When Can We Trust Regression Discontinuity Design Estimates from Close Elections? Evidence from Experimental Benchmarks

Online Appendix

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A Articles Using RDD

We reviewed more than sixty papers employing RDD in their main analyses that were published in three top political science journals (*American Political Science Review*, *American Journal of Political Science*, and the *Journal of Politics*) in 2016-2022. A list of these articles can be found below. We excluded papers using fuzzy regression discontinuity design or local randomization inference from our review, and also papers where RDD was not part of the main analyses are not included below.

In total, we reviewed 68 papers employing RDD in their main analyses. In about nine out of ten articles, the authors report local linear estimates, but MSE-optimal bandwidths are used in only about two-thirds of the published work. The remaining papers employ ad hoc bandwidths. Conventional inference is most prevalent (three out of four articles), and 31% of the publications report the robust inference of Calonico et al. (2014), in a small number of cases together with the conventional inference. A smaller share of papers (around 13%) also provide point estimates based on the approach by Calonico et al. (2014).

Figure OA1 shows proportion of articles using bias-corrected and robust inference by years. There is no visible trend, indicating that inference proposed by Calonico et al. (2014) has not become more prevalent among the profession over time.

Most articles that we surveyed were explicit about their modeling choices and described them accurately in the main text. However, in some cases we had to consult replication files to get full clarity. For instance, some authors who cite Calonico et al. (2014) or refer to their approach are only using the MSE-optimal point estimate without the robust inference.

Table OA1. Articles employing RDD published in three leading political science journals, 2016-2022.

		CIs		Point estimates			
Journal	Article	Robust	Conventional	Bias-corrected	Conventional	LLR	MSE
American Political Science Review	Croke et al. (2016)	0	1	0	1	1	0
American Political Science Review	Folke et al. (2016)	0	1	0	1	1	1
American Political Science Review	Holbein (2016)	0	1	0	1	0	0
American Political Science Review	Gulzar and Pasquale (2017)	0	1	0	1	1	0
American Political Science Review	Hainmueller et al. (2017)	0	1	0	1	1	0
American Political Science Review	Klašnja and Titiunik (2017)	1	0	0	1	1	1
American Political Science Review	Clinton and Sances (2018)	0	1	0	1	1	0
American Political Science Review	Dahlgaard (2018)	1	1	1	1	1	1
American Political Science Review	Fiva and Smith (2018)	0	1	0	1	1	1
American Political Science Review	Hall and Thompson (2018)	0	1	0	1	1	1
American Political Science Review	Mo and Conn (2018)	0	1	0	1	1	1
American Political Science Review	Szakonyi (2018)	0	1	0	1	1	1
American Political Science Review	Cavaille and Marshall (2019)	0	1	0	1	1	1
American Political Science Review	Challú et al. (2020)	0	1	0	1	1	0
American Political Science Review	Dasgupta and Kapur (2020)	1	0	1	0	1	1
American Political Science Review	Dynes and Holbein (2020)	0	1	0	1	1	1
American Political Science Review	Grumbach and Sahn (2020)	0	1	0	1	1	1
American Political Science Review	Gulzar et al. (2020)	0	1	0	1	1	0
American Political Science Review	Hassell et al. (2020)	0	1	0	1	1	1
American Political Science Review	Jassal (2020)	0	1	0	1	1	0
American Political Science Review	Lehmann and Masterson (2020)	0	1	0	1	1	0
American Political Science Review	Payson (2020)	0	1	0	1	1	1
American Political Science Review	Thompson (2020)	0	1	0	1	1	1
American Political Science Review	Cirone et al. (2021)	0	1	0	1	1	1
American Political Science Review	Gehring (2021)	0	1	0	1	1	1
American Political Science Review	Heide-Jørgensen (2021)	0	1	0	1	0	0
American Political Science Review	Reny and Newman (2021)	1	1	1	1	1	1
American Political Science Review	Walter (2021)	1	0	0	1	1	1
American Political Science Review	Haffert (2022)	0	1	0	1	1	0

Journal	Article	CIs		Point estimates		LLR	MSE
		Robust	Conventional	Bias-corrected	Conventional		
American Journal of Political Science	Broockman and Ryan (2016)	0	1	0	1	1	1
American Journal of Political Science	Coppock and Green (2016)	0	1	0	1	1	0
American Journal of Political Science	Hidalgo and Nichter (2016)	0	1	0	1	1	0
American Journal of Political Science	Holbein and Hillygus (2016)	0	1	0	1	1	0
American Journal of Political Science	Rueda (2017)	0	1	0	1	0	0
American Journal of Political Science	Thomas (2018)	0	1	0	1	0	0
American Journal of Political Science	Kim (2019)	0	1	0	1	1	1
American Journal of Political Science	Velez and Newman (2019)	1	0	0	1	1	1
American Journal of Political Science	Albertus (2020)	0	1	0	1	1	1
American Journal of Political Science	Hager and Hilbig (2020)	0	1	0	1	1	1
American Journal of Political Science	Fergusson et al. (2021)	1	0	1	0	1	1
American Journal of Political Science	Garz and Martin (2021)	0	1	0	1	0	0
American Journal of Political Science	Kogan et al. (2021)	1	0	1	0	1	1
American Journal of Political Science	Bove et al. (2024)	0	1	0	1	1	1
American Journal of Political Science	Feierherd (2022)	1	0	0	1	1	1
American Journal of Political Science	Gulzar et al. (2022)	1	0	0	1	1	1
American Journal of Political Science	Hollyer et al. (2022)	1	0	0	1	1	1
Journal of Politics	De Benedictis-Kessner and Warshaw (2016)	1	0	0	1	1	1
Journal of Politics	Caughey et al. (2017)	1	0	0	1	1	1
Journal of Politics	Eggers and Spirling (2017)	1	0	1	0	1	1
Journal of Politics	De Benedictis-Kessner (2018)	1	0	0	1	1	1
Journal of Politics	Mummolo (2018)	0	1	0	1	1	0
Journal of Politics	De Benedictis-Kessner and Warshaw (2020)	0	1	0	1	1	1
Journal of Politics	Feierherd (2020)	1	0	0	1	1	1
Journal of Politics	Fouirnaies and Hall (2020)	1	1	1	1	1	1
Journal of Politics	Schafer and Holbein (2020)	0	1	0	1	1	1
Journal of Politics	Sells (2020)	1	0	0	1	1	1
Journal of Politics	Boas et al. (2021)	1	1	1	1	1	1
Journal of Politics	Christensen and Garfias (2021)	0	1	0	1	1	1

Journal	Article	CIs		Point estimates		LLR	MSE
		Robust	Conventional	Bias-corrected	Conventional		
Journal of Politics	Croke (2021)	0	1	0	1	1	0
Journal of Politics	Esberg (2021)	0	1	0	1	1	1
Journal of Politics	Hobbs and Hopkins (2021)	0	1	0	1	1	1
Journal of Politics	Kirkland (2021)	0	1	0	1	1	1
Journal of Politics	Szakonyi (2021)	1	0	0	1	1	1
Journal of Politics	Weaver (2021)	0	1	0	1	1	0
Journal of Politics	Mangonnet et al. (2022)	0	1	0	1	0	0
Journal of Politics	Ravanilla et al. (2022)	1	0	1	0	1	1
Journal of Politics	Redeker (2022)	0	1	0	1	1	1
Journal of Politics	Trinh (2022)	0	1	0	1	0	0
Share		0.30	0.75	0.13	0.93	0.88	0.67

Notes: LLR refers to local linear regression, and MSE refers to MSE-optimal bandwidths.

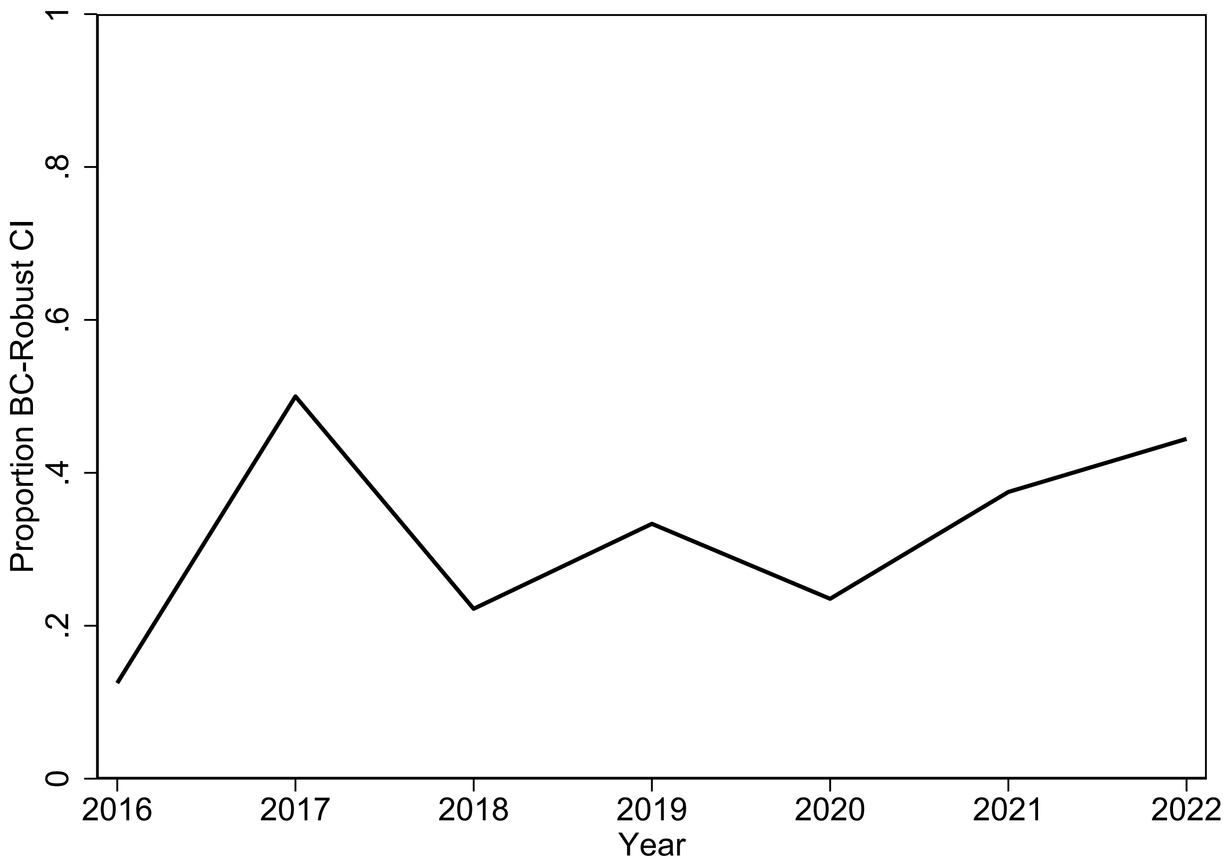

Figure OA1. Proportion of articles using bias-corrected and robust inference in three top political science journals

Notes: The figure shows proprotion of 68 RDD articles reviewed from American Political Science Review, American Journal of Political Science and the Journal of Politics, using bias-corrected and robust confidence intervals by years.

B Further Lessons from Brazil and Denmark

This section presents additional results using data from Brazil and Denmark. We also discuss substantive and methodological implications of our overall findings.

B.1 Data

For both Colombia and Finland, the conventional RDD specification estimates larger coefficients of the propensity of getting elected in $t+1$ compared to the lottery estimates. This raises the question whether this upward bias in the personal incumbency advantage is evidence of a potentially more widespread pattern? We also extend the analysis to Brazil and Denmark, two neighboring countries of Colombia and Finland, respectively. These countries provide an interesting point of comparison, as they feature similar political institutions, including similar open-list PR systems.

The 2005–2014 election results for Denmark come from Dahlgaard (2016), covering a total of $12,633$ candidate-election year observations. In Denmark, parties can choose between open and semi-open lists. Ties are also resolved by lotteries but do not occur frequently enough for statistical analysis.

The 2000-2008 election results for Brazil are obtained from the Brazilian electoral authority, the National Electoral Office (Tribunal Superior Eleitoral), and they cover a total of $586,706$ candidate-election year observations. In Brazil's open-list elections, ties occur more frequently but are not resolved with lotteries; instead, the oldest tied candidate gets nominated for office, which confounds a causal interpretation of this lottery estimate.

B.2 Main Findings

Table OA2 presents the estimation results. In Brazil, we find fairly small differences between the different implementations when looking at running at $t+1$ as the dependent variable, whereas we again find larger estimates for the conventional vis-à-vis the robust specification in Denmark. Furthermore, the estimates of the personal incumbency advantage are smaller for both countries

Table OA2. Effect of incumbency on winning next election and rerunning in Brazil and Denmark.

