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

Dimitri Maturano   Naercio Menezes-Filho*
Bruno Komatsu

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Abstract

We investigate how voters react to denialist campaigns in light of a global pandemic by looking at COVID-19's impact on the electoral performance of then incumbent Brazilian president Jair Bolsonaro (2019-2022). Oriented by the existence of differences in intercity commuting costs, we devise a novel instrument from epidemiological analysis of viral spread in the country. We exploit the fact that less isolated municipalities faced larger cumulative mortality rates to show deaths due to the disease brought severe electoral costs to Bolsonaro, ultimately leading to his loss. We attribute this result to voters' perception of recklessness stemming from his speeches, since they were seemingly supportive of lax sanitary measures and did not simply blame incumbents.

Keywords: COVID-19, Mortality, Elections, Populism
JEL Codes: D72, D91, H12, I18

*Corresponding author at Insper, Rua Quatá 300, Vila Olímpia, São Paulo/SP 04546-042, Brazil. DM: Insper and University of São Paulo (dimitricm@insper.edu.br); NMF: Insper and University of São Paulo (naercioamf@insper.edu.br); BK: Insper (brunokk@insper.edu.br).
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1 Introduction

During the Coronavirus pandemic leaders in democratic countries opted to not adopt too strict sanitary measures, expecting voters to not hold them responsible for the burdens of inevitable economic downturns.[1] Then Brazilian president, Jair Bolsonaro, not only did not display much concern for the disease, but repeatedly minimized its risks and encouraged 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 COVID-19 deaths impacted votes for the incumbent presidential candidate in the 2022 national elections. Drawing from epidemiological analysis of the Coronavirus' spread in Brazil, we devise a novel instrument inspired by intercity commuting costs to capture exogenous variation at the municipal level, and extract the impact of the pandemic's severity on Bolsonaro's loss. We depart from the fact that, early in 2020, the virus was primarily situated in large urban centers, which acted as radial spreaders to smaller communities, through highways and local road networks, in the country's innards (Castro et al. 2021; Nicolelis et al. 2021). As a result, municipalities further away from these urban centers were more isolated and relatively protected. As predicted by our model and seen in data, they first faced contamination later on, had vaccines available earlier on their epidemiological curves and faced less excess demand for health services, all of which led to lower mortality rates.

We present robust evidence that COVID-19 deaths drew a large share of voters away from Bolsonaro's platform, ensuring his opponent's victory. We estimate that each Coronavirus death per thousand inhabitants results on valid vote share variations between negative 1 and 2 percentage points (pp.). In the average municipality, in the first round, each death costed him between seven and ten votes; and the pandemic as a whole, 46.2 thousand votes per municipality, or 6.55 million votes in total. We argue that all else equal, had Bolsonaro not been tied to COVID-19 in voters' minds, his vote share would have grown by up to two and a half pp. between the 2018 and 2022 elections first round, rather than diminishing by nearly three. As a result, he would have almost been re-elected president in the first round, and easily won in the second. The magnitudes we find are so large, in fact, that all else constant, a mere reduction of 15% in deaths would suffice for Bolsonaro's victory – a task that could be accomplished merely by engaging in concentrated governmental efforts to adequately supply vaccination to the population, without any sort of additional non-pharmaceutical intervention (Araújo et al. 2023; Ferreira et al. 2023).

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).

These results are robust across different specifications and assumptions regarding viral spread throughout the country. Moreover, placebo tests show our instrument is uncorrelated with mortality rates from other causes – suggesting we adequately leverage exogenous variation through viral dynamics rather than relying on endogenous municipal characteristics –, and that COVID-19 deaths are uncorrelated to previous election results – shedding light on the plausibility of an exogenous instrument. 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, to his detriment.

Our research contributes to salient, yet still unexplored topics in the political economy of COVID-19 in Brazil. Existing literature on the pandemic has primarily dealt on the determinants of outbreak severity. Bruce et al. (2022) employ a regression discontinuity design to analyze the impact of mayor's gender on the severity of the pandemic; they find municipalities led by women faced less deaths overall, plausibly because they were more likely to enact non-pharmaceutical interventions. Literature also identifies a robust correlation between electoral support for Bolsonaro in 2018 and the likelihood of increased death rates 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), who suggest 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 and association between him and the disease led to his defeat in the 2022 national elections. Although some causes for Bolsonaro's victory in 2018 were already explored (see Barros and Santos Silva 2025), we are, to the best of our knowledge, the first to tie his defeat in 2022 to the COVID-19 pandemic.

Our paper also contributes to the vast body of research exploring informational aspects of electoral decisions, emotionally driven changes in voting patterns and attribution, and broad incentive-based political strategies, specially the branch of literature dealing with blame attribution, 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 and relative inelasticity in political preferences (Guriev and Papaioannou 2022). In such contexts, emotional rejection as described by

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); Malhotra and Kuo (2008) and Novaes and Schiumerini (2022); Besley and Case (1995), Ferraz and Finan (2011), and Forquesato (2022); 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).

Campante, Depetris-Chauvin, and Durante (2024) and conscious punishment for mismanagement as in Ferraz and Finan (2008) are difficult to separate, although we try to the best of our ability.

Our setup differ from existing research on emotions by investigating a scenario in which negative sentiments are the product of deliberate electoral strategy employed by the incumbent at hand, plausibly to rile up his most adherent electorate. 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), allowing understanding of voters' preferences in a still unknown setup.

The remainder 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 explores channels through which Bolsonaro could lose votes due to the pandemic. Section 6 concludes.

2 Data

In this section we describe the various datasets used. For summary statistics of used variables, see Table A1. For a detailed description of each variable, see Appendix B.

2.1 COVID-19

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, considered the most reliable source of information on the subject (Guedes et al. 2023). It provides thoroughly detailed information for each deceased person in Brazil, including their municipality of residence and basic cause of death; 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]

For infection data, we use daily municipal-level data compiled by the Ministry of Health (MS) jointly with individual State Health Departments, obtain-

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).

ing the date of first reported case per municipality and the sum of cases up to October 1, 2022, in a single municipal-level observation, analogously to the SIM/DATASUS death reports. We then divide said total by municipality's population by 100,000, gathering the municipal infection rate per hundred thousand inhabitants.

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. The average municipality faced approximately 343 deaths and 17 thousand confirmed cases per hundred thousand inhabitants. Smaller municipalities were less impacted: those 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. Larger municipalities were first hit by the virus, as a result earlier in the pandemic they faced larger infection and mortality rates (significant at the 5 and 1% levels, respectively). Further on, smaller municipalities remained protected to deaths (compared to larger municipalities), but the correlation between infection rates and size decreased, even becoming negative (albeit not statistically significant). This corroborates previous literature reporting concentration of COVID-19 cases and deaths in large municipalities early in the pandemic (Nicolelis et al. 2021), and its subsequent diffusion to smaller municipalities to the point of independence between municipality's size and infection rate, following the empirical findings of Castro et al. (2021).

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 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 format 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). He faced large negative valid vote share variations between the 2018 and 2022 elections, 46.2% to 43.6% in the first- and 55.5% to 49.4% in the second-round. The main opposition party PT, on the other hand, experienced a surge of nearly 19 percentage points in the first round between 2018 and 2022, and some of it is plausibly due to the change in party nominee, Luís Inácio Lula da Silva in 2022. This shift is not homogenous across municipalities; average support for Bolsonaro actually grew in smaller municipalities. The president's loss of support, in fact, seems to be located primarily in the largest cities, as average valid vote share variation in municipalities with less than 50,000 inhabitants (88% of the sample) grew by nearly one percentage point, in contrast to the decrease of 2.6 percentage points in the complete sample.

2.3 Geography

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 5,570 by 5,570 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. Despite the uneven distribution of the Brazilian population across municipalities, the distribution of municipalities surpassing the threshold is roughly reflective of the overall sample, see Table A2.

2.4 Municipal characteristics

This section briefly describes the full set of municipal controls necessary to ensure exogeneity of the instrument, and their sources. 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 kilometer.

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: Municipal isolation as a source of variation

We want to investigate impact the Coronavirus had on Jair Bolsonaro's performance in the 2022 elections. Since the president may have influenced the pandemic's outcome, there might be unobservable manners in which the two are correlated. We address endogeneity concerns by exploiting intercity isolation as a source of exogenous variation to instrument COVID-19 mortality rates. Section 3.1 describes what isolation entails, the econometric specification employed and its underlying assumptions; Section 3.2 reports our findings in tying the model to data.

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).

3.1 Empirical framework

We start our empirical analysis from the vast body of epidemiological research describing the Coronavirus pandemic's interiorization process throughout the Brazilian territory (Castro et al. 2021; Nicolelis et al. 2021). The literature describes how the virus probably initially arrived in São Paulo from Italy in late February and, in mere weeks, it made it to capital cities – particularly to the Northern and Northeastern macro-regions, through long-distance flights. The following month saw an unmitigated interiorization process to other regionally relevant cities, brought through medium-distance supply-lines using highways and small distance flights. By late March and early April, when the virus was still primarily present in regionally relevant cities, the virus was detected and state-governments action began; it decreased the speed of spreading towards smaller municipalities, but was too late to stop it's reach in medium-sized cities. This produced regional clusters of radial viral spreading centered on populous municipalities, which we call *large* for simplicity's sake, which communicate with smaller municipalities primarily through local roads. Nearly the entirety of the described process happened during COVID-19's first wave (February 23 to November 7, 2020, Moura et al. 2022).

