Policy diffusion across municipal governments: Experimental evidence from Brazil

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Motivation - 1

- How do public policy innovations diffuse across governments?
- Sub-national polities as "laboratories of democracy" (Osborne 1988)
- A vast literature in political science studies the correlates of policy diffusion
  - Geographic proximity, ideological similarity, administrative slack, professional legislatures, etc.
- A key empirical challenge is to separate two broad classes of "mechanisms"
  - Correlated preferences and environments
  - Peer effects / spillovers: Learning, competition, socialization
  - And the interaction of these two forces (e.g. how are spillovers concentrated by geography or ideology or economic similarity?)

Motivation - 2

- How do policymakers learn about effective policies?
  - Through education and training
  - From their staff
  - From experience and experimentation
  - From the media
  - **From peers**
  - ...
- What is the structure and importance of policymaker peer networks?

This paper

1. Causal evidence on diffusion of a policy innovation across municipalities
   - Randomized seeding of information about an effective policy
   - Test for spillovers in policy adoption to geographically, politically, and economically close/similar municipalities

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2. Elicit policymaker peer networks among mayors in Brazil using surveys
   - Who has more vs. less connections?
   - Test for homophily across mayor demographics, political variables, and geography
   - Does the structure of the social network line up with the pattern of policy diffusion seen above?

Literature

- Research in political science and economics on policy diffusion
  - Why and how policy innovations diffuse
    (Walker 1969; Graham et al. 2012; Mallinson 2020; Boehmke et al. 2020; Wang and Yang 2025)
  - Decreasing importance of geography and demographics and greater importance of party control in US states
    (DellaVigna and Kim, 2024)

  → *We provide causal evidence using a randomized controlled trial*

- Research in economics and political science on policymaker networks
  (Battaglini and Patacchini 2019 review)
  - Networks of legislators and their voting patterns
    (Patterson 1959; Fowler 2006; Battglini et al. 2019)
  - Social connections between politicians and the rest of society
    (Bertrand et al. 2014; Burgess et al. 2015; Cruz et al. 2017)

  → *We directly elicit networks using surveys + provide evidence from a new context*

Context

- Municipal governments in Brazil
  - 5,570 municipalities in 26 states
  - Mayors are highly autonomous and responsible for key state functions
  - Mayoral terms are 4 years, can serve at most 2 consecutive terms
- We partnered with a non-partisan confederation of municipal governments, which organizes a number of conferences each year
  - Attended by many mayors and sometimes municipal secretaries and local legislators
  - We conducted a field experiment and various surveys at these conferences (previous results in Hjort et al. 2021)

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Note: These are in partially overlapping samples. Only some field experiment participants were surveyed and some surveyed mayors were not in the field experiment.

Field experiment: Diffusion of a policy innovation

- Field experiment with 1,818 mayors attending a conference in Brasilia
- Treatment group *invited* to information session
  - Topic: Interventions to increase tax compliance
  - Cost-effective policy: reminder letters to taxpayers
  - 45-min presentation + policy brief based on impact evaluations.
  - About 40% of invited treatment group showed up for an information session
- **Key outcome**: use of reminder letters by municipality 1.5-2 years later

Information Sessions

Reminder Letter Example

Dear Sir/Madam,

Your municipal tax payments are due by **01 November 2016**.

Our statistics show that the **vast majority of your neighbors will pay their taxes on time**. We greatly appreciate your doing the same.

Don't forget to report your taxes accurately and in a timely manner to avoid the **risk of an audit**, which is a time-consuming and costly process that may lead to substantial financial and other penalties if your tax reporting is found to be wrong.

It is easy to pay your taxes. Please follow the enclosed instructions for more information.

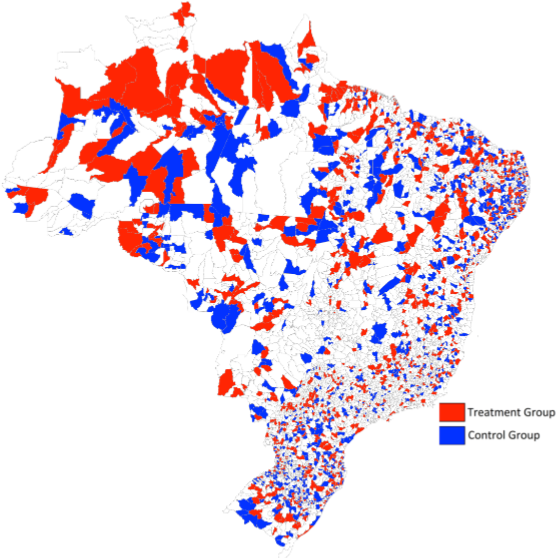
If you have already paid your taxes, thank you very much! If not, please act now.

Yours faithfully,
Name of Tax Authority

Why We Chose Tax-Reminder Letters

- Relevant problem in this context
  - 90% of municipalities raise some type of local tax
  - 15% of revenues are locally raised.
  - at least 20% of taxpayers do not comply with real estate taxes (De Cesare and Smolka, 2004)
- Reminder letters already used to some extent
- Limits the importance of other frictions → arguably a 'best case'
  - Low up-front financial cost
  - Simple to implement

Municipalities in the experiment



Direct effect: Being invited to info session increases use of reminder letters by 4 pp (ITT estimate from Hjort et al. 2021)

LHS Variable	(1) Adopted	(2) Adopted	(3) Adopted	(4) Adopted	(5) Adopted
Treatment	0.0402*	0.0422**	0.0392*	0.0469	0.0412*
	(0.0208)	(0.0206)	(0.0210)	(0.0321)	(0.0250)
Observations	2,271	2,269	2,054	912	1,357
Respondent	All	All	All	Mayor	Finance Staff
Attention Check	No	No	Yes	No	No
Mayor Characteristics	No	Yes	Yes	Yes	Yes
Municipal Characteristics	No	Yes	Yes	Yes	Yes
Clusters (Municipalities)	1465	1464	1412	912	1357
Mean Control	0.317	0.317	0.298	0.367	0.283

Testing for policy adoption spillovers

- Idea: exploit variation in the number of neighboring municipalities who were randomly treated
  - Vary definition of neighborhood to be state, meso-region, or distance bins
- Experiment not originally designed to measure spillovers (no randomized saturation design)
- Instead, rely on local variation in treatment intensity by chance
- Control for number of neighboring municipalities in the field experiment to begin with (since there is selection into conference)

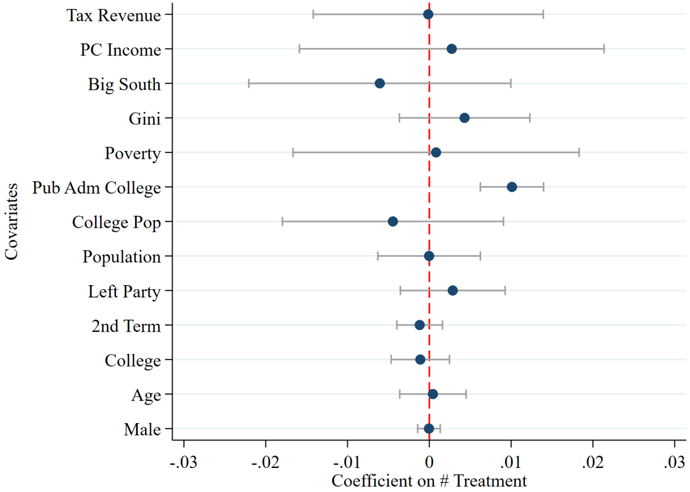
Econometric Specification

$$Y_{m,r} = \alpha + \beta \cdot \textbf{Number Treated}_{m,r} + \gamma \cdot \text{Number in Experiment}_{m,r} + \lambda T_m + \theta X_{m,r} + \epsilon_{m,r}$$

Where

- Y is an indicator for use of tax reminder-letters
- m indexes municipality and r indexes regions (states or meso regions or distance bins)
- β is the key coefficient and **Number treated** is the number of municipalities in the treatment group in region r, excluding m itself.
- T_m is the municipality's own treatment status, X is a vector of municipality controls
- Standard errors are clustered by region r
- Identifying assumption: Number of peers treated is exogenous conditional on controls

Balance: Number of neighbors treated uncorrelated with predetermined characteristics



Spillovers in policy adoption: within state

10 more municipalities in your state being treated increases your adoption by about 3 pp
Treatment had 15-18 pp effects on adoption through spillovers vs. just 4 pp from being directly treated

	Adopted (1)	Adopted (2)	Adopted (3)	Adopted (4)
Directly Treated	0.0371 *	0.0378 *	0.0514	0.0555
	(0.021)	(0.021)	(0.048)	(0.047)
Number treated in state	0.0027 **	0.0034 **	0.0027 *	0.0031 *
	(0.001)	(0.001)	(0.002)	(0.002)
Number in experiment in state	-0.0006	-0.0013 *	-0.0005	-0.0011
	(0.001)	(0.001)	(0.001)	(0.001)
Treatment * # Treated in state			0.0002	0.0005
			(0.003)	(0.003)
Treatment * # in Experiment in state			-0.0002	-0.0004
			(0.001)	(0.001)
Observations	2271	2269	2271	2269
Mayor/Municipal Characteristics	No	Yes	No	Yes
Mean Control	0.3174	0.3174	0.3174	0.3174

