Supplementary Materials for “Legislature Size and Welfare: Evidence from Brazil”

Contents

A.1 A Model of Legisture Size and Service Provision (Proofs)

In this section, we show the proofs for the model included in the main paper.

Proposition 1. *Public goods provision increases with larger legislatures if governing costs decrease in larger legislatures.*

Proof. To prove this result, we need to show that the mayor's expected utility satisfies the increasing differences in g and N. This means that, when increasing the size of the council, the optimal solution g^* should also increase. However, as N increases discretely, we cannot take the cross-partial derivative on N or use the implicit function theorem. Instead, we use monotone comparative statics to derive these results (Milgrom and Shannon 1994).

The mayor's expected utility satifies the increasing differences in g and N when, for $g > g'$ and $N+1 > N$,[1] we have:

$$\mathbb{E}\mathrm{U}(g, N+1) - \mathbb{E}\mathrm{U}(g', N+1) \geq \mathbb{E}\mathrm{U}(g, N) - \mathbb{E}\mathrm{U}(g', N)$$

After some substitutions, we have:

$$u(R-g-C_G(N+1))+B_M\pi(g)-u(R-g'-C_G(N+1))-B_M\pi(g') \geq u(R-g-C_G(N))+B_M\pi(g)-u(R-g'-C_G(N))-B_M\pi(g')$$

Which is equal to:

$$u(R-g-C_G(N+1)) - u(R-g'-C_G(N+1)) \geq u(R-g-C_G(N)) - u(R-g'-C_G(N))$$

By multiplying both sides by $\dfrac{1}{g-g'}$ and taking the limit when $g \longrightarrow g'$, we have:

$$u'(R-g-C_G(N+1)) \geq u'(R-g-C_G(N))$$

It is now clear that the function satisfies the increasing differences in g and N when the governing costs of a $N+1$-sized city council are lower than the governing costs of a N-sized city council:

$$C_G(N+1) \leq C_G(N)$$

□

[1] The requirement that the decision and type space are a complete lattice is satisfied for $\mathbb{R} \times \mathbb{N}$.

Proposition 2. *In the non-partisan reversal mechanism, governing costs always increase when legislature size increases.*

Proof. Comparing city councils of size N with those of size $N+1$, we find that the difference is costs is:

$$\begin{aligned} C_G(N+1) - C_G(N) &= \frac{(N+1)\delta R}{2(N+1)+1} - \frac{N\delta R}{2N+1} \\ &= \frac{\delta R}{(2N+3)(2N+1)} \\ &> 0 \end{aligned}$$

Therefore, costs always increase when legislature size increases.

□

Corollary 1. *In the non-partisan reversal mechanism, public goods provision decreases as legislature size increases.*

Proposition 3. *In the hybrid reversal mechanism, if* $\gamma \leq \frac{1}{p}\left[\frac{1}{(2N+1)(2N+3)}\right]$, *then governing costs increase as legislature size increases. Otherwise, such costs decrease when legislature size increases.*

Proof. When we compare the costs of N versus $N+1$ legislators, we find that:

$$\begin{aligned} C_G(N+1) - C_G(N) &= \frac{N+1}{2}\left(\frac{2\delta R}{2(N+1)+1} - p\right) + \left(\frac{N+1}{2} - \gamma(N+1)\right)p \\ &\quad - \frac{N}{2}\left(\frac{2\delta R}{2N+1} - p\right) - \left(\frac{N}{2} - \gamma N\right)p \\ &= \frac{\delta R}{(2N+3)(2N+1)}\left[1 - \gamma(2N+1)(2N+3)p\right] \end{aligned}$$

The conditions for the difference in governing costs to decrease when legislature size increases are as follows:

$$\gamma \geq \frac{1}{p}\left[\frac{1}{(2N+3)(2N+1)}\right] \equiv \underline{\gamma}$$

□

Corollary 2. *In the hybrid reversal mechanism, when the chances of electing a mayor-aligned city councilor are sufficiently high, then increasing council size lowers the bargaining costs for mayors.*

A.2 Variable Sources and Descriptive Statistics

Our data come mainly from Brazilian public agencies. Further information about them are available below.

Table 1: Data Sources

Source Code	Source Name	Data Provided	URL
DataSUS	Brazilian Health Ministry Data Service	Health care data	http://www.datasus.gov.br
IBGE	Brazilian Institute of Geography and Statistics	Geographic, economic, and demographic data	http://www.ibge.gov.br
INEP	Ministry of Education Data Service	Education performance	http://www.inep.gov.br
InterLegis	Senate Legislative Data Service	Legislative data	http://www.interlegis.leg.br
IPEA	Brazilian Institute of Applied Economics	Economic data	http://www.ipeadata.gov.br
MDS	Social Security Ministry	Coverage of social programs	http://www.mds.gov.br
TSE	Supreme Electoral Court	Electoral data	http://www.tse.jus.br

A.2.1 Outcomes Aggregated at the Municipal Level

- **Number of Seats 2000**: Number of city councilors in 2000 (source: TSE).
- **Population 2000**: City population according to the 2000 Brazilian Census (source: IBGE).
- **Per Capita GDP 2000 (Millions)**: Municipal per capita GDP measured by the Brazilian Census (source: IPEA).
- **Proportion of Poverty 2000**: Percentage of citizens earning less than R$ 70.00 per month (source: Social Development Ministry [MDS]).
- **Number of Seats 2004**: Number of city councilors in 2004 according to the Electoral Court (source: TSE).
- **Infant Mortality 2005–2008**: Number of children who died before reaching one year of age, divided by the number of children born alive, multiplied by 1,000 (source: DataSUS)
- **Postneonatal Mortality 2005–2008**: Number of children alive for at least 28 days who died before reaching one year of age, divided by the total number of children who lived for 28 days, multiplied by 1,000 (source: DataSUS)
- **Enrollment Elementary School 2005–2008**: Number of children enrolled in elementary schools, averaged by classroom size (K–4) (source: INEP).

- **Quality of Elementary School 2005–2008**: Average municipal IDEB scores. IDEB scores are estimated as follows. The Ministry of Education takes the average of the students' grades in math and Portuguese, then multiply the those numbers by the student yearly approval rate. INEP reweights the estimators to avoid schools and classroom specific effects (source: INEP, years: 2005, 2007).
- **Size of Mayoral Pre-Electoral Coalition 2004**: Number of elected councilors in the mayoral pre-electoral coalition (source: TSE)
- **Number of Appointed Bureaucrats 2005–2008**: Number of bureaucrats of the direct administration who were appointed to jobs in the municipality (source: IBGE, years: 2005, 2006, and 2008)
- **Number of Females Elected 2004**: Number of females elected to city council (source: TSE)
- **Number of Non-Whites Elected 2004**: Number of non-whites elected to the city council. We collect this data for municipalities less than 10,000 inhabitants away from the cutoffs (source: own compilation based on the TSE candidate pictures).
- **Competition per Seat 2004**: Number of people running for city councilor divided by the city council size (source: TSE)
- **Proportion Approved Legislation 2005**: Number of approved legislation in 2005 divided by the number of proposed legislation (source: InterLegis)

A.2.2 Legislation Dataset

We code the legislation approved by the councilors of 63 municipalities around a ten thousand inhabitants buffer from the council size thresholds. We classify the legislation into four categories:

- **Public Goods**: Legislation that provides public goods or services.
- **Oversight**: Legislation that requests information to the mayor's office or the bureaucracy about the provision of services.
- **Education and Health Care**: Legislation about education or health care provision.
- **Others**: Legislation that is not classified as local public goods, public goods, or oversight. Usually honors or procedures.

A.2.3 Online 2016 Former City Councilors Survey

We ran an online survey asking 174 councilors about their representation duties and how mayors allocate public services to expand his or her government coalition. The services we include are:

- **Councilors Job Appointments**: Whether mayors appoint supporters of the city councilors to bureaucratic jobs (source: survey).
- **Councilors Demands**: Whether mayors satisfy the public service demands of an allied councilor (e.g., build a health clinic in a councilor's neighborhood) (source: survey).
- **Councilors Personal Requests**: Whether mayors satisfy the private requests of an allied councilor (e.g., hire an ally in the bureaucracy) (source: survey).
- **Councilors Legislation**: Whether mayors support the councilors' legislative agenda (source: survey).
- **Councilors Constructions**: Whether mayors support councilors' requests for more public works (e.g. fix potholes in the councilor's neighborhoods) (source: survey).

