Closing the Health Gap in Brazil: Data-led Infrastructure Expansion

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Executive Summary

- Over the past several decades, Brazil has made tremendous improvements in terms of life expectancy and infant mortality in the course of developing a robust healthcare system to address the needs of its population. Equal access to high quality medical services remains an issue as evidenced by the distributions of the number of deaths and hospitalizations relative to population across municipalities. One challenge has been that the burden of disease is often difficult to identify because it cannot be measured by a single indicator, e.g., the mortality rate.
- Against this backdrop, the motivation of this analysis is to help policy makers in two ways: first, by developing a new comprehensive measure of disease burden which can be used to identify municipalities in need; and second, by examining the correlation between the burden of disease and various health infrastructure indicators. Based on these results, this analysis offers a policy recommendation regarding where and what kind of health infrastructure should be expanded to close the health gap at the municipality level. Key findings are as follows.
- First, we propose measuring the disease burden at the municipality level using the Municipal Public Health Index (MPHI), which explicitly incorporates current medical needs (as proxied by the number of deaths and hospitalizations per capita), future medical needs, and fiscal capacity (as proxied by income). Since subjective health conditions – our measure of future medical needs – are only available at the state level, we use a regression-based machine learning approach to predict them at the municipality level. The resulting MPHI shows that the burden of disease is generally higher in municipalities (1) that are in the northeast region and (2) along the coast.
- Second, by comparing the medical capital stock between the groups of municipalities with low burden of disease ("frontier municipalities") and those with high burden of disease ("catching-up municipalities"), we find that catching-up municipalities generally have fewer health professionals (general practitioners, nurses, pharmacists, etc.) and a lower amount of medical equipment (X-ray and ultrasound), but they have a greater number of general hospitals.
- Based on the above, we recommend increasing the number of all types of health care workers and the amount of medical equipment in municipalities with high disease burden as identified by our MPHI, so as to meet the medical needs of those communities and to promote full utilization of existing medical facilities, with the goal of reducing the number of deaths and hospitalizations.

1. Introduction

Over the past several decades, Brazil has made tremendous improvements in terms of life expectancy and infant mortality, outpacing the world and Latin America (Chart 1). This is a stark achievement in the development of a robust healthcare system that addresses the needs of its population.

Not all Brazilians, however, have equal access to high-quality medical services. Some pieces of evidence can be found in the distributions of the number of deaths and hospitalization relative to population across municipalities (Chart 2)

One potential solution towards achieving equal access to medical services is expanding the medical infrastructure in municipalities that have not been able to meet medical needs, i.e., those with a high burden of disease.

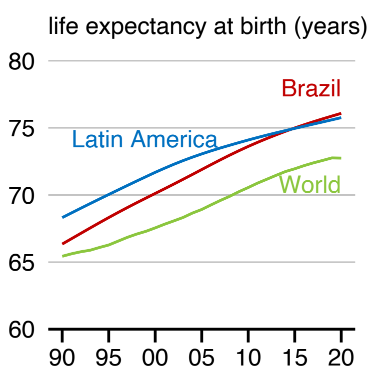
This is easier said than done. One of the challenges is that the burden of disease cannot be measured by a single indicator (e.g., the mortality rate) and, hence, must be evaluated in a multi-faceted manner. Another challenge is that, even if disease burden is assessed at the municipality level, it does not say what medical infrastructure should be expanded to best address this burden.

Against this backdrop, our analysis aims to achieve the following:

- **First, we develop a new comprehensive measure of burden of disease to inform policymakers on municipalities that are falling behind, including in terms of medical provision.** The features of this measure, which we call the Municipal Public Health Index, are that it incorporates multiple factors including future medical needs and that it can be constructed with relative ease compared to other measures.
- **Second, we analyze the correlation between the burden of disease according to the Municipal Public Health Index and various indicators of health infrastructure, based on which we make a policy recommendation of how to expand the health infrastructure in certain municipalities.** While the lack of time-series data does not allow us to conduct a full-fledged analysis regarding the effect of expanding health infrastructure on health status over time, we believe this to be a good starting point.

