# ONE YEAR OF THE COVID-19 PANDEMIC IN THE GLOBAL SOUTH: UNEVEN VULNERABILITIES IN BRAZILIAN CITIES

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With 3 figures, 2 tables and 1 appendix
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**Summary**: The first year of the COVID-19 pandemic in Brazil provided one of the most severe examples of its impacts on health and society. The country had death rates above the global average and acute impacts in increased unemployment, poverty, and threats to food security marked along ethnic and social lines. This study asks how different degrees of vulnerability between Brazilian cities lead to varying survival probabilities of their population in the phases of the pandemic in the country. To answer this question, this research presents a descriptive and analytic exploration of the relationship between vulnerability and COVID-19 from February 2020 to February 2021. We describe this period in seven distinct phases, characterised by geographic units, vectors of virus transmission, and infected cases and fatality numbers. In this context, we implement an exploratory survival analysis of COVID-19 fatalities using the Kaplan-Meier estimator (KME) in a set of cities with different social vulnerability degrees. The KME is a common analytic tool in medicine, and we implement it in a geographic investigation to focus on the temporal dimension of the crisis and examine socio-territorial vulnerability. Our results present a clear association between vulnerability and COVID-19 deaths. Highly vulnerable cities show low survival probabilities, and there are statistically significant differences in survival probability between low- and high-vulnerability cities. Further research should advance by investigating spatio-temporal dynamics, providing fine-resolution empirical information, and addressing behavioural components related to COVID-19 cases and deaths in the Global South.

**Zusammenfassung**: Das erste Jahr der COVID-19-Pandemie hatte gravierende gesundheitliche und gesellschaftliche Auswirkungen auf Brasilien. Die Sterblichkeitsrate in dem Land lag über dem weltweiten Durchschnitt und erhöhte Arbeitslosigkeit, Armut und die Bedrohung der Ernährungssicherheit zeigten sich entlang ethnischer und sozialer Grenzen. Dieser Artikel untersucht, inwieweit die Vulnerabilität brasilianischer Städte die Überlebenswahrscheinlichkeiten ihrer Bevölkerung in den verschiedenen Phasen der Pandemie beeinflusst. Um diese Frage zu beantworten, wird eine deskriptive und analytische Untersuchung des Zusammenhangs zwischen Vulnerabilität und COVID-19 von Februar 2020 bis Februar 2021 durchgeführt. Wir unterteilen diesen Zeitraum in sieben verschiedene Phasen, die durch geografische Einheiten, Vektoren der Virusübertragung sowie Fall- und Todesfallzahlen charakterisiert werden. Vor diesem Hintergrund führen wir eine explorative survival analysis basierend auf den COVID-19- Todesfällen mit dem Kaplan-Meier-Schätzverfahren (KME aus "Kaplan-Meier Estimator") in einer Reihe von Städten mit unterschiedlichem Grad an sozialer Vulnerabilität durch. KME ist ein gängiges Analyseinstrument aus der Medizin und wir setzen es in einer geografischen Untersuchung ein, um uns auf die zeitliche Dimension der Krise zu fokussieren und die sozio-territoriale Vulnerabilität zu untersuchen. Unsere Ergebnisse zeigen einen klaren Zusammenhang zwischen Vulnerabilität und COVID-19-Todesfällen. Hochgradig vulnerable Städte weisen eine niedrige Überlebenswahrscheinlichkeit auf, und es gibt statistisch bedeutende Unterschiede zwischen Städten mit geringer und hoher Vulnerabilität. Wir empfehlen für die weitere Forschung, die raum-zeitliche Dynamik zu untersuchen, fein aufgelöste empirische Informationen bereitzustellen sowie Verhaltenskomponenten im Zusammenhang mit COVID-19-Fällen und -Todesfällen im globalen Süden miteinzubeziehen.

**Keywords**: COVID-19, Brazil, survival analysis, vulnerability

## 1 Introduction

The first year of the coronavirus disease 2019 (COVID-19) pandemic in Brazil provided one of the most extreme examples of its impacts on health and society. Not only did Brazil present death rates above the global average (Castro et al. 2021a), but the country also faced severe secondary impacts that included suspension of domestic production, increased unemployment, poverty, and threats to food security. These impacts burgeoned upon existing structural fragilities in the economy and infrastructure. Economic fragilities include high dependence on commodity exports and a high degree of work informality. The country also lacked health infrastructure, with underinvestment and geographic centralisation (e.g., the concentration of intensive care unit [ICU] beds) reducing response capacity (ECLAC 2020).

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However, existing structural fragilities do not account entirely for the observed high incidence and death rates. These problems, combined with uneven and hierarchical features of Brazil's territory and society, set the stage for high overall fatality and blatant unequal distribution of the burdens of the pandemic. The high connectivity of "super-spreader cities" and enduring local inequalities show the long roots of the Brazilian social divide (Castro et al. 2021a, Castro et al. 2021b, Nicolelis et al. 2021). Beyond structural features, the lack of national coordination and overall stringency for non-pharmaceutical interventions (NPIs), conflicting information about prevention and treatment, and the lack of conforming to protective behaviour fuelled the poor performance of the country during the pandemic (Barberia et al. 2021, Candido et al. 2020).

In short, the impacts of the pandemic in Brazil were unevenly distributed and marked along ethnic and social lines. This research seeks to investigate the relationship between existing uneven characteristics, divergent response behaviour, and the impacts of COVID-19 in a large country in the Global South. Therefore, it is fitting to start this investigation by asking how vulnerability relates to COVID-19-related deaths during the first year of the pandemic in Brazil. As the first part of a more extensive investigation, this paper will examine vulnerability and COVID-19 deaths from an exploratory perspective using survival analysis focusing on the temporal dynamics of the first year of the pandemic in the country.

### 1.1 The first year of COVID-19 in Brazil

Official sources register the first case of COVID-19 in Brazil on 25 February 2020. By the end of the first year of the pandemic (24 February 2021), Brazil had 10,438,360 cases and 253,372 deaths. These figures rose sharply from March 2021 onwards, reaching 365,223 deaths at the end of May. Despite representing 2.71% of the global population, Brazil accounted for 10.57% of global COVID-19-related fatalities on 24 February 2021, signalling an abnormally high number of deaths over the period.

Evidence of the introduction of the virus in the country comes from genome sequencing, which shows that initial cases came through more than 100 international contacts, mainly from Europe (Candido et al. 2020). Following this introduction, the spread was fast: Before 30 days, COVID-19 reached all 27 states (Castro et al. 2021a). From March to May 2020, cases spread through the national highway and airport systems due to a lack of domestic travel restrictions. Those cities best connected to the heterogeneous and hierarchic transport system became super-spreaders (Nicolelis et al. 2021). This dynamic evolved until July with intense interaction between state and regional capitals and their areas of influence. As case numbers grew exponentially in the major cities, many people sought refuge in smaller towns, which resulted in dispersing cases to most of the country's territory. A return effect then occurred; as cases outgrew the hospital capacity in smaller cities, the population moved back to state and regional capitals, seeking ICU support. This led to a new surge of infections in the regional and state centres and an exponential increase in deaths due to the saturation of the health infrastructure, especially in São Paulo (Nicolelis et al. 2021). Contradictorily, these developments led to the relaxation of controls on social interaction across the country (i.e., NPIs). With the lack of controls and conflicting information, a series of super-spreader events occurred during festivities in late December (Christmas and New Year's Eve) and in February (Carnival). Finally, the last phase of this period presented the collapse of the health system across the country, with deaths peaking due to a lack of ICU beds, respirators, medicine, and medical staff from March to May 2021 (Observatório Covid-19 Fiocruz 2021).