Table 2: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
	Municipal Characteristics				
Number of Seats 2000	5,521	10.76	2.70	9	21
Population 2000	5,474	22,341.96	44,573.67	697	567,728
GDP Census 2000	5,474	0.13	0.46	0.00	13.57
Proportion of Poverty Census 2000	5,474	46.58	22.82	2.89	93.02
Number of Seats 2004	5,527	9.22	0.94	9	21
	Health Care Outcomes				
Infant Mortality 2005-2008	13,328	20.64	13.45	1.28	209.30
Postneonatal Mortality 2005-2008	6,113	9.29	8.64	0.59	200.00
	Education Outcomes				
Enrollment Elementary School 2005-2008	10,842	20.62	5.32	1.00	57.80
Quality of Elementary School 2005-2008	9,266	3.73	0.94	0.70	8.10
	Bargaining, Coalition, and Public Employment				
Mayoral Pre-electoral coalition Size 2004	5,522	4.86	1.71	0.00	17.00
Number of Appointed Bureaucrats 2005-2008	16,563	67.77	126.68	0	2,894
	Representation and Competition				
Number Female Elected 2004	5,526	1.12	1.20	0	8
Number Non-White Elected 2004	397	2.23	1.87	0	9
Competition per Seat 2004	5,527	6.27	3.82	1.00	25.83
Proportion Approved Legislation 2005	3,693	0.83	0.28	0.00	1.00
	Legislation Approved Data				
Legislation – Public Goods	346,553	0.76	0.43	0	1
Legislation – Oversight	346,553	0.03	0.18	0	1
Legislation – Education and Health	346,553	0.11	0.31	0	1
Legislation – Others	346,553	0.17	0.38	0	1
	Survey – Strategy to Consolidate Coalition Support				
Coalition Support – Councilors Job Appointments	174	0.64	0.48	0	1
Coalition Support – Councilors Demands	174	0.44	0.50	0	1
Coalition Support – Councilors Personal Requests	174	0.56	0.50	0	1
Coalition Support – Councilors Legislation	174	0.25	0.43	0	1
Coalition Support – Councilors Constructions	174	0.43	0.50	0	1

Notes: The legislation approved dataset contains information on 63 of the 202 municipalities 10 thousand inhabitants away from the council size thresholds. Survey summary statistics are unweighted. Numbers of cases vary due to missingness.

A.3 Threshold Manipulation, Sorting, and Pre-Treatment Consistency

McCrary (2008) proposes a measure of the distributional imbalance around the discontinuity, testing whether cases are more abundant on either side of the cutoff. In our sample, the McCrary statistic is 0.391 (SE = 0.299), showing no evidence of manipulation.

We run the Cattaneo et al. (2019) manipulation test, which is based on the density of the local polynomial estimator. We use local polynomials ranging from first to fourth order. As the null hypothesis implies that there is no manipulation, the p-values for each polynomial order are: local linear (p-value = 0.442); quadratic (p-value = 0.740); cubic (p-value = 0.998); and quartic (p-value = 0.620). Therefore, we also see no evidence of manipulation.

A.4 Population Thresholds in Brazil Before and After the 2003 Supreme Court Decision

Table 3 displays the number of municipalities by the thresholds we use in this paper.

Table 3: City council thresholds used in the paper

	Legislature Size	Min. Population	Max. Population	Num. Mun. Bin (2003 pop.)
1	9	0	47,619	5,029
2	10	47,620	95,238	317
3	11	95,239	142,857	89
4	12	142,858	190,476	43
5	13	190,477	238,095	30
6	14	238,096	285,714	21
7	15	285,715	333,333	13
8	16	333,334	380,952	13
9	17	380,953	428,571	6
10	18	428,572	476,190	6
11	19	476,191	523,809	4
12	20	523,810	571,428	5
13	21	571,429	1,000,000	13

To provide an overview of the data dispersion, Figure 1 plots the municipalities by their proximity to the cutoffs. In the map, we give the contour of every Brazilian city, coloring it by the proximity to the council size thresholds. Darker colors represent municipalities closer to the population thresholds. In regression discontinuity models, the closer a city is to the cutoff, the more influential it is in the estimation. Figure 1 also shows that the municipalities around the cutoff are reasonably well distributed across the country.

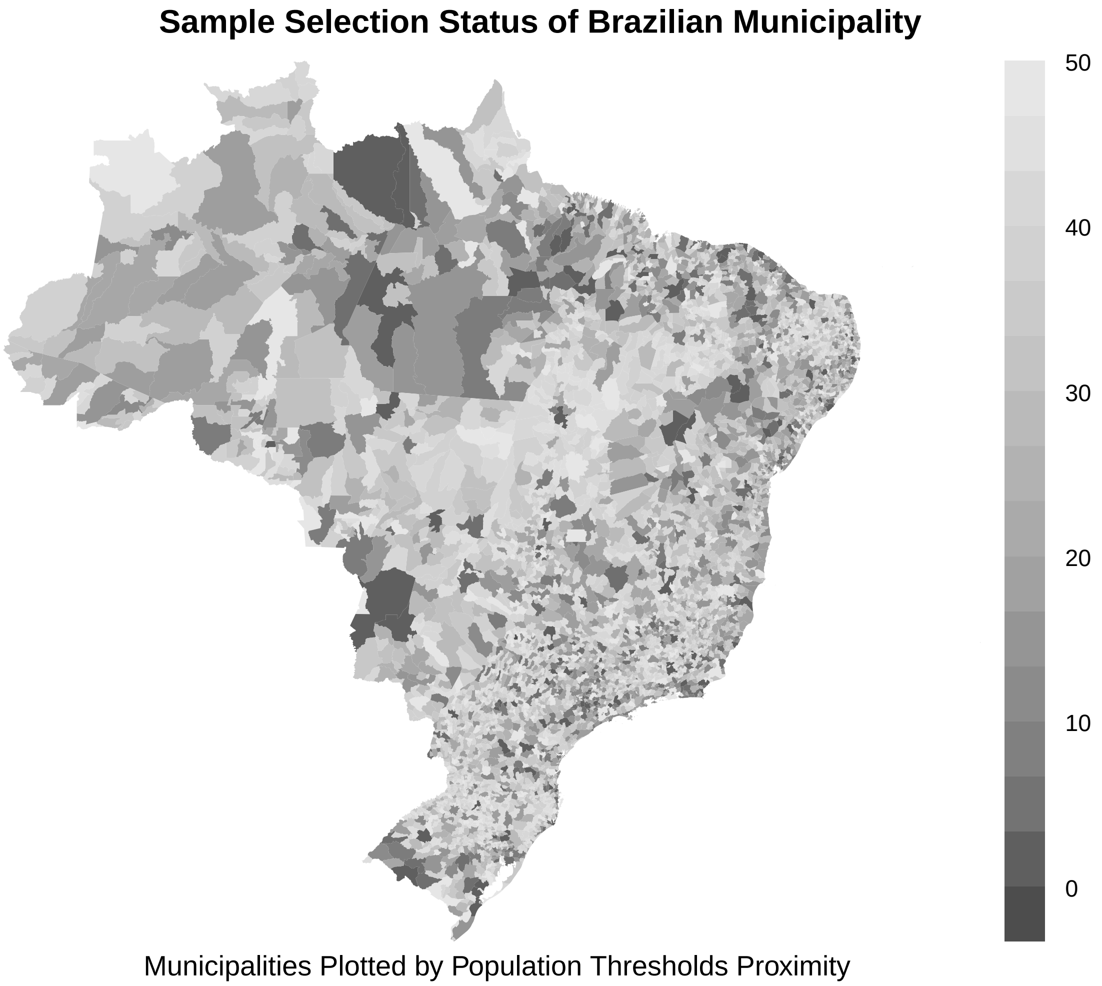

Figure 1: Municipalities and their Selection Status

A.5 Identification Strategy in Regression Discontinuity Designs with Multiple Thresholds

When estimating regression discontinuities with multiple cutoffs, authors usually pool all the discontinuities together to estimate the treatment effect on the outcomes of interest (Cattaneo et al. 2016). Let $C = \{c_0, c_1, \cdots, c_n, c_{n+1}\}$ be the set of cutoffs thresholds associated with the running variable X. The outcome variable is assumed to be Y. In the pooled model, the Local Average Treatment Effect (LATE) is:

$$LATE_{no\_controls} = \mathbb{E}\left[\lim_{x \downarrow c_i} \mathbb{E}[Y_i|X_i] - \lim_{x \uparrow c_i} \mathbb{E}[Y_i|X_i] | \forall c_i \in C\right]$$

Nevertheless, this may be problematic in our case as municipal characteristics may vary between cutoffs. For instance, population imbalance is a known source of heterogeneity. To ensure that cases are comparable, we add a set of controls Z_i to reduce heterogeneity. For instance, the population that determines the change from one threshold to another also determines all the cutoffs. As the population runs smoothly around each cutoff, it makes this variable an ideal control to add to our models. The new estimator is:

$$LATE_{controls} = \mathbb{E}\left[\lim_{x \downarrow c_i} \mathbb{E}[Y_i|X_i] - \lim_{x \uparrow c_i} \mathbb{E}[Y_i|X_i] | \forall c_i \in C, Z_i\right]$$

We control for population, GDP, whether the state is located in the Northeast region, seats before the 2003 decision, and year. We use a triangular kernel in our estimations, which gives more weigh to municipalities closer to each cutoff. To compute the optimal bandwidth, we use the Calonico et al. (2014) method. We vary the bandwidth from 50% to 200% of the optimal bandwidth size to assess whether our results are robust to bandwidth choice. We also use cluster-robust standard errors at the municipal level.

As it is uncommon for regression discontinuity designs to include control variables, we run a series of simulations to show that controlling for the variable that determines the assignment helps improve both the consistency and the efficiency of the estimates.

