Estimating the Effect of Discretion in Public Spending on Government Performance:

Evidence from Brazilian Municipalities

Andre Assumpcao   Ciro Biderman   George Avelino

UNC-Chapel Hill, FGV-EAESP, FGV-EAESP

Mar 16th, 2018

Motivation

Developing countries spend **US$820bn** per year on goods and services supplied by the private sector. Governments purchase medical supplies, school material, and construction services used to implement public policies.

Constituents thus have an interest not only on **what** goods and services governments are purchasing but also **how** governments are acquiring such items.

- When will the town build better roads?
- Should the government ask for three budget proposals for a school project or just one?
- How many insulin injections should be purchased given their expiry date and the number of people who need them?

Research Question

Does the imposition of harder, stricter procurement rules for government expenditure reduce corruption and misallocation of public resources?

Context

Random sample of 9,593 federal transfers to 1,139 Brazilian municipalities, between 2004-2010, to cover health and education expenditures for which we construct or collect data on:

- Corruption and mismanagement (**outcomes**)
- Procurement discretion (**treatments**)
- Municipal characteristics (**controls**)

Hypotheses

1. The imposition of harder, stricter procurement rules for public spending **reduces** corruption.
2. The imposition of harder, stricter procurement rules for public spending **reduces** the misallocation of public resources.

Findings

1. Stricter procurement rules have **no effect** on corruption.
2. Stricter procurement rules have only a **limited effect** on mismanagement.

Empirical Strategy

Regression discontinuity (RD) design where the application of procurement rules follows a strict monetary schedule established by Law 8,666/93.

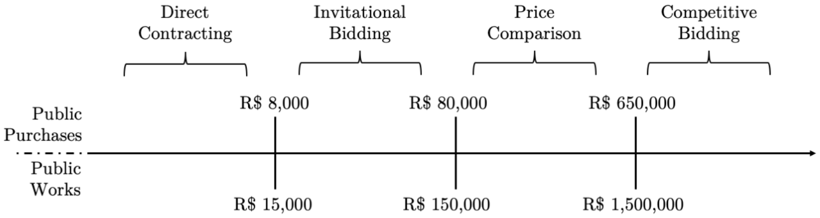

Figure 1: Law 8,666/93

By looking at federal transfers whose values fall in the vicinities of the discontinuities in procurement rules, we identify the **causal effect** of discretion on government performance.

Outcomes

The Office of the Comptroller-General (CGU) ran a random audit program of Brazilian municipalities expenditures between 2003 and 2015, which we use to code corruption and misallocation indicators serving as outcome variables in this project (Ferraz and Finan, 2008; 2011).

- **Binary:** whether the transfer contains evidence of corruption or mismanagement;
- **Share:** how many of each transfer's records are corruption or mismanagement-related;
- **Amount:** how much money was potentially lost to corruption or mismanagement.

In total, my preferred estimation yields 6 (outcomes) x [2 (purchases cutoffs) + 3 (works cutoffs) + 3 (pooled cutoffs)] = 48 parameter estimates.