OLS (Leave-one-out) estimation results. The dependent variable is a dummy which takes the value of 1 if respondent says the policy was adopted in municipality. Treatment Assignment is a dummy which takes the value of 1 if the mayor was assigned to the treatment group. # of Neighbors in Treatment refers to the total number of municipalities within state assigned to Treatment. # of Neighbors in Experiment refers to the total number of municipalities within state in the experiment. Robust standard errors clustered at the state level are in parenthesis. $*p < 0.1, **p < 0.05, ***p < 0.01$

Spillovers in policy adoption: within 137 meso regions

10 more municipalities in your meso region being treated increases your adoption by about 6-10 pp

	Adopted (1)	Adopted (2)	Adopted (3)	Adopted (4)
Directly Treated	0.0380 *	0.0391 *	-0.0047	-0.0066
	(0.021)	(0.021)	(0.045)	(0.044)
Number treated in meso-region	0.0071	0.0097 ***	0.0089 **	0.0110 **
	(0.005)	(0.004)	(0.004)	(0.004)
Number in exp. in meso-region	-0.0029	-0.0044 **	-0.0048 *	-0.0062 **
	(0.002)	(0.002)	(0.003)	(0.003)
Treatment * Number Treated			-0.0040	-0.0031
			(0.009)	(0.009)
Treatment * Number in Experiment			0.0041	0.0038
			(0.005)	(0.005)
Observations	2271	2269	2271	2269
Mayor/Municipal Characteristics	No	Yes	No	Yes
Mean Control	0.3174	0.3174	0.3174	0.3174

OLS (Leave-one-out) estimation results. The dependent variable is a dummy which takes the value of 1 if respondent says the policy was adopted in municipality. Treatment Assignment is a dummy which takes the value of 1 if the mayor was assigned to the treatment group. # of Neighbors in Treatment refers to the total number of municipalities within meso region assigned to Treatment. # of Neighbors in Experiment refers to the total number of municipalities within meso region in the experiment. Robust standard errors clustered at the meso region level are in parenthesis. $*p < 0.1, **p < 0.05, ***p < 0.01$

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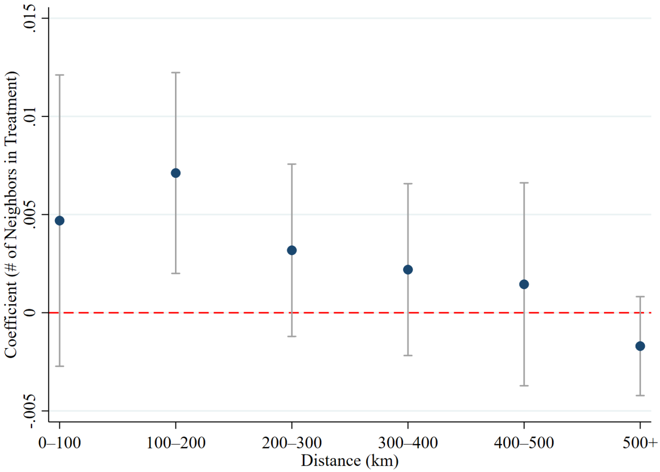
Spillovers in policy adoption: By distance bins



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Policy diffusion by geography, demographic, and political similarity

- So far, we considered spillovers by geographic proximity
- DellaVigna and Kim (2024) show that, in the US, policy diffusion across states is increasingly driven by political party (and less by geography and demographics/economics)

Limited evidence of spillovers within political party

Note: political parties are relatively weak in Brazil at municipal level. Possibly larger effects within state.

	Adopted	
	Nationwide	Within State
Directly Treated	0.0409**	0.0403*
	(0.0207)	(0.0235)
Number treated in own party	0.0011	0.0060
	(0.0014)	(0.0044)
Number in exp. in own party	-0.0006	-0.0020
	(0.0007)	(0.0025)
Observations	2,269	2,269
Mayor/Municipal Characteristics	Yes	Yes
Control mean	0.317	0.317

OLS estimation results. The dependent variable is a dummy which takes the value of 1 if respondent says the policy was adopted in municipality. Treatment Assignment is a dummy which takes the value of 1 if the mayor was assigned to the treatment group. # of Neighbors in Treatment refers to the total number of municipalities within political party assigned to Treatment. # of Neighbors in Experiment refers to the total number of municipalities within political party in the experiment. Robust standard errors clustered at the municipal level are in parenthesis. $*p < 0.1, **p < 0.05, ***p < 0.01$

Geography, demographics/economics, and politics

- We next take a broader view of policy diffusion networks:
  - Geographic proximity
  - Political / ideological similarity
  - Demographic / economic similarity
- Following DellaVigna and Kim (2024): For each pair of municipalities, we construct an index of distance along these dimensions
- And then we test for spillovers from the number treated within the closest n municipalities by each dimension

Constructing the measures of political and demographic/economic distance

For each pair of municipalities, we compute the absolute difference in each (standardized) variable and then average the differences to create an index

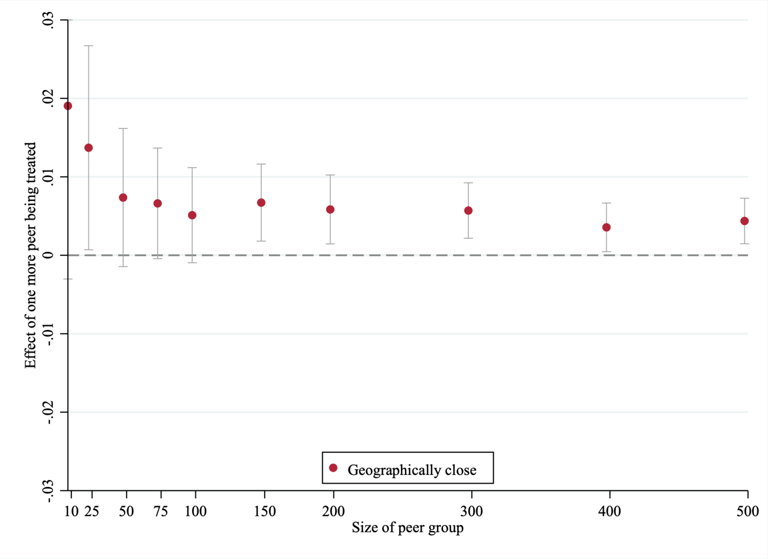
- Geographic Proximity: distance
- Political/Ideological Similarity: Political Index detail
  i. Share of votes for Bolsonaro in the 2018 presidential elections
  ii. Party ideology rated by political scientists (Bolognesi et al., 2022)
  iii. Party ideology rated by members of Congress (Zucco, 2017).
- Demographic/Economic Similarity:
  i. Log population
  ii. Share of urban population
  iii. Log income per capita
  iv. Share of employment in agriculture
  v. Share of employment in manufacturing
  vi. Poverty rate

Econometric Specification

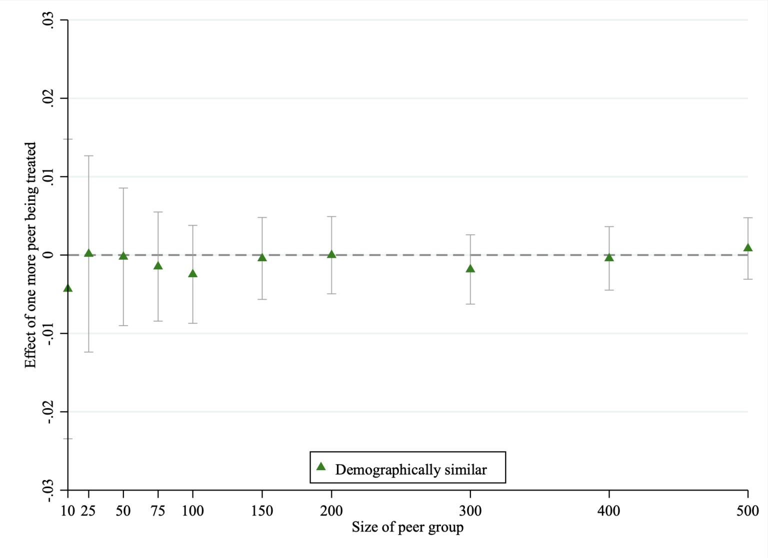
$$Y_m = \alpha + \sum_{i=1}^{3} \beta_i \cdot \textbf{Num treated}_{m,i} + \sum_{i=1}^{3} \gamma_i \, \text{Num in experim}_{m,i} + \lambda T_m + \theta X_m + \epsilon_m$$

- Similar identification strategy as before
- Key independent variable: number of municipalities randomly treated within the set of closest n municipalities by dimension
  - Vary n to consider smaller vs. larger peer groups
  - Vary closest n nationwide versus closest n within state
  - Always control for number of closest n municipalities in the experiment

