When Science Strikes Back

Tables and Figures

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Table of contents

Summary of Data Sources 1
Main Variables in the Study 2
Summary Statistics 2
Summary Statistics per Group 3
STEM mayors' most common occupations 5
Percentage of municipalities with a STEM mayor among top 2 per state 6
Municipalities with a STEM candidate (2016) 7
Impact of STEM mayor election on epidemiological outcomes 8
Baseline Characteristics - RD Estimates (Demographics) 8
Baseline Characteristics - RD Estimates (Health and Ideology) 9
Impact of STEM Leadership on Epidemiological Outcomes — RD estimates 9
STEM candidates' personal characteristics — RD estimates 10
Impact of STEM Candidate Elected in 2016 on Non-Pharmaceutical Interventions . 11
Impact of STEM mayor on epidemiological outcomes using different bandwidths . . 12
Impact of STEM mayor on non-pharmaceutical interventions (NPIs) using different bandwidths 13
Moderating effects of scientific intensity on the impact of STEM background 14
Moderating effects of city's development on the impact of STEM background 14

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	119	0.00	23.20	144.10	43.07
Female	119	0.00	0.07	1.00	0.25
Age	119	27.00	51.22	79.00	11.26
Education	119	4.00	6.97	7.00	0.28
Incumbent.when.elected	119	0.00	0.15	1.00	0.36
Party.ideology	119	-0.62	0.25	0.76	0.40
Deaths.per.100k.inhabitants	119	0.00	97.24	270.95	55.96
Hospitalizations.per.100k.inhabitants	119	38.37	359.71	1207.56	222.28
Cordon.sanitaire	82	0.00	0.46	1.00	0.50
Face.covering.required	80	0.00	0.98	1.00	0.16
Closure.of.non.essential.activities	81	0.00	0.78	1.00	0.42

	N	Min	Mean	Max	SD
Gathering.prohibition	81	0.00	0.98	1.00	0.16
Public.transport.restriction	79	0.00	0.52	1.00	0.50
Number.of.Non.Pharma..Interventions	78	1.00	3.71	5.00	0.90
Log.of.population.in.2010	119	7.76	10.02	13.67	1.17
Human.Development.Index	119	0.54	0.67	0.79	0.07
Per.capita.income	119	6.01	26.04	145.24	21.98
Population.density	119	1.19	83.98	741.57	116.57
Urban.population.rate	119	-80.55	-28.62	0.26	21.00
Men.population.rate	119	46.47	49.79	61.78	1.64
Physicians.per.1k.inhabitants	119	0.00	0.92	4.42	0.72
Health.municipal.spending.rate	119	15.51	23.34	35.98	4.84
Community.health.agency.coverage.rate	119	0.00	83.33	100.00	25.66
Hospital.beds.per.100k.population	119	0.00	149.28	816.50	145.82

Notes: This table aggregates the summary statistics of all the observations used in the study (413). Municipalities chosen were those that held ordinary elections in selected years (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. NPI data has null values since not all the mayors responded to the survey.

