When Science Strikes Back - Has a scientific background helped mayors against COVID-19?

the next time you listen to Borodin
remember he was just a chemist
who wrote music to relax;
(Charles Bukowski)

ABSTRACT

In this paper, we try to answer the question: "Has a scientific background helped leaders against COVID-19?". To do so, we use a regression discontinuity design in close mayoral races between STEM (science, technology, engineering and math) and Non-STEM candidates to estimate the causal impact of having a mayor with scientific background on COVID-19 epidemiological outcomes in Brazil. We find that STEM mayors reduced COVID-19 deaths and hospitalizations and one of their mechanisms was increasing the number of non-pharmaceutical interventions (NPIs), such as face mask obligatory usage. We also show that this estimated impact is not due to other observable mayoral characteristics, such as years of education, ideology, or gender. Our findings suggest that, overall, municipal leaders with STEM training better handled a scenario involving emergencies and small amounts of data and evidence. We argue that our results may indicate that investment in science and technology-related human capital produces non-expected externalities—such as improvements in public management issues.

Keywords: STEM, COVID-19, externalities, public-management, RDD.

1 INTRODUCTION

Leadership is an innate aspect of human behavior and, when lacking, progress in society, at the community, the national or individual level cannot be achieved. Sectors where providing leadership are several, ranging from politics, trade unions, business, military, sports and science. COVID-19 strikes surprised local and national leaders and its sudden hit demanded quick reactions to avoid contagions, hospitalizations, and deaths. But the scale of this particular crisis means that politicians, health service leaders and business leaders are among those now being tested as few of them could have anticipated. This means that the coronavirus crisis was also a crisis of leadership (Tourish, 2020). Bavik et al. (2021) conceptualized crisis leadership as “a leadership process around times of crisis, including times immediately prior to crises, the duration of crises as they unfold, and times immediately after the acute consequences of crises. In terms of leadership practice, the coronavirus crisis has generated different responses from leaders around the world. One case that exemplifies the purpose of this paper is the case of Angela Merkel described by an article in The Atlantic (Miller, 2020). The article’s main point was that Merkel’s educational and professional background as a scientist was her reasonable success in better handling the pandemic.

Even though there is no universal definition of a scientific professional (Beede et al., 2011, p. 2), a reasonable agreement exists around using their knowledge to solve problems and provide scientific and technological advances (Machado, Rachter, Schanaider, & Stussi, 2021). Besides that, some authors relate scientific education with the concept of "evidence-based". Therefore, we associate scientific training in leaders with the ability or practice of evidence-based thinking (West, 2012, p.1). Leaders with such training are able to draw evidence-based conclusions (Bybee, 2013, p.5), make evidence-based decisions dealing with uncertainty and data (English, 2016, p.4), and construct evidence-based explanations of real-world phenomena (Shernoff, Sinha, Bressler, & Ginsburg, 2017, p.3). The use of evidence in management is well documented in literature as "evidence-based management" (EBM).

Nevertheless, despite the consolidated notion that investing in science-related human capital is crucial for maintaining a nation’s competitiveness (Atkinson Mayo, 2010) and despite the increasing role of scientific research in public policy (Hjort, Moreira, Rao, & Santini, 2021), there seems to have been no conclusive results on the impact of leaders’ scientific background outside scientific fields, especially in leadership roles during a crisis. More broadly, some correlational studies have shown that human capital accumulation in science-related fields is highly associated with social positive externalities (Winters, 2014), such as firm-level innovation (Brunow, Birkeneder, & Rodríguez-Pose, 2018), and have also shown that science-related skills are used outside of scientific careers (Mellors-Bourne, Connor, & Jackson, 2011, p.129). On the other hand, more applied studies have found no robust impact of politicians' scientific background on public matters, such as public sector reforms (Bastos & Sánchez, 2021) and legislative voting about scientific issues (Goodwin, 2015) .

Empirically, many other confounding variables could be affecting the incumbent leader during a crisis, such as its health and science investments, citizens' wealth, or even its leader's other personal characteristics. Several studies have shown that policy outcomes are considerably affected by leaders' personal characteristics, such as ideology (Pettersson-Lidbom, 2008), education (Besley, Montalvo, & Reynal-Querol, 2011), age (Alesina, Cassidy, & Troiano, 2019), incumbency (Frey, 2021), professional background (Hyytinen, Meriläinen, Saarimaa, Toivanen, & Tukiainen, 2018; Kirkland, 2020, 2021; Kuliomina, 2021; Szakonyi, 2021). Besides that, the literature has already shown that mayors' personal characteristics, such as gender (Bruce, Cavgias, Meloni, & Remígio, 2022), affected epidemic outcomes during the pandemic. Nevertheless, to our knowledge, little is known about the role of public leaders' scientific knowledge and training in times of crisis, especially considering COVID-19 responses. Therefore, this paper aims to contribute in three different ways. Our first contribution comes from filling a gap in the literature by identifying whether there is a causal relationship between leaders' scientific background and leadership outcomes during times of crisis. We do so by applying a regression discontinuity design to answer the causal question: "Does a scientific background help leaders against COVID-19?". More specifically, we test two hypotheses regarding (i) the impact of mayors' scientific background on epidemiological outcomes and (ii) non-pharmaceutical interventions (NPIs) as a mediator of the first effect. Our thesis is that mayors with a scientific background reduced epidemiological outcomes during the COVID-19 crisis, in comparison with their counterfactual, and did so through the adoption of a higher number of NPIs.The second contribution of this paper is empirically testing a novel definition of science, technology, engineering and mathematical (STEM) occupations in the Brazilian context. We do so by creating that proxy of scientific literacy testing a new classification of STEM jobs in Brazil (Machado et al., 2021) and discussing the specific heterogeneity of the Brazilian STEM field. Our third contribution is by suggesting that the investment in scientific human capital may have more externalities than those already developed in the literature. By showing that STEM mayors had better results during the pandemic, we argue that public investments in science-related fields may produce externalities in public administration practices, such as using previous evidence to support the use of NPIs. Such measures were in the hands of mayors to be used against the virus, as a relevant mechanism provided by the Brazilian institutional background.

In the following sections we develop the hypotheses (Section 2), describe the data and the variables for our empirical analysis (Section 3), and present the Empirical approach (Section 4). In the final section 5, the results and discussion are included.

2 THEORETICAL FRAMEWORK

Leaders often go on a rampage with the intention of physical damage to another one. If they act quickly and prevent a health disaster, they risk being accused of exaggerating the threat. The threat becomes hypothetical while the pain is actual. Moreover, if the crisis is sufficiently contained or avoided altogether, gains may never become evident. Preventative action can be readily seen as an attack on people's jobs and their livelihoods – for nothing. Yet if they delay until the crisis is over, leaders are likely to be accused of complacency, inaction and responsibility for the deaths of perhaps millions of people (Tourish, 2020). The coronavirus crisis has revealed that these problems with leaders' decision-making have become more uncertain. As systems grow more complex and interconnected, the prospect of failure increases. This is particularly the case when they are tightly coupled – that is, when the failure of one part of the system endangers the functioning of the system as a whole (Clearfiel and Tilcsik, 2018).

This paper contributes to and bridges the literature on STEM literacy on the one hand, and "evidence-based management" (EBM) and the role experts' beliefs on the other. Therefore, STEM leaders could have used such an "evidence-based" approach to enhance management decisions. EBM is the process of obtaining evidence-based information on which decisions can be made. It is often used in areas such as medicine and public health, but it also has applications in fields such as engineering and education. EBM helps to ensure that decisions are based on the most current and reliable data available, rather than on opinions or beliefs about what should be done. The central goal behind EBM in policymaking is to improve government effectiveness by developing, evaluating, and using more rigorous evidence to guide decisions about program design, funding and implementation (Heinrich, 2007, p.256). For this to happen, some authors consider that public sector leaders must ensure not only that the public service has access to this evidence and expertise, but also is skilled in identifying its quality and applicability (Newman, Cherney, & Head, 2017, p.158). Nevertheless, the production of rigorous evidence during fast-emerging crises, such as the COVID-19 pandemic, is uncertain. Typically EBM considers randomized controlled trials (RCTs) as the golden standard for evidence, which was hard to achieve in 2020 because of time pressure and space constraints. Because of such difficulties, EBM has become more difficult to obtain during the pandemic. However, it is considered more than ever as being a crucial component for effective responses in governments' strategies (Yang, 2020, p.711). Therefore, this link between STEM evidence formation and management may have lowered the political willingness to deny scientists' recommendations by discouraging measures that could prevent the virus (Cabral, Ito, & Pongeluppe, 2021, p.2).

Therefore, we intend to contribute to the mentioned pieces of literature by testing the following hypothesis:

- **H1**: The election of a STEM candidate in 2016 caused a reduction in COVID-19 hospitalizations and deaths in 2020.
- **H2**: The higher number of non-pharmaceutical interventions - (NPIs) was a mechanism through which STEM mayors reduced affected these epidemiological outcomes.