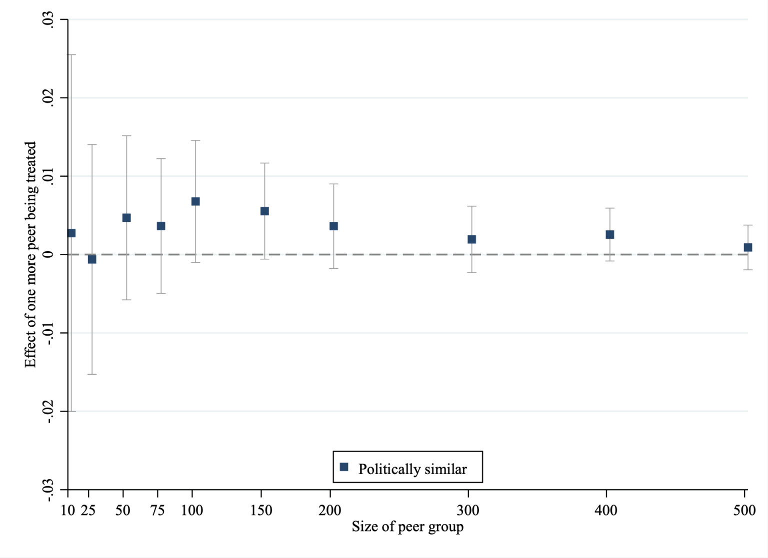
Spillovers from geographically closest municipalities nationwide



Spillovers from demographically/economically similar municipalities nationwide

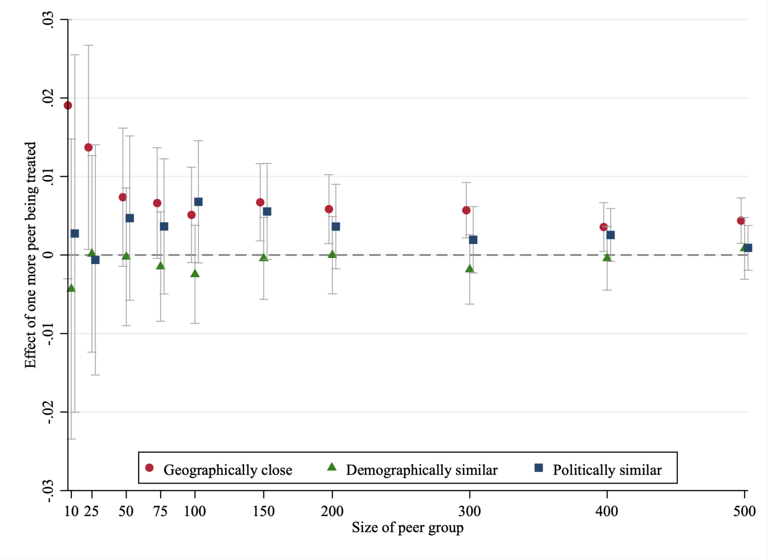


Spillovers from politically similar municipalities nationwide

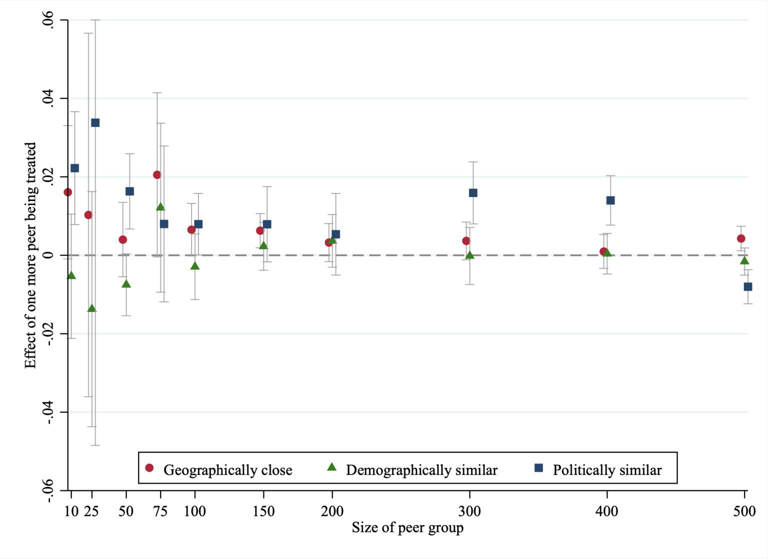


Combining geography, politics, and demographics

Spillovers strongest from geographically closest municipalities; But political similarity also matters



Politics matters more when looking within state



Regressions: Spillovers within state

Size of peer group	10	20	50	100	200
Directly Treated	0.0432	0.0420	0.0445*	0.0409	0.0392
	(0.0256)	(0.0248)	(0.0252)	(0.0248)	(0.0241)
Number of peers treated (Geographically close)	0.0159*	0.0180**	0.0036	0.0060*	0.0035
	(0.0084)	(0.0074)	(0.0046)	(0.0033)	(0.0024)
Number of peers treated (Demographically similar)	-0.0040	-0.0055	-0.0062	-0.0004	0.0031
	(0.0081)	(0.0058)	(0.0039)	(0.0035)	(0.0034)
Number of peers treated (Politically similar)	0.0235***	0.0200***	0.0171***	0.0106**	0.0046
	(0.0073)	(0.0067)	(0.0047)	(0.0040)	(0.0053)
Observations	2168	2168	2168	2168	2168
Controls	Yes	Yes	Yes	Yes	Yes
Predicted value when T and #T are 0	0.255	0.206	0.200	0.046	-0.044
Estimated aggregate spillover	0.061	0.110	0.115	0.271	0.362

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  1. Diffusion of information regarding the policy
     - It's existence
     - How to implement it
     - It's efficacy
     - ...
  2. And for the policy to seem to be a good idea / fit for the municipality that learns about it
- We next turn to examining the self-reported social networks between mayors, which possibly underlie step 1 above

Network eliciation survey question

In a survey of 829 mayors at the same conference, we asked the following question:

Could you please list the names of the currently serving mayors of other municipalities with whom you have talked regularly (on the phone or in person) during the last 6 months?

(List up to 10, starting with the mayor you talked to the most, then the mayor you talked to the second most, and so on. If you did not talk to any, leave this section blank).

Who is more connected? Mayor Characteristics

Younger, college-educated, 2nd term mayors have more connections

LHS Variable	(1) Number of Connections	(2) Number of Connections
Male	0.417	0.375
	(0.360)	(0.373)
Age (years)	-0.028 **	-0.028 **
	(0.011)	(0.011)
College Educated	0.519 **	0.455 *
	(0.245)	(0.248)
2nd Term	2.352 ***	2.358 ***
	(0.299)	(0.302)
Own political views (Left-Right 0/10)	0.141	0.131
	(0.116)	(0.117)
Leftist Political Party	0.115	0.095
	(0.244)	(0.246)
Constant	5.886 ***	6.434 ***
	(0.698)	(1.278)
R-squared	0.08	0.08
Observations	788	787
Municipal Characteristics	No	Yes

Notes: Response variable is number of connections (0/10). 'Own political views' is a standardized variable. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Testing for homophily: When are two mayors more likely to be connected?

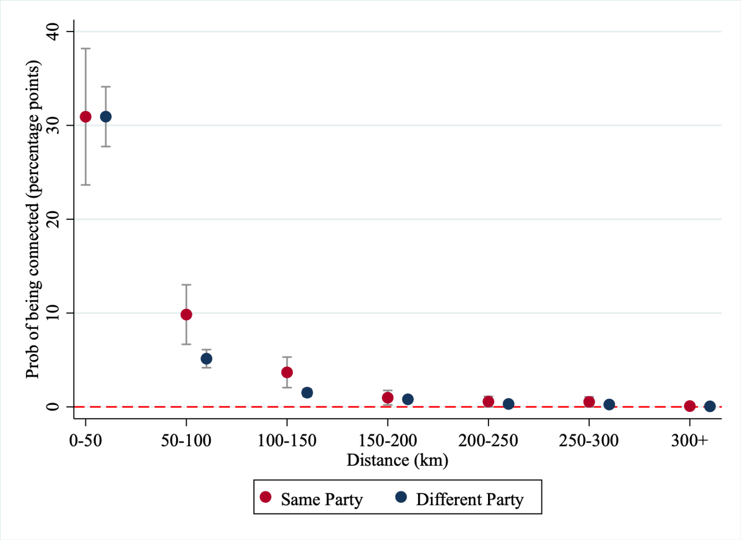
Geographic proximity is by far the biggest factor; Party, and ideological match also matter

	Pair of mayors connected									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Same gender	0.061***									-0.013
	(0.018)									(0.018)
Same age		0.023								0.028
		(0.017)								(0.018)
Similar education level			-0.002							-0.012
			(0.015)							(0.015)
Same party				0.194***						0.071**
				(0.038)						(0.036)
Same mandate					-0.024					-0.020
					(0.019)					(0.020)
Ideological distance (std)						-0.020***				-0.014*
						(0.008)				(0.008)
Same state							2.955***			1.346***
							(0.132)			(0.096)
Geographic distance (100km)								12.763***		12.078***
								(0.584)		(0.599)
Similar population									0.113***	-0.006
									(0.042)	(0.043)
Constant	0.160***	0.202***	0.210***	0.190***	0.227***	0.212***	0.008***	0.065***	0.201***	0.003
	(0.016)	(0.010)	(0.012)	(0.008)	(0.017)	(0.009)	(0.002)	(0.005)	(0.008)	(0.026)
Observations	334971	334971	334971	334971	334971	304590	334971	334971	334971	304590
R^2	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000	0.0265	0.0869	0.0000	0.0945

Notes: The sample includes 334,971 connections between municipalities' mayors. The dependent variable is a dummy that equals 1 if the mayors are connected. Ideological distance represents the standardized values of the difference in self-reported political views (Left-Right 0/10) between mayors. All other variables are binary, taking the value of 1 if both mayors belong to the same group based on gender, age (within a 5-year difference), education, state, population size (within a 100,000-inhabitant difference), geographic distance (within a 100km distance), political party, or electoral term. Robust standard errors clustered at the municipality level are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

