begin by estimating Equation 4 for Bolsonaro's share of votes in the first round by OLS. Results are reported in Table 4, column 1.[6] Our estimates are small in magnitude and not statistically different than zero at the usual levels after accounting for municipal controls and meso-regional intercepts. There are plausibly factors at play that could make these OLS estimates inconsistent. Support for the president is robustly correlated to increased mortality (Figueira and Moreno-Louzada 2023), and his influence over voters ultimately led them to adopt unsanitary behavior (Ajzenman, Cavalcanti, and Da Mata 2023). If, for instance, some unobserved measure of social conservatism increased susceptibility to COVID-19 through his denialist stances, while also decreasing vote loss in the absence of other confounders, the estimate in column 1 would have an upward bias.

Table 4: The impact of COVID-19 mortality on Jair Bolsonaro votes

	Δ Bolsonaro valid vote share, 1st round				2nd round
	OLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)
COVID-19	-0.000586	-0.0512***	-0.0543**	-0.0158***	-0.0122**
	(0.000729)	(0.0192)	(0.0253)	(0.00599)	(0.00480)
Mean value dep. var.	-2.628	-2.628	-2.628	-2.628	-6.026
Total population (logs)	Yes	Yes	Yes	Yes	Yes
Regional intercepts	Yes	No	Yes	Yes	Yes
Municipal controls	Yes	No	No	Yes	Yes
Population weights	Yes	Yes	Yes	Yes	Yes
Observations	5,563	5,570	5,570	5,563	5,563
R-squared	0.883	-0.259	0.357	0.853	0.924
N. clusters (regions)	133	133	133	133	133

Notes: The table reports the impact of COVID-19 mortality rate on Jair Bolsonaro's valid vote share variation, between the 2018 and 2022 presidential elections; mortality rate is measured per 100,000 inhabitants, cumulatively up until Oct. 1, 2022. Columns 1 and 5 uses OLS estimators for the first and second rounds; columns 2 to 4 use 2SLS estimators for the second round, and column 5 for the second round, jointly instrumenting municipal mortality rate by the natural logarithm of distance to *nearest large municipality* (defined by a population surpassing 50,000 inhabitants) and its interaction with the natural logarithm of municipality's population. Column 2 employs no controls except for the natural logarithm of municipality's population; column 3 additionally employs regional intercepts; columns 1, 4 and 5 employ regional intercepts and the vector of municipal controls listed in Table A1D; all columns employ municipality's population as analytical weight. Heteroskedasticity-robust standard errors clustered at the regional level are reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

6. All regressions use valid vote share variation as the dependent variable and municipality's size as analytical weights.

We account for these sources of bias by employing an instrumental variable estimator in which distance to NLM and the interaction between distance to NLM and municipality's size (all in logs) are used as a source of exogenous variation for severity of the COVID-19 outbreak in a municipality. Results are presented in columns 2 to 5: in column 2 we only control for municipality's size; in column 3, we also account for the entirety of variation between different regions by employing the vector of regional intercepts; in column 4, besides the regional intercepts, we also employ all observed municipal characteristics listed in Table A1D and described in Appendix B; in column 5 we present results for the second round, under the full set of controls.

By using solely exogenous severity in outbreak, our estimates increase substantially and acquire statistical significance: the point-estimate for the impact of COVID-19 mortality rate on Bolsonaro's valid vote share between 2018 and 2022 increases significantly from the OLS estimator in column 1 to the 2SLS estimator in column 2. Column 3 includes regional intercepts to address common regional trends, and municipal controls in column 4, which address remaining characteristics influencing political preferences and COVID-19 mortality. In doing so, the estimated magnitude of the coefficient is reduced by a factor of three, so that each COVID-19 death per 1,000 inhabitants reduces the president's vote share by 1.6 percentage points between 2018 and 2022.

In column 5 we use the vote share in the second round, finding a 20% decrease in magnitude from the first to the second round results, suggesting that for each five voters that cease to vote for Bolsonaro in the first round due to COVID-19, four effectively carry over to the second round, preferring the opposition Center-Left candidate Lula over Bolsonaro, who was their first choice in 2018. In the first round voters have a wider pool of candidates to chose from: they may opt for an alternative candidate closer to their overall alignment that is not the incumbent president, whereas in the second round they must choose either Bolsonaro, Lula, or abstaining from voting. By using valid vote share variation, our estimates reflect just aggregates swings from Bolsonaro to Lula, which explains higher aggregate reluctance of changes in voting patterns. It is however surprising how willing voters are, on aggregate, to move from Bolsonaro to Lula due to COVID-19, considering their policy differences. These results retain statistical significance upon drawing spatial clusters from different levels of municipal aggregation, rather than from the 133 regions we use as dummy variables (see Table A2).

The magnitude of these results imply that one COVID-19 death is estimated to dissuade, on average, 9.4 voters away from Bolsonaro's platform (7.3 in the second round). Moreover, linear extrapolations of these results would suggest that in the absence of COVID-19, all else constant, Bolsonaro would have won the 2022 election in the second round with a 6 percentage points advantage, rather than lagging behind his opponent by one point. It seems the presidential candidate change in the main opposition party, moreover, yielded votes for PT, but the gain would be insufficient in the absence of the pandemic, resulting in only a 2.5 percentage points net increase by swapping Fernando Haddad by Lula. Finally, it would seem the complete absence of the pandemic would not be necessary for Bolsonaro's victory: if just 15% of lives lost due to COVID-19 were saved, he would have won by a narrow margin in the second round. Research suggests such a task that could be accomplished merely by engaging in a concentrated governmental effort to adequately supply vaccination to the population, without any sort of non-pharmaceutical intervention (Araújo et al. 2023; Ferreira et al. 2023).

In studies where geography plays a large role, one source of concern is whether the instrument is particularly binding to one outlying region where the result is valid, in which case the instrument, rather than serving as a source of exogenous variation, captures joint movements in both variables in some specific region, resulting in a misleading interpretation of the phenomena.[7] In our setup this could be caused, for instance, by a small set of municipalities which faced deadlier COVID-19 outbreaks and switched votes away from Bolsonaro (not necessarily due to the pandemic) having their exposition to the virus uniquely ascribed by the instrument. We show this is not the case by filtering municipalities in the sample according to their region and size, and running the 2SLS estimation procedure. Results for the joint instrument F-statistic in the first-stage and point-estimates in the second-stage are reported in Table A3. Despite Northern and Mid-Western municipalities being overall more sheltered than Southern, Southeastern and Northeastern municipalities (see Table 1), the instrument and COVID-19's impact on the electorate seemingly hold in all regions, even if

7. For a systematic review of the issue, see Kelly (2020).

there are regional discrepancies. We also find that our results still hold for municipalities with less than 50,000 inhabitants, despite Brazil's demographic concentration primarily reflecting electoral shifts in larger municipalities. Finally, it seems the proposed instrument is weak when filtering out small municipalities, as is expected since larger municipalities are assumed to be hubs of viral spreading, whose contact with the virus is not necessarily bound by their distance to any other particular municipality.

4.3 Robustness

Our municipal isolation measure is built using the municipalities' distance to large municipalities, which are arbitrarily defined as those with more than 50,000 inhabitants. We first show that there is nothing in particular about this threshold which makes it necessary for the validity of our results. Municipal distance to a large city is robustly associated with its exposition to COVID-19 regardless of how we define a large city, providing additional evidence that distance is, ultimately, *as-if* random in our setup and variation in outbreak severity stemming from it is plausibly exogenous. We present first-stage and point-estimate results for the 2SLS estimator when we consider municipalities with more than 25,000 (columns 1 to 3) and 100,000 (columns 4 to 6) inhabitants as large in Table 5.

