Appendices to

Who Knows How to Govern?

February 20, 2024

Contents

A Survey Implementation and Ethical Considerations

A.1 Overview

Parameter	Details
Method	Telephone Interviews
Dates	October 2021-January 2022
Implementation	India-based survey firm, Across Research and Communication Private Limited
Sample Size	2,065 (1,142 winners and 923 runners-up)
Sampling Strategy	Random sample of 60 towns from 185 *nagar palikas* and *parishads*. Within each town, we randomly selected 20 wards for interviews.
Consent	Enumerators read an IRB-approved oral consent form, and proceeded with the interview only if the interviewee voluntarily consented to participate in the research study.
Compensation	No compensation
No Deception	As indicated in the IRB protocol, no deception was involved.
Ethics Review	The study was approved by American University's Institutional Review Board (Protocol Numbers IRB-2022-89 and IRB-2022-257).

A.2 Sampling Strategy

The survey was conducted in Fall 2021 across 60 small towns in Rajasthan. We removed Rajasthan's seven *nagar nigams* (municipal corporations, which govern large cities) plus one military cantonment. Our sample frame of towns covered all of Rajasthan's *nagar palikas* and *nagar parishads* (185 towns in total). We took a simple random sample of 60 towns.[29] The average sampled town has a population of 43,945 people, with a one standard deviation of 34,758 people. The most populous town in the sample has 165,294 people, and smallest has 10,000 people.[30] The smallest number of wards in our town sample is 20; the largest, 60. There are 2,160 wards across the 60 towns, which served as our sample frame of wards.

We created ward-wise lists of all winners (current incumbents) and runners-up across the 60 towns from the 2020 Rajasthan municipal elections. Next, we digitized information from affidavits that electoral candidates must submit to the state election commission to generate a comprehensive list of cell phone numbers for all winners and runners-up.[31] We then randomly selected 20 wards in each town for interviews.[32]

[29] 51 of these towns are *nagar palikas* and 9 are *nagar parishads*.

[30] Census of India 2011.

[31] Electoral data was downloaded from the Rajasthan Election Commission. We thank Anirvan Chowdhury and Shahana Sheikh for generously providing the affidavits for Rajasthan's 2020 municipal elections.

[32] For those towns with only 20 wards, all wards were sampled.

A.3 Contact Protocol

A survey firm based in north India carried out the interviews over the phone. We conducted interviews over the phone due to pandemic-time safety concerns. The team of enumerators included both men and women, with the latter assigned to interview female politicians. When enumerators could not reach a politician on the listed number, or when a politician declined to participate or could not be scheduled for an interview within a defined timeframe, enumerators were instructed to move up one ward number on the first replacement attempt and move down one ward number on the next replacement attempt (and repeat until a replacement was secured). Female politicians were replaced by other female politicians. The final number of surveyed councilors was 1,142, 35 percent of whom were women. 501 (44%) of the surveyed councilors were replacements. We turned to replacement respondents due to broken or wrong numbers (67), difficulty in scheduling an interview (222), or because the councilor (94) or someone in the councilor's family (66) declined the interview. The small number of remaining reasons included the councilor had passed away, no phone number was available through the affidavits, or the respondent was a chairperson. The final number of surveyed runners-up was 923, 34 percent of whom were women. 357 (39%) of the surveyed runners-up were replacements. This was due to broken or wrong numbers (71), missing phone numbers from the affidavits (68), difficulty in scheduling the interview (166), or because the runner-up (31) or someone in his or her family (16) declined the interview. The small number of other replacements were due to the runner-up having passed away since the 2020 municipal elections. The percentage of female politicians in our sample very closely matches the percentage of wards in each town that are "reserved" for women candidates — one-third — as mandated in the 74th Constitutional Amendment Act.

We were especially mindful of challenges in assessing the knowledge of female councilors. Our survey protocol ensured enumerators asked to speak to the female councilor directly, and to proceed with the interview only if she was directly on the line. We also asked respondents to turn off speakerphone if it was on to ensure a private conversation. Only 2 respondents in our sample insisted on conducting the interview on speakerphone. We also asked enumerators to code whether they could hear if respondents were getting any assistance from other household members in answering questions for specific modules of the survey. For the procedural knowledge module, we found 230 respondents (11.1%) received some assistance, and 29 respondents (1.4%) received heavy assistance. The overwhelming majority of the 259 respondents receiving assistance were women, and overall roughly 1 in 3 women received such assistance on their interview.

B Measuring Procedural Knowledge

B.1 Survey Measures

We measured various aspects of procedural knowledge most relevant to municipal governance. To develop contextually resonant indicators, we drew on extensive fieldwork and interviews with councilors and town bureaucrats. We also drew on a series of interviews with officials working in Rajasthan's Directorate of Local Bodies (DLB), which oversees the workings of urban local bodies across Rajasthan, and the City Managers Association of Rajasthan (CMAR), which works with the DLB on overseeing city governance. We read key central and state government documents that outline the workings of municipal governments, including the 74th Constitutional Amendment, the Rajasthan Municipal Act, reports by the State Finance Commission, and a handbook for elected representatives written by CMAR.

These materials, coupled with our qualitative interviews, reinforced the importance of procedural knowledge. Indeed, in a chapter on prerequisites for success, the municipal councilor handbook tells elected officials, "[You] should have enough knowledge to be successful. This knowledge includes knowing the legal provisions for getting work done, which government scheme can be arranged for the citizens of the ward, what is the format of the application, and what are the criteria for eligibility..."