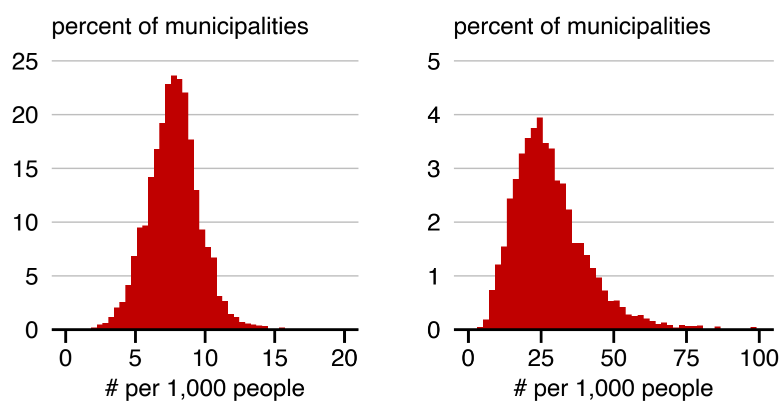
As the first step, we provide a quick overview of the current health indicators in Brazil.

Chart 1:
Life expectancy over time



Source: World Bank

Chart 2: Frequencies by municipalities (2020)
(i) # of deaths (ii) # of hospitalizations



Sources: Ministry of Health; Instituto Brasileiro de Geografia e Estatística

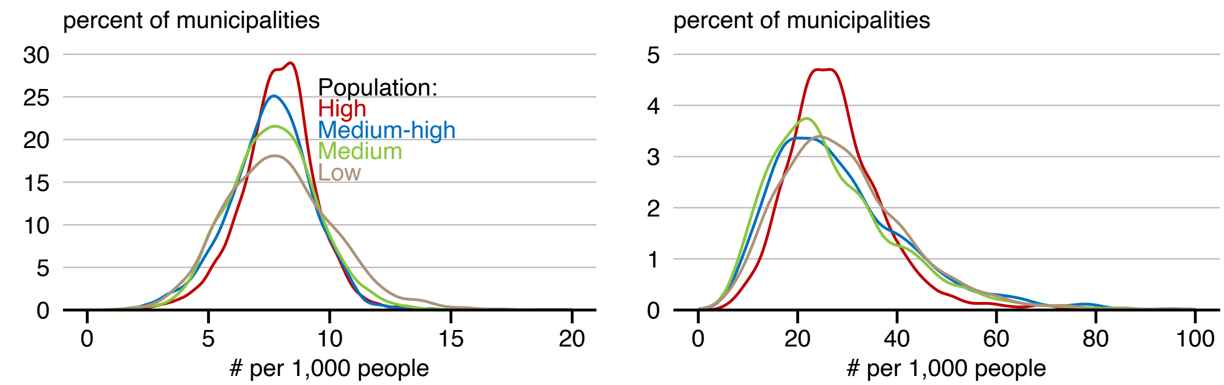
2. Characterizing health care in Brazil

Deaths and hospitalizations by population group

We divide the municipalities into four groups by population quartile to see whether the difference in the number of deaths or hospitalizations across municipalities comes from urban or rural settings (Chart 3). While the distributions do not differ substantially across population groups, we can observe some slight differences which include that the share of municipalities with more than 10 deaths per 1,000 people is higher in the low-population group and that the share of municipalities with more than 40 hospitalizations per 1,000 people is higher in bottom three population groups.