We intend to exploit intercity distance as a source of exogenous variation for COVID-19 severity in a municipality. Although the evolution of the disease in a municipality might be endogenous, its distance to a large municipality, conditional on fixed regional determinants predating the Coronavirus, provides a source of quasi-random assortment of outbreak timing and preparedness, justifying its use as an instrument to estimate the impact of COVID-19 deaths on electoral support. We propose municipalities further away from COVID-19 spreading hubs are less exposed to the virus in a series of manners, resulting in a delayed start and overall less severe pandemic, all else constant. This decrease in exposition is, however, not as binding to larger municipalities as it is to otherwise identical but smaller municipalities; the reason for this is that the larger a municipality is, more intense are its trading and commuting flows to and from other large municipalities, following neoclassical gravity models of trade. In limit cases, distance to any municipality is orthogonal to exposition, since they are so large they become radial spreaders themselves – the city of Manaus, for instance, appears to have imported the virus from São Paulo through airways as soon as it arrived in Brazil, despite their 2,690 kilometers distance.

Our first source of exogenous variation across municipalities is, therefore, their distance to large municipalities, in particular to their *nearest large municipality* (NLM), those which we assume are the viral spreaders. We calculate this distance by first identifying the set of municipalities with more than fifty thousand inhabitants, according to the 2022 Census, as an arbitrary threshold characterizing a municipality as sufficiently populous to be considered a Coronavirus radial spreader onto nearby municipalities. We find each municipality's centroid and plot their pairwise distance to every other municipality in a 5,570 by 5,570 origin-destination matrix, which we then use to find the distance each municipality has to its own NLM. Municipality m's distance to its NLM is, then, defined as

$$distNLM_m := \min_{n \neq m} \{dist(m,n) : pop_n > 50{,}000\},$$

where pop_n stands for municipality n's total population count and $dist(m,n)$ is the distance between municipalities m and n, calculated from the standard haversine formula:

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

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

The second source of exogenous variation is given by interacting the distance to NLM term with total population, thus allowing for differently sized municipalities to have differences in isolation even if they are equally distant to their NLM. This is particularly useful in cases where municipality m's NLM is n and municipality n's NLM is m, since we 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) by not allowing municipalities to be their own NLM.

In summary, the instrument's construction relies on "large" municipalities acting as (generative) radial spreaders of the Coronavirus; municipalities further away from large municipalities being, on average, more isolated than municipalities closer to large municipalities; and distance to large municipalities being, on average, less relevant to municipality's isolation the larger it is. In particular, we assume 50,000 inhabitants as the sufficiently populous threshold through which a municipality may be considered "large," and that each municipality has one relevant Coronavirus spreader, its NLM.

In using this decomposition, we model COVID-19 pandemic severity in a municipality directly as a linear function of observed variables. We can, therefore, precisely estimate municipal isolation under the three aforementioned simplifying assumptions, and test the strength of the correlation between COVID-19 mortality and the proposed instrument through the First-Stage regression equation

$$covid_{mr} = \pi_0 + \pi_1 \ln distNLM_{mr} + \pi_2 \ln distNLM_{mr} \times \ln pop_{mr} \\ + \pi_3 \ln pop_{mr} + X'_{mr}\pi_4 + R_r + \upsilon_{mr}, \quad (1)$$

where $covid_{mr}$ is the cumulative COVID-19 mortality rate per hundred thousand inhabitants in municipality m, in region r; $distNLM_{mr}$ is municipality m's distance to its NLM; pop_{mr} is total population of municipality m, in region r; X_{mr} is the vector of municipal-level controls listed in Appendix B; R_r is a 133-sized vector of dummy variables acting as regional intercepts; and υ_{mr} is the heteroskedastic random error term, clustered at the regional level.

From the notion of isolation we propose, should our estimates reflect theory suggesting mortality is decreasing with isolation, then $\pi_1 \leq 0 \leq \pi_2$. Moreover, if distance to large municipalities' impact on date of first infection has lasting consequences on cumulative mortality rates, our estimates of π_1 and π_2 should jointly be statistically different than zero.

We then use the arguably exogenous component of municipal isolation, the linear combination of $\ln distNLM_{mr}$ and $\ln distNLM_{mr} \times \ln pop_{mr}$, as a joint instrumental variable to gather the impact of cumulative COVID-19 mortality rates up to election day on electoral outcomes, as explicit in the following structural model:

$$\Delta voteshare_{mr} = \alpha + \beta covid_{mr} + \gamma \ln pop_{mr} + X'_{mr}\delta + R_r + \epsilon_{mr}, \qquad (2)$$

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. Since municipalities vary widely in size, not all are equally relevant to national elections. To consistently gather the aggregate impact, therefore, we weight all regression models by total inhabitants of municipalities.

Our interest in Equation 2 is estimating COVID-19's parameter, β. In line with recent developments in Instrumental Variables literature (Alvarez and Toneto 2024; Blandhol et al. 2022), the usage of covariates leads the estimand to not necessarily reflect Local Average Treatment Effects. Our goal, therefore, is correctly identifying β, rather than making strong causal statements. To do so, we still rely on traditional Two-Stages Least-Squares assumptions (Hansen 2022). These are stated below.

Assumption 1 (Instrument's Exogeneity)**.** Under a rich set of covariates, municipal isolation is conditionally uncorrelated with unobserved shifts in electoral outcomes, or

$$(\ln distNLM_{mr}, \ln distNLM_{mr} \times \ln pop_{mr}) \perp\!\!\!\perp \epsilon_{mr} \mid (\ln pop_{mr}, X_{mr}, R_r);$$

Assumption 2 (Instrument's Relevance)**.** Differences in municipal isolation lead to differences in the COVID-19 pandemic's severity, or

$$(\pi_1, \pi_2) \neq \mathbf{0};$$

Assumption 3 (Instrument's Monotonicity on Treatment)**.** Cumulative COVID-19 mortality rates must be monotonic – here, non-decreasing – functions of isolation, or

$$covid_{mr}(z_{mr}) \geq covid_{mr}(\tilde{z}_{mr}) \text{ for every } z_{mr} \leq \tilde{z}_{mr} \text{ and every } m,$$

where $z_{mr}, \tilde{z}_{mr} := \begin{bmatrix} \ln distNLM_{mr} & \ln distNLM_{mr} \times \ln pop_{mr} \end{bmatrix} \begin{bmatrix} -\pi_1 \\ -\pi_2 \end{bmatrix}$ are linear combinations representing different degrees of isolation for municipality m, in region r, with $\pi_1 \leq 0 \leq \pi_2$;

Assumption 4 (Full Rank)**.** Regressors in the First-Stage Equation (1) are linearly independent, or

$$\text{rank } [Z'Z] = K,$$

where $Z := (\ln distNLM_{mr}, \ln distNLM_{mr} \times \ln pop_{mr}, \ln pop_{mr}, X_{mr}, R_r)$ is a K-sized vector of exogenous regressors.

3.2 Isolation and mortality: First-stage results

Isolation, as we define it, is just the weighted combination of variables with the best linear fit in Equation 1. As a result, we do not observe it directly in data but can estimate it. To do so, we begin by running the First-Stage regression model and report Ordinary Least Squares (OLS) estimates of Equation 1 in Table 1. We change specifications to attest that, regardless of the model used, distance to a large municipality (more than fifty thousand inhabitants) is robustly correlated with a decrease in cumulative COVID-19 mortality rates up to October 1, 2022 (the day prior to the presidential election), and said correlation weakens the larger a municipality is. In other words, isolation seemingly reduces mortality.

Columns 1 to 3 present the expected result: Distance to NLM is robustly associated with a decrease in cumulative mortality rate (statistically different from zero with 95% to 99% confidence), but the association is weakening on municipality's size (statistically different from zero with 95% to 99% confidence). Interpretation is not as straightforward due to the interaction term, but the common variation, that when municipality's population is 1 inhabitant, is: a 1% increase in municipal distance to its NLM is correlated with a decrease between 1.1 and 1.4 deaths per 100,000 inhabitants.

For municipalities with 5,000 and 10,000 inhabitants, a 1% municipal increase in distance to its NLM decreases deaths between 0.5 and 0.3 and 0.4 and 0.2 persons per 100,000 inhabitants, respectively. Municipalities on the threshold, with 50,000 inhabitants exactly, have decreases as low as 0.2 and 0.1 deaths per 100,000 inhabitants after a 1% increase in distance, but a municipality would have to have between 178 to 343 thousand inhabitants for distance to cease to have an impact on its mortality rate, which would comprise of 3 to 1% of Brazilian municipalities. Since these estimates depend on threshold used, there is little point in deeper analyses in attempting to match the assumed threshold of orthogonality to the one found in data, for what Table 1 shows is isolation has a robust negative correlation with severity of the COVID-19 pandemic, as expected.

