Poverty, Party Alignment, and Reducing Corruption through Modernization: Evidence from Guatemala*

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Abstract

We show that once reductions in poverty decrease voter need for clientelism, it ultimately reduces corruption through political selection. After reductions in poverty open up the possibility of more programmatic (non-clientelistic) voting, voters seek to attribute blame for their previous economic circumstances. In their search for clarity of responsibility, voters default toward the easiest indicator: party alignment between subnational and national levels of government. Such dynamics reduce the bureaucratic advantages of alignment, and aligned politicians respond by reducing their corruption levels. To provide empirical tests for our theory, we employ a series of close-election regression discontinuity designs on mayoral races in Guatemala. We find broad empirical support for our theory when analyzing the number of audit violations committed, the amount of money misappropriated, and the reelection rates of aligned politicians. The results of our study help document how reductions in poverty decrease corruption through modernization, and how politics is central to the process. We conclude with a discussion of our findings' implications for clarity of responsibility theory and democratization more broadly.

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The practice of misusing entrusted power or public office for private gain has a familiar name: corruption.[1] Especially but not exclusively in developing countries, corruption takes many forms and manifests in many deleterious ways. For example, politicians and bureaucrats in Mexico and Colombia are infamous for accepting bribes from drug cartels, who fuel violence to such an extent that it lowers life expectancy (Dal Bó, Dal Bó and Di Tella, 2006; Aburto et al., 2016). In India, politicians who narrowly win public office quickly accumulate 3-5% more assets than second-place candidates who just barely lose, providing yet another example of how politics often facilitates egregious corruption (Fisman, Schulz and Vig, 2014).

Two of the most prominent remedies to corruption include improving institutional quality and increasing levels of economic development.[2] Although these are theoretically compelling explanations for corruption and its mitigation, extant literature suffers from three major drawbacks. First, the majority of the literature relies on corruption perceptions, not empirical measures of corruption.[3] Second, limited existing work uses objective subnational data,[4] and most of the literature that uses such data focuses almost exclusively only Brazil, making it difficult to disentangle the precise set of institutions and/or economic remedies that reduce corruption more broadly. Third, even less existing work shows how economic development and institutions interact over time with politics to produce different levels of corruption.[5] This third drawback is particularly significant given that corruption is mostly a political phenomenon.

[1] This sentence advances one of the most common definitions of corruption. For more on the definition of corruption, see, for example, Treisman (2000, 2007), Rose-Ackerman and Palifka (2016) and Søreide (2014).

[2] For more on how institutional quality affects levels of corruption, see, for example, Shleifer and Vishny (1993), Persson, Tabellini and Trebbi (2003), Lederman, Loayza and Soares (2005), Aidt and Dutta (2008), Aidt (2009), Dreher, Kotsogiannis and McCorriston (2009), and Ferraz and Finan (2011). For more on how economic development reduces corruption, see, for example, Mauro (1995), La Porta et al. (1999), and Treisman (2000, 2007).

[3] The literature that criticizes perception-based measures of corruption is extensive, but some of the most prominent critiques include Kurtz and Schrank (2007*a*,*b*), Langbein and Knack (2010), Thomas (2010), Gingerich (2013*a*), Bersch and Botero (2014), and Gisselquist (2014).

[4] For notable exceptions, see Ferraz and Finan (2008) on exposing corrupt politicians through the dissemination of audit results near elections; Gingerich (2013*b*) on ballot structure and party-directed corruption; Broms, Dahlström and Fazekas (2019) on public procurement outcomes and political competition; and Boas, Hidalgo and Melo (2019) on sanctioning corrupt politicians.

[5] See Pereira, Melo and Figueiredo (2009), Ferraz and Finan (2011), Brollo et al. (2013), and Klašnja (2015).

In this paper, we use objective, time-varying, subnational political and corruption data to show how economic development and institutions interact to reduce corruption through political selection. Our theoretical framework focuses on political party alignment between national and subnational governments.[6] In simpler terms, this paper examines the consequences for corruption when the president or prime minister's party in power has the same party in lower-level government entities.

On the one hand, the decentralization and clientelism literatures are clear that party alignment is an institutional configuration that facilitates resource-related bureaucratic advantages in both developed and developing countries.[7] On the other hand, party alignment serves as an indicator of the larger phenomenon of clarity of responsibility for misgovernance. Its basic premise is that clarity of responsibility is high under alignment. By extension, corruption is more prevalent under divided government, because politicians take advantage of the fact that voters have trouble assigning blame under such institutional circumstances (Schwindt-Bayer and Tavits, 2016).

A primary objective of this paper is to reconcile the aforementioned contrasting predictions of alignment on levels of corruption. To that end, we put forth a simple model. We theorize that in democracies with lower levels of economic development that facilitate clientelistic citizen-politician linkages,[8] clarity of responsibility does not necessarily lower corruption or reduce the supply of corrupt politicians. In such contexts, voters only punish

[6] de Remes (1999) calls party alignment "juxtaposed government", but we will use the term alignment given that it is more common in the literature.

[7] For a summary of how clientelism is fueled by "politicized public resources", see Greene (2007, 2010). Regarding decentralization, there is documented evidence of "budget-cycles" and favoritism in intergovernmental transfer allocation in at least the following countries: Brazil (Brollo and Nannicini, 2012); Chile (Corvalan, Cox and Osorio, 2018; Lara and Toro, 2019; Livert, Gainza and Acuña, 2019); China (Guo, 2009; Lü, 2015); Colombia (Drazen and Eslava, 2010); England (Fouirnaies and Mutlu-Eren, 2015); Ghana (Banful, 2011*a*,*b*); Guatemala (Sandberg and Tally, 2015); India (Velasco Rivera, 2020); Italy (Alesina and Paradisi, 2017); Mexico (Timmons and Broidy, 2013); Philippines (Labonne, 2016); Pakistan (Callen, Gulzar and Rezaee, 2020); Portugal (Veiga and Veiga, 2007; Veiga and Pinho, 2007; Aidt, Veiga and Veiga, 2011; Veiga and Veiga, 2013); Russia (Treisman and Gimpelson, 2001); Spain (Solé-Ollé and Sorribas-Navarro, 2008); USA (Ansolabehere, Snyder and Ting, 2003; Kriner and Reeves, 2012, 2015; Christenson, Kriner and Reeves, 2017; Hill and Jones, 2017); Uruguay (Manacorda, Miguel and Vigorito, 2011); and West Germany (Schneider, 2010).

[8] For a review of citizen-politician linkages, see Kitschelt (2000) and Kitschelt and Wilkinson (2007).

aligned politicians and the latter will only reduce their corruption levels after reductions in poverty open up the possibility of more programmatic (non-clientelistic) voting.

Declining poverty changes the calculus to engage in corruption and hold public office even under political alignment. When poverty declines, voters tend to rely less on clientelistic exchanges to meet basic needs and vote more on the basis of programmatic (policy-based) appeals (Kitschelt and Wilkinson, 2007; Magaloni, Díaz-Cayeros and Estévez, 2007; Weitz-Shapiro, 2012; Díaz-Cayeros, Estévez and Magaloni, 2016). Since voters are less reliant on clientelism in such a circumstance and no longer to need to "request-fulfill",[9] I argue that they are less tolerant of corrupt politicians as well. Essentially, when voters no longer need politicians share their corrupt proceed through clientelism, voters will tolerate corrupt politicians less. For their part, politicians respond to the change in voter preferences by no longer running for office, leading to a different landscape for political selection.[10] Prior to the declines in poverty, aligned politicians enjoy significant resource advantages relative to non-aligned politicians, but those resources advantages decrease much quicker relative to non-aligned politicians after a decline in poverty.

Under comparatively more difficult economic circumstances, voters are more supportive of aligned politicians because of their access to the spoils of the bureaucracy. With these resources, aligned politicians can buy the support of the masses, who in turn will be more likely to forgive corrupt politicians as long as part of the money is redistributed back to them in form of clientelistic transfers or discretionary spending. Because non-aligned politicians do not have as large of a resource pool at their disposal, their politicians have no choice but to rely on valence appeals, which are less compelling in a context of poverty. Overall, we aim to depict how politics, political institutions, and economic development interact to reduce corruption through modernization.[11]

[9] Request-fulfill is a term that entails when "citizens demand clientelistic benefits." (Nichter and Peress, 2017)

[10] For an excellent review of the literature on political selection, see Dal Bó and Finan (2018).

[11] By "modernization", I am referring to the prediction of modernization theory that economic growth or education leads to democratization (see Acemoglu and Robinson, 2018, 26).

To support our argument, we use objective, municipality-level data on corruption from Guatemala. It is not only a country with a long history of clientelism and corruption, but Guatemala recently expelled its United Nations-backed anti-corruption body, the International Commission Against Impunity (González, 2014; Sandberg and Tally, 2015; The Economist, 2019; Malkin, 2019). To obtain objective measures for corruption, we follow some pioneering recent work on Brazil, Mexico, Romania, and Bulgaria,[12] and rely on measures of municipal-level infractions and spending misapppropriation derived from audit reports. Our political data constitute the electoral results of municipal elections, and the poverty data come from the results of the 2002 and 2011 censuses of Guatemala.

To operationalize whether a municipality is doing better economically, we specifically compare municipalities that increased and decreased their poverty rates relative to the previous census. To causally identify the effects of alignment in both the increased and decreased poverty samples, we exploit a series of close-election regression discontinuity designs. To accommodate the concept of alignment, we modify Lee's (2008) framework for the incumbency advantage along the lines of Brollo and Nannicini (2012).

