When Science Strikes Back

Tables and Figures

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Summary of Data Sources

Table 1: Summary of Data Sources

Data Source	Description
Base dos Dados (Dahis et al., 2022) and Tribunal Superior Eleitoral (TSE)	Information on mayors and elections.
RAIS (Brazilian Ministry of Labor database)	Occupation data.

Data Source	**Description**
SIVEPGripe	Epidemiological outcomes data (hospitalizations, deaths).
2010 Brazilian National Census	Demographic data.
IEPS Data Index	Public health data.
Power and Rodrigues-Silveira (2019)	Ideological measures.
De Souza Santos et al. (2021) and National Confederation of Municipalities (CNI)	Data on Non-Pharmaceutical Interventions (NPIs) between May and July 2020.

Main Variables in the Study

Table 2: Main Variables in the Study

Variable	Description
Cases per 100k inhabitants	Number of COVID-19 cases per 100,000 inhabitants, based on municipal data.
Hospitalizations per 100k inhabitants	Number of hospitalizations due to COVID-19 per 100,000 inhabitants.
Deaths per 100k inhabitants	Number of deaths from COVID-19 per 100,000 inhabitants.
STEM candidate	Indicator for whether a candidate has worked in STEM for at least 6 months or holds a STEM degree.
STEM occupation	Defined as per CBO classification list by Machado et al. (2021).
STEM education	Based on data from Escavador, social media, and machine learning classification.
STEM winning margin	Vote margin between the first and second most-voted candidates, positive if a STEM candidate won.
Cohort	List of candidates registered in the 2016 local executive elections.
Tenure	Employment time in a STEM occupation, calculated using RAIS data.

Summary Statistics

Table 3: Summary Statistics

	N	Min	Mean	Max	SD
Tenure.in.STEM.job	899	0.00	18.09	168.10	37.00
Female	899	0.00	0.09	1.00	0.28
Age	899	21.00	50.06	86.00	10.94
Education	899	1.00	6.13	7.00	1.45
Incumbent.when.elected	899	0.00	0.21	1.00	0.41
Party.ideology	899	-0.69	0.30	0.76	0.36
Deaths.per.100k.inhabitants	899	0.00	5.18	7.22	1.02
Hospitalizations.per.100k.inhabitants	899	0.00	6.36	8.43	0.85
Cordon.sanitaire	300	0.00	0.55	1.00	0.50
Face.covering.required	296	0.00	0.95	1.00	0.21
Closure.of.non.essential.activities	297	0.00	0.77	1.00	0.42
Gathering.prohibition	297	0.00	0.98	1.00	0.15

	N	Min	Mean	Max	SD
Public.transport.restriction	295	0.00	0.47	1.00	0.50
Number.of.Non.Pharma..Interventions	294	1.00	3.72	5.00	0.90
Log.of.population.in.2010	899	7.07	9.72	14.49	1.18
Human.Development.Index	899	0.47	0.67	0.84	0.07
Per.capita.income	899	5.23	23.44	203.12	18.70
Population.density	897	0.40	103.33	6182.96	383.12
Urban.population.rate	899	-80.55	-30.40	1.00	20.77
Men.population.rate	899	46.37	50.21	71.21	1.66
Physicians.per.1k.inhabitants	899	0.00	0.83	6.18	0.67
Health.municipal.spending.rate	899	7.92	22.42	37.08	5.05
Community.health.agency.coverage.rate	899	0.00	87.02	100.00	21.68
Hospital.beds.per.100k.population	899	0.00	141.90	1218.84	150.01

Notes: This table aggregates the summary statistics of all the observations used in the study (899). Municipalities chosen were those that held ordinary elections in selected years (2016, 2020) whose mayor was elected in the first round and among the top two most voted was a STEM candidate and a Non-STEM one. NPI data has null values since not all the mayors responded to the survey.