Besides point estimates, Table 1 reports the F-statistic of $\pi_1 = \pi_2 = 0$ tests for each specification. Likewise, the result is statistically different from zero with 95% confidence even if we omit the vector of controls and regional intercepts, and becomes statistically different from zero with 99% confidence once we address for confounders. Consider, for instance, population density or urbanity of a municipality: the denser and more urban a municipality is, the easier it is for the Coronavirus to spread, and the disease becomes more deadly, even if its lethality decreases due to greater supply of healthcare services; more

Table 1: COVID-19 mortality rates and municipal isolation (First-Stage)

Dependent variable:	COVID-19 mortality rate		
	(1)	(2)	(3)
Distance to NLM (logs)	-141.1**	-119.0***	-110.8***
	(63.82)	(28.64)	(20.69)
Distance × Population (logs)	11.07**	9.887***	9.163***
	(5.430)	(2.754)	(2.092)
Mean value dep. var.	342.9	342.9	342.9
Joint F-stat (2, 132 df.)	3.943**	10.60***	20.27***
Total population (logs)	Yes	Yes	Yes
Municipal controls	No	Yes	Yes
Regional intercepts	No	No	Yes
Population weights	Yes	Yes	Yes
Observations	5,570	5,563	5,563
R-squared	0.268	0.687	0.802
N. clusters (regions)	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) and its interaction with the natural logarithm of municipality's population; mortality rate is measured per 100,000 inhabitants, cumulatively up until Oct. 1, 2022. Column 1 controls for total population in logs, and employs total inhabitants as weights; column 2 additionally controls for the list of municipal characteristics in Appendix B; column 3 additionally employs a dummy for each region. Heteroskedasticity-robust standard errors clustered at the regional level reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

isolated municipalities, however, are more rural and provide less opportunity for unwarranted contact. As a result, any estimates omitting these variables should reflect a negative bias on isolation, which reflects greater magnitudes for θ and ϕ estimates. These biases, however, are correlated and contaminate the estimates in similar manners; as a result, employing a rich set of covariates, despite reducing the magnitudes of estimators, increases the power of the test. The full correlation matrix between cumulative mortality rates and isolation, and each municipal control employed, is reported in Table A3; any covariate whose correlation pair has opposing signs should invite similar interpretations.

Since the estimands of Equation 1 are unobservable, we build an estimated isolation index

$$\hat{z}_{mr} := \begin{bmatrix} \ln distNLM_{mr} & \ln distNLM_{mr} \times \ln pop_{mr} \end{bmatrix} \begin{bmatrix} -\hat{\pi}_1 \\ -\hat{\pi}_2 \end{bmatrix},$$

where $\hat{\pi}_1, \hat{\pi}_2$ are point estimates from the fit in Table 1, Column 3. Figure 1 reports the distribution of this $\hat{z}_{mr}$ variable.[5]

5. We use this summary measure of isolation, normalized as

$$\frac{\hat{z}_{mr} - \min \hat{z}_{mr}}{\max \hat{z}_{mr} - \min \hat{z}_{mr}},$$

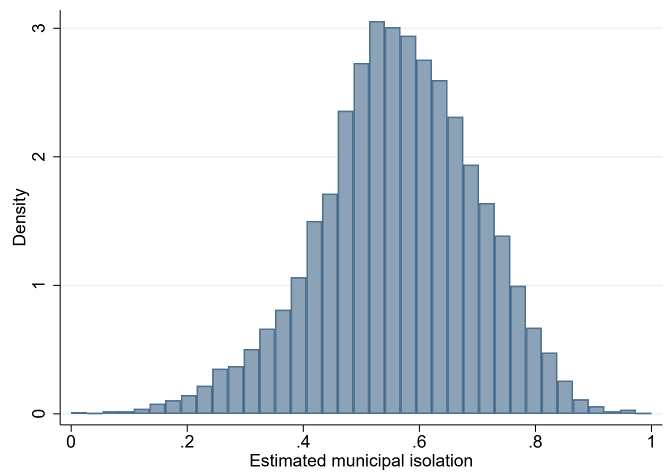
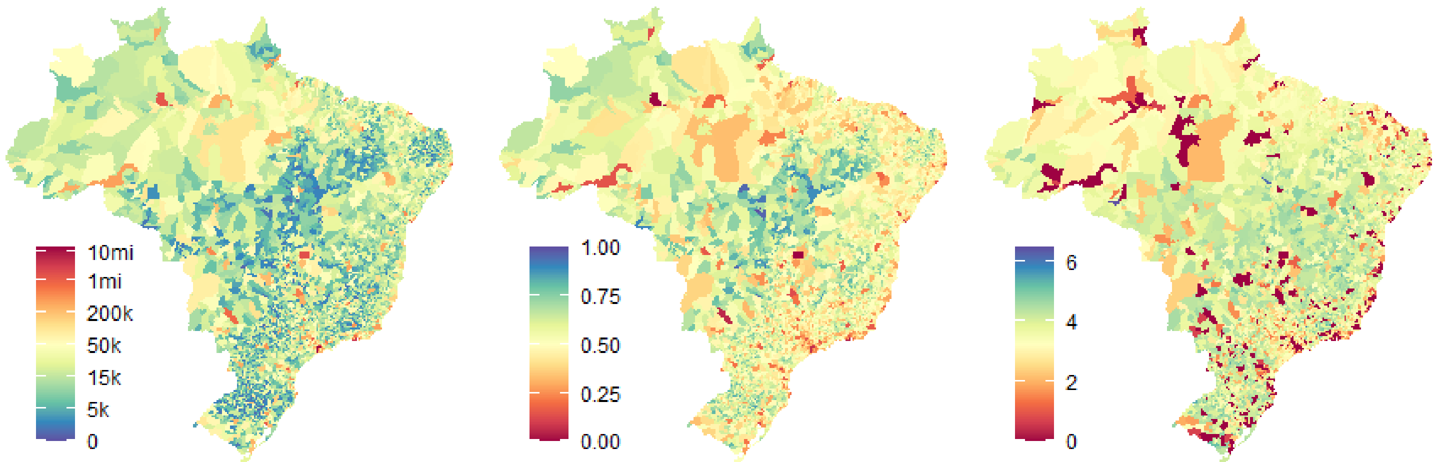


Figure 1: Estimated municipal isolation histogram

We use these estimates to create a visual representation of how the most populous municipalities act as spreading hubs to analyze viral spreading throughout the Brazilian territory. In Figure 2 we plot the distribution of Brazilian municipalities according to three different measures of exposition to COVID-19. Panel (a) evinces how uneven total population across municipalities is, with the vast majority of municipalities having fewer than 50 thousand inhabitants, and a handfew with millions. Panel (b) uses our estimates for municipal isolation to show that not only the populous municipalities are less isolated, but also those closer to them as well. Panel (c) shows how long it took, in log days, for the Coronavirus to reach each municipality from the first day which data is available (March 28, 2020). Overall, the maps highlight how the most populous municipalities were susceptible to be infected at the very beginning of the pandemic, and how they leverage their exposition onto nearby local economies, which are heavily dependent on them.

in a merely descriptive manner and for simplicity's sake. Where the exposition does not benefit from grouping distance and the interaction term, we opt to separate the instrument into its core components. This allows flexibility and ease of interpretation that is partially lost by this succinct measure.



(a) Total inhabitants (b) Estimated isolation (c) First case delay (logs)

Figure 2: Brazilian municipalities' exposure to COVID-19

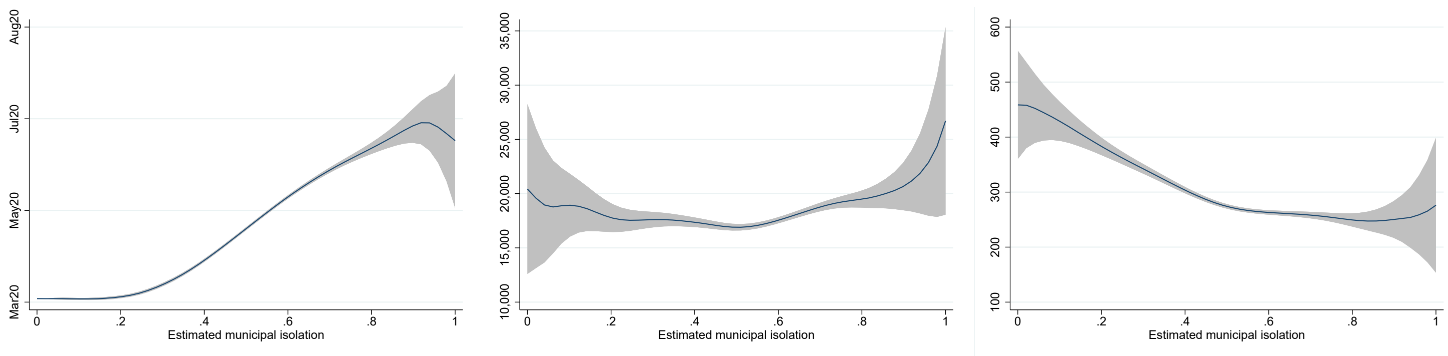
Notes: This figure reports distribution of Brazilian municipalities according to total inhabitants, normalized estimated municipal isolation, and log plus one days since March 28, 2020, for the Coronavirus to be first detected in a municipality. Colder colors reflect municipality's relative isolation from the virus, either by being small, distant from large municipalities, or having the virus detected later; warmer colors reflect municipality's relative exposure to the virus, either by being large, nearby large municipalities, or having the virus detected earlier.