Under multiple specifications, we consistently find that alignment yielded a significant decrease in corruption in the municipalities with decreased poverty. In some but not all cases, the result is similar for municipalities that reduced levels of extreme poverty relative to the previous census as well. That result does not travel to municipalities that did not decrease poverty from 2002 to 2011. Overall, the results suggest how poverty affects corruption, clientelism, and—especially given my close-election data—democratization writ-large.

Guatemala is an unlikely case for our argument. In January 2019, the country expelled the United Nations' International Commission Against Impunity (CICIG) anti-corruption body (The Economist, 2018). This backdrop suggests that the results of my study may travel other contexts, and that modernization is still a powerful antidote to corruption. If scholars accept the premise that reducing corruption also contributes to democratization

[12] See, for example, Ferraz and Finan (2008, 2011), Brollo et al. (2013), Zamboni and Litschig (2018), Klašnja (2015), Nikolova and Marinov (2017), Chong et al. (2015), and Larreguy, Marshall and Snyder (2019).

writ-large, especially given my close-election data, this study may also challenge prominent studies from Daron Acemoglu and James Robinson that allege that modernization theory is dead (Acemoglu et al., 2005, 2008, 2009; Acemoglu and Robinson, 2018).

1. Theoretical Framework

We provide a simple theoretical framework to understand the mechanisms through which poverty reduction or modernization decreases corruption through political selection. Our framework focuses on party alignment for a simple reason: aligned politicians have more possibilities than politicians from other parties to capture the spoils of the bureaucracy for both clientelistic and corrupt purposes (Greene, 2007; Brollo and Nannicini, 2012; Corvalan, Cox and Osorio, 2018; Velasco Rivera, 2020).

To better understand the advantages of alignment and how they are crucial to reduce corruption through political selection and modernization, let us first consider the local-level politician i's maximisation problem. Consistent with Magaloni, Díaz-Cayeros and Estévez (2007),[13] local-level politician i's personal budget constraint, b_i, comprises spending on public expenses and goods, g_i, as well as her private rents, r_i:

$$b_i = g_i + r_i \text{[14]} \tag{1}$$

Magaloni, Díaz-Cayeros and Estévez (2007) equate r merely with clientelism. By contrast, total rents, r, in our model consists of both money set aside for clientelism, c, and the

[13] The theoretical framework in Magaloni, Díaz-Cayeros and Estévez (2007) also forms the basis of Díaz-Cayeros, Estévez and Magaloni (2016).

[14] We assume b is exogenous and normalized to 1 without a loss of generality. We recognize that b could decrease as a result of corruption and/or clientelism in previous periods, but we assume exogeneity for simplicity purposes.

personal benefits of public office (corruption), p:

$$r = c + p, \quad where \quad c = \gamma r \tag{2}$$ [15]

Under Equation (2), we assume that c increases with r, meaning that the local-level politician devotes at least some portion of her rents toward clientelism. Although the politician may prefer to keep all of the rents for personal gain ($c = 0$), doing so would drastically hurt reelection prospects and thus future potential rent extraction levels as well. Given the possibility of reelection and how it drives politician behavior (e.g. Barro, 1973; Ferejohn, 1986), we distinguish between local-level politician i's favored levels of rent extraction in the current electoral period, $r_{i,1}$, as well as a potential future one, $r_{i,2}$:

$$r_i = r_{i,1} + r_{i,2} \tag{3}$$ [16]

Since the local-level politician i's chance of gaining reelection is a probabilistic outcome, we represent it with π, where $\pi' > 0$ and $\pi'' < 0$. That re-election probability, π, is also dependent on constituents' levels of satisfaction with local-level politician i, s_i, which we define for the current period as follows:

$$\begin{aligned} s_{i,1} &= W(g_{i,1}) + \beta_i^{1+a}\, W(\gamma r_{i,1}) \\ &= W(1 - r_{i,1}) + \beta_i^{1+a}\, W(\gamma r_{i,1}) \end{aligned} \tag{4}$$

Under Equation (4), $W(\cdot)$ is the satisfaction that the electorate derives from local-level politician i's rents and spending on public expenses or goods in the current period, such that $W' > 0$ and $W'' < 0$ (Baleiras, 1997; Baleiras and da Silva Costa, 2004).[17] Equation

[15] Because we cannot directly observe the distinction between c and p, we introduce $\gamma \in (0, 1)$ which denotes the fraction of rent used for clientelistic purposes. This is included in Appendix A to help with the calculation of the maximization problem.

[16] We frame the model explicitly for rents in period 1, $r_{i,1}$, where $r_{i,2}$ is taken to be given and assumed by the local-level politician as a future expectation of rents in period 2.

[17] Given Equation (1), Equation (4) also captures the inverse benefits that the electorate derives from the

(4) also introduces the possibility of party alignment, a, which takes a value of 1 if local-level politician i is aligned or 0 otherwise. We represent the electorate's discount rate of clientelistic benefits under a decrease in poverty through $\beta_i \in (0,1)$, making the discount rate under alignment for such electorates:

$$\beta^{1+a} = \beta^{1+1} \implies \beta^2 < \beta^1 \tag{5}$$

Our theory depends on β_i. In line with the conventional wisdom of the clientelism literature, we assume that reducing poverty leads voters to discount clientelism more and fairer, policy-based programmatic spending less (Kitschelt and Wilkinson, 2007; Stokes et al., 2013; Gonzalez-Ocantos, Kiewiet de Jonge and Nickerson, 2014). Consistent with Schwindt-Bayer and Tavits (2016), alignment signals clarity of responsibility for misgovernance, thereby yielding an even higher discount rate for clientelistic benefits than poverty reduction alone.

To represent local-level politicians i's full utility function, we introduce U($\cdot$). It captures local-level politician i's utility from rent extraction in the current period, $r_{i,1}$, rent extraction in a future period, $r_{i,2}$, and the private income that she can earn while out of office in that future period, $x_{i,2}$, such that $U' > 0$ and $U'' < 0$ (Brollo and Nannicini, 2012).[18] We specify that $x_{i,2} < r_{i,2}$ because politicians in countries with relatively high levels of corruption and clientelism can earn more in office than as a private citizen (e.g. Fisman, Schulz and Vig, 2014). Given Equation (3), the maximization problem for local-level politician's i can be represented as:

$$\max_{r_{i,1}} \; U(r_{i,1}) + \pi(s)\, U(r_{i,2}) + (1 - \pi(s))\, U(x_{i,2}) \tag{6}$$

Appendix A solves the maximization problem in Equation (6) for both the aligned and non-aligned local-level government entities. According to the solution of the maximization problem, the electorate starts highly discounting the clientelistic benefits associated with

local-level politician's rents in the current period, $r_{i,1}$.

[18] For more on how politicians trade-off rents in the current period compared to those in a future period, see Niehaus and Sukhtankar (2013) on the "golden goose effect."

local-level politician i having higher levels of rents after a reduction in poverty. Alignment entails an even higher discount rate on aligned politician's clientelistic activities, yielding repercussions for her reelection probabilities and future expected rents. The combination of poverty reduction, alignment, and changes in political selection thus lead to a discontinuity in corruption activity between aligned and unaligned local-level politicians.

2. Main Results

2.1. Descriptive Statistics

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Table 1: Descriptive Statistics of Infraction Variables

Panel A	Decrease Unaligned		Decrease Aligned		Increase Unaligned		Increase Aligned	
VARIABLES	mean	N	mean	N	mean	N	mean	N
Number of Infractions	8.807	969	6.376	348	8.183	920	5.472	271
Log Amount of Infractions	10.76	824	10.77	347	10.73	788	10.56	270
Number of Infractions: First 2 years of a Term	6	184	6.286	126	5.985	194	5.233	90
Log Amount of Infractions: First 2 years of a Term	10.57	183	10.66	125	10.61	193	10.27	89
Number of Infractions: Last 2 years of a Term	6.071	395	6.428	222	6.433	383	5.591	181
Log Amount of Infractions: Last 2 years of a Term	10.89	395	10.83	222	10.92	382	10.71	181
Number of Infractions: Last year of a Term	6.894	198	7.387	111	7.370	192	6.242	91
Log Amount of Infractions: Last year of a Term	11.19	198	11.24	111	11.19	191	10.98	91

Panel B	Decrease Unaligned		Decrease Aligned		Increase Unaligned		Increase Aligned	
VARIABLES	mean	N	mean	N	mean	N	mean	N
Number of Infractions	24.11	354	19.99	111	22.47	335	16.30	91
Log Amount of Infractions	11.66	354	12.23	111	11.54	335	11.84	91
Number of Infractions: First 2 years of a Term	12	92	12.77	62	12.09	96	10.47	45
Log Amount of Infractions: First 2 years of a Term	11.44	92	11.63	62	11.58	96	11.08	45
Number of Infractions: Last 2 years of a Term	12.05	199	12.86	111	12.83	192	11.12	91
Log Amount of Infractions: Last 2 years of a Term	11.75	199	11.79	111	11.82	192	11.56	91
Number of Infractions: Last year of a Term	6.894	198	7.387	111	7.408	191	6.242	91
Log Amount of Infractions: Last year of a Term	11.19	198	11.24	111	11.19	191	10.98	91

Note: Panel A shows results by years, while the Panel B shows results by electoral term. "Decrease" refers to the sample of municipalities where poverty had decreased between 2002 and 2011, while "Increase" refers to the sample where poverty increased between 2002 and 2011. All amounts are expressed in real terms and are deflated by the respective yearly GDP deflator.