Summary Statistics per Group

Table 4: Summary Statistics by Group

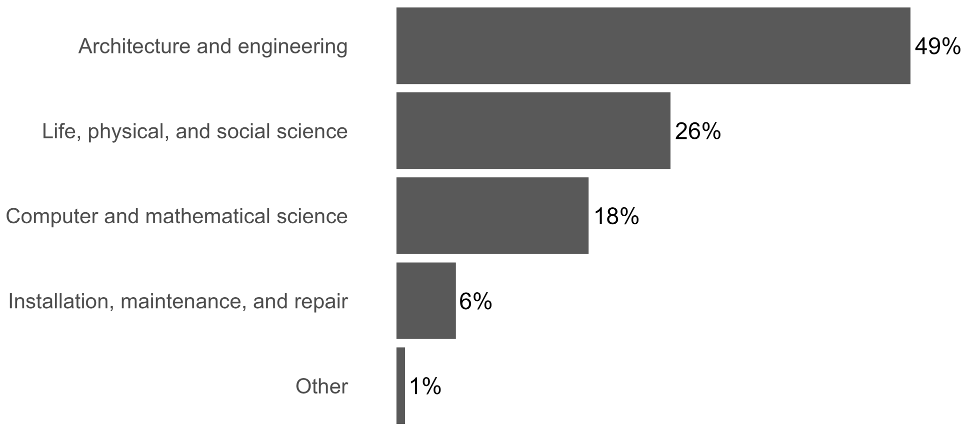
	Non-STEM (N=528)		STEM (N=371)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p
Tenure in STEM job	0.00	0.00	43.83	46.81	43.83	<0.01
Female	0.09	0.29	0.08	0.27	-0.01	0.67
Age	50.49	11.31	49.46	10.37	-1.03	0.16
Education	5.74	1.61	6.69	0.94	0.95	<0.01
Incumbent when elected	0.22	0.41	0.21	0.41	-0.01	0.71
Party ideology	0.30	0.34	0.29	0.38	-0.01	0.59
Deaths per 100k inhabitants	5.20	0.97	5.15	1.08	-0.05	0.46
Hospitalizations per 100k inhabitants	6.37	0.80	6.35	0.92	-0.02	0.68
Cordon sanitaire	0.58	0.50	0.51	0.50	-0.07	0.25
Face covering required	0.95	0.23	0.96	0.19	0.01	0.55

	Non-STEM (N=528)		STEM (N=371)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p
Closure of non-essential activities	0.75	0.43	0.79	0.41	0.04	0.45
Gathering prohibition	0.97	0.17	0.98	0.12	0.01	0.41
Public transport restriction	0.50	0.50	0.44	0.50	-0.05	0.37
Number of Non-Pharma. Interventions	3.74	0.89	3.68	0.91	-0.06	0.56
Log of population in 2010	9.81	1.20	9.58	1.14	-0.23	<0.01
Human Development Index	0.67	0.07	0.67	0.07	0.00	0.39
Per capita income	24.41	20.68	22.06	15.38	-2.36	0.05
Population density	106.89	376.35	98.25	393.05	-8.64	0.74
Urban population rate	-29.14	20.19	-32.19	21.48	-3.05	0.03
Men population rate	50.12	1.59	50.34	1.74	0.22	0.05
Physicians per 1k inhabitants	0.85	0.65	0.81	0.69	-0.04	0.42
Health municipal spending rate	22.34	5.10	22.53	4.97	0.19	0.58
Community health agency coverage rate	86.20	21.74	88.19	21.56	1.99	0.17
Hospital beds per 100k population	143.98	146.95	138.95	154.42	-5.03	0.62

Notes: This table aggregates the summary statistics per group of all the observations used in the study (899). Municipalities chosen were those that held ordinary elections in selected years (2016, 2020) whose mayor was elected in the first round and among the top two most voted was a STEM candidate and a Non-STEM one. NPI data has null values since not all the mayors responded to the survey.

STEM mayors' most common occupations

Figure 1: STEM mayors' most common occupations



Notes: This figure shows the top five occupations among the 371 STEM mayors in our sample. Municipalities chosen were those that held ordinary elections in selected years (2016, 2020) whose mayor was elected in the first round and among the top two most voted was a STEM candidate and a Non-STEM one.