Consider data distributed according to one of the four forms depicted in Figure 2. We add nine thresholds, at 0.1, 0.2, and so on until 0.9, to create different outcomes. The first three are sharp changes. First, we vary from one to 10, moving one step at each shift. In the second case, we add 1 to the first discontinuity, zero to the second, and -1 to the third, repeating this pattern for the remaining cutoffs. The estimated change should be equal to zero. In the third model, we again add one to the first cutoff, but $1 + 0.9$ to the second, $1 + 0.9 + 0.8$ to the third, and repeat this process until the last cutoff. This simulates a diminishing effect from one cutoff to the other. The previous three outcomes are the same as depicted here, plus a Normal random disturbance with mean equal to zero and variance equal to 0.01. We then run a thousand Monte Carlo simulations for each combination, fitting regressions with and without the running variable as a covariate.

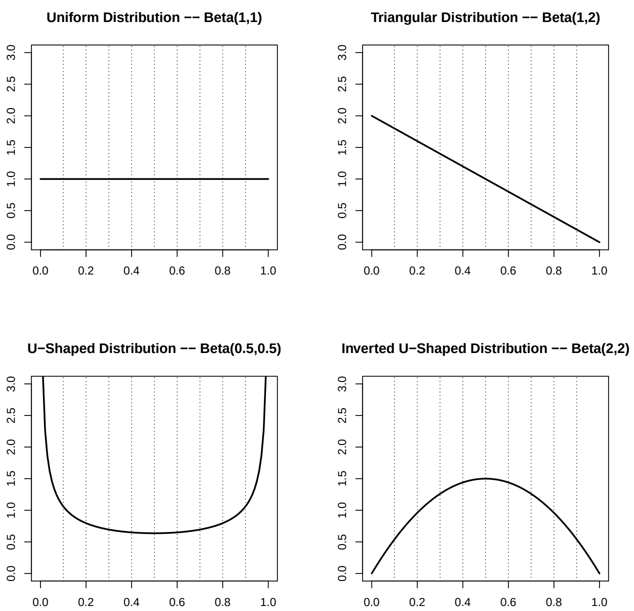

Figure 2: Simulation: RD with Multiple Thresholds – Data Distribution

A consistent estimator should fit either the first or the fourth data distributions. In the second distribution, the change should be equal to $(1, 0, -1, 1, 0, -1, 1, 0, -1)$, and the average change here is equal to zero. In the third model, the change should be $(0.9, 0.8, 0.7, 0.6, 0.5, 0.4, 0.3, 0.2, 0.1)$ and the average change should be equal to 0.5. We display the results in Figure 3, showing that the models with control variables are more consistent and efficient.

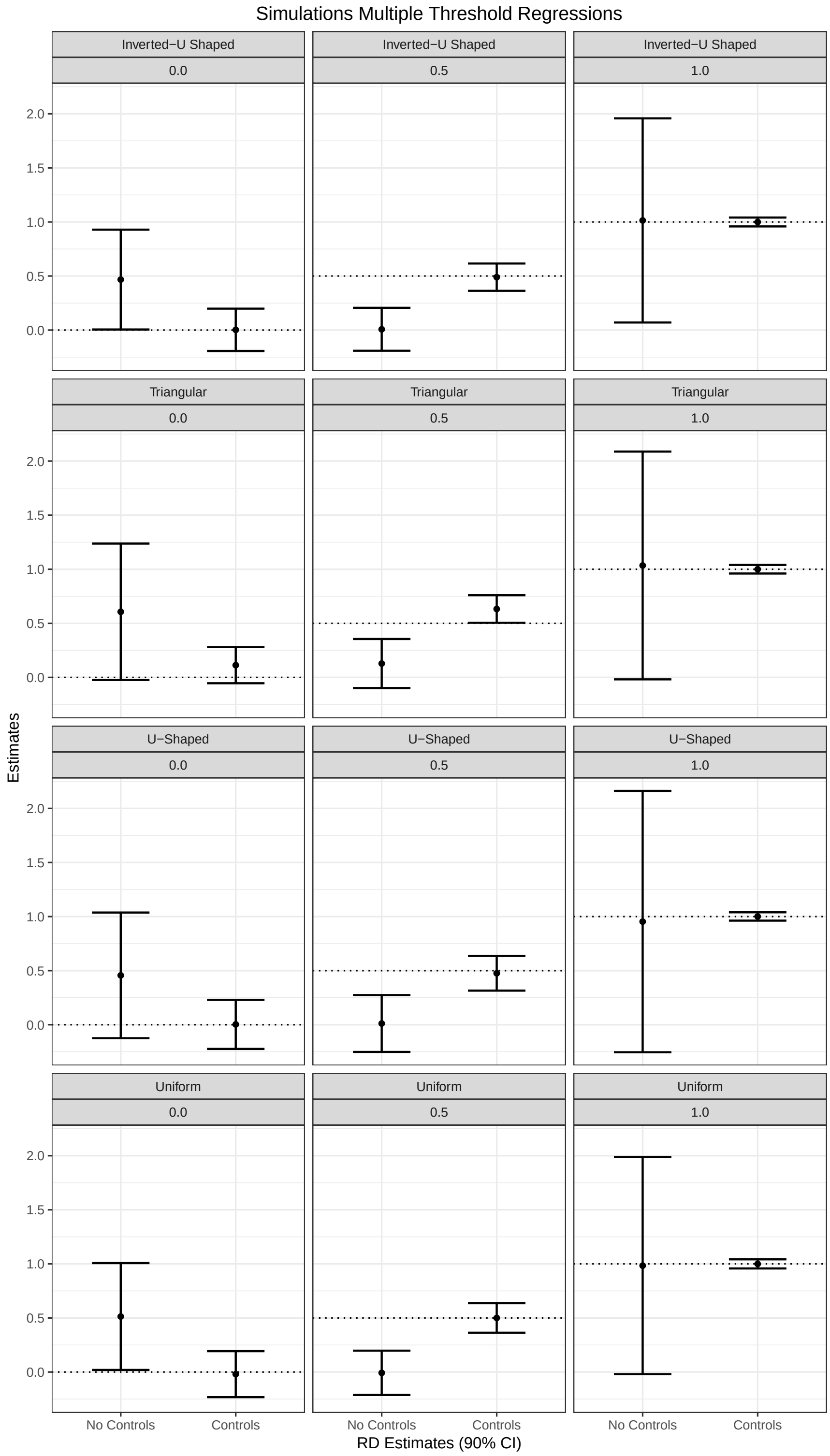

Figure 3: Estimations for the Different Data Generating Processes

A.6 Placebo Regressions for the Political Mechanism

Here we present the placebo regressions for the mechanism-aggregated outcomes. In Panel A of the main paper, we run the regression on alternative explanations. Only the number of female councilors changed significantly, but that is to be expected in at least 10% of cases. We have not collected data on non-white legislators for the placebo cutoffs; therefore, we leave it blank. In Panel B, we have the placebo regressions for the primary mechanism, which concerns bargaining costs and public appointed employees. As expected, the placebo regressions are statistically insignificant.

Table 4: Political Effects of Legislature Size – Placebo Cutoffs

	Panel A: Representation and Elections			
	Representation		**Elections & Leg. Productivity**	
	Num. Female Councilors	Num. Non-white Councilors	Candidates Per Seat	Prop. Laws Approved Council
LATE	0.65**		-0.72	-0.001
	(0.27)		(0.48)	(0.06)
N Left	4620		4621	2990
N Right	906		906	703
Eff N Left	414		567	356
Eff N Right	298		347	229
BW Loc Poly	4.874		6.104	5.583
BW Bias	8.789		10.312	8.89
	Panel B: Bargaining, Coalition, and Public Employment			
	Mayoral Coalition Size	Num. Politically Bureaucrats		
LATE	0.13	-0.58		
	(0.33)	(17.14)		
N Left	4618	13854		
N Right	904	2709		
Eff N Left	654	1345		
Eff N Right	394	915		
BW Loc Poly	6.813	5.127		
BW Bias	10.501	8.194		

Note: ***p < .01; **p < .05; *p < .1. RD estimates using Calonico et al. (2014) optimal bandwidth selection and triangular kernel. Robust standard errors, clustered at the municipal level, in parentheses. Controls: population, GDP per capita, number of seats in 2000, year, and dummy for Northeast region.

A.7 Sensitivity Analysis of Bandwidth Selection

In this section we present the sensitivity tests for bandwidth selection. Following the suggestion of Bueno and Tuñón (2015), we vary the bandwidth from 50% to 200% of the Calonico et al. (2014) estimate.