Summary Statistics per Group

Table 4: Summary Statistics by Group

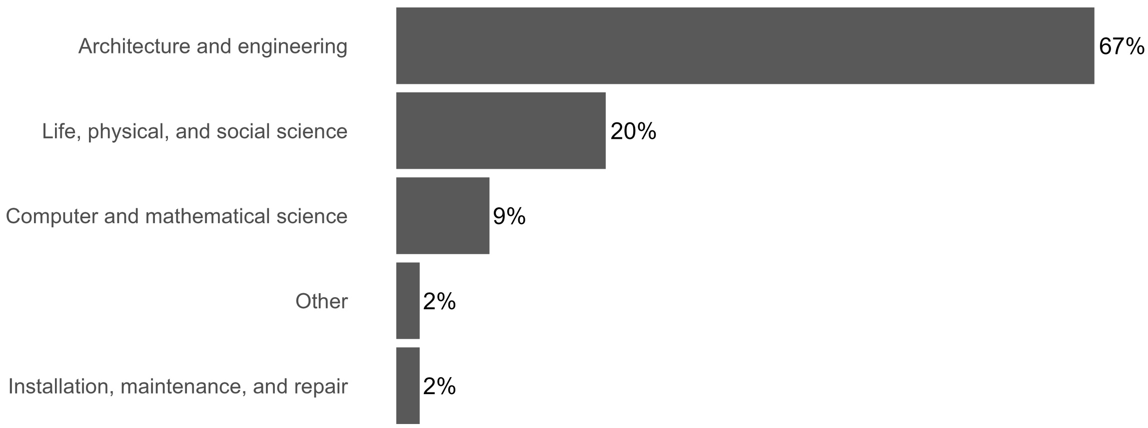
	Non-STEM (N=74)		STEM (N=45)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p
Tenure in STEM job	0.00	0.00	61.35	50.81	61.35	<0.01
Female	0.09	0.29	0.02	0.15	-0.07	0.08
Age	51.42	11.39	50.89	11.17	-0.53	0.80
Education	7.00	0.00	6.93	0.45	-0.07	0.32
Incumbent when elected	0.18	0.38	0.11	0.32	-0.06	0.32
Party ideology	0.27	0.39	0.21	0.42	-0.06	0.46
Deaths per 100k inhabitants	92.22	54.16	105.49	58.47	13.27	0.22
Hospitalizations per 100k inhabitants	352.23	222.18	372.00	224.40	19.76	0.64
Cordon sanitaire	0.48	0.50	0.44	0.50	-0.04	0.74

	Non-STEM (N=74)		STEM (N=45)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p
Face covering required	0.96	0.21	1.00	0.00	0.04	0.16
Closure of non-essential activities	0.77	0.43	0.79	0.41	0.03	0.77
Gathering prohibition	0.98	0.15	0.97	0.17	-0.01	0.82
Public transport restriction	0.60	0.50	0.41	0.50	-0.19	0.10
Number of Non-Pharma. Interventions	3.78	0.81	3.59	1.01	-0.19	0.38
Log of population in 2010	10.01	1.21	10.04	1.12	0.04	0.86
Human Development Index	0.67	0.07	0.68	0.06	0.01	0.55
Per capita income	25.56	23.99	26.81	18.44	1.25	0.75
Population density	87.75	108.53	77.78	129.76	-9.97	0.67
Urban population rate	-28.67	21.24	-28.55	20.83	0.12	0.98
Men population rate	49.72	1.89	49.92	1.10	0.20	0.47
Physicians per 1k inhabitants	0.90	0.73	0.95	0.70	0.05	0.70
Health municipal spending rate	23.14	5.02	23.68	4.58	0.53	0.55
Community health agency coverage rate	85.33	23.84	80.03	28.37	-5.30	0.30
Hospital beds per 100k population	144.35	148.34	157.38	142.86	13.03	0.64

Notes: This table aggregates the summary statistics per group of all the observations used in the study (413). Municipalities chosen were those that held ordinary elections in selected years (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. NPI data has null values since not all the mayors responded to the survey.

STEM mayors' most common occupations

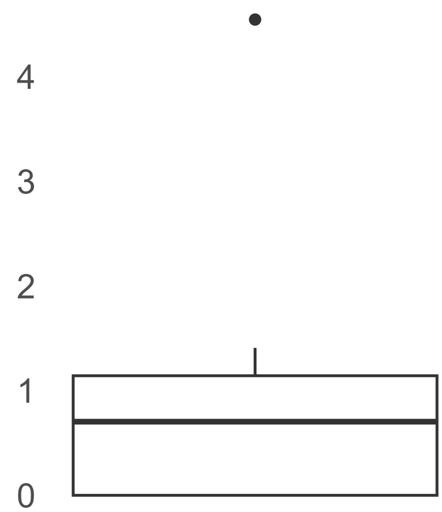
Figure 1: STEM mayors' most common occupations



Notes: This figure shows the top five occupations among the 164 STEM mayors in our sample. Municipalities chosen were those that held ordinary elections in selected years (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.