At the same time, these materials also hinted at the potential barriers to councilors acquiring procedural knowledge on their own. Many of these documents are lengthy and written in a verbose, technical fashion. The Rajasthan Municipal Act runs nearly 350 pages in length, and the CMAR official handbook is nearly 250 pages long. Neither are disseminated to councilors upon their election, nor is any training conducted in which the councilors learn the key pieces of information these documents contain.

Based on interviews and materials collected during our qualitative fieldwork, we identified the following ten domains:

1. **Constitutional Powers:** We asked respondents if they were aware of which constitutional provision instituted elections for urban local governments and devolved a series of powers to elected officials (the 74th Constitutional Amendment was coded as the correct answer).[33]

2. **Town Status:** We assessed if respondents knew the municipal tier their town was classified as, which determines structural features of local government, including the number and variety of personnel, and eligibility of public schemes.

3. **Master Plan:** We asked respondents if they knew whether their town had a master plan. Each town has a master plan that contains key information regarding how development and land use should unfold. Yet it was unclear if councilors were aware such plans existed, let alone took such plans into account when crafting council actions. If respondents knew their town had a master plan, we then asked what year range it

[33] India's 74th Constitutional Amendment Act outlines the rights and responsibilities of municipal governments, including a list of the specific public services that fall under their purview. The 74th CAA is widely cited in official documents; not having heard of it reflects a lack of exposure to the rules and regulations that undergird urban decentralization in India.

was valid for, and checked this against the actual master plans which we collected for every town across the state. To provide an example, the town of Bidasar has a master plan for which the valid year range is 2010-2031. Such year ranges are prominently displayed on the cover of master plans.[34]

4. **Land Tax:** We asked respondents a question about local taxes for land and housing, which is the most significant tax these towns levy on commercial and residential properties (Source: Rajasthan Municipal Act 2009, Point 102, Page 457). Specifically, we asked respondents if their town was empowered to collect taxes on housing and land ('yes' was coded as the correct answer).

5. **New Tax:** We asked respondents if their town council was empowered to propose new local taxes to collect. Municipalities in Rajasthan are permitted to propose and collect certain kinds of new taxes (e.g. on tourism, advertisements, and lighting) (Source: Rajasthan Municipal Act 2009, Point 103, Page 458). Such taxes are seen as an important tool to expanding the own-source revenue of towns. Again, we only asked respondents if their town was permitted to propose new local taxes ("yes" was coded as the correct answer).

6. **User Fees:** Another key revenue source for towns is levying user charges on residents for services like sewerage and waste management (Source: Rajasthan Municipal Act 2009, Point 104, Page 459). We asked respondents whether their town was allowed to charge such fees ('yes' was coded as the correct answer).

7. **Revenue Change (Octroi):** We assessed whether respondents were aware of a major change in their municipal budget, which was the abolishment of a point-of-entry tax (octroi). This tax used to be collected by individual towns, but with its abolishment the town now receives compensation from higher tiers of government. We asked respondents if their town could still collect octroi or not ('no' was coded as a correct answer).

8. **Spending Approval:** An key area of knowledge for councilors is to understand the rules surrounding municipal expenditure approvals. Below a specific threshold (Rs. 100,000 in *nagar palikas*; Rs. 200,000 in *nagar parishads*), municipal expenditures can be approved by the head bureaucrat in town (the executive officer or commissioner) without consulting the elected chairperson or elected councilors (Source: Rajasthan Municipal Purchase Rules 2015). Our question assesses whether respondents could identify the spending threshold below which the head bureaucrat can unilaterally approve work.[35]

[34] If the respondent provided the correct start year of the master plan (plus or minus one year, to provide a small degree of latitude), the respondent received 0.5 points. If the respondent provided the correct end year of the master plan (plus or minus one year), the respondent received 0.5 points. Respondents who correctly provided both years (plus or minus one for each stated year in the range) therefore received 1 point. Our coding of this variable was independently verified by a research assistant.

[35] If the respondent provided a number just below the threshold (for example, Rs. 99,999 in a *nagar palika*), we coded that as correct because the respondent understood it as a threshold and provided an understandable interpretation of the correct number. Our coding of this variable was independently verified by a research assistant.

9. **Budget Date:** Each town council is required to craft and approve (via council vote) an annual budget by February 15th (Source: Rajasthan Municipal Act 2009, Point 88, Page 453). Knowing this deadline is important, as the weeks leading up to this date are important for councilors. It is during this period that they can best ensure the needs of their ward are addressed in the budget.[36]

10. **Number of Council Meetings:** Meetings of elected representatives are seen as central to the workings of municipalities. Regular meetings are highlighted as essential for coordination, planning, and dispute resolution. Official state guidelines specify that council meetings should take place at least six times a year, each attended by a quorum of at least one third of all members (Source: Rajasthan Municipal Act 2009, Point 51, Page 407). We asked respondents what the official minimum number of times their council is expected to meet each year.

B.2 Creating Indices Using Factor Analysis

We perform the Kaiser-Meyer-Olkin factor adequacy test (see column 1 in Table 4). As a rule of thumb, the overall MSA should be closer to 1, and > 0.49. We report an overall MSA of 0.68, indicating their is sufficient empirical basis to proceed with a factor analysis. We also perform Bartlett's test, which checks whether the constituent items are uncorrelated. We want to reject the null hypothesis that they are uncorrelated. Column 2 in Table 4 reports the results from a Chi-squared test with $p < 0.001$, indicating that we can reject the null hypothesis.