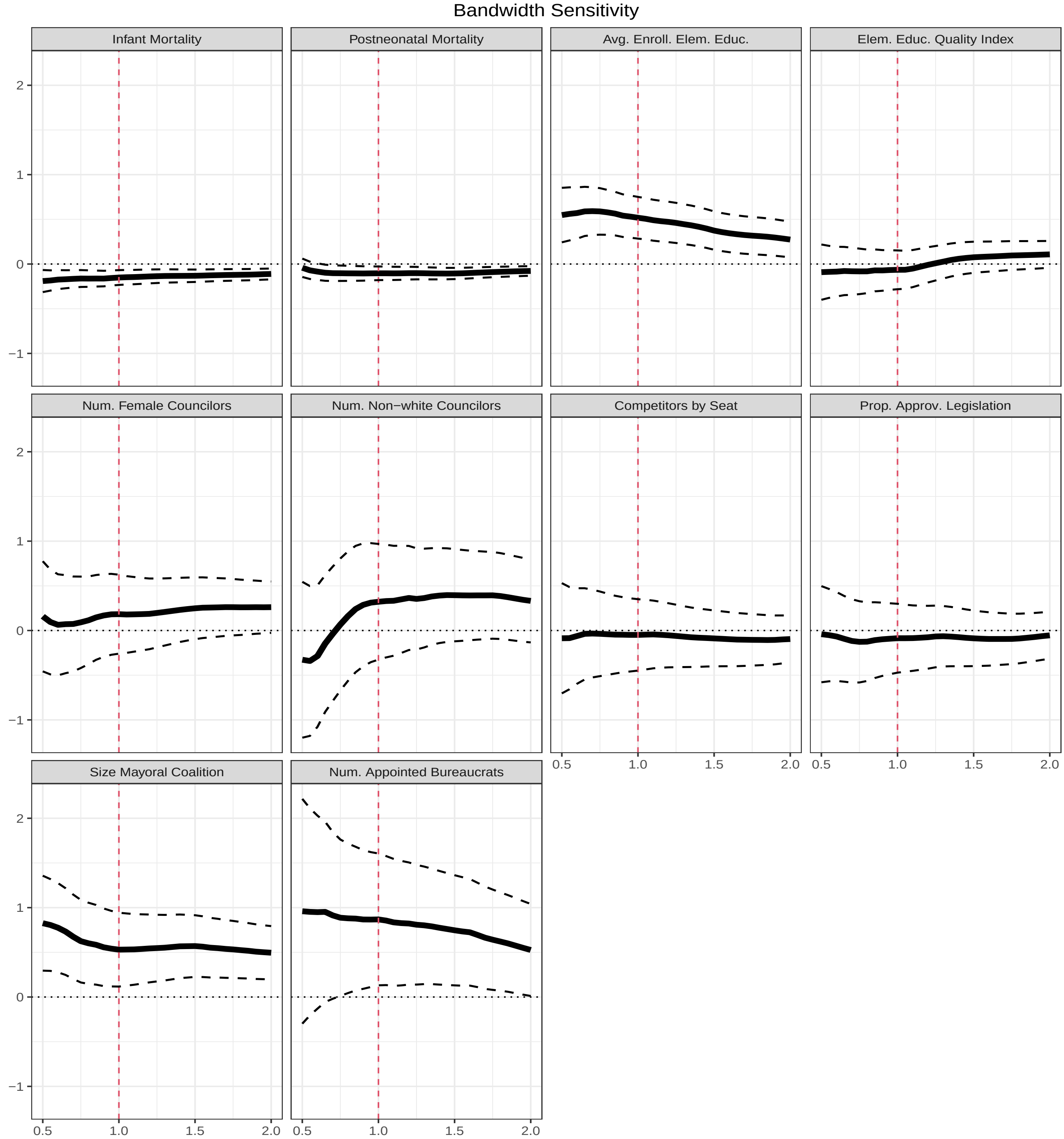

Figure 4: Bandwidth Sensitivity – Main Models

A.8 Sensitivity Analysis of State Characteristics

Given its massive size and large social inequalities, Brazil presents considerable geographic variation. In this respect, some states have such poor health care and education systems that they could be driving our results. We run the analysis dropping one state at a time to investigate this statewide heterogeneity. The results are in Figures 5 and 6.