Percentage of municipalities with a STEM mayor among top 2 per state

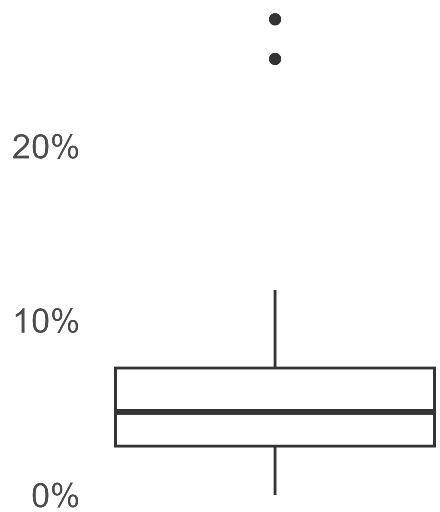
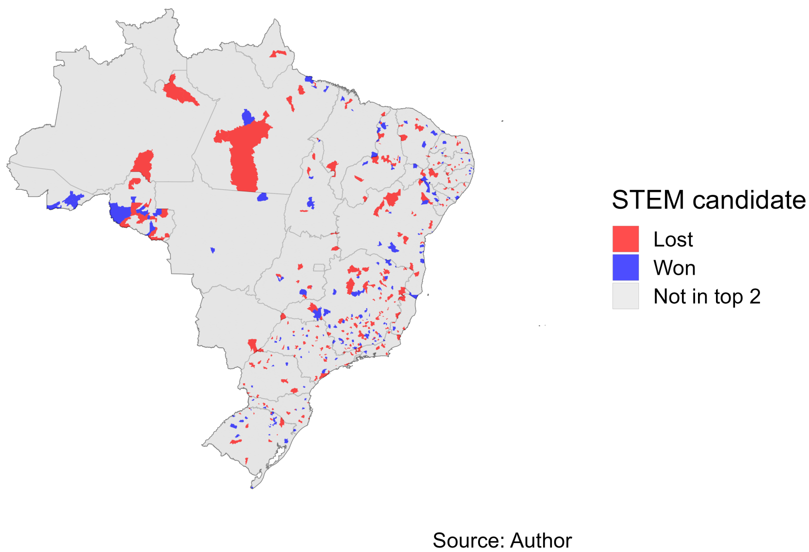


Figure 2: Percentage of municipalities with a STEM mayor among top 2 per state

Notes: This plot shows the distribution per state of the percentage of municipalities that had a STEM mayor among top 2 voted. Municipalities chosen were those that held ordinary elections in selected years (2016, 2020) whose mayor was elected in the first round and among the top two most voted was a STEM candidate and a Non-STEM one.

Municipalities with a STEM candidate (2016)

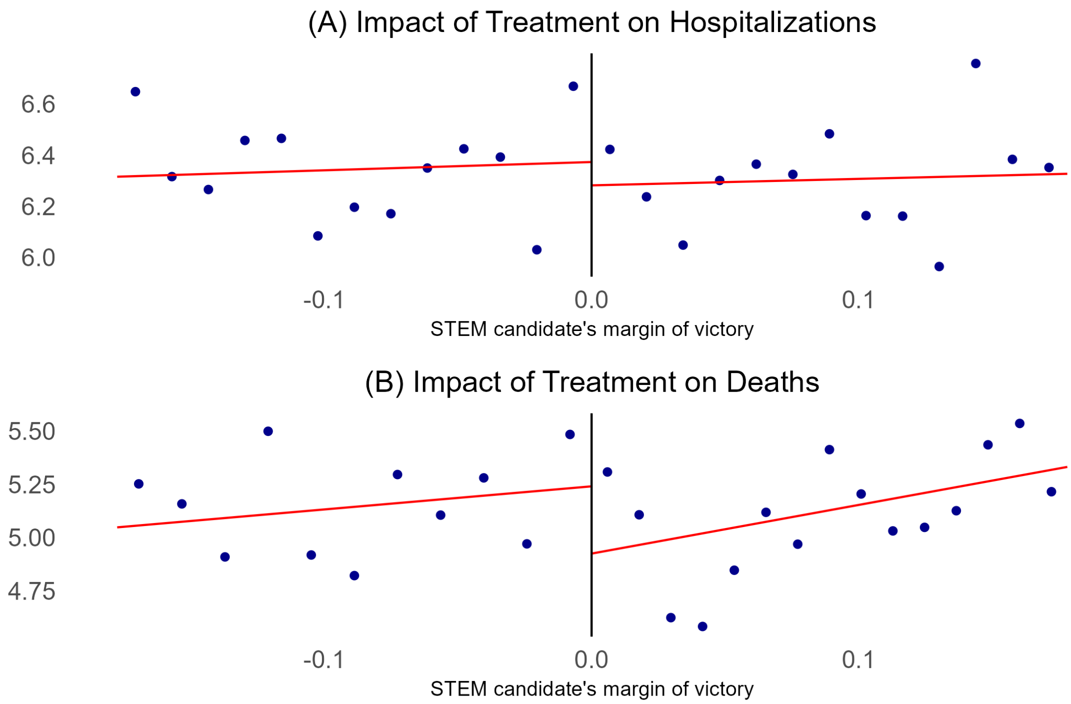
Figure 3: Municipalities with a STEM candidate (2016)



