

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

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## Abstract

Party alignment entails politicians sharing the same party at higher and lower levels of government, giving aligned politicians greater access to the spoils of the bureaucracy. Does the political-institutional configuration of party alignment thus necessarily lead to more corruption? Given that party alignment also signals clarity of political responsibility for corruption to voters, we theorize that party alignment can actually yield lower levels of corruption if two conditions are met. Using a regression discontinuity design and novel corruption data from Guatemalan municipal audit reports, we show that aligned politicians are less likely to engage in corruption if there is both significant electoral competition and voters' poverty levels are low or decreasing. The results of our study document how the reduction of corruption through modernization forces such as decreasing poverty takes place through political institutions.

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Keywords: corruption, poverty, political institutions

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The practice of misusing entrusted power or public office for private gain has a familiar name: corruption.<sup>1</sup> The consequences of corruption extend far and wide, hindering the achievement of development outcomes in rich and poor countries alike (e.g., [Olken and Pande, 2012](#); [Findley, Nielson and Sharman, 2014](#)). Often, politics is a driving force behind corruption’s intractability, which is why researchers have studied which types of political and institutional configurations facilitate or reduce corruption (e.g., [Gerring and Thacker, 2004](#); [Kunicová and Rose-Ackerman, 2005](#); [Treisman, 2007](#); [Golden and Mahdavi, 2015](#)).

In this study, we examine how corruption responds to the political-institutional configuration of party alignment: that is, when politicians’ parties match at higher and lower levels of government. Examples of party alignment include when a governor or mayor share the same political party as the president. Irrespective of its specific manifestation, party alignment is an institutional configuration that facilitates clarity of political responsibility. The latter “refers to institutional and partisan arrangements that make it easy for voters to monitor their representatives, identify those responsible for undesirable outcomes, and hold them accountable by voting them out of office” ([Schwindt-Bayer and Tavits, 2016](#), 1).

Party alignment, however, does not only facilitate clarity of responsibility. For example, party alignment yields greater access to the spoils of the bureaucracy, which incites clientelism and unfair party competition ([Greene, 2007, 2010](#)). Similarly, the decentralization literature convincingly shows that party alignment fuels politically-motivated spending and budget cycles in both developed and developing countries.<sup>2</sup> Under what conditions, then,

<sup>1</sup> For more on definitions of corruption, see, for example, [Søreide \(2014\)](#) and [Rose-Ackerman and Palifka \(2016\)](#).

<sup>2</sup> There is evidence of political budget cycles and favoritism in intergovernmental transfer allocation in at least the following countries: Argentina ([Garofalo, Lema and Streb, 2020](#)); Brazil ([Brollo and Nannicini, 2012](#); [Bueno, 2018](#)); 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](#)); Germany ([Kauder, Potrafke and Reischmann, 2016](#)); Ghana ([Banful, 2011a,b](#)); Guatemala ([Sandberg and Tally, 2015](#)); India ([Velasco Rivera, 2020](#)); Italy ([Carozzi and Repetto, 2016](#); [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](#); [Berry, Burden and Howell, 2010](#); [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](#)).

does party alignment yield less corruption from precisely the same politicians with more possibilities to engage in it?

Using a simple theoretical framework, we provide a theory to explain when aligned politicians engage in less corruption. To that end, the clarity of responsibility that alignment facilitates does not necessarily lower corruption, but it may do so if two conditions are met. First, aligned politicians must live in an area where levels of poverty are low or have recently declined. Essentially, economic circumstances must be relatively better by national standards. Second, aligned politicians must be susceptible to significant electoral competition, having won their position by a small margin of victory in the most recent election.

When economic circumstances are better, voters tend to rely less on clientelistic exchanges to meet basic needs.<sup>3</sup> By reducing the need for “request-fulfilling”,<sup>4</sup> we argue that better economic circumstances lead to less voter tolerance of corruption from aligned politicians as well. By contrast, under more difficult economic circumstances, voters are more supportive of aligned politicians due to their access and willingness to share the spoils of the bureaucracy for electoral gain.