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

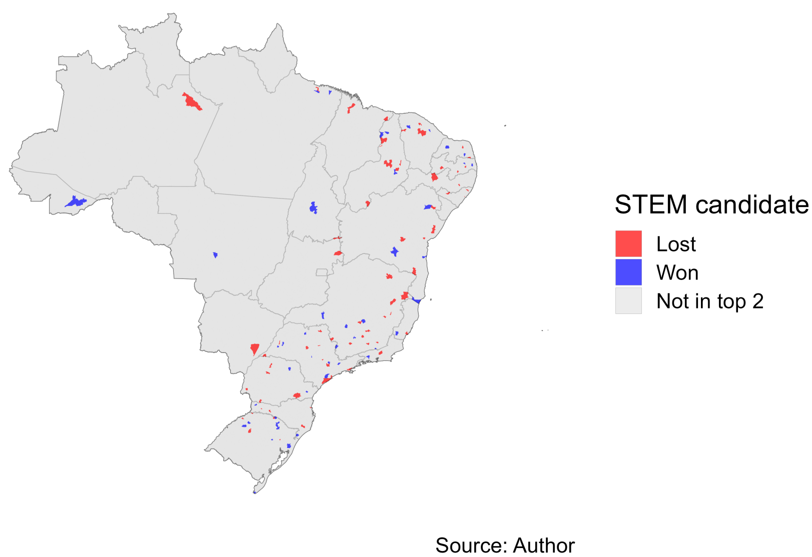
Figure 2: Percentage of municipalities with a STEM mayor among top 2 per state



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) 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)

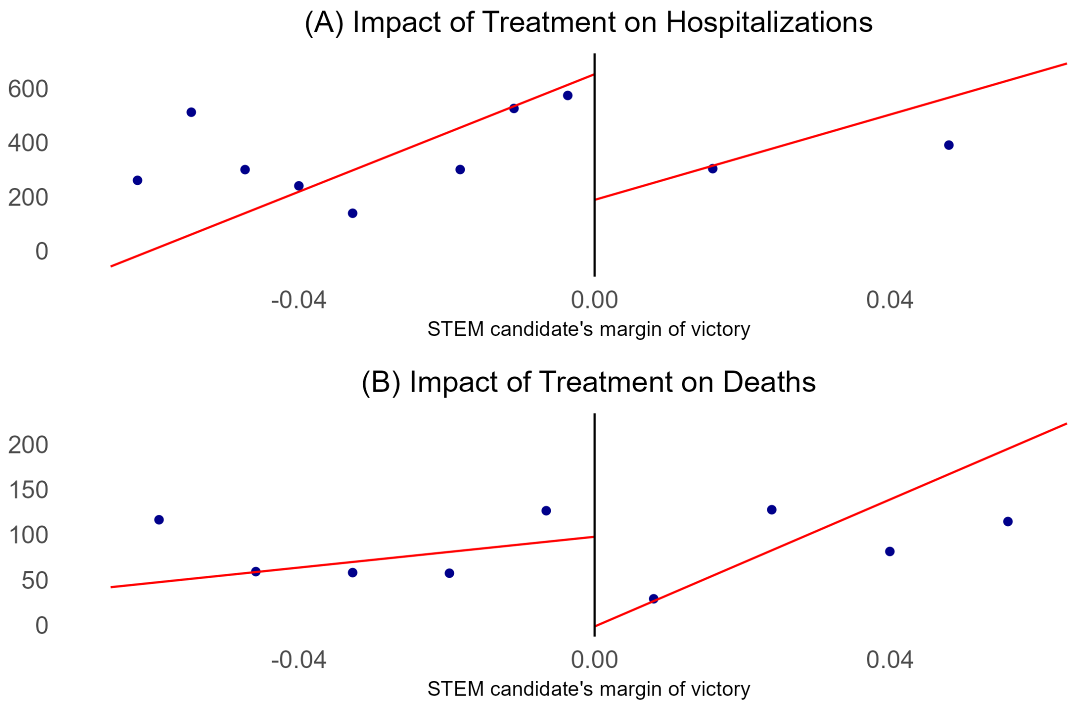
Figure 3: Municipalities with a STEM candidate (2016)



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. Municipalities chosen were those that held ordinary elections in selected years (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.