3 DATA AND DESCRIPTIVE STATISTICS

3.1 Data

Our sample includes all counties where a STEM candidate placed first or second in the 2016 mayoral elections. We only considered counties where elections were decided in a single round and classified as "ordinary elections" by the Superior Electoral Court of Brazil (TSE). In total, our sample has 98 municipalities. Within this sample, to estimate the causal effect of a STEM mayor in the epidemiological outcomes, only counties where the elections were decided by a small margin difference were considered in our regressions. Mayors' and elections data were collected and processed by the project Base dos Dados (Dahis, Carabetta, Scovino, Israel, & Oliveira, 2022).

Elections and mayors' characteristics: We use data from Tribunal Superior Eleitoral - TSE[1], to select the municipalities where a STEM mayor was one of the top two voted candidates. Besides that, we also collected candidates' characteristics, such as age, gender and occupation to serve as control covariates. To characterize a mayor as STEM or Non-STEM, our main data source comes from the linked employer-employee records RAIS (Relação Anual de Informações Sociais), a database from the Brazilian Ministry of Labor that offers comprehensive individual employee information on occupations and other characteristics of the formal labor market. Besides that, to refine our classification we also use data from social media, municipalities' websites, and "Escavador", a web page that aggregates personal public information.

Epidemiological outcomes: Based on the literature, we use data from SIVEP-Gripe[2] (Bruce et al., 2022) to build the outcomes variables for hospitalizations and deaths.

Baseline characteristics: Baseline variables were chosen to represent relevant characteristics related to demography, public health and ideology at the municipality level. The demographic characteristics source is the Brazilian National Census of 2010. Public health data comes from IEPS Data index[3] and the Ideology index follows the work from Power and Rodrigues-Silveira (2019)[4]

Policy mechanisms: This data set was built by the research team from de Souza Santos et al. (2021) and Brazil's National Confederation of Municipalities (CNI). The information gathered regards Non-Pharmaceuticals Interventions (NPIs), such as restriction of transportation and obligatory use of facial masks, adopted by mayors between May and

[1] Available at: https://basedosdados.org/dataset/br-tse-eleicoes?bdm_table=resultados_candidato_municipio . Date of access: 22/06/21.
[2] Available at: https://opendatasus.saude.gov.br/dataset/srag-2021-e-2022 and https://opendatasus.saude.gov.br/dataset/srag-2020. Date of access: 22/06/21.
[3] Available at: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/5P03UL. Date of access: 22/12/05.
[4] Available at: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/5P03UL. Date of access: 22/11/10.

July 2020. The mayors were surveyed by phone calls and 72.3% of all the 5568 Brazilian mayors participated. We replaced null values for the group (STEM/Non-STEM) mean.

3.2 Main variables

3.2.1 Dependent variables

Cases, Hospitalizations and Deaths per 100k inhabitants - `Y_hosp, Y_deaths`: We created these two variables to measure different levels of epidemiological impacts (medium and high). These outcomes were calculated per 100 inhabitants at the municipal level, which is a standard approach in epidemiological studies (Bruce et al., 2022, p.3). We computed hospitalizations and deaths registered as "SRAG-COVID-19" or "Non-specified SRAG" to determine these outcomes. For the cohort of mayors elected in 2016, we used outcomes reported from 2020/03/01 until 2020/11/30. We chose this period because the pandemic began to impact Brazil around May/2020. The ending period was chosen because local elections took place between 2020/11/15 and 2020/11/29, after which the management of municipalities became mixed between the incumbent and newly elected officials until the beginning of the next year. This period is called a "transitional government" (Rezende, 2019), and it would be difficult to determine whether the effects on epidemiological outcomes were caused by the incumbent or the newly elected mayor.

3.2.2 Independent variables

STEM candidate - `stem_job_4`:This is our main variable and our treatment. To define if a candidate is considered STEM, we first check, using the RAIS database, if he has worked at least 6 months in a STEM occupation. If that is the case, we then check if he has a STEM college degree. We use this method because candidates' bachelor information is not publicly available and time constraints make it difficult to search for degree information of the two most-voted candidates per 5570 municipalities in 2016 and 2020. Therefore, briefly, we created a dummy variable that assumes the value of 1 if the candidate fulfills the following conditions, or 0 if any of these are not present:

- **i**: has worked at least 6 months in a STEM occupation;
- **ii**: has a STEM bachelor's degree.

STEM occupation - A STEM occupation is defined as having its' classification number from the Classificação Brasileira de Ocupações (CBO) inside Machado et al. (2021) list of CBOs classified as STEM. In total, this list classifies 65 CBOs as STEM occupations, which represents 10.5% of all CBOs (Machado et al., 2021, p.10).

STEM bachelor's degree - `graduacao_stem`: To construct this variable, we use primary data from different sources. We first select only the candidates that are STEM candidates (see definition above). We then search for the candidate's name in "Escavador"[5], a web page that aggregates personal public information. If a candidate isn't on the page, we check his social media profiles. We then attribute the value of 1 for candidates that studied in a STEM field and 0 otherwise. In total, we have found information about 188 from 401 mayors (47%). In order to enlarge our sample, we have used a supervised machine learning algorithm that decides if the other mayors have or do not have a college degree, based on our 188 classifications and TSE public available data on mayors' characteristics. We can summarize our automatic classification process in the following steps. First, we defined what are STEM courses. We then used this definition to manually categorize, or "label," a subset of mayors' undergraduate degrees in our database (around 45% or approximately 188 observations). Finally, we use this data to train a boosting classification model (Schapire, 2003) and assess its performance. In practical terms, this method replicates the manual categorization of mayors' undergraduate degrees as STEM or Non-STEM.

STEM winning margin - `X`: This works as the running variable for our estimation. To create it we use data from TSE in order to point out the vote margin between the first and the second most-voted candidates. We attribute it a positive value if a STEM candidate won the election and a negative value otherwise.

Cohort - `coorte`: The cohort indicates the list of candidates registered in TSE for the local executive elections in the year 2016.

Tenure - `tenure`: Time of employment in a STEM occupation in months. Since we only observe RAIS data from 2003 until 2018, candidates that were already working in a STEM occupation in 2003 appear with higher number tenure. This happens because the tenure variable restarts every time a person changes jobs. Therefore, we could be misinterpreting this variable and measuring job stability, for example, instead of labor market experience or learning by doing skills. Therefore, we use a logarithm function that reduces extremes on the tenure measures, approximating the distance between them.

3.3 Descriptive statistics

The main variables and their descriptive statistics are presented in Table 1 and descriptive statistics by treated/non-treated municipalities in Table 2. The distribution of our treatment across the states shows a mean of 1.6% STEM candidates in 2016, as shown in Figure 1. These proportions go by our expectations, considering that the mean of STEM jobs in Brazil in 2017 was 2.9% (Machado et al., 2021, p.10). In 2016, the outlier is the state of Acre, as seen in Figure 2. It's hard to find structural reasons why that specific state is an outlier, but a possible explanation is the low number of municipalities in that

[5] Available at:`https://www.escavador.com/`. Date of access: 28/07/21.

Table 1 – Descriptive Statistics

	N	Min	Mean	Max	SD
Mayors' characteristics					
tenure_stem_job	98	0.00	72.38	477.00	120.83
female	98	0.00	0.09	1.00	0.29
age	98	27.00	50.90	79.00	11.21
education	98	7.00	7.00	7.00	0.00
incumbent_when_elected	98	0.00	0.16	1.00	0.37
party_ideology	98	-0.62	0.26	0.76	0.38
Municipalities' outcomes and NPIs					
deaths_per_100k	98	0.00	86.92	261.10	54.15
hospitalizations_per_100k	98	34.51	315.16	1070.03	196.45
cases_per_100k	98	327.42	2404.11	5864.04	1383.46
cordon_sanitaire	71	0.00	0.46	1.00	0.50
face_covering_required	70	0.00	0.94	1.00	0.23
closure_of_non_essential	70	0.00	0.74	1.00	0.44
gathering_prohibition	70	0.00	0.97	1.00	0.17
public_transport_restriction	68	0.00	0.50	1.00	0.50
number_of_npi	68	1.00	3.60	5.00	0.88
Municipalities' characteristics					
population_2010	98	2420	39 529.70	814230	87 006.05
illiteracy_rate	98	1.97	16.00	39.91	10.68
gini	98	0.29	0.49	0.79	0.06
hdi	98	0.54	0.68	0.79	0.07
pc_income	98	196.57	544.65	1098.31	229.53
density	98	2.07	84.75	741.57	124.07
urban_pop_rate	98	0.17	0.71	0.99	0.21
men_pop_rate	98	0.47	0.50	0.58	0.01
physician_per_1k	98	0.00	0.96	4.42	0.74
health_municipal_spending_rate	98	15.28	23.15	35.98	4.97
community_health_agency_rate	98	0.00	82.58	100.00	26.93
hosp_beds_per_100k_pop	98	0.00	163.06	816.50	165.00