The lack of a nationally coordinated strategy to contain virus contagion was a salient feature of the Brazilian case. The national government opted to focus on protecting economic activity and responding to the pandemic by treating cases at hospitals, a highly criticised posture (Castro et al. 2021a, Matta et al. 2021, Observatório Covid-19 Fiocruz 2021). This stance also imposed the burden of decision, financing, and implementation of responses on state and municipal actors and created intense conflicts between regulating authorities (Barberia & Gómez 2020). The ensuing heterogeneous response at the local level alternated restrictions and relaxation of control measures, at times following politically partisan lines. Research indicates Rio de Janeiro state as a case where political interference with sanitary measures led to a compromised response and the most intense dispersion of cases. In this case, issues include haphazard distribution of resources, ICU bed shortages, corruption accusations, and political infighting, among others (Castro et al. 2021a).

Brazil does not lack experience with pandemics, however. The *Sistema Único de Saúde* (SUS, translated as the Unified Health System) is unique as a universal, comprehensive, and free health system for countries above 100 million inhabitants and performed well against the HIV/AIDS pandemic (Castro et al. 2021a). Despite the differences between these pandemics (e.g., the contagion mechanism for COVID-19 is much faster), the country had integrated information systems, centralised coordination from the national to the community level, and a federated democratic health governance structure. Response measures against COVID-19 were, nonetheless, fragmented, stemming primarily from state-level coordination and, even then, prone to conflicts and contradictions (Barberia et al. 2021).

### 1.2 The uneven impacts of the pandemic in Brazil

Brazilian inequality fuels unevenness in the exposure to, resistance to, and resilience against the impacts of the pandemic (Castro et al. 2021a). On the national and regional scales, the high connectivity of urban centres and metropolitan regions makes them more exposed. During the first weeks of the pandemic, the international travel hubs were key spreaders (e.g., São Paulo, Rio de Janeiro, Brasília, Fortaleza, and Manaus). Overall, São Paulo led in cases and death numbers, followed by Belo Horizonte, Recife, Salvador, Fortaleza, and Teresina (Nicolelis et al. 2021). At the regional scale, highly connected cities presented cases first and in more significant numbers than less connected areas (Candido et al. 2020, Nicolelis et al. 2021). Between cities of similar connectivity, those with less strict NPIs or varying stringency over time had more cases than those implementing consistent measures (Barberia et al. 2021). Local and in-state spillover effects were frequent in urban agglomerations (e.g., metropolitan regions). Death figures varied geographically according to the saturation of the health system (i.e., more critical cases than ICU beds), notably during the later phases of the first year (Bezerra et al. 2020). At the urban scale, geographical factors include access to health services (e.g., ICU beds and mechanical respirators) (Pereira et al. 2021) and income when associated with ethnic profiles (i.e., deaths were more frequent among Black and Pardo[1] individuals) (Li et al. 2021).

A significant relationship exists between the prevalence of chronic non-communicable diseases (CNDs) and COVID-19 cases and deaths. CNDs are pre-existent health conditions that increase the risk of acquiring an infectious disease and the odds of dying once infected (Brasil & Ministério da Saúde 2020). Official data shows that 62% of the hospitalised patients[2] diagnosed with COVID-19 declared at least one CND. This figure rose to 72% of fatal cases (Brasil & Ministério da Saúde 2021). The relationship between CNDs and COVID-19 reinforces the uneven geographic expressions of the social determinants of health (SDOH). SDOH are the unequal conditions of living, growing, and ageing that impact health and well-being, generated by the unfair distribution of money, power, and resources between and within countries. They include environmental factors related to urbanisation, ranging from primary material conditions (i.e., housing, sanitation, and access to services such as health care) to community and societal aspects of urban living, such as social capital and neighbourhood security (Marmot 2005, Salgado et al. 2020). Therefore, these territorial components of SDOH interacted with behavioural, infrastructural, and territorial features to establish an uneven resistance to the pandemic at multiple scales (e.g., from international to community).

The relationship between the vulnerability to COVID-19 and preceding structural fragilities in the country also merits careful consideration. During the first weeks of the pandemic, the initial introduction of the virus came from international travellers, and the vulnerability to COVID-19 in Brazil seemed similar to that reported in Europe. During the initial stages of domestic transmission, intense restrictions on social activities from March to May 2020 meant that individuals directly involved in travel (e.g., lorry drivers) had distinct roles in spreading the virus. When the economic impact of restrictions pressured livelihoods, workers in other categories (e.g., cleaners, day labourers) started a trade-off between heightening their exposure and maintaining income. Local governments started to lower restrictive measures around May 2020, when virus vulnerability factors began to transition from age towards more classic environmental and social factors (e.g., lack of sewage or access to health services). At later stages, the social vulnerability would intensely interact with exposure and lack of resilience: Lacking or

[1] Pardo is an ethnic classification that mixes components from indigenous, black, and white phenotypical characteristics. Implemented as early as 1872, it still features in the official census.

[2] That is, cases grave enough to merit hospitalization. Figures reference the period from March 2020 to March 2021.

diminishing income brought isolation, hunger, and restricted access to services (including health care). These interactions would last through the first year, and the COVID-19 pandemic would increase the country's social divide. This context generated dire impacts in the form of short-term disenfranchisement, long-lasting health issues, and an enormous number of deaths among those already vulnerable: the urban poor, slum dwellers, the homeless, women, and non-White ethnicities (Li et al. 2021, Pereira et al. 2021).

The connections between COVID-19 and vulnerability are by far not exclusive to Brazil. In developed countries, studies mapped factors such as age, comorbidities, or access to health services as important drivers of mortality (Dowd et al. 2020, Grekousis et al. 2022). Among developing countries, the literature suggests a more diverse set of factors, including lack of infrastructure, housing, or transportation; inequalities according to ethnicity; economics; and environmental conditions (Fallah-Aliabadi et al., 2022). These studies fail, however, to provide integrative methods to connect structural, behavioural, and social features of vulnerability to COVID-19 outcomes. To this end, this investigation seeks to expand established vulnerability frameworks (Adger 2006, Boubacar et al. 2017, Pelling 2003) by proposing the integration of the inequalities embedded in the uneven characteristics of society and urbanisation with natural hazards (Elsey et al. 2016, Ezeh et al. 2017), adding COVID-19 to this set.