Baseline Characteristics - RD Estimates (Demographics)

Table 5: Baseline Characteristics - RD Estimates (Demography)

	PC income	Log Population	HDI	Density	% Masc. Pop
RD estimator	7.95	0.44	0.02	100.43	-0.36
	[3.32]	[4.68]	[0.02]	[48.88]	[0.53]
	<0.01***	0.21	0.18	<0.01***	0.44
Eff.N.obs.	125	112	104	103	128

	PC income	Log Population	HDI	Density	% Masc. Pop
Bandwidth	9.17	8.36	7.7	7.74	9.23

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) 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, triangular 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	2.66	0.14	-0.26	-37.43	-0.02
	[1.49]	[0.15]	[6.44]	[48.25]	[0.03]
	0.04**	0.25	0.82	0.52	0.56
Eff.N.obs.	142	110	148	127	131
Bandwidth	10.41	8.25	10.76	9.19	9.6

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) 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, triangular 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, conventional (non-robust) 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	-8.49	-12.21	-8.56	-6.91
	[18.01]	[18.07]	[14.97]	[13.67]
	0.99	0.75	0.39	0.44
Eff.N.obs.	139	139	139	176
Bandwidth	10	10	10.09	12.59
Panel B: Hospitalizations				
RD estimator	-34.39	-82.09	-39.74	-33.55
	[94.53]	[87.57]	[78.72]	[55.32]
	0.59	0.24	0.56	0.60
Eff.N.obs.	139	139	116	237
Bandwidth	10	10	8.52	17.86

Notes: This table reports the RD estimated impact of mayors with scientific background on deaths and hospitalizations by COVID-19 per hundred thousand inhabitants. Municipalities chosen were those that held ordinary elections in selected years (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, triangular kernel. Estimations (1) and (2) use optimal bandwidths calculated following Calonico et al. (2014), while estimations (3) and (4) use a 0.1% 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' gender. 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	-0.18	0.32	0.40	0.30
	[0.09]	[0.15]	[3.25]	[0.14]
	0.05*	0.02**	0.94	<0.01***
Eff.N.obs.	150	121	128	111
Bandwidth	10.86	9	9.24	8.29

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 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, triangular kernels. Optimal bandwidths were calculated following Calonico et al. (2014). We report robust-bias corrected p-values and conventional (non-robust) estimates and standard errors.