	Brazil				Denmark			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Running t+1								
Conventional	0.108	0.118	0.110	0.111	0.355	0.309	0.346	0.275
	[0.095,0.122]	[0.106,0.130]	[0.093,0.128]	[0.097,0.126]	[0.312,0.397]	[0.260,0.358]	[0.301,0.391]	[0.225,0.325]
Robust	0.104	0.111	0.096	0.095	0.300	0.242	0.266	0.210
	[0.083,0.125]	[0.096,0.127]	[0.069,0.122]	[0.074,0.115]	[0.250,0.349]	[0.188,0.297]	[0.216,0.317]	[0.147,0.273]
N	80921	260371	50129	152803	7947	8213	7389	7624
Bandwidth	2.07	6.69	1.30	3.93	7.10	8.16	5.45	6.03
Panel B: Elected t+1								
Conventional	-0.025	-0.022	-0.046	-0.036	0.288	0.252	0.269	0.225
	[-0.040,-0.010]	[-0.035,-0.009]	[-0.065,-0.027]	[-0.053,-0.018]	[0.250,0.326]	[0.208,0.295]	[0.227,0.312]	[0.178,0.272]
Robust	-0.056	-0.039	-0.061	-0.058	0.198	0.189	0.171	0.165
	[-0.079,-0.033]	[-0.057,-0.021]	[-0.092,-0.029]	[-0.082,-0.033]	[0.145,0.252]	[0.136,0.242]	[0.114,0.228]	[0.105,0.226]
N	59054	169986	36492	99970	6530	7757	5943	7081
Bandwidth	1.52	4.37	0.95	2.57	3.58	6.44	2.75	4.76
Bandwidth selector	MSE	MSE	CER	CER	MSE	MSE	CER	CER
Polynomial	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic

Notes: The dependent variable is equal to one if a candidate gets elected or re-runs in the next election, and zero otherwise, in Panels A and B, respectively. Estimates in columns (1) and (6) are based on the election lottery samples. Columns (2)-(5) and (7)-(10) present results from different RDD specifications. Robust and bias-corrected estimation uses the main bandwidth for the bias-correction. All RDD estimations use a rectangular kernel. The 95% confidence intervals are based on standard errors that are clustered by municipality and reported in brackets. We also account for clustering when computing the optimal bandwidths.

when we use the robust approach than what the conventional local linear estimation suggests

A graphical analysis of the data, provided in Figure OA2, shows that these differences can, again, be least partially attributed to differences in the curvature close to the cutoff. We can see in Panel A that there appears to be no indication of curvature close to the cutoff in Brazil—which is also reflected in the stability of the point estimates across various specifications. The point estimates are also stable across a range of bandwidths, except for the very smallest ones where the estimates became less stable and confidence intervals very large.

The Danish data look somewhat different. There is some curvature close to the cutoff, which also manifests itself as the point estimates becoming smaller as we make the bandwidth smaller. The plots in Panel B also sheds light on our findings regarding election in the subsequent elections: there similarly appears to be curvature in the CEF close to the cutoff that is not well captured by some specifications.

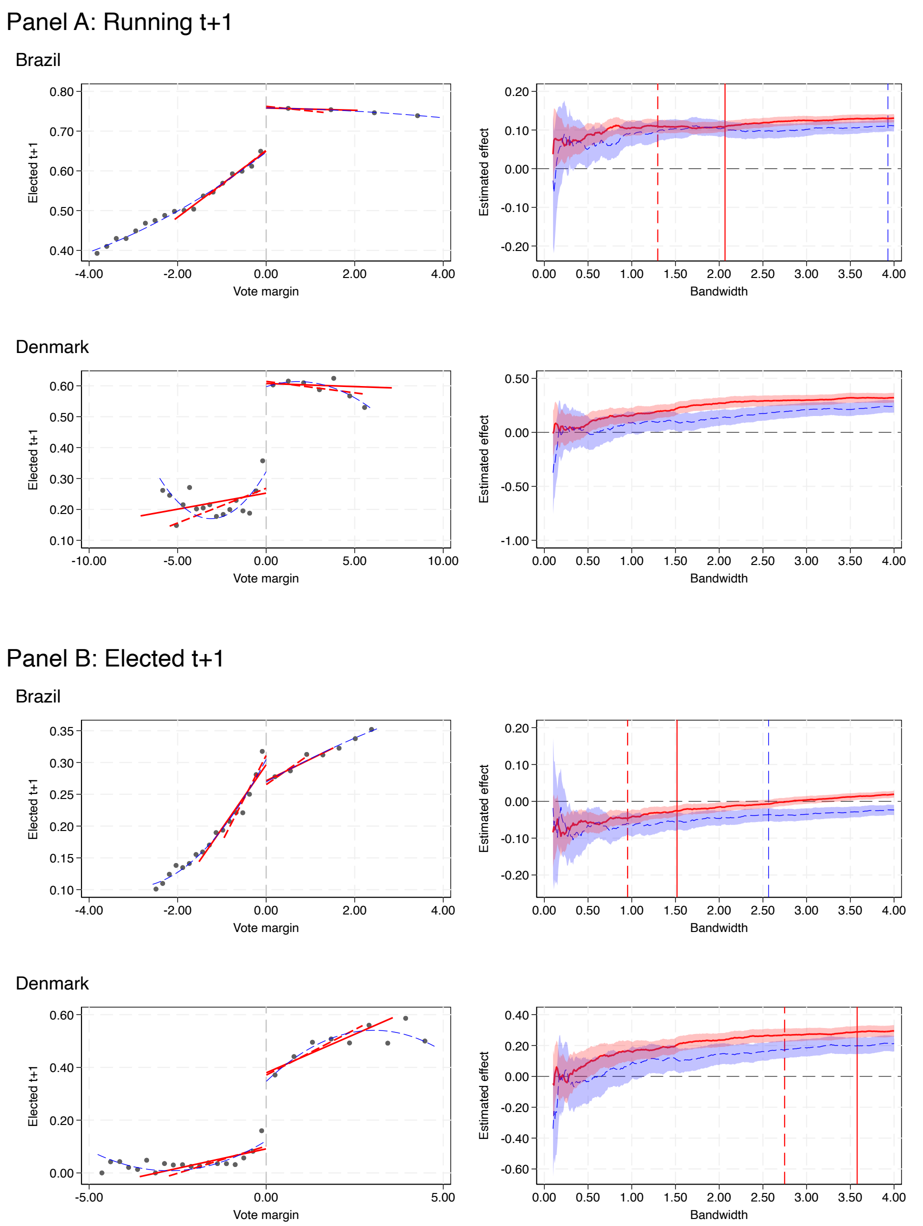

Figure OA2. RDD plots and conventional estimates across a range of bandwidths: Brazil and Denmark.

Notes: The figure shows RDD plots with binned averages (left) and RDD estimates across a range of bandwidths (right). The RDD plots show local linear (red line) and local quadratic (blue line) fits within CER-optimal (dashed lines) and MSE-optimal (solid lines) bandwidths. The dependent variable is running at $t+1$ in Panel A and getting elected at $t+1$ in Panel B. The right plots show point estimates and their 95% confidence intervals for the local linear (solid line) and local quadratic (dashed line) specification, obtained using a rectangular kernel, and for the lottery sample (black). Confidence intervals are based on standard errors clustered at the municipality level. The dashed red and blue vertical lines mark the CER-optimal bandwidths for the local linear and local quadratic estimation, respectively, and the solid vertical lines mark the MSE-optimal bandwidths.

B.3 Discussion

Substantively, these findings has two implications for our understanding of personal incumbency advantage and how it may vary across electoral systems.

First, given that most existing research on the personal incumbency advantage are based on the conventional specification, this raises concerns that—depending on the curvature—these estimates are somewhat inflated. Second, a sizeable body of work has documented that plurality and majoritarian systems, where typically fewer candidates run for election, generate larger incumbency advantages than proportional representation systems with multi-seat constituencies and longer party lists (Redmond and Regan 2015; Ariga 2015; Ariga et al. 2016; Dettman et al. 2017). However, our estimates show that even among countries with similar PR systems, there is substantial heterogeneity in terms of both the magnitude and sign of the incumbency advantage. This implies that variation in electoral systems is certainly not the sole, and possibly not even the main, explanation for the observed cross-country differences in incumbency advantage.

Future research should aim at providing a comprehensive set of incumbency effect estimates from a broad range of democratic countries—ideally using recent advances in RDD methodology. These estimates could then be subjected to a large-*N* descriptive analysis to investigate which contextual factors and electoral systems moderate the (individual) incumbency advantage.

Second, although the incumbency advantage estimates vary notably across countries, there is an effect of electoral victory on running again in three out of four cases. This helps us understand why politicians persist in democracies.

Our findings also have implications for methodological research on RDD. The overall patterns we describe echo past studies that show how sensitive RDD estimates, even when using larger samples, are to the details of the implementation (Gelman and Imbens 2019; Hyytinen et al. 2018). Further work is needed to explore whether the bias documented in this paper for estimates derived from close elections are also present in other RDD contexts. Given the central role that curvature has in our setting, future research—ideally leveraging new experimental benchmarks–should further illuminate the interactions between the curvature of the outcome variable and the performance of the different RDD estimators.

C Robustness Checks

This section reports a battery of robustness checks. We present further analyses using alternative bandwidths and assess robustness to the choice of kernel or order of the local polynomial.

C.1 Alternative Bandwidths

In the main analyses, we fix the bandwidth for bias-correction to be the same as the main bandwidth. However, we can also estimate separate optimal bandwidths for the main and bias estimation. We do so in Tables OA3 and OA4. The point estimates that we obtain from the conventional and robust bias-corrected estimation are remarkably similar throughout the tables. However, it is important to notice that we are unable to recover the experimental benchmarks for Colombia and Finland in Table OA4. This together with the graphical evidence from all countries suggests that using the optimal main bandwidth for bias estimation may be a better choice than using separate optimal bandwidths.

Table OA3. RDD estimates using optimal bandwidths for main estimation and bias correction: Running at $t+1$

	(1)	(2)	(3)	(4)
Panel A: Brazil				
Robust	0.105	0.116	0.109	0.111
	[0.091,0.120]	[0.104,0.129]	[0.092,0.127]	[0.096,0.126]
N	80921	260371	50129	152803
Main bandwidth	2.07	6.69	1.30	3.93
Bias bandwidth	6.27	11.46	6.27	11.46
Panel B: Colombia				
Robust	0.195	0.197	0.191	0.187
	[0.172,0.217]	[0.175,0.220]	[0.166,0.216]	[0.162,0.212]
N	45812	88944	31715	63086
Main bandwidth	4.38	9.75	2.98	6.28
Bias bandwidth	10.87	17.71	10.87	17.71
Panel C: Denmark				
Robust	0.351	0.305	0.344	0.273
	[0.307,0.395]	[0.255,0.355]	[0.298,0.389]	[0.223,0.324]
N	7947	8213	7389	7624
Main bandwidth	7.10	8.16	5.45	6.03
Bias bandwidth	21.78	18.72	21.78	18.72
Panel D: Finland				
Robust	0.021	0.020	0.005	-0.002
	[-0.005,0.048]	[-0.004,0.045]	[-0.027,0.038]	[-0.032,0.029]
N	51357	100561	34401	79847
Main bandwidth	1.48	3.50	1.05	2.37
Bias bandwidth	7.14	10.84	7.14	10.84
Bandwidth selector	MSE	MSE	CER	CER
Polynomial	Linear	Quadratic	Linear	Quadratic

Notes: The dependent variable is a dummy for re-running at $t+1$. 95% confidence intervals based on standard errors clustered at the municipality level are reported in brackets. We use a rectangular kernel.

Table OA4. RDD estimates using optimal bandwidths for main estimation and bias correction: Election at $t+1$

	(1)	(2)	(3)	(4)
Panel A: Brazil				
Robust	-0.029	-0.025	-0.047	-0.036
	[-0.044,-0.014]	[-0.038,-0.011]	[-0.067,-0.028]	[-0.054,-0.019]
N	59054	169986	36492	99970
Main bandwidth	1.52	4.37	0.95	2.57
Bias bandwidth	6.62	10.29	6.62	10.29
Panel B: Colombia				
Robust	0.048	0.047	0.044	0.038
	[0.030,0.065]	[0.029,0.066]	[0.023,0.066]	[0.016,0.060]
N	34526	72163	23618	49302
Main bandwidth	3.25	7.38	2.21	4.75
Bias bandwidth	14.68	14.24	14.68	14.24
Panel C: Denmark				
Robust	0.281	0.247	0.265	0.223
	[0.241,0.321]	[0.202,0.291]	[0.221,0.308]	[0.175,0.270]
N	6530	7757	5943	7081
Main bandwidth	3.58	6.44	2.75	4.76
Bias bandwidth	14.00	17.62	14.00	17.62
Panel D: Finland				
Robust	0.064	0.108	0.053	0.065
	[0.039,0.089]	[0.088,0.129]	[0.022,0.085]	[0.040,0.091]
N	30664	99582	20350	78807
Main bandwidth	0.96	3.43	0.68	2.33
Bias bandwidth	5.54	13.24	5.54	13.24
Bandwidth selector	MSE	MSE	CER	CER
Polynomial	Linear	Quadratic	Linear	Quadratic

Notes: The dependent variable is a dummy for getting elected at $t+1$. 95% confidence intervals based on standard errors clustered at the municipality level are reported in brackets. We use a rectangular kernel.