Figure 3 complements this by reporting non-parametric regressions of isolation on Coronavirus' first arrival and cumulative infection and mortality rates. It shows how less isolated municipalities were contaminated with the virus earlier on, with the most isolated ones having a nearly three months delay in first contact compared to the least isolated ones. More isolated municipalities also faced smaller death rates, but incurred in similar infection rates, in comparison to more isolated municipalities.

Intuitively, first contact with the virus may occur earlier in more exposed municipalities, but there is no obvious reason why more isolated municipalities suffer less deaths if they get infected at similar rates. One might inquire, for instance, whether differences in air-quality are not driving factors for increased COVID-19 deaths in less isolated cities. If large municipalities spread not only the virus but also pollution onto nearby communities, our instrument would capture compound exposition effects on mortality rates, and the F-statistics presented in Table 1 could erroneously display significance where the estimated parameters should be close to zero; in which case the instrumental approach would yield highly biased results.

We attest this is not the case by changing the First-Stage specification (Equation 1) to admit all other causes of death instead of COVID-19, testing the correlational coefficient between overall mortality rates and distance to NLM and its interaction with population (both in logs) for every year since 2008. Results are presented in Table 2. What our estimates show is our measure of isolation is not correlated with other causes of death: in no tested year distance to NLM, its interaction with population and both jointly are statistically significant at the usual levels (except the distance coefficient in 2019, which is significant at the 10% level), the estimates are all small in magnitude compared to the coefficients presented in Table 1, and are seemingly centered on zero.

We conclude stating more sheltered municipalities are robustly associated with less COVID-19 deaths per hundred thousand inhabitants, and this is mainly due to some property specific to the viral pandemic rather than, for instance, pollution, urban density or differences in lifestyle. The specific reasons municipal exposition accompanies earlier infections and increases in long-term mortality rates is, to our analysis of the pandemic's effect on electoral outcomes, unimportant; nonetheless, we expand compartmental modeling of epidemics to tie intercity distances with differences in infection timing and mortality rates. We present the model in Appendix **??**.



(a) First-case

(b) Infection rate

(c) Mortality rate

Figure 3: COVID-19 first detection date, infection and mortality rates, by estimated municipal isolation

Notes: The figure reports the non-parametric correlation between normalized estimated municipal isolation, and date of first COVID-19 detected case and cumulative infection and death rates up to Oct. 1, 2022, in the municipality. Optimal kernel and bandwidths calculated according to Cox (2021). 95% confidence interval in gray.

Table 2: First-Stage Placebo Tests – Municipal isolation and non-COVID deaths

Dependent variable: Yearly mortality rate, other causes of death				
	Distance to	Distance ×	Joint F-stat (2, 132 df.)	
Year	NLM (logs)	Population (logs)	Estimate	*p*-value
(1)	(2)	(3)	(4)	(5)
2008	3.577	-0.651	0.3055	0.7373
	(20.39)	(1.798)		
2009	-3.015	-0.004	0.224	0.7993
	(20.10)	(1.721)		
2010	3.368	-0.605	0.317	0.7290
	(20.58)	(1.754)		
2011	4.306	-0.469	0.054	0.9472
	(22.40)	(1.914)		
2012	-9.771	0.574	0.326	0.7227
	(19.58)	(1.688)		
2013	-12.87	1.097	0.228	0.7967
	(19.08)	(1.692)		
2014	-23.09	1.830	0.728	0.4847
	(20.04)	(1.772)		
2015	-26.90	2.027	1.295	0.2774
	(20.95)	(1.911)		
2016	-19.85	1.456	0.571	0.5661
	(20.65)	(1.797)		
2017	-12.20	0.966	0.238	0.7887
	(18.77)	(1.626)		
2018	-16.63	1.301	0.484	0.6172
	(18.41)	(1.641)		
2019	-31.80*	2.404	1.793	0.1705
	(18.83)	(1.641)		
2020	24.80	-2.673	1.590	0.2078
	(22.60)	(2.006)		
2021	3.211	-0.633	0.361	0.6976
	(23.17)	(2.058)		
2022	-17.31	1.205	0.800	0.4513
	(18.08)	(1.577)		

Notes: The table reports correlation between non-COVID-19 municipal mortality rate and the natural logarithm of distance to *nearest large municipality* and its interaction with the natural logarithm of municipality's population; for each year, mortality rate is measured cumulatively from January 1 to December 31. Column 1 presents the year of reference; columns 2 and 3 present each isolation component estimates; columns 4 and 5 present the F-statistic and *p*-value of that year's $\pi_1 = \pi_2 = 0$ test. All estimates weight for total inhabitants, control for total population in logs, the list of municipal characteristics in Appendix B and regional dummies vector. 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 Electoral impact of COVID-19

4.1 Results on Bolsonaro's vote share variation

We begin by estimating the structural model (Equation 2) for presidential candidate Jair Bolsonaro in the first and second rounds by Ordinary Least Squares (OLS). Results are reported in Table 3, columns 1 and 3. Our estimates are small in magnitude and not statistically different than zero at the usual levels. 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 increasing support between years in the absence of other confounders, the estimate in column 1 would have an upward bias.

We account for these sources of bias by employing a Two Stage Least Squares (2SLS) 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 for the first and second rounds are presented in columns 2 and 4. All columns employ regional intercepts to address common regional trends and a rich vector of municipal controls to address remaining characteristics influencing political preferences and COVID-19 mortality. Nonetheless, by using solely conditionally 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 more than 20 times from the OLS estimator in column 1 to the 2SLS estimator in column 2, for instance. Our estimates suggest that, on average, each COVID-19 death per 1,000 inhabitants reduces the president's vote share by nearly 1.6 percentage points.

In column 4 we use the vote share in the second round, finding a 23% decrease in magnitude from the first to the second round results. This suggests that between four in five and three in four voters who cease to vote for Bolsonaro in the first round due to COVID-19 effectively carry over to the second round, preferring the opposition Center-Left candidate Lula. 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 in the first round in 2018 to Lula in the second round in 2022 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

Table 3: Impact of COVID-19 deaths on votes for Jair Bolsonaro

Dependent variable:	Bolsonaro's valid vote share variation, 2022-2018			
	1st round		2nd round	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
COVID-19	-0.0006	-0.0158***	-0.0004	-0.0122**
	(0.0007)	(0.0060)	(0.0007)	(0.0048)
Mean value dep. var.	-2.628	-2.628	-6.026	-6.026
Total population (logs)	Yes	Yes	Yes	Yes
Municipal controls	Yes	Yes	Yes	Yes
Regional intercepts	Yes	Yes	Yes	Yes
Population weights	Yes	Yes	Yes	Yes
Observations	5,563	5,563	5,563	5,563
R-squared	0.883	0.853	0.935	0.924
N. clusters (regions)	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 3 use OLS estimators for the first and second rounds; columns 2 and 4 use 2SLS estimators for the first and second rounds, with the natural logarithm of distance to *nearest large municipality* and its interaction with the natural logarithm of municipality's population as instrument. All estimates weight for total inhabitants, control for total population in logs, the list of municipal characteristics in Appendix B and regional intercepts. Heteroskedasticity-robust standard errors clustered at the regional level are reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

regions we use as dummy variables (see Table A4).

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 all else constant, if voters drew no association between the Coronavirus and Bolsonaro, he 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, we estimate he would have gotten the 50% necessary share for victory 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 additional non-pharmaceutical intervention (Araújo et al. 2023; Ferreira et al. 2023).

Table 4: Heterogeneous impacts on presidential support (2SLS)

Dependent variable:	Bolsonaro's valid vote share variation, 1st round						
	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	-3.960	-0.458	-2.560	-2.519	-4.291	0.989
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
Municipal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional intercepts	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 large municipality* 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 estimates weight for total inhabitants, control for total population in logs, the list of municipal characteristics in Appendix B and regional intercepts. 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 studies where geography plays a large role, one source of concern is whether the instrument is particularly binding to one outlier 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.[6] 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 4. Despite Northern and Mid-Western municipalities being overall more sheltered than Southern, Southeastern and Northeastern municipalities (see Table A2), the instrument and COVID-19's impact on the electorate seemingly hold in all regions, even if there are regional heterogeneities. 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, but the proposed instrument seems to be weak when filtering out small municipalities. This 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.

4.2 Robustness

Our municipal isolation measure is built using 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 2SLS estimation results 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.