Chart 3: Distributions by quartile of population (per 1,000 people; 2020)

(i) Deaths (ii) Hospitalization

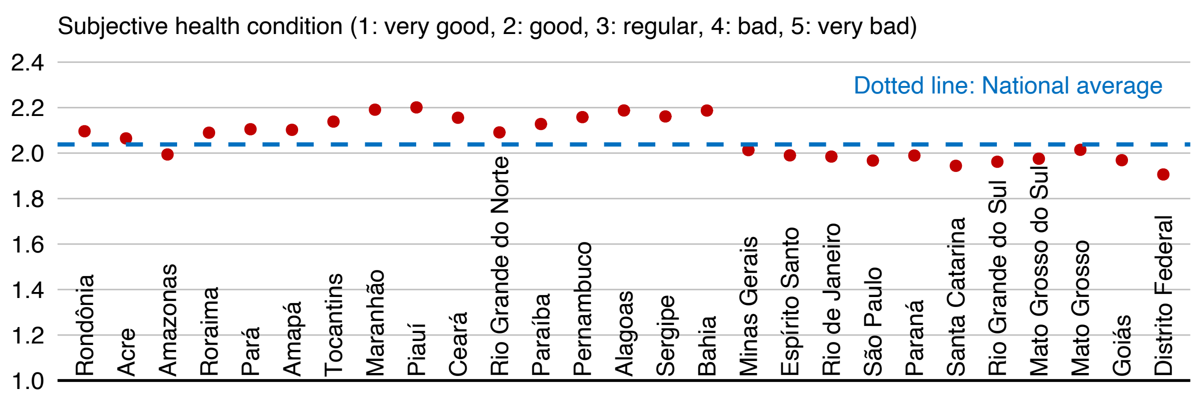


Note: "High": >75 percentile; "Medium-high": 50–75 percentile; "Medium": 25–50 percentile; "Low": <25 percentile.
Sources: Ministry of Health; Instituto Brasileiro de Geografia e Estatística (IBGE)

Subjective health conditions at the state level

The National Health Survey (PNS) asks respondents, among other things, to describe their state of health on a five-point scale from "very good" (1) to "very bad" (5). We consider the responses to this question as a measure of subjective health conditions. Using the publicly available dataset, we can aggregate the subjective health conditions at the state level. Chart 4, which plots the measure for all 27 states, reveals that there is some degree of variation. We will further explore this point in Section 3.2.

Chart 4: Subjective health conditions (2019)

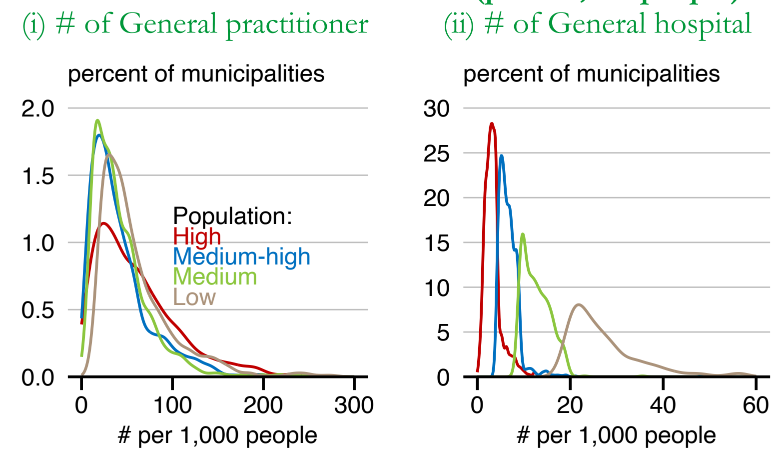


Source: IBGE

Health care access

Finally, we compare existing health care infrastructure by municipality group (the same classification as in Chart 3). We do not observe a clear relationship between the number of professionals and the size of the municipalities, although the number of hospitals appears to be greater for larger ones (Chart 5). We will examine whether this mismatch has anything to do with the health gap.