In columns 1 and 4 we present evidence suggesting the further away a municipality is from large municipalities (regardless of the definition we use to characterize them), the more sheltered it is from Coronavirus, and the aforementioned relation weakens according to municipality's own size. Moreover, the F-statistic reported for the null-hypothesis that the instrument lacks correlation with mortality rate presents equally strong evidence this is not the case, being statistically significant at the 0.01% level. Moreover, it seems that more strict definitions of large municipalities reduce the magnitude of first-stage estimates. This is due to increases in the population threshold for large municipality increasing average distance between municipalities and their NLM, while the theoretical measure of how sheltered a municipality is, therefore its exogenously assigned COVID-19 outbreak severity, remains constant. Regardless of the threshold employed, the independent variables in first-stage retain statistical significance both independently and jointly, allowing us to interpret the impact of COVID-19 mortality rate on Bolsonaro's valid vote share variation instrumented

Table 5: Robustness: Alternative thresholds characterizing "large municipalities" (2SLS)

Large munic. threshold:	More than 25,000 inhabitants			More than 100,000 inhabitants		
	COVID-19	Δ Bolsonaro		COVID-19	Δ Bolsonaro	
	(1st stage)	1st round	2nd round	(1st stage)	1st round	2nd round
	(1)	(2)	(3)	(4)	(5)	(6)
Distance to NLM (logs)	-125.9***			-90.86***		
	(24.15)			(17.18)		
Distance × Population (logs)	11.14***			7.390***		
	(2.433)			(1.737)		
COVID-19		-0.0127**	-0.0112**		-0.0208***	-0.0186***
		(0.00583)	(0.00453)		(0.00708)	(0.00677)
Mean value dep. var.	342.9	-2.628	-6.026	342.9	-2.628	-6.026
Joint F-stat (2, 132 df.)	16.88***			19.00***		
Total population (logs)	Yes	Yes	Yes	Yes	Yes	Yes
Regional intercepts	Yes	Yes	Yes	Yes	Yes	Yes
Municipal controls	Yes	Yes	Yes	Yes	Yes	Yes
Population weights	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,563	5,563	5,563	5,563	5,563	5,563
R-squared	0.803	0.864	0.926	0.802	0.830	0.908
N. clusters (regions)	133	133	133	133	133	133

Notes: The table reports how our estimates are not sensitive to "large municipalities"' size, as long as they are sufficiently relevant to the regional economy so they function as a focal hub of COVID-19 spreading. Columns 1 to 3 define a *large municipality* by a population surpassing 25,000 inhabitants; columns 4 to 6 define a *large municipality* by a population surpassing 100,000 inhabitants. Columns 1 and 4 report the correlation between distance to a large municipality and COVID-19 mortality rate per 100,000 inhabitants up to Oct. 1, 2022; columns 2, 3, 5 and 6 analyze the impact of the aforementioned COVID-19 mortality rate on Bolsonaro valid vote share variation between 2018 and 2022, jointly instrumented by the natural logarithm of distance to the *nearest large municipality* and its interaction with the natural logarithm of municipality's population; columns 2 and 5 for the elections first round, columns 3 and 6 for the second round. All columns employ regional intercepts, a vector of municipal controls listed in Table A1D, and municipality's population as analytical weight. Heteroskedasticity-robust standard errors clustered at the regional level are reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

by different distance variables, results are reported in columns 2, 3, 5 and 6.

In columns 2 and 5 we report vote share variation in the first round; in columns 3 and 6, in the second round. Overall results remain roughly unchanging with Bolsonaro losing between 1 and 2 percentage points for each COVID-19 death per thousand inhabitants, with vote loss being larger in the first than in the second round; results using distance to the nearest municipality with more than 25,000 inhabitants are significant at the 5% level, whereas results using distance to the nearest municipality with more than 100,000 inhabitants are significant at the 1% level.

We now modify Equation 4 to admit solely the interaction term between distance to NLM and municipality's size as an instrument to COVID-19 mortality to examine whether the main results hold. Since our measure of municipal isolation is composed of two statistically significant variables in the first-stage regression (see Table 2), the usage of only one of these variables as an instrument with the remaining as a control should be similar to the original estimate. The modified structural equation then becomes:

$$\Delta voteshare_{mr} = \alpha_a + \beta_a covid_{mr} + X'_{mr}\gamma_a + \delta \ln dist_m + \Lambda_{a,r} + \varepsilon_{a,mr}, \tag{5}$$

where the subscript a denotes the *altered* parameter to be estimated. If distance to NLM is indeed exogenous, we would expect our estimates for β_a in Equation 5 to be identical to those of β in Equation 4, and δ to be zero. We present these results in Table 6.

Since the first-stage regression is the same one presented in Table 2, we do not need to report it. Now the cumulative COVID-19 mortality rate up to October 1, 2022, is instrumented solely by the interaction between Distance to NLM and Total population (both in logs). Moreover, due to the (relatively) small correlation between distance and vote share variation, it is unsurprising for our results in columns 1 and 2 to be roughly identical to those originally found in Table 4 (p-values of 0.802 and 0.943 for the first and second round). In column 3 we also test vote share variation in the first round for candidates from the main opposition party, the center-left Workers' Party (PT); we find a 0.0147 percentage point increase in support in the first round for every COVID-19 death by 100,000 inhabitants (statistically significant at the 10% level), but important here is that distance's correlation with vote share variation is still not statistically significant at the usual levels.

Plausibility of exogeneity assumption: Placebo tests

Although distance should not impact voting patterns once we employ the full set of controls, we ensure our results do not capture some spurious correlation between isolation and variation in support by running an additional battery of tests estimating the electoral impacts of COVID-19 mortality on previous changes in electoral support. If any unobserved systematic

Table 6: Robustness: Alternative specification with Distance to NLM as a covariate (2SLS)

	Δ Bolsonaro, 1st round (1)	Δ Bolsonaro, 2nd round (2)	Δ PT, 1st round (3)
COVID-19	-0.0160**	-0.0121**	0.0147*
	(0.00660)	(0.00498)	(0.00834)
Distance to NLM (logs)	-0.0536	0.0125	0.267
	(0.214)	(0.175)	(0.258)
Mean value dep. var.	-2.628	-6.026	18.75
Total population (logs)	Yes	Yes	Yes
Regional intercepts	Yes	Yes	Yes
Municipal controls	Yes	Yes	Yes
Population weights	Yes	Yes	Yes
Observations	5,563	5,563	5,563
R-squared	0.852	0.924	0.902
N. clusters (regions)	133	133	133

Notes: The table reports how our estimates remain roughly unchanged by using the natural logarithm of distance to the nearest municipality with more than 50,000 inhabitants as an exogenous covariate rather than as an instrument. Columns 1 and 2 report the impact of cumulative COVID-19 mortality rate up to Oct. 1, 2022, on Bolsonaro's valid vote share variation between 2018 and 2022 in the first and second round of elections; column 3 reports the impact of municipality's COVID-19 mortality rate on PT's valid vote share variation between 2018 and 2022 in the first round of elections; all columns instrument COVID-19 mortality by the interaction between the natural logarithm of the distance to the nearest municipality with more than 50,000 inhabitants and the natural logarithm of municipality's population. All columns employ regional intercepts, a vector of municipal controls listed in Table A1D, and employ municipality's population as analytical weight. Heteroskedasticity-robust standard errors clustered at the regional level are reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

correlation was the cause for our results in the 2022 elections, we could expect it to also be present in previous elections. Results are reported in Table 7.