C.2 Choice of Kernel

Our main analyses use a rectangular kernel, i.e., all observations within the bandwidth get an equal weight. Figures OA4 and OA3 then report RDD results using alternative kernels, namely a triangular or an epanechnikov kernel. To facilitate comparisons, we also show the results using the rectangular kernel which we also use in our main analyses. The choice of kernel appears to be less important for the estimation results than other choices that an empiricist has to make.

Besides adjusting the kernel, we also follow Calonico et al. (2020) who note that setting the ratio between the main bandwidth and the bias bandwidth $\rho = 0.850$ is optimal when estimating a local linear regression with a triangular kernel and $\rho = 0.898$ is optimal for the epanechnikov kernel. With a local quadratic specification, $\rho = 0.887$ and $\rho = 0.924$ are optimal for the triangular and epanechnikov kernels, respectively. For the rectangular kernel, $\rho = 1$ is optimal, and we have followed this choice throughout our analyses.

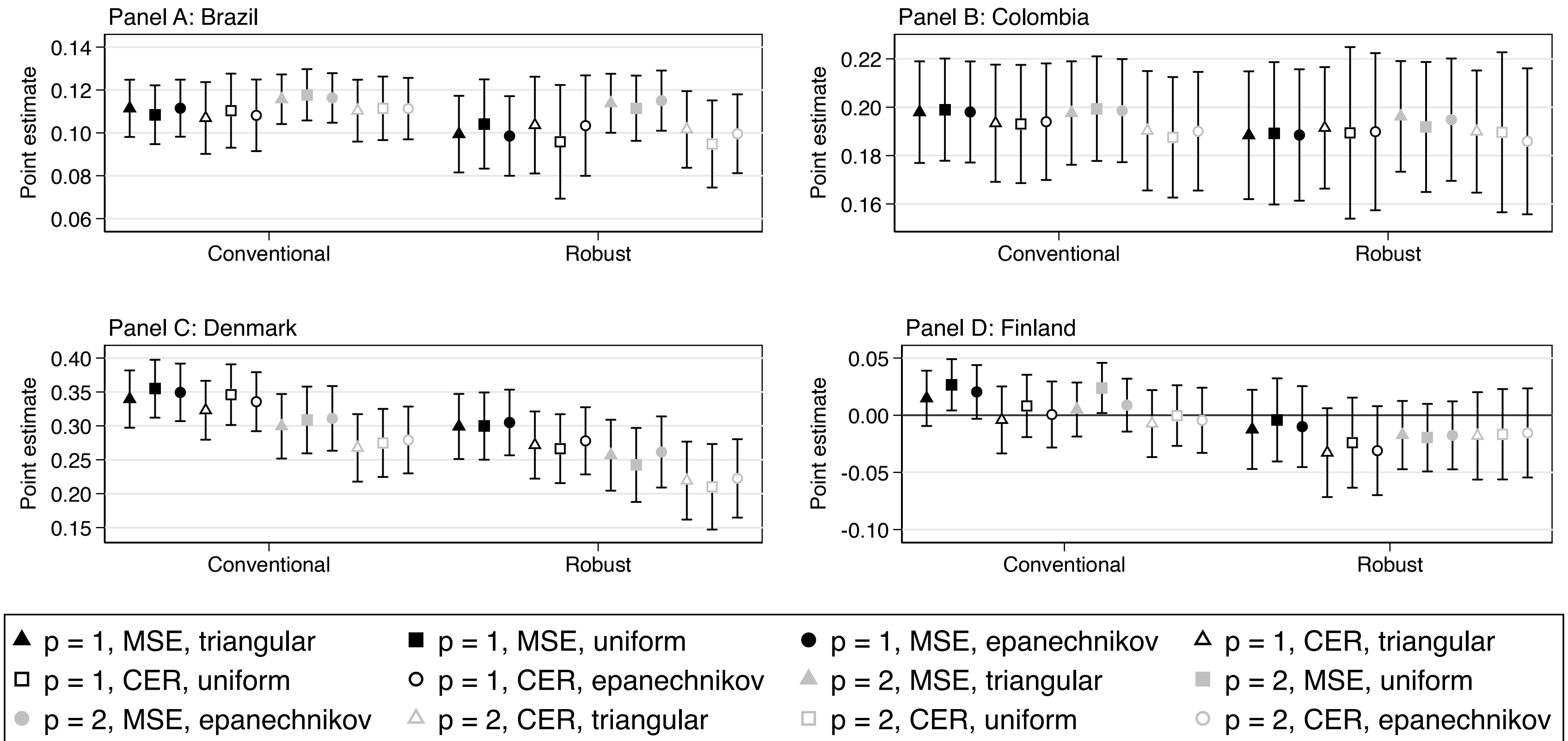

Figure OA3. RDD estimates using different kernels: Running at $t+1$.

Notes: The figure shows RDD estimates of the effect of incumbency on running in $t+1$. We vary the bandwidth selection method, order of polynomial, and the kernel. Specifications using a triangular kernel correspond to the results that we report in the main text. We also show the 95% confidence intervals of the point estimates that are constructed using standard errors clustered at the constituency level.

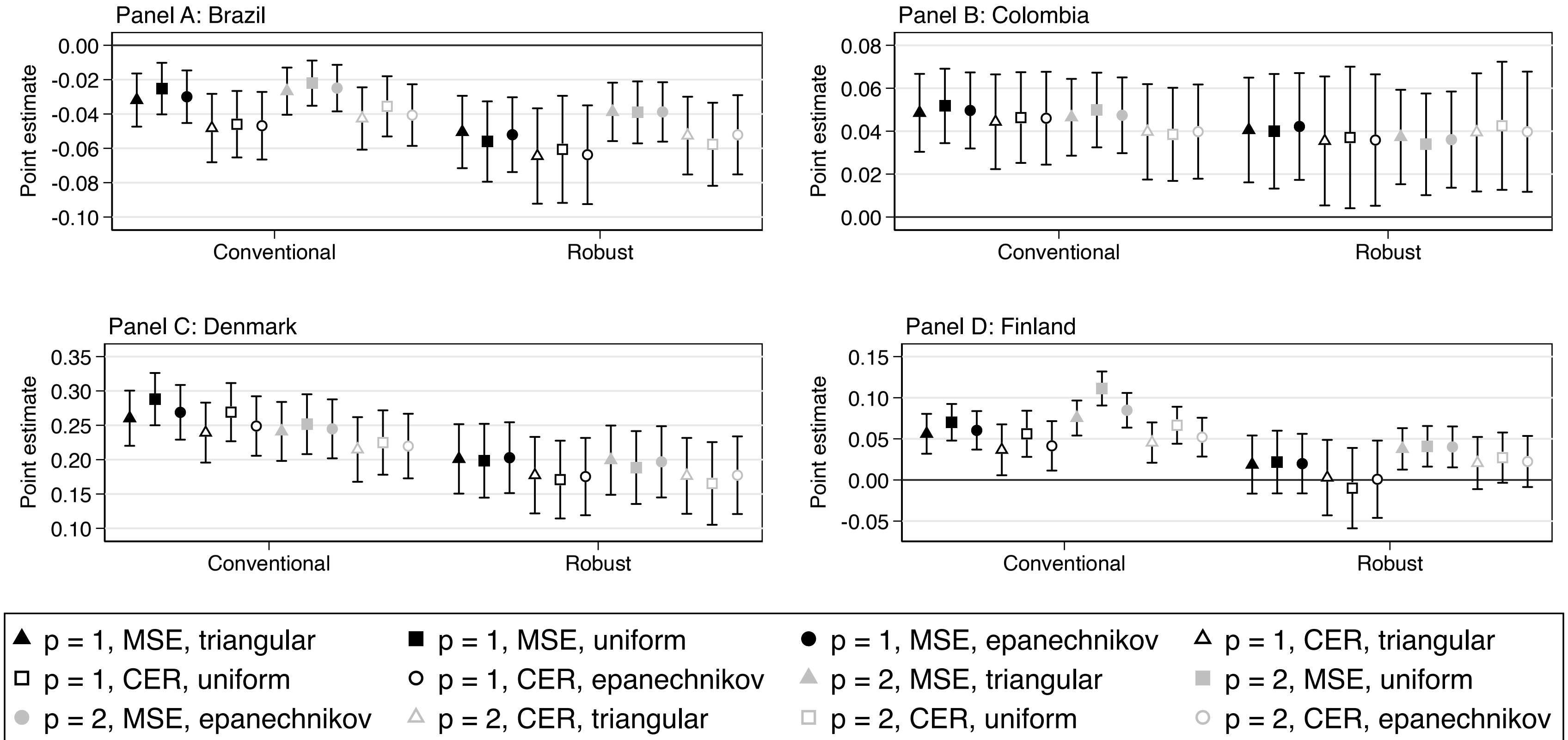

Figure OA4. RDD estimates using different kernels: Election at $t+1$.

Notes: The figure shows RDD estimates of the effect of incumbency on election at $t+1$. We vary the bandwidth selection method, order of polynomial, and the kernel. Specifications using a triangular kernel correspond to the results that we report in the main text. We also show the 95% confidence intervals of the point estimates that are constructed using standard errors clustered at the constituency level.

C.3 Polynomial Order

Our analyses thus far have focused on local linear and quadratic specifications. This is largely guided by the fact that the current research predominantly estimates such specifications. Recently, Pei et al. (2022) suggested that researchers should rely on the asymptotic mean squared error (AMSE) when choosing the order of the local polynomial that they use. In Tables OA6-OA7, we experiment with polynomials of order zero, one, two, three, and four, and estimate the AMSE for the conventional and the robust RD estimation. We can see that (a) the robust RD systematically outperforms the conventional RD; (b) estimation results acquired using the CER-optimal bandwidths always have a smaller AMSE than what we get when using the MSE-optimal bandwidths; and (c) 0th order polynomial always performs poorly in terms of the AMSE, but for larger polynomials, there are only very small differences when we use the robust RD.

Table OA5. RDD results on running at $t+1$ using alternative local polynomials (CER-optimal bandwidths).

	$p=0$	$p=1$	$p=2$	$p=3$	$p=4$
	(1)	(2)	(3)	(4)	(5)
Panel A: Brazil					
Conventional	0.095	0.110	0.111	0.115	0.114
	[0.072,0.118]	[0.093,0.128]	[0.097,0.126]	[0.100,0.129]	[0.099,0.128]
Robust	0.082	0.096	0.095	0.105	0.108
	[0.029,0.135]	[0.069,0.122]	[0.074,0.115]	[0.087,0.124]	[0.091,0.126]
N	6562	50129	152803	289172	415529
Bandwidth	0.20	1.30	3.93	7.44	11.21
AMSE (conventional)	0.00059	0.00042	0.00012	0.00017	0.00011
AMSE (robust)	0.00086	0.00021	0.00011	0.00009	0.00008
Panel B: Colombia					
Conventional	0.197	0.193	0.188	0.191	0.194
	[0.171,0.222]	[0.169,0.217]	[0.163,0.212]	[0.164,0.218]	[0.166,0.222]
Robust	0.197	0.189	0.190	0.179	0.182
	[0.143,0.250]	[0.154,0.225]	[0.157,0.223]	[0.146,0.212]	[0.149,0.215]
N	6619	31715	63086	88028	114102
Bandwidth	0.65	2.98	6.28	9.61	14.77
AMSE (conventional)	0.00237	0.00018	0.00016	0.00018	0.00024
AMSE (robust)	0.00086	0.00035	0.00028	0.00029	0.00027
Panel C: Denmark					
Conventional	0.373	0.346	0.275	0.306	0.214
	[0.338,0.409]	[0.301,0.391]	[0.225,0.325]	[0.256,0.356]	[0.156,0.272]
Robust	0.318	0.266	0.210	0.258	0.173
	[0.273,0.363]	[0.216,0.317]	[0.147,0.273]	[0.205,0.312]	[0.101,0.244]
N	6656	7389	7624	9454	8854
Bandwidth	3.81	5.45	6.03	14.79	11.19
AMSE (conventional)	0.00554	0.00607	0.00522	0.00330	0.00285
AMSE (robust)	0.00050	0.00075	0.00113	0.00081	0.00139
Panel D: Finland					
Conventional	0.025	0.008	-0.000	-0.014	-0.008
	[0.000,0.049]	[-0.019,0.035]	[-0.027,0.026]	[-0.041,0.014]	[-0.036,0.020]
Robust	-0.052	-0.024	-0.017	-0.020	-0.028
	[-0.112,0.008]	[-0.063,0.015]	[-0.056,0.023]	[-0.056,0.015]	[-0.063,0.006]
N	6810	34401	79847	108100	127026
Bandwidth	0.27	1.05	2.37	4.12	6.91
AMSE (conventional)	0.00637	0.00138	0.00045	0.00018	0.00023
AMSE (robust)	0.00096	0.00041	0.00030	0.00027	0.00024

Notes: The dependent variable is a dummy for re-running in the subsequent election. 95% confidence intervals based on standard errors clustered at the municipality level are reported in brackets. We use a triangular kernel and CER-optimal bandwidths. Bias-corrected estimation uses the same bandwidth for the main and bias estimation.