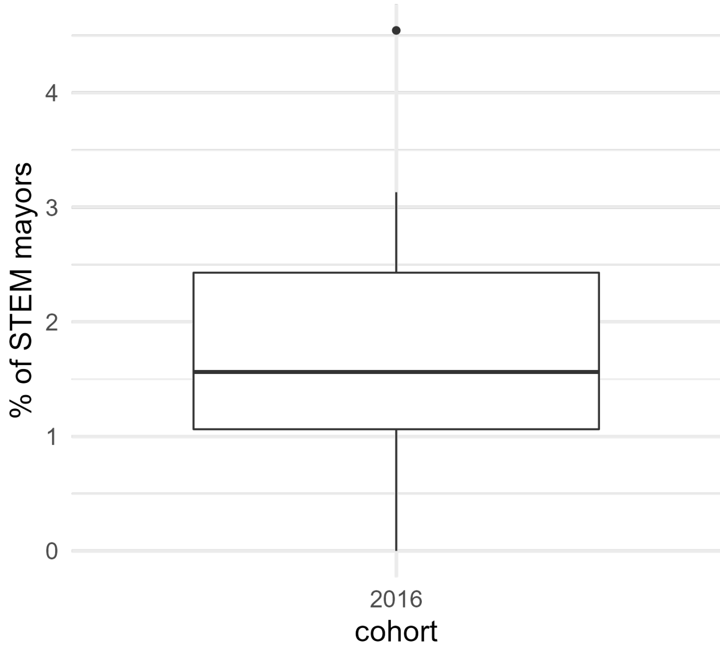
Notes: This table aggregates the summary statistics of all the observations used in the study (98). Municipalities chosen were those that held ordinary elections in 2016 whose mayor was elected in the first round and among the top two most voted was a STEM candidate. NPI data has null values since not all the mayors responded to the survey.

state (Acre is the third state with less number of municipalities). Therefore, electing a few STEM mayors could make it an outlier. Nevertheless, excluding it, Bahia and São Paulo are the top two with more STEM mayors in 2016.

Table 2 – Descriptive Statistics by Mayor Background

	Non-STEM Mayor (N=54)		STEM Mayor (N=44)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p
Mayors' characteristics						
tenure_stem_job	0.00	0.00	161.20	135.22	161.20	0.00
female	0.15	0.36	0.02	0.15	-0.13	0.02
age	50.44	11.19	51.45	11.35	1.01	0.66
education	7.00	0.00	7.00	0.00	0.00	
incumbent_when_elected	0.22	0.42	0.09	0.29	-0.13	0.07
party_ideology	0.28	0.36	0.22	0.40	-0.06	0.45
Municipalities' outcomes and NPIs						
deaths_per_100k	79.97	50.64	95.45	57.61	15.48	0.17
hospitalizations_per_100k	303.98	194.20	328.89	200.55	24.90	0.54
cases_per_100k	2339.52	1373.52	2483.37	1407.33	143.85	0.61
cordon_sanitaire	0.54	0.51	0.39	0.49	-0.15	0.20
face_covering_required	0.91	0.29	0.97	0.17	0.06	0.29
closure_of_non_essential	0.74	0.45	0.75	0.44	0.01	0.89
gathering_prohibition	0.97	0.17	0.97	0.17	0.00	0.97
public_transport_restriction	0.53	0.51	0.47	0.51	-0.06	0.63
number_of_npi	3.68	0.73	3.53	1.02	-0.15	0.50
Municipalities' characteristics						
population_2010	45996.76	111881.23	31592.86	39130.77	-14403.90	0.38
illiteracy_rate	17.05	11.06	14.72	10.17	-2.32	0.28
gini	0.49	0.06	0.49	0.07	0.00	0.83
hdi	0.68	0.07	0.68	0.06	0.01	0.55
pc_income	534.12	237.48	557.59	221.42	23.47	0.61
density	89.68	118.56	78.70	131.64	-10.98	0.67
urban_pop_rate	0.72	0.21	0.71	0.20	-0.01	0.82
men_pop_rate	0.50	0.02	0.50	0.01	0.00	0.54
physician_per_1k	0.93	0.76	1.00	0.72	0.07	0.65
health_municipal_spending_rate	22.38	5.06	24.10	4.74	1.72	0.09
community_health_agency_rate	84.30	25.76	80.47	28.47	-3.83	0.49
hosp_beds_per_100k_pop	161.37	178.08	165.14	149.40	3.77	0.91

Figure 1 – Percentage of STEM mayors per state

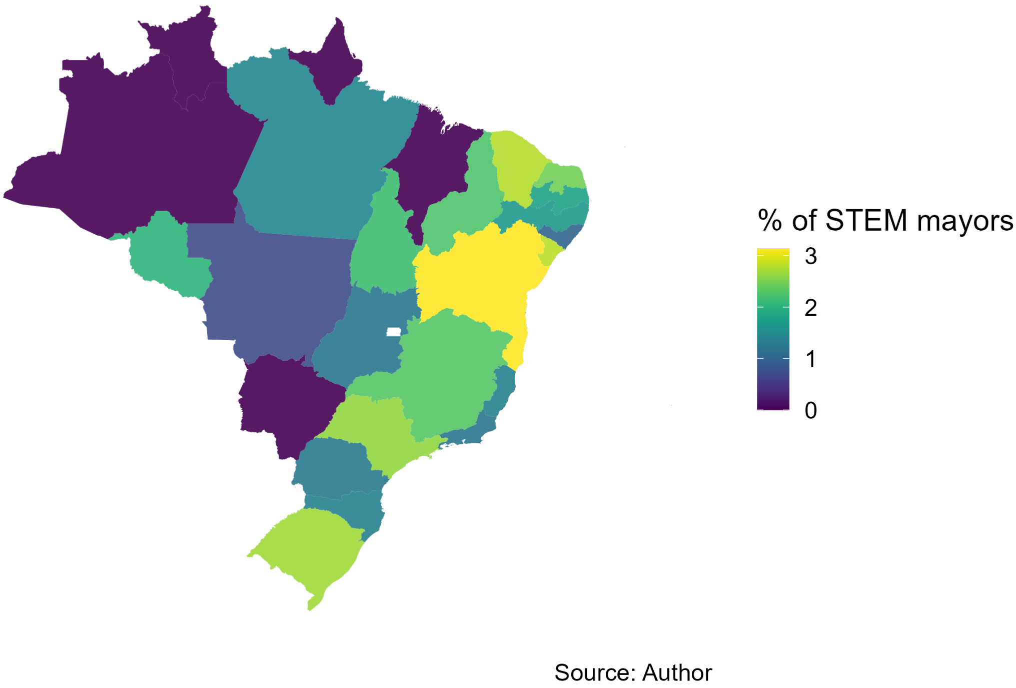


Notes: This plot shows the distribution of STEM mayors per state in the elections of 2016. Outlier is the state of Acrê.

The number of STEM mayors elected in 2020 is 23% bigger than in 2016. This may indicate that voters became more willing to choose STEM candidates during the pandemic. This could be a problem for the identification strategy, since our estimation may be biased in the selection. However, as shown in Chapter 4, we use an RD design to estimate the Local Average Treatment Effect among similar groups of municipalities with balanced baseline characteristics and also run robustness tests considering only the year 2016. Therefore, we expect to eliminate any selection bias.

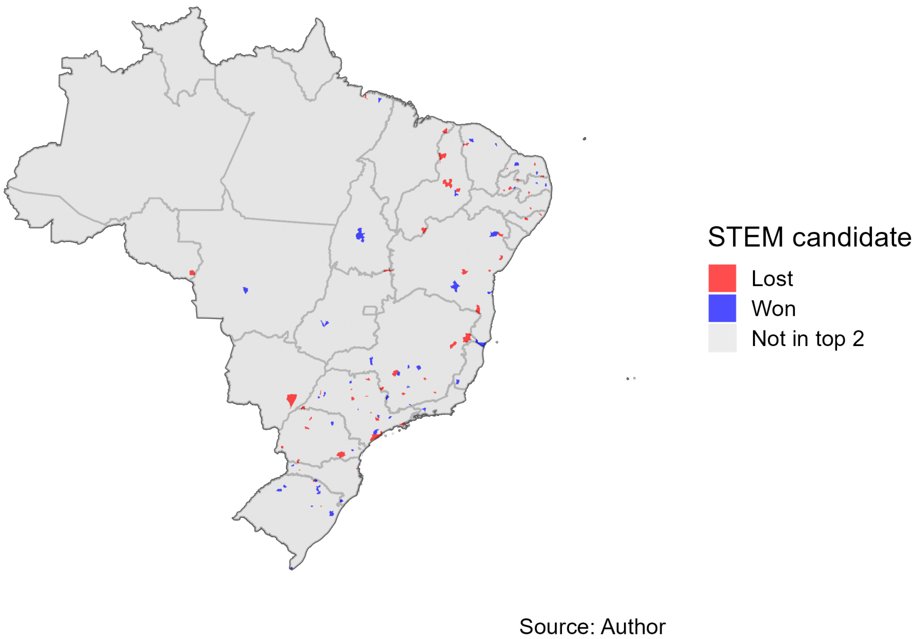
In Figure 3 we colored all 44 municipalities where a STEM candidate was among the top 2 voted in 2016. In red are the municipalities where the STEM candidate lost and in blue are the municipalities where the STEM candidate won. It's visible that most parts of the cities where a STEM candidate was among the top 2 voted are concentrated in the East of Brazil. Nevertheless, since our sample only includes the colored municipalities, we don't expect this regional distribution to bias our results. Besides that, as discussed later, our estimation strategy includes state-fixed effects to control for regional characteristics that are constant in time.

