Competence versus Priorities: Negative Electoral Responses to Education Quality in Brazil

Appendices

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Appendices

A Regression discontinuity design

A.1 Media attention to IDEB

In order to get a quantitative measure of media attention, we use the search tool of written media content aggregator Factiva, to search for news stories in Portuguese from within Brazil mentioning IDEB, between the date when the data was published and the day of the elections. For 2016, this search returns 254 pieces of news, more than half of which also included the word "target" or "targets". This can be compared to a baseline of over 52,000 pieces in the Factiva database for that same period, i.e. about 0.49% of the news pieces in that period mention IDEB. For the dates between the publication of IDEB results and municipal elections in 2012, searching for news mentioning IDEB returns 494 pieces of news, 37% of which include the word "target" or "targets". For 2008, the search returns 239 pieces.

In addition to this hit count metric, we also read a systematic sample of 200 articles that mentioned IDEB during the 2008, 2012, and 2016 election period. Of these 200 articles, 118 articles discussed the performance of a specific municipality on the IDEB. Of these 118 articles, 56% discussed meeting or failing to meet the target. Discussing municipal performance specifically in connection to the target became more common in later elections: in 2016, for example, 70% of IDEB-focused articles discussed the target specifically.

This data supports the idea that media coverage of municipal performance discusses both levels of achievement and how it relates to federal targets. While Factiva covers a large number of sources, it does not cover the universe of Brazilian media, and it is thus hard to judge how much coverage these search hit totals represent. To get a benchmark, we look for news pieces about Bolsa Família, the federal government's highly visible and often discussed conditional cash transfer program. For the same period from the publication of IDEB results up to election day in 2016, Factiva returns 215 pieces of news mentioning Bolsa Família versus 254 mentions of IDEB. Overall, it seems Brazilian written media pay significant attention to IDEB.

With respect to other media sources, the most direct piece of evidence on the salience of IDEB and IDEB targets specifically can be found in Varjão (2019). Varjão (2019) uses automated transcripts from 1/3 of all 2018 local community radio broadcasts in the states of São Paulo and Paraná to examine discussion of IDEB. The day after the release of IDEB, he found that 25% of radio stations discussed municipal performance.[1] Among those discussing municipal performance, 72% specifically discussed performance with respect to the federal targets. These findings from local media also suggest that federal targets are quite salient in media dicussions of IDEB.

[1] Varjão (2019) notes that this may be a lower bound, due to imperfections in the automated transcriptions and the fact that recordings were unavailable from the day that the IDEB was released.

A.2 Quantitative measures of citizen attention to IDEB

We use Google Trends data on searches made from within Brazil as a proxy for citizen demand for information about IDEB. Figure A.1 below compares the relative frequency of searches for "IDEB" and a number of highly salient policy issues.

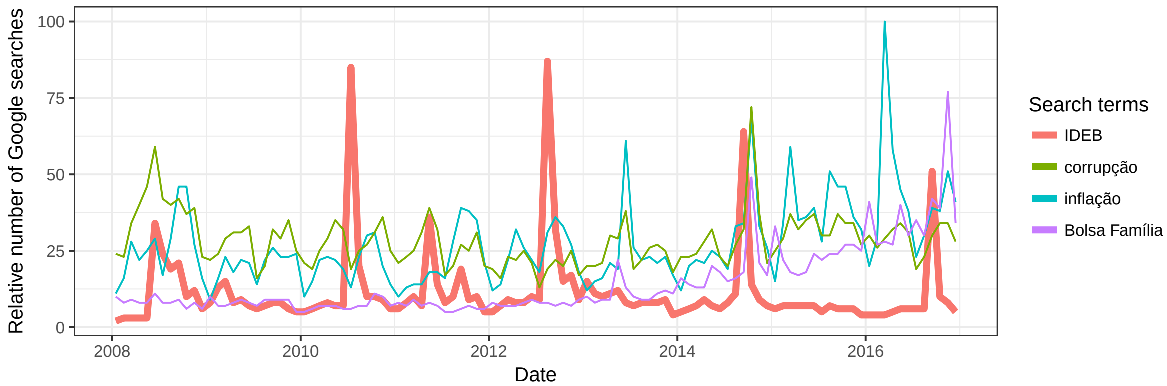


Figure A.1 – Relative frequency of Google searches in Brazil for the terms "IDEB", "corruption", "inflation", and "Bolsa Familia" from 2008 to 2016, by month. Data are from Google Trends.

A.3 Information release and election schedule

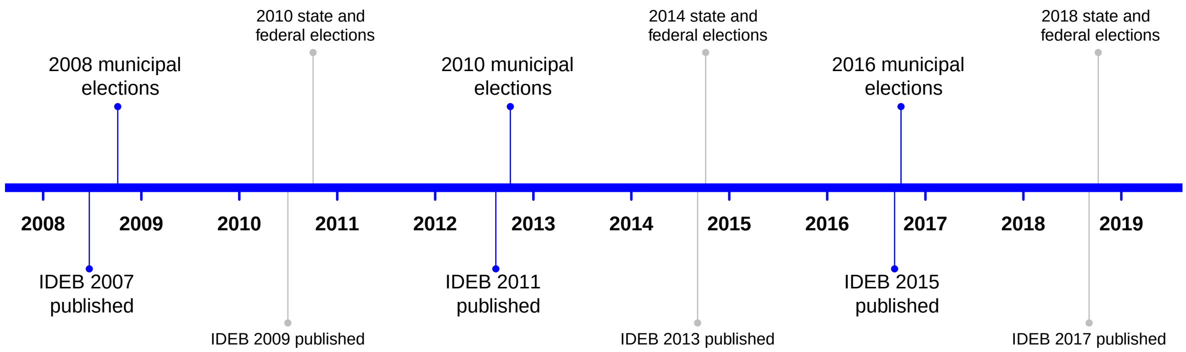


Figure A.2 – Timeline of the release of IDEB results and elections. See Table A.1 below for dates of each event.

ANRESC implemented	IDEB results published	First round of elections held	Time from results to elections
November 5-20, 2007	June 21, 2008	October 5, 2008	$<$18 weeks
October 19-30, 2009	July 1, 2010	October 3, 2010	$<$14 weeks
November 7-18, 2011	August 14, 2012	October 7, 2012	$<$8 weeks
November 11-21, 2013	September 5, 2014	October 5, 2014	$<$5 weeks
November 3-13, 2015	September 8, 2016	October 2, 2016	$<$ 4 weeks
October 23-November 3, 2017	September 3, 2018	October 7, 2018	$<$ 5 weeks

Table A.1 – Key dates in the IDEB and the electoral calendar. Municipal elections held in 2008, 2012 and 2016. State and federal elections held in years 2010, 2014 and 2018.

A.4 Continuity of the forcing variable

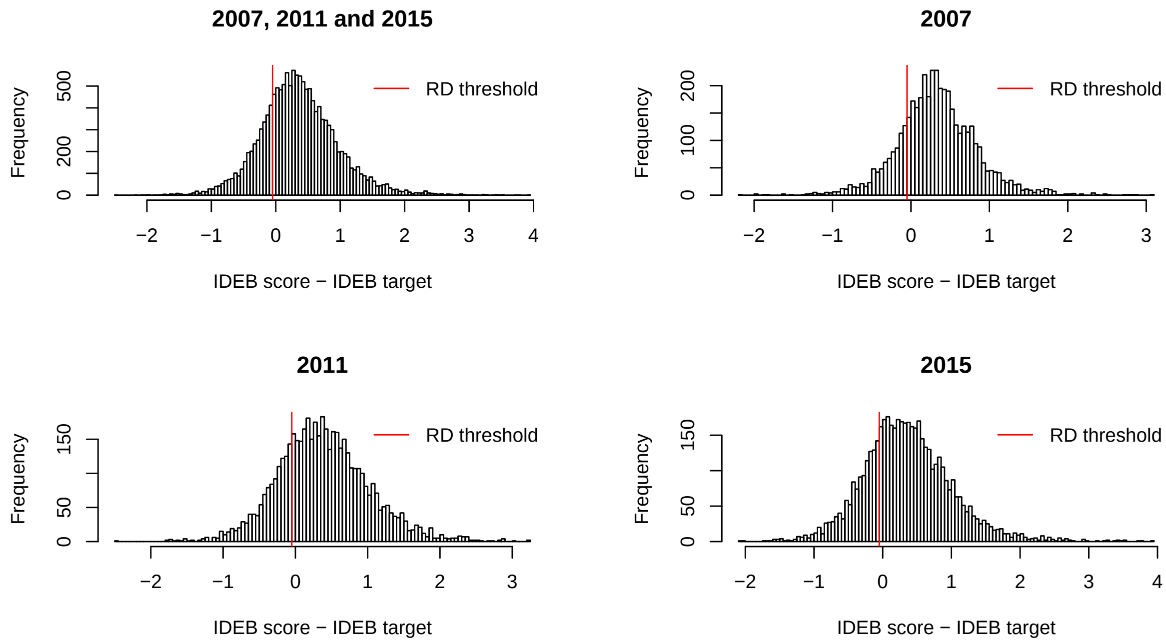


Figure A.3 – Histograms of the forcing variable, by test year.

While "a running variable with a continuous density is neither necessary nor sufficient for identification" (McCrary, 2008, 701), it is important to consider possible ways teachers, directors and politicians could be manipulating the forcing variable. IDEB targets are impossible to manipulate. They were defined a priori following technical criteria and published at the beginning of the period. IDEB scores are themselves composed of two parts: passing rates and learning outcomes. Passing rates are the most obvious lever that school and municipality leaders could manipulate. However, boosting passing rates is likely to lead to a decrease in test scores (since students who would otherwise not pass generally get lower scores): the system is in fact designed to disincentivize this type of manipulation. Last, learning outcomes are under *limited* control of school administrators and teachers. IDEB is precisely targeted at measuring their capacity of "manipulating" this variable, i.e. boosting learning. But boosting learning is difficult, and even units that manage to achieve significant gains in learning may miss their target, particularly if they had been lagging behind. The key fact here is that while teachers, directors and

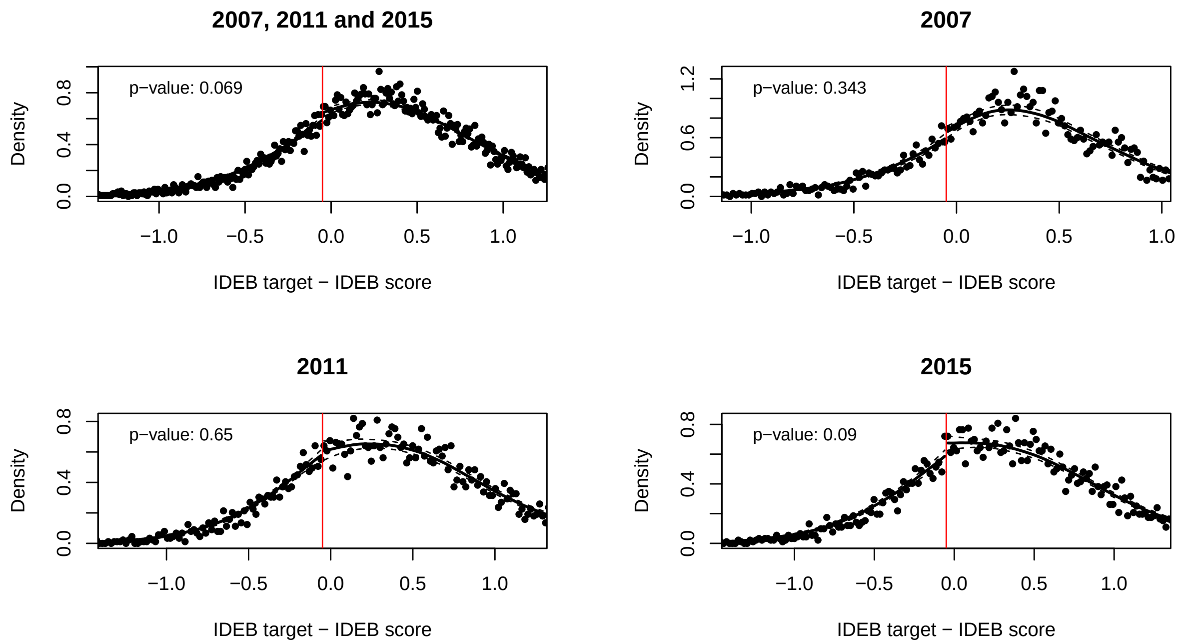


Figure A.4 – Density plots and results of the McCrary (2008) test for the forcing variable (IDEB score - IDEB target), by test year.

politicians may have some influence over the forcing variable, they cannot manipulate it *precisely*, which guarantees that, for municipalities around the threshold, treatment assignment is as-if-random (Lee and Lemieux, 2010).