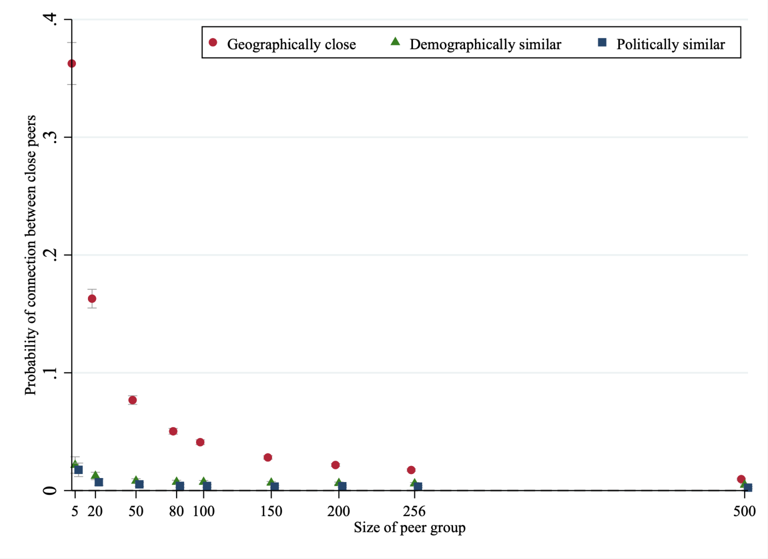
link

Distance, Party Affiliation, and Probability of Connection



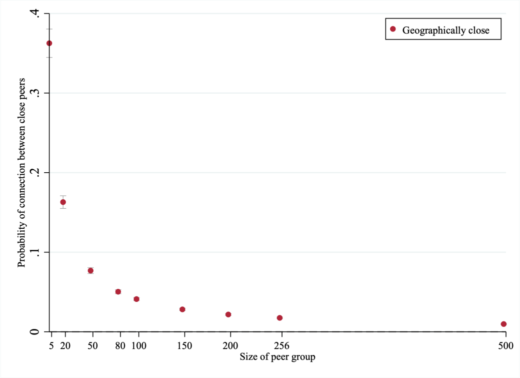
Geography is vastly more important as predictor of network connections

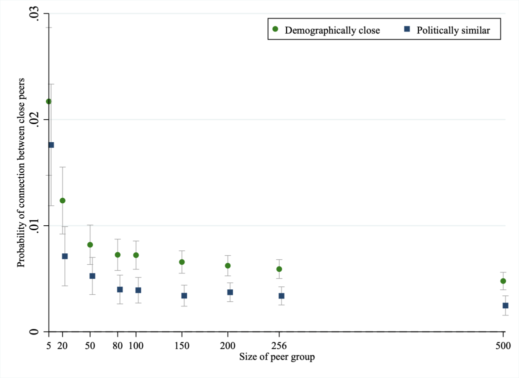
Within state



Demographics and politics matter too

Within state





Connecting policy spillovers to network connection probability

	Adoption
Directly Treated	0.0397*
	(0.021)
Expected # Connections in Treatment group	0.0573*
	(0.031)
Expected # Connections in Experiment	-0.0341***
	(0.019)
Observations	2248
Mayor/Municipal Characteristics	Yes
Mean Control	0.3190

OLS estimation results. The dependent variable is a dummy which takes the value of 1 if respondent says the policy was adopted in municipality. Treatment Assignment is a dummy which takes the value of 1 if the mayor was assigned to the treatment group. Expected # Connections in Treatment refers to the total number of municipalities in treatment weighted by their connection probability. Robust standard errors clustered at the municipal level are in parenthesis. $*p < 0.1, **p < 0.05, ***p < 0.01$

Summary and Conclusion - 1

- Robust evidence of policy spillovers from the randomized information provision regarding an effective policy
  - Quantitatively large effects
  - Info provision regarding effective policies becomes (much) more powerful once spillovers are considered
  - Spillover effects just as large for directly treated municipalities: suggests mechanism is *not* merely learning about existence of policy

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- Understanding role of geography, politics, and demographics/economics in directing spillovers
  - When considering all municipalities nationwide, geographic proximity is the strongest predictor of spillovers
  - Within state, political similarity is as strong a predictor (or stronger) than geographic proximity
  - No evidence of spillovers to other demographically/economically similar municipalities

Summary and Conclusion - 2

- Measured social networks of mayors to understand a possible channel for policy diffusion
  - Here, geography is vastly more important than demographics and politics
  - Cross-party conversations almost as likely as within-party connections when municipalities are close to each other
  - Political similarity plays a *relatively* more important role for policy diffusion than for mayoral connections
    - Suggests role for other actors than mayor?
    - Or that politically similar municipalities have similar policy environments?
    - Yet no role for demographics/economics in policy diffusion!

Backup slides

Balance Table

All respondents

Variables	Survey and Endline sample - All respondents Mean Control	Δ Treatment
Mayors' Characteristics		
Male	88.95	2.67
Age (years)	46.22	2.01 ***
College Educated	63.75	1.41
2nd Term	10.28	6.06 ***
Leftist Political Party	35.99	-1.15
Municipalities' Characteristics		
Population 2016	20.79	-2.31 **
College Educated Population	5.82	-0.29
Public Adm College Educated	32.78	0.48
Poverty	22.02	-1.25
Gini	49.73	-0.24
Big South	65.04	-0.95
Per Capita Income	506.25	6.64
Local Taxes Revenues (2010-15)	6.87	-0.71 **
Sample	389	465
Joint F-test (p-value)		0.00

Notes: Sample mean by experimental group in the sample that answered the CNG and endline surveys. Mean-comparison t-tests between groups. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Balance Table

Variables	Survey and Endline sample Mean Control	Δ Treatment
Mayors' Characteristics		
Male	90.00	2.00
Age (years)	46.61	1.91 *
College Educated	64.12	2.38
2nd Term	9.41	6.59 *
Leftist Political Party	35.29	0.21
Municipalities' Characteristics		
Population 2016	20.31	-2.28
College Educated Population	5.84	-0.16
Public Adm College Educated	33.02	0.27
Poverty	22.54	-2.81
Gini	49.84	-0.81
Big South	64.71	0.79
Per Capita Income	499.99	21.17
Local Taxes Revenues (2010-15)	6.63	-0.39
Sample	170	200
Joint F-test (p-value)		0.02

Notes: Sample mean by experimental group in the sample that answered the CNG and endline surveys. Mean-comparison t-tests between groups. *** p<0.01, ** p<0.05, * p<0.1

Predictors of Session Participation

LHS Variable	Information Session Participation			
	(1)	(2)	(3)	(4)
Number of Treatment Connections	0.0268	0.0224		
	(0.031)	(0.032)		
Any Treatment Connections			-0.0848	-0.0959
			(0.062)	(0.062)
Number of Connections in Experiment	-0.0005	-0.0696	0.0305 *	0.0271 *
	(0.021)	(0.070)	(0.016)	(0.016)
Constant	0.7371 ***	1.0051 ***	0.7479 ***	1.0284 ***
	(0.032)	(0.123)	(0.033)	(0.124)
Observations	343	343	343	343
Individual/Municipal Controls	No	Yes	No	Yes
R-squared	0.00	0.02	0.01	0.03

Linear probability results. Response variable is information session participation (1/0). We control for unbalanced characteristics in the sample (Male, College and 2nd term). Robust standard errors are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Predictors of Policy Adoption – Reminder Letters

All respondents

LHS Variable	Tax Reminders Adoption			
	(1)	(2)	(3)	(4)
Treatment	0.0683	0.0620	0.0671	0.0605
	(0.042)	(0.042)	(0.047)	(0.047)
# of Treated Connections	-0.0025	-0.0017		
	(0.022)	(0.022)		
Any Treated Connection			-0.0110	-0.0135
			(0.056)	(0.056)
Treatment*Treated Connections	0.0222	0.0212		
	(0.015)	(0.015)		
Treatment*Any Treated Connection			0.0206	0.0207
			(0.013)	(0.013)
# Connections in Experiment	-0.0218	-0.0198	-0.0475	-0.0429
	(0.024)	(0.024)	(0.069)	(0.069)
Constant	0.2644 ***	0.1872 ***	0.2703 ***	0.1896 ***
	(0.036)	(0.060)	(0.038)	(0.062)
Observations	848	848	848	848
Individual/Municipal Controls	No	Yes	No	Yes
R-squared	0.02	0.02	0.02	0.02

OLS estimation results. Dependent variable tax reminders adoption (1/0, if respondent says the policy was adopted in municipality). Treatment Assignment is a dummy which takes the value of 1 if the mayor was assigned to the treatment group. We control for individual characteristics (Male and 2nd term). Robust standard errors clustered at the municipality level are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Predictors of Beliefs Accuracy

LHS Variable	Beliefs accuracy			
	(1)	(2)	(3)	(4)
Treatment	0.1792	0.1645	0.2551	0.2488
	(0.368)	(0.372)	(0.379)	(0.384)
# of Treated Connections	-0.1567	-0.1533		
	(0.428)	(0.424)		
Any Treated Connection			0.2615	0.2613
			(0.598)	(0.596)
Treatment*Treated Connections	-0.2334 **	-0.2440 **		
	(0.117)	(0.117)		
Treatment*Any Treated Connection			-0.2578 **	-0.2659 **
			(0.112)	(0.112)
# Connections in Experiment	0.3702	0.3486	0.0861	0.0268
	(0.493)	(0.493)	(0.726)	(0.735)
Constant	-6.3841 ***	-6.0132 ***	-6.4365 ***	-6.0598 ***
	(0.297)	(0.477)	(0.303)	(0.480)
Observations	826	826	826	826
Individual/Municipal Controls	No	Yes	No	Yes
R-squared	0.01	0.01	0.01	0.01