Chart 5: Medical infrastructure (per 100,000 people)



Sources: Health Infrastructure Database; IBGE

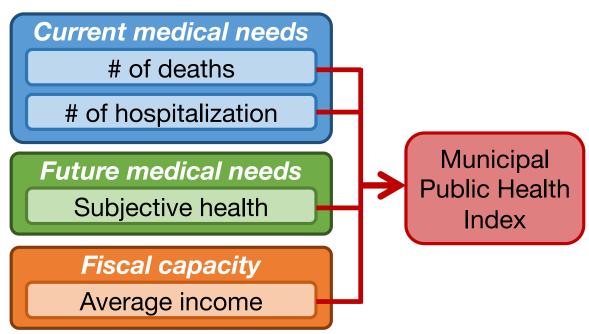
3. Measuring the disease of burden at the municipality level

3.1. Defining the burden of disease

We recognize the burden of disease to be determined by current and future medical needs as well as fiscal capacity. This perspective enables us to link the burden of disease with the necessary investment decision, which must be made in a forward-looking way. Every investment decision, however, has to be financed in one way or another. In this regard, it is also important to take fiscal capacity into account.

With these considerations, we construct the Municipal Public Health Index (MPHI) by synthesizing the indicators of both current and future medical needs. We use the numbers of deaths and hospitalization per capita as the indicator of current medical needs. We intend to use the subjective health conditions survey as the indicator of future medical needs. Finally, we use income as a proxy for tax revenue and, hence, fiscal capacity (Chart 6).

Chart 6: Our measure of disease of burden



3.2. Predicting the subjective health conditions at the municipality level

One of the challenges is that the data on subjective health conditions, introduced earlier, is only available at the state level.

We assume that the degree of variation in the PNS across states reflects differences in census data in various socioeconomic, demographic, and living conditions across municipalities. Some of the information contained in the census data includes average age, male ratio, access to a sewage system, and room density. This information is available at both the state and municipality level.

We estimate the subjective health conditions in municipalities using the relationship between subjective health conditions and socioeconomic status, demographics, and living conditions at the state level. To do so, we used a machine learning approach (see Technical Appendix for more details).

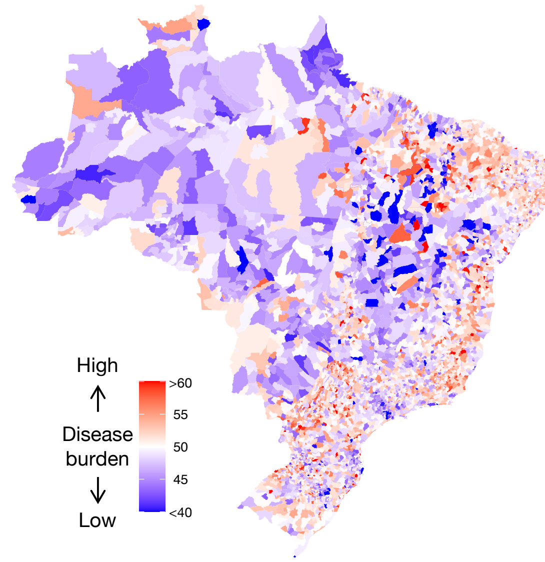
3.3. Municipal Public Health Index

We calculate the MPHI using the following two steps. First, we standardize all four indicators: deaths per capita; hospitalizations per capita; the subjective health conditions; and average income (inverted). A higher value implies a greater burden of disease for that municipality. This first step is necessary to make the indicators measured in different units comparable.

Second, we aggregate the three (standardized) indicators by taking a simple average.

Through these steps, we obtain the MPHI by municipality as shown in Chart 7. According to this analysis, the burden of disease is identified to be higher in municipalities that are located in the northeast region as well as in the coastal region.

Chart 7: Municipal Public Health Index



Source: Authors' calculation

4. Relationship with the existing medical infrastructure

We compare the medical capital stock between the groups of municipalities with low burden of disease ("frontier municipalities") and those with high burden of disease ("catching-up municipalities"). The former group is municipalities whose MPHIs are equal to or higher than the 75th percentile, and the latter is equal to or lower than the 25th percentile.

We notice that catching-up municipalities have fewer health professionals (general practitioners, nurses, pharmacists, and family physicians) and a lower amount of medical equipment (X-rays and ultrasounds). However, these municipalities have a greater number of general hospitals, health centers, and health management centers (Chart 8).