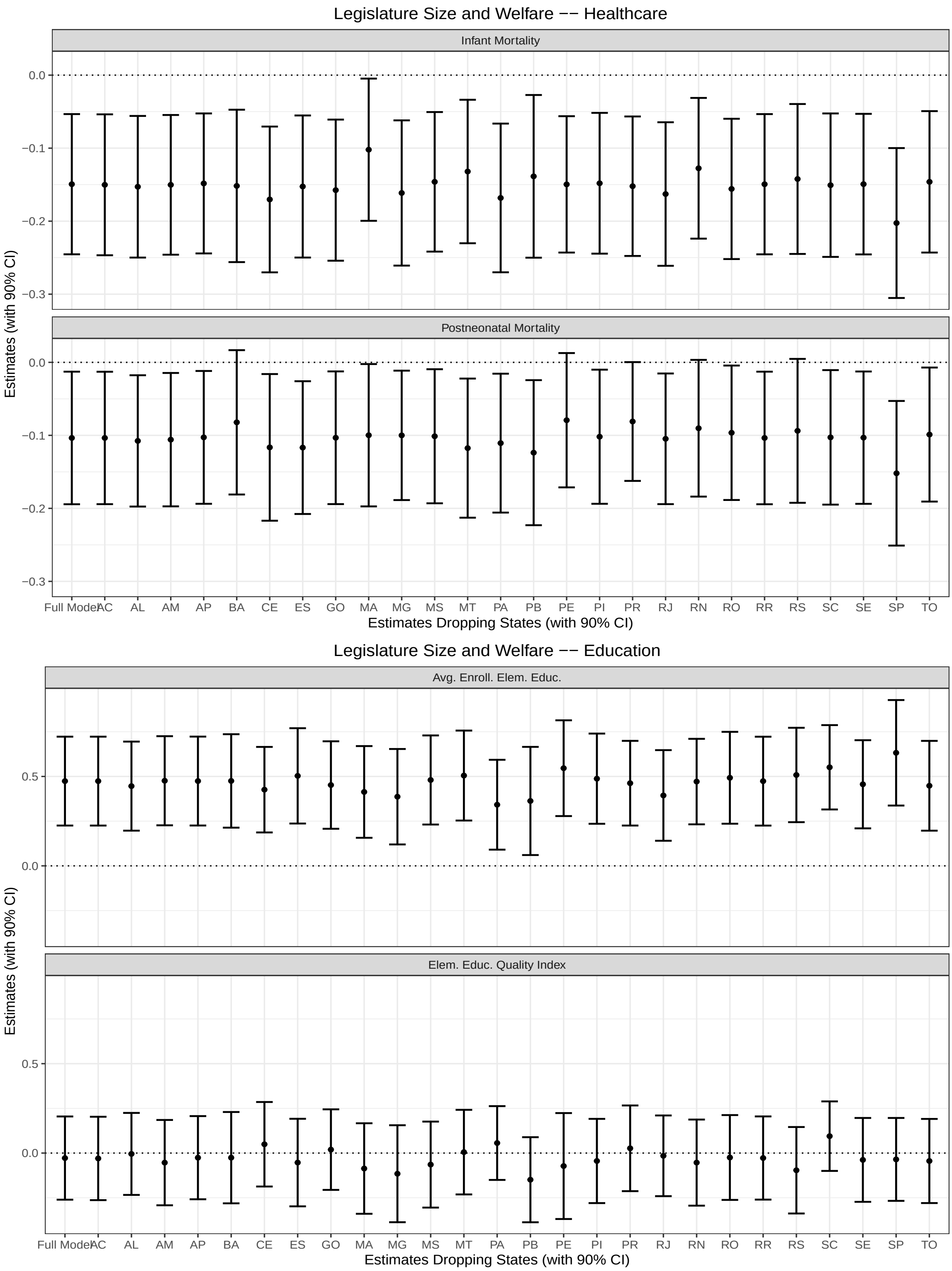

Figure 5: Sensitivity Analysis for the States in the Sample – Welfare Outcomes

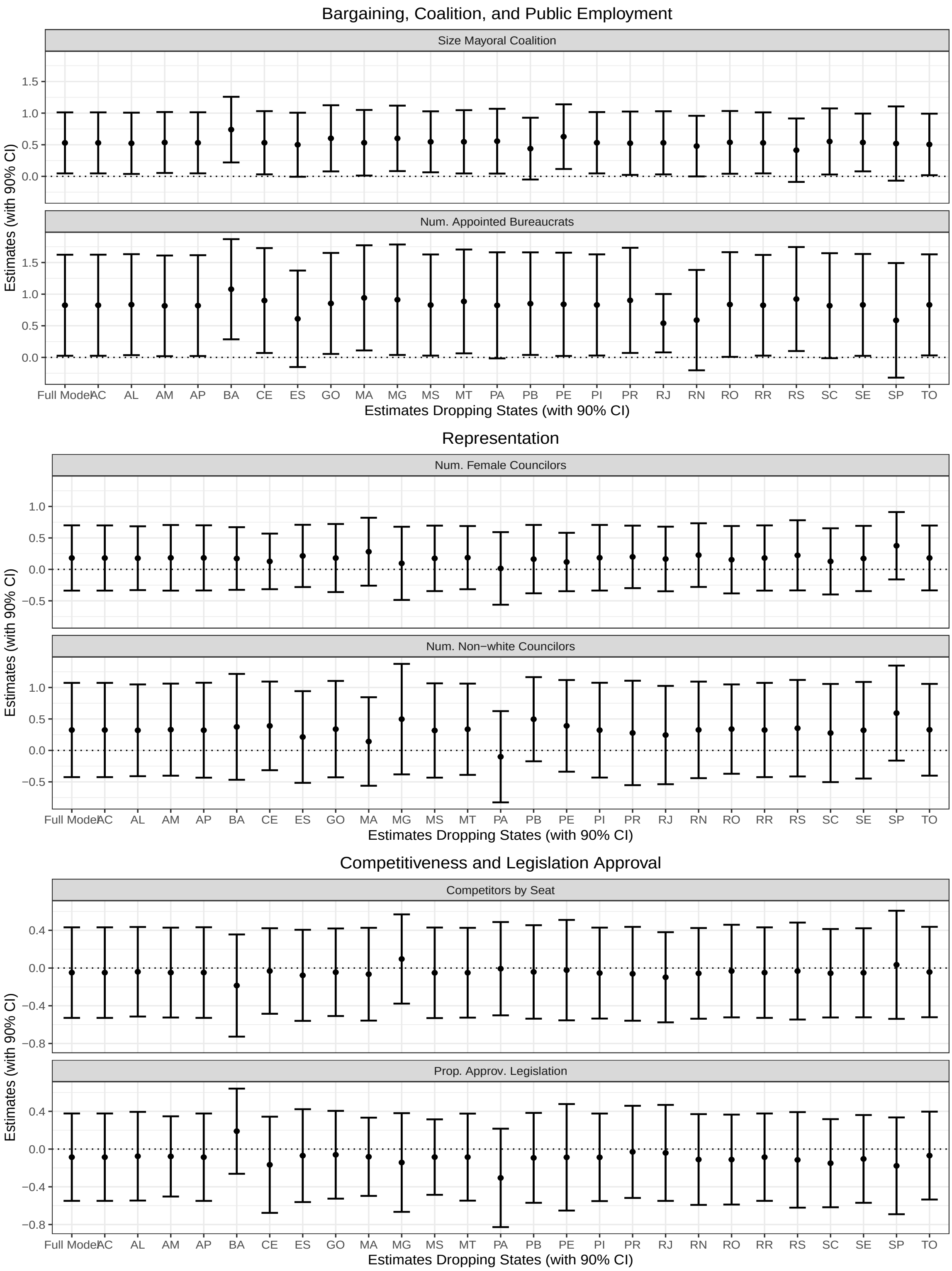

Figure 6: Sensitivity Analysis of State Characteristics – Mechanism Outcomes

A.9 Sensitivity Analysis of Model Functional Form

In the paper, we run all the regressions using local linear polynomials. However, to assess the robustness of our results, we also run every model using different polynomials, from local linear to a quartic, to show that our results are robust to different regression functional forms. The results are similar in all models, with significance changing only in the quartic polynomials. Figure 7 presents the results.

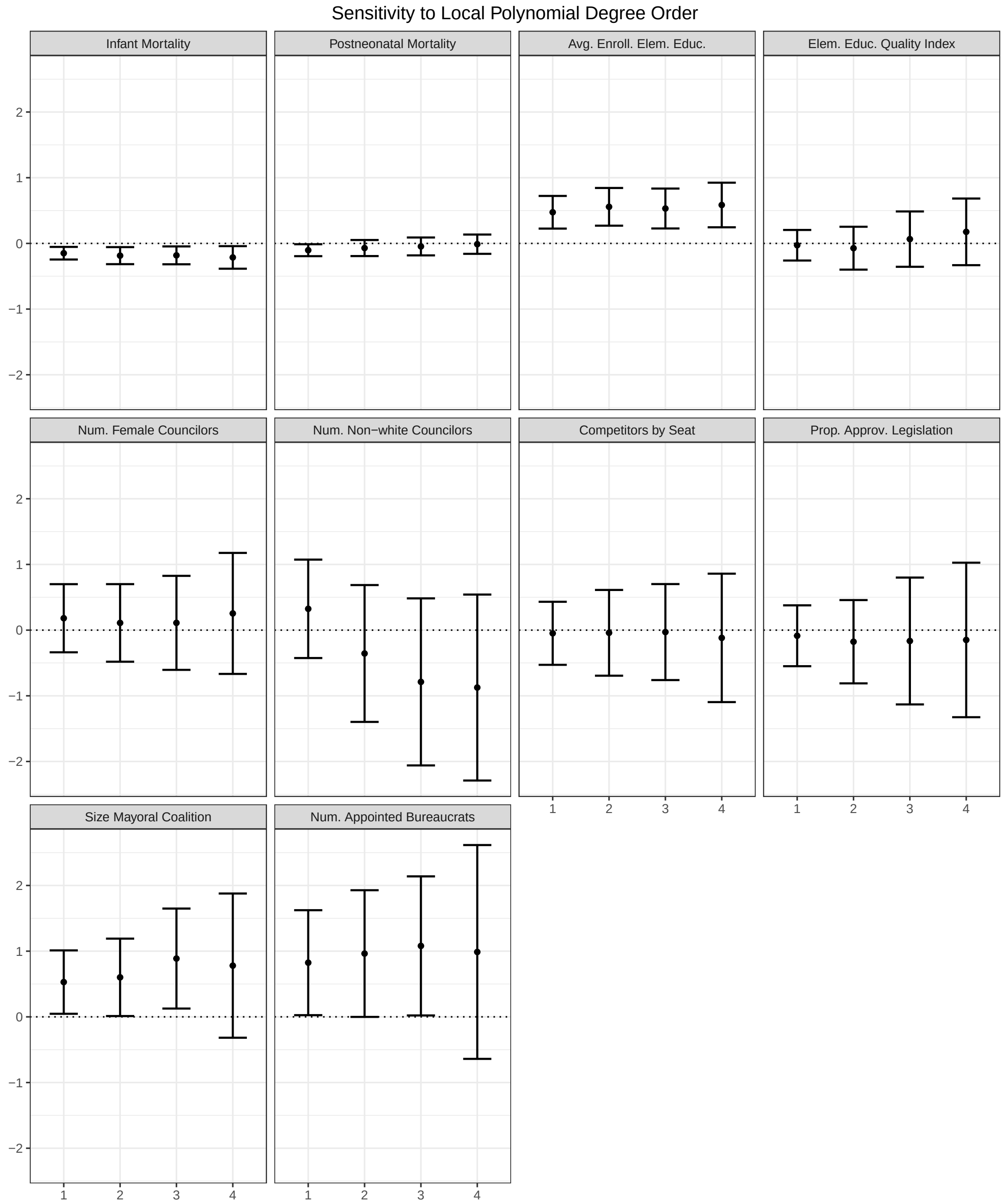

Figure 7: Sensitivity Analysis of Model Functional Form

A.10 Sensitivity Analysis of Covariates

Control variables play a major role in our model. To study the sensitivity to controls, we run the same regressions for all possible control combinations. Figure 8 displays the results for this sensitivity test.[2]

[2] *NC* stands for No Controls. The controls used are *gdp*, the municipal GDP in a given year; *nseats2000*, the number of seats before the 2003 Supreme Court decision; *northeast*, a dummy variable for Northeast Brazil; *pop2003*, population in 2003; and *year*.