In columns 1 to 4 we present valid vote share variation for PT between 2018 and 2014 (columns 1 and 3), and 2014 and 2010 (columns 2 and 4), in the first (columns 1 and 2) and second (columns 3 and 4) round of the elections; in columns 5 and 6 we present valid vote share variation for Right-Wing mayoral candidates between 2016 and 2012 (column 5), and 2012 and 2008 (column 6).[8] Our results are not statistically significant at the usual levels, seemingly centered on zero, and generally small in magnitude. Compared to the systematically small p-values we find for Bolsonaro's vote loss due to COVID-19 (all

8. Candidates are considered Right-wing if the average self-ascribed ideological score of their affiliated party, as stated by the party's elected congressmen, is greater than or equal to 5.5 in the year after the election (Zucco 2023). Further explanation is given in Section 5.

Table 7: Placebo Tests: Impact of COVID-19 on prior elections (2SLS)

	Presidential elections				Municipal elections	
	Δ PT, 1st round		Δ PT, 2nd round		Δ Right-Wing candidates	
	2018-2014	2014-2010	2018-2014	2014-2010	2016-2012	2012-2008
	(1)	(2)	(3)	(4)	(5)	(6)
COVID-19	0.00513	-0.0116	-0.0114	-0.0156	0.0912	-0.0105
	(0.0123)	(0.0149)	(0.0161)	(0.0127)	(0.0908)	(0.0822)
Mean value dep. var.	-12.43	-5.610	-7.383	-4.399	30.84	12.59
Total population (logs)	Yes	Yes	Yes	Yes	Yes	Yes
Regional intercepts	Yes	Yes	Yes	Yes	Yes	Yes
Municipal controls	Yes	Yes	Yes	Yes	Yes	Yes
Population weights	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,563	5,563	5,563	5,563	5,557	5,560
R-squared	0.850	0.715	0.833	0.740	0.238	0.231
N. clusters (regions)	133	133	133	133	132	132

Notes: The table reports the lack of estimated impact of COVID-19 mortality rates on elections that occurred prior to the pandemic. Columns 1 to 4 report the hypothetical impact of cumulative COVID- 19 mortality rate up to Oct. 1, 2022, on PT's presidential candidates valid vote share variation between the 2014 and 2018, and 2010 and 2014 elections, first and second round. Columns 5 and 6 report the hypothetical impact of cumulative COVID-19 mortality rate up to Nov. 14, 2020, on Right-Wing mayoral candidates' (defined by affiliation with party whose average score in Zucco 2023 is greater than 5.5) valid vote share variation between the 2012 and 2016, and 2008 and 2012 elections. All columns employ regional intercepts, a vector of municipal controls listed in Table A1D, and municipality's population as analytical weight. Heteroskedasticity-robust standard errors clustered at the regional level are reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

significant at the usual levels, see Table A2), the range of p-values implied in Table 7 (between 0.22 and 0.90) suggests little evidence that COVID-19 had any impact on prior elections, as is expected. Since the identification of incumbent candidates running for re-election needs to be done manually, for not necessarily the incumbent was originally elected in the first place, analyzing incumbency of non-presidential candidates becomes impracticable. Nonetheless, this is partially captured in columns 2 and 4, when we analyze vote share variation for the incumbent president Dilma Rousseff (PT). Since our design does not reflect any significant COVID-19 impact on electoral runs where we know there to be none, the effects we estimate in setups where it may have had an impact might truly be reflective of its causal link to shifts in electoral support.

4.4 Aggregate vote shifting patterns

The Coronavirus pandemic not only had an impact on the incumbent president Jair Bolsonaro; in Table 8 we report its' estimated impact on a selection of other candidates and on the fraction of non-valid votes between 2018 and 2022. In columns 1 and 2 we report valid vote share variation for PT candidates in the first and second round; in columns 3 to 7 we report valid vote share variation for a set of smaller parties; and in column 8 and 9, non-valid vote share variation in the first and second rounds. We begin by noticing how our results in Table 6, column 3, mirror the ones in Table 8, column 1. Although the differences are larger than the ones for Bolsonaro's estimates, it reinforces the idea that results in Table 6 reflect the larger pattern of distance to NLM being conditionally uncorrelated with electoral preferences. It is interesting to note how PT seemingly only gained electoral support in the second round of the election, this suggests how support for the party likely just reflects overall rejection for Bolsonaro, at least for those who were moved by COVID-19.

The apparent null impact COVID-19 had on non-valid vote share between elections in both rounds (columns 8 and 9) suggests voters, on aggregate, actually swapped their preferred candidate, rather than e.g. Bolsonaro's voters becoming disproportionately less likely to vote. Although PT surely drew part of Bolsonaro's votes in the second round (note how the estimated impact in column 2 is reflective of Bolsonaro's loss in Table 4, column 5), it is hard to assess how many votes were actually drawn from Bolsonaro's electorate since voters also swapped supported platforms in other manners: it might be the case Bolsonaro's 2018 voters decided to vote null in 2022, and null voters in 2018 decided, in similar proportions, to proportionally distribute their vote across parties.

Table 8: COVID-19 impact on opposition candidates and other electoral results (2SLS)

	Δ PT 1st round (1)	Δ PT 2nd round (2)	Δ NOVO 1st round (3)	Δ PDT 1st round (4)	Δ MDB 1st round (5)	Δ DC 1st round (6)	Δ PSTU 1st round (7)	Δ Null 1st round (8)	Δ Null 2nd round (9)
COVID-19	0.0135	0.0122**	0.00293*	0.00931	-0.00230	-0.00006	0.000260**	0.00003	-0.00144
	(0.00864)	(0.00480)	(0.00166)	(0.00824)	(0.00178)	(0.00005)	(0.000116)	(0.00273)	(0.00266)
Mean value dep. var.	18.75	6.026	-2.001	-9.257	2.951	-0.025	-0.031	-4.357	-4.924
Total population (logs)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Population weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,563	5,563	5,563	5,563	5,563	5,563	5,563	5,563	5,563
R-squared	0.904	0.924	0.899	0.913	0.916	0.299	0.490	0.770	0.921
N. clusters (regions)	133	133	133	133	133	133	133	133	133

Notes: The table reports the impact of COVID-19 mortality rate on a selection of opposition candidates' valid vote share variation, second round, and share of null votes; mortality rate is measured per 100,000 inhabitants, cumulatively up until Oct. 1, 2022, and is jointly instrumented by the natural logarithm of distance to *nearest large municipality* (defined by a population surpassing 50,000 inhabitants) and its interaction with the natural logarithm of municipality's population. Columns 1 and 2 report vote share variation for PT, in the first and second round of elections; columns 3 to 7 report vote share variation for NOVO, PDT, MDB, DC and PSTU in the first round; columns 8 and 9 report share of null or blank votes in the first and second rounds. All columns employ regional intercepts, a vector of municipal controls listed in Table A1D, and municipality's population as analytical weight. Heteroskedasticity-robust standard errors clustered at the regional level are reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

Columns 3 and 7 suggest the alternative Far-Right party (NOVO) and the Far-Left party (PSTU) experienced increases in support resultant of COVID-19 deaths (statistically different than zero at the 10% and 5% level, respectively), seemingly unmatched by any other (more moderate) party which ran in 2018 and 2022. Although crises generally increase overall support for radicals and populists (Braggion, Manconi, and Zhu 2020; Doerr et al. 2022; Hernández and Kriesi 2016), increase in support for NOVO is nearly eleven times larger than increase in support for PSTU. This suggests COVID-19 not only engendered anti-mainstream sentiments, as is expected, it even moved voters between Far-Right options, reflecting a consistent pattern of disapproval engendered towards the incumbent president.