A.5 Continuity of pre-treatment covariates

	RD estimate	Standard error	p-value
Mayor vote share in previous election	0.008	0.012	0.496
Incumbent mayor ran	-0.038	0.040	0.336
Herfindahl index of electoral results	-0.018	0.015	0.243
Mayor belongs to PT	-0.019	0.025	0.436
Mayor belongs to PSDB	0.023	0.029	0.426
Mayor belongs to PMDB	-0.036	0.037	0.334
Incumbent party ran	0.003	0.041	0.948
Population (logged)	0.057	0.080	0.474
Household monthly per capita income (2010)	10.773	15.002	0.473
Families in the Bolsa Família program	-14.190	175.056	0.935
Percent poor	0.008	0.012	0.496
Share of municipal employees tenured	-0.038	0.040	0.336
Radio and TV stations (2012)	-0.018	0.015	0.243
Enrolments in municipal schools (share of total)	-0.019	0.025	0.436
Municipal school enrolments (share of population)	0.023	0.029	0.426

Table A.2 – Continuity of pre-treatment covariates. The difference between municipalities where the IDEB target is met and those where it is missed is calculated using each covariate as the dependent variable in Equation 3, within the bandwidth specified by the Calonico et al. (2014) algorithm. Standard errors are consistent for heteroskedasticity (HC1).

A.6 Data constraints and characterization of the RDD effective sample

While we start from a potential universe of 16,700 municipality-period observations (5,565 in 2008 and 2012, and 5,570 in 2016), the RD design imposes a number of constraints in the data, detailed in Table A.3 below. With these constraints, the data effectively used for the RD models consist of 4,179 municipality-period observations where incumbent re-election is the dependent variable, and 2,868 where incumbent vote share is the dependent variable.[2] Most of the municipality-period observations that do not enter the RD data do so because they lack data on the dependent variable (since not all mayors are allowed to run for re-election) or data on the forcing variable (since not all municipalities receive both an IDEB score and an IDEB target).

Our results results are therefore valid for the subset of municipality-election observations where (i) there is a public IDEB score and target, (ii) the incumbent mayor is not barred from running (and, for the regressions of vote share, they actually run); (iii) the regular elections are valid and thus no supplementary elections are held; (iv) only one signal of municipal school quality is published; and (v) the IDEB score performance is sufficiently close to the target. While this set does not represent the whole population of municipalities in Brazil, it is the set for which it is meaningful to think of the causal impact of meeting the IDEB target on the electoral performance of the incumbent.

These constraints leave us with a subset of smaller and less competitive municipalities. Table A.4 characterizes the RDD effective sample in terms of the number of residents (logged), the percent of them who are poor (as defined by the federal statistics index), local political competitiveness (measured with a Herfindahl index of electoral concentration where numbers closer to 0 denote a more fragmented election and those closer to 1 a less

[2]The effective samples in Tables 1 and A5 are smaller because they exclude municipalities outside the RD bandwidth (i.e., where the performance of the municipality's school system was not sufficiently close to its target).

Table A.3 – Data constraints imposed on the RDD sample

Constraint imposed	Resulting N	Notes
None	16,700	All municipal-year observations in 2008, 2012, 2016
IDEB score is published	↪ 15,100	IDEB scores required for measuring the forcing variable. The most common reason for municipalities not having an IDEB score is that schools must have at least 20 students enrolled in the corresponding grade for their ANRESC scores to be calculated.
IDEB target is published	↪ 14,230	IDEB targets required for measuring forcing variable The most common reason for municipalities not having an IDEB target is not having baseline IDEB scores with which the Ministry calculates targets.
Mayor can run	↪ 9,869	Mayor eligibility required for measuring dependent variable. Mayors who are in their second consecutive term are barred from running.
Mayor has unique ID	↪ 9,860	Mayor ID required for measuring dependent variable. The Supreme Electoral Court data does not report mayor ID in a few cases, likely due to data entry errors.
No supplementary election held	↪ 9,677	Supplementary elections are held months or years after regular elections, and thus far away from IDEB data being released. The Supreme Electoral Court does not report data from the original elections, in places where it reports results for a supplementary election.
Only one IDEB signal	↪ 4,179	A municipality receiving two signals (one for primary and one for for middle schools) is likely to confuse their interpretation by voters and media. Primary schools are consistently associated to municipal governments, whereas municipal middle schools are generally associated to state governments. Since some but not all municipalities receive two signals, it is not possible to do a two-dimensional RDD that could identify their effect.
Mayor ran	↪ 2,868	Mayor running required for measuring vote share

competitive election), and the share of municipal workers who are tenured. Compared to all municipality-period observations, those that enter the RDD belong to less populous municipalities, with slightly lower incidence of poverty, and less electoral fragmentation.

	Dependent variable: Observation is included in:		
	RDD sample (compared to all)	RDD sample & within ± 0.4 bandwith (compared to all)	RDD sample & within ± 0.4 bandwith (compared to those in the RDD sample)
	(1)	(2)	(3)
Population (logged)	-0.046^{***}	-0.012^{***}	0.038^{***}
	(0.003)	(0.002)	(0.008)
Percent residents poor	-0.005^{***}	-0.002^{***}	0.0003
	(0.0002)	(0.0001)	(0.001)
Electoral concentration	0.110^{***}	0.042^{**}	-0.039
	(0.024)	(0.018)	(0.051)
Share workers tenured	0.022	0.045^{***}	0.110^{***}
	(0.015)	(0.011)	(0.035)
Constant	0.744^{***}	0.233^{***}	0.063
	(0.038)	(0.028)	(0.092)
Election fixed effects	✓	✓	✓
N	16,503	16,603	4,178
R^2	0.059	0.019	0.013

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A.4 – Characterization of the RDD effective sample. HC2 heteroskedasticity consistent standard errors in parentheses.

A.7 Alternative outcome: Incumbent vote-share

	Linear		Robust	
	(1)	(2)	(3)	(4)
IDEB target met	-0.031	-0.040*	-0.045	-0.055*
	0.022	0.023	0.029	0.031
Election cycle fixed effects	✓	✓	✓	✓
Controls		✓		✓
Bandwidth	0.365	0.332	0.365	0.332
N	1152	1047	1152	1047

*p<0.1; **p<0.05; ***p<0.01.

Table A.5 – Effect of reaching the IDEB target on the vote-share of the incumbent. The bandwidth is the optimal bandwidth determined by the algorithm of Calonico et al. (2014). Standard errors are consistent for heteroskedasticity (HC1 in models 1-2, and nearest-neighbor in models 3-4.)

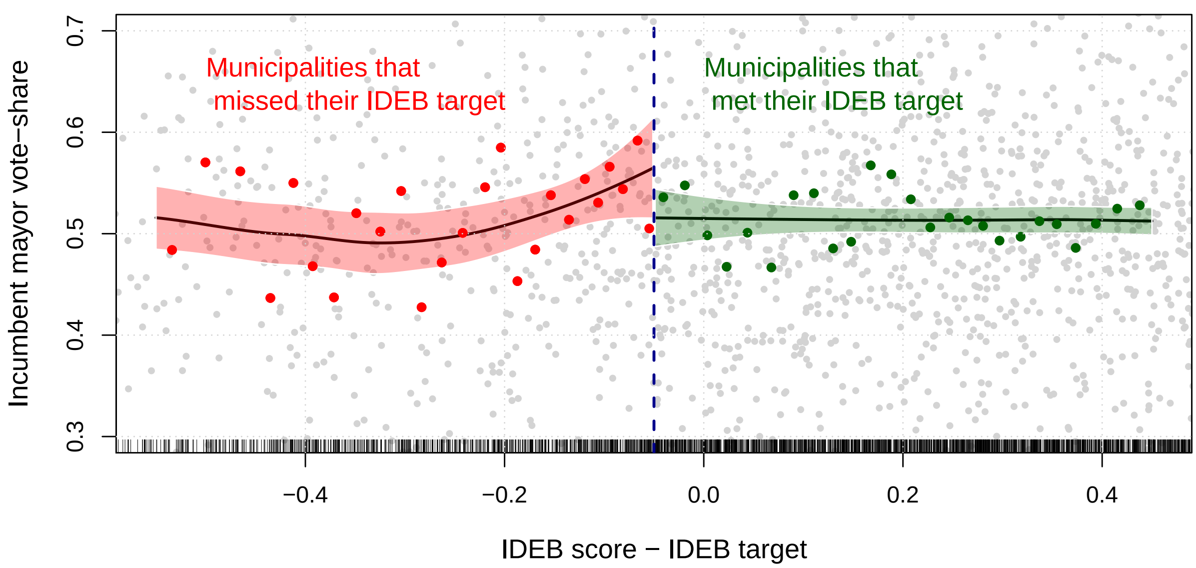


Figure A.5 – Relationship between meeting the IDEB target and vote share of the mayor. Grey dots are observations. Colored dots represent local averages for 50 equally-sized bins. Lines are loess regression lines estimated at both sides of the threshold with no controls. Shaded regions are their 95% confidence intervals.

RD results of the effect of meeting the IDEB on the vote-share of the incumbent are of similar standardized magnitude than those for re-election repoted in Table 1, but noisier. This is most likely due to the decrease in power stemming from a lower number of observations (municipalities where the mayor was allowed to run but chose not to are dropped from this sample but not that of Table 1). One may however be concerned that part of the difference may be driven by municipalities' IDEB performance driving incumbents' decisions to re-run. This is unlikely given the calendar for registering electoral candidates in Brazil: only in 2008 was this deadline *after* the release of IDEB scores.[3] Still, we test for this possibility by running the RD regression with whether the incumbent ran as a dependent variable. Table A.6 shows statistically insignificant results.