Table OA6. RDD results on election at $t+1$ using alternative local polynomials (CER-optimal bandwidths).

	$p=0$	$p=1$	$p=2$	$p=3$	$p=4$
	(1)	(2)	(3)	(4)	(5)
Panel A: Brazil					
Conventional	-0.049	-0.046	-0.036	-0.033	-0.033
	[-0.073,-0.024]	[-0.065,-0.027]	[-0.053,-0.018]	[-0.049,-0.018]	[-0.048,-0.017]
Robust	-0.062	-0.061	-0.058	-0.045	-0.044
	[-0.125,0.001]	[-0.092,-0.029]	[-0.082,-0.033]	[-0.065,-0.025]	[-0.063,-0.024]
N	5093	36492	99970	219803	337689
Bandwidth	0.16	0.95	2.57	5.65	8.75
AMSE (conventional)	0.00032	0.00041	0.00038	0.00020	0.00016
AMSE (robust)	0.00135	0.00030	0.00017	0.00011	0.00010
Panel B: Colombia					
Conventional	0.057	0.046	0.039	0.037	0.035
	[0.033,0.081]	[0.025,0.067]	[0.017,0.060]	[0.016,0.059]	[0.012,0.059]
Robust	-0.014	0.037	0.042	0.035	0.031
	[-0.070,0.041]	[0.004,0.070]	[0.013,0.072]	[0.007,0.062]	[0.002,0.061]
N	4254	23618	49302	82394	98243
Bandwidth	0.44	2.21	4.75	8.76	11.32
AMSE (conventional)	0.00266	0.00041	0.00015	0.00013	0.00017
AMSE (robust)	0.00104	0.00033	0.00026	0.00021	0.00024
Panel C: Denmark					
Conventional	0.326	0.269	0.225	0.216	0.185
	[0.293,0.359]	[0.227,0.312]	[0.178,0.272]	[0.169,0.263]	[0.134,0.237]
Robust	0.172	0.171	0.165	0.177	0.163
	[0.112,0.233]	[0.114,0.228]	[0.105,0.226]	[0.118,0.236]	[0.099,0.227]
N	3285	5943	7081	8404	8842
Bandwidth	1.10	2.75	4.76	9.02	11.13
AMSE (conventional)	0.01896	0.00837	0.00403	0.00204	0.00145
AMSE (robust)	0.00108	0.00100	0.00107	0.00093	0.00107
Panel D: Finland					
Conventional	0.079	0.056	0.067	0.088	0.048
	[0.048,0.109]	[0.028,0.084]	[0.044,0.089]	[0.066,0.110]	[0.023,0.072]
Robust	-0.037	-0.010	0.027	0.031	0.020
	[-0.111,0.036]	[-0.059,0.039]	[-0.003,0.058]	[0.006,0.056]	[-0.009,0.048]
N	3886	20350	78807	117833	123141
Bandwidth	0.17	0.68	2.33	5.26	6.12
AMSE (conventional)	0.00462	0.00279	0.00122	0.00151	0.00050
AMSE (robust)	0.00216	0.00071	0.00028	0.00019	0.00024

Notes: The dependent variable is a dummy for getting elected at $t+1$. 95% confidence intervals based on standard errors clustered at the municipality level are reported in brackets. We use a triangular kernel and CER-optimal bandwidths. Bias-corrected estimation uses the same bandwidth for the main and bias estimation.

Table OA7. RDD results on running at $t+1$ using alternative local polynomials (MSE-optimal bandwidths).

	$p=0$	$p=1$	$p=2$	$p=3$	$p=4$
	(1)	(2)	(3)	(4)	(5)
Panel A: Brazil					
Conventional	0.095	0.108	0.118	0.114	0.113
	[0.072,0.118]	[0.095,0.122]	[0.106,0.130]	[0.102,0.126]	[0.101,0.126]
Robust	0.082	0.104	0.111	0.114	0.115
	[0.029,0.135]	[0.083,0.125]	[0.096,0.127]	[0.100,0.128]	[0.101,0.130]
N	6562	80921	260371	447695	535478
Bandwidth	0.20	2.07	6.69	12.48	18.19
AMSE (conventional)	0.00059	0.00007	0.00008	0.00004	0.00004
AMSE (robust)	0.00086	0.00012	0.00006	0.00005	0.00005
Panel B: Colombia					
Conventional	0.197	0.199	0.199	0.196	0.197
	[0.171,0.222]	[0.178,0.220]	[0.178,0.221]	[0.172,0.219]	[0.173,0.222]
Robust	0.197	0.189	0.192	0.194	0.193
	[0.143,0.250]	[0.160,0.219]	[0.165,0.219]	[0.166,0.222]	[0.165,0.220]
N	6619	45812	88944	113949	133007
Bandwidth	0.65	4.38	9.75	14.73	22.03
AMSE (conventional)	0.00237	0.00014	0.00020	0.00016	0.00017
AMSE (robust)	0.00086	0.00023	0.00018	0.00019	0.00019
Panel C: Denmark					
Conventional	0.373	0.355	0.309	0.334	0.257
	[0.338,0.409]	[0.312,0.397]	[0.260,0.358]	[0.286,0.382]	[0.203,0.310]
Robust	0.318	0.300	0.242	0.283	0.202
	[0.273,0.363]	[0.250,0.349]	[0.188,0.297]	[0.231,0.335]	[0.140,0.264]
N	6656	7947	8213	10151	9448
Bandwidth	3.81	7.10	8.16	19.83	14.72
AMSE (conventional)	0.00554	0.00499	0.00486	0.00238	0.00313
AMSE (robust)	0.00050	0.00062	0.00089	0.00066	0.00110
Panel D: Finland					
Conventional	0.025	0.027	0.024	0.016	0.016
	[0.000,0.049]	[0.004,0.049]	[0.002,0.046]	[-0.007,0.040]	[-0.007,0.039]
Robust	-0.052	-0.004	-0.020	-0.018	-0.013
	[-0.112,0.008]	[-0.040,0.032]	[-0.049,0.010]	[-0.048,0.012]	[-0.041,0.015]
N	6810	51357	100561	122476	135907
Bandwidth	0.27	1.48	3.50	6.01	9.84
AMSE (conventional)	0.00637	0.00171	0.00060	0.00064	0.00056
AMSE (robust)	0.00096	0.00027	0.00020	0.00018	0.00017

Notes: The dependent variable is a dummy for re-running in the subsequent election. 95% confidence intervals based on standard errors clustered at the municipality level are reported in brackets. We use a triangular kernel and MSE-optimal bandwidths. Bias-corrected estimation uses the same bandwidth for the main and bias estimation.

Table OA8. RDD results on election at $t+1$ using alternative local polynomials (MSE-optimal bandwidths).

	$p = 0$	$p = 1$	$p = 2$	$p = 3$	$p = 4$
	(1)	(2)	(3)	(4)	(5)
Panel A: Brazil					
Conventional	-0.049	-0.025	-0.022	-0.017	-0.018
	[-0.073,-0.024]	[-0.040,-0.010]	[-0.035,-0.009]	[-0.029,-0.005]	[-0.030,-0.005]
Robust	-0.062	-0.056	-0.039	-0.031	-0.032
	[-0.125,0.001]	[-0.079,-0.033]	[-0.057,-0.021]	[-0.046,-0.016]	[-0.047,-0.017]
N	5093	59054	169986	362676	482799
Bandwidth	0.16	1.52	4.37	9.48	14.20
AMSE (conventional)	0.00032	0.00062	0.00033	0.00019	0.00017
AMSE (robust)	0.00135	0.00017	0.00009	0.00006	0.00006
Panel B: Colombia					
Conventional	0.057	0.052	0.050	0.048	0.046
	[0.033,0.081]	[0.034,0.069]	[0.032,0.067]	[0.031,0.066]	[0.026,0.066]
Robust	-0.014	0.040	0.034	0.042	0.037
	[-0.070,0.041]	[0.013,0.067]	[0.010,0.058]	[0.020,0.064]	[0.013,0.060]
N	4254	34526	72163	108651	121347
Bandwidth	0.44	3.25	7.38	13.44	16.88
AMSE (conventional)	0.00266	0.00018	0.00013	0.00015	0.00015
AMSE (robust)	0.00104	0.00021	0.00016	0.00014	0.00016
Panel C: Denmark					
Conventional	0.326	0.288	0.252	0.259	0.231
	[0.293,0.359]	[0.250,0.326]	[0.208,0.295]	[0.214,0.303]	[0.183,0.278]
Robust	0.172	0.198	0.189	0.197	0.173
	[0.112,0.233]	[0.145,0.252]	[0.136,0.242]	[0.147,0.247]	[0.118,0.227]
N	3285	6530	7757	9015	9434
Bandwidth	1.10	3.58	6.44	12.09	14.64
AMSE (conventional)	0.01896	0.00675	0.00330	0.00308	0.00235
AMSE (robust)	0.00108	0.00081	0.00083	0.00073	0.00085
Panel D: Finland					
Conventional	0.079	0.070	0.111	0.128	0.083
	[0.048,0.109]	[0.048,0.092]	[0.090,0.132]	[0.108,0.148]	[0.062,0.105]
Robust	-0.037	0.022	0.041	0.072	0.046
	[-0.111,0.036]	[-0.016,0.060]	[0.016,0.066]	[0.050,0.095]	[0.021,0.070]
N	3886	30664	99582	129881	133111
Bandwidth	0.17	0.96	3.43	7.67	8.71
AMSE (conventional)	0.00462	0.00213	0.00236	0.00246	0.00123
AMSE (robust)	0.00216	0.00044	0.00018	0.00013	0.00016

Notes: The dependent variable is a dummy for getting elected at $t+1$. 95% confidence intervals based on standard errors clustered at the municipality level are reported in brackets. We use a triangular kernel and MSE-optimal bandwidths. Bias-corrected estimation uses the same bandwidth for the main and bias estimation.

C.4 Controlling for Incumbency

Calonico et al. (2019) discuss the implementation of regression discontinuity designs with covariates. In Tables OA10 and OA9, we examine the robustness of our conclusions to controlling for incumbency which is something that we systematically observe across all the countries in our dataset. Furthermore, incumbency is perhaps the single most predictive variable of re-election and re-running.

The general conclusions remain largely unchanged when we include this covariate, even if the optimal bandwidths are slightly affected by controlling for incumbency. That said, one case where controlling for incumbency appears to matter more is the rerunning outcome in the case of Denmark. Qualitatively, it is still the case that rerunning rates are positively affected, but the bias-corrected and robust confidence intervals would suggest that this effect is not statistically significant.

Table OA9. RDD results on running at $t+1$ controlling for incumbency.