Figure 2 – Percentage of STEM mayors per state (2016)



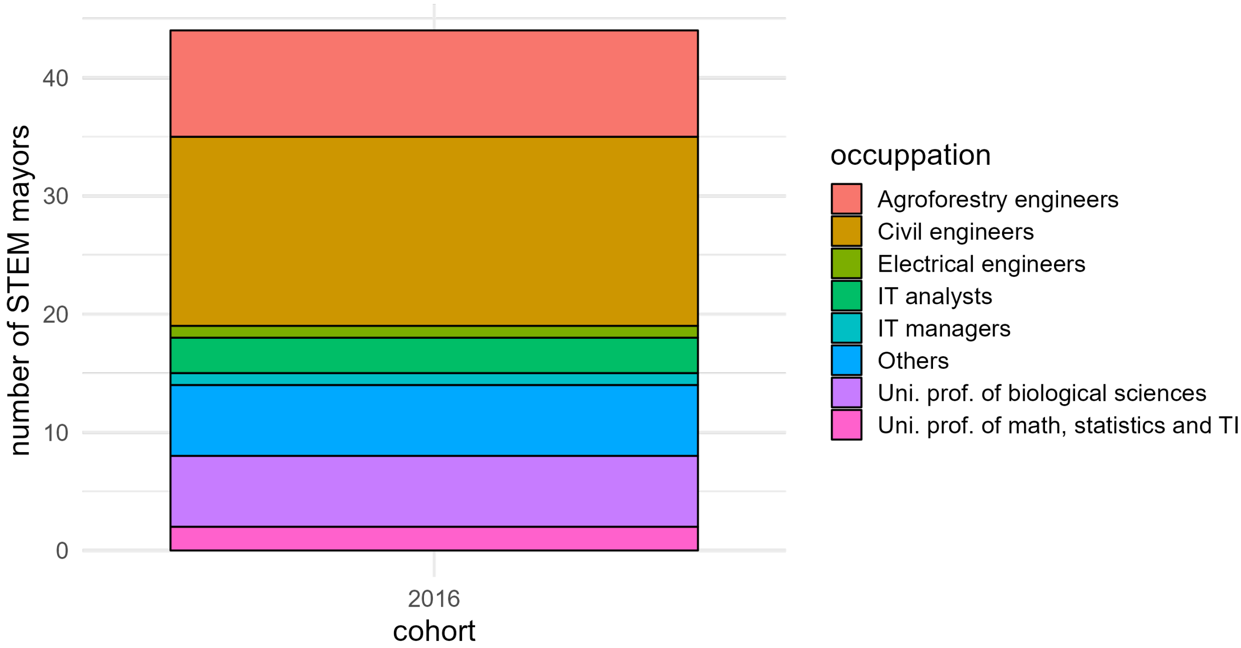
Notes: In this figure, we colored all states based on the percentage of STEM mayors' elected in 2016. The darker the state, the fewer STEM mayors it has elected. The state of Acre was removed because, as it is an outlier, its presence in the graph doesn't allow for comparing the numbers between the other states.

Figure 3 – Municipalities where a STEM candidate was among the top two most voted (2016)



Notes: In this figure, we colored all municipalities where a STEM candidate was among the top 2 voted in 2016. In red are the municipalities where the STEM candidate lost and in blue are the municipalities where the STEM candidate won. In gray are all the municipalities with no STEM candidate among the top two most voted.

Figure 4 – STEM candidates' most common occupations.



Notes: This figure shows the top five most common occupations among STEM mayors elected in 2016 or 2020.

We also try to understand what kind of STEM jobs the elected mayors have been working. To do it we look at candidates' most common occupations according to the four-digit classification CBOs in RAIS. As illustrated in Figure 4, the most common professions are engineers and university professors of biological courses. It is important to note and clarify that doctors are not considered STEM workers in our analysis. Even though there are broad STEM classifications that include health occupations in STEM (Kuenzi, 2008) - or even social scientists, psychologists, economists, and sociologists (NSB, 2012) - health occupations are not universally recognized in the STEM field, especially in the more restricted classifications (Green, 2007). Some authors justify that the health sector has its own dynamics, which differentiates it from the engineering and applied sciences, such as biology, physics, chemistry, mathematics, statistics, information technology, agronomy and others considered (Nascimento, Maciente, Gusso, Araújo, & Pereira, 2014) . In the United States there is an official definition for the occupations that are considered to belong to STEM areas according to Standard Occupational Classification (SOC) 2010 from the Bureau of Labor Statistics [6]. According to that classification, occupations are separated into: (i) Life and Physical Science, Engineering, Mathematics, and Information Technology Occupations; (ii) Social Science Occupations; (iii) Architecture Occupations; and (iv) Health Occupations. Doctors belong with the last, but not with the first one. Following this method, as done by other studies on STEM occupations in Brazil (Nascimento et al., 2014), Machado (2021) creates her classification, the one that is used in this paper.

[6] https://www.bls.gov/soc/Attachment_C_STEM.xls

Even though we do not define doctors as STEM workers, some graduated doctors may have worked in a STEM job, such as a biomedical. If that were the case, we could be measuring not the effect of STEM background on epidemiological outcomes, but rather the effect of health professionals on these. Since only 2.7% of elected candidates declared themselves to be doctors, we consider that our estimation is really measuring the effect of STEM backgrounds. Besides that, as expected and discussed in the Results section, there is a relevant difference in the percentage of female mayors' between STEM and Non-STEM groups, and also incumbent mayors (non-expected). Finally, it's remarkable that all baseline characteristics chosen are aligned even in the full sample. This may indicate that municipalities that elect STEM mayors are not that different from municipalities that elect Non-STEM mayors and comparing. Nevertheless, as it's generally recognized, that may exist unobserved characteristics that could affect epidemiological outcomes and also the probability of electing a STEM mayor, biasing estimates that consider the full sample. In order to avoid that bias and estimate a causal effect, we develop the following empirical framework.

4 EMPIRICAL FRAMEWORK

4.1 Estimation Strategy

Identifying the causal impact of a policymaker's professional background on epidemiological outcomes is a difficult task. By simply comparing municipalities with STEM candidates and without STEM candidates, we are likely to estimate biased outcomes. This is the case since our dependent variables may be correlated with variables that could also influence the mayor's professional background. Also, one of the main difficulties in our empirical design is the limited number of observations near the cutoff. This is the case since the number of treated cities isn't big already. As already shown in Figure 1, the mean of STEM candidates in 2016 is 1.6%. Besides that, the RD design accounts for municipality-specific omitted variables, however, it does not control for mayors' characteristics. These characteristics, such as level of education and ideology, could be relevant to the epidemiological outcomes in which we are interested (Bruce et al., 2022, p.8). Therefore, one of the main challenges of our research is to control for some of these characteristics to better understand the mechanism through which STEM education could act upon the epidemiological outcomes. Following Calonico, Cattaneo, Farrell, and Titiunik (2019), in our specifications (2) and (4), from Table 4, we control for mayors' personal characteristics that appear to have a discontinuity near the cutoff.