Chart 8: Comparison of the medical capital stock (per 100,000 people)

	Medical professionals				Medical facilities				Medical equipment	
Municipalities	Pharmacist	General practitioner	Nurse	Family physician	Health center	General hospital	Speciality care clinic	Health management	X-ray	Ultrasound
Frontier (Low burden)	24	58	110	17	28	4	22	7	36	22
Catching-up (High burden)	16	30	94	15	42	7	13	10	17	13

Note: Each red square indicates the greater of the two.

5. Policy recommendation on health infrastructure expansion

Based on the above, we recommend the government increase the number of all types of health care workers and the amount of medical equipment in municipalities with high burden of disease as identified by our MPHI. This is done with the goal of fully utilizing the existing medical facilities in these municipalities and, eventually, reducing the number of deaths and hospitalizations. We also recommend collecting all data by municipality so that these kinds of needs analyses and infrastructural improvements can be iterative and more accurately calculated in the future.

Technical Appendix

Chart 2

- Mortality and hospitalization data are obtained from the Mortality Information System and the Hospitalizations Information System, respectively. The number of deaths is calculated as the sum of deaths from causes classified in Chapters 1–18 and 20 in the ICD-10 (Chapters 19 and 21 are not included due to data unavailability). The number of hospitalizations is calculated as the sum of hospitalizations from causes classified in all Chapters 1–21.[1] The missing observations are treated as zero.
- For each municipality, the numbers of deaths and hospitalizations are divided by the population according to the Brazilian Census in 2010 and then multiplied by 1,000 to obtain the numbers of deaths and hospitalizations per 1,000 people, which are used in the charts.

Details on predicting the subjective health conditions at the municipality level

- **We predict the subjective health conditions at the municipality level in the following three steps.** See Chart A1 (p. 9) for a visual explanation.

Step 1: Aggregate the Census data at the state level

We begin by aggregating the National Health Survey (PNS) dataset at the state level. This survey was conducted by the Instituto Brasileiro de Geografia e Estatística in 2019 in an effort to evaluate the health conditions of the people in Brazil. The variable of our interest is the subjective health score (J00101) which comes with a five-point scale from "very good" (1) to "very bad" (5). This variable will be our dependent variable. For aggregation, we use the weights (V00281), which are adjusted for the likelihood of selection and rate of non-response by sex and age category.

Next, we aggregate the 2010 Census at the state level. The Census consists of two datasets: those from the household survey and the individual survey. First, the household survey dataset contains the following pieces of information for each municipality: the number of households; average room density; average household size; share of households by types of wall materials; share of households with toilets, sewage, water, garbage collection system, and electricity. We aggregate the household survey at the state level using the number of households as weights. Second, the individual survey dataset provides the following variables for each municipality: population; share of the male population; average age; share of population by race (white, black, Asian, mixed, and indigenous). We aggregate the individual survey at the state level using the population as weights.

[1] Chapter 1: Certain Infectious and Parasitic Diseases; Chapter 2: Neoplasms; Chapter 3: Disease of the blood and blood-forming organs and certain disorders involving the immune mechanism; Chapter 4: Endocrine, Nutritional, and Metabolic Diseases; Chapter 5: Mental, Behavioral and Neurodevelopmental disorders; Chapter 6: Diseases of the Nervous System; Chapter 7: Diseases of the Eye and Adnexa; Chapter 8: Diseases of the Ear and Mastoid Process; Chapter 9: Diseases of the Circulatory System; Chapter 10: Diseases of the Respiratory System; Chapter 11: Diseases of the Digestive System; Chapter 12: Diseases of the Skin and Subcutaneous Tissue; Chapter 13: Diseases of the Musculoskeletal System and Connective Tissue; Chapter 14: Diseases of Genitourinary System; Chapter 15: Pregnancy, Childbirth, and the Puerperium; Chapter 16: Certain Conditions Originating in the Perinatal Period; Chapter 17: Congenital malformations, deformations, and chromosomal abnormalities; Chapter 18: Symptoms, signs, and abnormal clinical and laboratory findings, not elsewhere classified; Chapter 19: Injury, poisoning, and certain other consequences of external causes; Chapter 20: External Causes of Morbidity; Chapter 21: Factors influencing health status and contact with health services.