Notes: In this figure, we colored all municipalities in our 2016 sample, that is, where a STEM candidate was among the top two most voted. 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.

Impact of STEM mayor election on epidemiological outcomes

Figure 4: 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 the form of log(outcome + 1). Municipalities chosen were those that held ordinary elections in selected years (2016, 2020) whose mayor was elected in the first round and among the top two most voted was a STEM candidate and a Non-STEM one.

Baseline Characteristics - RD Estimates (Demographics)

Table 5: Baseline Characteristics - RD Estimates (Demography)

	PC income	Log Population	HDI	Density	% Masc. Pop
RD estimator	-3.19	-0.22	0.00	0.90	0.42
	[3.05]	[0.23]	[0.01]	[45.06]	[0.36]
	0.30	0.35	0.82	0.98	0.24
Eff.N.obs.	366	406	352	388	555

	PC income	Log Population	HDI	Density	% Masc. Pop
Bandwidth	13.16	14.68	12.6	14.29	22.47

Notes: This table reports the RD estimated impact of mayors with scientific background on demographic baseline characteristics. Municipalities chosen were those that held ordinary elections in selected years (2016, 2020) whose mayor was elected in the first round and among the top two most voted was a STEM candidate and a Non-STEM one. All specifications use state fixed-effects, uniform kernel and optimal bandwidths calculated following Calonico et al. (2014). We report robust-bias corrected p-values, conventional (non-robust) estimates and standard errors.

Baseline Characteristics - RD Estimates (Health and Ideology)

Table 6: Baseline Characteristics - RD Estimates (Health and Ideology)

	% Health municipal spending	Doctors per 1k pop.	Community health agents program	Hosp. beds per 100k pop.	Mun. ideology index
RD estimator	1.29	-0.03	2.31	-44.30	0.00
	[0.88]	[0.11]	[4.00]	[31.54]	[0.02]
	0.14	0.75	0.56	0.16	0.85
Eff.N.obs.	484	337	410	386	375
Bandwidth	17.95	11.96	14.89	14.16	13.63

Notes: This table reports the RD estimated impact of mayors with scientific background on health and ideology baseline characteristics. Municipalities chosen were those that held ordinary elections in selected years (2016, 2020) whose mayor was elected in the first round and among the top two most voted was a STEM candidate and a Non-STEM one. All specifications use state fixed-effects, uniform kernel and optimal bandwidths calculated following Calonico et al. (2014). The ideology column regards mayors' party ideology, whereas negative numbers represent left-wing parties and positive right-wing (Power & Rodrigues-Silveira, 2019).We report robust-bias corrected p-values, estimates and standard errors.