6. For a systematic review of the issue, see Conley and Kelly (2025).

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

	More than 25,000 inhabitants			More than 100,000 inhabitants		
Dependent variable:	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
Municipal controls	Yes	Yes	Yes	Yes	Yes	Yes
Regional intercepts	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 the size of "large municipalities," 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 estimates weight for total inhabitants, control for total population in logs, the list of municipal characteristics in Appendix B and regional intercepts. 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 1 and 4 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 the Coronavirus, and that this 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, retaining statistical significance at the 1% level for the three tested thresholds. It also 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. Nonetheless, the exogenous regressors 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 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. Results are not, however, significantly different from each other at the usual levels upon varying the "large municipality" definition.

We modify the structural model to admit only one of each of instrument's components as an instrumental variable for COVID-19 mortality rate, introducing the other as a covariate. Since our measure of municipal isolation is composed of two statistically significant variables in the first-stage regression (see Table 1), the usage of only one of these variables as an instrument with the remaining as a control should be similar to the original estimate. If distance to NLM is indeed exogenous, we would expect our estimates under this new specification to be close to the baseline results for the structural model, presented in Table 3. We present these results in Table 6.[7]

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) in columns 1 and 3; and solely by Distance to NLM (in logs) in columns 2 and 4. These variables seem to not be consistently different than zero in any direction, and are not statistically significant at the usual levels. Likewise, estimates for the impact COVID-19 had on Jair Bolsonaro are very similar to baseline results shown in Table 3: decreases of 1.58 and 1.22 votes per death per thousand inhabitants in the first and second round, versus 1.60 to 1.55, and 1.21 to 1.22 in Table 6 – none statistically different from each other, and all statistically different from zero at the 5% and 1% levels in the first and

7. Since the first-stage regression is the same one presented in Table 1, we supress it.

second rounds.

Table 6: Alternative specifications of the structural model (2SLS)

Dependent variable:	Bolsonaro's valid vote share variation, 2022-2018			
	1st round		2nd round	
	(1)	(2)	(3)	(4)
COVID-19	-0.0160**	-0.0155***	-0.0121**	-0.0122***
	(0.00660)	(0.00554)	(0.00498)	(0.00472)
Distance to NLM (logs)	-0.0536		0.0125	
	(0.214)		(0.175)	
Distance × Population (logs)		-0.00443		0.00103
		(0.0175)		(0.0145)
Mean value dep. var.	-2.628	-2.628	-6.026	-6.026
Total population (logs)	Yes	Yes	Yes	Yes
Municipal controls	Yes	Yes	Yes	Yes
Regional intercepts	Yes	Yes	Yes	Yes
Population weights	Yes	Yes	Yes	Yes
Observations	5,563	5,563	5,563	5,563
R-squared	0.852	0.854	0.924	0.924
N. clusters (regions)	133	133	133	133

Notes: The table reports how our estimates remain roughly unchanged by using each instrument component 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 round of elections; columns 3 and 4, on the second round. Columns 1 and 3 instrument COVID-19 mortality by the interaction between distance to NLM and total population (in logs); columns 2 and 4 instrument COVID-19 mortality by municipalities distance to their NLM (in logs). All estimates weight for total inhabitants, control for total population in logs, the list of municipal characteristics in Appendix B and regional intercepts. Heteroskedasticity-robust standard errors clustered at the regional level are reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

4.3 Placebo tests

Although distance should not impact voting patterns under 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 election pairs. If any undue correlation is the cause for our results in the 2022 election, we could expect it to also be present in previous elections. Table 7 shows no correlation where we know there to be none.

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

Dependent variable:	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
Municipal controls	Yes	Yes	Yes	Yes	Yes	Yes
Regional intercepts	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 estimates weight for total inhabitants, control for total population in logs, the list of municipal characteristics in Appendix B and regional intercepts. 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 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 significant at the usual levels, see Table A4), the range of p-values implied in Table 7 (between 0.22 and 0.90) suggests our specification finds no evidence for COVID-19 to have any impact on elections that occurred prior to the pandemic, as is the case. 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, our estimates in setups where it may have had an impact might truly be reflective of its estimand.

4.4 Aggregate vote shifting patterns

If Coronavirus led the incumbent candidate Jair Bolsonaro to a loss of votes, one might inquire to whom these votes went. Table 8 reports the estimated impact of COVID-19 deaths 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 the main opposition party, PT, faced no significant increase in support due to COVID-19 in the first round, despite its nearly 20 percentage points surge in votes, from 29.3% in 2018 to 48.0% in 2022. Its large and significant increase in the second round, therefore, suggests how support for the party likely merely reflects overall rejection towards Bolsonaro, rather than a successful effort of the party in instrumentalizing the pandemic for its own electoral benefit, at least for those who were moved by COVID-19. Moreover, the Coronavirus seemingly caused no impact on non-valid vote share between elections in both rounds (columns 8 and 9). This suggests voters, on aggregate, actually swapped their preferred candidate, rather than 2018 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 3, column 4), it is hard to

8. Candidates are considered Left- or Right-Wing according to average party score in Zucco (2023). A detailed explanation is offered Section 5.

assess how many votes were actually drawn from Bolsonaro's electorate since voters also might have swapped supported platforms in other manners: it might be the case, for instance, that Bolsonaro's 2018 voters decided to vote null in 2022, and null voters in 2018 decided, in similar proportions, to distribute their vote across their favored parties.

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), a result 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 the anxiety caused by the Coronavirus pandemic not only engendered anti-mainstream sentiments, as is expected, it moved voters between Far-Right options, reflecting a consistent pattern of voters disapproval towards the incumbent president. Estimated increase in support for NOVO, however, represents less than 20% of votes Bolsonaro lost due to COVID-19, and is not enough for the party not to lose support between elections, plausibly due to changes in its running candidate.

It appears that, on aggregate, greater municipal exposition to COVID-19 deaths led voters away from Bolsonaro's platform, but in no organized manner. Initially they may have opted for similar politicians, but in the second round they opted for the only alternative to the president. 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 (5) we investigate a few in detail.

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

Dependent variable:	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
Municipal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional intercepts	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* 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 estimates weight for total inhabitants, control for total population in logs, the list of municipal characteristics in Appendix B and regional intercepts. Heteroskedasticity-robust standard errors clustered at the regional level are reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

5 Mechanisms

There are four main channels through which voting could be affected by COVID-19 deaths. First, voters might refrain from supporting a candidate if they disagree with implemented policy – in this case, if they generally want stringent sanitary policy despite stating otherwise (Oliver 2020); then, reduced support might be a reaction to politicians' inadequacy as policy suppliers. Second, they might create a negative association between any politician in charge and the pandemic, regardless of actions taken and speeches professed. Third, they might create a negative association between Bolsonaro specifically and the pandemic, blaming him for deaths, even in places where non-pharmaceutical intervention and vaccination were adequately delivered by local and state authorities. Fourth, they might see Bolsonaro's speeches as reckless displays, which signal lack of preparedness even if they support the message.

We disentangle the first mechanism from the rest by exploiting the fact that strictness of sanitary policy was a heavily partisan issue during the pandemic (Touchton et al. 2021). We proxy support for stringent sanitary policy through a Left-Right dichotomy, assigning candidates the average self-ascribed ideological score of their party's elected congressmen at the year they take office (Zucco 2023). 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. Table 9 shows estimates for COVID-19 impact on Right-Wing, Far-Right, and Bolsonaro's parties' mayoral candidates.

Column 1 reports 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 similar to those in Table 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). From columns 2, 3 and 4 we argue less stringent sanitary measures did not harm electoral prospects of mayoral candidates, and Right-Wing candidates might have actually benefited from them (at the 10% significance level), which follows from voters' stated preference (Oliver 2020). These gains seem to not carry over to Far-Right and Bolsonaro's parties' candidates, however, plausibly due to stronger association with him.

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

Dependent variable:	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
Municipal controls	Yes	Yes	Yes	Yes
Regional intercepts	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 estimates weight for total inhabitants, control for total population in logs, the list of municipal characteristics in Appendix B and regional intercepts. Heteroskedasticity-robust standard errors clustered at the regional level are reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

It could be argued that voters may have changed their minds along the pandemic, endorsing lax sanitary measures by the municipal election in late 2020, and by 2022 endorsing stringent measures. Even if this is the case, we still find strong evidence suggesting COVID-19 deaths until November 2020, which did not harm the electoral prospects of Right-Wing mayoral candidate, led to decreases in support for Bolsonaro; see Table A5. This is not enough to ensure punishment is directed at the incumbent presidential candidate, however. In a similar manner to natural disasters and economic crises, which are known to harm incumbents even in scenarios in which they are blameless (Malhotra and Kuo 2008; Novaes and Schiumerini 2022), voters could indiscriminately punish incumbents for the Coronavirus. We attest this is not the case by analyzing the performance of incumbent gubernatorial candidates in the 2022 elections, with vote share variation to a candidate's performance to their own past performance, if they were the winner of the 2018 election for state government.[9] Results are shown in Table 10.