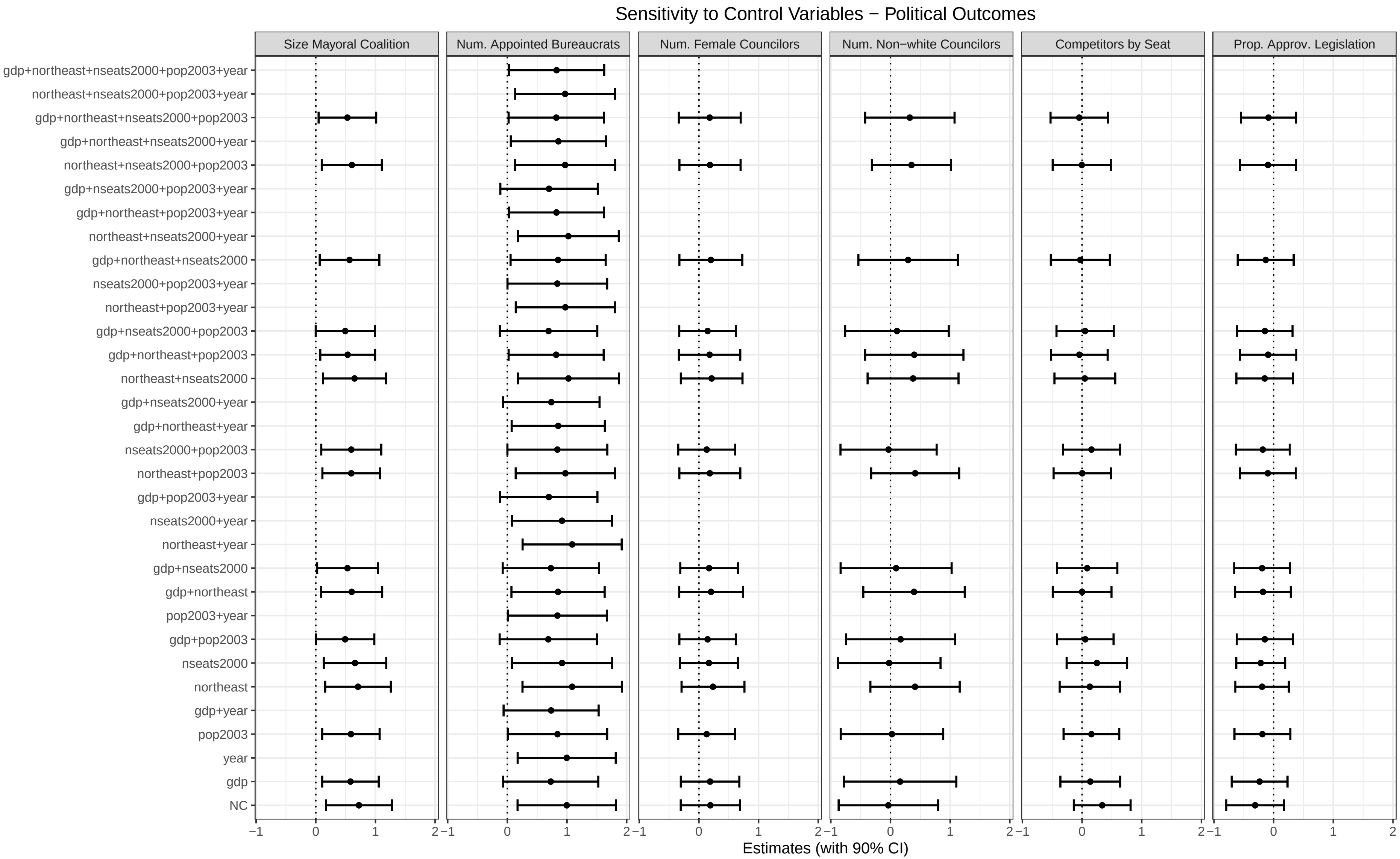

Figure 8: Sensitivity Analysis of Control Variables

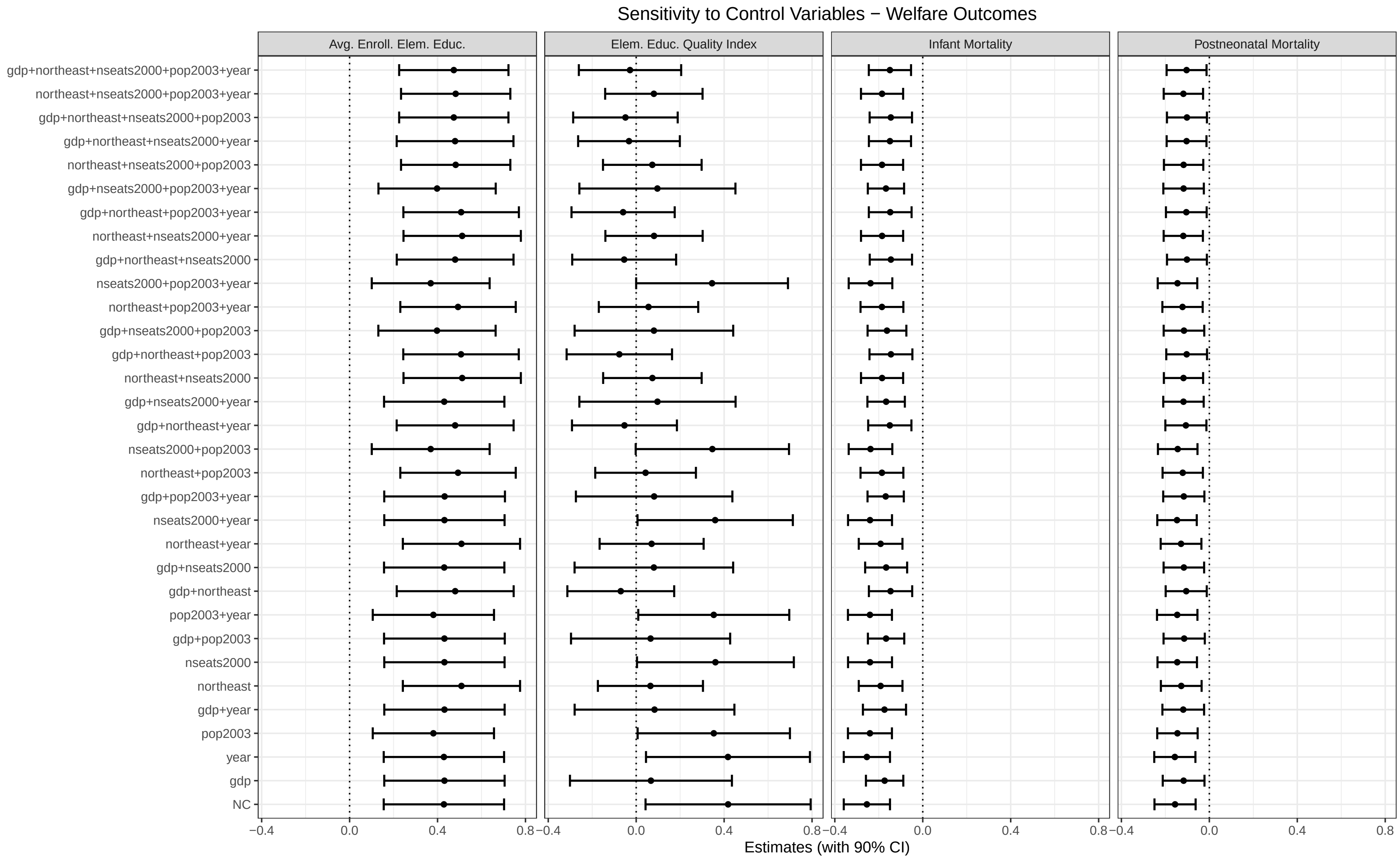

Figure 9: Sensitivity Analysis of Control Variables

For instance, changes in controls substantially affect the quality of elementary education, where some sets of control variables leading to a positive effect. However, most combinations of controls were insignificant.

We included the model with all controls to be conservative in our estimations. This is because the full model is significant only when most of the combinations also are significant. Regarding the point estimates, our variable choices tend to keep the models which have smaller coefficient sizes.

A.11 Sensitivity Analysis of Additional Cutoffs

Here we evaluate the robustness of our results when we change the number of cutoffs. We run a series of regressions limiting the population sizes to half the cutoffs, starting from the second cutoff to the last. This strategy is similar to adding one cutoff at a time. The results are stable and do not change our main conclusions. Moreover, there are no clear increasing or decreasing patterns, which would indicate the existence of differential returns. Figures 10 and 11 display the results for the main cutoffs.