Table 4: Suitability Tests

Overall MSA	Bartlett P Value
0.68	Chisq=935.87,p=0

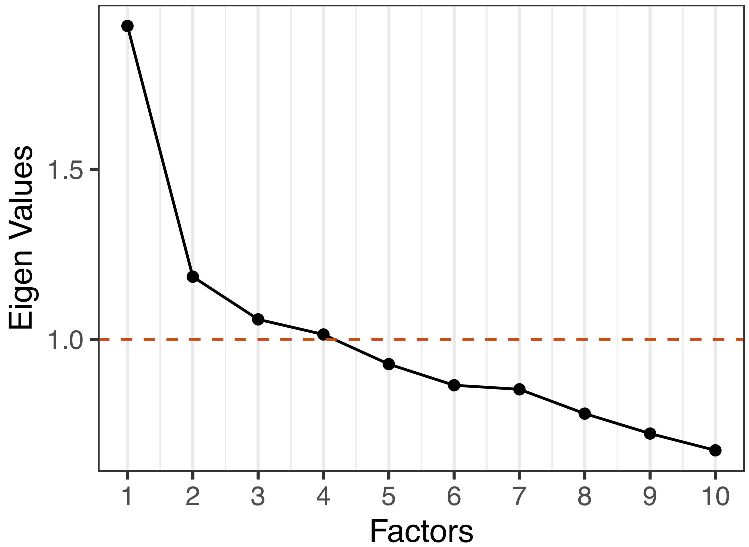
[a] Results for the Kaiser-Meyer-Olkin Factor Adequacy Test in (1), and Bartlett's Test in (2)

Next, we compute eigenvalues to identify the optimal number of factors. Figure 7 shows the eigenvalues for different number factors. The eigenvalues are below 1 when there are five or more factors. This suggests the optimal number of factors is four.

Using this information, we conduct a factor analysis specifying four factors. The factor loadings are reported in Table 5. The first factor places weight on measures of revenue power, particularly the town's ability to impose a land tax, waste fees, and new taxes. The second factor is primarily composed of expenditure items: the EO's spending rules, the date by which the town council must approve the budget, and the minimum number of council meetings to be held in a year. The third factor gives considerable weight to general items,

[36] If a respondent stated February 15th, that observation was coded as a 1. If a respondent generally stated February, or provided a date in February other than the 15th, that observation was coded as a 0.5. Our coding of this variable was independently verified by a research assistant.

Figure 7: Eigenvalues



Note: The figure shows the eigenvalues (on y-axis) for different number of factors (on the x-axis). A dashed red line separates eigenvalues greater than 1 with those below 1.

specifically knowledge about the town master plan and constitutional provision for local government. The fourth factor, much like our overall index, draws on measures of spending rules (EO's spending power), revenue power (Octroi abolished), and constitutional provisions (town status).

Table 5: Factor Loadings

	Factor1	Factor2	Factor3	Factor4
Know Constitutional Provision	0.048	-0.014	0.132	-0.073
Know Town Status	-0.020	0.064	0.662	0.023
Know Master Plan Years	-0.051	-0.042	-0.033	0.454
Know Octroi Abolished	0.170	0.054	0.044	0.304
Know Land Tax	0.065	0.266	-0.030	0.045
Know New Tax	1.001	-0.022	-0.012	0.004
Know Waste Fees	-0.063	0.330	0.046	0.224
Know EOs Spending Power	-0.017	0.501	-0.098	-0.067
Know Min Number of Meetings	-0.001	0.478	0.094	-0.017
Know Budget Date	-0.054	-0.047	-0.005	0.248

C Urban Decentralization in India

The Government of India passed the 74th Constitutional Amendment Act in 1992, devolving political and fiscal powers to municipal governments. The Act mandates that municipalities hold elections every five years — cities and towns are carved into wards, and voters in each ward directly elect a ward councilor to represent their area of the city in the municipal council. The Act further tasks municipalities with providing a range of public goods and services, including town planning, maintaining roads and bridges, solid waste management, fire services, slum improvement, street lighting, and producing birth and death registrations. The responsibilities of municipalities are further specified by state-level municipal acts. In our study context, this is the Rajasthan Municipal Act.

Municipalities have significant resources to carry out their roles and responsibilities. They receive annual fiscal transfers for capital expenditures from the state and central governments. Between 2016 and 2020, a typical town in Rajasthan received, on average, Rs. 20.1 million (255,731 USD) from the state finance commission every year, and Rs. 3.23 million (41,095 USD) from the central finance commission every year. Municipalities decide how these transfers—the largest source of their capital receipts—are locally spent. Overall, municipal authorities had, on average, Rs. 102.3 million (1.30 million USD) for capital expenditure every year in the same five year period.[37] In Rajasthan, municipalities also receive annual compensation for the removal of the local Octroi (point of entry) tax in the early 2000s. Municipalities are further empowered to levy local fees, including user fees for street cleaning and solid waste management, and a range of local taxes, most importantly property tax and land conversion tax. Moreover, they receive funding for specific central and state programs. Recent examples include the Swachh Bharat Mission (a sanitation program) and the Swarna Jayanti Shahri Rojgar Scheme (an urban livelihoods training program).

Scholars have documented several shortcomings of urban decentralization in India, especially surrounding tax collection, administrative capacity, and citizen participation (Jacob and Jacob 2022). Nevertheless, municipalities are key points of governance, representation, and service delivery in urban India. These local governments have considerable resources and authority. Urban residents routinely turn to councilors for assistance and to request infrastructure and services. They are also significantly more likely to report contacting their municipal councilor for assistance than their member of the state legislative assembly (MLA) or national member of parliament (MP) (CSDS-Lokniti and Azim Premji University 2019). In short, India's municipal governments are not paper institutions. They play a central role in everyday governance in the country's expanding cities and towns.