Results

	Corruption Outcomes			Mismanagement Outcomes		
	Indicator I *(Binary)*	Indicator II *(Share)*	Indicator III *(Amount)*	Indicator I *(Binary)*	Indicator II *(Share)*	Indicator III *(Amount)*
Variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Purchases Estimates					
Proc. Category 1	0.117	0.037	234	0.049	-0.006	64
	(0.095)	(0.055)	(442)	(0.078)	(0.081)	(648)
	[n = 2098]	[n = 2087]	[n = 1934]	[n = 2129]	[n = 2097]	[n = 1924]
Proc. Category 2	-0.034	0.032	2,827	-0.100*	-0.055	-4,524
	(0.067)	(0.048)	(3,838)	(0.059)	(0.059)	(4,748)
	[n = 2686]	[n = 2106]	[n = 2058]	[n = 2553]	[n = 2328]	[n = 2261]
	Works Estimates					
Proc. Category 1	-0.210	-0.039	61	-0.416**	-0.291*	-4,611*
	(0.143)	(0.078)	(1,482)	(0.190)	(0.178)	(2,802)
	[n = 330]	[n = 362]	[n = 314]	[n = 485]	[n = 485]	[n = 423]
Proc. Category 2	0.043	0.009	537	0.016	-0.006	-726
	(0.102)	(0.058)	(8,614)	(0.079)	(0.076)	(11,265)
	[n = 1185]	[n = 1014]	[n = 1050]	[n = 944]	[n = 858]	[n = 892]
Proc. Category 3	0.043	0.158	221478	0.171	-0.077	-88,510
	(0.307)	(0.183)	(281,249)	(0.212)	(0.251)	(340,566)
	[n = 313]	[n = 228]	[n = 205]	[n = 51]	[n = 157]	[n = 276]
	Pooled Estimates					
Proc. Category 1	-0.025	-0.054*	-425	0.098*	0.091*	-114
	(0.058)	(0.033)	(291)	(0.054)	(0.050)	(451)
	[n = 2256]	[n = 2263]	[n = 1964]	[n = 1977]	[n = 2019]	[n = 1905]
Proc. Category 2	-0.018	0.009	1,344	-0.064	-0.040	-572
	(0.043)	(0.030)	(3,078)	(0.044)	(0.041)	(3,486)
	[n = 3767]	[n = 2896]	[n = 2846]	[n = 2460]	[n = 2436]	[n = 4584]
Proc. Category 3	0.099	0.085	76,083	-0.006	-0.050	-1,869
	(0.128)	(0.069)	(59,995)	(0.081)	(0.079)	(79,197)
	[n = 517]	[n = 568]	[n = 626]	[n = 732]	[n = 751]	[n = 423]

Mismanagement Binary

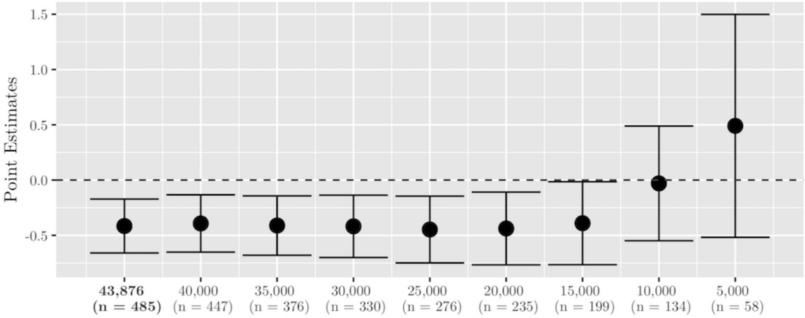

Figure 3: Outcome 1

Interpretation: imposing stricter rules on bureaucrats when hiring private contractors in public works projects reduces the probability of finding mismanagement problems in these projects by **41.9 percentage points**.

Mismanagement Share

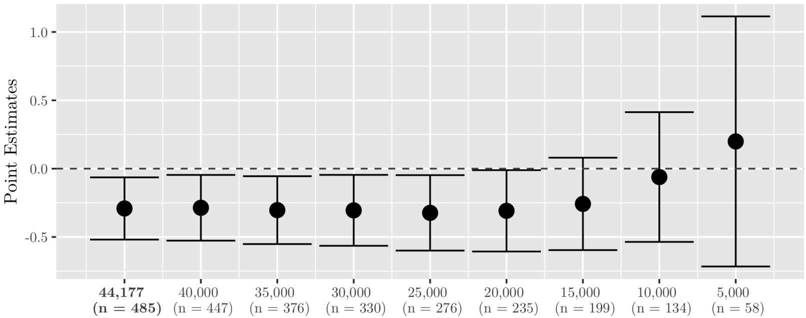

Figure 4: Outcome 2

Interpretation: imposing stricter rules on bureaucrats when hiring private contractors in public works projects reduces the share of mismanagement problems found by auditors by **29.1 percentage points**.