In Brazil, critical gaps also exist in the intersection between the direct impacts of COVID-19 (i.e., health issues and deaths) and the secondary effects of the pandemic. Secondary effects are caused by the disease (lower life expectancy, decreased quality of life) and by response measures (i.e., decreased economic activity and employment, increased inequalities). This study proposes structuring a comparable, replicable methodology utilising open data to fill the gap of a multidimensional vulnerability framework oriented towards the Global South. To this end, this research presents an exploratory analytical approach based on vulnerability as the first stage in developing such a framework. This study asks how different degrees of vulnerability between Brazilian cities lead to varying survival probabilities of their population in the phases of the pandemic in the country. The central hypothesis is that the population in more vulnerable cities would have lower probabilities of surviving COVID-19 during the first year of the pandemic. This research presents an exploratory survival analysis of deaths during the first year of the pandemic in Brazil to test this hypothesis. This analysis focuses on the temporal dimension of the crisis and controls for vulnerability in the territory and society by selecting a set of cities with different Social Vulnerability Index (SVI) values (IPEA 2015). In the context of geographical research, this study seeks to advance on the correlation of COVID-19 to spatial characteristics of certain locations, namely the vulnerability of a selected set of cities.

The following section presents the design of this study, utilising open and authoritative data sets to estimate the survival probability for each epidemiological week of the first year. Next, we present the methods for survival analysis, to be exact the Kaplan-Maier Estimator (KME). The presentation of results follows, highlighting the consistent effects of vulnerability to COVID-19 fatalities during the period, albeit under some uncertainty. We discuss these findings and present the context for further studies. These include addressing the components of vulnerability (i.e., exposure, resistance, and resilience), using other survival analysis tools such as multivariate Cox regression analysis, implementing analysis on finer spatial scales, developing fieldwork, and performing modelling experiments that will follow in future articles and developments of the database created here.

## 2 Methods

This investigation implements an exploratory approach combining descriptive and bivariate analysis between vulnerability and COVID-19 deaths in Brazil during the first year of the pandemic. We propose this design to assess the dynamic of COVID-19 deaths over time. To this end, we describe the first year of the pandemic based on existing sources and data and then implement survival analysis with the KME. The KME provides the survival probability curves for different populations in the country. Survival analysis is a widespread analysis technique in medical research, including studies related to COVID-19 (Chen et al. 2020, X. Li et al. 2020, Shang et al. 2021). We decided on survival analysis with the KME because it is a statistically robust method for comparing populations (Collet 2003) and is simple to interpret in the interdisciplinary context of integrative geography. Therefore, the innovation here lies in applying a technique from medical research to an interdisciplinary problem, such as the relationship between vulnerability and COVID-19.

In this context, this analysis advances research on the geographies of disease and ill health by linking long-term human behaviour (i.e., accumulated patterns of socio-territorial vulnerability) to short-term impacts of the pandemic (i.e., fatalities).

## 2.1 Methodological design

The study design considers the group of Brazilian cities with more than 100,000 inhabitants. From these cities, we analyse the SVI (IPEA 2015), selecting five examples from the distribution of vulnerability in the country. This sample seeks to describe the country in its diversity through a synthetic measure of vulnerability. This approach presents the advantage of simplicity, encapsulating geographic factors in a single measure, which is beneficial for our first advance on the topic and welcomes further complexity in other stages of research.

The SVI is a measure derived from the territorial and demographic characteristics of the country. The index uses 2010 census data (the latest available), and Figure 1 demonstrates its national distribution. The index overcomes the limitations of poverty measures by including sixteen indicators in three main dimensions: urban infrastructure, human capital, and work and income. This widened approach to deprivation targets the multiple dimensions of human development, going beyond income by relating deprivation to livelihoods and access to assets at the household scale. The data varies from 0 to 1 (with 0 meaning no vulnerability) (IPEA 2015). Death figures come from Brasil.IO, an open data initiative that aggregates cases and death figures reported by municipal health authorities (Brasil.IO 2021). Brasil.IO has a

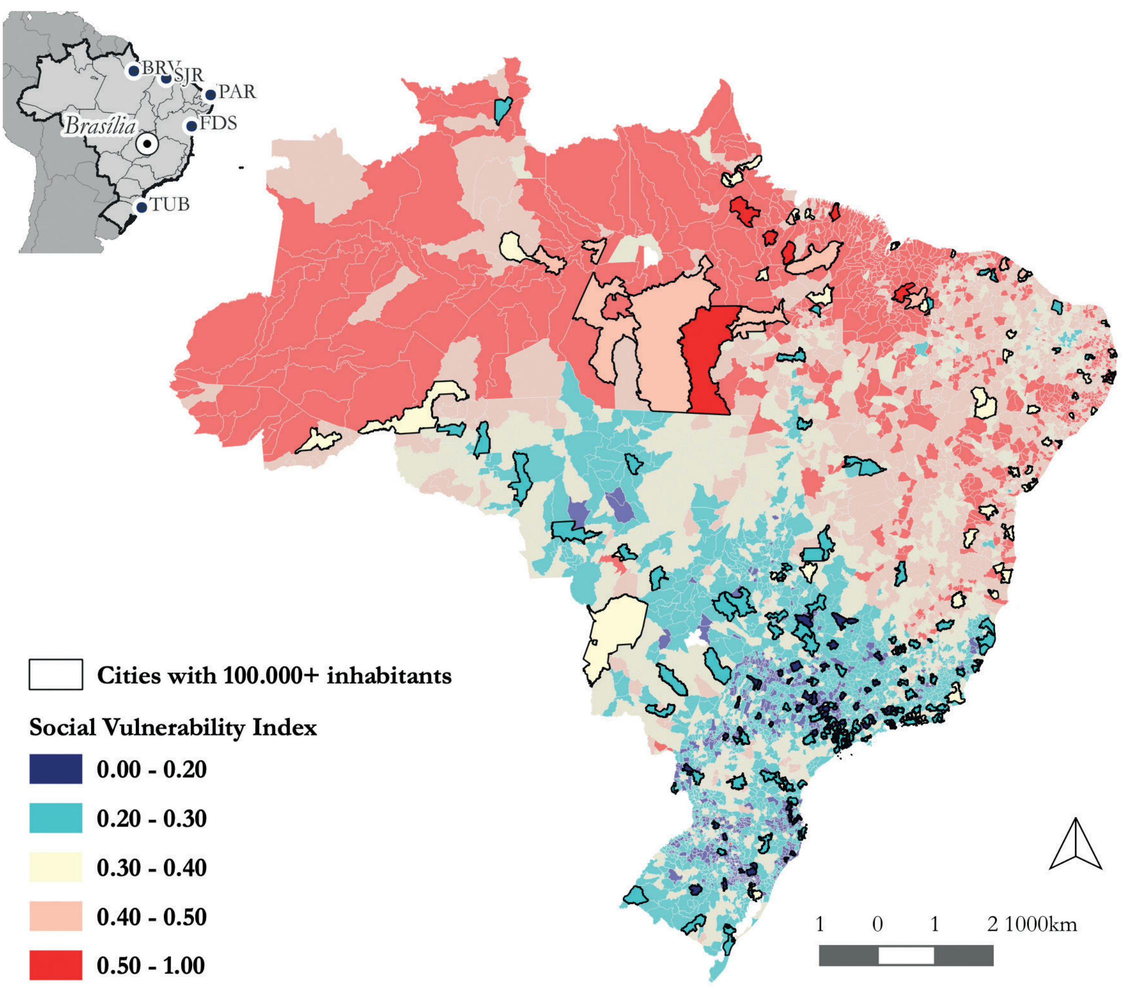


**Fig. 1: Social vulnerability index distribution in Brazil and location of cities in the sample**

significant reputation, and prominent scientific publications feature it as a data source (Castro et al. 2021a, Nicolelis et al. 2021). This analysis considers death figures more reliable than COVID-19 cases, as regional differences severely influence the latter in testing policies (i.e., most cities only test patients with severe symptoms during hospital admission, but there are exceptions).