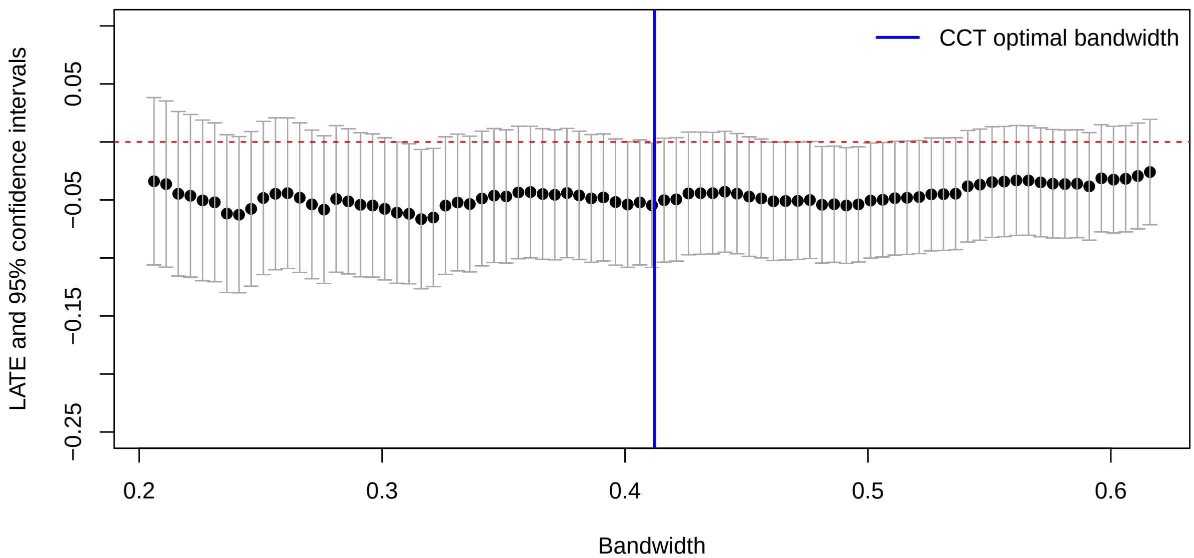
	Linear		Robust	
	(1)	(2)	(3)	(4)
IDEB target met	-0.038	-0.038	-0.042	-0.044
	0.040	0.035	0.050	0.052
Election cycle fixed effects	✓	✓	✓	✓
Controls		✓		✓
Bandwidth	0.470	0.446	0.470	0.446
N	2087	1998	2087	1998

*p<0.1; **p<0.05; ***p<0.01.

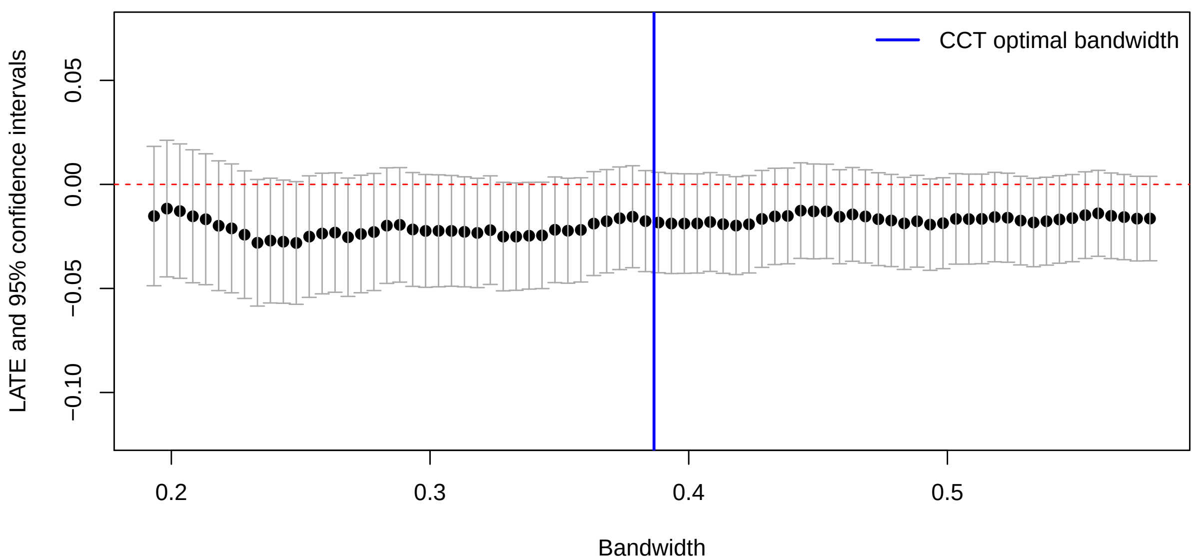
Table A.6 – Effect of reaching the IDEB target on whether the mayor runs for re-election. The bandwidth is the optimal bandwidth determined by the algorithm of Calonico et al. (2014). Standard errors are consistent for heteroskedasticity (HC1 in models 1-2, and nearest-neighbor in models 3-4.)

[3]Candidates had to register their candidacies by July 7 in 2008, July 5 in 2012, and August 15 in 2016.

A.8 Alternative bandwidths



(a) Mayor re-election



(b) Mayor vote-share

Figure A.6 – Robustness of the treatment effect shown in model 2 in Tables 1 and A5 to alternative bandwidths.

A.9 Alternative discontinuity thresholds as placebo tests

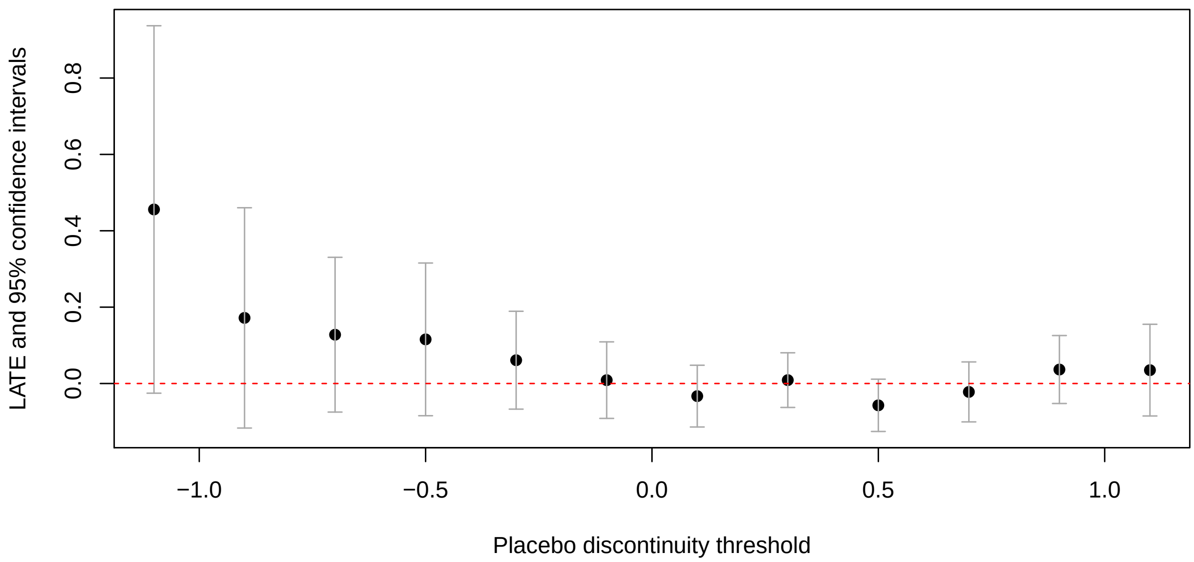


Figure A.7 – Placebo tests using alternative discontinuity thresholds for Model 2 in Table 1.

A.10 Alternative sample: no restrictions

As described in Section 4.1.1 and Appendix A6, our main results impose a number of constraints on the sample (observations where mayors are allowed to run, no supplementary elections are held, and municipalities receive only one IDEB signal). Here we present results lifting those constraints. Effects are smaller and less precisely estimated, but remain negative in all specifications.

	Linear		Robust	
	(1)	(2)	(3)	(4)
IDEB target met	-0.023	-0.025	-0.021	-0.021
	0.022	0.021	0.028	0.029
Election cycle fixed effects	✓	✓	✓	✓
Covariates		✓		✓
Bandwidth	0.393	0.383	0.393	0.383
N	6293	6155	6293	6155

*p<0.1; **p<0.05; ***p<0.01.

Table A.7 – Effect of reaching the IDEB target on the re-election of the incumbent. The bandwidth is the optimal bandwidth determined by the algorithm of Calonico et al. (2014). Standard errors are consistent for heteroskedasticity (HC1 in models 1-2, and nearest-neighbor in models 3-4.)

	Linear		Robust	
	(1)	(2)	(3)	(4)
IDEB target met	-0.019*	-0.019	-0.024	-0.025
	0.011	0.012	0.015	0.016
Election cycle fixed effects	✓	✓	✓	✓
Covariates		✓		✓
Bandwidth	0.520	0.423	0.520	0.423
N	3853	3236	3853	3236

*p<0.1; **p<0.05; ***p<0.01.

Table A.8 – Effect of reaching the IDEB target on the vote-share of the incumbent. The bandwidth is the optimal bandwidth determined by the algorithm of Calonico et al. (2014). Standard errors are consistent for heteroskedasticity (HC1 in models 1-2, and nearest-neighbor in models 3-4).

A.11 Heterogeneity by municipal school enrolments

To test whether municipalities with more parents of children enrolled in municipal schools tend to have a more positive response to school quality signals, we examine heterogeneous local average treatment effects or HLATEs in the RD setup by whether the number of kids enrolled in municipal schools, as a share of the overall population, is high (i.e. in the upper quartile). To do so, we expand Equation 3 by including an indicator for high enrolments (H_{mj}) and its interactions with treatment, with the forcing variable, and with treatment and the forcing variable, so as to allow for separate slopes. We include the same covariates here as in the main specification (X).

$$\begin{aligned} Y_{mj} = \alpha + \beta_1 T_{mj} + \beta_2 \tilde{D}_{mj} + \beta_3 T_{mj} \tilde{D}_{mj} + H_{mj}(\lambda_1 + \lambda_2 T_{mj} + \lambda_3 T_{mj} \tilde{D}_{mj} + \lambda_4 \tilde{D}_{mj}) + \\ + \sum_{g=2}^{3} \gamma_g I[g = j] + \sum_{k=1}^{K} \theta^k X_{mj}^k + \varepsilon_{mj} \end{aligned} \tag{1}$$

Results, shown in Table A.9, suggest that in places where there is a larger number of voters with children enrolled in municipal schools the effect of meeting the IDEB target on the re-election of the mayor gets reversed, although this difference is not statistically significant.

	(1)	(2)
IDEB target met	-0.091*	-0.102**
	0.049	0.045
IDEB target met $\times$ High enrolments	0.096	0.150
	0.159	0.151
Election cycle fixed effects	✓	✓
Covariates		✓
Bandwidth	0.372	0.385
N	1701	1764
IDEB target met + interaction	0.005	0.048
	0.145	0.137

*p<0.1; **p<0.05; ***p<0.01.

Table A.9 – Effect of reaching the IDEB target on re-election of the mayor, by whether the municipality has a high level of enrollments in municipal schools. `High enrolments` is an indicator for whether the number of children enrolled in municipal schools as a share of the total population is in the upper quartile. The bandwidth is the optimal bandwidth determined by the algorithm of Calonico et al. (2014). Standard errors are consistent for heteroskedasticity (HC1).