Step 2: Regress PNS subjective health conditions on the Census data

As shown in Chart 4 in the main text, there is variability in the subjective health conditions across states. We assume this reflects differences in various socioeconomic and hygiene conditions as comprehensively documented in the Census. Based on this assumption, as the second step, we empirically examine the relationship between subjective health conditions and demographic characteristics at the state level.

Our empirical strategy is to estimate the three different models using ordinary least squares. As mentioned earlier, the dependent variable is the subjective health conditions we calculated in the first step. We have the following 21 potential independent variables: average room density; average household size; share of households by types of wall materials (masonry, rigged wood, Taipa, used wood, straw, other materials, or no walls); share of families with toilets, sewage, water, garbage collection system, or electricity; share of the male population; average age; percentage of population by race (white, black, Asian, mixed, or indigenous). The number of observations is 27, the number of states in Brazil.

The three regression models are the simple model (short model), the kitchen-sink (long model), and the LASSO model. A brief explanation of each model is as follows:

- ✓ **Simple model:** We use the arbitrarily chosen four independent variables: room density, sewage, water, and average age.
- ✓ **Kitchen-sink model:** We use almost all the potential independent variables in this model. Given that the number of potential independent variables is close to the observations, we decide to include the following 14 variables on the right-hand side of the regression equation: room density. This model should be referred to as a sort of kitchen-sink model, strictly speaking, but we refer to this simply as a kitchen-sink model for simplicity.
- ✓ **LASSO model:** The third model is a regression-based machine learning model, and appropriate independent variables will be automatically chosen from the pool of 21 potential independent variables.[2]

We separate the sample into two parts: 70 percent goes to the training sample, and 30 percent goes to the test sample. We estimate the models using the training sample and evaluate the performance based on the root mean squared error (RMSE) in the test sample, i.e., out-of-sample RMSE. The results of the performance check are shown in Chart A2. We confirm that the LASSO model performs better than the simple and kitchen-sink models.

[2] The least absolute shrinkage and selection operator, or LASSO, is a method for estimating the regression coefficients by minimizing the following equations:

$$\hat{\beta}_{\lambda}^{LASSO} = \arg\min_{\beta}\left[\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij}\right)^2 + \lambda\sum_{j=1}^{p}\left|\beta_j\right|\right]$$

where λ is a penalty parameter and p is the number of coefficients in the model.

In the case of positive penalty parameter, the method penalizes the non-zero values of coefficients, which results in assigning zero to the coefficients of the variables that are less important. We choose λ based on a cross-validation procedure.

Step 3: Predict municipal health scores based on the relationship at the state level

Finally, we use the relationship identified in the second step to predict the subjective health score at the municipality level.

- Finally, we address some caveats. The biggest shortcoming of this analysis is the small sample size. It will be an interesting extension of this analysis if the PNS-based subjective health conditions become available even for some selected municipalities. Second, given the small number of observations, we only sought potential independent variables from the Census; it would also be worth further exploring the deep determinants of subjective health conditions.

Details on the Municipal Public Health Index

- Each of the four indicators is standardized to a mean of 50 and a standard deviation of 10. The choices of 50 for the mean and 10 for the standard deviation are arbitrary, and they can be set at different values because the MPHI is seen as ordinal instead of cardinal.
- In the main text, we put the map of the MPHI to get the big picture. But this technical appendix provides a list of the top 20 and bottom 20 municipalities just for illustrative purposes. We do not include this list in the main text because we consider it best to use the MPHI to get the overall idea about the public health status in small groups of municipalities, and not in a way to compare two adjacent municipalities on which is doing better. This is because each of the three indicators can vary from year to year, especially in small municipalities.
- For this analysis, we took a simple average of the four standardized indicators to integrate the indices into one indicator. We did so because we took an agnostic approach about which indicator has the highest importance and which does not. This does not, however, limit the potential users of the MPHI to stick to this particular construction method. Instead, this is one illustration that the index can be easily modified to suit the different needs of policymakers. For example, if a policymaker wants to put more emphasis on mortality, then the weight placed on the number of deaths per capita can be raised.