By selecting cities with more than 100,000 inhabitants, we seek to implement a "most similar approach" that avoids inflated variance found in cities with smaller population sizes. Therefore, we aim to counteract a limitation of data, which is that despite the large numbers of aggregated fatalities across the country, weekly quantities for individual cities vary greatly, due to factors that are at times not epidemiologically relevant (e.g., tallying and processing issues).

The study includes a sample of five cities at significant points in the SVI distribution from the group of cities under consideration. These cities have SVI scores closer to the minimum; the median values of the 25, 50, and 75 percentiles; and the maximum SVI value in the country. When more than one city had the same SVI score, we selected the one with a larger population, as presented in Table 1 and Figure 1. This sample includes cities with a range of geographical conditions (e.g., from the North to the South regions), encapsulating different political, social, and territorial factors, and seeks to provide a significant, albeit limited, representation of the country during the period. This sample might inadvertently include some bias because we only restrict the minimum number of inhabitants and not the maximum. Forthcoming analysis should also address other sources of bias, such as the regional, social, or political context.

## 2.2 Analytical method

This research implements a survival analysis using the KME to compare the survival function of inhabitants who died from COVID-19 in a sample of large Brazilian cities. Survival analysis evaluates the time until a particular event occurs. Medical research uses survival analysis to evaluate the effect of a treatment in different cohorts (e.g., those taking medication and those taking a placebo) or the impact of behaviour on mortality. Its applications are broader, though, including event history analysis in political science (Box-Steffensmeier & Jones 1997). Its central elements are the events (e.g., death of a patient) and the duration until the patient faces the event (i.e., the length from the time of origin until the event).

As any experiment needs to be completed within a given time, the KME delimits a window in which it considers the probabilistic curve of events. In the case of this study, we observe the fatalities during the first year of the pandemic and set aside fatalities after this period or the absolute majority of people who are still alive. The KME, therefore, has a temporal frame and gains strength by comparing what the method calls "reduced groups" of a population (Kaplan & Meier 1958). This grouping allows us to analyse the statistical structural differences of subpopulations without leaning on other assumptions. Smokers and non-smokers in a population are the groups used in a classic application of this non-parametric analysis to the problem of deaths due to lung cancer. In this study, we deal with cities that show different vulnerability degrees and deaths over 53 weeks. With this research setup, we can thus draw causal conclusions between the cities as if the analysis were a quasi-experiment performed statistically.

**Tab. 1: Descriptive statistics for the cities in the sample**

| City name/State | Population (2020) | SVI score | Approximate SVI quantile | Accumulated COVID-19 cases (24.02.2021) | Accumulated COVID-19 deaths (24.02.2021) |
|---|---|---|---|---|---|
| Tubarão/SC | 106.422 | 0.121 | Minimum value | 14,062 | 218 |
| Parnamirim/RN[3] | 267.036 | 0.247 | 25% | 16,051 | 256 |
| Feira de Santana/BA[3] | 619.609 | 0.336 | 50% | 29,106 | 498 |
| São José de Ribamar/MA[3] | 179.028 | 0.449 | 75% | 1,748 | 151 |
| Breves/PA[3] | 103.497 | 0.603 | Maximum value | 3,578 | 102 |
| **Brazil** | **211,707,713** | **0.326** | **-** | **10,438,360** | **253,372** |

Source: authors, based on data from IPEA (2015). Brazilian state acronyms, by region, are: North: AC=Acre, AP=Amapá, AM=Amazonas, PA=Pará, RO=Rondônia, RR=Roraima, and TO=Tocantins; Northeast: AL=Alagoas, BA=Bahia, CE=Ceará, MA=Maranhão, PB=Paraíba, PE=Pernambuco, PI=Piauí, RN=Rio Grande do Norte, and SE=Sergipe; Center-West: DF=Distrito Federal, GO=Goiás, MT=Mato Grosso, and MS=Mato Grosso do Sul; Southeast: ES=Espírito Santo; MG=Minas Gerais; RJ=Rio de Janeiro; and SP=São Paulo; South: PR=Paraná; RS=Rio Grande do Sul; and SC=Santa Catarina.

The advantage of this method is that it enables the analysis of binary models (e.g., alive or dead status) with qualitative and discrete dependent variables (represented as reduced groups) along with the temporal development of discrete events (Collet 2003). Equation 1 defines the survival function.

$$S_t = \prod_{k=1}^{t} (1\text{-}h_t)$$

$S_t$ estimates the survival probability of a person at time t, which is the product of probabilities of not experiencing a death event in each of the intervals up to and including time t. $h_t$ represents the conditional likelihood of death at time t.

**Equation 1: Survival function in the Kaplan-Meier Estimator. Source: Collet (2003).**

The KME provides a graphical representation of events along a timeline. The categorical dependent variable expresses the phenomenon that we seek to explain. The independent variable is the product of probabilities that the death event has not occurred at a given time (or that the event occurs after time t). Based on these probabilities, it is possible to test the main argument that the different groups have varying risks of death (Cleves et al. 2008) based on their vulnerability degrees.

Using the KME, this analysis estimates the survival functions composed of the COVID-19 fatalities in five cities (i.e., survival probability is the independent variable). The dependent data are the fatalities in each of the five cities and the time at which they took place (represented in epidemiological weeks). This analysis presents cities selected according to their degrees of vulnerability. This means that when classifying Brazilian cities larger than 100,000 inhabitants according to their SVI, this analysis includes those nearest to the median of each quartile as representatives of different degrees of vulnerability. As we consider only fatal cases for the sampled cities during the analysis period, the probability starts with 1 at time 0 (i.e., when there is a 100% chance of dying after that moment) and ends at probability 0 at time 53 (when all individuals under consideration were already dead). The analysis timeframe considers the first year of COVID-19 in Brazil, starting on 25.02.2020 and lasting until 24.02.2021, encompassing 53 weeks, whereas data was available until 17.04.2021. We aggregate deaths at the week scale, with the official Brazilian epidemiological weeks[3] as the reference.