We construct a sharp regression discontinuity (RD) strategy. Through it, we expect to estimate the causal impact of having a STEM candidate on epidemiological outcomes. Our strategy has the following specification:

$$y_{ms} = \alpha + \beta \text{STEMcandidate}_{ms} + f(\text{STEMcandidateVoteMargin}_{ms}) + \lambda_s + \text{Z}_{ms} + \varepsilon_{ms} \quad (4.1)$$

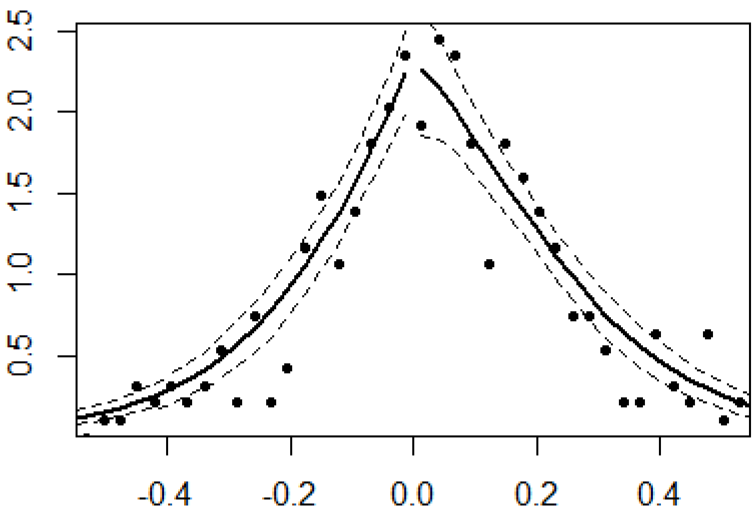
In the previous equation, m denotes a municipality, and s denotes a state. $STEMcandidateVoteMargin_{ms}$ is the margin of victory of the STEM mayor candidate in an election where the second place is a non-STEM candidate. This variable assumes a positive value if the winner was a STEM candidate and the second place was a non-STEM candidate. Likewise, it assumes a negative value if the opposite takes place. The independent variable $STEMcandidate_{ms}$ receives the value 1 if the running variable $STEMcandidateVoteMargin_{ms} >= 0$ and zero otherwise. We assume that $f(.)$ is a flexible polynomial on both sides of the threshold. We estimate an optimal bandwidth using the non-parametric procedure from (Calonico, Cattaneo, & Titiunik, 2014). Our coefficient of interest β estimates the effect of having a STEM candidate mayor on outcome y_{ms}. We denote λ_s as a state election fixed-effect term, following (Calonico et al., 2019, p.10), and Z is a vector of control variables, that include mayors' personal characteristics, such as age (the only one in our main specification).

4.2 Identification Strategy

The key assumption behind a sharp RD design is that the probability of treatment assignment changes discontinuously, from 0 to 1, at the cutoff. Therefore, it´s possible to identify causal effects for the individuals whose scores are near this threshold (Cunningham, 2021). In our case, the key assumption is that the probability of $STEMcandidate_{ms} == 1$ changes discontinuously at $STEMcandidateVoteMargin_{ms}$ near 0. However, to interpret our coefficient of interest β as causal we need to satisfy the two validity conditions of a RD design: (i) the treatment does not affect baseline covariates; and (ii) there is no manipulation of the running variable near the threshold. The (i) condition means that our sample must be balanced between treated and untreated observations in their baseline characteristics. In Table 3 we show that all our baseline characteristics are balanced.

We show in Figure 5 that $STEMcandidateVoteMargin_{m}$ does not present any discontinuity near the cutoff. We test this using a McCrary test in which the p-value achieves 0.93, therefore, indicating that there is no manipulation in our running variable.

Figure 5 – McCrary test



Notes: McCrary test shows that there is no discontinuity (p-value 0.93) near the cutoff, indicating that there is no manipulation in our running variable.

Table 3 – Baseline characteristics - RD estimates

	Demography							Health				Ideology
	Gini	PC income	Population	Illiteracy	HDI	Ln Density	% Masc. Pop	% Health spend.	Docs.	CHA program	Hosp. beds	Mun. ideo.
RD estimator	-0.01	33.74	0.13	-3.87	0.00	0.74	0.00	1.36	-0.28	-17.89	11.19	-0.07
Conv. sd.	[0.03]	[73.10]	[0.32]	[1.87]	[0.02]	[0.38]	[0.01]	[2.70]	[0.32]	[11.24]	[82.83]	[0.05]
Robust pv.	0.51	0.46	0.50	0.57	0.41	0.51	0.75	0.50	0.58	0.99	0.18	0.28
Eff.number.obs.	34	31	29	34	35	34	22	38	35	37	40	35
Window	7.13	6.29	5.95	7.07	7.64	7.23	4.37	8.39	7.61	7.95	8.64	7.42

Notes: This table reports the RD estimates for the election of mayors with scientific background on municipalities' baseline characteristics in 2015 in Brazilian municipalities. All specifications use state fixed-effects, triangular kernel and optimal bandwidths calculated following Calonico et al. (2014). Baseline variables were chosen to represent relevant characteristics related to demography, public health and ideology at the municipality level. We report robust-bias corrected p-values, conventional (non-robust) estimates and standard errors.

5 RESULTS

5.1 Main results

The tests presented in the previous section demonstrate that municipalities governed by almost elected Non-STEM mayors are an appropriate counterfactual for those headed by barely elected STEM mayors. This approach provides a consistent estimate of the impact of a mayor with a STEM background election on epidemiological outcomes during the COVID-19 crisis. In all our four specifications, the election of mayors with a STEM background caused a reduction in hospitalizations and deaths of COVID, rejecting the null hypothesis, as shown in Table 4 and Figure 6. These first findings go according to what we expected since the literature has already shown that mayors' personal characteristics, such as gender (Bruce et al., 2022), affected epidemic outcomes during the pandemic.

In all our specifications we consider state-fixed effects, as shown in Equation (4.1). We chose a specification with state-fixed effects because of a few reasons. First, it allows us to control for unobserved heterogeneity across states. Besides that, adding fixed effects turn our estimates more efficient without biasing them (Calonico et al., 2019). Moreover, we compare the performance of cities subject to similar state regulations since governors have autonomy in enforcing NPIs. Finally, Brazil is a large, continental country with many municipalities. Because of this, when adding fixed effects we decrease the chances of comparing areas where COVID-19 waves behaved differently at the time we selected the outcomes.

Considering the mean of epidemiological outcomes in the non-STEM municipalities, our preferred specification (2) indicates that municipalities managed by STEM mayors experienced 51.46 fewer deaths per 100k inhabitants (p-value = 0.01). This effect accounts for 63.61 percent of the average number of deaths (The mean rate of deaths for Non-STEM municipalities inside the 7.47 window margin was 80.9 deaths per 100k inhabitants) among municipalities that elected a non-STEM mayor. In the second column, we show that treated municipalities had 291.76 fewer hospitalizations per 100k inhabitants (p-value = 0.01). This amount equalizes 91.12 percent of the average number of hospitalizations among municipalities that elected a non-STEM mayor (The mean rate of deaths for Non-STEM municipalities inside the 6.79 window margin was 320 hospitalizations per 100k inhabitants). We also run specifications with a 10% winning window fixed. We do so because the optimal window changes when adding covariates, and therefore, it's hard to comprehend the effect of covariates in the previous sample (a larger window will include more municipalities in the sample). All specifications provide evidence that STEM mayors caused a reduction in hospitalizations and deaths by COVID-19.

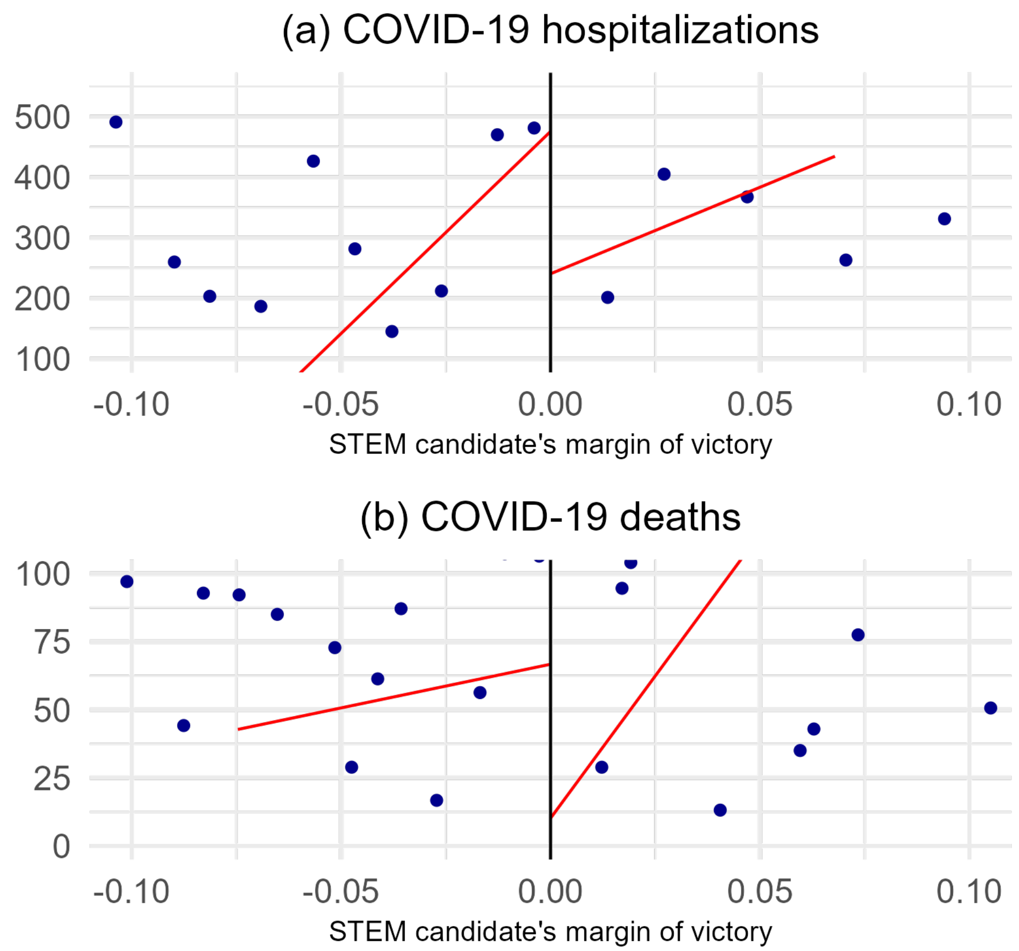
The optimal bandwidth calculated for this specification, following (Calonico et al., 2014) is 6.79% for hospitalizations and 10.80% for deaths. This bandwidth results in an effective number of observations of 34 for hospitalizations and 35 for deaths. Our results indicate that the impact of having a mayor with a STEM background on the reduction in deaths and hospitalizations due to the COVID-19 virus is statistically significant at the 1% level for deaths and hospitalizations.