[37] Figures based on authors' copies of small town budget sheets. Conversion to U.S. dollar based on the Internal Revenue Services' 2022 yearly average currency exchange rate for India (1 USD = 78.598 INR).

D Procedural Knowledge and Governing Efficacy

We report the results from an ordinary least squares regression specification:

$$Y_{i,k} \sim \beta_1(\text{Knowledge}) + \beta_2(\text{Age}) + \beta_3(\text{Female}) + \beta_4(\text{Marginalized Group}) + \beta_5(\text{Education}) + \beta_6(\text{Won Prior Elections}) + \beta_7(\text{Log Household Income}) + \beta_8(\text{Hindu}) + \beta_9(\text{BJP Supporter}) + \gamma_k$$

Where $Y_{i,k}$ is a measure of representational efficacy for the ith politician in town k; γ_k is a town-level fixed effect; and β_1 is the parameter of interest. β_1 captures the partial correlation between procedural knowledge and a particular measure of representational efficacy.

Table 6: Does Knowledge Predict Representational Efficacy?

	Budget Making	Pol Active	Connected	Residents Seek Help
Procedural Knowledge	0.09	0.12^{***}	0.54^{***}	1.22^{***}
	(0.07)	(0.03)	(0.06)	(0.22)
Age	−0.00	−0.00	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Female	0.02	0.00	-0.16^{***}	−0.02
	(0.02)	(0.01)	(0.02)	(0.08)
Marginalized Group	0.00	0.01	−0.02	−0.02
	(0.02)	(0.01)	(0.02)	(0.07)
Education	0.01^{**}	0.00	0.01^{**}	0.01
	(0.00)	(0.00)	(0.00)	(0.01)
Won Prior Elections	0.01	0.00	0.02	0.09^{**}
	(0.01)	(0.00)	(0.01)	(0.03)
log(Household Income)	−0.00	0.00	−0.00	0.01
	(0.01)	(0.00)	(0.00)	(0.02)
Hindu	0.02	−0.00	0.06^{*}	−0.14
	(0.03)	(0.01)	(0.03)	(0.09)
BJP Supporter	-0.07^{***}	−0.00	-0.05^{**}	0.04
	(0.02)	(0.01)	(0.02)	(0.06)
Adj. R^2	0.10	0.01	0.19	0.02
Num. obs.	1071	1957	1957	1957

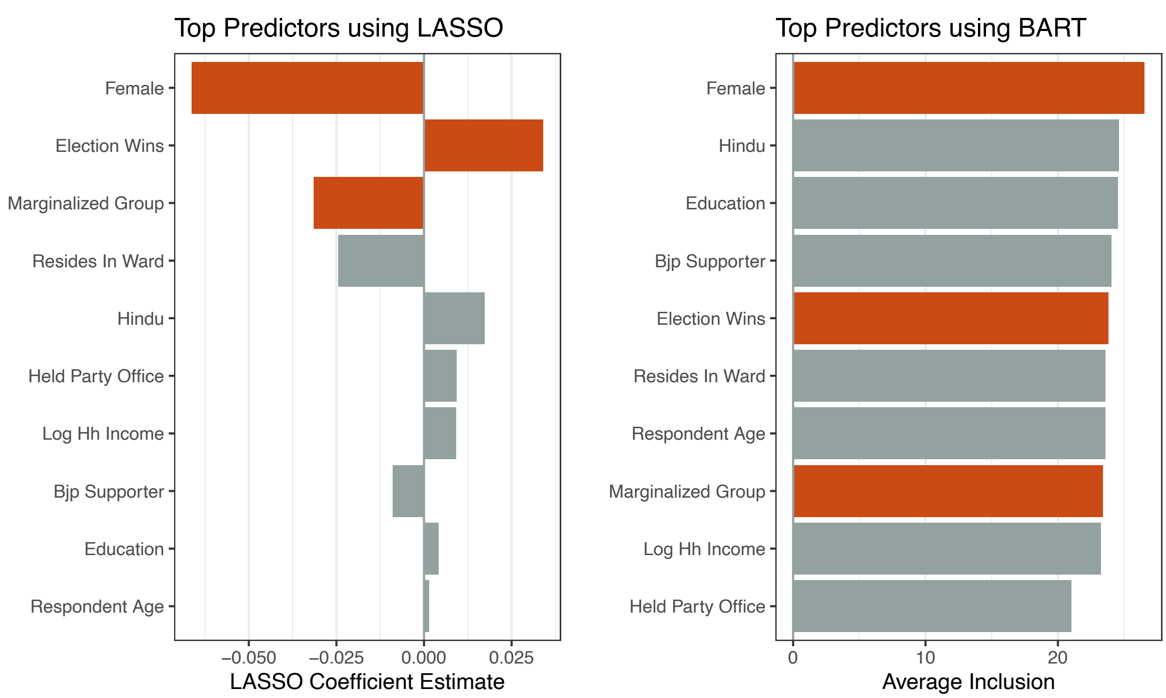
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

E Selecting Predictors Using Machine Learning

In Table 3 we report correlates of procedural knowledge using a multivariate regression. We assess the robustness of these empirical associations using two types of machine learning variable selection procedures: LASSO and BART. These procedures show that our results are not highly sensitive to model specifications.[38] In Figure 8 (see left panel), we report the LASSO coefficient estimates for ten background characteristics, ranging from politicians' age, gender, religion, education, religion, and caste to whether they reside in the ward, whether they support the BJP, whether they have held official positions in a party organization, and their political experience (number of prior election wins).