## 3 Results

The phases of the COVID-19 pandemic during the first year in the country are presented in Table 2. The existing literature provides plenty of evidence for Phases 1 through 4 (Candido et al. 2020, Castro et al. 2021a, Nicolelis et al. 2021), whereas we outline Phases 5 through 7 based on available case data and ongoing research. Phase 1 reflects the initial introduction of the virus from international travel, notably from Italy and the USA (Candido et al. 2020). Phase 2 shows domestic-level dissemination through national highways and domestic flights. In the first week, the contagion reached seven Brazilian states (São Paulo, Rio de Janeiro, Bahia, the Federal District, Alagoas, Minas Gerais, and Rio Grande do Sul). Before 30 days following the introduction, it was present in every state (Roraima was the last, on 21 March). In Phase 3, domestic-level transmission took root through intra-regional and intra-urban contagion fuelled by work relationships, notably among front-end attendants and essential and domestic workers (Matta et al. 2021). The increase in domestic-level transmission signalled a transition from higher socio-economic classes towards lower-paid workers, with more significant proportions of Black and Pardo individuals and concentrations moving away from central neighbourhoods towards the cities' peripheries (Li et al. 2021). Lack of resistance (e.g., due to CNDs, malnutrition, or lack of access to the health infrastructure) became critical as cases led to deaths. Mortality among traditionally vulnerable populations (e.g., women, along with Black and Pardo ethnicities) grew (Baqui et al. 2020, Li et al. 2021), outpacing the initial internationally exposed (and mostly White) travellers. In Phase 3, domestic spread at the national scale followed 26 major land routes (and river routes in Amazonas) connecting state and regional capitals. In Phase 4, the result of a self-reinforcing dynamic occurred between regional health centres and the country's hinterland. When people travelled to smaller cities seeking less exposure, they inadvertently brought the contagion with them. Those suffering from COVID-19 in these small cities, along with their accompanying relatives, would then seek ICU beds in health centres, bringing more contagion that led to doubling figures, reaching 4,437,986 cases by September. From September to November 2020, the fifth

[3] For the Brazilian Epidemiological Calendar, see the Health Ministry website http://portalsinan.saude.gov.br/calendario-epidemiologico-2020/43-institucional/171-calendario-epidemiologico-2021.

**Tab. 2: Major phases of the first year of the COVID-19 pandemic in Brazil, according to the literature and secondary data. Source: authors, based on data from Brasil.IO (2021).**

| Phase | Geographic unit | Main vectors | Approximate dates | Week numbers* | Acc. cases** | Acc. deaths** |
|---|---|---|---|---|---|---|
| 1 | Global international hubs | International airports | 02.2020–03.2020 | 1–5 | 3,669 | 97 |
| 2 | National and regional centres | National highways and domestic flights | 04.2020–05.2020 | 6–13 | 348,836 | 22,165 |
| 3 | State capitals and regions of influence | State highways and road transport | 06.2020–07.2020 | 14–21 | 2,058,210 | 78,643 |
| 4 | National and regional health service centres | Local hospitals' saturation | 08.2020–09.2020 | 22–30 | 4.437,986 | 135,018 |
| 5 | Population centres at every scale | Relaxation of NPIs, during conflicts between authorities (federal/local) | 10.2020–mid 11.2020 | 31–38 | 5,708,802 | 163,207 |
| 6 | Population centres at every scale | Increased social interaction on holidays | late 11.2020–02.2021 | 39–53 | 10,438,360 | 253,372 |
| 7 | National and regional health service centres | Health system collapse | 02.2021–05.2021 | 54–60 | 13,675,356 | 365,223 |

* We adopted a simplified linear numbering of weeks to describe the period. Week 1 is equivalent to the epidemiological week 09 of 2020, and week 60 equates to the epidemiological week 15 of 2021. ** Accumulated cases and deaths take the last day of the last epidemiological week in the period as a reference. That is, phase 1 has data up to 28.03.2020 and phase 7 up to 17.04.2021.

phase presented overall relaxation of NPIs across the country, with a gradual return to normal levels of social interaction, despite the increase in cases and the first death spikes. This relaxation was conflictive, resulting in institutional disputes between branches of government on national, state, and local scales (Barberia & Gómez 2020).

Even though some cities remained stringent, the limited measures in others, combined with increased travel during national holidays at the end of the year and Carnival, created a series of super-spreader events in the sixth phase of the pandemic (from November 2020 to February 2021). In this phase, Brazil's performance stood out as contrary to the trend in other countries with more than 100,000 deaths in the period (the United States of America, Mexico, India, the United Kingdom, and Italy), signalling the contribution of local factors (Observatório Covid-19 Fiocruz 2021). During this phase, cases reached 10 million, and the first local collapses of the health system occurred. The first capital to breakdown was Manaus (Amazonas), where scenes of asphyxiating patients were prominent when oxygen production was insufficient. This context would result in the final phase for the period, marked by the health system's failure across the country on 22 March, when no state capital had less than 80% occupation of its ICU beds and 18 had more than 90%. Deaths would peak at 4,148 per day on 8 April (Observatório Covid-19 Fiocruz 2021).

Based on this context, we then compare the populations of different cities and their survival curves using the KME. First, we estimate the survival probabilities of the population of the more vulnerable cities (i.e., the city with the maximum SVI, Breves/PA[3] [BRV], and the city at the 75th percentile, São José de Ribamar/MA[3] [SJR]). Then, we contrasted these cities against the less vulnerable ones (i.e., cities with SVI scores at the 25th percentile and the minimum, Parnamirim/RN[3] [PAR] and Tubarão/SC[3] [TUB], respectively). The median SVI value provides a definitive reference (Feira de Santana/BA [FDS]). For this paper, the hypothesis is that survival functions will present divergent behaviour (considering time and death events) due to differences in the degree of vulnerability of the cities in the sample.

Figure 2 presents the accumulated absolute death plots for the five-city sample, selected based on their vulnerability degrees. These curves describe the evolution of deaths over time and compare these cities against the pandemic phases, albeit including potential bias from the definition of the group of cities under consideration. During Phase 1 (weeks 1 to 5), there are no deaths in the sample, which is consistent with expectations, as cases were concentrated in major international hubs (e.g., São Paulo, Rio de Janeiro). Phase 2 presents the first deaths in the sample, notably among the more vulnerable cities of BRV and SJR. All cities except TUB have accelerated growth in deaths during Phase 3. Deaths proliferate in PAR, FDS, and SJR, with the latter experiencing 53% of its total

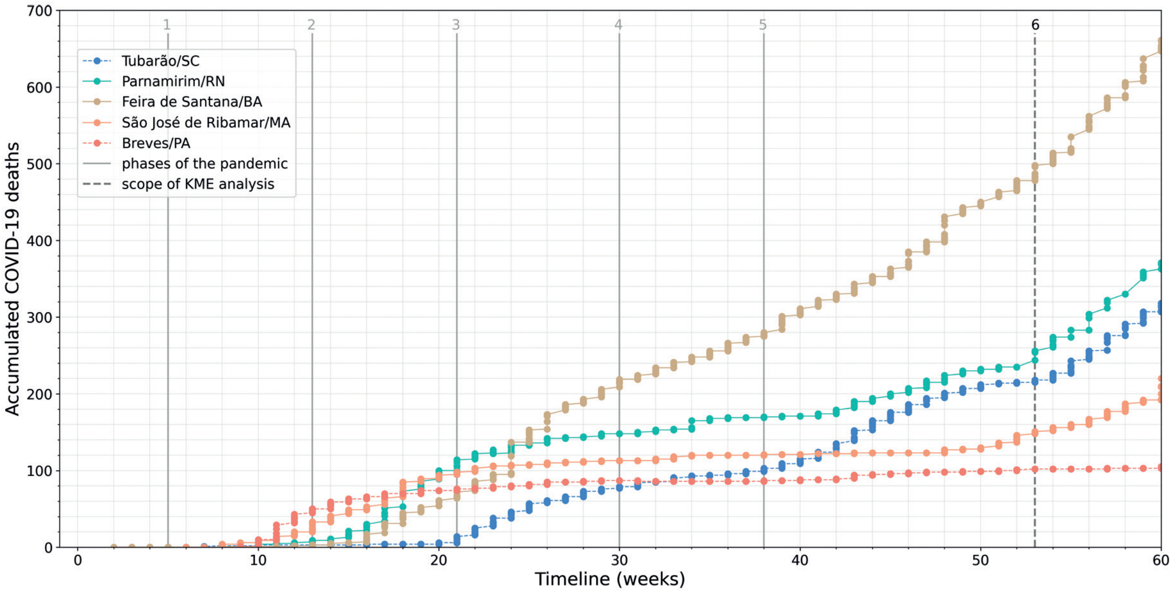


**Fig. 2: Accumulated deaths for the five selected Brazilian cities, from week 0 (25.02.2020) to week 53 (24.02.2021). Source: authors, based on data from Brasil.IO (2021).**