B Randomized control trial

B.1 Distribution of ANA-based school quality scores

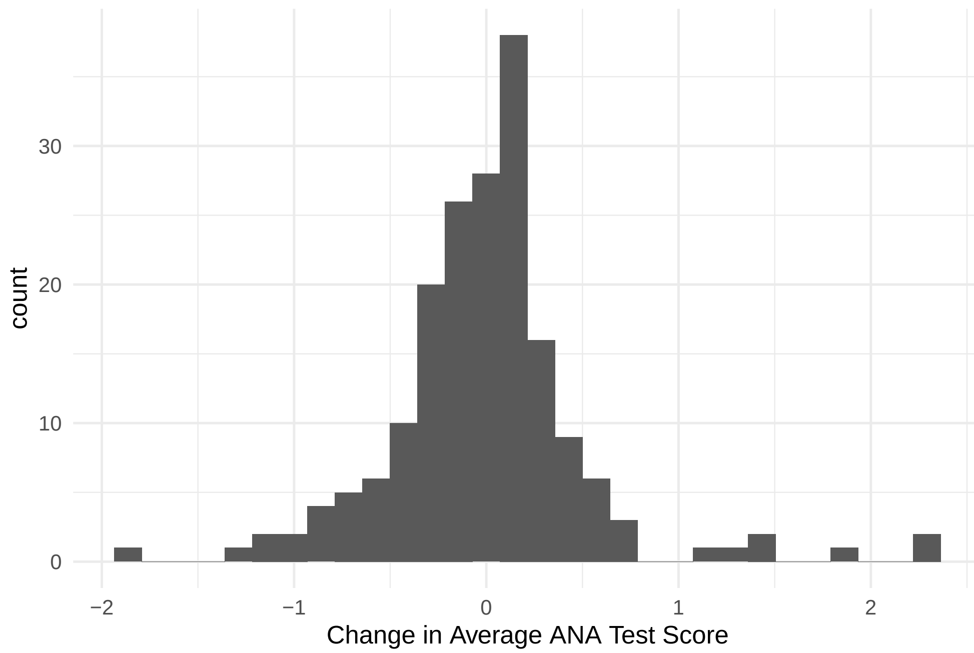
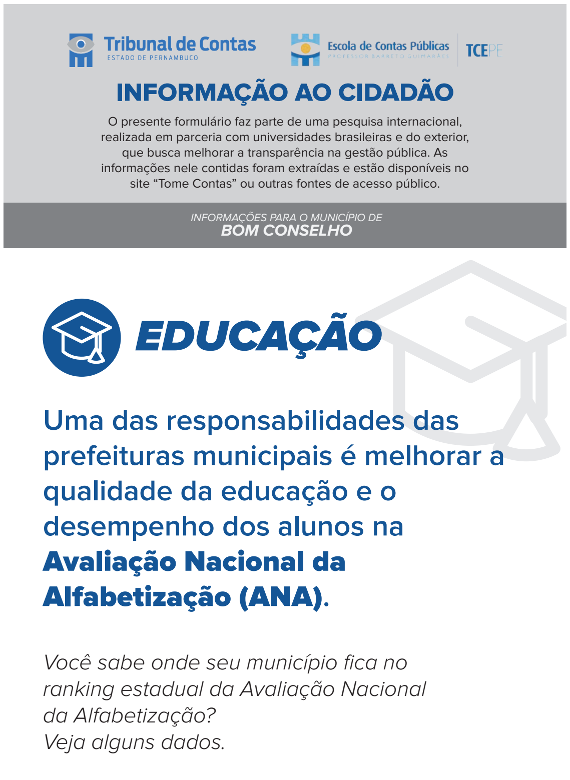


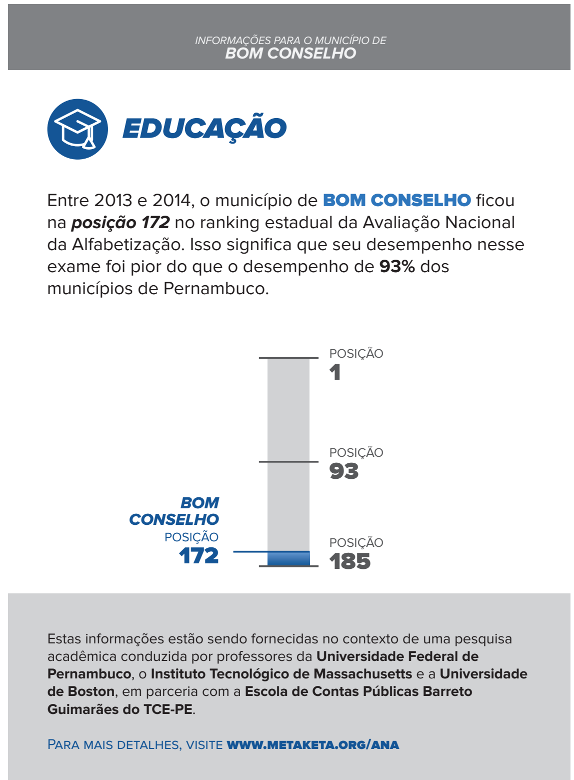
Figure B.8 – ANA distribution

B.2 Flyers Used in Experiment

Examples of the flyers used to deliver treatment information are contained in Figure B.9a (front side) and Figure B.9b (back side).



(a) Front of the flyer



(b) Back of the flyer

Figure B.9 – Example of flyers Distributed to Voters

B.3 Legality of the Intervention

Some scholars have questioned the legality of conducting electoral field experiments in Brazil that do not involve partnerships with parties or candidates, given strict regulations governing campaign advertising (Cunow and Desposato, 2015; Desposato, 2015). Doubts about the legality of interventions involving flyers spring from Article 38 of Law 9504 of September 1997, which governs elections. With respect to "the dissemination of electoral advertising via the distribution of leaflets, stickers, flyers, and other printed material," it holds that such items "shall be published under the responsibility of the party, coalition, or candidate." However, this law does not precisely define what counts as "electoral advertising." Those sections that come closest to a definition suggest that, to be considered electoral advertising, a message must explicitly ask for votes. Article 26, paragraph 2 states that: "The following are considered electoral expenditures, subject to registry and to the limits set by this Law ... direct and indirect advertising and publicity, via any medium of dissemination, intended to win votes." Likewise, Article 36-A, which governs campaigning prior to the official start date, holds that references to potential candidates "do not count as early electoral advertising as long as they do not explicitly ask for votes." Hence, a full reading of the law suggests that flyers that do not mention voting are not subject to the limits of Article 38 because they do not count as electoral advertising.

To check our interpretation of Law 9504, we submitted a request for clarification to Brazil's Superior Electoral Court (TSE). Their response quoted Articles 26 and 38, as cited above, indicating that these were the relevant portions of the law bearing on the question of the legality of flyers. However, they told us that they could not provide any analysis or interpretation of the law, and that for that purpose we should contact a specialist attorney.

A condition of our partnership with the State Accounts Court of Pernambuco was that they would have the opportunity to review and approve all study materials before they went to the field. We submitted drafts of the flyers, which were reviewed by a TCE-PE Councilor who is a former judge of the Regional Electoral Court of Pernambuco (TRE-

PE), as well as a Substitute Councilor who is a law professor. They requested several changes to the draft version which we implemented prior to conducting the study.

Based on our inquiries with relevant legal authorities and specialists, we concluded that our intervention did not violate Brazilian law.

B.4 Example Ballot

An example of the secret ballot used to measure vote field experiment is contained in Figure B.10.

Figure B.10 – Secret Ballot for Measuring Vote Choice

PARA PREFEITO DE ABREU E LIMA

	NOME	NÚMERO	PARTIDO	
	KATIANA GADELHA	12	PDT	
	FLAVIO GADELHA	15	PMDB	
	PR. MARCOS JOSÉ	40	PSB	
	BRANCO / NULO			

26310 1

B.5 Covariates

As explained in the main text, we use a lasso procedure to select covariates to include in our regression adjustment. The pre-specified covariates are listed in Table B.10. Most variables are originally likert-scale variables and we convert them to numeric interval variables. For categorical variables with many categories (`race`, `religion`, `muni_biggest_problem`), we collapse all categories with less than 5% of respondents into an "other" category and expand the variable to a set of dichotomous variables representing each possible value.

Variable	Definition
female	Female
Age	Age
politics_interest	Interest in politics
turnout_2012	Turnout in 2012 local elections
vote_2012	Voted for incumbent in 2012
turnout_2014	Turnout in 2014 national elections
vote_2014	Presidential candidate voter voted for in 2014
partisan	Identifies with a party
muni_biggest_prob	Most important problem in the municipality
politician_helped	Had received help from a politician
govt_eval_baseline	Evaluation of the municipal government at baseline
acc_eval_baseline	Evaluation of mayor's handling of the municipal accounts at baseline
uncertain_acc_baseline	Uncertainy over evaluation of handling of municipal accounts at baseline
edu_eval_baseline	Evaluation of mayor's handling of education
uncertain_edu_baseline	Uncertainty over evaluation of handling of education at baseline
tce_knowledge	Heard about the State Accounts Tribunal
ana_knowledge	Heard about ANA
child_school	Has a child in municipal school
confid_fedgov	Confidence in the federal government
confid_justice	Confidence in the Judiciary
confid_tce	Confidence in the State Accounts Tribunal
confid_muni	Confidence in the municipal government
acc_responsible	Degree to which mayor responsible for accounts status
edu_responsible	Degree to which mayor responsible for education
prob_vote_buying	Probability incumbent will attempt to buy vote
prob_vote_monitoring	Probability vote is not secret
prob_vote_count	Probability vote count is correct
acc_rejected_prior	Prior over whether municipal accounts are rejected
tce_prior_cert	Uncertainty about accounts status prior
ana_prior	Prior over ANA performance
edu_prior_uncert	Uncertainty over ANA prior
years_edu	Years of education
race	Race
religion	Religion
income	Income
relative_wellbeing	Perceived relative wellbeing
edu_rank1	Ranks handling of education as more important than handling of accounts.
acc_rank1	Ranks handling of account as more important than education.

Table B.10 – Covariates for the Pernambuco Field Experiment.

B.6 Experimental Results without Covariate Adjustment

	All	Parents	Not Parents	All
Treatment	-0.0317	-0.0489	-0.0145	-0.0128
	(0.0229)	(0.0529)	(0.0286)	(0.0279)
Treatment x Rank	0.0003	-0.0013	0.0008^{*}	0.0009^{*}
	(0.0004)	(0.0009)	(0.0005)	(0.0005)
Treatment x Rank x Parents				-0.0020^{**}
				(0.0009)
Num. obs.	1709	525	1184	1709

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B.11 – Experimental results without covariate adjustment. Experimental block coefficients are omitted. HC2 heteroskedasticity consistent standard errors in parentheses.

Results from the experiment without any covariate adjustment (aside from adjustment for experimental blocks) are presented in Table B.11.

B.7 Robustness to Other Interactions

	All	Parents	Not Parents
Treatment	-0.0572^{***}	-0.0751^{**}	-0.0422^{*}
	(0.0198)	(0.0364)	(0.0239)
Treatment x Rank	0.0004	-0.0009	0.0008^{**}
	(0.0003)	(0.0006)	(0.0004)
Num. obs.	1709	525	1184

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B.12 – Experimental results with additional interactions. These estimates are from the regression models reported in Table 2 augmented with the interaction between the treatment and age, income, and years of education. HC2 heteroskedasticity consistent standard errors in parentheses.

In the discussion of the contrasting results of the experimental intervention on parents of children enrolled in municipal schools and non-parents, we note that parents tend to be younger, poorer, and less educated than non-parents. Given these differences, we control for these covariates by including them as additional interactions in the first three specifications found in Table 2. The findings that parents punish bad performers and that non-parents tend to punish good performers are robust to including these covariates as additional interactions, as shown in Table B.12. The point estimates in Table B.12 reported on the interaction between the intervention and performance on the ANA are almost identical to those reported in Table 2.

Similar to the concern about the correlates of having children in municipal school, another potential issue is that the the ranking of changes in ANA performance is correlated with other municipal attributes at may driving the observed heterogeneity in treatment effects. Specifically, one concern is that municipalities that performed well on the ANA in 2012 had only limited room for improvement in 2014. If this were the case, then high performing municipalities would be lower ranked on our ranking (which measures change) on average. To assess whether this may be driving the results, we control for the interaction of treatment and performance on the ANA exam in 2012. Results in Table B.13 show

	All	Parents	Not Parents
Treatment	-0.0556^{***}	-0.0674^{*}	-0.0429^{*}
	(0.0196)	(0.0352)	(0.0240)
Treatment x Rank	0.0003	-0.0011	0.0009^{*}
	(0.0004)	(0.0007)	(0.0005)
Num. obs.	1709	525	1184

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B.13 – Robustness of Experimental Results to Including Interaction between Treatment and Baseline ANA Performance. Covariates omitted. Covariates demeaned so treatment coefficient is estimated average treatment effect. HC2 heteroskedasticity consistent standard errors in parentheses.

that inclusion of this interaction has no appreciable effect on our results.

B.8 Heterogeneity by Priors

The result in Figure 2 might be explained by a correlation between rank and voter expectations. If voters in higher performing municipalities expected even better performance than the actual rank, while those in lower performing municipalities had properly calibrated expectations, then we would expect a negative interaction like the one we found. To test for this possibility, we estimate heterogeneity by the *gap* between voters' prior belief over their municipality's rank (measured at baseline) and the actual rank.