Table 2: Descriptive statistics of covariates

Panel A	Decrease Unaligned		Decrease Aligned		Increase Unaligned		Increase Aligned	
VARIABLES	mean	N	mean	N	mean	N	mean	N
Extreme Poverty Rate	24.94	1,047	25.35	348	16.52	1,006	15.53	272
Gini coefficient	24.87	1,047	25.29	348	24.93	1,006	23.94	272
Total Poverty Rate	72.54	1,047	70.96	348	66.23	1,006	65.09	272
Percentage of Mayor Reelected	0.307	1,005	0.217	332	0.331	968	0.0945	254
Log Population	10.28	1,047	10.22	348	10.33	1,006	10.12	272
Log Public Goods Spending (per capita)	5.790	582	5.518	348	5.512	580	5.744	272

Panel B	Decrease Unaligned		Decrease Aligned		Increase Unaligned		Increase Aligned	
VARIABLES	mean	N	mean	N	mean	N	mean	N
Percentage of Mayor Reelected	0.306	333	0.214	103	0.320	316	0.122	82
Extreme Poverty Rate	26.13	354	27.91	111	19.13	335	19.83	91
Gini coefficient	25.56	354	26.17	111	25.56	335	25.26	91
Total Poverty Rate	73.87	354	73.37	111	68.44	335	68.84	91
Log Population	10.27	354	10.23	111	10.33	335	10.10	91
Log Public Goods Spending (per capita)	6.673	199	6.556	111	6.351	193	6.625	91

Note: Panel A shows results by years, while the Panel B shows results by term. “Decrease” refers to the sample of municipalities where poverty decreased between 2002 and 2011, while “Increase” refers to the sample where poverty increased between 2002 and 2011. Public Goods Spending amount is expressed in real terms and deflated by the respective yearly GDP deflator.

2.2. RDD Results for Corruption

Table 3: RDD Estimates for Infraction Count by Year

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-1.626***	-2.228***	-0.855	-1.204	-1.209*	-1.627**
	(0.553)	(0.724)	(0.608)	(0.799)	(0.630)	(0.782)
Observations	601	601	569	569	569	569
Effective observations	[186,138]	[178,136]	[146,102]	[154,104]	[140,86]	[146,102]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.00329	0.00209	0.159	0.132	0.0549	0.0375
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.100	0.0960	0.0765	0.0852	0.0705	0.0769
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-1.166*	-1.693**	-0.563	-0.963	-0.895	-1.421*
	(0.596)	(0.768)	(0.629)	(0.798)	(0.648)	(0.792)
Observations	601	601	569	569	569	569
Effective observations	[182,136]	[182,138]	[146,102]	[154,104]	[144,98]	[146,102]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0505	0.0275	0.371	0.228	0.167	0.0726
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0967	0.0981	0.0762	0.0870	0.0733	0.0790

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results without year fixed effects, while Panel B shows results with year fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 4: RDD Estimates for Infraction Count by Electoral Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-11.46***	-14.07***	-8.176**	-10.12**	-7.859**	-8.948**
	(3.075)	(4.204)	(3.637)	(4.327)	(3.423)	(4.143)
Observations	195	195	179	179	179	179
Effective Observations	[54,43]	[62,49]	[44,32]	[57,45]	[44,32]	[57,44]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.000194	0.000819	0.0246	0.0194	0.0217	0.0308
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0901	0.104	0.0737	0.111	0.0726	0.106
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-3.607*	-5.402**	-1.615	-3.220	-2.493	-5.052*
	(1.883)	(2.731)	(2.166)	(2.825)	(2.295)	(2.953)
Observations	195	195	179	179	179	179
Effective observations	[62,49]	[61,49]	[46,35]	[53,42]	[45,34]	[47,35]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0554	0.0479	0.456	0.254	0.278	0.0871
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.107	0.104	0.0831	0.0968	0.0762	0.0866

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results without term fixed effects, while Panel B shows results with term fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 5: RDD Estimates for Infraction Amount (log) by Year

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-0.766***	-0.684**	-0.529**	-0.539*	-0.663**	-0.685**
	(0.218)	(0.327)	(0.268)	(0.318)	(0.275)	(0.322)
Observations	598	598	566	566	566	566
Effective observations	[206,145]	[158,114]	[132,76]	[150,104]	[132,82]	[170,126]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.000438	0.0367	0.0480	0.0899	0.0158	0.0333
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.117	0.0844	0.0625	0.0839	0.0686	0.0964

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-0.737***	-0.652**	-0.462*	-0.493	-0.561**	-0.621*
	(0.219)	(0.326)	(0.273)	(0.324)	(0.276)	(0.332)
Observations	598	598	566	566	566	566
Effective Observations	[206,145]	[158,114]	[132,76]	[150,104]	[132,76]	[150,104]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.000748	0.0454	0.0905	0.128	0.0419	0.0618
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.115	0.0845	0.0616	0.0844	0.0645	0.0848

Note: Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Panel A shows results without year fixed effects, while Panel B shows results with year fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 6: RDD Estimates for Infraction Amount (log) by Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-1.234***	-1.196**	-1.074***	-1.026**	-1.009***	-1.056**
	(0.426)	(0.543)	(0.385)	(0.507)	(0.369)	(0.466)
Observations	195	195	179	179	179	179
Effective observations	[48,37]	[56,45]	[45,34]	[51,38]	[47,35]	[51,38]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.00377	0.0275	0.00527	0.0429	0.00627	0.0235
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0737	0.0947	0.0802	0.0906	0.0870	0.0909
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-0.816**	-0.759	-0.644*	-0.568	-0.722*	-0.700
	(0.370)	(0.468)	(0.377)	(0.482)	(0.371)	(0.484)
Observations	195	195	179	179	179	179
Effective observations	[49,39]	[57,48]	[45,34]	[52,40]	[47,35]	[53,43]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0274	0.105	0.0877	0.239	0.0518	0.148
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0792	0.0979	0.0778	0.0959	0.0863	0.0985

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results without term fixed effects, while Panel B shows results with term fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

2.3. RDD Results for Reelection

Table 7: RDD Estimate for Reelection

Panel A: Including 2012 Elections

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-0.316	-0.334	-0.357*	-0.403*	-0.419**	-0.528**
	(0.197)	(0.228)	(0.208)	(0.232)	(0.203)	(0.219)
Observations	106	106	106	106	106	106
Effective observations	[39,22]	[45,33]	[38,22]	[45,27]	[35,21]	[45,26]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.109	0.143	0.0861	0.0822	0.0385	0.0160
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.118	0.174	0.113	0.149	0.100	0.145

Panel B: Including 2008 and 2012 Elections

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-0.286*	-0.326*	-0.408***	-0.417**	-0.420***	-0.431***
	(0.155)	(0.171)	(0.152)	(0.167)	(0.146)	(0.167)
Observations	179	179	179	179	179	179
Effective observations	[46,35]	[68,56]	[46,35]	[68,56]	[46,35]	[66,49]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0648	0.0562	0.00705	0.0124	0.00402	0.00967
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0837	0.148	0.0822	0.148	0.0826	0.136