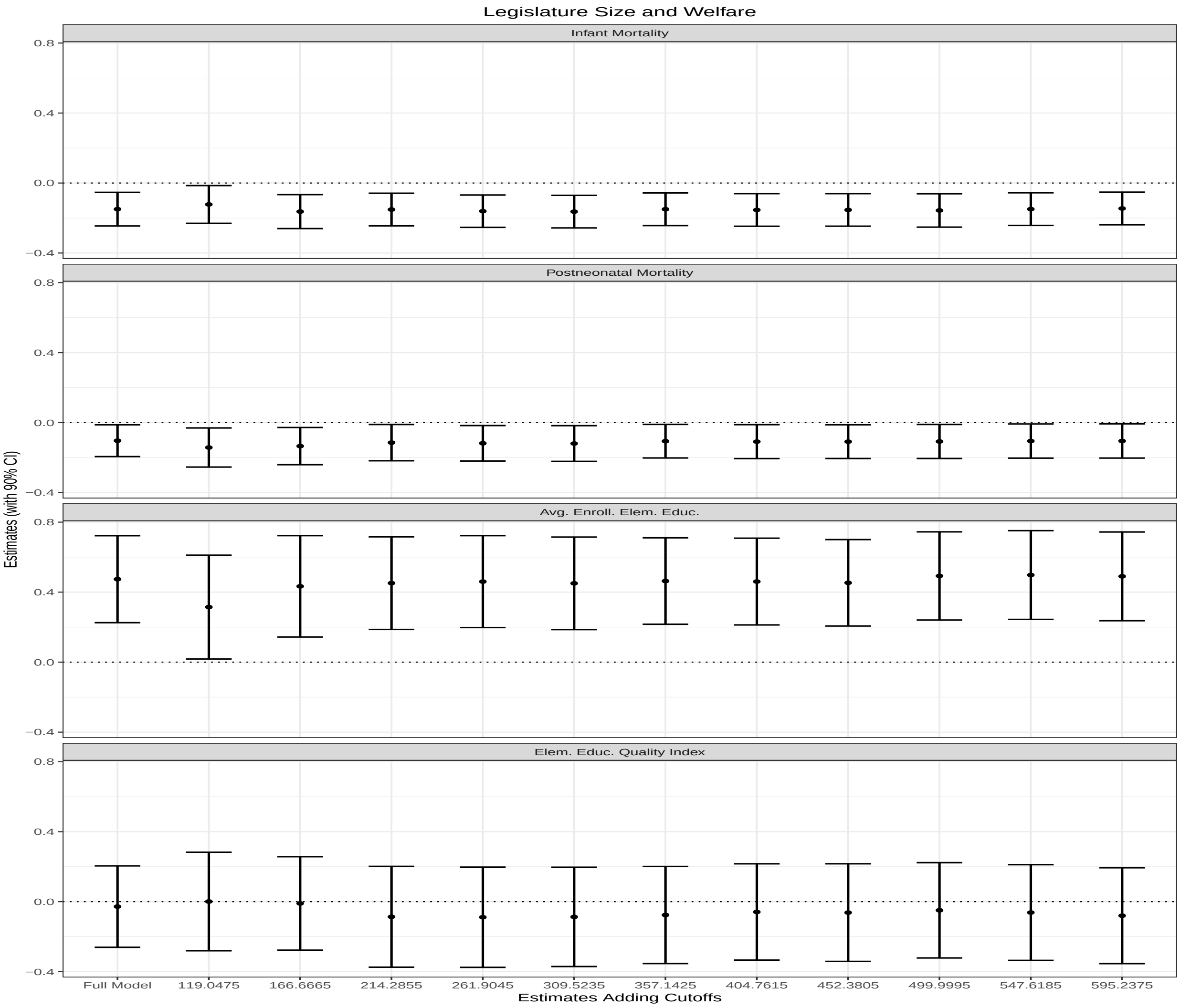

Figure 10: Sensitivity to Additional Cutoffs – Welfare Outcomes

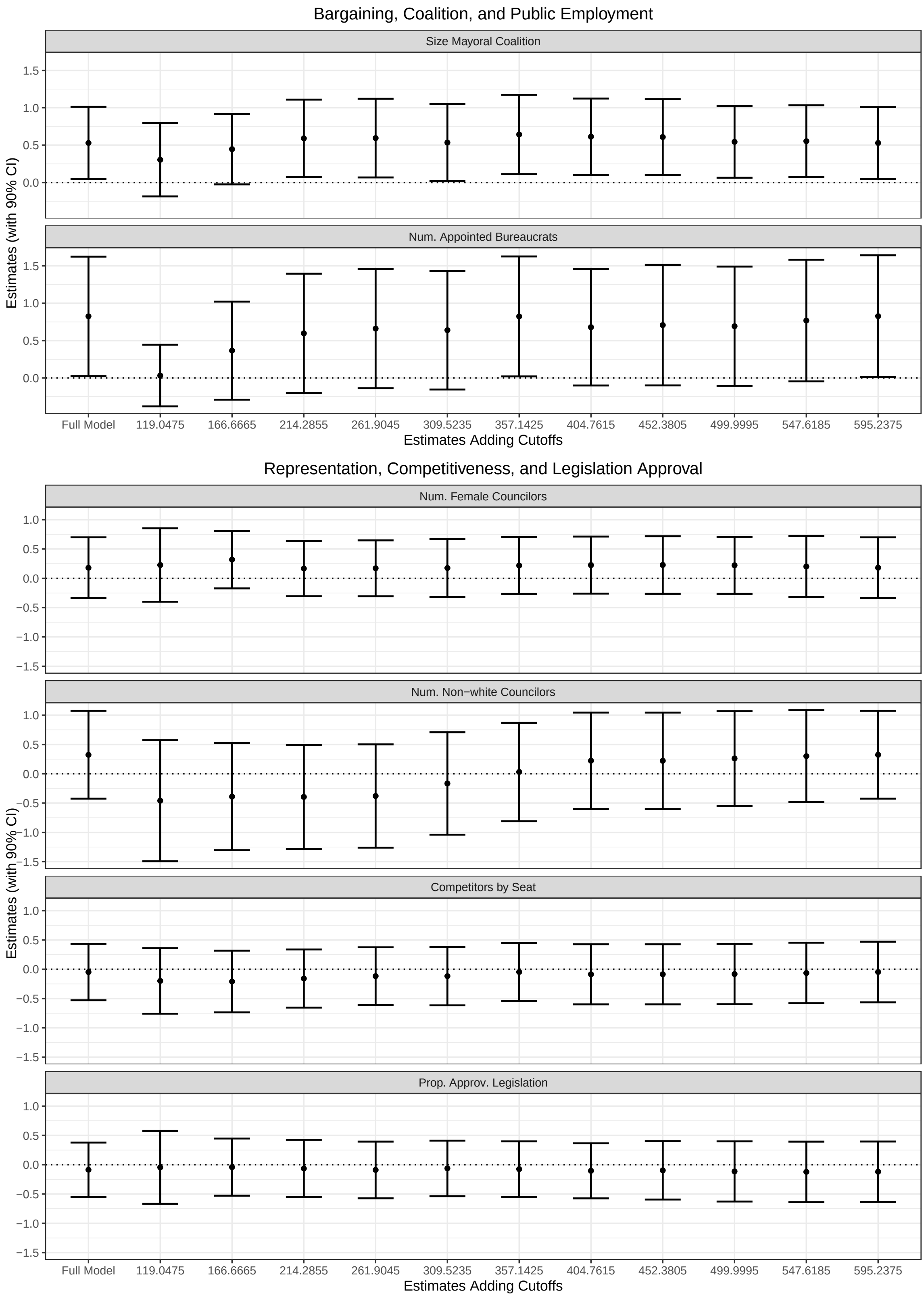

Figure 11: Sensitivity to Additional Cutoffs – Mechanism Outcomes

A.12 Mayor's Characteristics, Revenues, and Transfers from the Central Government

Two alternative explanations may confound our results. First, the mayor's selection could be affected by the size of the city council, thus public welfare improves due to the quality of the mayor and not because of the partisan mechanism we have described. Second, the partisan mechanism could be capturing a dynamic similar to Weingast et al. (1981) "law of 1/n", whereby welfare improvements are caused by higher available revenues. This section shows that none of these concerns are valid in our case.

A.12.1 Mayors' Characteristics

We select four characteristics of the city mayors: gender, level of schooling, whether the mayor was reelected in 2004, and whether the mayor was reelected in 2008. The results in Table 5 show no variation in council size and mayoral characteristics.

Table 5: Mayor Characteristics

	Female Mayor	**Mayor w. College Degree**	**Reelected Mayor 2004**	**Reelected Mayor 2008**
LATE	0.07	-0.06	-0.09	0.06
	(0.08)	(0.13)	(0.10)	(0.14)
N Left	5069	5069	5184	5183
N Right	335	335	343	343
Eff N Left	299	226	192	231
Eff N Right	184	154	141	159
BW Loc Poly	11.738	9.655	8.508	9.596
BW Bias	17.104	15.762	13.338	14.741

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$

Local linear RD Estimates using CCT Optimal Bandwidth Selection and Triangular Kernel.

Quadratic Robust Standard Errors in Parentheses.

Controls: population, GDP per capita, number of seats in 2000, year, and dummy for Northeast region.

A.12.2 Revenues and Transfers

In Table 6, we run another series of models on federal transfers and revenue raised within the municipalities. There is only a negligible effect on education transfers, yet it is barely significant at 10%. The other indicators remain insignificant.

Table 6: Transfers and Revenue

	Total Transfers	FPM Transfers	Education Transfers	Total Revenue
LATE	0.03	-0.03	0.18*	0.06
	(0.04)	(0.03)	(0.10)	(0.04)
N Left	15555	15555	15460	14668
N Right	1029	1029	1028	998
Eff N Left	804	258	349	626
Eff N Right	516	273	333	442
BW Loc Poly	10.617	4.568	6.005	9.253
BW Bias	16.447	8.243	11.412	15.092

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$

Local linear RD estimates using CCT optimal bandwidth selection and triangular kernel.

Quadratic robust standard errors in parentheses.

Controls: population, GDP per capita, number of seats in 2000, year, and dummy for Northeast region.

A.13 Legislation Dataset

In Fall 2018, we collected data on the legislation approved by the city councils of 63 municipalities, all of which were 10 thousand inhabitants away from the thresholds we discussed above. There are 202 municipalities 10 thousand inhabitants away from the cutoff, but only 63 had relevant information about local legislation between 2005 to 2008.

We hand-coded 1% of the dataset (3,466 cases) and applied a Supporting Vector Machine (SVM) algorithm to the remaining 99% cases to classify the legislation. First, we trained and tested the accuracy of the SVM classifier on 80% of the dataset. Then, we ran the training algorithm on the complete hand-coded data and predicted the remaining cases.[3]

We hand-coded these data according to four characteristics:

1. **Local Public Goods**: Whether the bills provided a local public good or service to citizens. For instance, bills that aim to fix street potholes, staff a given health clinic, or purchase equipment to a given school.
2. **Oversight**: Legislation requesting information on the status of service provision.
3. **Health Care and Education**: Bills on education and health care, broadly defined.
4. **Others**: Legislation not categorized as any of the previous three, such as honors to notable citizens.