Mismanagement Amount

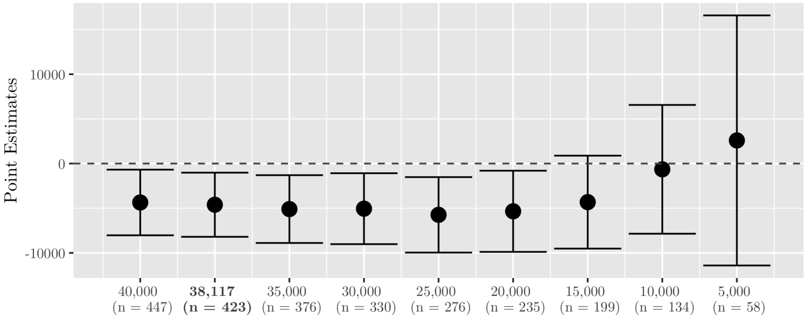

Figure 5: Outcome 3

Interpretation: imposing stricter rules on bureaucrats when hiring private contractors in public works projects reduces the amount lost to mismanagement by **R$4,611** (**$1,155** using the current exchange rate).

Results are robust!

1. We run covariate balance tests across cutoffs and include covariates in regressions.

Results are robust!

1. We run covariate balance tests across cutoffs and include covariates in regressions.
2. We use robust standard errors, clustered at the municipal level, and health, education, and auditing fixed effects.

Results are robust!

1. We run covariate balance tests across cutoffs and include covariates in regressions.
2. We use robust standard errors, clustered at the municipal level, and health, education, and auditing fixed effects.
3. We run the McCrary (2008) test for manipulation of the running variable and throw away the last cutoff in the goods/services procurement type.

Results are robust!

1. We run covariate balance tests across cutoffs and include covariates in regressions.
2. We use robust standard errors, clustered at the municipal level, and health, education, and auditing fixed effects.
3. We run the McCrary (2008) test for manipulation of the running variable and throw away the last cutoff in the goods/services procurement type.
4. Optimal bandwidth selection comes from Calonico, Cattaneo, and Titiunik (2015), but we also run our local (quadratic) regressions at smaller bandwidths.

Results are robust!

1. We run covariate balance tests across cutoffs and include covariates in regressions.
2. We use robust standard errors, clustered at the municipal level, and health, education, and auditing fixed effects.
3. We run the McCrary (2008) test for manipulation of the running variable and throw away the last cutoff in the goods/services procurement type.
4. Optimal bandwidth selection comes from Calonico, Cattaneo, and Titiunik (2015), but we also run our local (quadratic) regressions at smaller bandwidths.
5. There are two falsification tests showing that our significant mismanagement effects are not spurious. . .

Falsification Tests 1

Is this result spurious? Using **fake purchases** cutoffs for works transfers, the answer is **no**.

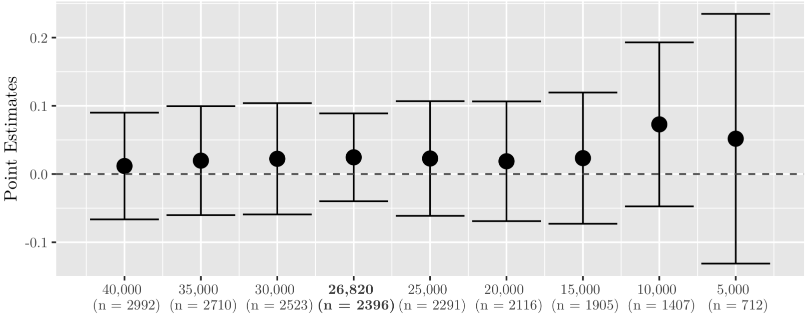

Figure 6: Mismanagement Binary Placebo 1

Falsification Tests 2

Isn't this just a random discontinuity due to chance? Using **non-procurement** transfers, the answer is also **no**.