It appears that, on aggregate, greater municipal exposition to COVID-19 deaths led voters away from Bolsonaro's platform. Initially, they opted for similar politicians, then for anyone else. While we are unable to observe individual's choices, it is likely that ideologically-driven 2018 Bolsonaro voters were more inclined to nullify their votes in 2022, whereas 2018 null voters became more incline to vote for PT in 2022. If, however, voters are not ideologically-driven (Degan and Merlo 2009), any collective pattern and individual mechanism might be consistent with our findings. In the following section we investigate a few in detail.

5 Mechanisms

Three well established electoral mechanisms might explain our results. First, voters might actually prefer stricter sanitary policy despite stating otherwise (Oliver 2020) and punish politicians who enacted lax measures, which they were displeased with. Second, voters might associate government leaders with the pandemic regardless of policy implemented, leading all incumbents to endure electoral losses in 2022. Third, something unique about Bolsonaro's dealing with the pandemic might have engendered the anger of voters, who punished him in the following election.

Since strictness of sanitary policy was a heavily partisan issue during the pandemic (Touchton et al. 2021), we can proxy support for it through the Left-Right dichotomy. We do so by assigning candidates the average self-ascribed ideological score of elected congressmen of their party in Zucco (2023), at the year they take office; we consider Right-Wing the candidates affiliated to parties with ideological score greater than or equal to 5.5, and Far-Right those affiliated to parties with ideological score greater than or equal to 7; we also analyze mayoral candidates in the same party Bolsonaro was last affiliated to (PSC in 2016 and PSL in 2020). Since Right-Wing politicians were more likely to enact lax sanitary measures, decreases in support for them would suggest voters punish insufficient stringency on life-saving policies. In Table 9 we report this is not the case.

Table 9: COVID-19 impact on Right-Wing mayoral candidates (2SLS)

	COVID-19 (1st stage)	Δ Right-Wing	Δ Far-Right	Δ Bolsonaro's Party
	(1)	(2)	(3)	(4)
Distance to NLM (logs)	-46.48***			
	(10.71)			
Distance × Population (logs)	3.956***			
	(1.024)			
COVID-19		0.477*	-0.0224	-0.0769
		(0.249)	(0.149)	(0.0536)
Mean value dep. var.	86.78	0.459	2.959	1.066
Joint F-stat (2, 132 df.)	12.18***			
Total population (logs)	Yes	Yes	Yes	Yes
Regional intercepts	Yes	Yes	Yes	Yes
Municipal controls	Yes	Yes	Yes	Yes
Population weights	Yes	Yes	Yes	Yes
Observations	5,563	5,556	5,556	5,556
R-squared	0.812	0.217	0.274	0.128
N. clusters (regions)	133	132	132	132

Notes: The table reports the impact of COVID-19 mortality rate on Right-Wing mayoral candidates' valid vote share variation, between 2016 and 2020. Column 1 reports the correlation between cumulative COVID-19 mortality rates up to Nov. 14, 2020, and the natural logarithm of distance to nearest municipality with more than 50,000 inhabitants and its interaction with municipality's population; columns 2 to 4 report the impact of COVID-19 mortality rate on Right-Wing mayoral candidates vote share, instrumented by the natural logarithm of distance to the nearest municipality with more than 50,000 inhabitants and its interaction with the natural logarithm of municipality's population. Column 2 dependent variable is valid vote share variation for candidates affiliated to parties whose average score is greater than or equal to 5.5 in Zucco (2023); column 3, for candidates affiliated to parties whose average score is greater than or equal to 7; column 4, for candidates affiliated to PSC in 2016 and PSL in 2020. All columns employ regional intercepts, a vector of municipal controls listed in Table A1D, and municipality's population as analytical weight. Heteroskedasticity-robust standard errors clustered at the regional level are reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

In column 1 we report municipal cumulative COVID-19 mortality rate per hundred thousand inhabitants up to November 14, 2020, the day prior to the first round of the mayoral election; the column also reports the result of the first-stage regression for the remaining columns. Reported estimates are very similar to those discussed in Section 4.1, albeit smaller in magnitude since both distance and population are the same, but the Coronavirus had still not claimed as many victims (see Table A1). In columns 2, 3 and 4 we use the aforementioned criteria to characterize mayoral candidates according to support for policy. Our results suggest Right-Wing mayoral candidates actually received large electoral gains during the pandemic (significant at the 10% level), which follows from voters' stated preference (Oliver 2020), but those gains did not carry over to Far-Right candidates or those in Bolsonaro's party, plausibly due to stronger association with him.

We also examine whether voters were not blaming incumbents in general for the Coronavirus pandemic, and the deaths resultant from it during their term, by focusing on incumbent gubernatorial candidates in the 2022 election. We analyze municipal vote share variation in the first and second round for the 2022 candidates who also won the 2018 gubernatorial race, which limits our sample of municipalities to those in just 17 of the 27 states.[9] We report results in Table 10.

Despite the observed growth in support for governors in office, our estimates for the impact of cumulative COVID-19 mortality rate in the municipality on incumbent support are not statistically significant at the usual levels, with associated p-values for the impact of the pandemic ranging between 0.32 and 0.88. Our results seemingly do not support the general idea that crises themselves harm incumbents' electoral prospects: state governments who imposed sanitary measures might have reduced voters' perception of negligence, such that deaths were not impactful on ballots. Moreover, it is plausible that, if governors presented more moderate rhetoric regarding the virus, otherwise perceived recklessness or insufficient policy on state's behalf could be partially shifted onto the federal government (Bauer et al. 2023). Regardless of the mechanism at play, we conclude Bolsonaro's loss of support is not explained by electoral punishment resultant of him being in office during the COVID-19 pandemic.

Since neither incumbency nor policy were guiding factors explaining Bolsonaro's loss, we

9. Acre, Amazonas, Federal District, Espírito Santo, Goiás, Mato Grosso, Minas Gerais, Pará, Paraíba, Paraná, Rio de Janeiro, Rio Grande do Norte, Rio Grande do Sul, Rondônia, Roraima, and Santa Catarina.