Results for treatment heterogeneity by the gap between voters expectations and reality can be found in Figure B.11. As is clearly evident from the plotted regression line, there is no substantive interaction between this gap and the effect of the treatment. The overall effect of treatment is negative, but this negative effect does not moderate among

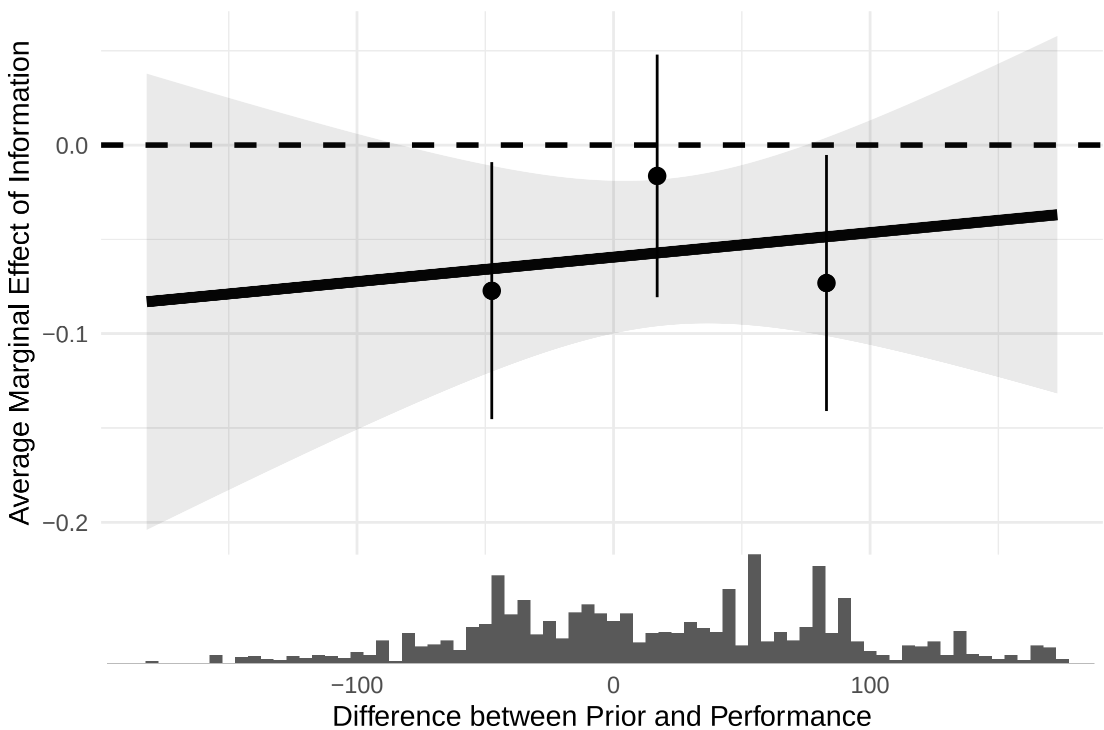


Figure B.11 – Effect of Treatment by Gap Between Voters' Prior and Municipal Performance. Negative values indicate worse performance than expected, while positive values indicate better performance than expected. 90% Confidence Intervals are shown. Histogram shows marginal distribution of the data by the gap.

voters who are positively surprised by the information. The tercile approach largely corroborates the linear interaction model, though there is some weak indication of a non-linearity with voters in the middle of the distribution punishing the incumbent slightly more than incumbents at the tails of the distribution.

B.9 Experiment Covariate Balance

Variable	Mean Difference	SD	SE	Permutation p-value
partisan	0.0626	0.49	0.0215	0.0095
turnout_2012	-0.0413	0.353	0.0167	0.0255
acc_rank1	-0.0349	0.435	0.0188	0.067
acc_eval_baseline	0.103	1.31	0.0536	0.073
politician_helped	0.0266	0.402	0.0184	0.177
confid_justice	0.121	2.08	0.093	0.198
tce_knowledge	-0.0285	0.497	0.0217	0.207
confid_muni	0.12	2.3	0.0995	0.252
edu_rank1	-0.0217	0.434	0.019	0.279
politics_interest	0.0477	0.962	0.042	0.295
confid_tce	0.0967	1.96	0.0935	0.339
turnout_2014	-0.0142	0.302	0.0141	0.359
acc_rejected_prior	-0.0203	0.44	0.0193	0.305
confid_fedgov	0.0957	2.1	0.0933	0.336
edu_eval_baseline	0.0571	1.26	0.0516	0.289
govt_eval_baseline	-0.0596	1.38	0.0579	0.329
uncertain_acc_baseline	-0.0418	1.29	0.0506	0.444
vote_2012	0.0155	0.484	0.0206	0.456
edu_responsible	-0.0504	1.61	0.055	0.388
tce_prior_cert	-0.018	0.598	0.0248	0.511
child_school	-0.013	0.461	0.0209	0.573
edu_prior_uncert	0.0157	0.567	0.0221	0.497
prob_vote_monitoring	-0.0277	1.15	0.0495	0.596
age	0.361	16.3	0.79	0.678
income	0.0214	1.46	0.0627	0.749
years_edu	-0.069	4.82	0.215	0.76
relative_wellbeing	0.00827	0.595	0.0268	0.773
ana_knowledge	0.00475	0.426	0.0189	0.806
female	-0.00524	0.5	0.0242	0.843
ana_prior	-0.506	51.8	2.52	0.856
prob_vote_count	0.0075	1.13	0.0407	0.862
prob_vote_count	0.0075	1.13	0.0407	0.872
acc_responsible	0.00844	1.56	0.0539	0.878
uncertain_edu_baseline	-0.00465	1.35	0.0538	0.93

Table B.14 – Covariate Balance for the Pernambuco Experiment. The mean difference column reports estimated ATE for pre-treatment covariates specified in PAP. SD is standard deviation of variable. Permutation p-value is computed using 2000 permutations of the treatment variable. Most imbalanced variables are at the top of the table, as variables are ordered by the absolute value of the mean difference divided by the standard deviation.

Covariate balance is presented in Table B.14. All variables in Table B.10 are included, except for the non-ordinal categorical variables (`race`, `vote_2014`, `religion`, `muni_biggest_prob`). p-values calculated using permutation inference with 2000 permuted treatment realizations.

B.10 Attrition

	(1)	(2)
Treatment	-0.003	-0.004
	(0.016)	(0.016)
Treatment x rank		0.000
		(0.000)
Treatment x vote_2012		-0.032
		(0.036)
Treatment x govt_eval_baseline		0.006
		(0.017)
Treatment x child_school		-0.014
		(0.038)
Treatment x confid_muni		0.008
		(0.010)
N	2047	2047

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table B.15 – Correlation of Treatment with Attrition in the Pernambuco Experiment. These estimates are from a regression of an attrition indicator on treatment, covariates, treatment by covariate interactions, and block fixed effects. All covariates were demeaned. Coefficients on covariate main effects and block strata are omitted.

In the field experiment, 338 respondents were not re-interviewed. Differential attrition by treatment status could lead to biased estimates, so we check correlation of treatment with attrition. In the first column of Table B.15, we show that there is no statistically or substantively significant correlation between treatment and an attrition indicator. The second column shows results from a specification with interactions between the treatment variable and predictive covariates. Details on covariates can be found in Table B.10. We find no statistically significant interactions. Overall, we find no evidence of differential attrition.

B.11 Results for Pre-Registered Hypotheses

As mentioned in the main text, our analytical specification for the field experiment departs from that which was pre-registered with Evidence in Governance and Politics (EGAP) prior to analysis. In concert with the broader initiative of which this study was a part, our pre-specified approach conditions on whether information is "good news" or "bad news" (measured dichotomously) relative to a respondent's priors. By contrast, in the main text, we ignore priors and condition only on the municipality's continuous performance ranking.

For the treatment arm involving information about school performance, we pre-specified 23 distinct hypothesis tests. Results from these tests can be found in Table B.16. As shown in line 1 of the table, our main overall finding from the paper is similar when using the pre-specified approach. Information that is "good news" relative to priors reduces the probability of voting for the incumbent by 0.083, significant at the 0.05 level. By comparison, for respondents in the best tercile of ANA performance (ignoring priors), treatment information has an effect of -0.073, similarly significant at the 0.05 level. Hence, regardless of whether we condition on priors, respondents punish good performance.

We refer readers to the pre-analysis plan for complete details, but will describe here the main variables and subsets of the data used in each specification. The subset "Good News" refers to individuals who received information that is more positive than their priors (or equal to priors and better than or equal to the statewide median), while "Bad News" refers to individuals who received information that is worse than their priors (or equal to priors and worse than the statewide median). "All" refers to all individuals regardless of the content of information received.

The outcome variables are as defined as follows:

- `vote`: Equals 1 if the respondent reports voting for the incumbent, 0 otherwise (including abstention and blank/null votes).
- `turnout`: Equals 1 if the respondent reports voting in the 2016 election, 0 otherwise.

Family	Hypothesis	Outcome	Parameter	Subset	Estimate	SE	p-value
1	1a	vote	ana	Good News	-0.083	0.033	0.013
1	1b	vote	ana	Bad News	-0.041	0.028	0.137
2	2	vote	ana x uncertain_edu	Good News	0.001	0.001	0.177
2	2	vote	ana x uncertain_edu	Bad News	0.000	0.001	0.445
2	3	vote	ana x edu_rank1	Good News	-0.094	0.074	0.202
2	3	vote	ana x edu_rank1	Bad News	-0.061	0.066	0.355
2	4	vote	ana x edu_rank1 x uncertain_edu	Good News	-0.002	0.050	0.964
2	4	vote	ana x edu_rank1 x uncertain_edu	Bad News	-0.040	0.052	0.443
2	5a	vote	ana x child_school	Good News	-0.030	0.071	0.678
2	5a	vote	ana x child_school	Bad News	-0.067	0.061	0.274
2	5b	vote	ana x child_school x uncertain_edu	Good News	0.074	0.051	0.148
2	5b	vote	ana x child_school x uncertain_edu	Bad News	0.086	0.045	0.057
3	7a	turnout	ana	Good News	-0.714	0.577	0.217
3	7b	turnout	ana	Bad News	0.021	0.013	0.105
4	8a	valid_vote	ana	Bad News	0.027	0.020	0.185
4	8b	valid_vote	ana x govt_eval	Bad News	0.045	0.036	0.207
4	9	edu_eval	ana	Good News	-0.009	0.087	0.918
4	9	edu_eval	ana	Bad News	-0.059	NaN	NaN
4	10	edu_eval	ana x uncertain_edu	Good News	-0.081	0.057	0.157
4	10	edu_eval	ana x uncertain_edu	Bad News	0.013	0.054	0.805
4	11	uncertain_edu_eval	ana	All	-0.017	0.032	0.592
4	12	info_import	ana	All	-0.047	0.028	0.098
4	13	ana_correct	ana	All	4.244	1.954	0.030

Table B.16 – Results for Pre-Registered Hypotheses. See pre-analysis plan for details.

- `valid_vote`: Using a secret ballot, equals 1 if the respondent reports having voted for any candidate for mayor, and 0 if s/he reports having abstained or cast a blank or null vote.
- `edu_eval`: The respondent's evaluation of the incumbent's management of schools at endline: (1) "excellent," (2) "good," (3) "regular," (4) "bad," or (5) "horrible."
- `uncertain_edu_eval`: The respondent's certainty about `edu_eval`: "very sure," (2) "sure," (3) "unsure," or (4) "very unsure."
- `info_import`: Equals 1 if the respondent said that "what I learned during the campaign about the mayor" was one of the three most important factors in their decision-making; 0 otherwise.
- `ana_correct`: The degree to which the respondent's post-treatment belief about the municipality's ANA ranking is accurate: `184 - |ana_posterior - ana_rank|`.