Impact of STEM Leadership on Epidemiological Outcomes — RD estimates

Table 7: Impact of STEM Leadership on Epidemiological Outcomes — RD estimates

	(1)	(2)	(3)	(4)
Panel A: Deaths				
RD estimator	-0.21	-0.23	-0.40	-0.36
	[0.25]	[0.25]	[0.20]	[0.20]
	0.40	0.35	0.05**	0.08*
Eff.N.obs.	412	412	475	481
Bandwidth	15	15	17.56	17.81
Panel B: Hospitalizations				
RD estimator	-0.07	-0.10	-0.08	-0.12
	[0.18]	[0.18]	[0.14]	[0.13]
	0.71	0.59	0.58	0.35
Eff.N.obs.	412	412	444	468
Bandwidth	15	15	16.26	17.27

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 the form of log(outcome + 1). Municipalities chosen were those that held ordinary elections in selected years (2016, 2020) whose mayor was elected in the first round and among the top two most voted was a STEM candidate and a Non-STEM one. All specifications use state fixed-effects, uniform kernel. Estimations (3) and (4) use optimal bandwidths calculated following Calonico et al. (2014), while estimations (1) and (2) use a 0.15% 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' personal characteristics. We report robust-bias-corrected p-values, coefficients and standard errors.

STEM candidates' personal characteristics — RD estimates

Table 8: STEM candidates' personal characteristics — RD estimates

	Women	Incumbent	Age	Mayors' party ideology
RD estimator	-0.21	0.11	-0.76	0.14
	[0.06]	[0.09]	[2.06]	[0.07]
	<0.01***	0.23	0.71	0.05*
Eff.N.obs.	438	335	476	345
Bandwidth	15.99	11.88	17.66	12.24

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' personal characteristics. In the second column, the measure of 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, uniform kernels. Optimal bandwidths were calculated following Calonico et al. (2014). We report robust-bias corrected p-values, estimates and standard errors.

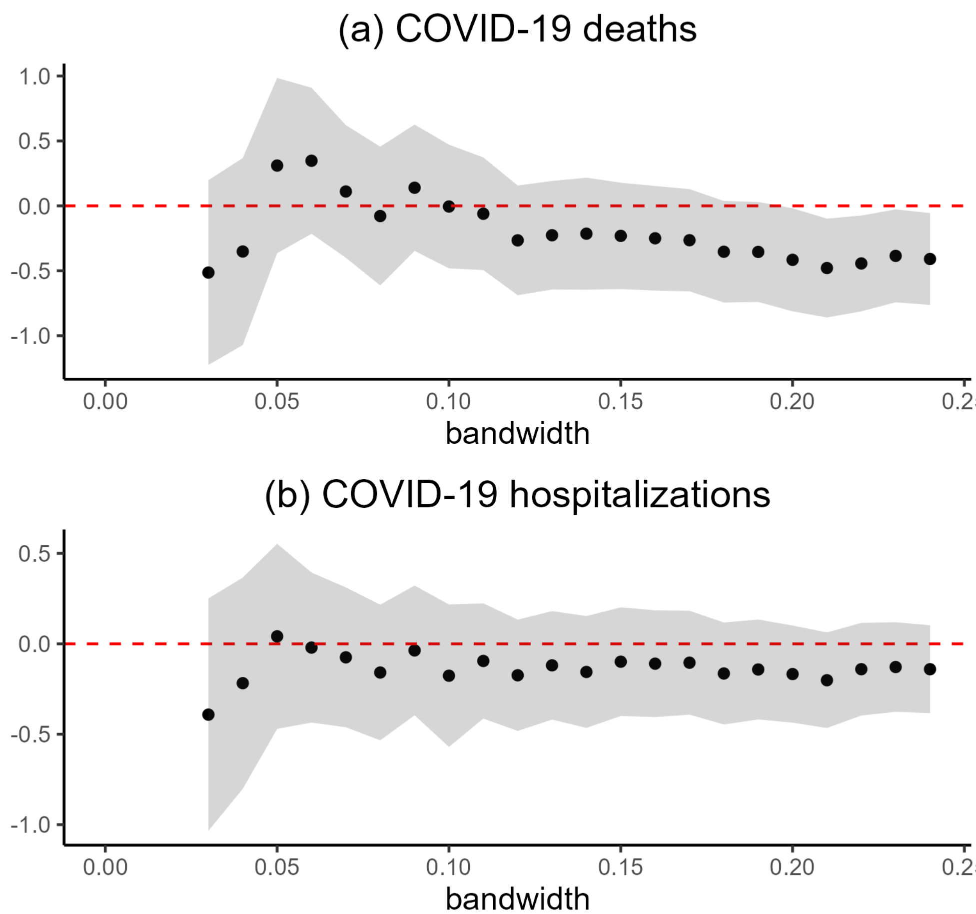
Impact of STEM Candidate Elected in 2016 on Non-Pharmaceutical Interventions