Note: Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

2.4. RDD Plots

Figure 1: RDD plots for Infraction Count and Amount

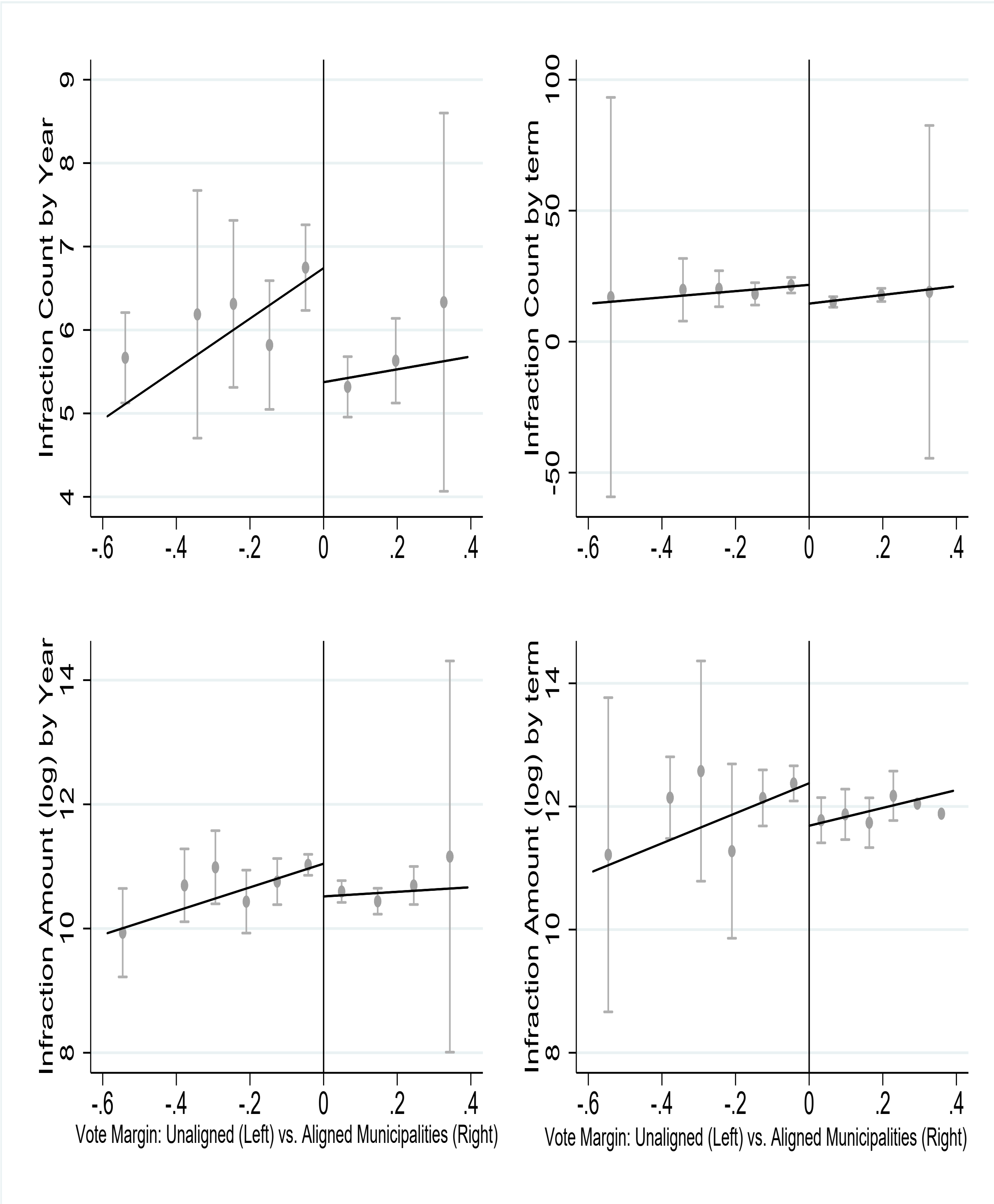
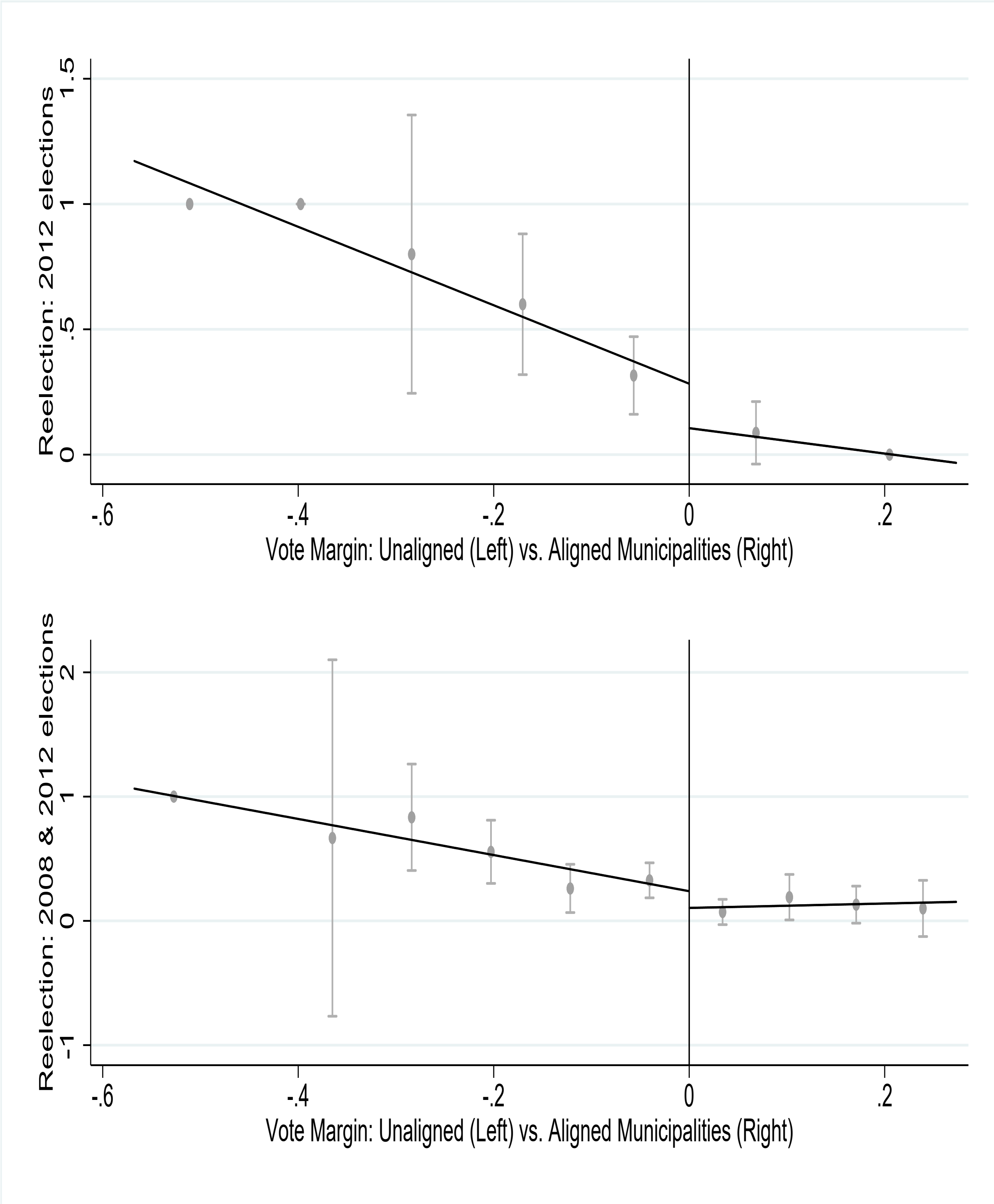


Figure 2: RDD plots for Reelection



Appendix

A. Theoretical Derivation

We solve for the following maximisation problem for the local-level politician:

$$\begin{gathered}\max_{r_{i,1}} U(r_{i,1}) + \pi(s)U(r_{i,2}) + [1-\pi(s)]U(x_{i,2}) \\ \text{where } s_i = W(1-r_{i,1}) + \beta_i^{1+a}W(\gamma r_{i,1})\end{gathered} \tag{7}$$

Accordingly, we can rewrite the maximization problem as follows:

$$\max_{r_{i,1}} U(r_{i,1})+\pi(W(1-r_{i,1})+\beta_i^{1+a}W(\gamma r_{i,1}))U(r_{i,2})+[1-\pi(W(1-r_{i,1})+\beta_i^{1+a}W(\gamma r_{i,1}))]U(x_{i,2}) \tag{8}$$

The corresponding First-Order Condition (F.O.C.) for Equation (7) is:

$$\begin{aligned}0 =& U'(r_{i,1}) + U(r_{i,2})\pi'(W(1-r_{i,1}) + \beta_i^{1+a}W(\gamma r_{i,1}))[-W'(1-r_{i,1}) + \gamma\beta_i^{1+a}W'(\gamma r_{i,1})] \\ &- U(x_{i,2})\pi'(W(1-r_{i,1}) + \beta_i^{1+a}W(\gamma r_{i,1}))[-W'(1-r_{i,1}) + \gamma\beta_i^{1+a}W'(\gamma r_{i,1})]\end{aligned} \tag{9}$$

Collecting like terms and bringing them to the other side, Equation (8) can be rewritten as:

$$U'(r_{i,1}) =[U(r_{i,2}) - U(x_{i,2})]\pi'(W(1-r_{i,1}) + \beta_i^{1+a}W(\gamma r_{i,1}))[W'(1-r_{i,1}) - \gamma\beta_i^{1+a}W'(\gamma r_{i,1})] \tag{10}$$

The F.O.C. for aligned municipalities ($a = 1$) is then:

$$U'(\overline{r_{i,1}}) =[U(r_{i,2}) - U(x_{i,2})]\pi'(W(1-\overline{r_{i,1}}) + \beta_i^2W(\gamma\overline{r_{i,1}}))[W'(1-\overline{r_{i,1}}) - \gamma\beta_i^2W'(\gamma\overline{r_{i,1}})] \tag{11}$$

and the F.O.C. for unaligned municipalities ($a = 0$) is:

$$U'(\underline{r_{i,1}}) = [U(r_{i,2}) - U(x_{i,2})]\pi'(W(1 - \underline{r_{i,1}}) + \beta_i W(\gamma \underline{r_{i,1}}))[W'(1 - \underline{r_{i,1}}) - \gamma\beta_i W'(\gamma \underline{r_{i,1}})] \quad (12)$$

where $\overline{r_{i,1}}$ and $\underline{r_{i,1}}$ are the optimal rent for the aligned and unaligned mayors, respectively. Accordingly, it follows that $\overline{r_{i,1}} = r_{i,1} * -z < r_{i,1}* < r_{i,1} * +k = \underline{r_{i,1}}$ where $z, k > 0$.[19] ■

[19] The result follows from similar structural implications as derived in Brollo and Nannicini (2012, Proof of Proposition 1).