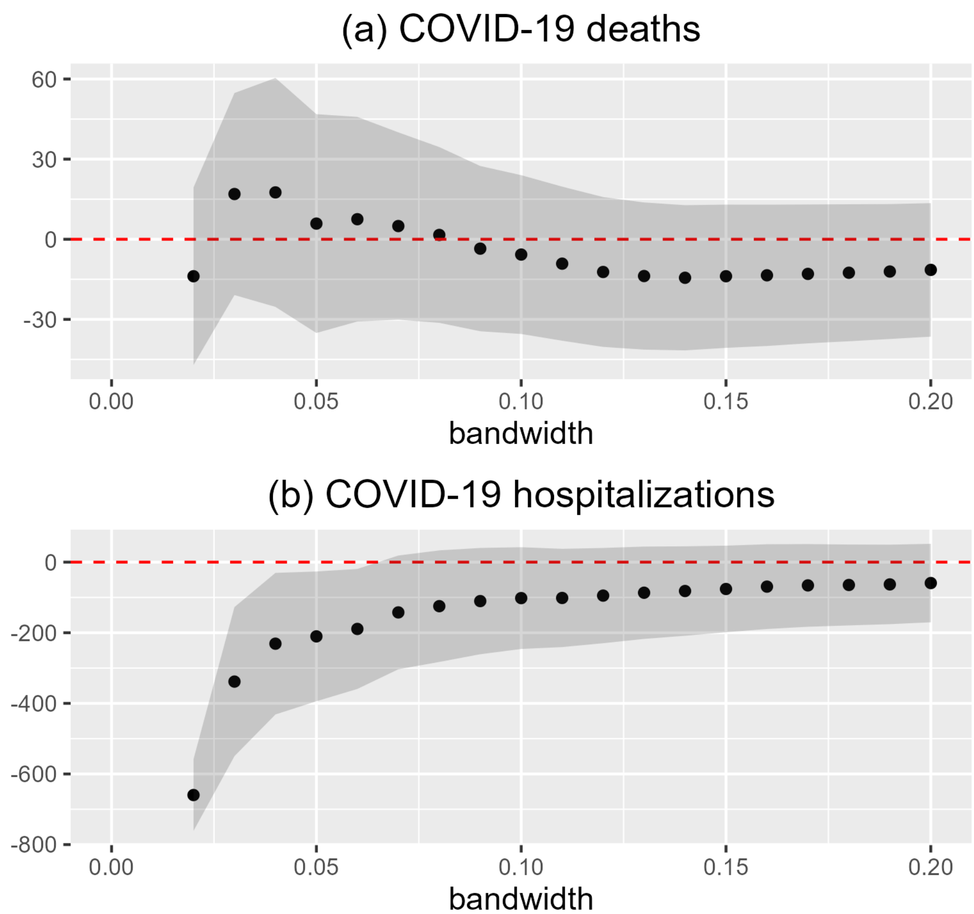
Impact of STEM Candidate Elected in 2016 on Non-Pharmaceutical Interventions

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	0.52	0.20	0.05	0.22	0.37	-0.31
	[0.33]	[0.07]	[0.19]	[0.17]	[0.27]	[0.17]
	<0.01***	0.01**	0.59	0.06*	<0.01***	0.16
Eff.N.obs.	95	97	97	97	95	98
Bandwidth	10	10	10	10	10	10

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, triangular 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, conventional (non-robust) estimates and standard errors.