The outcome in this analysis is the index of overall knowledge. The left panel shows gender is the top predictor of knowledge. Female politicians are roughly seven percentage points less knowledgeable than their male counterparts. Political experience (number of election wins) is also associated with higher knowledge. Fixing all other factors, an additional election win increases overall knowledge by three percentage points. Finally, ethnicity or being a member of a marginalized group is also a top predictor of knowledge. Politicians from marginalized groups are approximately three percentage points less knowledgeable than politicians from elite or dominant groups.

Figure 8: Selecting Predictors with Machine Learning Algorithms



Next, we use Bayesian Additive Regression Trees (BART), a highly flexible, non-

[38]LASSO is a multivariate regression which selects variables that are most predictive of an outcome. Unlike ordinary least squares, it "drops" or shrinks the coefficient on variables that are not predictive of an outcome to zero. In other words, if our original model specification includes variables that are not predictive of knowledge, LASSO will drop them from the regression.

parametric, machine learning algorithm that identifies variables most predictive of an outcome. A strength of BART is its ability to flexibly model interaction between predictor variables. Since our original regression specification did not include any interaction terms, BART allows us to discover covariate profiles that are most predictive of knowledge.[39]

In the right panel, we report the proportion of times each predictor gets used in BART. Here, gender is a top predictor of overall knowledge. Gender is included 26.5% of the time. Political experience (number of election wins) is included 23.8% of the time. Belonging to a marginalized group is included approximately 23.4% of the time. We note that education, religion (Hindu) and partisan affiliation (BJP supporter) are also top predictors using this method. Education and religion are included 25% of the time, while partisan affiliation is 24% of the time.[40] However, these variables have small coefficients when using OLS or LASSO.

Across both methods then, gender and political experience, and to a lesser degree marginalized ethnic status appear to be the most robust predictors of overall knowledge. In Table 3, both gender gaps and ethnic status gaps are especially pronounced for procedural knowledge regarding spending rules and revenue powers, which in many ways represent the core channels through which local representatives finance and deliver local development to their constituents.

[39]The procedure involves constructing "regression trees" in which the data is repeatedly partitioned based on predictors, with the goal of capturing maximum variation in the outcome. The more a variable is used to partition the data, the more predictive it is of the outcome. In other words, average inclusion is a measure of variable importance. For more on the method, see Hill, Linero, and Murray (2020).

[40]The BART analysis is conducted on R version 4.3.2 in R Studio version 2023.12.0+369, operated on an Intel Dual Core i5 1.8 GHz chip. Results may differ when operating R and R Studio on an Apple chip, even after setting seed. When using an Apple chip, gender is included 27.2% of the time, political experience 24.1% of the time, and marginalized group 23.1% of the time.

F Regression Discontinuity

We assess the impact of incumbency using a close elections regression discontinuity design. In the context we study (municipal ward elections), winners win their election, on average, by 106 votes (17 percentage points), with the 25th percentile at 32 votes (5.9 percentage points) and 75th percentile at 145 votes (23.9 percentage points). We use the margin of victory (in percentage points) as the forcing variable in the regression discontinuity design.

F.1 Design Tests

Following the recommendations in Cattaneo, Idrobo, and Titiunik (2019), we validate the regression discontinuity design by checking for sorting around the cut-point (McCrary Density Test) and for any discontinuous changes in covariate values at the cut-point using the same specification as the main analysis.

Table 7 reports the densities to the left and right of the cut-point, the difference in densities, and whether that difference is statistically significant. We fail to reject the null hypothesis of no difference in densities. There is prima facie evidence of no sorting around the cut-point.

Table 7: McCrary Density Test

Densities				
Left	Right	Difference	t statistic	p
0.022	0.026	0.004	1.028	0.304

[a] This table reports the forcing variable's densities at the cut-point, and performs the McCrary Density test using the rddensity package in R.

Table 8 reports the difference at the cut-point for a variety of respondent characteristics like age, gender, social group status, education level, household income, religious identity, partisanship, and residency status. Column 4 shows that there is no statistically significant difference at the cut-point for any of these covariates. There is no evidence of discontinuous changes in covariate values at the cut-point.

Table 8: Discontinuous Changes in Covariates

				Confidence Interval		
Covariate	Estimate	SE	p	Lower	Upper	Bandwidth
Age	-0.651	1.783	0.715	-4.146	2.844	18.360
Female	-0.055	0.073	0.456	-0.198	0.089	16.429
Marginalized Group	0.021	0.067	0.752	-0.111	0.153	20.490
Education	0.055	0.580	0.925	-1.082	1.192	18.357
Household Income	-9890.883	9563.911	0.301	-28635.804	8854.039	14.709
Hindu	0.057	0.052	0.269	-0.044	0.159	16.806
BJP Supporter	0.083	0.072	0.254	-0.059	0.225	17.370
Resides in Ward	-0.024	0.050	0.634	-0.123	0.075	22.403
Aligned with Chairperson	0.088	0.074	0.231	-0.056	0.233	18.042

Note:
The difference at the cut-point was estimated using rdrobust in R, specifying a first-order polynomial (p=1), triangular kernel weights, and MSE-optimal bandwidths. We report the robust, bias-corrected estimate and HC2 robust standard error. This is identical to the primary outcome specification in the paper.

F.2 Estimates

Table 9 reports the main results shown in Figure 6.