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

Dependent variable:	Δ Incumbent governors	
	1st round	2nd round
	(1)	(2)
COVID-19	-0.0126	-0.142
	(0.0820)	(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
Municipal controls	Yes	Yes
Regional intercepts	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 estimates weight for total inhabitants, control for total population in logs, the list of municipal characteristics in Appendix B and regional intercepts. Heteroskedasticity-robust standard errors clustered at the regional level are reported in parentheses; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

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

9. The 16 (out of 27) states not filtered out, therefore, are 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.

incumbent support are not statistically significant at the usual levels, with associated p-values for impact of the pandemic equal to 0.88 and 0.32 in the first and second round. 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, ineptitude or insufficiency in state policy could be partially shifted onto the federal government. We are led to believe Bolsonaro's loss of support is not explained by indiscriminate electoral association with whoever held office during the COVID-19 pandemic.

We conclude by stating that, since neither incumbency nor policy were guiding factors explaining Bolsonaro's loss of support, his engagement with the pandemic was unsavory to voters, either consciously or unconsciously. Although we are unable to disentangle backward- and forward-looking behavior among voters – whether they felt remorse or anger from voting to someone who minimized their or their loved ones' suffering, or they saw his reckless behavior and speeches as a signal of unfitness to lead – we find that Bolsonaro uniquely faced large vote losses as a result of Coronavirus pandemic's severity.

6 Conclusion

In this paper we argue Coronavirus pandemic's severity led to substantial decreases in municipal support for the Far-Right Brazilian president Jair Bolsonaro. We theorize his frequent uncouth remarks throughout the pandemic, his repeated urges for the population to agglomerate, for local and state authorities to lift sanitary measures, and even instances in which he scorned COVID-19 victims, drove away large shares of his 2018 voters towards the Center-Left opposition candidate Lula, in 2022. Our estimates suggest that, all else equal, a moderate decrease of less than a fifth of total deaths would suffice for his re-election.

One must not perceive his reckless statements as simple recurring mistakes, however. In line with the literature dealing on populism, this could be interpreted as a deliberate strategy to rile up voters, specially those most loyal to his platform – even if this strategy backfired, which our identification is insufficient in testing: If his speeches uniformly raise support across municipalities, but COVID-19 deaths primarily raise concern and grief on a local level, his speeches could even have positive impacts on his electoral performance, despite loss of support among voters and regions most affected.

We concluding by noting how populists usage of reckless speech as a tool of correspondence to *the people*, in opposition to *the elites*, might be insufficient when said speech reaches the people struggling, and prudent governmental action is required in order to save lives.

References

Ajzenman, Nicolás, Tiago Cavalcanti, and Daniel Da Mata. 2023. "More than Words: Leaders' Speech and Risky Behavior during a Pandemic." *American Economic Journal: Economic Policy* 15 (3): 351–371. https://doi.org/10.1257/pol.20210284.

Alvarez, Luis A.F., and Rodrigo Toneto. 2024. "The interpretation of 2SLS with a continuous instrument: A weighted LATE representation." *Economics Letters* 237:111658. https://doi.org/10.1016/j.econlet.2024.111658.

Araújo, Samantha Rodrigues de, João Flávio de Freitas Almeida, Lásara Fabrícia Rodrigues, and Elaine Leandro Machado. 2023. "Preventable COVID-19 cases and deaths by alternative vaccination and non-pharmacological intervention policies in Brazil." *Revista Brasileira de Epidemiologia* 26:e230054. https://doi.org/10.1590/1980-549720230054.

Auray, Stéphane, and Aurélien Eyquem. 2020. "The macroeconomic effects of lockdown policies." *Journal of Public Economics* 190:104260. https://doi.org/10.1016/j.jpubeco.2020.104260.

Barros, Laura, and Manuel Santos Silva. 2025. "Economic shocks, gender, and populism: Evidence from Brazil." *Journal of Development Economics* 174:103412. https://doi.org/10.1016/j.jdeveco.2024.103412.

Bauer, Michal, Jana Cahlíková, Julie Chytilová, Gérard Roland, and Tomáš Želinský. 2023. "Shifting Punishment onto Minorities: Experimental Evidence of Scapegoating." *The Economic Journal* 133 (652): 1626–1640. https://doi.org/10.1093/ej/uead005.

BBC. 2021. "CPI da Covid: executivo da Pfizer confirma que governo Bolsonaro ignorou ofertas de 70 milhões de doses de vacinas." *BBC News* (May 13, 2021). https://www.bbc.com/portuguese/brasil-57104347.

Besley, Timothy, and Anne Case. 1995. "Does Electoral Accountability Affect Economic Policy Choices? Evidence from Gubernatorial Term Limits." *The Quarterly Journal of Economics* 110 (3): 769–798. https://doi.org/10.2307/2946699.

Blandhol, Christine, John Bonney, Magne Mogstad, and Alexander Torgovitsky. 2022. *When is TSLS Actually LATE?* Working Paper, Working Paper Series 29709. National Bureau of Economic Research. https://doi.org/10.3386/w29709.

Brader, Ted. 2005. "Striking a Responsive Chord: How Political Ads Motivate and Persuade Voters by Appealing to Emotions." *American Journal of Political Science* 49 (2): 388–405. https://doi.org/10.1111/j.0092-5853.2005.00130.x.

Braggion, Fabio, Alberto Manconi, and Haikun Zhu. 2020. "Credit and social unrest: Evidence from 1930s China." *Journal of Financial Economics* 138 (2): 295–315. https://doi.org/10.1016/j.jfineco.2020.05.001.

Bruce, Raphael, Alexsandros Cavgias, Luis Meloni, and Mário Remígio. 2022. "Under pressure: Women's leadership during the COVID-19 crisis." *Journal of Development Economics* 154:102761. https://doi.org/10.1016/j.jdeveco.2021.102761.

Bursztyn, Leonardo. 2016. "Poverty and the Political Economy of Public Education Spending: Evidence from Brazil." *Journal of the European Economic Association* 14 (5): 1101–1128. https://doi.org/10.1111/jeea.12174.

Campante, Filipe, Emilio Depetris-Chauvin, and Ruben Durante. 2024. "The Virus of Fear: The Political Impact of Ebola in the United States." *American Economic Journal: Applied Economics* 16 (1): 480–509. https://doi.org/10.1257/app.20220030.

Carrança, Thais. 2023. "Censo do IBGE: a polêmica sobre tamanho da população que pode tirar dinheiro de municípios." *BBC News* (January 5, 2023). https://www.bbc.com/portuguese/brasil-64170957.

Castanho Silva, Bruno, Mario Fuks, and Eduardo Ryô Tamaki. 2022. "So thin it's almost invisible: Populist attitudes and voting behavior in Brazil." *Electoral Studies* 75:102434. https://doi.org/10.1016/j.electstud.2021.102434.

Castro, Marcia C., Sun Kim, Lorena Barberia, Ana Freitas Ribeiro, Susie Gurzenda, Karina Braga Ribeiro, Erin Abbott, Jeffrey Blossom, Beatriz Rache, and Burton H. Singer. 2021. "Spatiotemporal pattern of COVID-19 spread in Brazil." *Science* 372 (6544): 821–826. https://doi.org/10.1126/science.abh1558.

Chiplunkar, Gaurav, and Sabyasachi Das. 2021. "Political institutions and policy responses during a crisis." *Journal of Economic Behavior & Organization* 185:647–670. https://doi.org/10.1016/j.jebo.2021.03.018.

Chitolina, Lia, Miguel Nathan Foguel, and Naercio Aquino Menezes-Filho. 2016. "The Impact of the Expansion of the Bolsa Família Program on the Time Allocation of Youths and Their Parents." *Revista Brasileira de Economia* 70 (2): 183–202. https://doi.org/10.5935/0034-7140.20160009.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber. 2020. *The Cost of the Covid-19 Crisis: Lockdowns, Macroeconomic Expectations, and Consumer Spending.* Working Paper, Working Paper Series 27141. National Bureau of Economic Research. https://doi.org/10.3386/w27141.

Conley, Timothy G., and Morgan Kelly. 2025. "The standard errors of persistence." *Journal of International Economics* 153:104027. https://doi.org/10.1016/j.jinteco.2024.104027.

Cox, Nicholas. 2021. *LOCALP: Stata module for kernel-weighted local polynomial smoothing.* https://EconPapers.repec.org/RePEc:boc:bocode:s458001.

De Souza, Carlos Dornels Freire, Michael Ferreira Machado, Adeilton Gonçalves Da Silva Junior, Bruno Eduardo Bastos Rolim Nunes, and Rodrigo Feliciano Do Carmo. 2021. "Airports, highways and COVID-19: An analysis of spatial dynamics in Brazil." *Journal of Transport & Health* 21:101067. https://doi.org/10.1016/j.jth.2021.101067.

Degan, Arianna, and Antonio Merlo. 2009. "Do voters vote ideologically?" *Journal of Economic Theory* 144 (5): 1868–1894. https://doi.org/10.1016/j.jet.2008.10.008.

Doerr, Sebastian, Stefan Gissler, José-Luis Peydró, and Hans-Joachim Voth. 2022. "Financial Crises and Political Radicalization: How Failing Banks Paved Hitler's Path to Power." *The Journal of Finance* 77 (6): 3339–3372. https://doi.org/10.1111/jofi.13166.