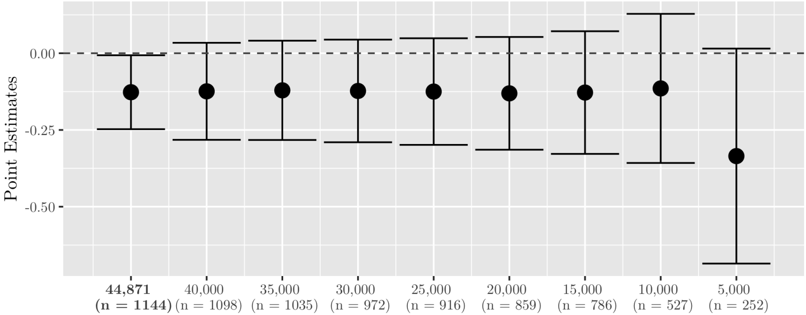

Figure 7: Mismanagement Binary Placebo 2

Scientific Contribution

1. **No evidence that lower discretion** in public spending reduces corruption.
2. **Limited welfare effect:** A back-of-the-envelope calculation shows limited restricting procurement: Law 8,666/93 prevents only 5.98% of resource misallocation.
3. **Top-down legislation is ineffective:** legislation to limit discretion becomes meaningless with inflation and when rules are too hard to follow.
4. Not discussed in this presentation... but we also developed text analysis algorithm to read in each transfer and assign it to procurement types (in appendix).

Supplemental Material

Summary Statistics

Panel A: Service Order Level

	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Amount (in R$)	9,593	449,858	3,060,374	65	36,000	204,721	236,198,658
Infraction Count	9,593	2.398	2.172	0	1	3	18
Corruption Indicator I (Binary)	9,593	0.398	0.489	0	0	1	1
Corruption Indicator II (Share)	9,593	0.195	0.294	0	0	0.3	1
Corruption Indicator III (Amount)	9,593	125,695	954,252	0	0	29,427	49,282,832
Mismanagement Indicator I (Binary)	9,593	0.746	0.435	0	0	1	1
Mismanagement Indicator II (Share)	9,593	0.619	0.407	0	0	1	1
Mismanagement Indicator III (Amount)	9,593	268,168	2,618,568	0	0	122,000	236,198,658

Figure 8: Panel A: Variables at the Service Order Level

Summary Statistics

Panel B: Municipal Level

	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Urban Population (Share)	1,139	0.642	0.221	0.042	0.476	0.826	1
Female (Share)	1,139	0.505	0.015	0.461	0.495	0.512	0.658
Illiteracy Rate	1,139	0.168	0.099	0.016	0.083	0.254	0.428
GDP per capita	1,139	11,890	11,696	2,463	5,046	14,749	153,770
Gini Index	1,139	0.512	0.066	0.318	0.469	0.555	0.783
Human Development Index	1,139	0.654	0.072	0.469	0.592	0.714	0.862
Poverty Rate	1,139	0.250	0.184	0.003	0.078	0.404	0.755
Presence of AM Radio	1,139	0.237	0.425	0	0	0	1
Education Council Established	1,139	0.781	0.413	0	1	1	1
Health Council Established	1,139	0.969	0.173	0	1	1	1
Seat of Judiciary Branch	1,139	0.514	0.500	0	0	1	1
Vote Margin	1,139	0.168	0.188	0.0003	0.047	0.211	1
Mayor Reelection Rate	1,139	0.293	0.451	0	0	1	1