Notes: OLS estimation results. The dependent variable is the absolute difference between self-reported beliefs about effect sizes of policy on local tax revenues, and the informed effect size of the reminder letters policy during the information session. We control for unbalanced characteristics in the sample (Male and 2nd term). Robust standard errors clustered at the municipality level are in parenthesis. * p ¡ 0.1, ** p ¡ 0.05, *** p ¡ 0.01

Testing for homophily: bivariate regressions

	Connection (p.p.)	Constant (p.p.)
Mayors' characteristics		
Same gender	0.05 ***	0.12
	(0.011)	(0.010)
Similar age	0.03 ***	0.15
	(0.011)	(0.006)
Similar level of education	0.01	0.16
	(0.010)	(0.007)
Geographical characteristics		
Same state	2.34 ***	0.00
	(0.090)	(0.001)
Similar population size	0.08 ***	0.16
	(0.024)	(0.005)
Political characteristics		
Same party	0.13 ***	0.15
	(0.024)	(0.005)
Same Electoral Term	-0.02 *	0.18
	(0.012)	(0.011)
Ideological distance	-0.01 **	0.18
	(0.003)	(0.009)

Notes: The sample includes 620,156 connections between municipalities' mayors. The dependent variable is a dummy that equals 1 if the mayors are connected. Ideological distance represents the standardized values of the difference in self-reported political views (Left-Right 0/10) between mayors. All other variables are binary, taking the value of 1 if both mayors belong to the same group based on gender, age (within a 5-year difference), education, state, population size (within a 100,000-inhabitant difference), political party, or electoral term. Robust standard errors clustered at the municipality level are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Testing for homophily: Directed

	Pair of mayors connected									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Same gender	0.042***									-0.004
	(0.011)									(0.012)
Same age		0.013								0.016
		(0.010)								(0.010)
Similar education level			0.001							-0.005
			(0.009)							(0.009)
Same party				0.124***						0.046**
				(0.021)						(0.020)
Same mandate					-0.017					-0.015
					(0.011)					(0.011)
Ideological distance (std)						-0.012***				-0.008*
						(0.004)				(0.005)
Same state							1.821***			0.787***
							(0.078)			(0.055)
Geographic distance (100km)								8.171***		7.840***
								(0.364)		(0.376)
Similar population									0.078***	0.003
									(0.022)	(0.022)
Constant	0.094***	0.124***	0.127***	0.116***	0.141***	0.131***	0.004***	0.036***	0.123***	-0.002
	(0.009)	(0.006)	(0.007)	(0.005)	(0.009)	(0.005)	(0.001)	(0.003)	(0.005)	(0.016)
Observations	669942	669942	669942	669942	669942	609180	669942	669942	669942	609180
R^2	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0164	0.0581	0.0000	0.0630

Notes: The sample includes 669,942 connections between municipalities' mayors. The dependent variable is a dummy that equals 1 if the mayors are connected. Ideological distance represents the standardized values of the difference in self-reported political views (Left-Right 0/10) between mayors. All other variables are binary, taking the value of 1 if both mayors belong to the same group based on gender, age (within a 5-year difference), education, state, population size (within a 100,000-inhabitant difference), geographic distance (within a 100km distance), political party, or electoral term. Robust standard errors clustered at the municipality level are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

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Testing for homophily: Composite Index

NATIONAL

Distance (in rank)	Connection: Within geogr. dist.	Within demogr. dist.	Within polit. dist.	N	R2	Mean Difference Tests: (1x2)	(1x3)	(2x3)
2	0.4748 *** (0.0135)	0.0059 ** (0.0024)	0.0011 (0.0011)	4555442	0.0935	0.0000	0.0000	0.0711
5	0.3614 *** (0.0089)	0.0068 *** (0.0016)	0.0032 *** (0.0010)	4555442	0.1355	0.0000	0.0000	0.0528
10	0.2578 *** (0.0062)	0.0040 *** (0.0010)	0.0027 *** (0.0008)	4555442	0.1377	0.0000	0.0000	0.2669
15	0.2012 *** (0.0048)	0.0039 *** (0.0009)	0.0026 *** (0.0006)	4555442	0.1259	0.0000	0.0000	0.1934
20	0.1649 *** (0.0040)	0.0035 *** (0.0007)	0.0027 *** (0.0006)	4555442	0.1127	0.0000	0.0000	0.3316
35	0.1063 *** (0.0025)	0.0030 *** (0.0005)	0.0021 *** (0.0004)	4555442	0.0819	0.0000	0.0000	0.1817
50	0.0791 *** (0.0018)	0.0030 *** (0.0004)	0.0019 *** (0.0004)	4555442	0.0648	0.0000	0.0000	0.0533
65	0.0627 *** (0.0014)	0.0030 *** (0.0004)	0.0021 *** (0.0003)	4555442	0.0529	0.0000	0.0000	0.0752
80	0.0518 *** (0.0012)	0.0029 *** (0.0003)	0.0022 *** (0.0003)	4555442	0.0445	0.0000	0.0000	0.1008
100	0.0421 *** (0.0010)	0.0027 *** (0.0003)	0.0020 *** (0.0003)	4555442	0.0367	0.0000	0.0000	0.1052
150	0.0288 *** (0.0007)	0.0023 *** (0.0002)	0.0016 *** (0.0002)	4555442	0.0259	0.0000	0.0000	0.0110
200	0.0219 *** (0.0005)	0.0022 *** (0.0002)	0.0014 *** (0.0002)	4555442	0.0200	0.0000	0.0000	0.0021
256	0.0173 *** (0.0004)	0.0021 *** (0.0002)	0.0013 *** (0.0001)	4555442	0.0159	0.0000	0.0000	0.0003
500	0.0089 *** (0.0002)	0.0016 *** (0.0001)	0.0009 *** (0.0001)	4555442	0.0084	0.0000	0.0000	0.0000

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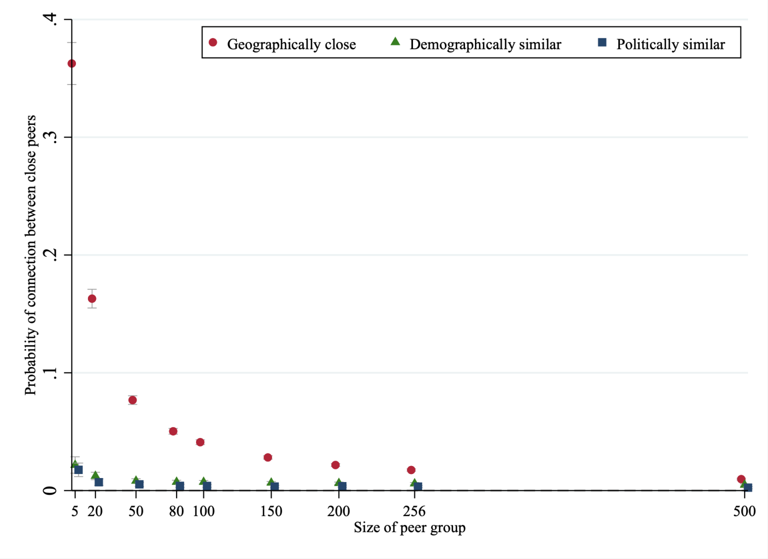
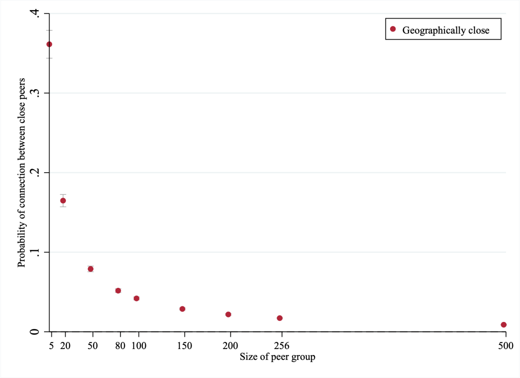
Testing for homophily: Composite Index