Other notes on future considerations

- One of the things that this analysis did not explicitly take into account is that the major causes of deaths or hospitalizations vary a lot among municipalities. For instance, pregnancy, childbirth, and puerperium account for 18 percent of hospitalization at the median. Still, it only accounts for a few percent in some municipalities and around 50 percent in some municipalities (Chart A4). Another example is the diseases of respiratory system. It accounts for 13 percent of hospitalization in a typical municipality, but this is a more severe cause of hospitalization in some municipalities and less so in others. These pieces of evidence might imply that municipalities have different medical needs, and such conditions are better met with a tailor-made strategy for health infrastructure expansion.
- It is also worth considering whether expanding infrastructure in each municipality will be effective. It may be more cost-effective if the government invests in regional hubs across the country. While the availability of data does not allow us to do a deep dive into developing an investment plan that incorporates this aspect, i.e., the accessibility to other municipalities, which heavily depends on whether a municipality is in an urban or rural area, we think this is an interesting avenue for future analysis.

Chart A1: Visual illustration of the method to predicting subjective health conditions

Step 1

Code		PNS	Census data							
State	Municipality	Health score	Room density	···	Sewage	Water	···	Male ratio	Average age	···
11	110001	?	1.63	···	0.02	0.94	···	0.511	41.0	···
11	110002	?	1.76	···	0.08	0.99	···	0.507	43.1	···
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
11	110180	?	1.56	···	0.01	0.97	···	0.511	46.2	···
12	120001	?	1.99	···	0.12	0.93	···	0.529	43.7	···
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Aggregate at the state level

Code		PNS	Census data							
State		Health score	Room density	···	Sewage	Water	···	Male ratio	Average age	···
11		2.096	1.76	···	0.23	0.95	···	0.509	43.5	···
12		2.064	2.19	···	0.39	0.86	···	0.502	44.0	···
⋮		⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Step 2

Code		PNS	Census data							
State	Municipality	Health score	Room density	···	Sewage	Water	···	Male ratio	Average age	···
11	110001	?	1.63	···	0.02	0.94	···	0.511	41.0	···
11	110002	?	1.76	···	0.08	0.99	···	0.507	43.1	···
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
11	110180	?	1.56	···	0.01	0.97	···	0.511	46.2	···
12	120001	?	1.99	···	0.12	0.93	···	0.529	43.7	···
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Regress Census data on health score from PNS

Code		PNS	Census data							
State		Health score	Room density	···	Sewage	Water	···	Male ratio	Average age	···
11		2.096	1.76	···	0.23	0.95	···	0.509	43.5	···
12		2.064	2.19	···	0.39	0.86	···	0.502	44.0	···
⋮		⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Step 3

Code		PNS	Census data							
State	Municipality	Health score	Room density	···	Sewage	Water	···	Male ratio	Average age	···
11	110001	?	1.63	···	0.02	0.94	···	0.511	41.0	···
11	110002	?	1.76	···	0.08	0.99	···	0.507	43.1	···
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
11	110180	?	1.56	···	0.01	0.97	···	0.511	46.2	···
12	120001	?	1.99	···	0.12	0.93	···	0.529	43.7	···
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Predict based on the relationship at the state level

Code		PNS	Census data							
State		Health score	Room density	···	Sewage	Water	···	Male ratio	Average age	···
11		2.096	1.76	···	0.23	0.95	···	0.509	43.5	···
12		2.064	2.19	···	0.39	0.86	···	0.502	44.0	···
⋮		⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Chart A2: Performance check