Table 10: COVID-19 impact on incumbent gubernatorial candidates (2SLS)

	1st round (1)	2nd round (2)
COVID-19	-0.0126 (0.0820)	-0.142 (0.144)
Mean value dep. var.	3.662	1.000
Joint F-stat	4.068** (2, 58 df.)	1.062 (2, 13 df.)
Total population (logs)	Yes	Yes
Regional intercepts	Yes	Yes
Municipal controls	Yes	Yes
Population weights	Yes	Yes
Observations	2,028	608
R-squared	0.810	0.333
N. clusters (regions)	59	14

Notes: The table reports the impact of COVID-19 mortality on incumbent gubernatorial candidates' valid vote share variation, between the 2018 and 2022 in the first and second round; mortality rate is measured per 100,000 inhabitants, cumulatively up until Oct. 1, 2022, and is jointly instrumented by the natural logarithm of distance to nearest municipality with more than 50,000 inhabitants and its interaction with the natural logarithm of municipality's population. All columns employ regional intercepts, a vector of municipal controls listed in Table A1D, and municipality's population as analytical weight. Heteroskedasticity-robust standard errors clustered at the regional level are reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

are led to believe something unique about his engagement with the pandemic was unsavory to voters, either consciously or unconsciously, driving away a sufficiently large portion of his 2018 electorate to cost him re-election. We theorize the driving factor of disapproval were his frequent uncouth comments throughout the pandemic, of his repeated urges for the population to engage in unsanitary activities and local and state authorities to lift sanitary measures that could save lives, and even instances in which he scorned COVID-19 victims. Figure 3 plots daily COVID-19 death tolls and the dates of some of Bolsonaro's widely shared denialist statements.

If voters were concerned about the pandemic around the time of his statements, specially if they faced the hospitalization or death of a loved one, the president's rhetoric might have activated emotional responses of grief and anger, and been a deal breaker to those who elected him in 2018. While a large part of Bolsonaro's popular appeal (stemming from his rough persona and populist rhetoric, which first elected him) was kept in 2022, it appears some of it was lost as a result of the pandemic. We conclude reaffirming the literature

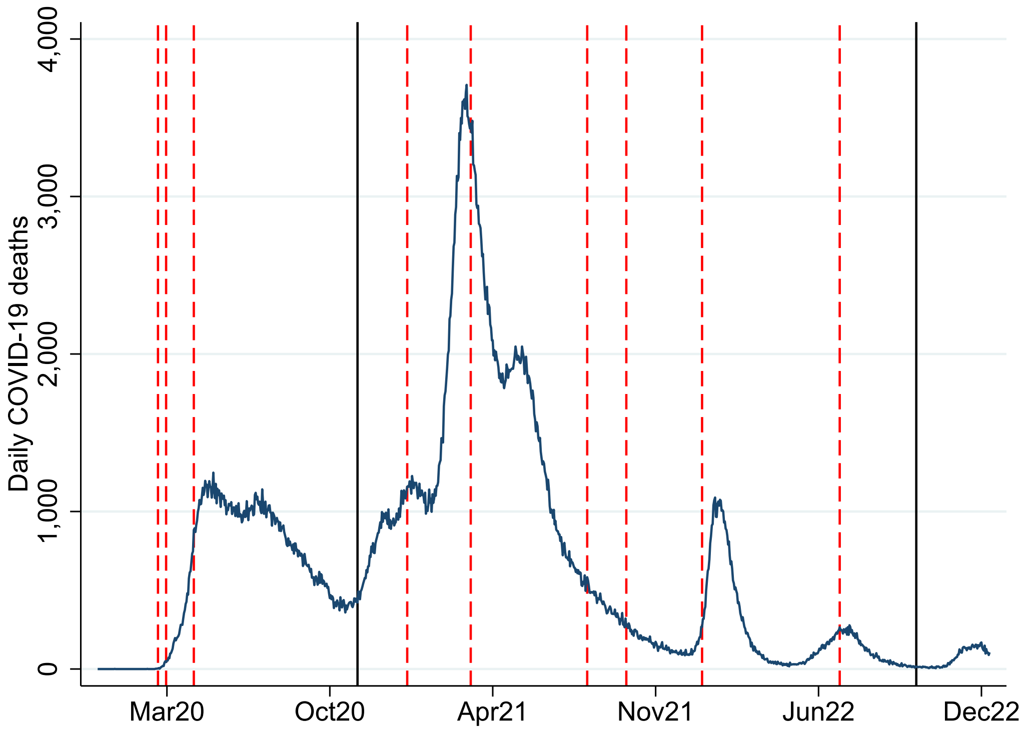

Figure 3: Evolution of the Coronavirus pandemic in Brazil

Notes: The figure reports daily COVID-19 confirmed deaths in Brazil from January 1, 2020 to December 31, 2022. The red dashed lines report some of Bolsonaro's public appearances in which he engages in COVID-19 denialism or anti-vaccine rhetoric (Ajzenman, Cavalcanti, and Da Mata 2023; CB 2021; CNN 2020; Folha 2021, 2022; Garcia, Gomes, and Viana 2020; Maia 2021; Nexo 2022; Reuters 2020); the black solid lines highlight the municipal (November 15, 2020) and presidential (October 2, 2022) elections first round.

by exploring a scenario where it seems that voters' perception of malpractice due to the incumbent's unsuccessful communication strategy fostered fear and anger, culminating in radical shifts in voting patterns which ultimately flipped the election.

6 Conclusion

Although the precise death toll which can be attributed to federal negligence and ideological affinity during the Coronavirus pandemic in Brazil is still uncertain, literature unambiguously points towards a significant number. Our results deal in the opposite relation, showing that perceived responsibility for the severity of crisis harmed the electoral prospects of then incumbent president Jair Bolsonaro. Our investigation brings to attention two interesting results. First, it appears the president was uniquely burdened with the electoral cost of

COVID-19 deaths, plausibly due to his reckless and dismissive denialism campaign relating to the disease, ultimately leading to his defeat even under our most conservative estimates.

Second, despite voters supporting lax, economic-oriented sanitary policy during the pandemic, they still punished the increased deaths on who they perceived to be responsible, even if lax sanitary policies would inevitably result in the occurrence of avoidable deaths, plausibly due to his increased association with them, or a general disgust of his unnecessarily rough treat on the delicate situation. We are led to believe voters in municipalities where more deaths occurred were more likely to face his statements as deal-breakers, opting for the opposition candidate Lula instead.

Other than complementing the literature of political accountability and emotional impacts as strong drivers of electoral change, our findings have implications for numerous other instances in which politicians do not have a clear idea of the electorally popular positions, voters do not have consistent preferences, or can be manipulated into supporting politics and politicians which they knowingly or unknowingly disapprove of. While official statements serve a signaling purpose which might have ultimately harmed the president, uncouth statements were not uncommon to Bolsonaro's speeches prior to the COVID-19 pandemic, even plausibly mobilizing his electorate, as is well understood to be the case for populists (Guriev and Papaioannou 2022). It is curious however how these specific statements, when landing on more sensitive voters (for instance, those more likely to have faced the loss of a loved one), might radically flip their political positions.

Our findings evince the necessity of voters being informed of their preferences to consistently act and adopt positions which reflect their tastes, so they can be cognizant of subtler signals. Moreover, it deals on politicians' necessity to accurately understand voters' preferences and devise optimal strategy to satisfy their electorate, even if the strategy is partly rhetorical. Finally, it reiterates media's responsibility to inform voters, otherwise the signal Bolsonaro desired to transmit would be muted, even if that were to happen for his own sake.