Figure 9: Panel B: Variables at the Municipal Level

Covariate Balance Tests

	Purchases		Works		
Municipal Variables:	Cutoff 1	Cutoff 2	Cutoff 1	Cutoff 2	Cutoff 3
Urban Population (Share)	0.756	0.775	0.297	0.702	0.617
Female (Share)	0.281	0.078*	0.005***	0.857	0.157
Illiteracy Rate	0.159	0.169	0.220	0.140	0.949
GDP	0.284	0.140	0.995	0.721	0.502
Gini Index	0.153	0.163	0.071*	0.712	0.457
Human Development Indicator	0.105	0.205	0.227	0.107	0.826
Poverty Rate	0.079*	0.109	0.454	0.097*	0.679
Presence of AM Radio	0.799	0.359	0.002***	0.315	0.388
Education Council Established	0.430	0.301	0.056*	0.275	0.523
Health Council Established	0.844	0.274	0.648	0.469	0.160
Seat of Judiciary Branch	0.002***	0.004***	0.158	0.516	0.400
Vote Margin	0.815	0.918	0.728	0.242	0.900
Mayor Reelection Rate	0.785	0.332	0.726	0.745	0.250
Sample Size (Below; Above)	(363; 835)	(877; 555)	(70; 177)	(406; 238)	(33; 15)

Notes: we used the Calonico et al. (2015) bandwidths calculated in table 6. In total, there are 36 unique bandwidths from the combinations across procurement type, outcome, and cutoff. We narrow down to one single bandwidth per procurement type and cutoff by focusing only on the most important outcome, performance indicator I, such as we had done for table 5. We compute the bandwidth for both the corruption and the mismanagement version of indicator I and use the smaller bandwidth across the two for robustness purposes, as we want like to narrow down on the samples across cutoffs as much as possible.*p<.1; **p<.05; ***p<.01

Figure 10: Covariate Balance

Bandwidth Tests

		Corruption Outcomes			Management Outcomes		
		Indicator I	Indicator II	Indicator III	Indicator I	Indicator II	Indicator III
Purchases	Cutoff 1	26,564	26,327	22,671	27,393	26,554	22,364
	Cutoff 2	45,854	35,566	34,547	43,431	39,460	38,455
	Cutoff 3	323,425	281,940	289,857	205,542	213,622	226,386
Works	Cutoff 1	29,960	33,076	28,276	43,876	44,177	38,117
	Cutoff 2	74,779	65,067	67,447	60,251	55,164	56,915
	Cutoff 3	1,001,774	862,717	825,342	340,947	739,532	956,064
Pooled	Cutoff 1	23,987	24,116	18,606	18,852	19,546	17,728
	Cutoff 2	51,276	39,937	39,263	33,164	32,725	60,868
	Cutoff 3	287,165	304,498	323,916	356,322	362,109	245,302

Notes: These are the Cattaneo et al. (2016, 2018) optimal, data-driven bandwidth sizes, regardless of whether the multiple cutoffs are cumulative or not. We use the average across purchases and works bandwidths for RD manipulation and covariate balance tests.

Figure 11: Bandwidth Tests

Falsification Tests 1

Is this result spurious? Using **fake purchases** cutoffs for works transfers, the answer is **no**.

Mismanagement Share

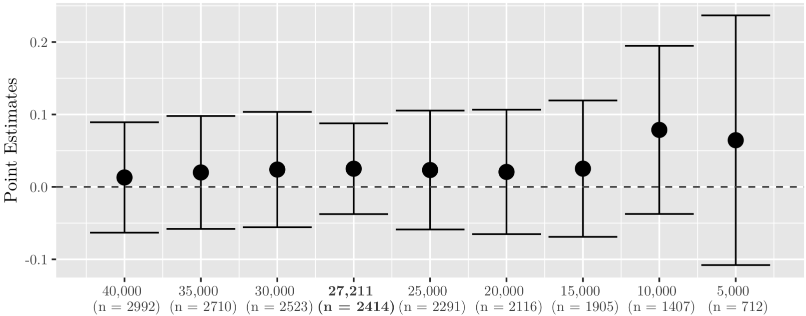

Figure 12: Mismanagement Share Placebo 1

Falsification Tests 1

Is this result spurious? Using **fake purchases** cutoffs for works transfers, the answer is **no**.