Model	In-sample RMSE	Out-of-sample RMSE
Simple	0.039	0.079
Kitchen-sink (sort of)	0.016	0.092
LASSO	0.024	**0.062**

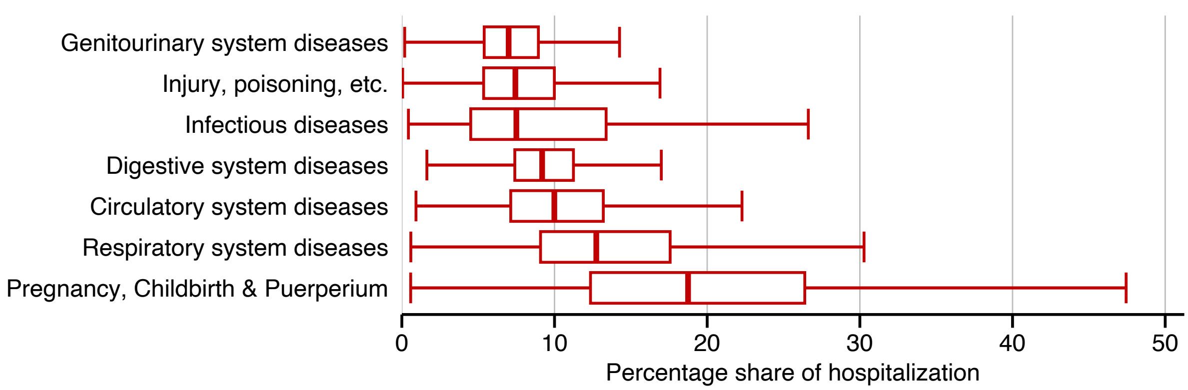
Note: See Technical Appendix for details.
Source: Authors' calculation

Chart A3: Municipalities with top and bottom 20 MPHIs

Top	State	Municipality	Worst	State	Municipality
1	Santa Catarina	Florianópolis	1	Maranhão	Passagem Franca
2	São Paulo	Santana de Parnaíba	2	Piauí	São Raimundo Nonato
3	Distrito Federal	Brasília	3	Santa Catarina	Treze de Maio
4	Espírito Santo	Vitória	4	Piauí	Fronteiras
5	Santa Catarina	Balneário Camboriú	5	Bahia	São Miguel das Matas
6	São Paulo	Santa Cruz da Conceição	6	Bahia	Wanderley
7	Santa Catarina	Treze Tílias	7	Santa Catarina	Ponte Serrada
8	Paraná	Curitiba	8	Paraíba	Santo André
9	São Paulo	Valinhos	9	Bahia	Cristópolis
10	Pernambuco	Fernando de Noronha	10	Goiás	São Miguel do Passa Quatro
11	Rio Grande do Sul	Carlos Barbosa	11	Piauí	São Braz do Piauí
12	Minas Gerais	Nova Lima	12	Piauí	Wall Ferraz
13	Rio de Janeiro	Niterói	13	Piauí	Parnaguá
14	São Paulo	São Paulo	14	Bahia	Itiruçu
15	Rio Grande do Sul	Chuí	15	Paraíba	Uiraúna
16	Minas Gerais	Belo Horizonte	16	Paraíba	Brejo dos Santos
17	Rio Grande do Sul	Porto Alegre	17	Piauí	Simões
18	Rio Grande do Sul	Caxias do Sul	18	Paraná	Santa Mariana
19	Santa Catarina	Joaçaba	19	Maranhão	São Félix de Balsas
20	Rio Grande do Sul	Garibaldi	20	Goiás	Indiara

Source: Authors' calculation

Chart A4: Major causes of hospitalization in Brazil



Note: The chart plots only the subset of diseases for which the median percentage share of hospitalization is higher than 5 percent. Outliers are not shown. The data are from 2010.
Sources: Ministry of Health; Instituto Brasileiro de Geografia e Estatística