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A Additional Tables and Figures

Table A1: Summary statistics of Brazilian municipalities

	Obs.	Mean	Std. Dev.	Min.	Max.
Table A: COVID-19 variables, rates per 100,000 inhabitants					
Mortality rate until Nov. 14, 2020	5,570	86.78	49.91	0	397.4
Mortality rate until Oct. 01, 2022	5,570	342.9	121.9	0	885.3
Infection rate until Nov. 14, 2020	5,570	2,826	1,705	0	26,233
Infection rate until Oct. 01, 2022	5,570	17,041	8,092	211.2	56,462
First reported case (Day)	5,570	Apr13, 20	24.57	Mar28, 20	Jan05, 22
First reported death (Day)	5,562	May07, 20	55.03	Mar28, 20	Jun26, 22
First case and death delay (Days)	5,562	24.54	39.55	0	766
Table B: Main candidates valid vote share					
%Bolsonaro (2018, 1st round)	5,570	46.24	16.61	1.942	83.89
%Bolsonaro (2022, 1st round)	5,570	43.61	14.33	5.592	83.98
Δ%Bolsonaro (1st round)	5,570	-2.628	4.792	-21.17	26.77
%PT (2018, 1st round)	5,570	29.29	19.22	3.633	93.24
%PT (2022, 1st round)	5,570	48.04	15.36	10.35	92.14
Δ%PT (1st round)	5,570	18.75	8.610	-14.80	60.17
%Bolsonaro (2018, 2nd round)	5,570	55.47	19.51	2.008	92.96
%Bolsonaro (2022, 2nd round)	5,570	49.44	15.60	6.143	88.99
Δ%Bolsonaro (2nd round)	5,570	-6.026	6.111	-20.90	24.42
Table C: Geographic variables ("large municipality" if over 50,000 inhabitants)					
Distance to NLM	5,570	41.35	50.52	1.287	535.3
Distance to NLM (logs)	5,570	3.275	0.922	0.252	6.283
Distance × Population (logs)	5,570	38.51	9.687	2.548	80.60

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Table A1: Summary statistics of Brazilian municipalities (Continued)

	Obs.	Mean	Std. Dev.	Min.	Max.
Estimated isolation, $Z'\hat{\Pi}$	5,570	-9.945	59.08	-236.1	92.19
Large municipality dummy	5,570	0.685	0.465	0	1
Table D: Municipal controls ("large municipality" if over 50,000 inhabitants)					
Total population (logs)	5,570	12.06	2.050	6.725	16.25
Population density	5,570	1,574	2,583	0.150	13,417
SUS beds per 100,000 pop.	5,570	160.7	113.5	0	1,957
Non-SUS beds per 100,000 pop.	5,570	78.24	77.87	0	1,041
ESF coverage (%)	5,570	76.08	21.42	0	100
ESF teams per 100,000 pop.	5,570	25.01	12.71	0	209.8
Agr. GDP share (%)	5,570	7.952	12.53	0	88.00
Agr. per capita GDP (logs)	5,570	0.674	0.794	0	5.320
Avg. PBF benefit	5,570	642.8	149.9	231.5	2,348
PBF expenditure (logs)	5,570	3.511	0.817	-0.970	5.960
Homicide rate (logs)	5,570	3.097	1.012	0	5.425
Urban (%)	5,565	84.70	20.13	4.179	100
Male (%)	5,565	49.00	1.593	45.76	81.09
Children ($<$ 15 yo., %)	5,565	24.13	4.428	7.267	51.48
Youngsters (15 $\vdash$ 30 yo., %)	5,565	26.97	2.120	14.90	43.84
Adults (30 $\vdash$ 60 yo., %)	5,565	38.22	4.067	19.22	47.60
Elderly ($\geq$ 60 yo., %)	5,565	10.68	2.809	2.569	29.22
Avg. age	5,565	31.51	2.749	19.11	44.26
Avg. personal income	5,565	893.75	448.66	128.77	2,210.72
Avg. household income	5,565	2,627.97	1,212.68	464.43	6,707.76
Avg. weekly working hours	5,565	39.55	2.616	19.78	55.78

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Table A1: Summary statistics of Brazilian municipalities (Continued)

	Obs.	Mean	Std. Dev.	Min.	Max.
Avg. fertility rate	5,565	1.865	0.380	1.343	3.283
Gini-index	5,565	0.545	0.070	0.284	0.808
White people (%)	5,565	47.85	21.05	0.666	99.58
Black people (%)	5,565	7.397	4.765	0	55.11
Asian people (%)	5,565	1.105	0.736	0	12.80
Mixed-Race people (%)	5,565	43.19	18.81	0.271	90.82
Native people (%)	5,565	0.455	2.919	0	88.56
Literacy (%)	5,565	89.55	8.130	54.58	98.74
Primary school (%)	5,565	44.44	9.624	13.21	62.63
Secondary school (%)	5,565	37.01	10.42	5.908	57.49
High school (%)	5,565	21.99	7.953	1.199	41.69
College (%)	5,565	6.247	4.254	0.126	21.88
On welfare (%)	5,565	21.78	5.755	6.410	49.50
Commuting (%)	5,565	13.16	13.99	0	69.75
Returns home (%)	5,565	93.78	3.958	39.72	99.60
Economically active (%)	5,565	57.83	6.529	17.18	91.27
Job search (%)	5,565	9.899	3.117	0	25.71
Formal employment (%)	5,565	49.55	16.97	1.595	83.23
Government employment (%)	5,565	5.436	2.909	0	41.43
Informal employment (%)	5,565	48.56	17.53	15.68	98.40
Employers (%)	5,565	1.892	1.072	0	8.768
Evangelicals (%)	5,565	22.36	8.455	0.422683	85.84
Immigrants (%)	5,565	14.94	11.73	0	76.55
Migrants avg. residency time	5,563	20.15	5.36	0.450	57

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Table A1: Summary statistics of Brazilian municipalities (Continued)

	Obs.	Mean	Std. Dev.	Min.	Max.
Private permantent household (%)	5,565	98.78	2.090	16.85	100
Private improvised household (%)	5,565	0.191	0.390	0	19.28
Collective households (%)	5,565	1.025	2.062	0	83.15
Houses (%)	5,565	88.29	11.97	16.62	100
Apartments (%)	5,565	9.948	11.54	0	63.80
Jail (%)	5,565	0.4951444	1.933	0	83.04239
Alternative housing (%)	5,565	1.269	1.191	0	34.94
Homeowning households (%)	5,565	73.58	7.400	26.80	97.05
Tenant households (%)	5,565	17.90	6.930	0.336	45.47
Alternative arragements (%)	5,565	8.514	4.042	0.837	66.61
Avg. renting value	5,565	332.37	146.27	30.00	999.21
Avg. household's density	5,565	0.680	0.189	0.410	4.287
Waste disposal (%)	5,565	65.42	30.52	0	100
Water plumbing (%)	5,565	93.57	11.78	5.161	100
Garbage collection (%)	5,565	86.73	18.81	0	100
Electricity (%)	5,565	98.56	4.037	29.52	100
Radio (%)	5,565	80.55	10.59	13.28	100
Television (%)	5,565	94.71	6.355	19.91	100
Washing machine (%)	5,565	46.03	26.07	0.244	92.98
Fridge (%)	5,565	93.15	9.489	16.66	100
Telephone (%)	5,565	87.32	13.93	11.32	98.44
Computer (%)	5,565	37.36	18.45	0.440	72.70
Internet (%)	5,565	29.77	16.88	0	68.63
Automobile (%)	5,565	49.70	15.15	1.590	93.50

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Table A1: Summary statistics of Brazilian municipalities (Continued)

	Obs.	Mean	Std. Dev.	Min.	Max.
State capital dummy	5,570	0.229	0.420	0	1
Airport dummy	5,570	0.422	0.494	0	1
International dummy	5,570	0.237	0.425	0	1
Coastal dummy	5,570	0.238	0.426	0	1
NLM region dummy	5,570	0.837	0.369	0	1
Borders NLM dummy	5,570	0.746	0.435	0	1
Latitude	5,570	-17.07	8.273	-33.65	4.685
Longitude	5,570	-45.88	6.060	-73.44	-32.42

Notes: All estimates employ municipality's population as analytical weights.