Table 9: RD Estimates

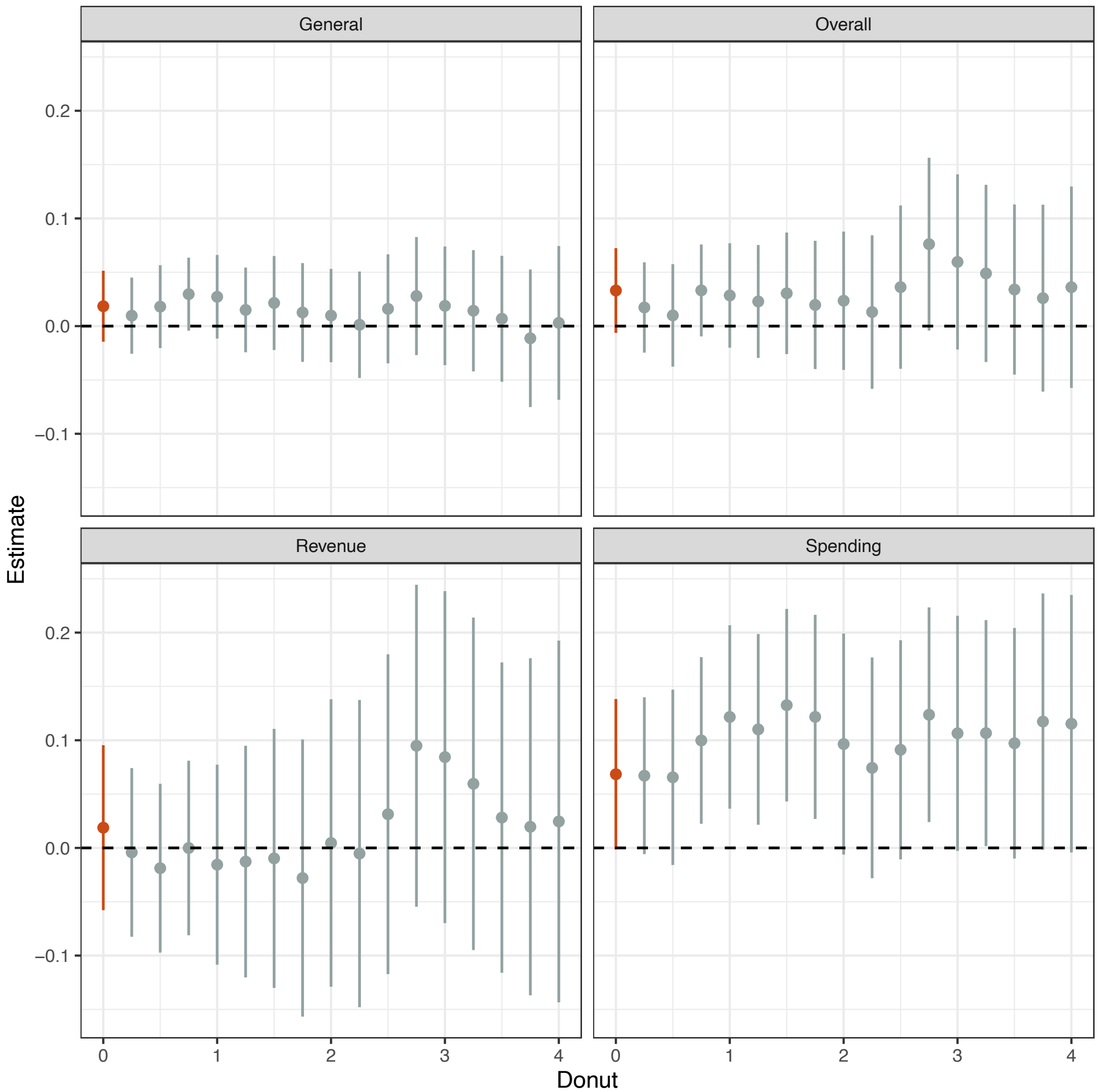
Outcome	Estimate	SE	p	CI(Low)	CI(High)	MSE BW
Overall Knowledge	0.033	0.020	0.100	-0.006	0.072	23.237
Legal Provisions	0.018	0.017	0.273	-0.015	0.051	19.674
Revenue Powers	0.019	0.039	0.631	-0.058	0.095	20.040
Spending Rules	0.068	0.036	0.055	-0.002	0.138	18.284

[a] Note: This table reports the RD estimates using a first-order polynomial (p=1), triangular kernel, and MSE-optimal bandwidth. We report the robust estimate, standard error, and associated p value.

F.3 Donut RD

For robustness, we check the sensitivity of our findings to observations near the cut-point. We implement a "donut" regression discontinuity design in which observations within certain distance of the cut-point on either side ($\pm\theta$) are dropped from the analysis, and the difference at the cut-point is re-estimated with the remaining data. Figure 9 reports these estimates for different donut sizes, $\theta \in \{0, 0.25, 0.5, 0.75, 1, \cdots, 3.5, 3.75, 4\}$. Note that when the donut size is zero ($\theta = 0$), no observations are dropped, and the results are identical to the main analysis. These are reported in orange.

Figure 9: Donut RDs



Note: The figure shows the difference at the cut-point in a close-elections regression discontinuity design, dropping observations $\pm\theta$ around the cut-point. The main result, when no observations are dropped (i.e. $\theta = 0$), is shown in orange. The figure reports the robust estimate, standard error, and confidence interval generated by the `rdrobust` package in R when using the MSE optimal bandwidth, triangular weights, and a first-order polynomial. Estimates in Table 10.