Table 4 – Impact of STEM leadership on epidemiological outcomes - RD estimates

	(1)		(2)		(3)		(4)	
	Hospitalizations	Deaths	Hospitalizations	Deaths	Hospitalizations	Deaths	Hospitalizations	Deaths
RD estimator	-151.91	-90.79	-291.76	-51.46	-95.97	-36.50	-105.01	-37.82
Conv. sd.	[105.47]	[33.38]	[103.01]	[24.04]	[98.34]	[20.54]	[97.80]	[20.58]
Robust pv.	0.08*	0.01***	0.01***	0.01***	0.03**	0.05**	0.02**	0.04**
Eff.number.obs.	37	29	34	35	45	45	45	45
Window	8.36	5.92	6.79	7.47	10	10	10	10
Bandwidth	CCT Opt.	CCT Opt.	CCT Opt.	CCT Opt.	Fixed	Fixed	Fixed	Fixed
Pers.charact.			X	X			X	X

Notes: This table reports the RD estimated impact of mayors with scientific background on deaths and hospitalizations by COVID-19 per hundred thousand inhabitants in 2020 in Brazilian municipalities. All specifications use state fixed-effects and triangular kernel. Estimations (1) and (2) use optimal bandwidths calculated following Calonico et al. (2014), while estimations (3) and (4) use a 10% vote margin difference between the two most voted candidates, in order to best understand the inclusion of covariates. Estimations (2) and (4) control for mayors' age. We report robust-bias corrected p-values and conventional (non-robust) estimates and standard errors.

Figure 6 – Impact of STEM mayor election on epidemiological outcomes



Notes: This figure reports the RD estimated impact of mayors with scientific background on deaths and hospitalizations by COVID-19 per hundred thousand inhabitants in 2020 in Brazilian municipalities. These results represent the impact of our main estimation (2) that uses first-degree polynomial, state fixed-effects, triangular kernel, optimal bandwidths calculated following Calonico et al. (2014) and control for mayors' age.

In order to better comprehend the effect of STEM background on epidemiological outcomes, we consider specification (2) as our preferred. While specification (1) accounts for municipality-specific omitted variables, as assumed in an RD design for close elections, it does not control for individual characteristics of mayors that are relevant to policymaking. Examples of personal characteristics that may be cofounders are age (Alesina et al., 2019), education (Besley et al., 2011), ideology (Pettersson-Lidbom, 2008), reelection incentives (Frey, 2021) and gender (Bruce et al., 2022). Therefore, we test whether those STEM candidates who win close races against Non-STEM candidates are different in observable characteristics.

By examining Table 5 we notice that the STEM group has older mayors than the Non-STEM one. Then, we run specification (2) controlling for mayors' age, besides fixed effects, following Calonico et al. (2019).

Table 5 – STEM candidates' personal characteristics - RD estimates

	Women	Incumbent	Age	Party ideology
RD estimator	-0.06	0.12	6.76	0.05
Conv. sd.	[6.81]	[0.21]	[4.15]	[0.10]
Robust pv.	0.41	0.56	0.09*	0.73
Eff.number.obs.	46	46	35	37
Window	10.5	10.55	7.47	8.11
Bandwidth	CCT Opt.	CCT Opt.	CCT Opt.	CCT Opt.

Notes: This table reports our RD estimates of the association between STEM mayors and four outcomes. In the first column, we see the effect on mayors' gender. In the second column, the outcome measure if mayors were incumbents. The third column measures the effect of mayors' age. The fourth column regards mayors' party ideology, whereas negative numbers represent left-wing parties and positive right-wing (Power & Rodrigues-Silveira, 2019). All specifications use state fixed-effects, triangular kernels, and first-degree polynomials. Optimal bandwidths were calculated following Calonico et al. (2014). We report robust-bias corrected p-values and conventional (non-robust) estimates and standard errors.

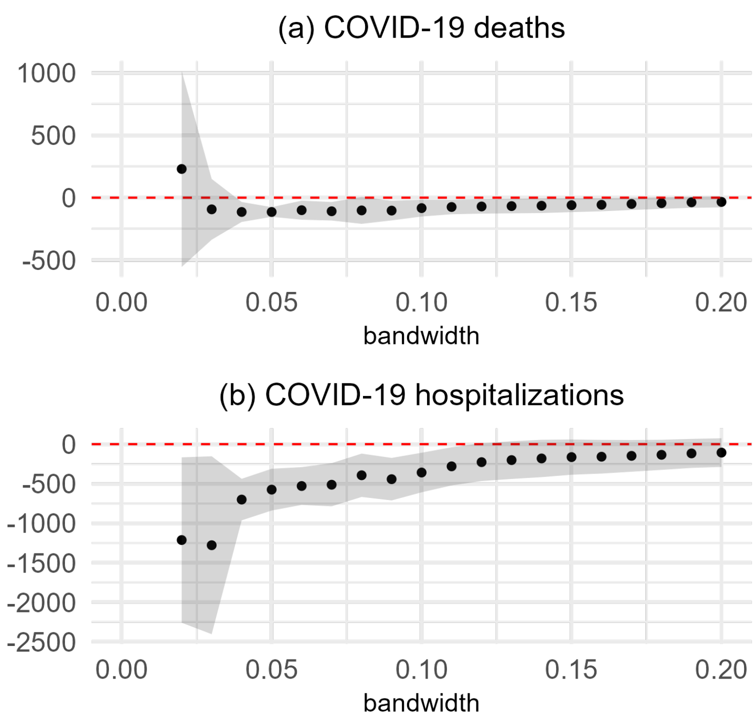
Our results remain very similar and robust, suggesting that our findings are driven by STEM mayors' non-observable characteristics. The optimal bandwidth calculated for this specification, following Calonico et al. (2014), and the effective number of observations are, respectively, 11.89% and 198 for hospitalizations, and 10.49% and 181 for deaths. We also notice in Table 5 a high difference in educational levels between Non-STEM and STEM candidates that has a p-value of 12%. Even though it's not statistically significant at 90% level, it's a relevant topic of discussion, since a strong difference in educational levels could indicate that the STEM background and epidemiological outcomes have a co-founder that is education. In other words, highly educated mayors could be the ones to better manage the pandemic and, then, our estimates would be biased. To check if this is the case, we run our mechanism section (Section 5.3) with a specification in which we only compare STEM mayors with Non-STEM mayors that have at least a college degree.

To test with these estimations hold even with other polynomial format assumptions, we rerun our specifications creating specifications (3) and (4) by fixing the window at a 10% winning margin. It's interesting to notice that the size of the effect gets larger when accounting for age differences between STEM and Non-STEM municipalities. This means that the age of mayors is negatively correlated with their impact on reducing epidemiological outcomes — an initial indication that our model is robust. The impact of our treatment remains statistically significant, negative, and in the same signal across this and all four specifications. Nevertheless, other tests must be done in order to prove the robustness of our estimates.

5.2 Robustness checks

We run a series of tests to check if our results that STEM mayors reduced deaths and hospitalization by COVID in their municipalities are robust. The first test is to run the same specification showed in Equation (4.1) that estimated the coefficients in (2), Table 4, but with different windows instead of the optimal bandwidth. As shown in Figure 7, the results of deaths only are statistically significant after a 3% margin of votes between the STEM candidate and the Non-STEM candidate. We understand that, since our sample is small, low windows have higher standard errors, which turn the results non-statistically significant, even though estimates' magnitude and signal are the same as in larger windows. Besides that, municipalities that are outliers could influence the results if their candidate were elected with a low margin. When the bandwidths get larger, around 15% percent, we also can not reject the null hypothesis. This is also expected, since municipalities that elected STEM mayors with very large margins may be very different from municipalities where they had a close race, and that's exactly what regression discontinuity designs try to address.

Figure 7 – Impact of STEM mayor on epidemiological outcomes using different bandwidths



Notes: This figure reports the RD estimated impact of mayors with scientific background on deaths and hospitalizations by COVID-19 per hundred thousand inhabitants in 2020 in Brazilian municipalities. In the horizontal axis, we test different winning margins (bandwidth) between the elected mayor and the second most voted. These results represent the impact of our main estimation (2) that uses first-degree polynomial, state fixed-effects, triangular kernel, and control for mayors' age.