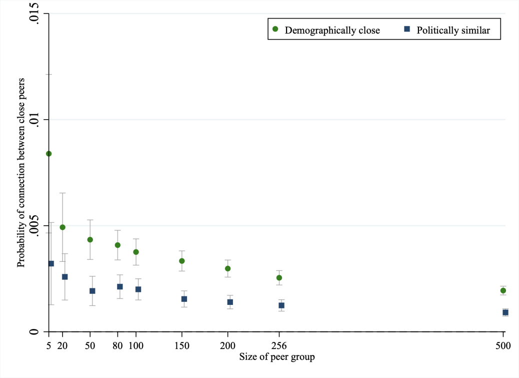
NATIONAL



Testing for homophily: Composite Index

NATIONAL





Testing for homophily: Composite Index

STATE

Distance	Connection					Mean Difference Tests		
(in rank)	Within geogr. dist.	Within demogr. dist.	Within polit. dist.	N	R2	(1x2)	(1x3)	(2x3)
2	0.4790 ***	0.0346 ***	0.0177 ***	306851	0.1034	0.0000	0.0000	0.0158
	(0.0136)	(0.0058)	(0.0046)					
5	0.3631 ***	0.0174 ***	0.0182 ***	306851	0.1459	0.0000	0.0000	0.8477
	(0.0091)	(0.0034)	(0.0029)					
10	0.2597 ***	0.0114 ***	0.0101 ***	306851	0.1470	0.0000	0.0000	0.6503
	(0.0064)	(0.0023)	(0.0021)					
15	0.2007 ***	0.0095 ***	0.0093 ***	306851	0.1305	0.0000	0.0000	0.9082
	(0.0050)	(0.0018)	(0.0017)					
20	0.1634 ***	0.0097 ***	0.0076 ***	306851	0.1142	0.0000	0.0000	0.2712
	(0.0041)	(0.0015)	(0.0014)					
35	0.1049 ***	0.0077 ***	0.0066 ***	306851	0.0799	0.0000	0.0000	0.4595
	(0.0026)	(0.0012)	(0.0011)					
50	0.0771 ***	0.0071 ***	0.0055 ***	306851	0.0601	0.0000	0.0000	0.1821
	(0.0019)	(0.0009)	(0.0009)					
65	0.0610 ***	0.0063 ***	0.0047 ***	306851	0.0473	0.0000	0.0000	0.1480
	(0.0015)	(0.0008)	(0.0008)					
80	0.0506 ***	0.0058 ***	0.0044 ***	306851	0.0388	0.0000	0.0000	0.1606
	(0.0012)	(0.0007)	(0.0007)					
100	0.0414 ***	0.0056 ***	0.0042 ***	306851	0.0309	0.0000	0.0000	0.1321
	(0.0010)	(0.0007)	(0.0006)					
150	0.0284 ***	0.0057 ***	0.0036 ***	306851	0.0195	0.0000	0.0000	0.0060
	(0.0008)	(0.0005)	(0.0005)					
200	0.0219 ***	0.0056 ***	0.0039 ***	306851	0.0140	0.0000	0.0000	0.0126
	(0.0006)	(0.0005)	(0.0004)					
256	0.0176 ***	0.0053 ***	0.0034 ***	306851	0.0104	0.0000	0.0000	0.0034
	(0.0005)	(0.0005)	(0.0004)					
500	0.0100 ***	0.0041 ***	0.0025 ***	306851	0.0042	0.0000	0.0000	0.0243
	(0.0004)	(0.0005)	(0.0005)					

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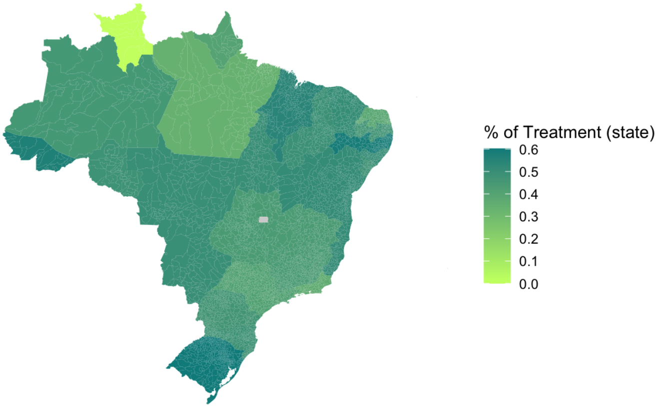
Variation in Policy innovation: % of Treatment in State



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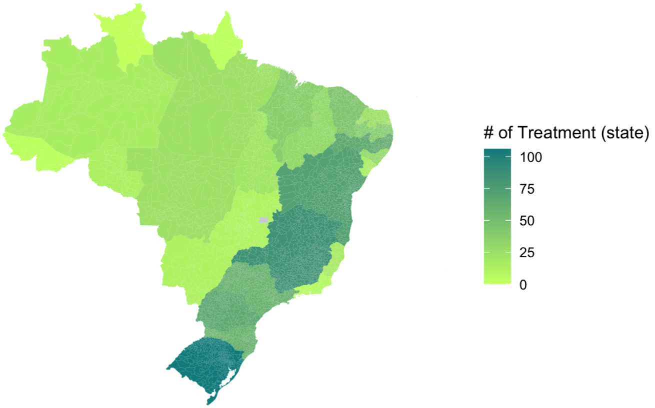
Variation in Policy innovation: # of Treatment in State



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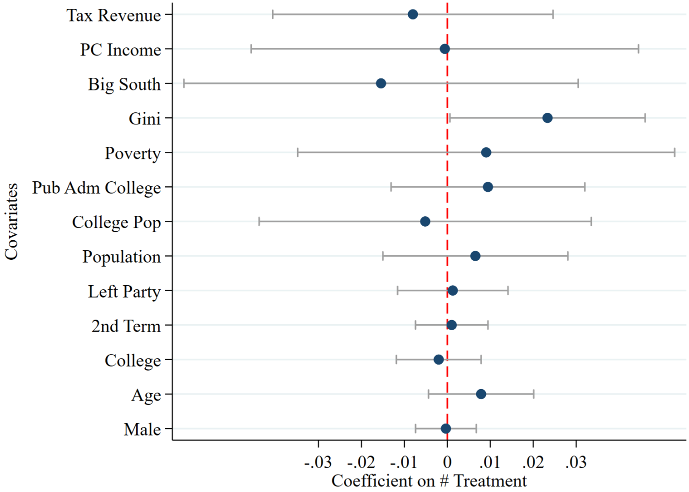
Balance: Placebo regressions using predetermined covariates # of Treated Neighbors in your meso region



Diffusion of policy innovation

information of policy-effectiveness to a sample of municipalities spills over to the adoption of that policy in the vicinity of treated municipalities

	Adopted (1)	Adopted (2)	Adopted (3)	Adopted (4)
Treatment	0.0382	0.0396	0.1469	0.1222
	(0.024)	(0.023)	(0.200)	(0.179)
% of Treatment in region	0.4693 **	0.5269 ***	0.5751 **	0.6060 **
	(0.209)	(0.151)	(0.253)	(0.288)
Treatment * % of Treatment in region			-0.2233	-0.1697
			(0.419)	(0.371)
Observations	2271	2269	2271	2269
Mayor/Municipal Characteristics	No	Yes	No	Yes
Mean Control	0.3174	0.3174	0.3174	0.3174

OLS (Leave-one-out) estimation results. The dependent variable is a dummy which takes the value of 1 if respondent says the policy was adopted in municipality. Treatment Assignment is a dummy which takes the value of 1 if the mayor was assigned to the treatment group. Share of Treatment in State refers to the total number of municipalities assigned to treatment divided by the total number of municipalities included in the experiment in that state. Robust standard errors clustered at the state level are in parenthesis. $*p < 0.1, **p < 0.05, ***p < 0.01$

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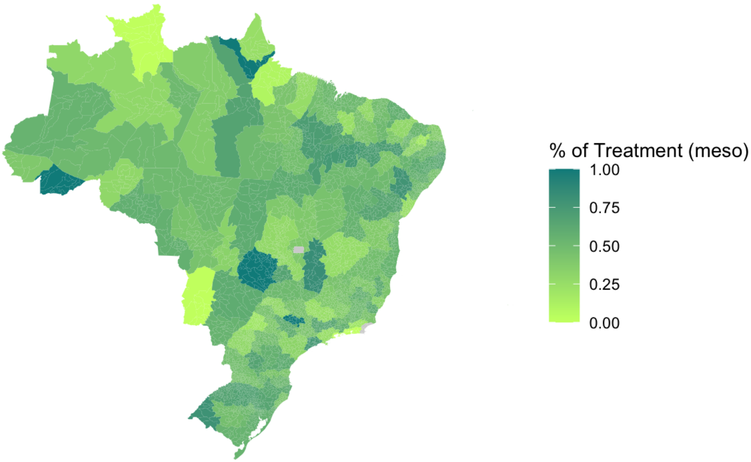
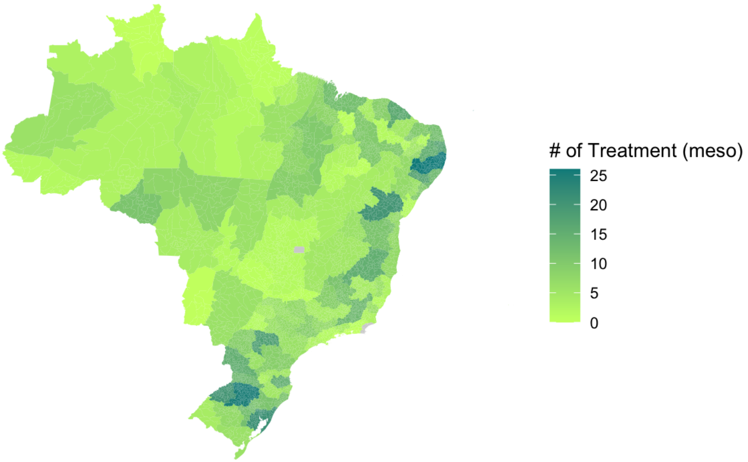
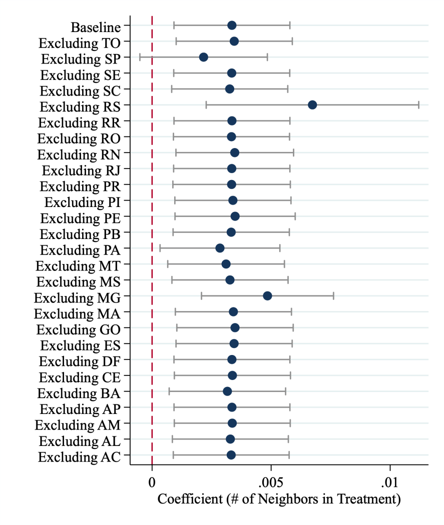
Variation in share of treated by meso region