Table 9: Impact of STEM Candidate Elected in 2016 on Non-Pharmaceutical Interventions in 2020

	Total NFI	Masks	Restrictions atv.	Restrictions circu.	Restrictions transp.	Sani barriers
Robust	0.74	0.22	-0.21	0.31	0.60	-0.01
	[0.34]	[0.10]	[0.20]	[0.17]	[0.28]	[0.27]
	0.03**	0.02**	0.29	0.07*	0.04**	0.97
Eff.N.obs.	70	50	52	71	69	42
Bandwidth	7.24	5.01	5.15	7.12	7.06	4.31

Notes: This figure reports the RD estimated impact of mayors with scientific background on the adoption of non-pharmaceutical interventions (NPIs) in 2020. 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 and a Non-STEM one. All specifications use state fixed-effects, uniform kernel and optimal bandwidths calculated following Calonico et al. (2014). 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, estimates and standard errors.

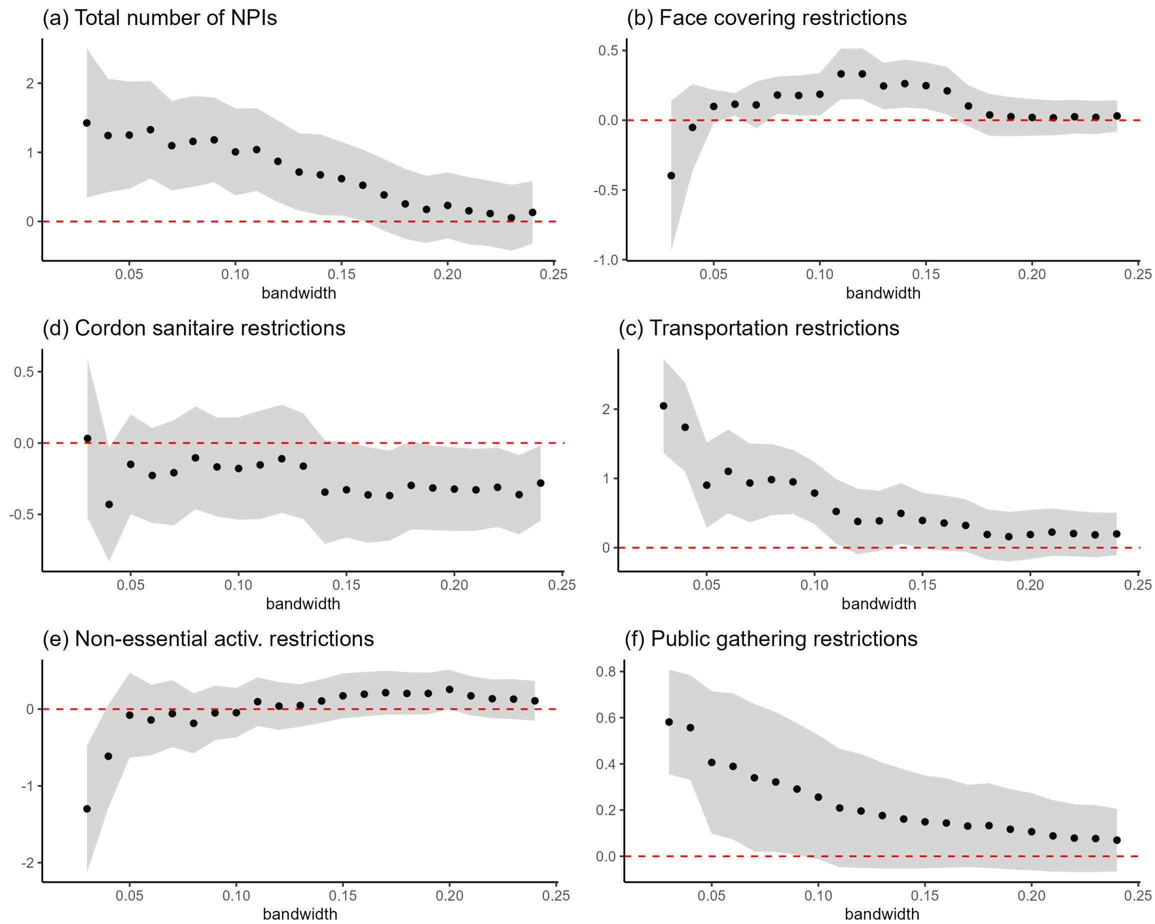
Impact of STEM mayor on epidemiological outcomes using different bandwidths