B. When Extreme Poverty Decreases

B.1. RDD Tables

Table 8: RDD Estimates for Infraction Count by Year

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-1.537***	-2.224***	-1.292*	-1.540*	-1.525**	-2.207**
	(0.576)	(0.770)	(0.670)	(0.808)	(0.689)	(0.870)
Observations	670	670	625	625	625	625
Effective observations	[179,152]	[187,156]	[138,122]	[172,144]	[128,110]	[138,126]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.00765	0.00387	0.0540	0.0567	0.0270	0.0112
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0903	0.0912	0.0723	0.0936	0.0691	0.0735
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-1.333**	-1.982**	-1.120*	-1.302	-1.370*	-2.074**
	(0.604)	(0.777)	(0.678)	(0.805)	(0.703)	(0.871)
Observations	670	670	625	625	625	625
Effective Observations	[179,152]	[191,162]	[138,126]	[180,158]	[134,114]	[140,130]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0274	0.0107	0.0983	0.106	0.0514	0.0172
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0903	0.0944	0.0732	0.0972	0.0702	0.0772

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results without year fixed effects, while Panel B shows results with year fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 9: RDD Estimates for Infraction Count by Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-6.890**	-6.661*	-8.121***	-8.497**	-9.876***	-10.66***
	(2.984)	(3.428)	(3.045)	(3.498)	(3.144)	(3.908)
Observations	217	217	194	194	194	194
Effective Observations	[60,58]	[81,83]	[44,44]	[68,62]	[41,41]	[58,54]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0209	0.0520	0.00765	0.0151	0.00168	0.00638
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0962	0.167	0.0858	0.140	0.0734	0.108
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-3.612*	-5.132*	-3.687	-4.472	-4.792**	-6.266**
	(2.037)	(2.733)	(2.295)	(2.847)	(2.392)	(2.919)
Observations	217	217	194	194	194	194
Effective observations	[59,54]	[64,60]	[42,43]	[58,54]	[41,42]	[56,53]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0762	0.0604	0.108	0.116	0.0451	0.0319
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0915	0.103	0.0794	0.108	0.0750	0.102

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results without term fixed effects, while Panel B shows results with term fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 10: RDD Estimates for Infraction Amount (log) by Year

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-0.452*	-0.650**	-0.313	-0.412	-0.389	-0.555
	(0.255)	(0.321)	(0.273)	(0.333)	(0.281)	(0.341)
Observations	667	667	622	622	622	622
Effectiveness observations	[155,142]	[155,142]	[132,114]	[140,130]	[138,122]	[152,134]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0763	0.0425	0.252	0.216	0.166	0.104
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0794	0.0781	0.0699	0.0783	0.0716	0.0882
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-0.441*	-0.639**	-0.290	-0.400	-0.336	-0.490
	(0.255)	(0.320)	(0.275)	(0.335)	(0.281)	(0.340)
Observations	667	667	622	622	622	622
Effective observations	[155,142]	[155,142]	[128,110]	[140,130]	[128,106]	[140,130]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0833	0.0463	0.292	0.232	0.233	0.149
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0793	0.0783	0.0688	0.0788	0.0666	0.0773

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results without year fixed effects, while Panel B shows results with year fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

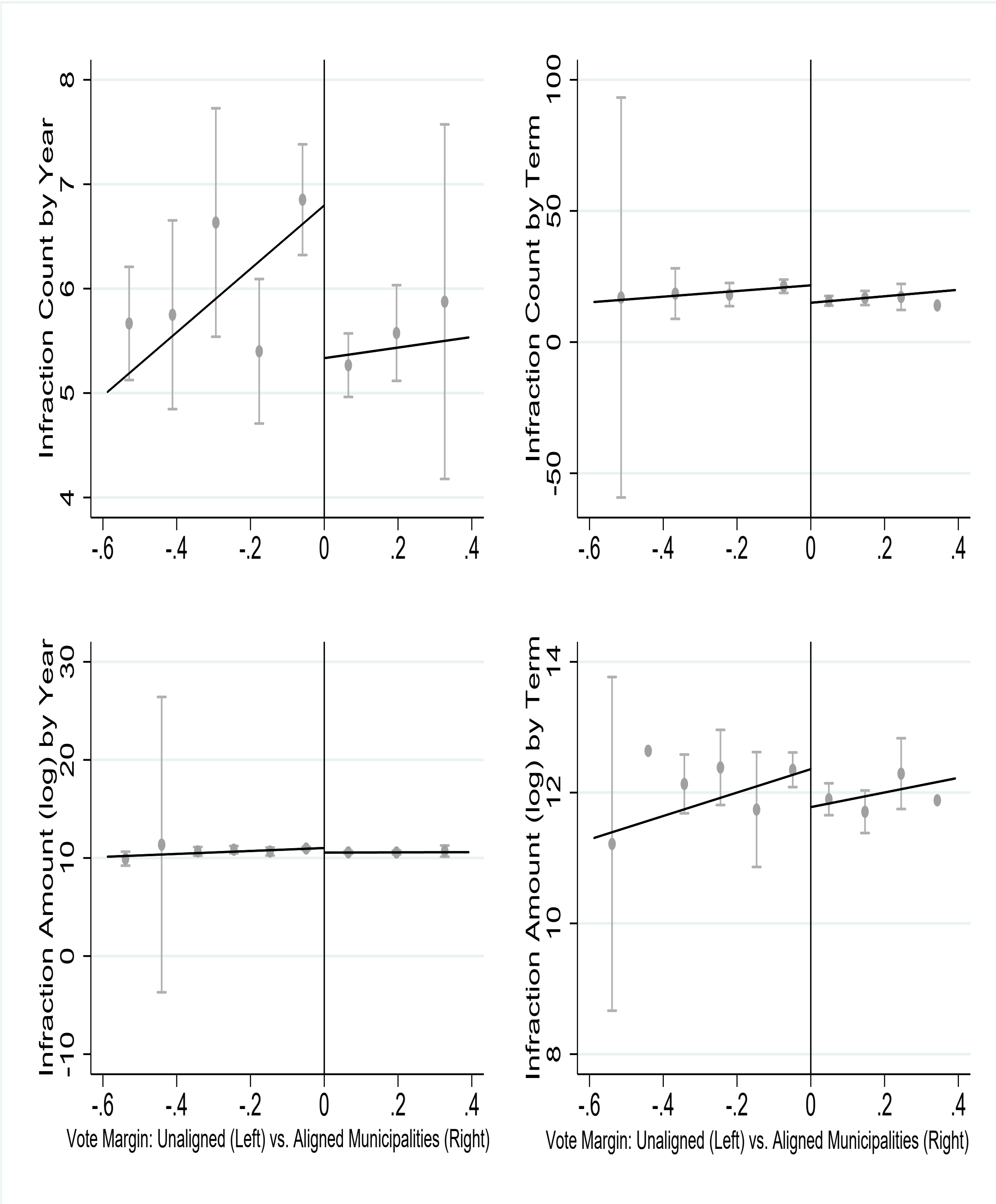
Table 11: RDD Estimates for Infraction Amount (log) by Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-0.710*	-0.766	-0.612*	-0.698	-0.691**	-0.937**
	(0.395)	(0.486)	(0.353)	(0.490)	(0.329)	(0.470)
Observations	217	217	194	194	194	194
Effective observations	[49,46]	[60,56]	[51,48]	[51,48]	[54,53]	[44,44]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0726	0.115	0.0829	0.154	0.0358	0.0461
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0714	0.0957	0.0918	0.0927	0.100	0.0848
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-0.551	-0.567	-0.364	-0.371	-0.505	-0.640
	(0.358)	(0.428)	(0.327)	(0.464)	(0.318)	(0.462)
Observations	217	217	194	194	194	194
Effective observations	[49,46]	[61,59]	[53,52]	[53,53]	[56,53]	[52,50]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.123	0.186	0.266	0.424	0.112	0.166
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0723	0.0997	0.0967	0.0996	0.102	0.0955

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results without term fixed effects, while Panel B shows results with term fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

B.2. RDD Plots

Figure 3: RDD plots for Infraction Count and Amount



C. When Poverty Increases

Table 12: RDD Estimates for Infraction Count by Year

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	0.748	0.430	1.049	0.379	0.540	0.525
	(0.946)	(1.321)	(0.758)	(1.322)	(0.949)	(1.166)
Observations	756	756	706	706	582	582
Effective observations	[201,216]	[235,290]	[204,274]	[220,286]	[139,185]	[193,278]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.429	0.745	0.166	0.774	0.569	0.652
Order of Polynomial	1	2	1	2	1	2
Bandwidth	0.109	0.154	0.145	0.159	0.111	0.187
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	1.004	0.389	0.844	0.926	0.591	0.673
	(0.817)	(1.327)	(0.912)	(1.092)	(1.066)	(1.215)
Observations	756	756	706	706	582	582
Effective observations	[227,272]	[235,290]	[190,214]	[254,324]	[135,171]	[189,274]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.219	0.769	0.355	0.397	0.579	0.580
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.139	0.153	0.114	0.192	0.0968	0.180

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results without year fixed effects, while Panel B shows results with year fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 13: RDD Estimates for Infraction Count by Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	3.348	2.544	-0.210	-1.162	-2.342	1.740
	(4.026)	(5.221)	(4.534)	(5.747)	(4.700)	(6.485)
Observations	246	246	220	220	194	194
Effective observations	[67,68]	[83,94]	[54,59]	[68,86]	[46,55]	[55,71]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.406	0.626	0.963	0.840	0.618	0.789
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0997	0.157	0.0897	0.149	0.0914	0.127
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	3.472	1.676	2.558	2.775	0.868	1.744
	(2.372)	(4.106)	(2.955)	(3.758)	(3.451)	(4.648)
Observations	246	246	220	220	194	194
Effective observations	[87,96]	[83,93]	[62,68]	[79,96]	[48,55]	[56,77]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.143	0.683	0.387	0.460	0.801	0.708
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.163	0.156	0.115	0.180	0.0946	0.138

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results without term fixed effects, while Panel B shows results with term fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 14: RDD Estimates for Infraction Amount (log) by Year