deaths during the period. This is consistent with the pandemic phases in the country, as the medium-sized cities in the sample started to receive more cases from state capitals as domestic-level transmission became the rule. The more vulnerable cities (BRV and SJR) reach a plateau in Phase 4, with death growth levelling off afterwards. PAR and FDS still present growth, and TUB accelerates, reaching 80 deaths sharply. Phase 5 presents a continued increase in deaths in FDS, which remains consistent throughout the following period. The other cities in the sample are stable in this phase and start to differentiate only during the next stage. In Phase 6, FDS sustains its growth, reaching 498 deaths in week 53. TUB has accelerated deaths, progressing rapidly from 80 to 218 deaths, a similar behaviour to PAR, the other less vulnerable city. The most vulnerable cities (BRV and SJR) are stable during the last phase, and the latter presents a renewed increase in deaths only in week 54, which is outside the scope of the analysis.

Figure 3 presents the survival probability curves and their confidence intervals for the selected cities. The lines represent the estimated survival probability as a function of time for each level of vulnerability (represented by each city), whereas the shaded areas show the 95% confidence intervals. This analysis allows for the evaluation of the proportional evolution of death rates in each city. This neutralises the bias from the city population size found in Figure 2, complementing the analysis and showing the impact of vulnerability on survival probabilities.

The behaviour indicated in the survival probability curves is sufficiently different in statistical terms. This is demonstrated by the shaded part of the probability curves that show consistent behaviour throughout the period and no overlap between the confidence intervals of the cities, except in the early weeks of the timeline (weeks 0 through 10), when trends are still differentiating. More specifically, the curves show that the populations of TUB and PAR (cities with lower vulnerability) have greater survival probabilities for much a longer period than those of SJR and BRV (cities with higher vulnerability) during the analysis period. TUB has the most significant survival probability in the sample, and the survival curves decline as vulnerability increases. The clear distinction between the high- and low-vulnerability groups first increases from week 20, grows further at week 34, and only diminishes after week 50, when all probabilities approach zero. These distinctions remain statistically significant under additional testing using a log-rank test, which is available in the appendix. This test shows a statistically significant difference between the groups and contradicts the null hypothesis (i.e., no difference).

The temporal variation of the curves demonstrates a sharp initial decrease in the survival probability for the city with the highest vulnerability (BRV), followed by a stabilisation from weeks 10 to 34. This implies that the impacts of the pandemic were more severe sooner and that this city's population had lower chances of survival in comparison

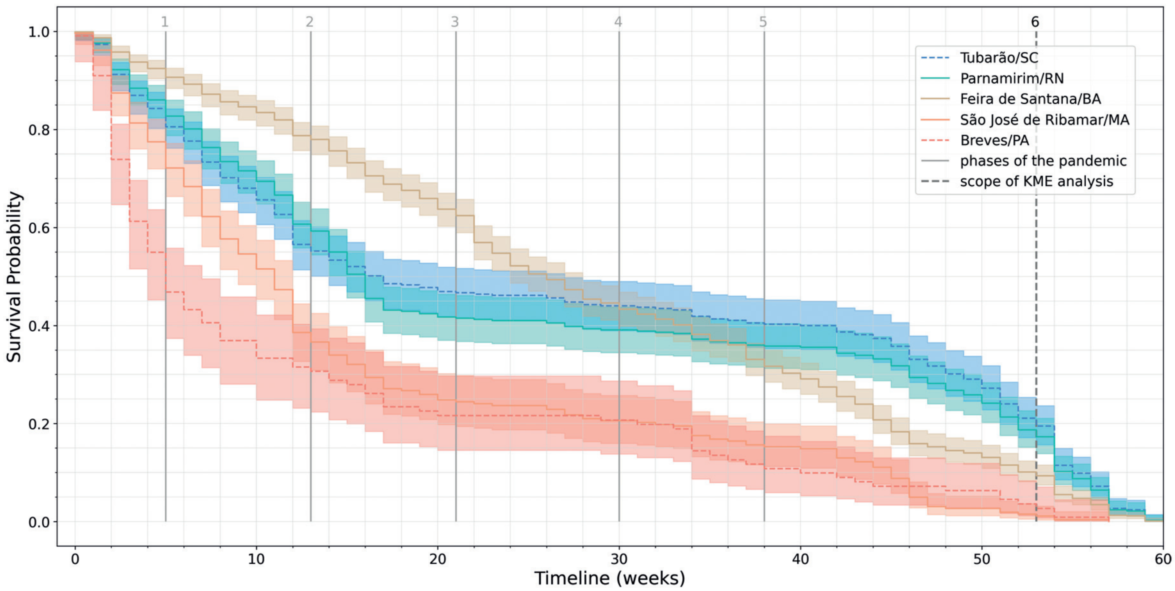


**Fig. 3: Survival function for the five selected Brazilian cities using the KME, from week 0 (25.02.2020) to week 53 (24.02.2021). Source: authors, based on data from Brasil.IO (2021).**

with the others in the sample. TUB, the city with the lowest vulnerability, has a milder decrease in survival probability and reaches a plateau from week 18 to week 42. Then, it presents a shaper decrease in survival, which is expected, as fatalities tend toward zero by the end of the analysis. This means that the population of this city had a greater survival probability for a longer period than the others in the sample. The exception is the somewhat unexpected behaviour of FDS, which varies linearly during the period. Figure 2 partially demonstrates this exceptional character as well, showing a sustained growth in deaths during the analysis. The evolution of survival probabilities indicated by the KME shows that the populations in cities with higher vulnerability had marked decreases in their survival chances already at the initial phases, dropping to roughly 0.3 at week 10, 0.2 on week 30, and as low as 0.15 on week 34. This indicates low resilience, derived from high vulnerability, and contrasts the behaviour exhibited by the low-vulnerability cities.

The confidence intervals of the survival probability curves touch at several points in the timeline, which is consistent with expected results. Curves touch within the pairs of vulnerability degrees (e.g., between TUB and PAR) but not between pairs (e.g., between PAR and SJR). This means the BRV curve touches that of SJR from weeks 12 on, indicating some uncertainty about the explanatory potential of the vulnerability–fatalities relationship. Despite BRV showing the lowest survival probability, its probabilities mix with SJR to the degree that analysing BRV and SJR separately could be misleading. The same behaviour is present between TUB and PAR. However, we see that, for almost the entire analysed period, the statistical differences between the pairs with the highest and lowest vulnerability are evident, and occasional overlaps are due to the construction of the study (i.e., limited to the beginning and end of the curves).