Ferraz, Claudio, and Frederico Finan. 2008. "Exposing Corrupt Politicians: The Effects of Brazil's Publicly Released Audits on Electoral Outcomes." *The Quarterly Journal of Economics* 123 (2): 703–745. https://doi.org/10.1162/qjec.2008.123.2.703.

———. 2011. "Electoral Accountability and Corruption: Evidence from the Audits of Local Governments." *American Economic Review* 101 (4): 1274–1311. https://doi.org/10.1257/aer.101.4.1274.

Ferreira, Leonardo Souto, Flavia Maria Darcie Marquitti, Rafael Lopes Paixão da Silva, Marcelo Eduardo Borges, Marcelo Ferreira da Costa Gomes, Oswaldo Gonçalves Cruz, Roberto André Kraenkel, Renato Mendes Coutinho, Paulo Inácio Prado, and Leonardo Soares Bastos. 2023. "Estimating the impact of implementation and timing of the COVID-19 vaccination programme in Brazil: a counterfactual analysis." *The Lancet Regional Health – Americas* 17 (100397). https://doi.org/10.1016/j.lana.2022.100397.

Figueira, Guilherme, and Luca Moreno-Louzada. 2023. "Messias' Influence? Intra-Municipal Relationship between Political Preferences and Deaths in a Pandemic." *Estudos Econômicos* 53 (2): 343–373. https://doi.org/10.1590/1980-53575324gfll.

Firoozi, Daniel. 2024. "Economic Distress and Electoral Consequences: Evidence from Appalachia." *The Review of Economics and Statistics* 106 (3): 778–793. https://doi.org/10.1162/rest_a_01184.

Forquesato, Pedro. 2022. *Who Benefits from Political Connections in Brazilian Municipalities.* Working Paper. https://doi.org/10.48550/arXiv.2204.09450.

Garz, Marcel, and Gregory J. Martin. 2021. "Media Influence on Vote Choices: Unemployment News and Incumbents' Electoral Prospects." *American Journal of Political Science* 65 (2): 278–293. https://doi.org/10.1111/ajps.12539.

Gentzkow, Matthew. 2006. "Television and Voter Turnout." *The Quarterly Journal of Economics* 121 (3): 931–972. https://doi.org/10.1162/qjec.121.3.931.

Gerard, François, Joana Naritomi, and Joana Silva. 2021. *Cash Transfers and Formal Labor Markets: Evidence from Brazil.* Discussion Paper 16286. CEPR.

Graham, James, and Murat Ozbilgin. 2021. "Age, industry, and unemployment risk during a pandemic lockdown." *Journal of Economic Dynamics and Control* 133:104233. https://doi.org/10.1016/j.jedc.2021.104233.

Grais, Rebecca F., J. Hugh Ellis, and Gregory E. Glass. 2003. "Assessing the impact of airline travel on the geographic spread of pandemic influenza." *European Journal of Epidemiology* 18 (11): 1065–1072. https://doi.org/10.1023/A:1026140019146.

Guedes, Octavio. 2021. "CPI da Covid: Governo Bolsonaro recusou 11 vezes ofertas para compras de vacina." *G1* (April 27, 2021). https://g1.globo.com/politica/blog/octavio-guedes/post/2021/04/27/cpi-da-covid-governo-bolsonaro-recusou-11-vezes-ofertas-para-compras-de-vacina.ghtml.

Guedes, Ricardo, Gilson José Dutra, Cecilia Machado, and Marina Aguiar Palma. 2023. "Avaliação dos dados de mortes por COVID-19 nas bases dos cartórios do RC-Arpen, SIVEP-Gripe e SIM no Brasil em 2020." *Cadernos de Saúde Pública* 39 (3): e00077222. https://doi.org/10.1590/0102-311XPT077222.

Guriev, Sergei, and Elias Papaioannou. 2022. "The Political Economy of Populism." *Journal of Economic Literature* 60 (3): 753–832. https://doi.org/10.1257/jel.20201595.

Hansen, Bruce. 2022. *Econometrics.* Princeton University Press. ISBN: 9780691235899.

Hernández, Enrique, and Hanspeter Kriesi. 2016. "The electoral consequences of the financial and economic crisis in Europe." *European Journal of Political Research* 55 (2): 203–224. https://doi.org/10.1111/1475-6765.12122.

Hoehn-Velasco, Lauren, Adan Silverio-Murillo, and Jose Roberto Balmori de la Miyar. 2021. "The long downturn: The impact of the great lockdown on formal employment." *Journal of Economics and Business* 115:105983. https://doi.org/10.1016/j.jeconbus.2021.105983.

IBGE, Instituto Brasileiro de Geografia e Estatística. 2017. *Divisão regional do Brasil em regiões geográficas imediatas e regiões geográficas intermediárias.* IBGE, Coordenação de Geografia. ISBN: 9788524044182.

Lancet, The. 2020. "COVID-19 in Brazil: "So what?"." *The Lancet* 395 (10235): 1461. https://doi.org/10.1016/S0140-6736(20)31095-3.

Li, Shengwu. 2017. "Obviously Strategy-Proof Mechanisms." *American Economic Review* 107 (11): 3257–87. https://doi.org/10.1257/aer.20160425.

Lindgren, Karl-Oskar, and Kare Vernby. 2016. "The electoral impact of the financial crisis: Evidence using district-level data." *Electoral Studies* 44:214–224. https://doi.org/10.1016/j.electstud.2016.08.007.

Lindvall, Johannes. 2014. "The electoral consequences of two great crises." *European Journal of Political Research* 53 (4): 747–765. https://doi.org/10.1111/1475-6765.12055.

Malhotra, Neil, and Alexander G. Kuo. 2008. "Attributing Blame: The Public's Response to Hurricane Katrina." *The Journal of Politics* 70 (1): 120–135. https://doi.org/10.1017/S0022381607080097.

Marino, Angelo Kisil, and Naercio Menezes-Filho. 2023. "Lockdown and COVID-19: Brazilian Evidence." *Estudos Econômicos* 53 (2): 217–256. https://doi.org/10.1590/1980-53575321amnm.

Menezes-Filho, Naercio, Bruno Kawaoka Komatsu, and Luana Villares. 2023. "The impacts of COVID-19 hospitalizations on non-COVID-19 deaths and hospitalizations: A panel data analysis using Brazilian municipalities." *PLOS ONE* 18, no. 12 (December): 1–13. https://doi.org/10.1371/journal.pone.0295572.

Monte, Ferdinando, Stephen J. Redding, and Esteban Rossi-Hansberg. 2018. "Commuting, Migration, and Local Employment Elasticities." *American Economic Review* 108 (12): 3855–90. https://doi.org/10.1257/aer.20151507.

Moura, Erly Catarina, Juan Cortez-Escalante, Fabrício Vieira Cavalcante, Ivana Cristina de Holanda Cunha Barreto, Mauro Niskier Sanchez, and Leonor Maria Pacheco Santos. 2022. "Covid-19: temporal evolution and immunization in the three epidemiological waves, Brazil, 2020–2022." *Revista de Saúde Pública* 56:105. https://doi.org/10.11606/s1518-8787.2022056004907.

MS, Ministério da Saúde. 2021. *Orientações sobre causas de mortes no contexto da COVID-19: Respostas às perguntas mais frequentes.* Technical report. http://bvsms.saude.gov.br/bvs/publicacoes/orientacoes_causas_mortes_covid-19_perguntas.pdf.

Nicolelis, Miguel A. L., Rafael L. G. Raimundo, Pedro S. Peixoto, and Cecilia S. Andreazzi. 2021. "The impact of super-spreader cities, highways, and intensive care availability in the early stages of the COVID-19 epidemic in Brazil." *Scientific Reports* 11 (1): 13001. https://doi.org/10.1038/s41598-021-92263-3.

Novaes, Lucas M., and Luis Schiumerini. 2022. "Commodity Shocks and Incumbency Effects." *British Journal of Political Science* 52 (4): 1689–1708. https://doi.org/10.1017/S0007123421000478.

Ogeda, Pedro, Emanuel Ornelas, and Rodrigo R. Soares. 2024. "Labor Unions and the Electoral Consequences of Trade Liberalization." *Journal of the European Economic Association,* jvae020. https://doi.org/10.1093/jeea/jvae020.

Oliver, Laura. 2020. "Most people see COVID-19 as an economic crisis first, health risk second, survey finds." *World Economic Forum* (March 18, 2020). https://www.weforum.org/agenda/2020/03/covid-19-public-perception-economic-health-crisis-coronavirus-pandemic-ipsos/.

Piketty, Thomas. 2000. "Voting as Communicating." *The Review of Economic Studies* 67 (1): 169–191. https://doi.org/10.1111/1467-937X.00126.

Prunas, Ottavia, Joshua L. Warren, Forrest W. Crawford, Sivan Gazit, Tal Patalon, Daniel M. Weinberger, and Virginia E. Pitzer. 2022. "Vaccination with BNT162b2 reduces transmission of SARS-CoV-2 to household contacts in Israel." *Science* 375 (6585): 1151–1154. https://doi.org/10.1126/science.abl4292.