	(1)	(2)	(3)	(4)
Panel A: Brazil				
Conventional	0.112	0.109	0.098	0.110
	[0.095,0.129]	[0.094,0.125]	[0.076,0.119]	[0.090,0.130]
Robust	0.086	0.110	0.089	0.081
	[0.060,0.111]	[0.090,0.131]	[0.056,0.123]	[0.054,0.109]
N	47717	130581	29906	77401
Bandwidth	2.78	7.76	1.75	4.56
Panel B: Colombia				
Conventional	0.227	0.220	0.216	0.229
	[0.204,0.250]	[0.197,0.243]	[0.189,0.242]	[0.203,0.255]
Robust	0.208	0.221	0.216	0.202
	[0.176,0.240]	[0.193,0.249]	[0.177,0.255]	[0.169,0.236]
N	37744	78980	26354	57717
Bandwidth	5.18	13.10	3.53	8.44
Panel C: Denmark				
Conventional	0.223	0.193	0.219	0.155
	[0.128,0.317]	[0.079,0.307]	[0.115,0.323]	[0.036,0.274]
Robust	0.141	0.092	0.087	0.085
	[0.010,0.271]	[-0.044,0.229]	[-0.055,0.228]	[-0.071,0.240]
N	1220	1379	1107	1281
Bandwidth	4.84	7.73	3.73	5.74
Panel D: Finland				
Conventional	0.032	0.019	0.012	-0.001
	[0.010,0.055]	[-0.003,0.042]	[-0.017,0.040]	[-0.029,0.026]
Robust	-0.013	-0.015	-0.035	-0.017
	[-0.052,0.025]	[-0.046,0.015]	[-0.075,0.005]	[-0.058,0.024]
N	48060	98641	32011	77660
Bandwidth	1.40	3.37	0.99	2.28
Bandwidth selector	MSE	MSE	CER	CER
Polynomial	Linear	Quadratic	Linear	Quadratic

Notes: The dependent variable is a dummy for re-running in the subsequent election. 95% confidence intervals based on standard errors clustered at the municipality level are reported in brackets. We use a rectangular kernel. Bias-corrected estimation uses the same bandwidth for the main and bias estimation.

Table OA10. RDD results on election at $t+1$ controlling for incumbency.

	(1)	(2)	(3)	(4)
Panel A: Brazil				
Conventional	-0.032	-0.016	-0.041	-0.049
	[-0.053,-0.011]	[-0.033,0.002]	[-0.068,-0.014]	[-0.073,-0.025]
Robust	-0.046	-0.047	-0.077	-0.050
	[-0.078,-0.013]	[-0.071,-0.023]	[-0.120,-0.034]	[-0.083,-0.017]
N	31906	94365	19563	56129
Bandwidth	1.86	5.58	1.16	3.28
Panel B: Colombia				
Conventional	0.057	0.064	0.056	0.046
	[0.037,0.077]	[0.045,0.084]	[0.031,0.081]	[0.021,0.070]
Robust	0.050	0.044	0.036	0.046
	[0.018,0.082]	[0.017,0.071]	[-0.003,0.075]	[0.012,0.080]
N	26054	58937	17752	40393
Bandwidth	3.49	8.66	2.37	5.58
Panel C: Denmark				
Conventional	0.267	0.208	0.249	0.194
	[0.192,0.341]	[0.115,0.301]	[0.166,0.332]	[0.085,0.303]
Robust	0.179	0.149	0.157	0.134
	[0.069,0.289]	[0.022,0.275]	[0.033,0.281]	[-0.004,0.271]
N	1249	1375	1149	1280
Bandwidth	5.28	7.64	4.07	5.68
Panel D: Finland				
Conventional	0.065	0.104	0.055	0.065
	[0.042,0.087]	[0.083,0.125]	[0.026,0.084]	[0.042,0.088]
Robust	0.024	0.042	-0.019	0.023
	[-0.016,0.064]	[0.017,0.067]	[-0.070,0.031]	[-0.008,0.054]
N	28636	97707	19070	76629
Bandwidth	0.91	3.31	0.65	2.24
Bandwidth selector	MSE	MSE	CER	CER
Polynomial	Linear	Quadratic	Linear	Quadratic

Notes: he dependent variable is a dummy for getting elected at $t+1$. 95% confidence intervals based on standard errors clustered at the municipality level are reported in brackets. We use a rectangular kernel. Bias-corrected estimation uses the same bandwidth for the main and bias estimation.

C.5 Alternative Outcomes

In this subsection, we consider two alternative outcomes: election and vote share at $t+1$, conditional on re-running. It is important to bear in mind that whether to re-run or not is an endogenous choice and thus conditioning the regression analysis on re-running may bias the results; see (De Magalhães 2015) for further discussion. Nevertheless, we see some value in this exercise as it will allow us to examine variables that have a different distribution than election at $t+1$ without conditioning on rerunning or rerunning at $t+1$.

The lottery estimates suggest a negative effect on the conditional election at $t+1$ outcome in Colombia and a null effect in Finland. For Colombia, the point estimate is -0.147 ($p \approx 0.01$), and for Finland, it is -0.003 ($p \approx 0.94$). Similarly, we find a negative albeit statistically insignificant effect of election at t on subsequent vote shares in Colombia (-0.304, $p \approx 0.11$) and no effect in Finland (0.012, $p \approx 0.84$).

Lessons from RDD estimation are in line with these lottery-based estimates (see Tables OA11 and OA12). Moreover, the conditional estimates for Brazil and Denmark are qualitatively in line with the main results, with the effects being negative and statistically significant for Brazil, and positive and statistically significant for Denmark.

Table OA11. RDD results on election at $t+1$, conditional on rerunning.

	(1)	(2)	(3)	(4)
Panel A: Brazil				
Conventional	-0.104	-0.098	-0.125	-0.115
	[-0.123,-0.084]	[-0.115,-0.082]	[-0.150,-0.100]	[-0.136,-0.093]
Robust	-0.139	-0.115	-0.146	-0.127
	[-0.169,-0.109]	[-0.137,-0.093]	[-0.186,-0.106]	[-0.156,-0.098]
N	40520	113019	25695	73704
Bandwidth	1.57	5.15	0.99	3.02
Panel B: Colombia				
Conventional	-0.045	-0.044	-0.043	-0.065
	[-0.076,-0.015]	[-0.073,-0.015]	[-0.081,-0.006]	[-0.101,-0.029]
Robust	-0.052	-0.067	-0.069	-0.046
	[-0.100,-0.005]	[-0.105,-0.028]	[-0.127,-0.011]	[-0.095,0.003]
N	15041	30961	10614	22969
Bandwidth	2.89	7.53	1.97	4.85
Panel C: Denmark				
Conventional	0.282	0.240	0.255	0.197
	[0.214,0.351]	[0.167,0.312]	[0.181,0.328]	[0.116,0.279]
Robust	0.154	0.159	0.118	0.135
	[0.061,0.248]	[0.067,0.250]	[0.016,0.220]	[0.031,0.239]
N	2213	2718	2014	2496
Bandwidth	3.08	6.15	2.36	4.56
Panel D: Finland				
Conventional	0.104	0.103	0.076	0.059
	[0.072,0.136]	[0.070,0.136]	[0.040,0.112]	[0.024,0.094]
Robust	0.052	0.046	0.060	0.046
	[0.005,0.100]	[0.008,0.084]	[-0.002,0.122]	[-0.001,0.093]
N	20958	47883	14350	36840
Bandwidth	1.10	2.89	0.79	1.96
Bandwidth selector	MSE	MSE	CER	CER
Polynomial	Linear	Quadratic	Linear	Quadratic

Notes: The dependent variable is a dummy for being elected in the subsequent election, conditional on rerunning. 95% confidence intervals based on standard errors clustered at the municipality level are reported in brackets. We use a rectangular kernel. Bias-corrected estimation uses the same bandwidth for the main and bias estimation.

Table OA12. RDD results on vote share at $t+1$, conditional on rerunning.

	(1)	(2)	(3)	(4)
Panel A: Brazil				
Conventional	-0.390	-0.398	-0.466	-0.421
	[-0.508,-0.271]	[-0.503,-0.294]	[-0.606,-0.326]	[-0.545,-0.297]
Robust	-0.495	-0.420	-0.562	-0.467
	[-0.657,-0.333]	[-0.547,-0.293]	[-0.769,-0.355]	[-0.621,-0.313]
N	24567	68012	15901	45592
Bandwidth	1.77	6.10	1.11	3.58
Panel B: Colombia				
Conventional	-0.134	-0.144	-0.119	-0.146
	[-0.273,0.005]	[-0.282,-0.006]	[-0.274,0.036]	[-0.304,0.013]
Robust	-0.139	-0.140	-0.125	-0.170
	[-0.323,0.044]	[-0.307,0.027]	[-0.341,0.091]	[-0.363,0.023]
N	17031	32298	12102	24321
Bandwidth	3.33	8.13	2.26	5.24
Panel C: Denmark				
Conventional	0.618	0.436	0.754	0.653
	[0.092,1.143]	[-0.118,0.990]	[0.210,1.298]	[0.079,1.227]
Robust	0.834	0.816	0.608	0.880
	[0.190,1.477]	[0.161,1.472]	[-0.057,1.273]	[0.139,1.620]
N	1078	1317	996	1230
Bandwidth	3.57	8.09	2.76	6.02
Panel D: Finland				
Conventional	0.034	0.042	0.019	0.002
	[-0.036,0.105]	[-0.035,0.120]	[-0.055,0.094]	[-0.072,0.076]
Robust	-0.025	-0.015	-0.060	-0.019
	[-0.108,0.059]	[-0.091,0.061]	[-0.155,0.036]	[-0.099,0.062]
N	29928	90531	19861	68051
Bandwidth	0.94	2.87	0.67	1.95
Bandwidth selector	MSE	MSE	CER	CER
Polynomial	Linear	Quadratic	Linear	Quadratic

Notes: The dependent variable is (within-municipality) vote share in the subsequent election, conditional on rerunning. 95% confidence intervals based on standard errors clustered at the municipality level are reported in brackets. We use a rectangular kernel. Bias-corrected estimation uses the same bandwidth for the main and bias estimation.

D Validity Analysis

We conclude by assessing the validity of our RDD results. We do so by estimating different RD specifications using artificial cutoffs for treatment, and by testing whether there is manipulation of the running variable close to the cutoff.

D.1 Placebo Cutoffs

We estimate our RDD model using placebo cutoffs and plot the point estimates in Figures OA5 and OA6. Here we move the cutoff artificially to the left or right of the real cutoff and repeat the estimation.

The first purpose of these tests is to provide an indirect test of key assumption of the continuity (of the conditional expectation of potential outcomes at the cutoff). While this smoothness assumption is not directly testable at the cutoff, because the treatment status changes there, it should also hold in other locations of the forcing variable.

The second purpose of the placebo cutoff tests is to analyze whether the implementation is appropriate. As the issues of misspecifying the relationship between the forcing variable and the outcome are most likely not specific to the cutoff, the placebo cutoff test are informative of implementing (specification and inference) the RDD in a wrong way.

The figures plotting the results using the Calonico et al. (2014) approach rarely show any statistically significant effects where they should not appear, indicating that this specification is more appropriate for all the countries (and that the design is valid). This is true in particular for the specifications that use CER-optimal bandwidths. In contrast, conventional local linear or quadratic specifications often fail the placebo cutoff analysis, indicating that the specification is wrong.