The independent and moderator variables are defined as follows:

- `ana`: Equals 1 for respondents assigned to receive information on municipal performance on the ANA, 0 otherwise.

- uncertain_edu: The respondent's certainty about the respondent's own evaluation of the incumbent's management of schools. Takes on integer values from 1 ("totally sure") to 7 ("not at all sure").
- edu_rank1: Equals 1 if respondent ranks education above financial management in importance, 0 otherwise.
- child_school: Equals 1 if the respondent has a child in municipal schools, 0 otherwise.
- govt_eval: The respondent's evaluation of the incumbent's administration at endline: (1) "excel- lent," (2) "good," (3) "regular," (4) "bad," or (5) "horrible."

C Online survey experiment

C.1 Respondent recruitment via Facebook ads

We recruited respondents for the online survey experiment via Facebook ads, a well-established, low-cost method for subject recruitment in comparative politics (Boas et al., 2020). Targeted Facebook users saw advertisements offering a chance to win 100 Brazilian reais (about 24 US dollars) for taking a survey, with a 1/100 probability of winning. To ensure a diverse sample, ads were targeted to respondents in distinct strata of region and age. We also excluded Brazil's 300 largest municipalities from our advertising campaign in order to recruit enough respondents from small and medium-sized municipalities, which make up the immense majority of the sample in the RDD and field experiment. Finally, to increase statistical power, we more heavily targeted states where a larger share of municipalities did not meet their IDEB target, which is the less common outcome. We aimed to recruit 3,000 Brazilians, and ended up surveying 3,118 respondents.

C.2 Survey experiment covariate balance

We examine balance in covariates by regressing each of them on the treatment indicator. We do this for the group as a whole, and for the two subsets of individuals in municipalities that met or did not meet their IDEB target. Table C.17, C.18 and C.19 present the results. Across all three comparisons treatment and control groups are balanced on covariates.

	Mean treatment	Mean control	SD	p value
region_north	0.085	0.091	-2.270	0.533
region_centerwest	0.074	0.076	-0.673	0.852
region_southeast	0.315	0.338	-4.854	0.179
region_south	0.199	0.179	5.016	0.153
priority_education	2.258	2.262	-0.339	0.924
priority_healthcare	1.797	1.798	-0.073	0.984
priority_economy	3.793	3.750	3.299	0.361
priority_socialassistance	3.929	3.964	-3.166	0.378
priority_security	3.223	3.226	-0.288	0.935
had_heard_of_ideb	0.703	0.693	2.085	0.562
age	33.335	33.580	-2.002	0.582
female	0.625	0.618	1.525	0.671
race_white	0.449	0.467	-3.472	0.333
race_brown	0.418	0.394	4.865	0.173
race_other	0.133	0.139	-1.983	0.584
education	6.547	6.455	4.111	0.256

Table C.17 – Covariate balance for the online survey experiment: All respondents

	Mean treatment	Mean control	SD	p value
region_north	0.078	0.090	-4.415	0.318
region_centerwest	0.079	0.082	-1.128	0.794
region_southeast	0.351	0.367	-3.488	0.417
region_south	0.194	0.173	5.270	0.209
priority_education	2.258	2.270	-1.030	0.808
priority_healthcare	1.795	1.802	-0.605	0.889
priority_economy	3.762	3.742	1.581	0.714
priority_socialassistance	3.917	3.961	-3.962	0.359
priority_security	3.267	3.226	3.443	0.412
had_heard_of_ideb	0.702	0.700	0.540	0.900
age	33.458	34.031	-4.763	0.279
female	0.622	0.614	1.457	0.734
race_white	0.461	0.482	-4.223	0.324
race_brown	0.410	0.386	4.828	0.257
race_other	0.129	0.131	-0.805	0.851
education	6.523	6.448	3.366	0.433

Table C.18 – Covariate balance for the online survey experiment: Respondents in municipalities that had met their IDEB target

	Mean treatment	Mean control	SD	p value
region_north	0.099	0.094	1.669	0.797
region_centerwest	0.064	0.061	1.430	0.825
region_southeast	0.238	0.261	-5.296	0.428
region_south	0.211	0.196	3.836	0.554
priority_education	2.257	2.240	1.494	0.818
priority_healthcare	1.801	1.789	1.222	0.857
priority_economy	3.859	3.773	6.696	0.310
priority_socialassistance	3.954	3.971	-1.522	0.814
priority_security	3.128	3.227	-8.584	0.192
had_heard_of_ideb	0.704	0.676	6.024	0.366
age	33.068	32.413	5.161	0.422
female	0.634	0.627	1.363	0.836
race_white	0.424	0.427	-0.512	0.938
race_brown	0.435	0.413	4.292	0.512
race_other	0.141	0.160	-5.389	0.425
education	6.598	6.474	5.558	0.412

Table C.19 – Covariate balance for the online survey experiment: Respondents in municipalities that had not met their IDEB target

C.3 Ranking of policy areas by respondents

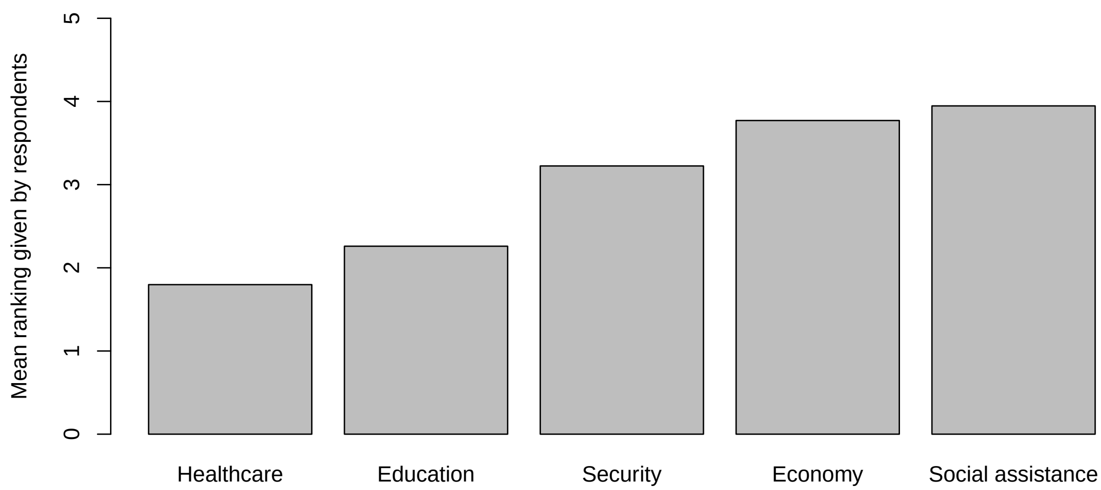


Figure C.12 – Mean ranking given by online survey respondents when asked to rank policy areas according to the priority they should be given by their municipal government

C.4 Additional, pre-specified results

	Dependent variable: 'How much do you agree with the following statements about the mayor?' on a 1-4 scale (1 = disagree completely, 4 = agree completely)							
	They invested a lot in...				They improved the quality of...			
	Education	Healthcare	Social Assistance	Security	Education	Healthcare	Social Assistance	Security
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatment_pos	0.215***	0.126***	0.097**	0.120***	0.199***	0.125***	0.094**	0.148***
	(0.044)	(0.046)	(0.042)	(0.043)	(0.046)	(0.047)	(0.042)	(0.044)
Constant	2.420***	2.374***	2.370***	2.246***	2.483***	2.374***	2.410***	2.302***
	(0.030)	(0.032)	(0.029)	(0.030)	(0.031)	(0.032)	(0.029)	(0.030)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2,190	2,190	2,190	2,190	2,190	2,190	2,190	2,190
R^2	0.025	0.020	0.011	0.016	0.021	0.013	0.014	0.016

*p<0.1; **p<0.05; ***p<0.01

Table C.20 – Survey experiment results: Positive treatment (individuals in municipalities that met their IDEB target)

	Dependent variable: 'How much do you agree with the following statements about the mayor?' on a 1-4 scale (1 = disagree completely, 4 = agree completely)							
	They invested a lot in...				They improved the quality of...			
	Education	Healthcare	Social Assistance	Security	Education	Healthcare	Social Assistance	Security
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatment_neg	-0.066	-0.042	-0.089	0.002	-0.160^{**}	-0.050	0.002	-0.013
	(0.068)	(0.074)	(0.066)	(0.066)	(0.070)	(0.073)	(0.065)	(0.066)
Constant	2.214^{***}	2.218^{***}	2.275^{***}	2.038^{***}	2.293^{***}	2.234^{***}	2.255^{***}	2.121^{***}
	(0.049)	(0.053)	(0.047)	(0.048)	(0.050)	(0.052)	(0.047)	(0.048)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	925	925	925	925	925	925	925	925
R^2	0.030	0.030	0.032	0.020	0.037	0.027	0.039	0.038

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table C.21 – Survey experiment results: Negative treatment (individuals in municipalities that did not meet their IDEB target)

	Dependent variable: 'How much do you agree with the following statements about the mayor?' on a 1-4 scale (1 = disagree completely, 4 = agree completely)							
	They invested a lot in...				They improved the quality of...			
	Education	Healthcare	Social Assistance	Security	Education	Healthcare	Social Assistance	Security
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatment_pos	0.292***	0.179***	0.176***	0.199***	0.288***	0.190***	0.181***	0.211***
	(0.054)	(0.057)	(0.052)	(0.053)	(0.056)	(0.058)	(0.052)	(0.054)
treatment_pos:priority_education_low	−0.258***	−0.172*	−0.253***	−0.232**	−0.274***	−0.207**	−0.289***	−0.187**
	(0.095)	(0.100)	(0.090)	(0.093)	(0.098)	(0.100)	(0.090)	(0.094)
priority_education_low	0.148**	0.029	0.075	0.036	0.162**	0.069	0.098	0.040
	(0.064)	(0.068)	(0.061)	(0.063)	(0.066)	(0.068)	(0.061)	(0.064)
Constant	2.375***	2.370***	2.350***	2.236***	2.431***	2.357***	2.383***	2.291***
	(0.038)	(0.040)	(0.036)	(0.037)	(0.039)	(0.040)	(0.036)	(0.037)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2,190	2,190	2,190	2,190	2,190	2,190	2,190	2,190
R^2	0.037	0.029	0.023	0.026	0.032	0.022	0.030	0.028

*p<0.1; **p<0.05; ***p<0.01

Table C.22 – Survey experiment results: Positive treatment (individuals in municipalities that met their IDEB target), by whether they give high or low priority to education. `priority_education_low` is an indicator for whether respondents' give below-median priority to education.

	Dependent variable: 'How much do you agree with the following statements about the mayor?' on a 1-4 scale (1 = disagree completely, 4 = agree completely)							
	They invested a lot in...				They improved the quality of...			
	Education	Healthcare	Social Assistance	Security	Education	Healthcare	Social Assistance	Security
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatment_neg	−0.090	−0.041	−0.046	−0.055	−0.186**	−0.023	−0.015	−0.040
	(0.084)	(0.091)	(0.081)	(0.082)	(0.086)	(0.090)	(0.081)	(0.082)
treatment_neg:priority_education_low	0.112	−0.012	−0.137	0.149	0.128	−0.086	0.062	0.080
	(0.148)	(0.160)	(0.143)	(0.144)	(0.152)	(0.158)	(0.142)	(0.145)
priority_education_low	0.096	0.127	0.104	−0.085	0.068	0.118	0.134	−0.029
	(0.106)	(0.115)	(0.103)	(0.104)	(0.109)	(0.113)	(0.102)	(0.104)
Constant	2.178***	2.178***	2.246***	2.074***	2.258***	2.198***	2.213***	2.135***
	(0.061)	(0.066)	(0.059)	(0.059)	(0.062)	(0.065)	(0.058)	(0.059)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	925	925	925	925	925	925	925	925
R^2	0.061	0.049	0.047	0.038	0.058	0.046	0.061	0.050

*p<0.1; **p<0.05; ***p<0.01

Table C.23 – Survey experiment results: Negative treatment (individuals in municipalities that did not meet their IDEB target), by whether they give high or low priority to education. `priority_education_low` is an indicator for whether respondents' give below-median priority to education.