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	0.252	-0.212	0.286	-0.215	0.315	-0.118
	(0.312)	(0.473)	(0.298)	(0.479)	(0.302)	(0.500)
Observations	754	754	704	704	580	580
Effective observations	[212,232]	[220,268]	[199,248]	[203,262]	[146,210]	[146,226]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.419	0.654	0.336	0.653	0.297	0.814
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.117	0.134	0.128	0.138	0.121	0.131
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	0.287	-0.242	0.360	0.147	0.264	0.268
	(0.301)	(0.474)	(0.276)	(0.422)	(0.323)	(0.419)
Observations	754	754	704	704	580	580
Effective observations	[220,246]	[220,264]	[207,274]	[235,292]	[138,181]	[182,265]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.342	0.610	0.192	0.728	0.414	0.523
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.122	0.132	0.147	0.168	0.110	0.172

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results without year fixed effects, while Panel B shows results with year fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 15: RDD Estimates for Infraction Amount (log) by Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	0.590	0.282	0.319	0.0640	0.215	0.280
	(0.360)	(0.587)	(0.421)	(0.625)	(0.419)	(0.600)
Observations	246	246	220	220	194	194
Effective observations	[76,75]	[77,86]	[57,64]	[66,83]	[49,58]	[57,79]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.101	0.631	0.448	0.918	0.608	0.640
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.120	0.135	0.102	0.136	0.105	0.146
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	0.605*	0.139	0.526	0.210	0.501	0.345
	(0.321)	(0.593)	(0.348)	(0.556)	(0.369)	(0.567)
Observations	246	246	220	220	194	194
Effective observations	[77,83]	[77,81]	[65,74]	[67,83]	[52,62]	[56,78]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0599	0.814	0.130	0.706	0.174	0.543
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.131	0.124	0.122	0.137	0.115	0.143

Note: Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Panel A shows results without term fixed effects, while Panel B shows results with term fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

D. When Extreme Poverty Increases

Table 16: RDD Estimates for Infraction Count by Year and Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	1.120	0.800	1.472	1.212	0.686	1.844
	(1.085)	(1.455)	(0.908)	(1.247)	(1.340)	(2.157)
Observations	687	687	650	650	526	526
Effective observations	[186,182]	[226,254]	[192,220]	[246,280]	[127,133]	[136,166]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.302	0.582	0.105	0.331	0.609	0.393
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.110	0.159	0.133	0.192	0.0899	0.116
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	2.112	0.565	0.370	-0.851	-1.533	0.411
	(4.888)	(6.320)	(5.187)	(6.618)	(5.349)	(6.711)
Observations	224	224	205	205	179	179
Effective observations	[62,54]	[73,77]	[56,50]	[66,73]	[48,45]	[55,65]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.666	0.929	0.943	0.898	0.774	0.951
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0919	0.144	0.0883	0.144	0.0930	0.142

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results by year, while Panel B shows results electoral term. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 17: RDD Estimates for Infraction Amount (log) by Year and Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	0.169	-0.0756	0.139	0.164	0.126	-0.142
	(0.354)	(0.501)	(0.354)	(0.411)	(0.353)	(0.557)
Observations	685	685	648	648	524	524
Effective observations	[195,200]	[213,242]	[181,188]	[251,280]	[137,168]	[138,190]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.633	0.880	0.695	0.690	0.720	0.799
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.117	0.151	0.116	0.203	0.119	0.132
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	0.360	0.0738	0.229	0.0170	0.156	0.298
	(0.446)	(0.702)	(0.489)	(0.692)	(0.488)	(0.579)
Observations	224	224	205	205	179	179
Effective observations	[65,60]	[71,72]	[57,54]	[66,71]	[49,48]	[64,77]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.420	0.916	0.639	0.980	0.750	0.607
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.113	0.132	0.0989	0.138	0.106	0.179

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results by year, while Panel B shows results by electoral term. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

E. Last 2 years

E.1. When Poverty Decreases

Table 18: RDD Estimates for Infraction Count by Year and Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-2.179**	-2.796**	-1.327	-1.773	-1.639*	-2.219*
	(0.874)	(1.114)	(0.928)	(1.136)	(0.979)	(1.261)
Observations	389	389	357	357	357	357
Effective observations	[100,80]	[118,96]	[88,64]	[106,86]	[88,62]	[92,70]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0127	0.0121	0.153	0.119	0.0943	0.0786
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0824	0.101	0.0735	0.0978	0.0717	0.0834
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-4.107**	-5.470**	-2.584	-3.540	-2.591	-3.781
	(1.720)	(2.208)	(1.795)	(2.229)	(1.967)	(2.481)
Observations	194	194	178	178	178	178
Effective observations	[53,41]	[62,49]	[45,34]	[57,44]	[44,33]	[52,38]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0169	0.0132	0.150	0.112	0.188	0.128
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0887	0.105	0.0793	0.105	0.0749	0.0911

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results by year, while Panel B shows results by electoral term. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 19: RDD Estimates for Infraction Amount (log) by Year and Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-1.253***	-1.415***	-1.016***	-1.208***	-1.004***	-1.162**
	(0.384)	(0.466)	(0.363)	(0.460)	(0.375)	(0.468)
Observations	388	388	356	356	356	356
Effective observations	[88,66]	[112,86]	[92,70]	[104,76]	[100,72]	[118,91]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.00110	0.00240	0.00514	0.00867	0.00739	0.0129
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0684	0.0910	0.0827	0.0939	0.0888	0.116

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B						
RD Estimate	-1.164***	-1.195**	-0.989**	-1.054**	-0.912**	-1.016**
	(0.425)	(0.511)	(0.410)	(0.514)	(0.384)	(0.512)
Observations	194	194	178	178	178	178
Effective observations	[48,37]	[62,49]	[46,34]	[56,43]	[53,43]	[59,46]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.00611	0.0194	0.0158	0.0401	0.0176	0.0474
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0742	0.105	0.0810	0.103	0.0996	0.120

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results by year, whereas Panel B shows results by term. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

E.2. When Extreme Poverty Decreases

Table 20: RDD Estimates for Infraction Count by Year and Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-1.594**	-2.381**	-1.469	-1.908*	-1.494	-2.275*
	(0.800)	(1.042)	(0.928)	(1.159)	(0.998)	(1.304)
Observations	432	432	387	387	387	387
Effective observations	[109,102]	[121,116]	[84,86]	[104,100]	[76,74]	[82,80]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0463	0.0223	0.113	0.0997	0.134	0.0810
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0887	0.0972	0.0763	0.0955	0.0680	0.0721
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-2.564	-3.693*	-2.765	-3.558	-3.696*	-4.846**
	(1.614)	(2.144)	(1.794)	(2.261)	(1.950)	(2.424)
Observations	216	216	193	193	193	193
Effective observations	[59,54]	[67,60]	[44,44]	[58,54]	[41,43]	[53,53]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.112	0.0849	0.123	0.116	0.0580	0.0456
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0932	0.105	0.0851	0.105	0.0754	0.0987

Note: Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Panel A shows results by year, while Panel B shows results by electoral term. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 21: RDD Estimates for Infraction Amount (log) by Year and Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-0.949**	-1.211***	-0.614*	-0.869*	-0.579	-0.766*
	(0.382)	(0.445)	(0.362)	(0.459)	(0.358)	(0.438)
Observations	431	431	386	386	386	386
Effective observations	[89,82]	[111,102]	[88,88]	[106,106]	[102,96]	[132,115]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0130	0.00646	0.0900	0.0584	0.106	0.0805
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0642	0.0895	0.0861	0.0978	0.0938	0.132
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-0.846**	-0.925*	-0.551	-0.748	-0.560	-0.807
	(0.405)	(0.472)	(0.385)	(0.505)	(0.347)	(0.505)
Observations	216	216	193	193	193	193
Effective observations	[47,44]	[65,60]	[50,48]	[58,54]	[58,54]	[60,55]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0368	0.0501	0.152	0.138	0.106	0.110
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0702	0.104	0.0907	0.108	0.111	0.115

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results year, while Panel B shows results term. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

F. Last 1 Year

F.1. When poverty Decreases

Table 22: RDD Estimates for Infraction Count by Year and Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-2.351**	-2.999**	-1.705	-1.810	-1.713	-1.827
	(1.011)	(1.439)	(1.094)	(1.530)	(1.189)	(1.596)
Observations	195	195	179	179	179	179
Effective observations	[67,53]	[65,52]	[52,42]	[57,44]	[52,40]	[57,44]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0200	0.0372	0.119	0.237	0.150	0.253
Order of Polynomial	1	2	1	2	1	2
Bandwidth	0.126	0.122	0.0966	0.109	0.0945	0.110
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-2.351**	-2.999**	-1.730	-1.837	-1.326	-1.393
	(1.011)	(1.439)	(1.094)	(1.530)	(1.277)	(1.631)
Observations	195	195	179	179	179	179
Effective observations	[67,53]	[65,52]	[53,42]	[57,44]	[50,36]	[57,44]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0200	0.0372	0.114	0.230	0.299	0.393
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.126	0.122	0.0966	0.109	0.0892	0.109

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A provides estimates by year, and Panel B provides estimates by electoral term. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 23: RDD Estimates for Infraction Amount (log) by Year and Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-1.147**	-1.119*	-0.894**	-1.010*	-0.902**	-1.048*
	(0.460)	(0.603)	(0.438)	(0.603)	(0.411)	(0.576)
Observations	194	194	178	178	178	178
Effectiveness observations	[49,39]	[56,45]	[51,38]	[53,42]	[56,44]	[53,43]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0127	0.0638	0.0411	0.0938	0.0283	0.0687
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0776	0.0952	0.0908	0.0974	0.104	0.0983
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-1.163**	-1.115*	-0.903**	-1.001*	-0.818*	-0.999*
	(0.471)	(0.602)	(0.416)	(0.600)	(0.418)	(0.593)
Observations	195	195	179	179	179	179
Effective observations	[48,39]	[56,45]	[53,43]	[53,43]	[57,44]	[53,42]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0134	0.0639	0.0298	0.0953	0.0502	0.0920
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0752	0.0959	0.0998	0.0989	0.108	0.0975