## 4 Discussion

The survival curves do not offer grounds to reject the hypothesis of this study, suggesting the influence of vulnerability on the probability of survival against COVID-19. This result is in line with previous research that indicates a correspondence between increasing vulnerability and the impacts of COVID-19 (Baggio et al. 2021, Li et al. 2021). By adopting a synthetic vulnerability index as the control variable, this analysis indirectly accounts for variations in its different dimensions. This simplified approach provides an exploration of the link between vulnerability and the direct impacts of COVID-19, with results that are sufficient to support the current hypothesis.

The research design presented in this paper is exploratory and, therefore, limited. It uses a small sample of cities and does not control for other alternative explanations. The decision to use a synthetic index for vulnerability has the advantage of simplicity but implies the acceptance of the associated factors. In the same light, the study is not explicit about geographical variations (e.g., from social, political, or regional factors) that are potentially associated with COVID-19 fatalities. These and other sources of alternative explanations should be addressed in future and expanded versions of this design. Literature also indicates certain factors that this analysis omits, including structural, behavioural, and policy features. Noteworthy structural features are the hierarchy between city centres (e.g., differentiation in connectivity, centrality, and polarisation that lead to increased exposure) (Nicolelis et al. 2021, Pereira et al. 2021). Behavioural factors consist of mobility intensity between and within cities (Kraemer et al. 2020) and adherence to NPIs (e.g., social distancing and restricting movement) (Barberia et al. 2021, Candido et al. 2020). Finally, policy factors include integrating social, health, and education policies (e.g., providing income supplements, advising on mask-wearing) (Ha et al. 2020).

This analysis also includes personal differentiating factors only in an implicit manner within the vulnerability index. Further studies should consider social and demographic characteristics such as ethnicity, income, education, and gender explicitly. The geographic distribution of these factors and the associated SDOH are critical topics for intra-urban studies that still merit development. Furthermore, considering SDOH and behaviour in multidimensional approaches to COVID-19 vulnerability has significant potential to orient policy during recovery. One example is providing temporary hospital and ICU beds, which further exacerbates inequalities in health infrastructure, is costly, is prone to corruption, and has a limited effect beyond the critical response phases. This analysis suggests positive feedback between the uneven character of Brazilian society and territory and the COVID-19 pandemic, though. This feedback suggests alternative solutions such as improving the existing resistance and resilience of the population, therefore centring on social fairness and long-term improvement. Measures could include minimum income policies, the provision of access to potable water, and fighting malnutrition (Matta et al. 2021). These solutions would significantly improve resilience in high-vulnerability conditions (e.g., among homeless or slum-dwellers) and create conditions that promote adherence to NPIs.

This research offers topical contributions to both the geography of diseases and illnesses and the spatial distribution of health policies. Regarding the first topic, this approach is easily reproducible in other contexts. Researchers can replicate it with data for other countries or regions with minor adjustments. The simple data requirements also mean these methods are accessible to regions in the Global South, where disaggregate data is scarce, less frequently updated, or non-existent (Elsey et al. 2016). To this end, the source code for this analysis features in the appendix. These methods also provide an exploratory tool to assess the correlation of synthetic vulnerability indexes on fine spatial and temporal scales (i.e., individual cities and epidemiological weeks). Despite the currently limited sample, the methods presented here can be expanded to larger groups of cities, correlating vulnerability and COVID-19 using large data sources. Furthermore, the SVI synthesises aspects of urban infrastructure, human capital, and work and income. This integration provides an overarching measure of social and environmental factors that connects research on COVID-19 with broader geographic themes (Ezeh et al. 2017). One example of social characteristics of the population and places that further research should explore is the inequality and power structures that are deeply entwined with the contrasting vulnerability levels found in Brazilian society and exemplified in this study's sampled cities.

This investigation also provides potential policy outlooks. Considering the provision and accessibility of health services, this contribution indicates that improvements in basic living conditions and infrastructure (e.g., minimum income, sewage) contribute to lowering the demand for health services even during viral pandemics (Cummins et al. 2007). By identifying vulnerability hot spots, future research can also predict where future demand is likely to concentrate, as well as the ability to point to structural inequalities that contribute to systemic risks (Sillmann et al. 2022).

Methodologically, forthcoming studies from this group plan to explore direct and secondary impacts of COVID-19 in detail. The next logical step is to expand the generalisation of the analysis with the Cox proportional hazards model (Cox et al. 1984). With this model, one can regress the survival probabilities against vulnerability and other factors such as mobility degree, size, and rank of the city (in the Brazilian urban network hierarchy). Along these lines, a more significant number of cases would provide a more consistent sample, and similar experiments within the country's five regions (North, Northeast, Centre-West, South-West, and South) could show regional variations in the vulnerability–survival relationship. Investigation into finer geographical scales could also provide insights into the behavioural components of resilience (e.g., adherence to NPIs and motivations for non-compliance).

Complementary to SDOH and demographic features of resistance, behavioural components affect exposure and resilience. During the first year of the pandemic, the lack of access to work and livelihoods threatened a significant part of the Brazilian population that could not work remotely or had informal work (Matta et al. 2021). In this group are the essential workers from care and health professions, along with commerce employees, such as supermarket cashiers, drivers, and delivery personnel. The pandemic also affected a large portion of the urban informal workers, who either work on the street (e.g., street sellers, car washers) or survive on hand-to-mouth income with sporadic employment in construction, gardening, and cleaning. Similar impacts also pressured rural workers in the Global South, threatening livelihoods (Petersen et al. 2021). The absence of comprehensive social support measures during the pandemic meant that these workers could not effectively socially isolate themselves (Matta et al. 2021) or had to survive on reduced income for an indeterminate time. We argue for further analysis into vulnerability considering trade-offs between livelihood preservation and protective behaviour.

In contrast, other groups in Brazil did not adhere to NPIs due to ideological motivations. Certain people behaved in ways not protective to either themselves or society due to a series of resistances, similar to examples in the USA, France, or Germany (e.g., *Querdenker* or anti-maskers) (Hu et al. 2021, Rose-Redwood et al. 2020). Within this group are conspiracy theorists, advocates of preventive treatment (e.g., hydroxychloroquine treatment), supporters of thanatopolitics (Sparke & Anguelov 2020), and those against vaccination (Barberia et al. 2021). For research in geography, these deviations from the behavioural norm are especially interesting in responses to COVID-19. These deviations impose changes to exposure and vulnerability at concise time scales and at the individual's resolution, challenging aggregate or averaged approaches. Therefore, when considering the continuation of the study at hand, measures of vulnerability to COVID-19 should include behaviour as a critical component, directed by ideological motivations or guided by livelihood preservation at fine temporal and spatial scales.