Pulejo, Massimo, and Pablo Querubín. 2021. "Electoral concerns reduce restrictive measures during the COVID-19 pandemic." *Journal of Public Economics* 198:104387. https://doi.org/10.1016/j.jpubeco.2021.104387.

Touchton, Michael, Felicia Marie Knaul, Héctor Arreola-Ornelas, Thalia Porteny, Mariano Sánchez, Oscar Méndez, Marco Faganello, et al. 2021. "A partisan pandemic: state government public health policies to combat COVID-19 in Brazil." *BMJ Global Health* 6 (6): e005223. https://doi.org/10.1136/bmjgh-2021-005223.

Valsecchi, Michele, and Ruben Durante. 2021. "Internal migration networks and mortality in home communities: Evidence from Italy during the Covid-19 pandemic." *European Economic Review* 140:103890. https://doi.org/10.1016/j.euroecorev.2021.103890.

Wu, Jennifer D., and Gregory A. Huber. 2021. "How Does Job Loss Affect Voting? Understanding Economic Voting Using Novel Data on COVID-19 Induced Individual-Level Unemployment Shocks." *American Politics Research* 49 (6): 568–576. https://doi.org/10.1177/1532673X211026831.

Xavier, Diego Ricardo, Eliane Lima e Silva, Flávio Alves Lara, Gabriel R. R. e Silva, Marcus F. Oliveira, Helen Gurgel, and Christovam Barcellos. 2022. "Involvement of political and socio-economic factors in the spatial and temporal dynamics of COVID-19 outcomes in Brazil: A population-based study." *The Lancet Regional Health – Americas* 10:100221. https://doi.org/10.1016/j.lana.2022.100221.

Zucco, Cesar. 2023. *Brazilian Legislative Surveys (Waves 1-9, 1990-2021).* V. 1. Harvard Dataverse. https://doi.org/10.7910/DVN/WM9IZ8.

Appendix

A Additional Tables

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 vaccine admnistered (Day)	5,570	Jan19, 21	2.120	Jan17, 21	Mar04, 21
Case to vaccination delay (Weeks)	5,570	40.23	3.380	-50.00	44.28
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
Large municipality dummy	5,570	0.685	0.465	0	1
Table D: Municipal characteristics ("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

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Table A1: Summary statistics of Brazilian municipalities (Continued)

	Obs.	Mean	Std. Dev.	Min.	Max.
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
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

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Table A1: Summary statistics of Brazilian municipalities (Continued)

	Obs.	Mean	Std. Dev.	Min.	Max.
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	0.423	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
Private permanent 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	0.495	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
State capital dummy	5,570	0.229	0.420	0	1
Airport dummy	5,570	0.422	0.494	0	1

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Table A1: Summary statistics of Brazilian municipalities (Continued)

	Obs.	Mean	Std. Dev.	Min.	Max.
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 statistics employ municipality's population as analytical weights.

Table A2: 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 macro-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 nearest large municipality (NLM) in kilometers, standard deviations in parentheses.

Table A3: Correlation coefficients between COVID-19, isolation and covariates

	COVID-19 mortality rate	Estimated isolation ($\hat{z}_{mr}$)
Population density	0.3278	-0.5813
SUS beds per 100,000 pop.	0.1673	-0.1264
Non-SUS beds per 100,000 pop.	0.4598	-0.5392
ESF coverage (%)	-0.4311	0.5974

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Table A3: Correlation coefficients between COVID-19, isolation and covariates (Continued)

	COVID-19 mortality rate	Estimated isolation ($\hat{z}_{mr}$)
ESF teams per 100,000 pop.	-0.3714	0.7034
Agr. GDP share (%)	-0.3566	0.6654
Agr. per capita GDP (logs)	-0.2837	0.6845
Avg. PBF benefit	-0.2601	0.2992
PBF expenditure (logs)	-0.4748	0.3937
Homicide rate (logs)	0.0076	-0.2434
Urban (%)	0.6136	-0.7143
Male (%)	-0.4668	0.7400
Children (< 15 yo., %)	-0.5544	0.4152
Youngsters (15 ⊢ 30 yo., %)	-0.3422	-0.1104
Adults (30 ⊢ 60 yo., %)	0.5942	-0.4760
Elderly (≥ 60 yo., %)	0.2717	0.1181
Avg. age	0.4904	-0.1883
Avg. personal income	0.3797	-0.1315
Avg. household income	-0.0677	-0.1586
Avg. weekly working hours	0.0245	-0.2080
Avg. fertility rate	-0.3946	0.1768
Gini-index	-0.0903	0.1202
White people (%)	0.6095	-0.5978
Black people (%)	0.6232	-0.8107
Asian people (%)	0.6359	-0.7935
Mixed-Race people (%)	0.6243	-0.7861
Native people (%)	0.5766	-0.6947
Literacy (%)	0.5632	-0.7217
Primary school (%)	0.5567	-0.7435
Secondary school (%)	0.3714	-0.1640
High school (%)	0.1901	-0.5477
College (%)	-0.4133	0.6431
On welfare (%)	0.0164	0.0231
Commuting (%)	0.4111	-0.5245
Returns home (%)	-0.6080	0.7770
Economically active (%)	0.3274	-0.3762
Job search (%)	0.5796	-0.6492

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Table A3: Correlation coefficients between COVID-19, isolation and covariates (Continued)

	COVID-19 mortality rate	Estimated isolation ($\hat{z}_{mr}$)
Formal employment (%)	0.0238	-0.0132
Government employment (%)	-0.5875	0.6519
Informal employment (%)	0.4301	-0.3817
Employers (%)	0.3492	-0.3893
Evangelicals (%)	0.1774	-0.2514
Immigrants (%)	0.3840	-0.1436
Migrants avg. residency time	0.1156	-0.4914
Private permanent household (%)	-0.0559	-0.0069
Private improvised household (%)	-0.1691	0.2264
Collective households (%)	0.0886	-0.0358
Houses (%)	-0.4870	0.7218
Apartments (%)	0.4873	-0.7270
Jail (%)	0.0427	-0.0292
Alternative housing (%)	0.1056	-0.1660
Homeowning households (%)	-0.3406	0.2650
Tenant households (%)	0.4773	-0.5910
Alternative arragements (%)	-0.1950	0.5283
Avg. renting value	0.5488	-0.7352
Avg. household's density	-0.2984	0.1109
Waste disposal (%)	0.5492	-0.6096
Water plumbing (%)	0.5013	-0.3911
Garbage collection (%)	0.6066	-0.6579
Electricity (%)	0.3752	-0.3690
Radio (%)	0.4196	-0.3130
Television (%)	0.5128	-0.5491
Washing machine (%)	0.5947	-0.6352
Fridge (%)	0.5758	-0.4901
Telephone (%)	0.5843	-0.6031
Computer (%)	0.6116	-0.7289
Internet (%)	0.6020	-0.7484
Automobile (%)	0.3392	-0.1485
State capital dummy	0.3596	-0.6825
Airport dummy	0.2966	-0.5651

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Table A3: Correlation coefficients between COVID-19, isolation and covariates (Continued)

	COVID-19 mortality rate	Estimated isolation ($\hat{z}_{mr}$)
International dummy	0.1867	-0.3634
Coastal dummy	0.1361	-0.2682
NLM region dummy	0.1362	-0.1761
Borders NLM dummy	0.2123	-0.4451
Latitude	-0.3684	0.1520
Longitude	-0.2226	-0.0268

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

Table A4: 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 N	Joint F-stat	p-value	Effective N	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 1, column 3) we analyze variation in standard errors in ln distance to NLM (more than 50,000 inhabitants) and ln distance to NLM $\times$ 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 structural model regression (Table 3, column 2) 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 total population in logs, regional intercepts, and the list of municipal characteristics in Appendix B as controls, and municipality's population as analytical weight.

Table A5: Impact of earlier COVID-19 deaths on votes for Jair Bolsonaro

Dependent variable:	Bolsonaro's valid vote share variation, 2022-2018			
	1st round		2nd round	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
COVID-19	-0.0007	-0.0371**	0.0013	-0.0281**
	(0.0021)	(0.0160)	(0.0018)	(0.0117)
Mean value dep. var.	-2.628	-2.628	-6.026	-6.026
Total population (logs)	Yes	Yes	Yes	Yes
Municipal controls	Yes	Yes	Yes	Yes
Regional intercepts	Yes	Yes	Yes	Yes
Population weights	Yes	Yes	Yes	Yes
Observations	5,563	5,563	5,563	5,563
R-squared	0.883	0.853	0.935	0.924
N. clusters (regions)	133	133	133	133

Notes: The table reports the impact of early COVID-19 mortality rates 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 Nov.14, 2020. Columns 1 and 3 use OLS estimators for the first and second rounds; columns 2 and 4 use 2SLS estimators for the first and second rounds, with the natural logarithm of distance to nearest large municipality and its interaction with the natural logarithm of municipality's population as instrument. All estimates weight for total inhabitants, control for total population in logs, the list of municipal characteristics in Appendix B and regional intercepts. 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 section presents a detailed description of each variable used as control (vector X_{mr} in Equations 1 and 2), 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.