C.5 Results with weights to approximate the voter population in the RDD

	Dependent variable: 'How much do you agree with the following statements about the mayor?' on a 1-4 scale (1 = disagree completely, 4 = agree completely)							
	They invested a lot in...				They improved the quality of...			
	Education	Healthcare	Social Assistance	Security	Education	Healthcare	Social Assistance	Security
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatment_pos	0.204***	0.114	0.066	0.091	0.182**	0.097	0.054	0.116
	(0.073)	(0.077)	(0.070)	(0.072)	(0.077)	(0.077)	(0.069)	(0.073)
Constant	2.433***	2.377***	2.387***	2.258***	2.482***	2.379***	2.420***	2.313***
	(0.051)	(0.054)	(0.049)	(0.050)	(0.054)	(0.054)	(0.048)	(0.051)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2,190	2,190	2,190	2,190	2,190	2,190	2,190	2,190
R^2	0.025	0.020	0.011	0.016	0.021	0.013	0.014	0.016

*p<0.1; **p<0.05; ***p<0.01

Table C.24 – Survey experiment results: Positive treatment (individuals in municipalities that met their IDEB target). Data reweighted by education level according to census figures for municipalities within the RDD bandwidth (column 1 in Table D.31).

	Dependent variable: 'How much do you agree with the following statements about the mayor?' on a 1-4 scale (1 = disagree completely, 4 = agree completely)							
	They invested a lot in...				They improved the quality of...			
	Education	Healthcare	Social Assistance	Security	Education	Healthcare	Social Assistance	Security
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatment_neg	-0.060	-0.014	-0.070	0.004	-0.104	-0.038	0.017	0.025
	(0.116)	(0.124)	(0.110)	(0.107)	(0.116)	(0.122)	(0.105)	(0.108)
Constant	2.230^{***}	2.208^{***}	2.292^{***}	2.054^{***}	2.286^{***}	2.234^{***}	2.267^{***}	2.130^{***}
	(0.083)	(0.089)	(0.079)	(0.077)	(0.084)	(0.087)	(0.076)	(0.078)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	925	925	925	925	925	925	925	925
R^2	0.030	0.030	0.032	0.020	0.037	0.027	0.039	0.038

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table C.25 – Survey experiment results: Negative treatment (individuals in municipalities that did not meet their IDEB target). Data reweighted by education level according to census figures for municipalities within the RDD bandwidth (column 1 in Table D.31).

	Dependent variable: 'How much do you agree with the following statements about the mayor?' on a 1-4 scale (1 = disagree completely, 4 = agree completely)							
	They invested a lot in...				They improved the quality of...			
	Education	Healthcare	Social Assistance	Security	Education	Healthcare	Social Assistance	Security
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatment_pos	0.275***	0.148	0.147*	0.168**	0.265***	0.149*	0.129	0.171**
	(0.084)	(0.090)	(0.081)	(0.083)	(0.090)	(0.090)	(0.080)	(0.086)
treatment_pos:priority_education_low	−0.252*	−0.100	−0.286**	−0.294**	−0.277*	−0.205	−0.266*	−0.190
	(0.150)	(0.162)	(0.145)	(0.149)	(0.160)	(0.161)	(0.143)	(0.153)
priority_education_low	0.160	−0.026	0.085	0.061	0.175	0.063	0.097	0.019
	(0.103)	(0.111)	(0.099)	(0.102)	(0.110)	(0.110)	(0.098)	(0.105)
Constant	2.382***	2.388***	2.369***	2.250***	2.433***	2.367***	2.400***	2.310***
	(0.060)	(0.064)	(0.057)	(0.059)	(0.064)	(0.064)	(0.057)	(0.061)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2,190	2,190	2,190	2,190	2,190	2,190	2,190	2,190
R^2	0.152	0.132	0.130	0.158	0.111	0.139	0.128	0.138

*p<0.1; **p<0.05; ***p<0.01

Table C.26 – Survey experiment results: Positive treatment (individuals in municipalities that met their IDEB target), by whether they give high or low priority to education. `priority_education_low` is an indicator for whether respondents' give below-median priority to education. Data reweighted by education level according to census figures for municipalities within the RDD bandwidth (column 1 in Table D.31).

	Dependent variable: 'How much do you agree with the following statements about the mayor?' on a 1-4 scale (1 = disagree completely, 4 = agree completely)							
	They invested a lot in...				They improved the quality of...			
	Education	Healthcare	Social Assistance	Security	Education	Healthcare	Social Assistance	Security
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatment_neg	−0.080	−0.063	−0.038	−0.018	−0.139	−0.076	−0.013	−0.023
	(0.128)	(0.145)	(0.126)	(0.124)	(0.136)	(0.135)	(0.116)	(0.126)
treatment_neg:priority_education_low	0.089	0.080	−0.116	−0.007	0.192	0.041	0.080	0.058
	(0.232)	(0.262)	(0.227)	(0.224)	(0.245)	(0.243)	(0.210)	(0.227)
priority_education_low	0.070	0.0003	0.037	−0.014	−0.045	0.010	0.110	0.008
	(0.166)	(0.188)	(0.163)	(0.161)	(0.176)	(0.174)	(0.151)	(0.163)
Constant	2.203***	2.217***	2.270***	2.069***	2.273***	2.239***	2.234***	2.159***
	(0.093)	(0.105)	(0.091)	(0.090)	(0.098)	(0.097)	(0.084)	(0.091)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	925	925	925	925	925	925	925	925
R^2	0.254	0.213	0.272	0.197	0.253	0.260	0.311	0.285

*p<0.1; **p<0.05; ***p<0.01

Table C.27 – Survey experiment results: Negative treatment (individuals in municipalities that did not meet their IDEB target), by whether they give high or low priority to education. `priority_education_low` is an indicator for whether respondents' give below-median priority to education. Data reweighted by education level according to census figures for municipalities within the RDD bandwidth (column 1 in Table D.31).

C.6 Results with a lower threshold to define respondents who give low priority to education

	Dependent variable: 'How much do you agree with the following statements about the mayor?' on a 1-4 scale (1 = disagree completely, 4 = agree completely)							
	They invested a lot in...				They improved the quality of...			
	Education	Healthcare	Social Assistance	Security	Education	Healthcare	Social Assistance	Security
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatment_pos	0.238***	0.133***	0.129***	0.146***	0.231***	0.142***	0.113**	0.166***
	(0.047)	(0.050)	(0.045)	(0.047)	(0.049)	(0.050)	(0.045)	(0.047)
treatment_pos:priority_education_very_low	−0.263*	−0.170	−0.289**	−0.266*	−0.265*	−0.285*	−0.217	−0.169
	(0.141)	(0.148)	(0.133)	(0.138)	(0.145)	(0.149)	(0.134)	(0.140)
priority_education_very_low	0.269***	0.199*	0.203**	0.175*	0.271***	0.309***	0.191**	0.159
	(0.098)	(0.103)	(0.092)	(0.096)	(0.101)	(0.103)	(0.093)	(0.097)
Constant	2.393***	2.358***	2.350***	2.230***	2.455***	2.347***	2.396***	2.289***
	(0.033)	(0.034)	(0.031)	(0.032)	(0.034)	(0.035)	(0.031)	(0.032)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2,190	2,190	2,190	2,190	2,190	2,190	2,190	2,190
R^2	0.035	0.029	0.019	0.025	0.030	0.026	0.023	0.023

*p<0.1; **p<0.05; ***p<0.01

Table C.28 – Survey experiment results: Positive treatment (individuals in municipalities that met their IDEB target), by whether they give high or low priority to education. `priority_education_very_low` is an indicator for whether respondents' place three or more policy areas as more important than education.

	Dependent variable: 'How much do you agree with the following statements about the mayor?' on a 1-4 scale (1 = disagree completely, 4 = agree completely)							
	They invested a lot in...				They improved the quality of...			
	Education	Healthcare	Social Assistance	Security	Education	Healthcare	Social Assistance	Security
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatment_neg	−0.098	−0.050	−0.080	0.003	−0.158**	−0.057	−0.020	−0.020
	(0.073)	(0.080)	(0.071)	(0.071)	(0.075)	(0.078)	(0.070)	(0.072)
treatment_neg:priority_education_very_low	0.160	−0.118	−0.203	0.057	−0.119	−0.153	0.004	0.039
	(0.223)	(0.243)	(0.216)	(0.218)	(0.230)	(0.239)	(0.215)	(0.219)
priority_education_very_low	0.171	0.238	0.308**	0.095	0.299*	0.193	0.284*	0.123
	(0.157)	(0.171)	(0.153)	(0.154)	(0.162)	(0.169)	(0.152)	(0.154)
Constant	2.210***	2.205***	2.250***	2.037***	2.270***	2.234***	2.234***	2.116***
	(0.052)	(0.057)	(0.051)	(0.051)	(0.054)	(0.056)	(0.050)	(0.051)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	925	925	925	925	925	925	925	925
R^2	0.071	0.051	0.054	0.049	0.059	0.051	0.065	0.054

*p<0.1; **p<0.05; ***p<0.01

Table C.29 – Survey experiment results: Negative treatment (individuals in municipalities that did not meet their IDEB target), by whether they give high or low priority to education. `priority_education_very_low` is an indicator for whether respondents' place three or more policy areas as more important than education.

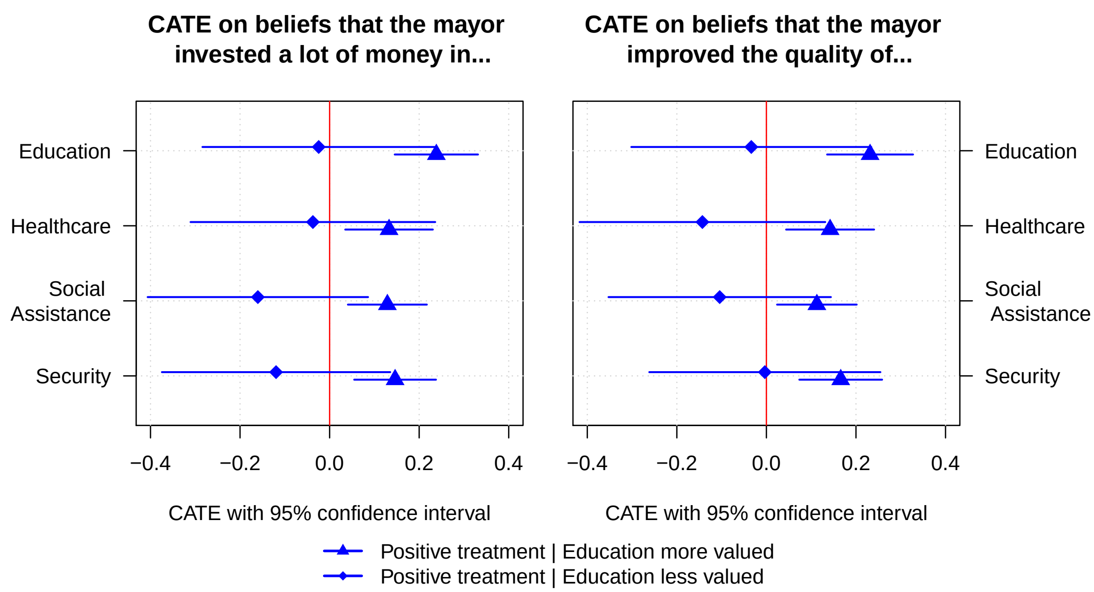


Figure C.13 – Conditional Average Treatment Effects (CATE) of receiving positive information about the quality of schools on respondents' agreement with statements about the mayor, by whether they give very low priority to education. Outcomes are measured in scales that go from 1 ("disagree completely") to 4 ("agree completely"). The "education more valued" group is composed of those who rank education among their top three priorities. The "education less valued" group is composed of those who rank at least three policy areas above education.