Table 10: Donut RD Results

Donut	BW	DV	Estimate	SE	p	CI (L)	CI (H)	Dropped
0.00	19.70	General	0.018	0.017	0.273	-0.015	0.051	0
0.25	18.25	General	0.010	0.018	0.592	-0.026	0.045	21
0.50	18.07	General	0.018	0.020	0.358	-0.020	0.057	42
0.75	21.26	General	0.030	0.017	0.086	-0.004	0.064	57
1.00	18.70	General	0.027	0.020	0.169	-0.012	0.066	78
1.25	18.57	General	0.015	0.020	0.454	-0.024	0.054	98
1.50	17.93	General	0.021	0.022	0.335	-0.022	0.065	117
1.75	17.94	General	0.013	0.023	0.590	-0.033	0.059	130
2.00	19.80	General	0.010	0.022	0.658	-0.034	0.053	151
2.25	17.59	General	0.001	0.025	0.961	-0.048	0.051	169
2.50	17.92	General	0.016	0.026	0.535	-0.035	0.067	187
2.75	17.31	General	0.028	0.028	0.319	-0.027	0.083	202
3.00	18.04	General	0.019	0.028	0.503	-0.036	0.074	224
3.25	18.18	General	0.014	0.029	0.620	-0.042	0.071	233
3.50	16.94	General	0.007	0.030	0.819	-0.052	0.065	245
3.75	16.73	General	-0.011	0.033	0.729	-0.075	0.053	267
4.00	15.54	General	0.003	0.036	0.935	-0.068	0.074	286
0.00	23.27	Overall	0.033	0.020	0.099	-0.006	0.072	0
0.25	19.82	Overall	0.017	0.021	0.419	-0.025	0.059	21
0.50	16.80	Overall	0.010	0.024	0.683	-0.038	0.058	42
0.75	21.35	Overall	0.033	0.022	0.128	-0.010	0.076	57
1.00	18.88	Overall	0.028	0.025	0.250	-0.020	0.077	78
1.25	18.06	Overall	0.023	0.027	0.393	-0.030	0.075	98
1.50	17.13	Overall	0.030	0.029	0.290	-0.026	0.087	117
1.75	16.34	Overall	0.020	0.030	0.518	-0.040	0.079	130
2.00	15.39	Overall	0.024	0.033	0.472	-0.041	0.088	151
2.25	14.81	Overall	0.013	0.036	0.719	-0.058	0.084	169
2.50	15.17	Overall	0.036	0.039	0.349	-0.040	0.112	187
2.75	15.11	Overall	0.076	0.041	0.063	-0.004	0.156	202
3.00	15.94	Overall	0.060	0.042	0.151	-0.022	0.141	224
3.25	16.31	Overall	0.049	0.042	0.244	-0.033	0.131	233
3.50	17.13	Overall	0.034	0.040	0.400	-0.045	0.113	245
3.75	16.53	Overall	0.026	0.044	0.558	-0.061	0.113	267
4.00	16.14	Overall	0.036	0.048	0.449	-0.057	0.130	286
0.00	20.07	Revenue	0.019	0.039	0.631	-0.058	0.095	0
0.25	18.53	Revenue	-0.004	0.040	0.917	-0.083	0.074	21
0.50	19.95	Revenue	-0.019	0.040	0.638	-0.097	0.060	42
0.75	20.52	Revenue	0.000	0.041	0.999	-0.081	0.081	57

Table 10: Donut RD Results *(continued)*

Donut	BW	DV	Estimate	SE	p	CI (L)	CI (H)	Dropped
1.00	17.21	Revenue	-0.016	0.047	0.743	-0.108	0.077	78
1.25	15.41	Revenue	-0.013	0.055	0.817	-0.120	0.095	98
1.50	14.81	Revenue	-0.010	0.061	0.874	-0.130	0.111	117
1.75	13.68	Revenue	-0.028	0.066	0.670	-0.157	0.101	130
2.00	13.77	Revenue	0.005	0.068	0.947	-0.129	0.138	151
2.25	13.64	Revenue	-0.005	0.073	0.942	-0.148	0.137	169
2.50	14.26	Revenue	0.031	0.076	0.680	-0.117	0.180	187
2.75	14.69	Revenue	0.095	0.076	0.214	-0.055	0.244	202
3.00	14.89	Revenue	0.084	0.079	0.284	-0.070	0.239	224
3.25	15.42	Revenue	0.060	0.079	0.450	-0.095	0.214	233
3.50	17.24	Revenue	0.028	0.074	0.702	-0.116	0.172	245
3.75	16.31	Revenue	0.020	0.080	0.806	-0.137	0.176	267
4.00	16.03	Revenue	0.025	0.086	0.774	-0.143	0.193	286
0.00	18.32	Spending	0.068	0.036	0.055	-0.001	0.138	0
0.25	18.13	Spending	0.067	0.037	0.071	-0.006	0.140	21
0.50	16.58	Spending	0.066	0.042	0.114	-0.016	0.147	42
0.75	17.89	Spending	0.100	0.039	0.011	0.022	0.177	57
1.00	16.39	Spending	0.122	0.043	0.005	0.036	0.207	78
1.25	17.05	Spending	0.110	0.045	0.015	0.022	0.199	98
1.50	16.23	Spending	0.133	0.046	0.004	0.043	0.222	117
1.75	16.24	Spending	0.122	0.048	0.012	0.027	0.217	130
2.00	16.17	Spending	0.096	0.052	0.066	-0.006	0.199	151
2.25	16.44	Spending	0.074	0.052	0.155	-0.028	0.177	169
2.50	17.08	Spending	0.091	0.052	0.079	-0.011	0.193	187
2.75	17.67	Spending	0.124	0.051	0.015	0.024	0.223	202
3.00	17.58	Spending	0.106	0.056	0.056	-0.003	0.216	224
3.25	18.08	Spending	0.107	0.054	0.046	0.002	0.212	233
3.50	18.50	Spending	0.097	0.055	0.075	-0.010	0.204	245
3.75	16.85	Spending	0.117	0.061	0.053	-0.002	0.236	267
4.00	18.02	Spending	0.115	0.061	0.059	-0.004	0.235	286

F.4 Specification Curves

As a measure of robustness, we check the sensitivity of our findings to RD specifications. For each outcome, we estimate the robust bias-corrected difference at the cut-point using different data-driven bandwidth selection procedures included in `rdrobust` package (more below), polynomial specifications (p= $\{1, 2, 3\}$), and kernels (`triangular`, `epanechnikov`, and `uniform`).