Variation in number treated by meso region



State Spillovers - Leave-one-out



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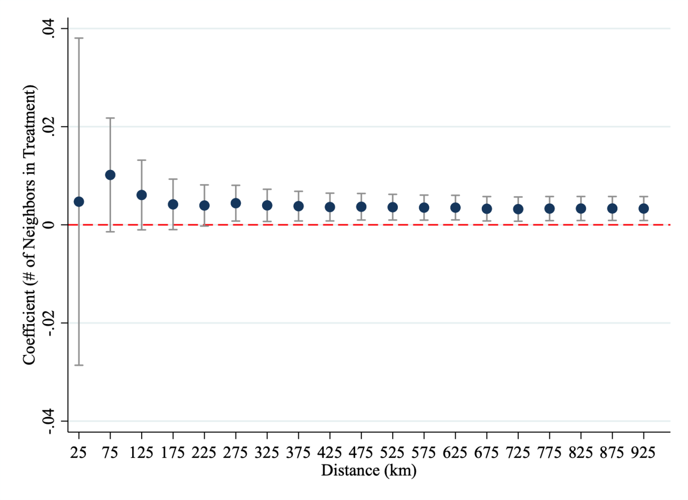
Spillovers - Distance



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Spillovers by Index regressions: Descriptives

# of Treatment Municipalities within 150 closest	Mean	SD	Min	Max
Geographical Distance	25.746	10.034	3	58
Demographical Distance	30.291	7.645	10	50
Political Distance	24.310	5.658	9	41

Statistics for the number of municipalities within treatment inside a 150 distance in terms of different rankings. Geographical distance looks at the 150 closest (in km) municipalities, and counts how many are within the treatment group. Demographical distance looks at the 150 most similar municipalities in terms of urban population percentage, per capita income, total population, poverty rate and employment shares in agriculture and industry. Political distance takes into account the mayor's party ideology (fitted from 0, most left-winged, to 10, most right-winged) and the vote share for former president Jair Bolsonaro in the 2018 presidential election.

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Spillovers by Index regressions: Regression Table

Rank Distance	Adopted (1)	Adopted (2)
Treatment	0.0493 **	0.0470 **
	(0.021)	(0.022)
Tr. within Geog. Rank	0.0070 ***	0.0066 ***
	(0.002)	(0.002)
Tr. within Demog. Rank	-0.0007	-0.0021
	(0.003)	(0.003)
Tr. within Polit. Rank	0.0059 **	0.0050
	(0.003)	(0.003)
Exp. within Geog. Rank	-0.0045 ***	-0.0035 **
	(0.002)	(0.002)
Exp. within Demog. Rank	0.0011	0.0020
	(0.002)	(0.002)
Exp. within Polit. Rank	-0.0053 ***	-0.0035
	(0.002)	(0.002)
Observations	2246	2244
Mayor/Municipal Controls	No	Yes
Mean Control	0.3174	0.3174

Statistics for the number of municipalities within treatment inside a 150 distance in terms of different rankings. Geographical distance looks at the 150 closest (in km) municipalities, and counts how many are within the treatment group. Demographic distance looks at the 150 most similar municipalities in terms of urban population percentage, per capita income, total population, poverty rate and employment shares in agriculture and industry. Political distance takes into account the mayor's party ideology (fitted from 0, most left-winged, to 10, most right-winged) and the vote share for former president Jair Bolsonaro in the 2018 presidential election.

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Political Index: methodology

Bolognesi et al. (2022):

- Researches surveyed 571 members of the Brazilian Political Science Association (BPSA) on the current existing parties ideology, ranking from 0 (extreme left-winged) to 10 (extreme right-winged).
- Each respondent ranked each one of the 35 different political parties represented in the National Congress. We take the mean across all responses per party, and use that as the ideological position.

Brazilian Legislative Survey, eighth wave (Zucco, 2017)

- Researchers surveyed 145 Brazilian parliament members (from both Senate and Deputy Chamber), asking for their opinions on the 17 major parties political classification, from 1 (extreme left) to 10 (extreme right).
- We take the mean across all responses per party, and use that as the ideological position.

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Demographic index: State level

Size of peer group	10	20	50	100	200
Directly Treated	0.041	0.041	0.041	0.040*	0.038*
	(0.024)	(0.024)	(0.024)	(0.023)	(0.022)
Number of peers treated	0.002	0.002	0.002	0.005**	0.006***
	(0.008)	(0.006)	(0.004)	(0.003)	(0.002)
Observations	2269	2269	2269	2269	2269
Controls	Yes	Yes	Yes	Yes	Yes
Predicted value when T and #T are 0	0.312	0.307	0.297	0.211	0.118
Avg. number treated	2.281	4.475	10.499	19.517	33.804
Estimated aggregate spillover	0.005	0.010	0.020	0.106	0.200

Geographic index: State level

Size of peer group	10	20	50	100	200
Directly Treated	0.042^{*}	0.040	0.041	0.040	0.040
	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)
Number of peers treated	0.022^{**}	0.021^{**}	0.005	0.006^{**}	0.002
	(0.009)	(0.008)	(0.005)	(0.003)	(0.002)
Observations	2269	2269	2269	2269	2269
Controls	Yes	Yes	Yes	Yes	Yes
Predicted value when T and #T are 0	0.277	0.245	0.276	0.211	0.236
Avg. number treated	1.788	3.475	8.405	16.557	32.935
Estimated aggregate spillover	0.039	0.071	0.040	0.106	0.080

Political index: State level

Size of peer group	10	20	50	100	200
Directly Treated	0.044	0.044*	0.044*	0.042*	0.041
	(0.026)	(0.025)	(0.025)	(0.025)	(0.024)
Number of peers treated	0.024***	0.020***	0.014***	0.010***	0.008***
	(0.007)	(0.006)	(0.005)	(0.003)	(0.003)
Observations	2168	2168	2168	2168	2168
Controls	Yes	Yes	Yes	Yes	Yes
Predicted value when T and #T are 0	0.273	0.242	0.191	0.140	0.087
Avg. number treated	1.758	3.573	8.748	16.966	30.413
Estimated aggregate spillover	0.043	0.073	0.124	0.177	0.230

Demographic index: National level

Size of peer group	50	100	150	200	500
Directly Treated	0.042**	0.041**	0.043**	0.043**	0.043**
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Number of peers treated	-0.001	-0.003	-0.000	-0.000	0.001
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Observations	2269	2269	2269	2269	2269
Controls	Yes	Yes	Yes	Yes	Yes
Predicted value when T and #T are 0	0.327	0.368	0.320	0.329	0.221
Avg. number treated	10.252	20.087	29.730	39.202	94.579
Estimated aggregate spillover	-0.011	-0.052	-0.004	-0.013	0.094

Geographic index: National level

Size of peer group	50	100	150	200	500
Directly Treated	0.041**	0.041**	0.040*	0.039*	0.038*
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Number of peers treated	0.007	0.006*	0.007***	0.006**	0.005***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.001)
Observations	2269	2269	2269	2269	2269
Controls	Yes	Yes	Yes	Yes	Yes
Predicted value when T and #T are 0	0.254	0.221	0.137	0.126	-0.061
Avg. number treated	8.643	17.247	25.741	34.264	82.985
Estimated aggregate spillover	0.062	0.095	0.180	0.191	0.379

Political index: National level

Size of peer group	50	100	150	200	500
Directly Treated	0.044**	0.043**	0.043**	0.043**	0.044**
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Number of peers treated	0.006	0.008*	0.006**	0.004	0.001
	(0.005)	(0.004)	(0.003)	(0.003)	(0.001)
Observations	2168	2168	2168	2168	2168
Controls	Yes	Yes	Yes	Yes	Yes
Predicted value when T and #T are 0	0.270	0.194	0.164	0.180	0.210
Avg. number treated	7.960	16.062	24.142	32.190	80.237
Estimated aggregate spillover	0.046	0.122	0.152	0.136	0.106

All indexes: National level

Size of peer group	50	100	150	200	500
Directly Treated	0.0430**	0.0415**	0.0418**	0.0419**	0.0419**
	(0.0212)	(0.0211)	(0.0211)	(0.0211)	(0.0212)
Number of peers treated (Geographically close)	0.0068	0.0050	0.0067***	0.0057**	0.0043***
	(0.0045)	(0.0031)	(0.0025)	(0.0022)	(0.0015)
Number of peers treated (Demographically similar)	-0.0004	-0.0023	-0.0005	-0.0000	0.0009
	(0.0045)	(0.0032)	(0.0027)	(0.0025)	(0.0020)
Number of peers treated (Politically similar)	0.0047	0.0070*	0.0057*	0.0038	0.0009
	(0.0054)	(0.0040)	(0.0031)	(0.0027)	(0.0015)
Observations	2168	2168	2168	2168	2168
Controls	Yes	Yes	Yes	Yes	Yes
Predicted value when T and #T are 0	0.224	0.164	0.019	-0.001	-0.197
Estimated aggregate spillover	0.092	0.153	0.297	0.317	0.513

Correlation between indexes: National level

Size of peer group	Geographical Index & Demographical Index	Geographical Index & Political Index	Demographical Index & Political Index
10	-0.0001	0.0314	0.0147
20	0.0659	0.0858	0.0095
50	0.0673	0.1019	0.0241
80	0.0506	0.1246	0.0074
100	0.0512	0.1016	-0.0088
150	0.0225	0.1264	-0.0013
200	0.0078	0.1254	-0.0317
256	-0.0030	0.1415	-0.0460
500	-0.0587	0.1267	-0.0241

Notes: The sample includes 2188 observations. The table reports, for each size of peer group, the correlation between the residuals of 'number of treated peers' across two indexes at the national level, where residuals are obtained after controlling for the 'Number of peers in the experiment'.