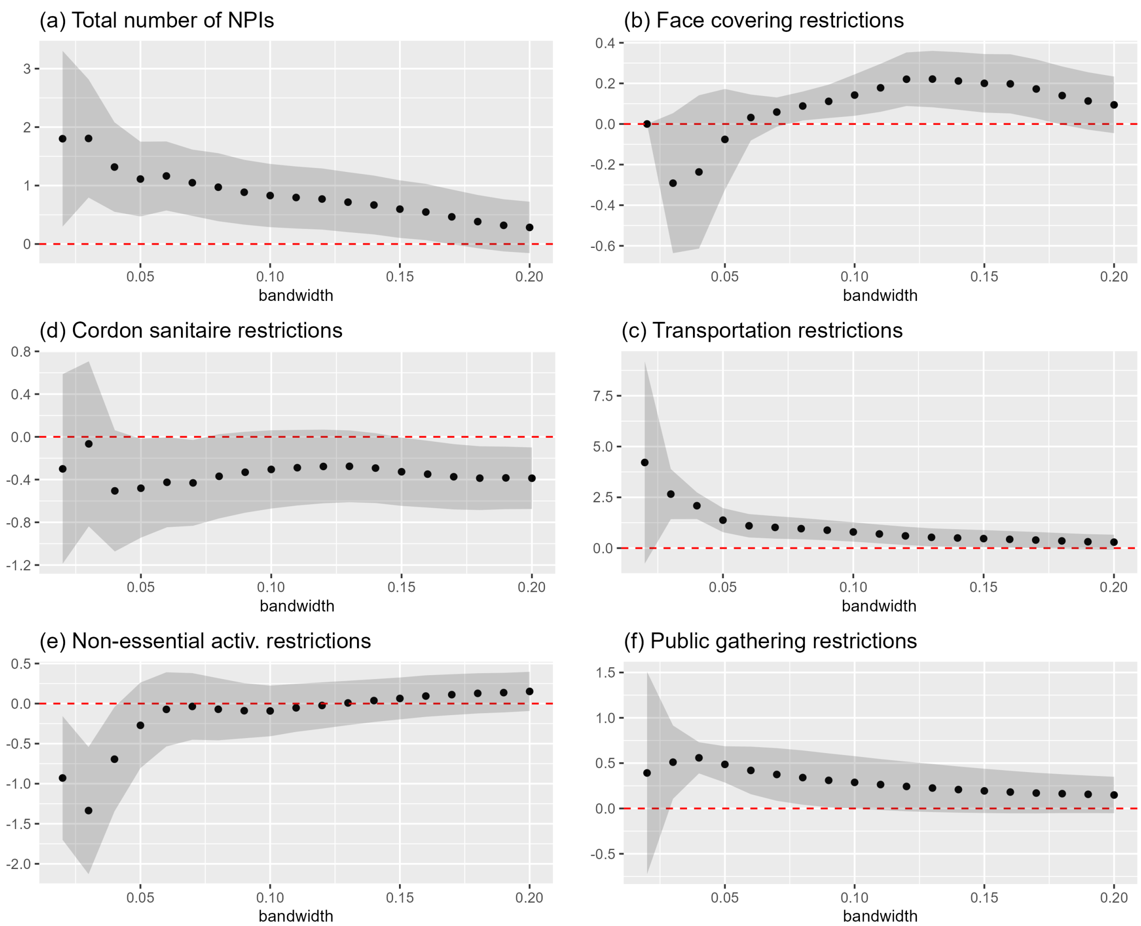
Impact of STEM mayor on epidemiological outcomes using different bandwidths



Notes:
This figure reports the RD estimated impact of mayors with scientific background on deaths and hospitalizations by COVID-19 per hundred thousand inhabitants. Municipalities chosen were those that held ordinary elections in selected years (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. 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.

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) 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, triangular kernel, and control for mayors' gender.

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	−27.581	−25.311	0.015
	(27.787)	(94.926)	(0.703)
Tenure Moderation Effect			−0.164
			(0.104)
Woman	1.454	−2.033	0.043
	(2.425)	(8.286)	(0.050)
mulher	−23.807	−3.806	0.731
	(24.495)	(83.678)	(0.545)
Observations	139	139	95
R^2	0.052	0.078	0.109
Adjusted R^2	−0.793	−0.743	−1.463
F Statistic	0.794 (df = 5; 73)	1.230 (df = 5; 73)	0.694 (df = 6; 34)
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. Municipalities chosen were those that held ordinary elections in selected years (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. The analysis incorporates moderation effects of scientific intensity, measured by tenure. The model controls for mayors' gender, and includes state fixed-effects.

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

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

	Dependent variable:		
	Hospitalizations	Deaths	NFI
	(1)	(2)	(3)
STEM Background	−11.607	61.048	0.263
	(21.386)	(67.395)	(0.425)
2015 Revenue	0.410	6.037^{***}	−0.010
	(0.563)	(1.773)	(0.011)
Revenue Modereration Effect	−0.257	-7.249^{***}	0.011
	(0.691)	(2.177)	(0.012)
Woman	−12.898	−8.464	0.108
	(17.031)	(53.672)	(0.301)
Observations	139	139	95
R^2	0.034	0.141	0.034
Adjusted R^2	−0.212	−0.077	−0.278
F Statistic	0.638 (df = 6; 110)	3.015^{***} (df = 6; 110)	0.422 (df = 6; 71)
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. Municipalities chosen were those that held ordinary elections in selected years (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. The analysis incorporates moderation effects of cities' level of development, indicated by revenue. The model controls for mayors' gender, and includes state fixed-effects.