Panel A: Brazil

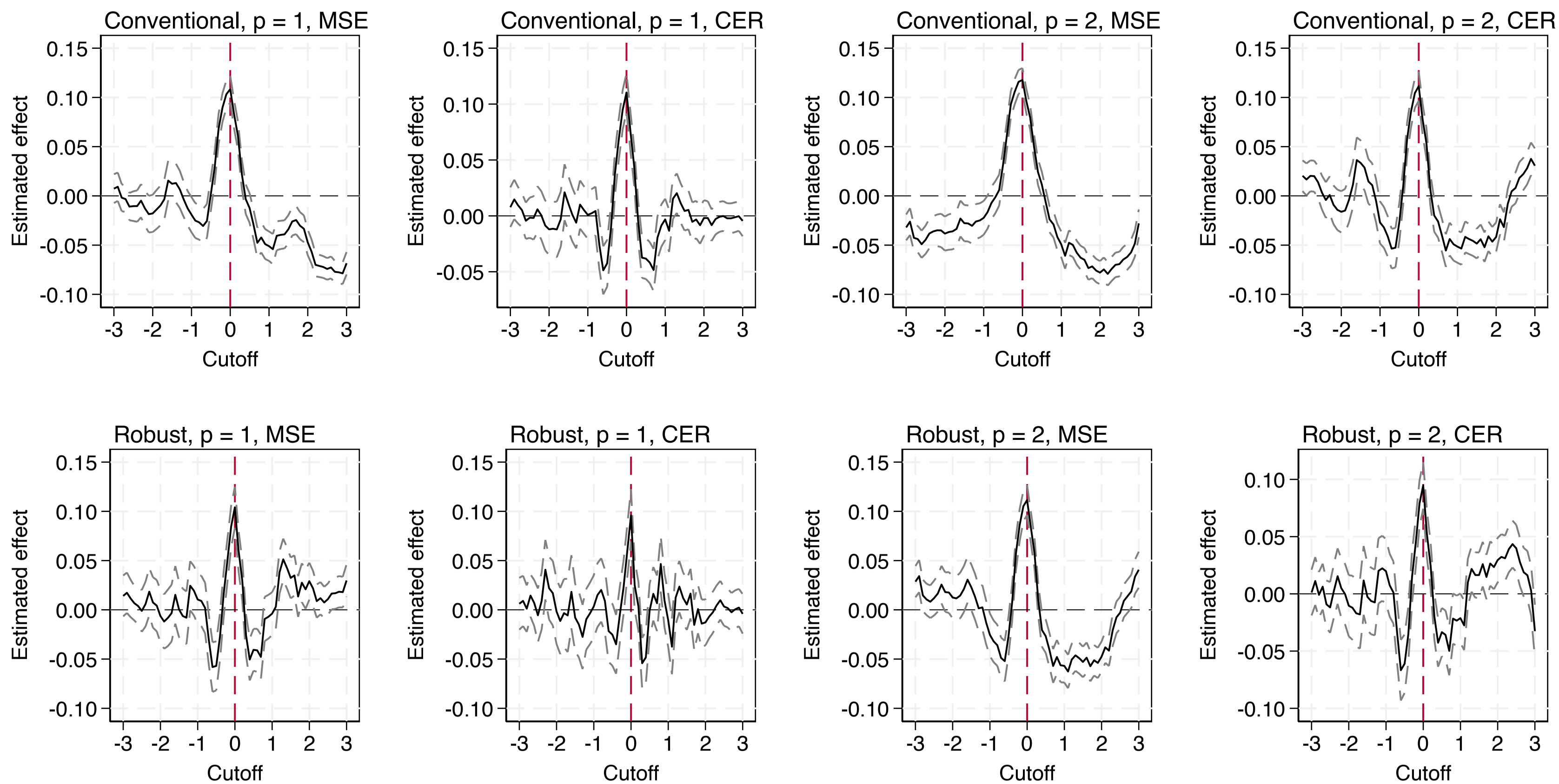

Figure OA5. RDD estimates using artificial cutoffs: Running at $t+1$.

Panel B: Colombia

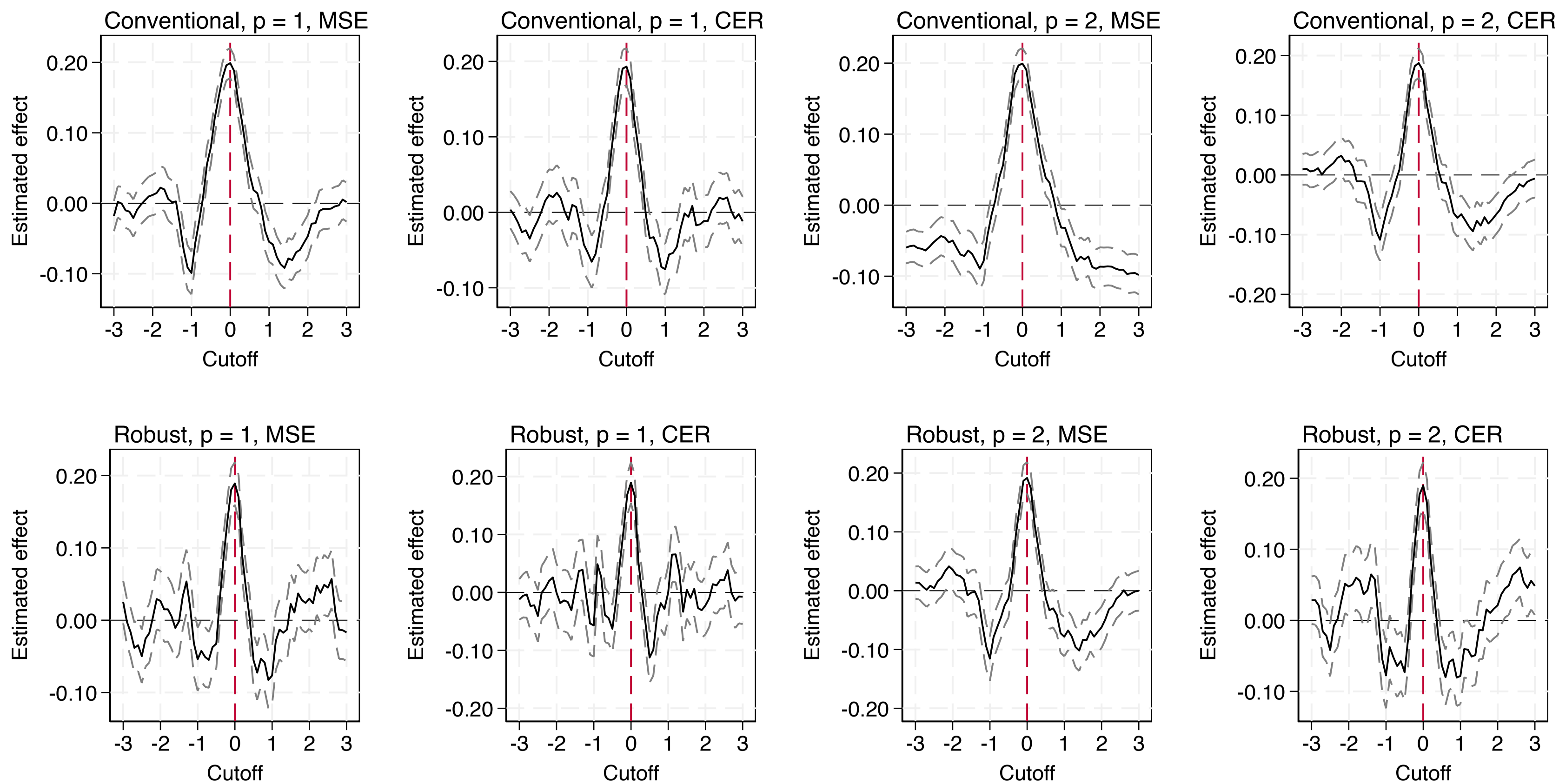

Figure OA5. RDD estimates using artificial cutoffs: Running at $t + 1$.

Panel C: Denmark

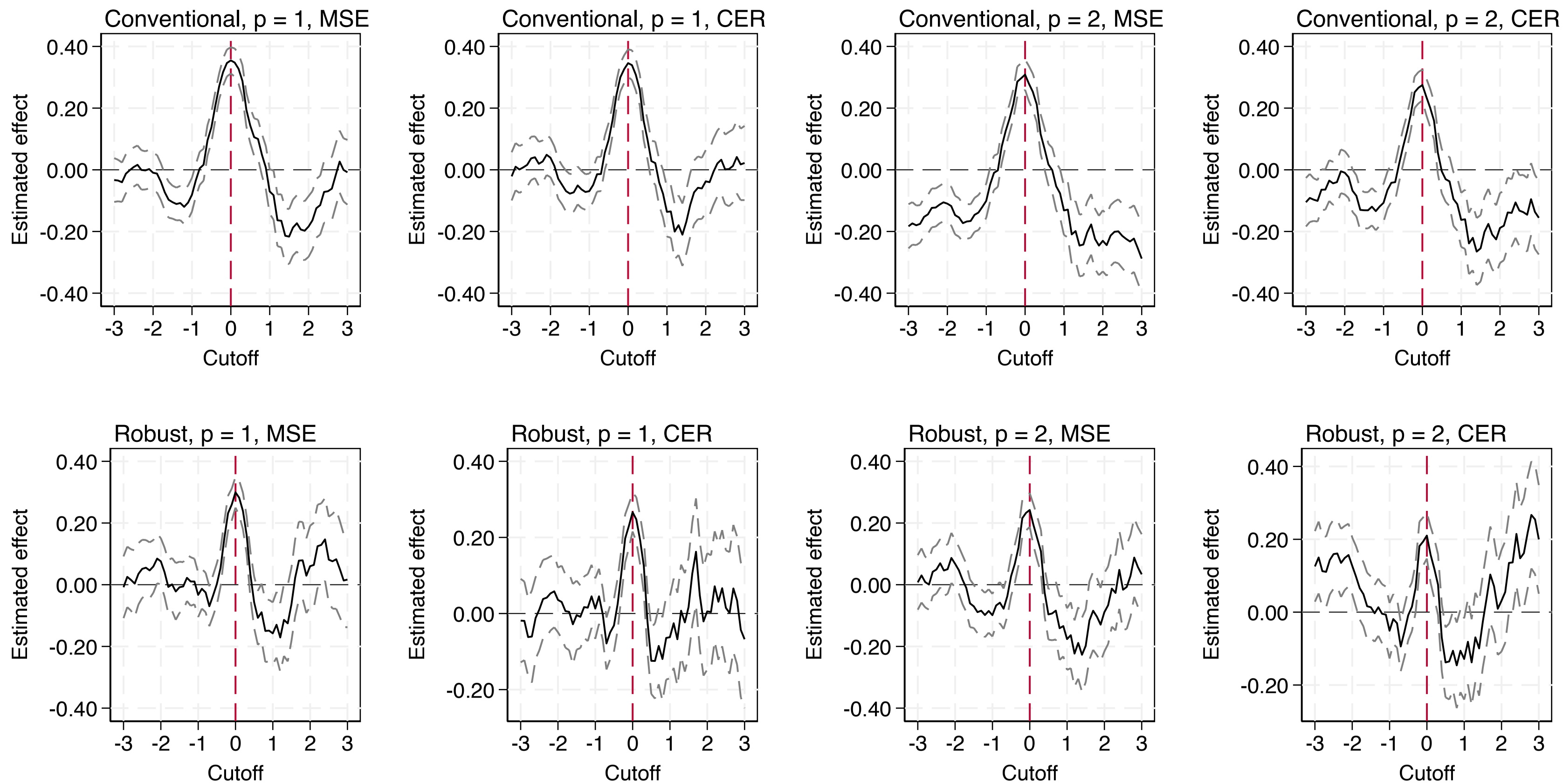

Figure OA5. RDD estimates using artificial cutoffs: Running at $t+1$.

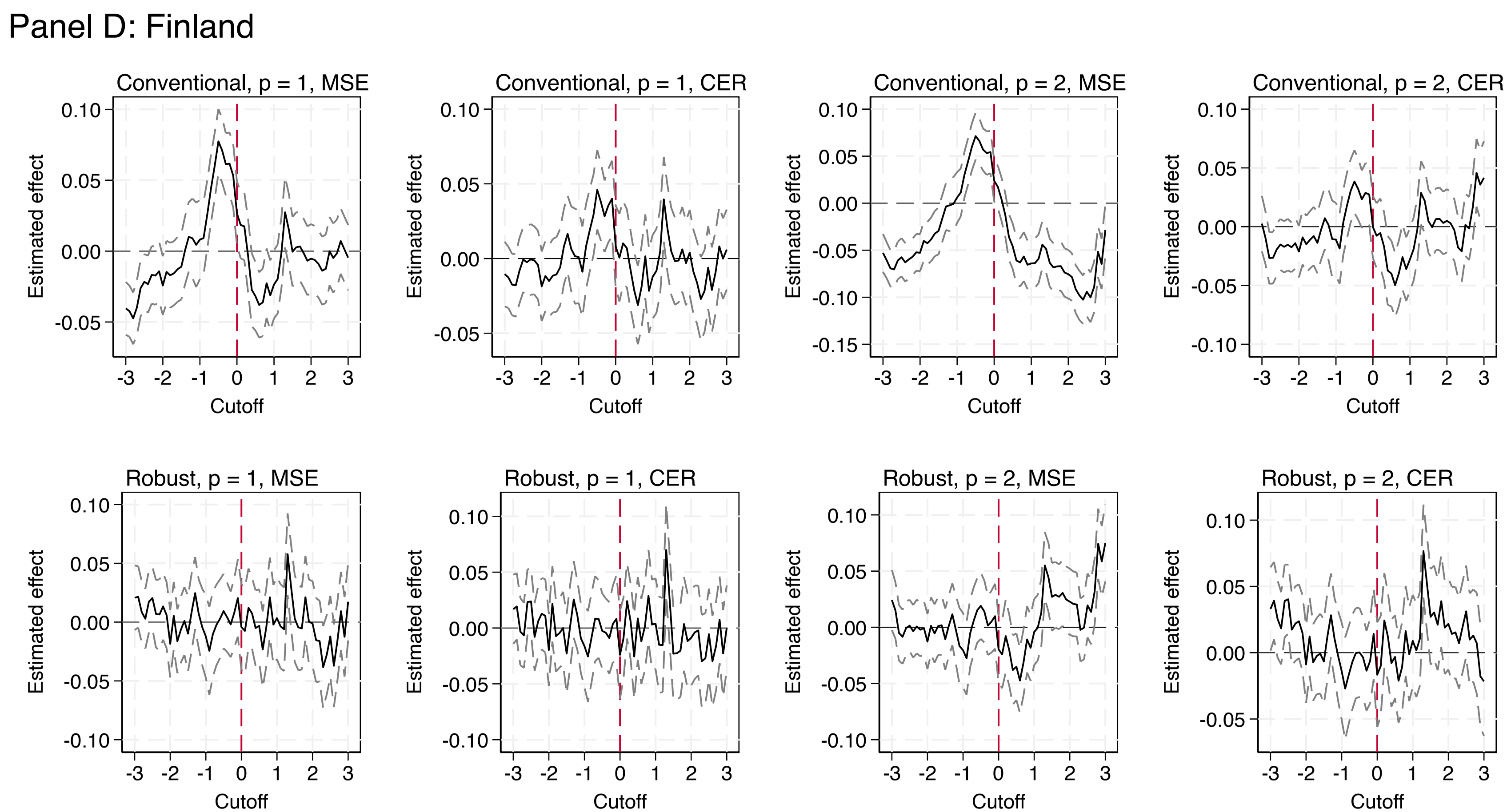

Figure OA5. RDD estimates using artificial cutoffs: Running at $t+1$.