Table 7 shows the classification accuracy for each of the variables that we have hand-coded. In all models, we set cost to 10 to avoid overfitting.

[3]We tested SVM, Naïve Bayes, Random Forests, and Neural Networks for this task. We have chosen SVM as it gives the highest prediction rate of all of the algorithms we have tried. We use a simple bag-of-words classifier provided by the 'RTextTools' package for 'R' (Collingwood et al. 2013).

Table 7: Accuracy of SVM Classifier (tested in 20% of the data)

Variable	**Accuracy**
Local Public Goods	93.8
Oversight	94.9
Education and Health Care	92.5
Others	93.5

After we classified all the bills, we added the frequency of each category to the main paper. We have also added the productivity per legislator, which consists of the ratio of the legislation approved in the municipality in the four-year term, divided by the council size. As expected, the results changed little when we used this alternative measure.

A.14 City Councilors Survey

From November 21st to December 1st, 2016, we surveyed former city councilors elected for the 2005-2008 term. We asked them how mayors secure electoral support, which services are commonly discussed in the city council, and which services give them the highest electoral yield.

We sent 3,240 emails to politicians who had ran in the 2016 election and held public offices in 2005. On December 1st, we closed the pool and obtained 174 responses. Figure 12 displays the distribution of responses.

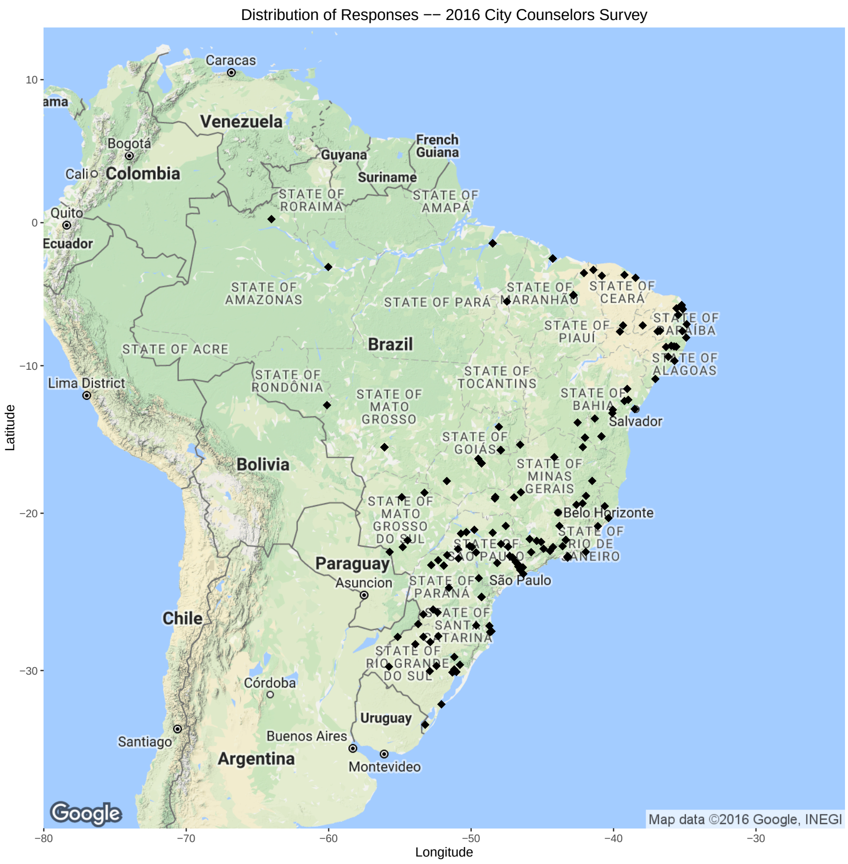

Figure 12: Geographical Distribution of Survey Responses

To weight the survey, we use the Legislative Census, conducted by *Interlegis* on the behalf of the Brazilian Senate. The company was hired to improve the quality of Brazilian government branches. We include the following categories in the weighting procedure: region of Brazil, legislature size (9 to 15 or more), gender, and age less than 39. We use the proportions in each bin to weight the graphs and statistics generated after the raking process.[4] Table 8 shows the sample, population, and weighted proportions.

Table 8: Proportions for each bin used in the weighting process

	Sample Proportions	Population Proportions	Weighted Proportions
Age less than 39	0.50	0.34	0.34
Female	0.18	0.12	0.12
Number of Seats = 9	0.83	0.90	0.90
Number of Seats = 10	0.10	0.06	0.06
Number of Seats = 11	0.01	0.02	0.01
Number of Seats = 12	0.01	0.01	0.01
Number of Seats = 13	0.006	0.005	0.005
Number of Seats = 14	0.01	0.004	0.005
Number of Seats = 15 or more	0.02	0.009	0.008
Region = Central-West	0.11	0.08	0.08
Region = Northeast	0.33	0.32	0.32
Region = North	0.05	0.08	0.08
Region = Southeast	0.30	0.30	0.30
Region = South	0.20	0.21	0.21

The survey included the following questions of interest:

1. No Brasil é comum que o prefeito tenha de negociar para ter maioria na Câmara de Vereadores. Com que frequência, o(a) Sr(a) acha que o prefeito usa os seguintes dispositivos para conseguir apoio?
2. Quais dessas atividades o(a) Sr(a) acredita serem mais comuns no trabalho da maioria dos vereadores?
3. Quais dessas atividades o(a) Sr(a) acredita que ajudam mais um vereador durante a eleição?

English translation:

1. In Brazil, mayors commonly negotiate to establish a government majority in the city council. How often do you think mayors use the following goods in exchange for support?
2. Which of those activities do city councilors perform most often in their duties?
3. Which of the following activities do you believe helps city councilors the most in elections?

The second question is particularly relevant to our argument, as it indicates whether councilors engage in activities that give them high electoral yields. Figure 13 shows the results for each of the activities we analyzed.

[4] The ‘survey‘ package for ‘R‘ describes the raking process in more detail (Lumley et al. 2004). In summary, it iterates the post-stratification procedure until the sample marginals match the population marginals for all variables.

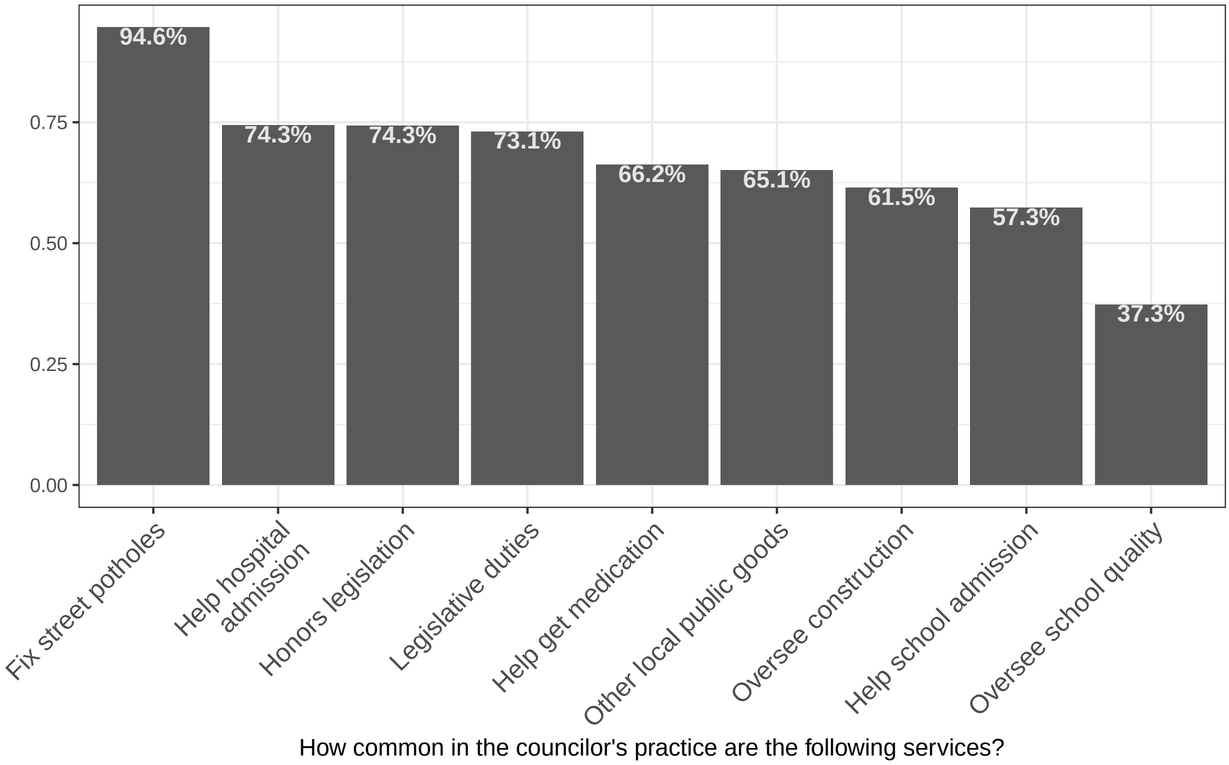

Figure 13: City Councilor's Common Activities

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