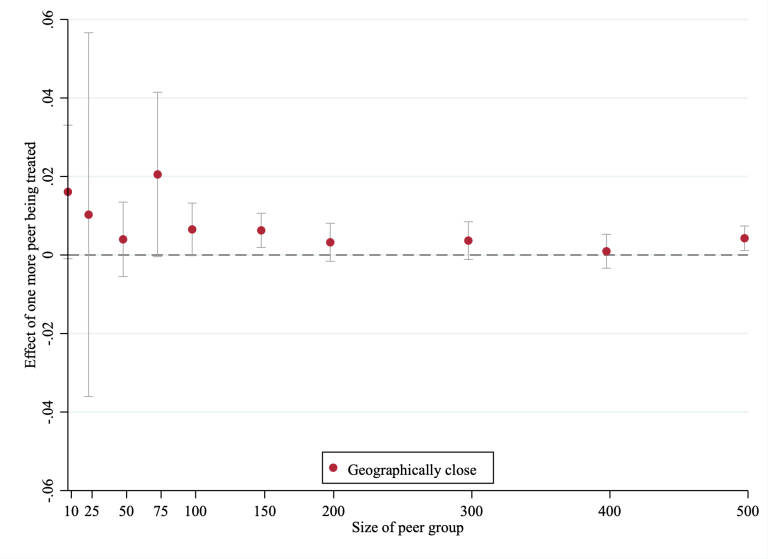
Correlation between indexes: State level

Size of peer group	Geographical Index & Demographical Index	Geographical Index & Political Index	Demographical Index & Political Index
10	0.0862	0.0539	0.1876
20	0.1324	0.1037	0.2878
50	0.0476	0.0990	0.4516
80	0.0085	0.0799	0.5557
100	-0.0253	0.0776	0.6096
150	-0.1111	0.0488	0.7072
200	-0.1492	0.0135	0.7649
256	-0.1450	-0.0662	0.8631
500	-0.2451	-0.2063	0.9724

Notes: The sample includes 2188 observations. The table reports, for each size of peer group, the correlation between the residuals of 'number of treated peers' across two indexes at the state level, where residuals are obtained after controlling for the 'Number of peers in the experiment'.

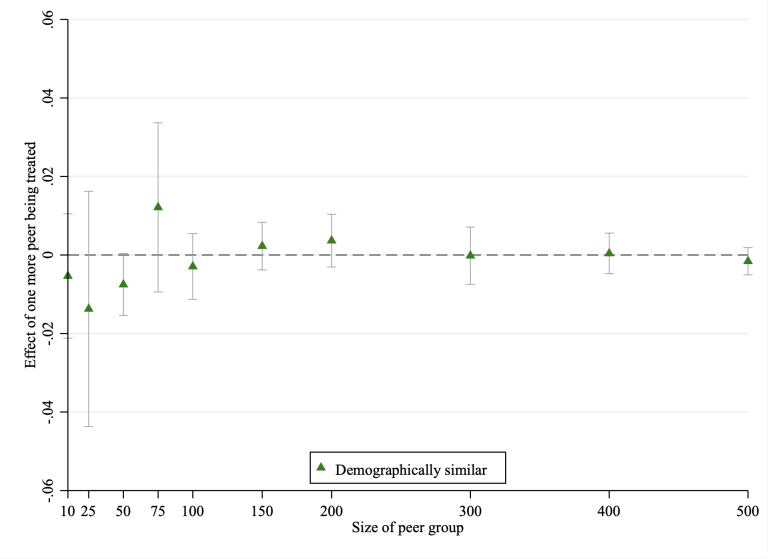
Unpacking Spillovers: geographic proximity

STATE



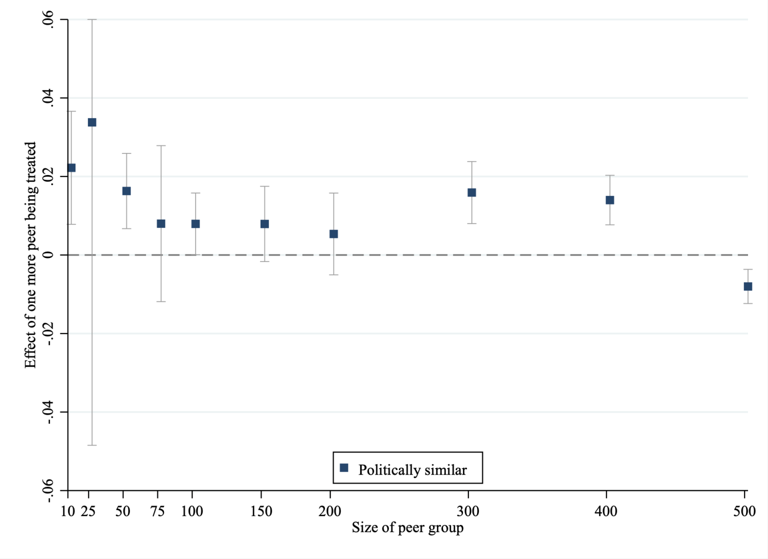
Unpacking Spillovers: demographic proximity

STATE



Unpacking Spillovers: political proximity

STATE



Surveyed Mayors: Summary Statistics

Variables	Survey sample Mean	(sd)
Mayors' Characteristics		
% Male	88	(32)
Age (years)	47	(10)
% College Educated	65	(48)
% 2nd Term	15	(36)
% Leftist Political Party	35	(48)
Municipalities' Characteristics		
Population 2016 (thousands)	19	(23)
Per Capita Income (R$)	498	(226)
Observations	829	

Notes: Sample mean and standard deviation.

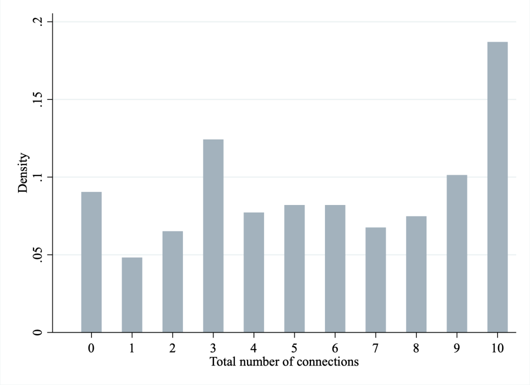
Comparing surveyed mayors with the population of mayors

Surveyed mayors are more educated, less experienced, from smaller municipalities than average

Variables	Survey Sample		All Municipalities		Means Difference	
Mayors' Characteristics						
% Male	88	(32)	88	(32)	-0	(1.200)
Age (years)	47	(10)	49	(16)	-2	(0.588)
% College Educated	65	(48)	52	(50)	12	(1.861)
% 2nd Term	15	(36)	23	(42)	-8	(1.541)
% Leftist Political Party	35	(48)	34	(47)	1	(1.774)
Municipalities' Characteristics						
Population 2016 (thousands)	19	(23)	37	(217)	-18	(7.576)
Per Capita Income (R$)	498	(226)	494	(243)	5	(9.008)
Observations	829		5570			

Notes: Sample mean and standard deviation. Mean-comparison t-tests between groups.
*** p<0.01, ** p<0.05, * p<0.1

Network links: Distribution of number of mayoral connections listed



Variable	Connections
Observations	829
Mean	5.6
Std. Dev.	3.3
P10	1
P25	3
P75	9
P90	10

Notes: The sample includes 829 municipalities where a mayor answered the survey.

Who is more connected? Municipality Characteristics

Municipality characteristics *do not* explain number of connections

LHS Variable	(1) Number of Connections	(2) Number of Connections
Population (std)	1.624	1.714
	(1.247)	(1.205)
% of College Educated Population	0.132 *	0.103
	(0.069)	(0.069)
% of Public Adm College Educated	-0.002	-0.005
	(0.008)	(0.008)
% in Poverty	0.007	0.011
	(0.021)	(0.021)
Gini Index	-2.133	-2.091
	(2.581)	(2.535)
In Big South (0/1)	0.093	0.055
	(0.406)	(0.400)
Per Capita Income (std)	-0.053	0.023
	(0.312)	(0.302)
Local Tax Revenues (std)	-0.418 *	-0.382 *
	(0.227)	(0.210)
Constant	5.924 ***	6.434 ***
	(1.124)	(1.278)
R-squared	0.01	0.08
Observations	828	787
Mayors' Characteristics	No	Yes

Notes: Response variable is number of connections (0/10). 'Population', 'Per Capita Income' and 'Local Tax Revenues' are mean standardized variables. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$