In terms of bandwidth selectors, we include the following: one common MSE-optimal bandwidth selector (`mserd`), two different MSE-optimal bandwidth selectors (`msetwo`), one common MSE-optimal bandwidth selector for the sum of regression estimates (`msesum`), a selector that picks $min(\text{mserd}, \text{msesum})$, a selector that picks $median$(mserd, msesum, msetwo) for each side of the cut-off separately, one common CER-optimal bandwidth selector (`cerrd`), two different CER-optimal bandwidth selectors (`certwo`), one common CER-optimal bandwidth selector for the sum of regression estimates (`cersum`), a selector that picks $min(\text{cerrd}, \text{cersum})$, and a selector that picks $median(\text{cerrd}, \text{certwo}, \text{cersum})$ for each side of the cut-off separately.

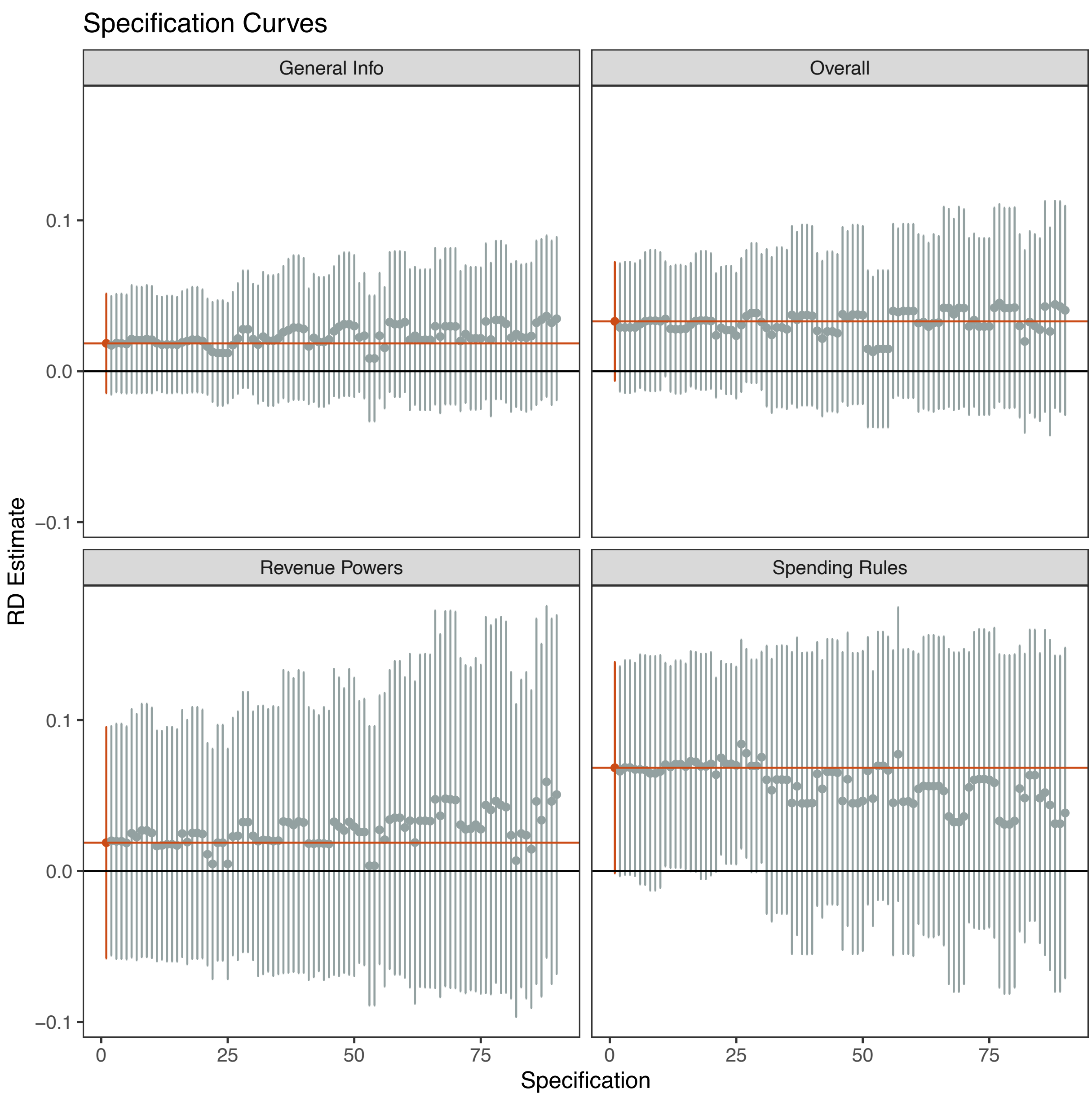


Figure 10: The figure shows, for each knowledge outcome, estimates of the difference at the cut-point using different RD specifications when we vary polynomials, bandwidth selectors, and weighting kernels. The estimate from the main specification is shown in orange.