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results by year, while Panel B shows results by electoral term. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

F.2. When Extreme Poverty Decreases

Table 24: RDD Estimates for Infraction Count by Year and Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-1.990*	-1.942	-1.441	-1.560	-1.356	-1.643
	(1.029)	(1.228)	(1.053)	(1.531)	(1.158)	(1.545)
Observations	217	217	194	194	194	194
Effective observations	[56,51]	[78,69]	[58,54]	[58,54]	[44,44]	[58,54]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0533	0.114	0.171	0.308	0.242	0.288
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0897	0.141	0.105	0.111	0.0863	0.108
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-2.564	-3.693*	-2.765	-3.558	-3.696*	-4.846**
	(1.614)	(2.144)	(1.794)	(2.261)	(1.950)	(2.424)
Observations	216	216	193	193	193	193
Effective observations	[59,54]	[67,60]	[44,44]	[58,54]	[41,43]	[53,53]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.112	0.0849	0.123	0.116	0.0580	0.0456
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0932	0.105	0.0851	0.105	0.0754	0.0987

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results by year, while Panel B shows results by term. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 25: RDD Estimates for Infraction Amount (log) by Year and Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-0.863**	-0.936*	-0.453	-0.675	-0.309	-0.641
	(0.437)	(0.546)	(0.436)	(0.579)	(0.383)	(0.573)
Observations	216	216	193	193	193	193
Effective observations	[49,47]	[60,55]	[46,45]	[56,53]	[58,54]	[57,54]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0484	0.0861	0.299	0.244	0.420	0.264
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0727	0.0944	0.0883	0.103	0.109	0.104
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-0.876**	-0.928*	-0.435	-0.673	-0.468	-0.766
	(0.445)	(0.541)	(0.415)	(0.579)	(0.414)	(0.573)
Observations	217	217	194	194	194	194
Effective observations	[47,44]	[60,58]	[52,49]	[56,54]	[53,52]	[56,53]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0489	0.0866	0.295	0.245	0.258	0.181
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0708	0.0962	0.0944	0.103	0.0970	0.103

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results by year, while Panel B shows by term. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

G. First 2 Years

G.1. When Poverty Decreases

Table 26: RDD Estimates for Infraction Count by Year and Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-0.964	-0.956	-0.193	-0.201	-0.632	-1.219
	(0.754)	(1.024)	(0.824)	(1.024)	(0.928)	(1.213)
Observations	212	212	212	212	212	212
Effective observations	[72,42]	[74,42]	[62,34]	[70,42]	[66,36]	[70,42]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.201	0.351	0.815	0.845	0.496	0.315
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.102	0.105	0.0894	0.100	0.0927	0.100
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-6.659***	-6.364**	-5.179*	-6.792*	-4.115*	-5.665
	(2.432)	(2.717)	(2.714)	(3.770)	(2.475)	(3.637)
Observations	195	195	179	179	179	179
Effective observations	[62,49]	[86,76]	[52,40]	[59,46]	[55,43]	[57,44]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.00618	0.0192	0.0564	0.0716	0.0964	0.119
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.106	0.192	0.0955	0.117	0.101	0.108

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results by year, while Panel B shows results by term. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 27: RDD Estimates for Infraction Amount (log) by Year and Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	0.155	0.290	0.306	0.367	0.174	0.131
	(0.308)	(0.352)	(0.299)	(0.344)	(0.362)	(0.415)
Observations	210	210	210	210	210	210
Effective observations	[50,24]	[62,34]	[50,24]	[62,34]	[50,24]	[60,34]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.616	0.411	0.307	0.287	0.631	0.753
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0596	0.0887	0.0597	0.0893	0.0589	0.0861
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-5.829**	-6.524**	-4.512**	-5.180	-3.502	-3.581
	(2.350)	(3.309)	(2.193)	(3.638)	(2.174)	(3.552)
Observations	195	195	179	179	179	179
Effective Observations	[54,41]	[63,51]	[57,44]	[53,42]	[55,43]	[51,38]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0131	0.0486	0.0396	0.154	0.107	0.313
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0896	0.115	0.106	0.0971	0.101	0.0904

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results by year, while Panel B shows results by electoral term. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

G.2. When Extreme Poverty Decreases

Table 28: RDD Estimates for Infraction Count by Year and Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-1.332*	-1.450	-0.785	-0.866	-0.911	-1.277
	(0.772)	(0.959)	(0.812)	(0.987)	(0.844)	(1.043)
Observations	238	238	238	238	238	238
Effective observations	[58,44]	[84,56]	[58,44]	[84,56]	[56,44]	[80,54]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0843	0.131	0.334	0.380	0.280	0.221
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0824	0.118	0.0811	0.116	0.0801	0.110
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-4.175*	-4.895	-5.005**	-6.061*	-5.512**	-6.228*
	(2.235)	(3.362)	(2.278)	(3.295)	(2.320)	(3.200)
Observations	217	217	194	194	194	194
Effective observations	[67,60]	[71,64]	[55,53]	[60,55]	[51,48]	[60,55]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0617	0.145	0.0280	0.0658	0.0175	0.0516
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.110	0.121	0.102	0.119	0.0928	0.116

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results by year, while Panel B shows results by electoral term. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 29: RDD Estimates for Infraction Amount (log) by Year and Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	0.187	0.267	0.204	0.272	0.234	0.109
	(0.355)	(0.390)	(0.353)	(0.396)	(0.362)	(0.418)
Observations	236	236	236	236	236	236
Effective observations	[52,34]	[70,48]	[52,34]	[64,44]	[52,34]	[64,44]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.598	0.495	0.563	0.492	0.518	0.795
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0609	0.0939	0.0651	0.0894	0.0641	0.0889
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-2.570	-2.617	-3.314*	-3.900	-3.676**	-3.804
	(1.832)	(3.183)	(1.839)	(3.008)	(1.763)	(2.997)
Observations	217	217	194	194	194	194
Effective observations	[75,65]	[64,59]	[60,55]	[55,53]	[58,54]	[53,52]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.161	0.411	0.0715	0.195	0.0371	0.204
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.130	0.102	0.119	0.102	0.111	0.0976

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results by year, while Panel B shows results by electoral term. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

H. Results for the Whole Sample (i.e. When Poverty is not Considered)

Table 30: RDD Estimates for Infraction Count by Year

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-0.117	-0.506	0.192	0.0415	-0.165	-0.0762
	(0.621)	(0.900)	(0.598)	(0.880)	(0.668)	(0.886)
Observations	1,357	1,357	1,275	1,275	1,151	1,151
Effective observations	[421,379]	[467,453]	[420,401]	[446,473]	[327,310]	[395,441]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.850	0.574	0.748	0.962	0.804	0.932
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.119	0.146	0.133	0.158	0.110	0.160
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	0.0229	-0.179	0.388	0.490	0.0425	-0.0280
	(0.639)	(0.877)	(0.634)	(0.807)	(0.690)	(0.715)
Observations	1,357	1,357	1,275	1,275	1,151	1,151
Effective observations	[403,365]	[467,463]	[392,373]	[486,505]	[325,308]	[474,517]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.971	0.838	0.541	0.544	0.951	0.969
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.113	0.151	0.121	0.178	0.104	0.218

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results without year fixed effects, while Panel B shows results with year fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 31: RDD Estimates for Infraction Count by Term

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-2.133	-4.067	-2.852	-4.456	-5.290*	-4.460
	(2.677)	(3.932)	(2.841)	(4.019)	(3.171)	(4.021)
Observations	440	440	398	398	372	372
Effective observations	[133,120]	[148,141]	[117,108]	[134,133]	[99,93]	[123,127]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.426	0.301	0.315	0.268	0.0953	0.267
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.112	0.135	0.108	0.140	0.0926	0.140
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	0.258	-0.278	1.231	1.418	-0.728	-0.0200
	(1.974)	(2.718)	(2.012)	(2.527)	(2.242)	(2.994)
Observations	440	440	398	398	372	372
Effective observations	[133,120]	[153,154]	[124,118]	[156,164]	[101,101]	[124,132]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.896	0.919	0.541	0.575	0.746	0.995
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.113	0.150	0.120	0.182	0.0999	0.144

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results without term fixed effects, while Panel B shows results with term fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 32: RDD Estimates for Infraction Amount (log) by Year

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-0.177	-0.334	-0.0991	-0.181	-0.126	-0.237
	(0.220)	(0.291)	(0.217)	(0.290)	(0.226)	(0.311)
Observations	1,352	1,352	1,270	1,270	1,146	1,146
Effective observations	[388,353]	[459,435]	[369,337]	[432,439]	[318,307]	[365,377]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.422	0.251	0.649	0.534	0.578	0.445
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.103	0.141	0.110	0.149	0.102	0.137
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-0.143	-0.280	-0.0533	-0.0233	-0.0648	-0.100
	(0.225)	(0.291)	(0.222)	(0.270)	(0.218)	(0.293)
Observations	1,352	1,352	1,270	1,270	1,146	1,146
Effective observations	[376,352]	[459,439]	[365,335]	[470,487]	[326,308]	[379,407]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.526	0.335	0.811	0.931	0.766	0.732
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0994	0.141	0.104	0.171	0.106	0.149

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results without year fixed effects, while Panel B shows results with year fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 33: RDD Estimates for Infraction Amount (log) by Term