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 the form of log(outcome + 1). Municipalities chosen were those that held ordinary elections in selected years (2016, 2020) whose mayor was elected in the first round and among the top two most voted was a STEM candidate and a Non-STEM one. 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, uniform kernel, and control for mayors' personal characteristics.

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

Figure 5: 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 non-pharmaceutical interventions. Municipalities chosen were those that held ordinary elections in selected years (2016, 2020) whose mayor was elected in the first round and among the top two most voted was a STEM candidate and a Non-STEM one. 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, uniform kernel, and control for mayors' personal characteristics.

Moderating effects of scientific intensity on the impact of STEM background

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Table 10: Moderating effects of scientific intensity on the impact of STEM background

	Dependent variable:		
	Hospitalizations	Deaths	NFI
	(1)	(2)	(3)
STEM Background	-0.386^{*}	-0.159	-0.117
	(0.221)	(0.160)	(0.211)
Tenure Moderation Effect	0.011	0.013	0.034^{*}
	(0.021)	(0.015)	(0.020)
Observations	412	412	295
R^2	0.019	0.034	0.031
Adjusted R^2	-0.067	-0.051	-0.079
F Statistic	0.803 (df = 9; 378)	1.466 (df = 9; 378)	0.929 (df = 9; 264)
Note:			*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents the estimated impact of mayors with scientific background on COVID-19 deaths and hospitalizations per hundred thousand inhabitants in the form of log(outcome + 1). Municipalities chosen were those that held ordinary elections in selected years (2016, 2020) whose mayor was elected in the first round, winning by a maximum difference of 15%, and among the top two most voted was a STEM candidate and a Non-STEM one. The analysis incorporates moderation effects of scientific intensity, measured by work tenure. The model controls for mayors' personal characteristics, and includes state fixed-effects.

Moderating effects of city's development on the impact of STEM background

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Notes: This table presents the estimated impact of mayors with scientific background on COVID-19 deaths and hospitalizations per hundred thousand inhabitants in the form of log(outcome + 1). Municipalities chosen were those that held ordinary elections in selected years (2016, 2020) whose mayor was elected in the first round, winning by a maximum difference of 15%, and among the top two most voted was a STEM candidate and a Non-STEM

Table 11: Moderating effects of cities' development on the impact of STEM background

	Dependent variable:		
	Hospitalizations	Deaths	NFI
	(1)	(2)	(3)
STEM Background	-0.481^{**}	-0.219	0.058
	(0.216)	(0.173)	(0.201)
Revenue Modereration Effect	0.011	0.006	0.006
	(0.007)	(0.005)	(0.006)
Observations	412	412	295
R^2	0.059	0.095	0.031
Adjusted R^2	0.033	0.070	-0.007
F Statistic	2.495^{***} (df = 10; 400)	4.206^{***} (df = 10; 400)	0.904 (df = 10; 283)
Note:			*p<0.1; **p<0.05; ***p<0.01

one. The analysis incorporates cities' level of development, indicated by revenue in 2015. The model controls for mayors' personal characteristics, and includes state fixed-effects.