Mismanagement Amount

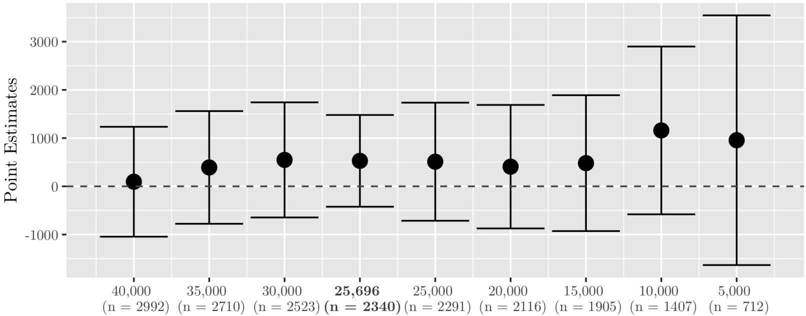

Figure 13: Mismanagement Amount Placebo 1

Falsification Tests 2

Aren't we mixing up purchases and works transfers and picking up a confounding effect? Using **non-procurement** transfers, the answer is also **no**.

Mismanagement Share

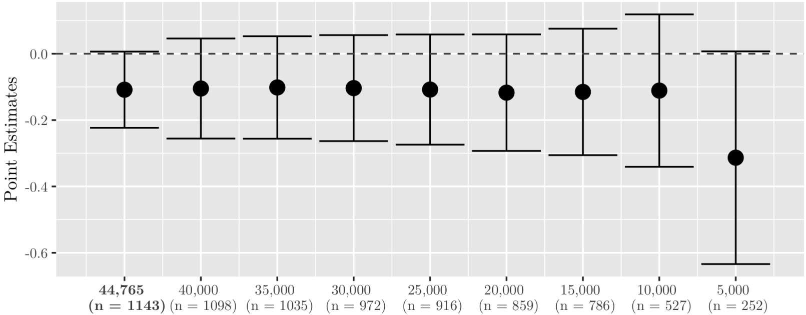

Figure 14: Mismanagement Share Placebo 2

Falsification Tests 2

Aren't we mixing up purchases and works transfers and picking up a confounding effect? Using **non-procurement** transfers, the answer is also **no**.

Mismanagement Amount

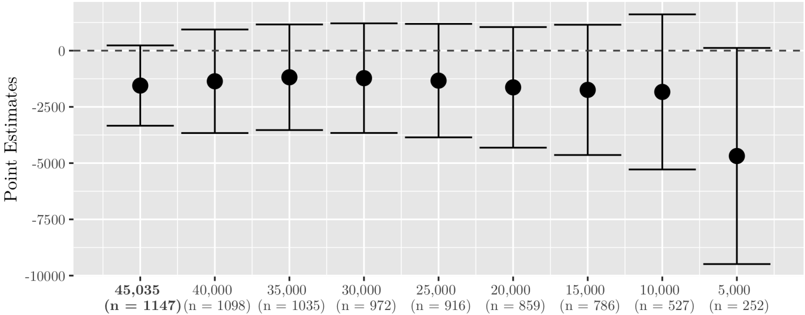

Figure 15: Mismanagement Amount Placebo 2

Cost-Benefit Analysis

Cost	Type	Avg. Loss (in R$)	# Obs.	Total (in R$)
Corruption	Purchases	2,491	1,934	4,818,570
Mismanagement	Purchases	10,659	1,924	20,508,793
Corruption	Works	2,871	314	901,789
Mismanagement	Works	10,529	423	4,454,134
			Total Cost (A)	30,683,288
Benefits				
Works	Mismanagement	-4,611	423	-1,950,453
			Total Benefit (B)	-1,950,453
Welfare Effects				
$A - B$	*Total Cost (in R$) in the absence of Benefit*			32,633,741
$100 \times B/(A - B)$			*% Cost Reduction*	5.98
$A_{works} - B$	*Works Cost (in R$) in the absence of Benefit*			7,306,377
$100 \times B/(A_{works} - B)$			*% Works Cost Reduction*	26.69

Figure 16: Back-of-the-envelope Calculation

The End

Andre Assumpcao
Ph.D. Candidate
Department of Public Policy
The University of North Carolina at Chapel Hill
aassumpcao.github.io