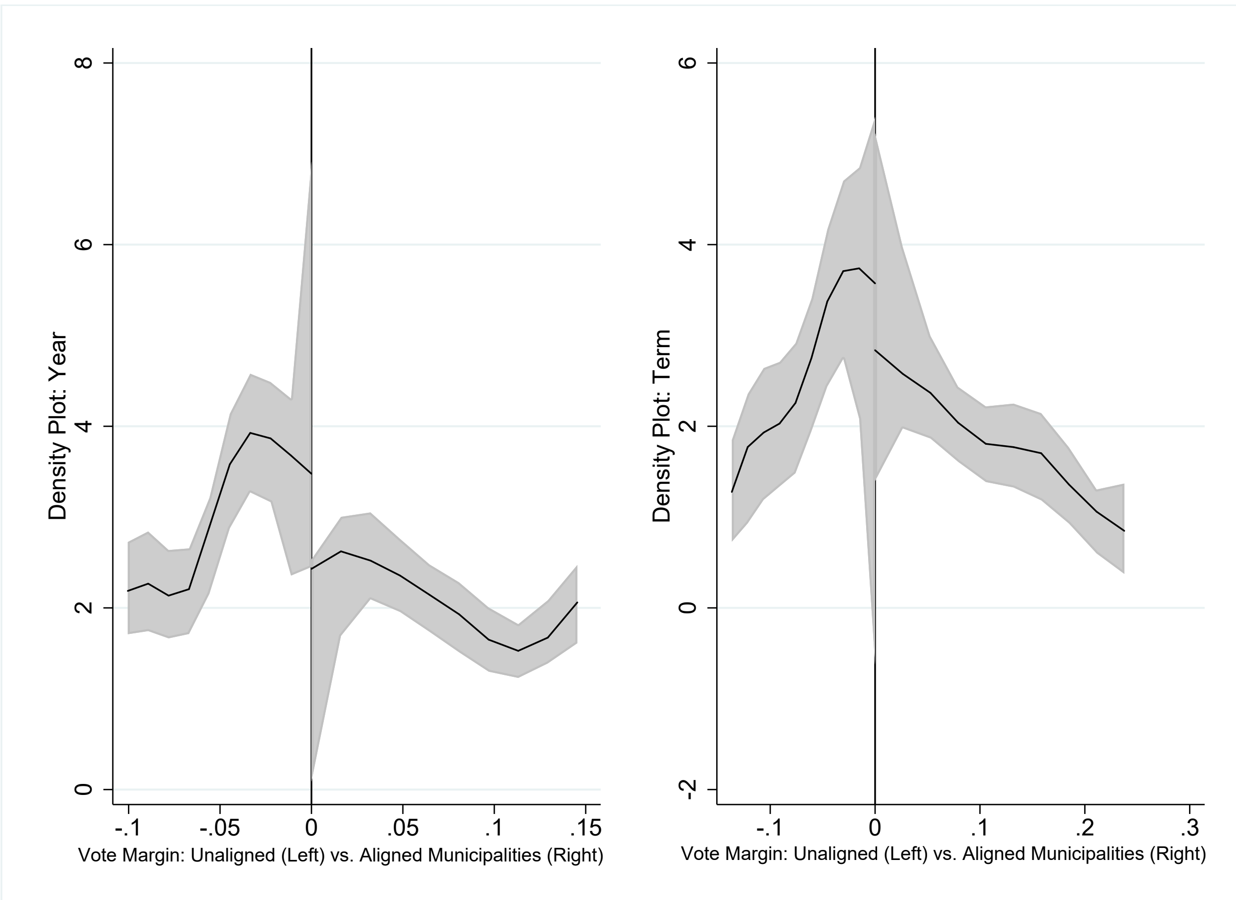
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-0.0559	-0.377	0.0278	-0.286	-0.198	-0.215
	(0.248)	(0.405)	(0.244)	(0.411)	(0.286)	(0.398)
Observations	440	440	398	398	372	372
Effective observations	[148,142]	[146,136]	[136,142]	[132,132]	[108,103]	[124,132]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.822	0.351	0.909	0.487	0.489	0.588
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.136	0.130	0.149	0.135	0.109	0.145
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-0.0186	-0.201	0.162	0.0562	0.0677	0.0596
	(0.253)	(0.367)	(0.244)	(0.353)	(0.257)	(0.359)
Observations	440	440	398	398	372	372
Effective observations	[132,120]	[146,136]	[126,124]	[136,142]	[109,107]	[125,135]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.942	0.585	0.508	0.874	0.793	0.868
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.111	0.130	0.124	0.148	0.113	0.148

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results without term fixed effects, while Panel B shows results with term fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

I. RDD Robustness Checks

I.1. Density Plots: Year and Term

Figure 4: RDD plots for Infraction Count and Amount



I.2. RDD Estimates eliminating Outliers

Table 34: RDD Estimates for Infraction Count by Term and Year

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-6.603**	-11.18***	-6.364**	-8.121**	-6.545**	-7.549**
	(2.624)	(3.697)	(2.962)	(3.594)	(3.094)	(3.831)
Observations	182	182	167	167	167	167
Effective Observations	[65,54]	[57,50]	[46,38]	[59,48]	[39,34]	[51,43]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0118	0.00250	0.0317	0.0238	0.0344	0.0488
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.138	0.118	0.0911	0.137	0.0753	0.111
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-1.633***	-2.187***	-1.023*	-1.361*	-1.452**	-1.957***
	(0.526)	(0.713)	(0.612)	(0.734)	(0.621)	(0.732)
Observations	591	591	559	559	559	559
Effective Observations	[189,138]	[179,138]	[142,98]	[167,118]	[131,82]	[144,102]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.00190	0.00217	0.0945	0.0636	0.0193	0.00754
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.102	0.0982	0.0733	0.0949	0.0669	0.0808

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results for term, while Panel B shows results year.To avoid excessive ommissions, Term results are winsorized at top/bottom 10% level, while Year results are winsorized at top/bottom 5%. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

Table 35: RDD Estimates for Infraction Amount (log) by Term and Year

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	-0.832***	-0.809**	-0.721***	-0.675*	-0.677***	-0.671**
	(0.310)	(0.390)	(0.234)	(0.367)	(0.237)	(0.333)
Observations	177	177	163	163	163	163
Effective Observations	[44,35]	[57,45]	[53,40]	[47,34]	[53,40]	[46,34]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.00729	0.0384	0.00207	0.0660	0.00424	0.0442
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0762	0.105	0.109	0.0902	0.106	0.0901
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RD Estimate	-0.577**	-0.547*	-0.377	-0.414	-0.502*	-0.498
	(0.226)	(0.327)	(0.270)	(0.323)	(0.274)	(0.324)
Observations	585	585	555	555	555	555
Effective Observations	[178,134]	[158,112]	[126,74]	[152,102]	[130,74]	[172,126]
Covariates	None	None	Some	Some	All	All
Conventional p-value	0.0107	0.0942	0.163	0.201	0.0670	0.124
Order of polynomial	1	2	1	2	1	2
Bandwidth	0.0970	0.0867	0.0598	0.0857	0.0647	0.0979

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results for term, while Panel B shows results year.To avoid excessive ommissions, Term results are winsorized at top/bottom 10% level, while Year results are winsorized at top/bottom 5%. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Columns 1 and 2 do not use any controls. Columns 3 and 4 use population (log) and a reelection dummy as controls. Columns 5 and 6 use population (log), reelection dummy, Gini coefficient, and log public goods spending (per capita) as controls.

I.3. RDD Estimates at Varying Cutoffs

Table 36: RDD Estimates for Infraction Count and Amount (log) by Term

Panel A	(-5%)	(5%)	(-10%)	(10%)	(-15%)	(15%)
RD Estimate	1.627	-0.156	-1.364	-11.33***	2.513	4.428
	(4.443)	(4.276)	(4.809)	(3.959)	(5.739)	(4.614)
Observations	195	195	195	195	195	195
Effective Observations	[36,66]	[44,24]	[30,58]	[28,22]	[17,24]	[23,16]
Conventional p-value	0.714	0.971	0.777	0.00423	0.661	0.337
Order of polynomial	1	1	1	1	1	1
Bandwidth	0.102	0.0745	0.103	0.0627	0.0716	0.0633
Panel B	**(-5%)**	**(5%)**	**(-10%)**	**(10%)**	**(-15%)**	**(15%)**
RD Estimate	0.571	-0.578	-0.879*	-0.819	-0.656	0.658
	(0.420)	(0.448)	(0.510)	(0.578)	(1.044)	(0.638)
Observations	195	195	195	195	195	195
Effective Observations	[36,62]	[27,14]	[29,49]	[34,25]	[16,19]	[14,15]
Conventional p-value	0.174	0.197	0.0849	0.157	0.530	0.302
Order of polynomial	1	1	1	1	1	1
Bandwidth	0.0957	0.0427	0.0895	0.0735	0.0608	0.0465

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Panel A shows results for infraction count, while Panel B shows results infraction amount.All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of victory on each side of the cutoff that Calonico, Cattaneo and Titiunik's (2014) data-driven algorithm deems to be a close election. Effective observations correspond to the observations that fall within the data-driven bandwidth—with those preceding the comma on the left side of the cutoff, and observations after the comma corresponding to those on the right of the cutoff. Per Gelman and Imbens (2019), estimations only rely on polynomials of the first and second order. Results are similar when looking at Years and not Terms. Significant effects in Panel A and Panel B were found to be due to the effect of outlier and reduced sample away from cutoff.

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