Table A2: Different spatial correlation effects on main estimates (2SLS)

	First stage ($\hat{\pi}_1 = -110.8$, $\hat{\pi}_2 = 9.163$)			Second stage ($\hat{\beta} = -0.0158$)		
Cluster level	Effective Obs.	Joint F-stat	p-value	Effective obs.	Std. Error	p-value
Munic. (rob.)	5,357	23.546	< 0.0001	5,358	0.00427	0.0002
Micro-region	509	24.524	< 0.0001	509	0.00518	0.0023
Meso-region	132	20.271	< 0.0001	132	0.00599	0.0084
State	26	24.791	< 0.0001	26	0.00680	0.0202
Macro-region	4	27.154	0.0047	4	0.00826	0.0560

Notes: The table reports variation in significance in our main estimates according to different structures of spatial correlation which we allow. For the first stage regression (Table 2, column 6) we analyze variation in standard errors in ln distance to NLM (more than 50,000 inhabitants) and ln distance to NLM × ln population drawn from different samples of spatial clusters, and report the number of effective observations used to calculate the F-statistic for the joint hypothesis test that $\pi_1 = \pi_2 = 0$, the F-statistic, and its associated p-value; for the second stage regression (Table 4, column 4) we analyze variation in standard errors in the cumulative COVID-19 mortality rate per 100,000 inhabitants up to October 1, 2022, and report the estimated standard errors, the number of effective observations, and the p-value associated with the t-test implied by the standard error column. At all levels of clustering, regressions employ specific intercepts for each intermediary geographic region (meso-region), the vector of municipal control variables described in Appendix B, and municipality's population as analytical weight.

Table A3: Heterogeneous impacts on presidential support (2SLS)

	Δ Bolsonaro valid vote share, 1st round						
Filter:	No North	No Northeast	No Southwest	No South	No Mid-West	Large	Small
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
COVID-19	-0.00869**	-0.0150**	-0.0221*	-0.0180***	-0.0148**	-0.000135	-0.0204*
	(0.00400)	(0.00687)	(0.0115)	(0.00637)	(0.00629)	(0.0148)	(0.0113)
Mean value dep. var.	-3.117	-3.96	-.458	-2.56	-2.519	-4.291	.989
Joint F-stat	16.241***	16.087***	5.13***	20.893***	21.78***	1.173	4.926***
Degrees of freedom	2, 110	2, 90	2, 99	2, 111	2, 117	2, 126	2, 131
Total population (logs)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Population weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,114	3,769	3,895	4,377	5,097	657	4,906
R-squared	0.869	0.836	0.799	0.855	0.860	0.940	0.618
N. clusters (regions)	111	91	100	112	118	127	132

Notes: The table reports the impact of COVID-19 mortality rate on Jair Bolsonaro's valid vote share variation excluding certain sets of municipalities; mortality rate is measured per 100,000 inhabitants, cumulatively up until Oct. 1, 2022, and is jointly instrumented by the natural logarithm of distance to nearest municipality with more than 50,000 inhabitants and its interaction with the natural logarithm of municipality's population. Columns 1 to 5 exclude municipalities from the highlighted region; columns 6 and 7 include solely municipalities with more and less than 50,000 inhabitants, respectively. All columns employ regional specific intercepts, a vector of municipal control variables, described in detail in Appendix B, and employ municipality's population as analytical weight. Heteroskedasticity-robust standard errors clustered at the regional level are reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

B Full description of municipal characteristics

This appendix presents a detailed description of each variable used as control (vector X_{mr} in Equations 3 and 4), briefly referenced in Section 2.4, and labeled according to Table A1D. All the data is at the municipal level, the lowest level of government in Brazil.

Total population: Municipality's total inhabitants. Used to characterize "large municipalities" according to different thresholds, as analytical weights in the regressions, and used (in logs) as a control in all regressions. *Source:* Demographic Census 2022, IBGE.

Population density: Average total inhabitants per squared kilometer in municipality. *Source:* Demographic Census 2022, IBGE.

SUS beds per 100,000 pop.: Number of hospital beds available which are managed by the Unified Healthcare System per 100,000 inhabitants. *Source:* DATASUS National Registry of Health Service Providers/MS.

Non-SUS beds per 100,000 pop.: Number of hospital beds available which are not managed by the Unified Healthcare System per 100,000 inhabitants. *Source:* DATASUS National Registry of Health Service Providers/MS.

ESF coverage: Estimated share of population covered by *Estratégia Saúde da Família*, the Brazilian universal primary healthcare coverage program. *Source:* Primary Care Information and Management Services/MS.

ESF teams: Number of *Estratégia Saúde da Família* teams hired per 100,000 inhabitants in the municipality. *Source:* Primary Care Information and Management Services/MS.

Agr. GDP share: Agrarian estimated participation in the composition of municipal GDP. *Source:* IBGE's municipal GDP estimates.

Agr. per capita GDP: Agrarian estimated municipal per capita GDP, in reais; used in logs added to 1, to address large variations in activity and fully urban municipalities. *Source:* IBGE's municipal GDP estimates.

Avg. PBF benefit: Average monthly value received from PBF across beneficiaries, in reais. *Source:* Department of Evaluation, Information Management and Unique Registry.

PBF expenditure: Average monthly per capita expenditure on PBF across total population, in log reais. *Source:* Department of Evaluation, Information Management and Unique Registry.

Homicide rate: Homicide rate per 100,000 inhabitants; used in logs added to 1, to address large variations in municipal violence and those without any occurrence. *Source:* Violence Atlas 2017, Institute of Applied Economic Research.

Urban: Share of inhabitants residing in the urban region. *Source:* Demographic Census 2010, IBGE.

Males: Share of male inhabitants. *Source:* Demographic Census 2010, IBGE.

Children: Share of inhabitants with less than 15 years of age. *Source:* Demographic Census 2010, IBGE.

Youngsters: Share of inhabitants with 15 up to 30 years of age. *Source:* Demographic Census 2010, IBGE.

Adults: Share of inhabitants with 30 up to 60 years of age. *Source:* Demographic Census 2010, IBGE.

Elderly: Share of inhabitants with 60 or more years of age. *Source:* Demographic Census 2010, IBGE.

Avg. age: Average age of inhabitants, in years. *Source:* Demographic Census 2010, IBGE.

Avg. personal income: Average monthly total personal income in reais. *Source:* Demographic Census 2010, IBGE.

Avg. household income: Average monthly total household income in reais. *Source:* Demographic Census 2010, IBGE.

Avg. weekly working hours: Average total weekly working hours among the employed. *Source:* Demographic Census 2010, IBGE.

Avg. fertility rate: Average number of children born per woman. *Source:* Demographic Census 2010, IBGE.

Gini-index: Gini-index of households' per capita total earnings. *Source:* Demographic Census 2010, IBGE.

White people: Share of inhabitants who identify as ethnically "White". *Source:* Demographic Census 2010, IBGE.

Black people: Share of inhabitants who identify as ethnically "Black". *Source:* Demographic Census 2010, IBGE.