Notes: The dependent variable is a dummy for re-running at $t+1$. Figures show RD estimates using artificial cutoffs, and corresponding 95% confidence intervals constructed using standard errors clustered at the municipality level. The left-hand side figures use the conventional approach, whereas the right-hand side figures use the CCT approach. We use optimal bandwidths estimated at the true cutoff, and a rectangular kernel.

Panel A: Brazil

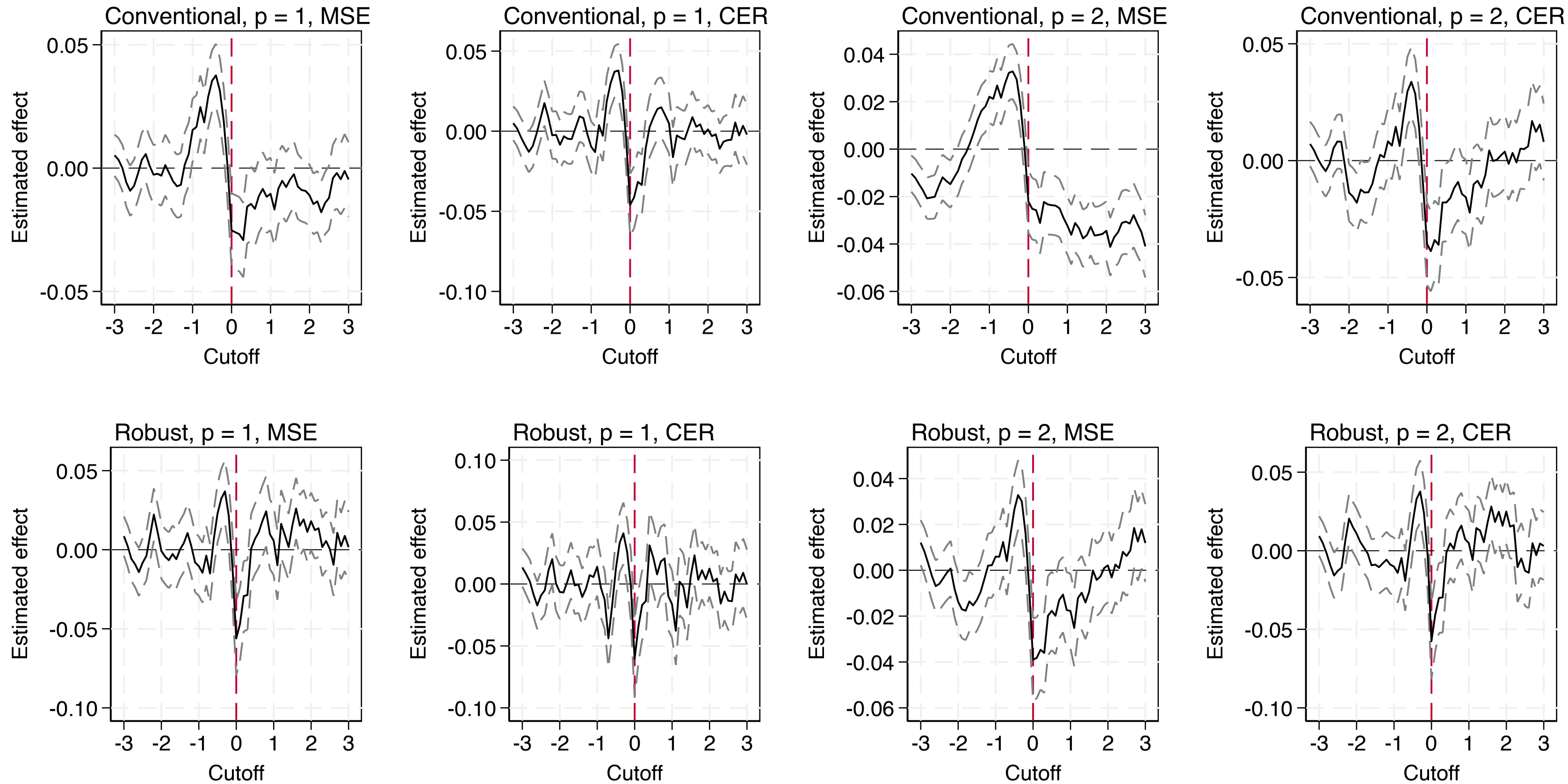

Figure OA6. RDD estimates using artificial cutoffs: Elected at $t+1$.

Panel B: Colombia

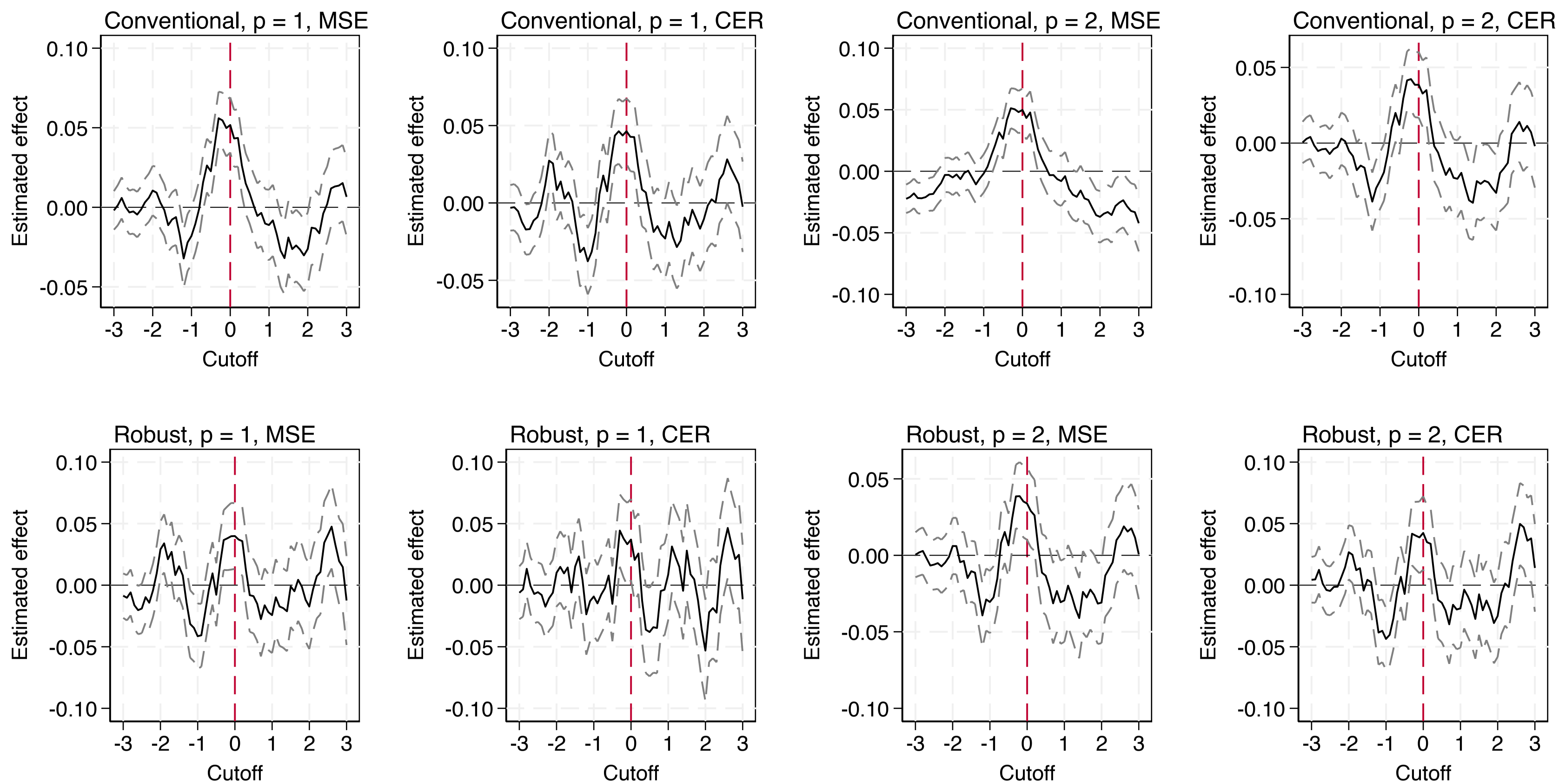

Figure OA6. RDD estimates using artificial cutoffs: Elected at $t + 1$.

Panel C: Denmark

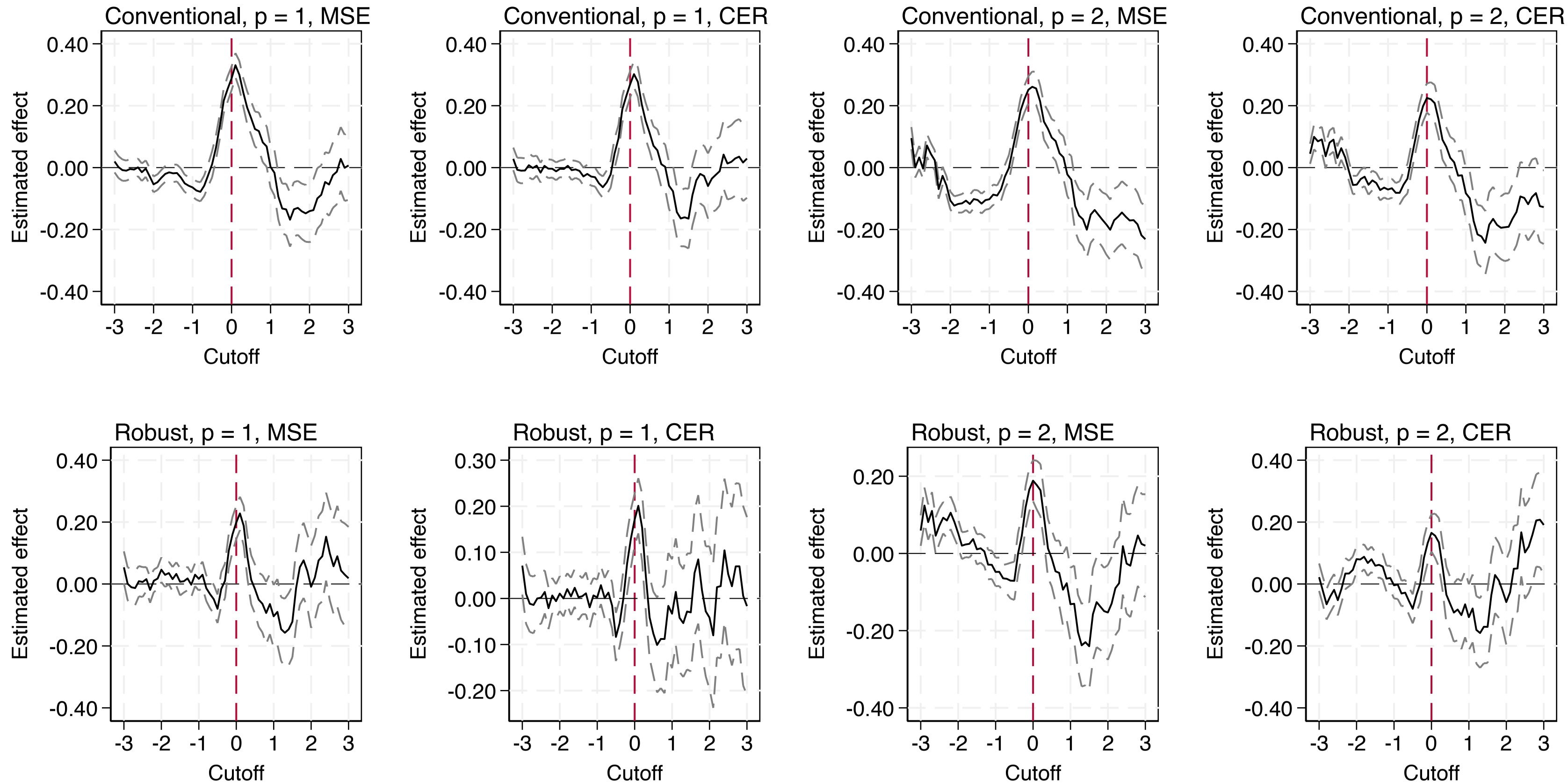

Figure OA6. RDD estimates using artificial cutoffs: Elected at $t+1$.