Another way to test the robustness of our estimates is by using another definition of

STEM as the treatment. We do so by only using TSE mayors' occupational data. We first define, for every profession registered in the TSE in 2016, if it is a STEM profession. We classify as STEM engineers, biomedical, chemists, statisticians, TI technicians, astronomers, mathematicians, physicists, and computer programmers. All the others are classified as Non-STEM professions. Since we are not using the profession of "mayor", we are only selecting first mandate STEM candidates, so no incumbent STEM mayors were included in this sample and, therefore, we drop the Non-STEM incumbent mayors.

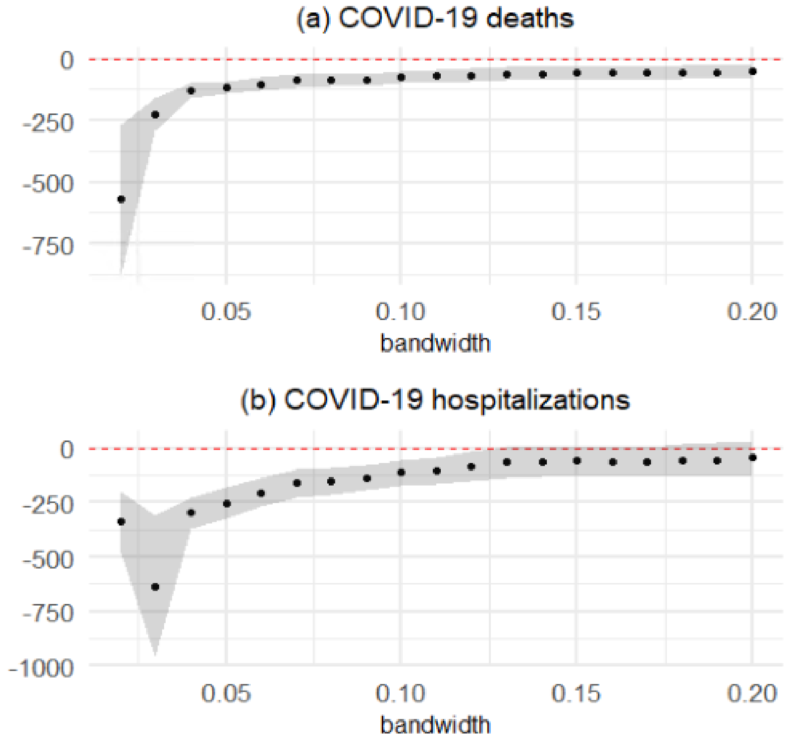
All baseline characteristics are aligned, except for municipalities' ideology at the Robust specification (but is balanced considering conventional p-value and standard errors) Figure 8. We then run a regression on epidemiological outcomes with different windows to see if this new definition has a similar impact as our main definition of STEM. We find similar results, as shown in Figure 9. Mayors' characteristics are unbalanced for gender and party ideology. By this classification, STEM mayors were more left-wing and had fewer women. This last difference was expected since the under-representation of women in STEM fields is a well-documented disparity that has been the focus of national and international public policy efforts to improve diversity in STEM fields (Wang & Degol, 2017). Also by controlling for it we expect to find a higher impact for STEM mayors, since one study has shown that female mayors caused a large, negative, and significant decrease in the number of deaths and hospitalizations from COVID-19 (Bruce et al., 2022). The left-wing inclination of STEM candidates is harder to explain.

Figure 8 – Baseline characteristics - RD estimates for STEM mayors (TSE robustness classification)

Baseline Characteristis - RD estimates												
	Analfabetismo	Gini	Renda PC	População 2010	Idhm	% Pop. Urb.	% Pop. Hom.	% de Saúde na Despesa Total	Médicos por 1k habitantes	Cobertura Est. Saúde da Família	Leitos SUS por 100k habitantes	Ideologia
RD estimator	-0.45	-0.01	-35.74	-0.02	-0.01	0.01	0.01	-1.36	0.23	0.55	-41.56	0.04
	[1.07]	[0.02]	[51.98]	[0.27]	[0.02]	[0.03]	[0.00]	[2.05]	[0.27]	[7.68]	[46.26]	[0.03]
	0.54	0.97	0.68	0.94	0.43	0.88	0.17	0.60	0.16	0.88	0.54	0.02**
Eff.number.obs.	49	52	48	55	52	56	37	57	42	57	52	37
Bandwidth	11.03	12.62	10.12	13.01	11.92	13.48	8.39	14.06	8.82	14.44	12.43	8.07

Notes: This table reports the RD estimates for the election of mayors with scientific background on municipalities' baseline characteristics in 2015 in Brazilian municipalities. We now use only TSE data to define a STEM mayor in order to test another definition of STEM as a robustness test. All specifications use state fixed-effects, triangular kernel and optimal bandwidths calculated following Calonico et al. (2014). Baseline variables were chosen to represent relevant characteristics related to demography, public health and ideology at the municipality level. We report robust-bias corrected p-values, conventional (non-robust) estimates and standard errors.

Figure 9 – Impact of STEM mayor on epidemiological outcomes using different bandwidths (TSE robustness classification)



Notes: This figure reports the RD estimated impact of mayors with scientific background on deaths and hospitalizations by COVID-19 per hundred thousand inhabitants in 2020 in Brazilian municipalities. We now use only TSE data to define a STEM mayor in order to test another definition of STEM as a robustness test. In the horizontal axis, we test different winning margins (bandwidth) between the elected mayor and the second most voted. These results represent the impact of our main estimation (2) that uses first-degree polynomial, state fixed-effects, triangular kernel, and control for mayors' gender, parties' ideology and municipalities' ideology.

5.3 Mechanisms

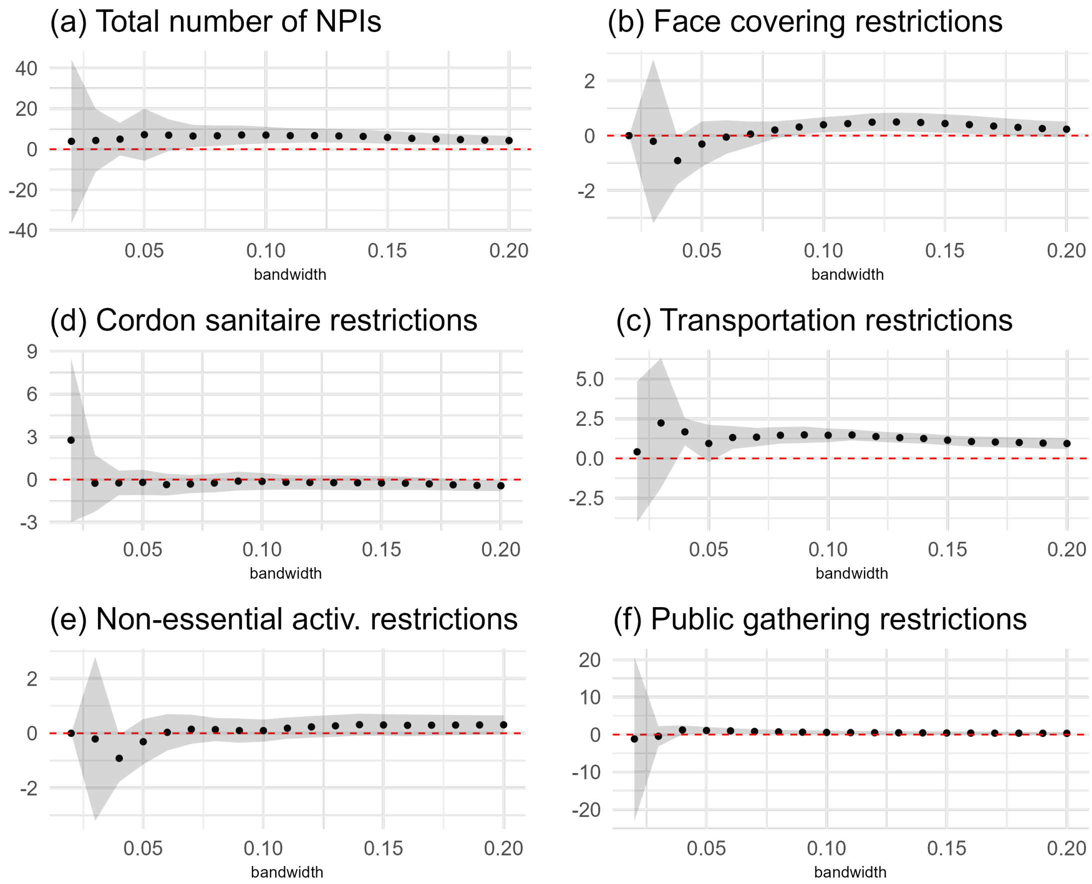
Finally, using our main sample and specification, we test whether a municipality with a STEM mayor has raised the number of NPIs, which is expected to lower the number of hospitalizations and deaths by COVID-19. Following the results of Table 6. We see that STEM mayors caused the adoption of a higher number of non-pharmaceutical interventions. This was done mainly through face-covering restrictions, public gathering restrictions, public transport restrictions and cordon sanitaire restrictions. More specifically, our results show that STEM mayors' caused an increase of 2.19 (p-value 0.00) NPIs. This amount equalizes 55.86 percent of the average number of NPIs among municipalities that elected a non-STEM mayor (the mean rate of NPIs for Non-STEM municipalities inside the 7.3 window margin was 3.92). We also run the same test with different bandwidths to increase the robustness of our estimates, as seen in Figure 10.