## 5 Conclusion

The first year of the COVID-19 pandemic in the uneven Brazilian society provided extreme examples of its impacts on health and well-being. This paper presents some of these impacts and explores how the underlying differences in vulnerability influence their repercussions in five representative cities during this period. Our results present a clear association between vulnerability and COVID-19 deaths. The more vulnerable cities in the sample had lower survival probabilities than those of lower vulnerability during the whole length of the study. By looking at the temporal dynamic of the first year of the pandemic, this study provides insights into the different phases of the pandemic in the country. The more vulnerable cities in the sample presented earlier spikes in deaths and sharper increases during the initial phases of the pandemic (e.g., Phases 2 and 3 in Table 2), signalling lower resistance to contagion. The consistent difference in survival probability between low- and high-vulnerability cases supports the argument for SDOH in COVID-19 fatalities.

This exploratory approach provides insights into the connection between vulnerability, behaviour, and the impacts of COVID-19 in a large, unequal, developing country. This study shows the contribution of behaviour in COVID-19 vulnerability through the mismatch between death rates and relaxation of NPIs during the latter phases of the pandemic in Brazil (Phases 5 through 7 in Tab. 2). This striking characteristic of Brazil leaves many questions regarding the social impacts of individual and community decision-making on protective behaviour that begs further research from a geographic perspective (e.g., concerning society, space, and time).

As the long-term nature of the crisis dawns on the academic community, future research should focus on integrative approaches around the primary and secondary effects of COVID-19 in the Global South. First, the spatio-temporal dynamics of COVID-19 and its interaction with environmental and demographic factors at the community scale is a substantial gap in research. Insight into this would provide much-needed evidence and guidance for policymaking in actionable yet tractable complexity. Second, research requires empirical evidence that represents the differences in society in a timely and accurate manner. Updated social indicators at the community scale would allow research to move away from aggregate and imprecise measures that compound the impacts on the most vulnerable by focusing on averaged expectations of resilience and resistance. Third, behaviour is an essential component in preventing contagion and curbing deaths. To orient response measures to more efficient and fair policies, research must account for the motivation to adopt (or resist) protective behaviour. In this direction, research must address contradicting phenomena, such as poor people betting on their lives when they choose to protect their livelihoods by increasing their exposure. For fairness' sake, research must also address the affluent, ideologically oriented denialism that hampered Brazilian response policies during this period.

Finally, the issues addressed in this paper are central to the pandemic recovery efforts in Brazil. It is impossible to lessen the direct impact of the pandemic in the country, with over 600,000 dead and still unaccounted for damages to life expectancy and quality. Compounding these harms, the indirect impacts will also challenge the country in the coming years. As livelihoods were lost, education was postponed, and savings were depleted, many families will struggle to face eventual upcoming crises. With reduced economic activity and increased inequality, the country is also severely more limited in managing inherent future risks after the first year of the pandemic than it was before. These compounding stressors show how systemic shocks have consequences beyond the immediate area or time of effect. The systemic quality of natural shocks is, in turn, embedded in the socio-environmental vulnerability-versus-COVID-19 relationship analysed in this paper. Climate change is a highly probable future stressor for the country, with potential global impacts that could lead to spillover effects similar to those from the pandemic (IPCC 2021). If the country wants to learn lessons from the COVID-19 crisis, it would do well to address systemic risks by improving multidimensional resilience.

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## Appendix

### Extended methods

The practice of using survival analysis aims at analyzing the relationship between variables to identify the explanatory variables for the modelling. As a first step, a log-rank test helps us to rule out the idea that the survival functions are equal (i.e., the null hypothesis) by indicating a statistically significant difference between populations. In our case, we selected five cities with different degrees of vulnerability, which refer to the median points at the 0, 25, 50, 75, and 100 quantiles of the Social Vulnerability Index (SVI) (IPEA 2015). For each of these cities, we observed COVID-19 death events (Brasil.IO 2021) during 53 weeks, from February 2020 to February 2021. Table A1 presents the results of the log-rank test for these cities, considering the events in these 53 weeks and tests whether the cities present equal survival functions.

| City name/State | Approximate SVI quantile | Events observed | Events expected |
|---|---|---|---|
| Breves/PA | 100<br>maximum value | 110 | 23.64 |
| São José de Ribamar/MA | 75 | 262 | 208.35 |
| Feira de Santana/BA | 50 | 780 | 952.90 |
| Parnamirim/RN | 25 | 422 | 374.77 |
| Tubarão/SC | 0<br>minimum value | 375 | 389.34 |
| **Total** | | **1,949** | **1,949** |
| $Chi^2(4) = 389.49$<br>$Pr > Chi^2 = 0.0000$ | | | |

**Tab. A1: log-rank test results for levels of cities' vulnerability**

The log-rank test checks for equality between strata for the vulnerability variable. It has a p-value of 0,0000, indicating statistical significant differences. Therefore, vulnerability would be included as a potential candidate for the final model.

Under survival functions, this appendix explores the proportional hazard regression with help of the Cox Proportional Hazard Model (Cleves et al. 2008, Chapter 9). In this model, two populations will be running the following experiment:

$$hazard\ ratio\ (t, x_{1,} x_0) = \frac{h\ (t, x_1, \beta)}{h\ (t, x_0, \beta)} = e^{\beta\ (x_1 - x_0)}$$

The determinants for the occurrence of a defined event or not (called hazard ratio of death) will be explained by the data of vulnerability. The generalization of the model takes form as Cox & Oakes (1985) have indicated.

$$h(t, x) = exp^{x'\beta}$$

Where for the different populations χ, the model approximates the hazard ratio for a baseline h0 and the regression coefficients ßi. Since each city represent a different degree of vulnerability (from the SVI quantiles), we chose to code vulnerability as a categorical variable and we analyze with a dummy approach. The Table A2 shows the results for this Cox regression, which takes Breves/PA as the baseline.

| Dummy variables | Coefficients | Std. errors | z | p>\|z\| |
|---|---|---|---|---|
| São José de Ribamar/MA | -1.333917 | .1147102 | -11.63 | 0.000 |
| Feira de Santana/BA | -1.799799 | .1043954 | -17.24 | 0.000 |
| Parnamirim/RN | -1.447441 | .1081719 | -13.38 | 0.000 |
| Tubarão/SC | -1.611916 | .1097128 | -14.69 | 0.000 |
| **Number of observations : 1,949** | | | | |
| LR $Chi^2(4)$ = 226,25<br>Pr> $Chi^2$= 0,0000 | | | | |

**Tab. A2: Cox regression results for levels of cities' vulnerability**

The most important interpretation is the direction of the coefficients. In these results, the coefficients are negative with respect to the baseline of the regression. This means that, if all other variables are constant, a given inhabitant of one of these populations has a lower probability of dying at the time of the study than an inhabitant of the baseline. These results are in line with our expectations, and indicate that cities with higher vulnerability have lower survival probability. In this sense, an increase in vulnerability in the model leads to an increase in hazard.

These results do not provide additional evidence to falsify the hypothesis. They complement and strengthen the Kaplan-Meier Estimator (KME) implemented in our main analysis. The results of the log-rank test and the Cox regression, therefore, provide additional support for the results from KME. The same limitations in controls remain, though. Therefore, further research should explore for other control variables and interaction effects in this context.

## Code and data availability

The code and data used in the KME analysis are available at https://github.com/alexandrepereiraarq/covidgi.