Asian people: Share of inhabitants who identify as ethnically "Yellow". *Source:* Demographic Census 2010, IBGE.

Mixed-Race people: Share of inhabitants who identify as ethnically "Brown". *Source:* Demographic Census 2010, IBGE.

Native people: Share of inhabitants who identify as ethnically "Indigenous". *Source:* Demographic Census 2010, IBGE.

Literacy: Share of inhabitants with basic literacy skills (capable of reading and writing simple messages). *Source:* Demographic Census 2010, IBGE.

Primary school: Share of inhabitants who have completed the primary educational cycle, "Ensino Fundamental 1". *Source:* Demographic Census 2010, IBGE.

Secondary school: Share of inhabitants who have completed the secondary educational cycle, "Ensino Fundamental 2". *Source:* Demographic Census 2010, IBGE.

High school: Share of inhabitants who have completed the tertiary educational cycle, "Ensino Médio". *Source:* Demographic Census 2010, IBGE.

College: Share of inhabitants who have completed college or university education, "Ensino Superior". *Source:* Demographic Census 2010, IBGE.

On welfare: Share of inhabitants who received some form of benefit from social insurance system or some other government welfare program. *Source:* Demographic Census 2010, IBGE.

Commuting: Share of employed inhabitants who work in a municipality different from the one they reside in. *Source:* Demographic Census 2010, IBGE.

Returns home: Share of employed inhabitants who go to and from work on a daily basis, in opposition to those who only return home sporadically. *Source:* Demographic Census 2010, IBGE.

Economically active: Share of work-aged inhabitants participating in the workforce, regardless of employment status. *Source:* Demographic Census 2010, IBGE.

Job search: Share of unemployed inhabitants who were actively looking for a job. *Source:* Demographic Census 2010, IBGE.

Formal employment: Share of employed inhabitants working according to a formally signed wage contract establishing employment ties. *Source:* Demographic Census 2010, IBGE.

Government employment: Share of employed inhabitants working for the government. *Source:* Demographic Census 2010, IBGE.

Informal employment: Share of employed inhabitants working without a formally signed wage contract establishing employment ties; either working as subsistence farmers, performing gigs, or otherwise autonomous employment situations or in unpaid positions. *Source:* Demographic Census 2010, IBGE.

Employers: Share of employed inhabitants who manage their own businesses, employ others, or are otherwise classified as "job creators". *Source:* Demographic Census 2010, IBGE.

Evangelicals: Share of inhabitants who identify with the evangelical Christianity faith of any denomination. *Source:* Demographic Census 2010, IBGE.

Immigrants: Share of inhabitants who were born in a different Brazilian state or country than the one they currently reside in. *Source:* Demographic Census 2010, IBGE.

Migrants' avg. residency time: Migrants' average time of residency in the state of current residence, in years. *Source:* Demographic Census 2010, IBGE.

Private permanent household: Share of households residing in residential buildings, which they do not share with other households; includes households living in apartment buildings. *Source:* Demographic Census 2010, IBGE.

Private improvised household: Share of households residing in non-residential buildings, slums, or other alternative housing situations (tents, vehicles, etc.), which they do not share with other households. *Source:* Demographic Census 2010, IBGE.

Collective household: Share of households residing in buildings which are shared between multiple households. *Source:* Demographic Census 2010, IBGE.

Houses: Share of households residing in residential houses, regardless of type of household. *Source:* Demographic Census 2010, IBGE.

Apartments: Share of households residing in apartment buildings, regardless of type of household. *Source:* Demographic Census 2010, IBGE.

Jail: Share of households residing in the penitentiary system, applies only to collective households. *Source:* Demographic Census 2010, IBGE.

Improvised residencies: Share of private improvised or collective households residing in non-residential buildings, slums, or other alternative housing situations. *Source:* Demographic Census 2010, IBGE.

Homeowners: Share of private permanent households who own the building which they reside in. *Source:* Demographic Census 2010, IBGE.

Tenants: Share of private permanent households who do not own the building which they reside in, and pay rent to the home-owning person or corporation. *Source:* Demographic Census 2010, IBGE.

Alternative arrangements: Share of private permanent households who do not own the building which they reside in nor pay rent to the homeowner; residence is secured through occupation, leasing, concession, rent is payed by someone else, etc. *Source:* Demographic Census 2010, IBGE.

Avg. renting value: Average monthly payment of rent in reais, applies only to tenants. *Source:* Demographic Census 2010, IBGE.

Avg. household's density: Average number of residents per room in private permanent households. *Source:* Demographic Census 2010, IBGE.

Waste disposal: Share of private permanent households served by the public sewage or rainwater network, or with a septic tank. *Source:* Demographic Census 2010, IBGE.

Water plumbing: Share of private permanent households served by the public water distribution network. *Source:* Demographic Census 2010, IBGE.

Garbage collection: Share of private permanent households served by the public garbage disposal network. *Source:* Demographic Census 2010, IBGE.

Electricity: Share of private permanent households with access to electricity. *Source:* Demographic Census 2010, IBGE.

Radio: Share of private permanent households with ownership of at least one radio system, independent or integrated with other appliances. *Source:* Demographic Census 2010, IBGE.

Television: Share of private permanent households with ownership of at least one television system, regardless of technology used as long as functional. *Source:* Demographic Census 2010, IBGE.

Washing machine: Share of private permanent households with ownership of at least one automated washing machine. *Source:* Demographic Census 2010, IBGE.

Fridge: Share of private permanent households with ownership of at least one fridge, regardless of power-source used. *Source:* Demographic Census 2010, IBGE.

Telephone: Share of private permanent households with ownership of at least one conventionally installed telephone or functional cellphone. *Source:* Demographic Census 2010, IBGE.

Computer: Share of private permanent households with ownership of at least one computer. *Source:* Demographic Census 2010, IBGE.

Internet: Share of private permanent households with access to the internet in their computer or phone. *Source:* Demographic Census 2010, IBGE.

Automobile: Share of private permanent households with ownership of at least one car or motorcycle. *Source:* Demographic Census 2010, IBGE.

State capital dummy: Dummy variable admitting value 1 when the municipality in question is one of 26 state capitals or the Federal District, and 0 otherwise. *Source:* Superior Electoral Court.

Airport dummy: Dummy variable admitting value 1 when the municipality in question has a public airport, and 0 otherwise. *Source:* National Civil Aviation Agency's list of public airfields.

International dummy: Dummy variable admitting value 1 when the municipality in question has a public airport which is listed by the International Air Transport Association or the

International Civil Aviation Organization, and 0 otherwise. *Source:* IP2Location geolocation database.

Coastal dummy: Dummy variable admitting value 1 when the municipality in question has access to the sea, and 0 otherwise. *Source:* IBGE's list of coastal municipalities.

NLM region dummy: Dummy variable admitting value 1 when the municipality in question is situated in the same region of its *nearest large municipality* (NLM), and 0 otherwise. Varies according to the threshold used to characterize "large municipalities" (50,000 inhabitants by default). *Source:* IBGE's territorial network.

Borders NLM dummy: Dummy variable admitting value 1 when the municipality in question borders its NLM, and 0 otherwise. Varies according to the threshold used to characterize "large municipalities" (50,000 inhabitants by default). *Source:* IBGE's territorial network.

Latitude & Longitude: Location of a municipality's centroid in decimal degrees; jointly, they are used to build the origin-destination matrix of pairwise haversine distances between municipalities. *Source:* IBGE's territorial network.