Table 6 – Impact of STEM leadership on NPIs - RD estimates

	Total NFI	Masks	Restrictions atv.	Restrictions circu.	Restrictions transp.	Sani barriers
Robust	2.19	0.55	0.34	0.47	1.16	-0.29
	[0.72]	[0.18]	[0.21]	[0.27]	[0.20]	[0.28]
	0.00***	0.00***	0.11	0.08*	0.00***	0.31
Eff.number.obs.	22	25	26	26	31	24
Window	7.3	7.56	7.98	8.18	10.83	6.49
Bandwidth	CCT Opt.	CCT Opt.	CCT Opt.	CCT Opt.	CCT Opt.	CCT Opt.
Pers.charact.	X	X	X	X	X	X

Notes: This figure reports the RD estimated impact of mayors with scientific background on the adoption of non-pharmaceutical interventions (NPIs) in 2020 in Brazilian municipalities. Following the order of the columns, the interventions are: total number of NPIs, face-covering restrictions, non-essential activities restrictions, public gathering restrictions, public transport restrictions and cordon sanitaire restrictions (the control of people entering and leaving the city), as published by de Souza Santos et al. (2021). All specifications use state fixed-effects and triangular kernels and control for mayors' age. We report robust-bias corrected p-values, conventional (non-robust) estimates and standard errors.

Figure 10 – Impact of STEM mayor on non-pharmaceutical interventions (NPIs) using different bandwidths



Notes: This figure reports the RD estimated impact of mayors with scientific background on deaths and hospitalizations by COVID-19 per hundred thousand inhabitants in 2020 in Brazilian municipalities. In the horizontal axis, we test different winning margins (bandwidth) between the elected mayor and the second most voted. These results represent the impact of our main estimation (2) that uses first-degree polynomial, state fixed-effects, triangular kernel, and control for mayors' age.

6 FINAL DISCUSSION

In this paper we investigate and answer the question: Has a scientific background helped mayors against COVID-19? We demonstrate a significant amount of evidence showing that the election of mayors with a scientific background caused a significant reduction in hospitalizations and deaths from COVID-19, mediated through an increase in non-pharmaceutical interventions. We consider this our first contribution since other studies have found no robust impact of scientific background on public administration issues (Bastos & Sánchez, 2021; Goodwin, 2015), and no other study, to our knowledge, has shown a causal impact of science as a vocational background that is statistically significant. This impact is even more relevant considering that other professional backgrounds - such as police officers, military, and physicians - or even highly educated mayors weren't capable of reducing these epidemiological outcomes, as previously demonstrated Section 5.2.

We also did our second contribution by empirically testing a novel definition of STEM in the Brazilian literature, where the debate around the term is still incipient and the definition is even vaguer (Machado et al., 2021, p.2). We did so by testing Machado's definition of STEM occupation in the context of STEM graduates in non-STEM jobs (Mellors-Bourne et al., 2011), more specifically, in local political jobs. We have shown that Brazilian STEM mayors are mainly civil and agroforestry engineers. This is relevant to our discussion because national public data on mayors—which comes from the TSE (the Electoral Office), only state their occupation as "engineer" or reflect occupations that were self-declared at the time of election. It thus may fail to account for electoral interest bias in declaring its own profession. For example, many mayors that worked as engineers declared themselves to be "entrepreneurs" and not engineers. This is important because it helps explain why we see so few STEM mayors in TSE data. It could be that the percentage of engineers in Brazil is low, or it could be that, as we have shown, they are not self-declaring as such.

Finally, this particular effect of science as a vocational background has a notable implication for public policies. Besides labor markets' advantages (Black et al., 2021) and externalities in private firms' innovation (Brunow et al., 2018) and performance (Siepel, Camerani, & Masucci, 2021), our results suggest that public investments in STEM education and professions may produce other externalities, such as better policy outcomes in areas such as public health. We also contribute by linking the pieces of literature on STEM and Evidence-based Management. To do so we theoretically suggest that STEM mayors' may have achieved better epidemiological outcomes using their acquired knowledge of evidence and applying it in public administration. Nevertheless, we don't consider that our results ask for more mayors with a scientific background. The impact on epidemiological outcomes may be achieved through other measures, instead of a STEM-related formation, such as reducing information frictions between scientists and politicians by making research information directly and easily available to policymakers (Hjort et al., 2021, p.1477).

A limitation of our study is the restricted external validity of a regression discontinuity design. Since we only consider municipalities where a mayor with a science background was elected by a close margin, our results can not be extrapolated to all municipalities that elected such mayors. Besides that, we do not empirically test what is inside our STEM proxy that causes the impact. That means we don't know exactly what it was in a candidate's STEM education or experience that made them raise the number of NPIs and lower the number of hospitalizations and deaths. Such mediation effects could have been a trained mindset to use scientific research and take evidence-based decisions. The earlier choice of a STEM course could even be correlated with other personal characteristics, such as cognitive bias (Coenen, Borghans, & Diris, 2021), that made STEM mayors perform better in epidemiological outcomes during the pandemic.

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APPENDIX A – LIST OF CBOS CLASSIFIED AS STEM

This table was obtained from (Machado et al., 2021).

code_cbo2002	occupation
1223	Diretores de operações de obras em empresa de construção
1236	Diretores de tecnologia da informação
1237	Diretores de pesquisa e desenvolvimento
1413	Gerentes de obras em empresa de construção
1425	Gerentes de tecnologia da informação
1426	Gerentes de pesquisa e desenvolvimento e afins
2011	Profissionais da biotecnologia
2012	Profissionais da metrologia
2021	Engenheiros de controle e automação, engenheiros mecatrônicos e afins
2030	Pesquisadores das ciências biológicas
2031	Pesquisadores das ciências naturais e exatas
2032	Pesquisadores de engenharia e tecnologia
2033	Pesquisadores das ciências da saúde
2034	Pesquisadores das ciências da agricultura
2111	Profissionais da matemática
2112	Profissionais de estatística
2122	Engenheiros em computação
2123	Administradores de tecnologia da informação
2124	Analistas de tecnologia da informação
2131	Físicos
2132	Químicos
2133	Profissionais das ciências atmosféricas e espaciais e de astronomia
2134	Geólogos, oceanógrafos, geofísicos e afins
2140	Engenheiros ambientais e afins

code_cbo2002	occupation
2142	Engenheiros civis e afins
2143	Engenheiros eletricistas, eletrônicos e afins
2144	Engenheiros mecânicos e afins
2145	Engenheiros químicos e afins
2146	Engenheiros metalurgistas, de materiais e afins
2147	Engenheiros de minas e afins
2148	Engenheiros agrimensores e engenheiros cartógrafos
2149	Engenheiros de produção, qualidade, segurança e afins
2211	Biólogos e afins
2212	Biomédicos
2221	Engenheiros agrossilvipecuários
2222	Engenheiros de alimentos e afins
2341	Professores de matemática, estatística e informática do ensino superior
2342	Professores de ciências físicas, químicas e afins do ensino superior
2343	Professores de arquitetura e urbanismo, engenharia, geofísica e geologia do ensino superior
2344	Professores de ciências biológicas e da saúde do ensino superior
2513	Profissionais em pesquisa e análise geográfica
3001	Técnicos em mecatrônica
3003	Técnicos em eletromecânica
3011	Técnicos de laboratório industrial
3012	Técnicos de apoio à bioengenharia
3111	Técnicos químicos
3112	Técnicos de produção de indústrias químicas, petroquímicas, refino de petróleo, gás e afins
3115	Técnicos em controle ambiental, utilidades e tratamento de efluentes

code_cbo2002	occupation
3121	Técnicos em construção civil (edificações)
3122	Técnicos em construção civil (obras de infraestrutura)
3123	Técnicos em geomática
3161	Técnicos em geologia
3171	Técnicos de desenvolvimento de sistemas e aplicações
3172	Técnicos de suporte e monitoração ao usuário de tecnologia da informação.
3180	Desenhistas técnicos, em geral
3181	Desenhistas técnicos da construção civil e arquitetura
3182	Desenhistas técnicos da mecânica
3183	Desenhistas técnicos em eletricidade, eletrônica, eletromecânica, calefação, ventilação e refrigeração
3185	Desenhistas projetistas de construção civil e arquitetura
3186	Desenhistas projetistas da mecânica
3187	Desenhistas projetistas da eletrônica
3201	Técnicos em biologia
3212	Técnicos florestais
3253	Técnicos de apoio à biotecnologia
3951	Técnicos de apoio em pesquisa e desenvolvimento