Panel D: Finland

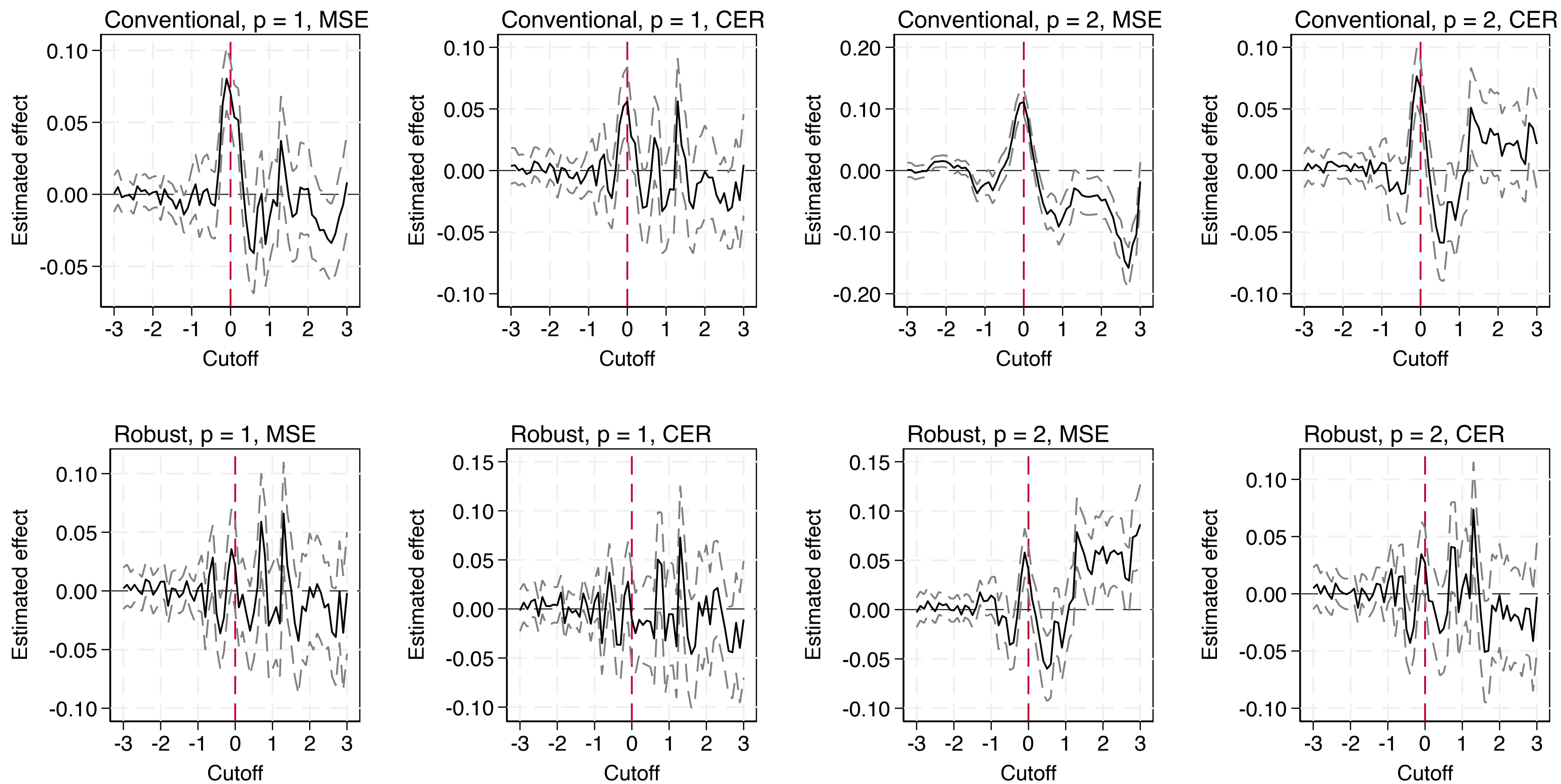

Figure OA6. RDD estimates using artificial cutoffs.

Notes: The dependent variable is a dummy for getting elected at $t + 1$. Figures show RD estimates using artificial cutoffs, and corresponding 95% confidence intervals constructed using standard errors clustered at the municipality level. The left-hand side figures use the conventional approach, whereas the right-hand side figures use the CCT approach. We use optimal bandwidths estimated at the true cutoff, and a rectangular kernel.

D.2 Randomness of the Lottery Outcomes

In this subsection, we provide evidence supporting the claim that the lotteries are not manipulated. In particular, we regress five covariates determined before the outcome of the lottery on an indicator for being elected in a lottery. These variables (that are systematically observed in both Colombia and Finland) are the number of votes, within-party vote share, within-municipality vote share, an indicator for being female, and an indicator for being an incumbent. Note that party and municipality level variables ought to be balanced by default, as the lotteries take place within political parties (in a given local election).

In Table OA13, we see that these variables are balanced between lottery winners in both Colombia and Finland. This points to the outcomes of these lotteries truly being random. For additional evidence for Finland, we also refer to Hyytinen et al. (2018).

Table OA13. Covariate balance for lotteries.

	Votes	Within-party vote share	Within-municipality vote share	Female	Incumbent
	(1)	(2)	(3)	(4)	(5)
Elected	2.447	-0.026	-0.033	-0.009	0.059
	[0.544,4.351]	[-0.080,0.028]	[-0.098,0.031]	[-0.081,0.064]	[-0.020,0.139]
N	463	463	463	463	365
Elected	0.453	-0.003	-0.769	0.007	-0.024
	[-0.152,1.057]	[-0.098,0.092]	[-2.942,1.404]	[-0.047,0.060]	[-0.074,0.026]
N	1351	1351	1351	1351	1351

Notes: The table shows balance of different pre-determined covariates between the lottery winners and losers. 95% confidence intervals based on standard errors clustered at the municipality level are reported in brackets.

D.3 Manipulation of the Running Variable

To further assess the validity of our findings, we conduct the following two tests. First, Table OA14 shows the effect of getting elected on the lagged dependent variable, i.e., incumbency. (Eggers and Spirling 2017) argue that this variable is a convenient summary statistic that is "a natural attribute to focus on as we look for systematic differences between winners and losers of close elections." There are no differences between close winners and losers in terms of their incumbency status. Second, we verify that the density of the running variable evolves smoothly at the cutoff. This is, indeed, the case. Figure OA7 reports the conventional McCrary (2008) test graphically, and Table OA15 shows results from the density test proposed by Cattaneo et al. (2018).

Table OA14. Covariate smoothness test.

	(1)	(2)	(3)	(4)
Panel A: Brazil				
Conventional	-0.024	-0.028	-0.015	-0.022
	[-0.044,-0.003]	[-0.045,-0.010]	[-0.041,0.011]	[-0.045,0.002]
Robust	-0.019	-0.026	-0.034	-0.022
	[-0.050,0.013]	[-0.049,-0.002]	[-0.075,0.007]	[-0.053,0.010]
N	37410	109989	23209	65286
Bandwidth	2.18	6.52	1.37	3.83
Conventional	0.011	-0.002	0.014	-0.001
	[-0.009,0.031]	[-0.023,0.018]	[-0.010,0.038]	[-0.025,0.024]
Robust	0.002	0.003	-0.024	0.007
	[-0.027,0.032]	[-0.024,0.029]	[-0.061,0.012]	[-0.027,0.040]
N	29218	61116	20051	42032
Bandwidth	3.93	9.06	2.67	5.84
Panel C: Denmark				
Conventional	0.147	0.112	0.071	0.028
	[0.053,0.242]	[0.005,0.220]	[-0.035,0.176]	[-0.089,0.145]
Robust	-0.095	-0.071	-0.142	-0.161
	[-0.241,0.051]	[-0.210,0.067]	[-0.307,0.023]	[-0.321,-0.001]
N	1050	1335	935	1227
Bandwidth	3.23	6.71	2.49	4.99
Conventional	0.014	0.038	0.012	0.004
	[-0.012,0.041]	[0.012,0.063]	[-0.021,0.044]	[-0.022,0.030]
Robust	0.010	-0.012	0.009	-0.009
	[-0.033,0.052]	[-0.041,0.016]	[-0.044,0.061]	[-0.047,0.029]
N	26968	90128	18016	67523
Bandwidth	0.86	2.84	0.61	1.93
Bandwidth selector	MSE	MSE	CER	CER
Polynomial	Linear	Quadratic	Linear	Quadratic

Notes: The dependent variable is a dummy for being an incumbent. 95% confidence intervals based on standard errors clustered at the municipality level are reported in brackets. We use a rectangular kernel.

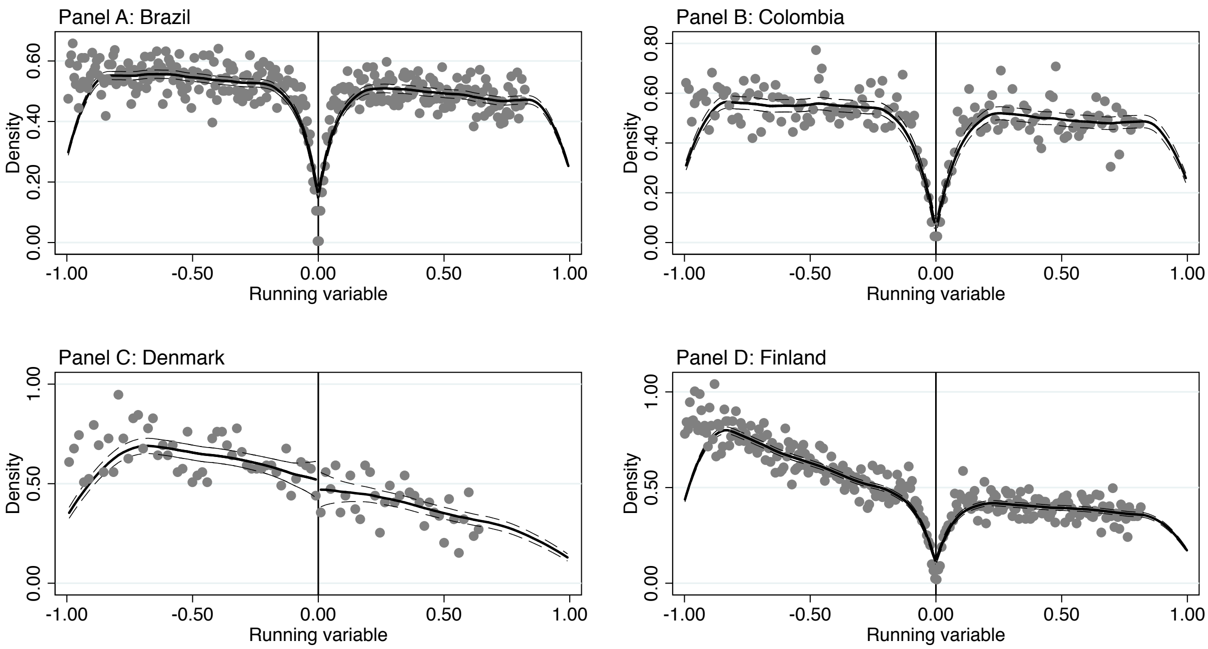

Figure OA7. McCrary density test.

Notes: The figure illustrates McCrary (2008) density test graphically. Dashed lines are the 95% confidence intervals constructed using bootstrapped standard errors. We restrict the running variable between -1 and 1 and omit electoral ties at the cutoff.

Table OA15. Density test.

	Conventional		Robust	
Country	*T*	*p*	*T*	*p*
Brazil	0.82	0.41	0.25	0.80
Colombia	-0.18	0.86	0.02	0.98
Denmark	-0.96	0.34	-0.32	0.75
Finland	3.22	0.00	0.23	0.82

Notes: Table shows the density test statistics and respective *p*-values from Cattaneo et al. (2018) test. We restrict the running variable between -1 and 1 and omit electoral ties at the cutoff.

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