D Additional Analysis

D.1 Null relationship between municipal education spending and school quality scores

To examine whether there is a relationship between municipal education spending and municipal primary school quality scores, we use official data from Brazil's National Treasury (FINBRA) and from the Ministry of Education. We first calculate the relative increase in spending and IDEB scores between 2013 and 2017 (dividing the increase by the baseline level), and regress the first on the second:

The resulting slope coefficient measures the association between spending in education and school quality indicators. By using a first-differenced model, we get rid of any time-invariant confounding. Results are presented in Table D.30 below. There is no statistically significant association between increases in spending and any of the measures of school quality improvement that we consider: whether the municipality met its IDEB target in 2017, the increase of IDEB scores in the period, the increase in the gap between the IDEB score and the IDEB target in the period, and the increase in IDEB scores relative to scores at baseline. The latter is our preferred specification, since it accounts for baseline levels of IDEB. Figure D.14 presents this null relationship from Model 4. All in all, the data suggest increases in spending are not correlated with increases in school quality.

Menezes Filho et al. (2009) reach a similar conclusion after analyzing the relationship between municipal spending in education school performance in 2005. Monteiro (2015) finds a null relationship between increased education spending and test scores, leveraging as an instrumental variable increases in municipal revenue stemming from oil royalties.

	IDEB target met in 2017	Δ 2013 - 2017 in IDEB:		
		Score	Score - Target	Score, rel. to 2013
	(1)	(2)	(3)	(4)
Δ 2013 - 2017 in education spending, relative to 2013	0.082	0.022	0.026	0.00001
	(0.064)	(0.064)	(0.051)	(0.016)
N	4,886	4,653	4,632	4,653
R^2	0.001	0.00003	0.00004	0.000

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table D.30 – Relationship between municipal spending in primary education and performance of municipal primary education schools in IDEB. HC2 heteroskedasticity consistent standard errors in parentheses. Intercept omitted from the table.

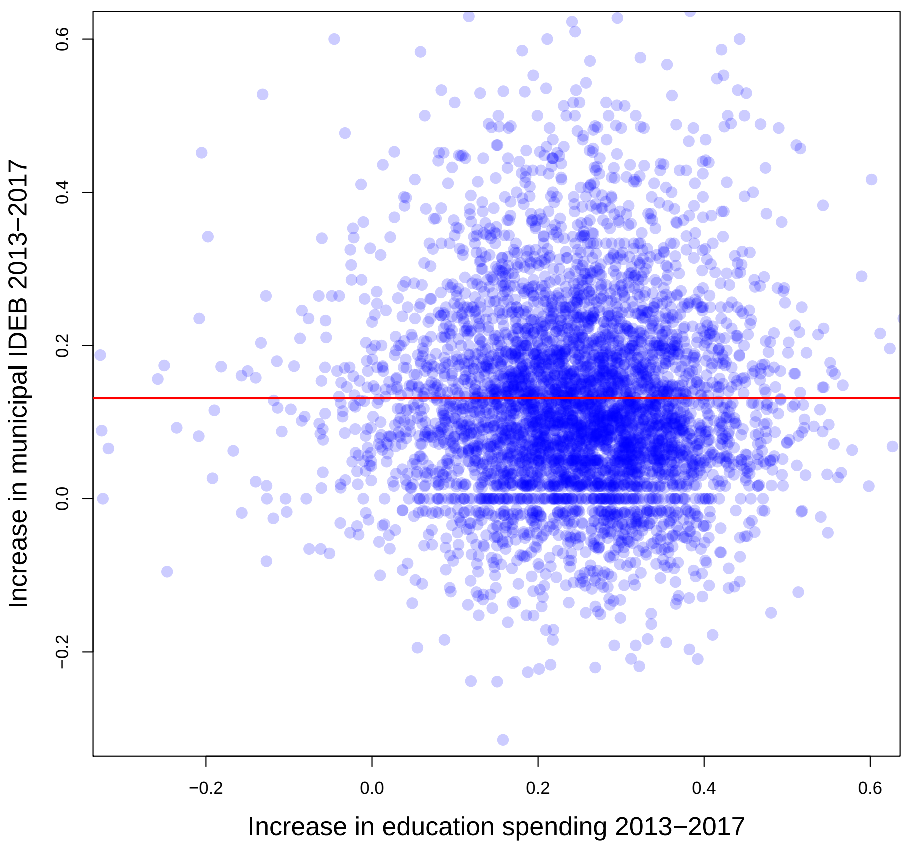


Figure D.14 – Relationship between relative increases in municipal education spending and relative increases in municipal school quality scores. Red line is the regression line from Model 4 in Table D.30.

D.2 Sample Comparisons

Table D.31 – Sample Statistics

	RDD: Reelection	Census (Municipalities)	Panel Survey	Online Survey	Census (Individuals)
Municipality					
Median Population	9,000.5	10,934	27,912	37,164	145,705
Region					
Center-West	10.1	8.4	0	7.5	7.3
Northeast	14.3	32.2	100	30.6	26.6
North	11.9	8.1	0	10.4	7.4
Southeast	39.5	30	0	32.6	43.8
South	24.2	21.3	0	18.9	14.9
Race					
White	50.3	47.1	28.7	45.8	49.2
Black	6.7	7.1	9.2	9.9	8.2
Brown	41.2	44.1	58.9	40.6	41
Other	1.8	1.6	3.2	3.7	1.5
Education					
Less than Primary	58.9	60.5	56.8	4.1	45.3
Primary	15	14.7	11.3	11.9	16.7
Secondary	20.6	19.8	26.6	54.7	28
Higher	5.6	5.1	5.3	29.3	10
Other					
Median Age	39.7	39.3	38	32	38
Male	50.5	50.3	49.6	37.8	48.2

Figures are percentages, except for median population and median age. RDD figures are municipal-level averages of census data for all unique municipalities within the bandwidth, weighting each municipality equally. Survey and Brazilian census figures weight each individual equally. Education is the highest level completed. Census figures are for residents 18 and older, except for median municipal population. All census data are from 2010.

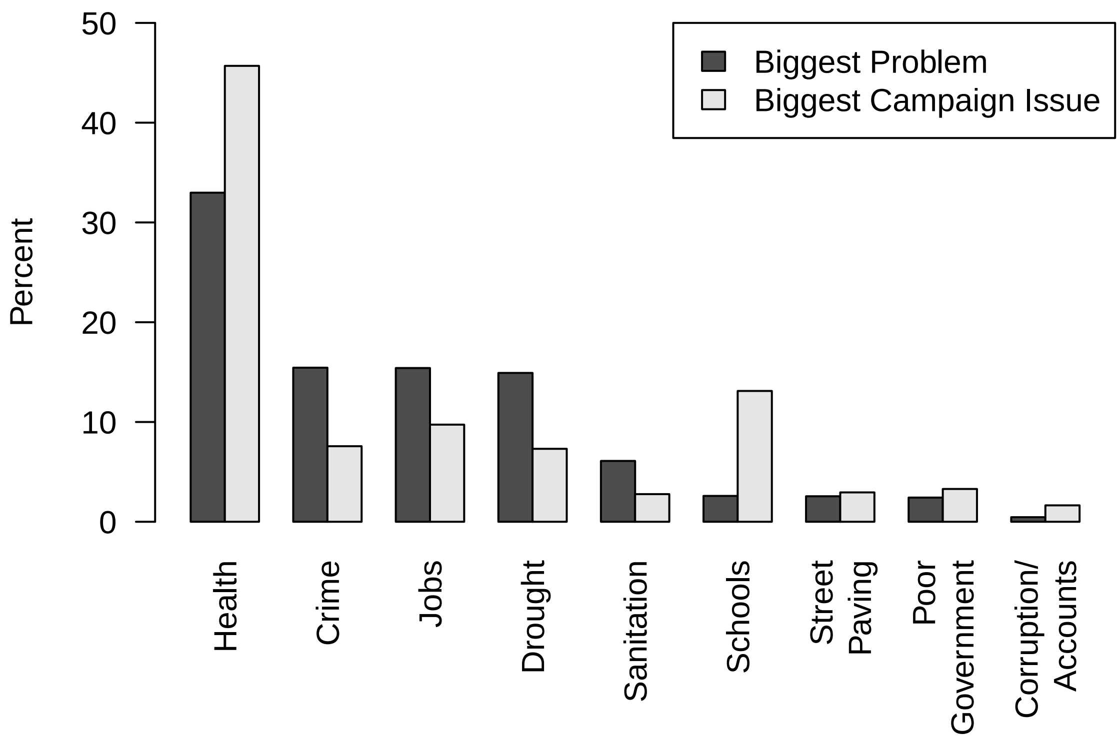
D.3 Education versus Other Problems

Table D.32 – Most Serious Problem Facing the Country: AmericasBarometer

	Average	2019	2017	2014	2012	2010	2008	2007
Security	21.6	17.6	8.0	26.6	18.3	24.4	26.9	29.7
Health	15.8	15.1	8.6	25.2	21.3	14.0	17.5	9.1
Corruption	13.4	16.4	19.0	14.0	12.0	8.5	10.8	13.3
Unemployment	13.3	18.0	17.8	3.7	8.1	12.1	13.4	20.3
Poverty/Inequality	6.2	1.0	0.8	5.9	8.0	9.5	10.2	8.4
Economy	5.4	6.6	19.2	3.3	1.9	3.4	2.1	1.1
Drugs	4.0	0.9	1.0	6.6	7.0	6.7	4.5	1.6
Education	3.6	4.0	1.3	4.1	5.7	3.9	4.1	2.2

Entries are percentage of respondents spontaneously mentioning each item. Some categories combine similar items labeled separately in the data files.

Figure D.15 – Biggest Problem and Biggest Campaign Issue in the Municipality: Pernambuco Survey



D.4 Predictors of Education as a Problem or Priority

Table D.33 – Predictors of Education as a Problem or Priority

	DV: Education as a...		
	Problem (LAPOP)	Problem (Panel)	Priority (Online)
	(1)	(2)	(3)
Education	0.149^{***}	0.056^{**}	0.093^{***}
	(0.016)	(0.028)	(0.017)
Age	-0.006	-0.027^{***}	0.001
	(0.004)	(0.009)	(0.003)
Female	0.130	0.382	0.106
	(0.109)	(0.235)	(0.079)
White	0.356^{***}	0.065	-0.222^{**}
	(0.127)	(0.255)	(0.089)
Black	0.146	-0.011	-0.097
	(0.179)	(0.442)	(0.135)
IDEB Gap	-0.063	0.454	-0.025
	(0.138)	(0.286)	(0.069)
Constant	-4.243^{***}	-3.623^{***}	0.232
	(0.312)	(0.519)	(0.194)
Observations	9,138	3,192	3,118
Log Likelihood	$-1,424.485$	-356.147	$-1,965.454$
Akaike Inf. Crit.	2,880.969	726.294	3,952.909

NOTE: Entries are logistic regression coefficients with estimated standard errors in parentheses. Model 1 analyzes the biggest problem facing the country using the 2008, 2010, 2012, 2014, 2017, and 2019 waves of the AmericasBarometer by LAPOP and includes region and year fixed effects. Model 2 analyzes the biggest problem facing the municipality using the Pernambuco panel survey. Model 3 analyzes priorities in the municipality using the online survey and includes region fixed effects. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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