Electoral competition amplifies the effects of better economic circumstances on aligned politicians’ corruption levels. Winning elections by small margins, for example, signals to aligned politicians that they have less room to capture rents if they wish to gain reelection—and obtain rents in the future. Given that politicians in most countries earn more in office than as private citizens (Fisman, Schulz and Vig, 2014), reelection prospects drive aligned politicians to temper their corruption levels if their close-election win gives them less ability to extract rents. For their part, parties want to gain as many positions as possible, too. Accordingly, parties have an incentive to discourage corruption from their aligned

<sup>3</sup> For general overviews regarding the relationship between poverty and clientelism, see Kitschelt and Wilkinson (2007) and Stokes et al. (2013, Chapter 6). For related empirical analyses, see Kitschelt and Kselman (2013), Gonzalez-Ocantos, Kiewiet de Jonge and Nickerson (2014), Jensen and Justesen (2014), and Szwarcberg (2015).

<sup>4</sup> Request-fulfilling entails “citizens demand[ing] clientelistic benefits” (Nichter and Peress, 2017).

members especially in or after close races—i.e., when voters are more engaged, clarity of responsibility is highest, and corruption scandals are thus more electorally costly. However, these same incentives are not present when unaligned politicians barely win their positions in poorer electorates. The lack of clarity of responsibility means that unaligned politicians can deflect blame on the opposition and not suffer the same reelection consequences when they misappropriate resources to meet voters’ increased utility for clientelistic spending.

To support our theory that stresses how party alignment’s conditional effect on corruption depends on both political competition and voters’ economic circumstances, we examine new municipality-level data on corruption from Guatemala. The country is not only relatively poor and has a long history of clientelism and corruption but also, in 2019, expelled its United Nations-backed anti-corruption body, the International Commission Against Impunity (CICIG) (González, 2014; Sandberg and Tally, 2015; *The Economist*, 2019; Malkin, 2019). The myriad protests and widespread international media coverage of the CICIG expulsion underscores the relevance of corruption for Guatemala’s political discourse and democratic stability more broadly.

Unlike the corruption perceptions data that dominate the literature, our data correspond to actual measures of corruption that we draw from audit reports produced by the Guatemala’s Comptroller General (*Contraloría General de Cuentas*). Following Denly (2020), we find no biases regarding the independence, distribution, and intensity/dosage of the audits, which helps them overcome potential measurement-related threats to inference (see Kurtz and Schrank, 2007*a,b*; Hollyer, 2018). Additionally, because the data are subnational, they do not exhibit level of analysis problems that plague many corruption studies (see Gingerich, 2013).

To operationalize whether a municipality is performing better economically, we specifically compare municipalities with low and high poverty levels (i.e., those above and below the median poverty level); municipalities with increased and decreased poverty rates relative to the previous census; and all municipalities—i.e., not subsetting by poverty. To causally

identify the effects of alignment in the different samples, we exploit a series of close-election regression discontinuity designs.

We find that alignment yields a significant decrease in both of our measures of corruption in the municipalities with decreased and lower poverty. For example, in our base specification for infractions committed in each electoral term, aligned municipalities commit an average of 13.73 fewer infractions in the decreased-poverty sample, and 6.09 fewer infractions in the low-poverty sample. Numerous robustness checks show similar patterns, including when we employ [Calonico et al.’s \(2019\)](#) new method to control for the influence of covariates in the regression discontinuity estimates.

In most cases, alignment reduces corruption in municipalities with low or decreasing extreme poverty as well, suggesting that the theory has broad reach. Consistent with our theory, none of these results travel to municipalities in the high-poverty or poverty-increasing samples. Analysis of the full sample (i.e., not splitting the sample according to poverty levels or changes) provides results that are similarly consistent with our theory. Notably, all specifications in the full sample are substantively and statistically insignificant, suggesting the limits of current understanding of clarity of responsibility theory (see [Schwindt-Bayer and Tavits, 2016](#)).

At the broadest possible level, the results of this study help scholars re-evaluate how the institutional and modernization approaches to corruption dovetail.<sup>5</sup> As [Fisman and Golden \(2017, 15-16\)](#) explain, previous research has not found much empirical support for the modernization approach in poor countries. We would argue that is the case because poverty cannot be analyzed in isolation from the institutions that cause it ([Acemoglu, Johnson and Robinson, 2005](#)). Along these lines, the political-institutional configuration of party alignment only reduces corruption if politicians are susceptible to significant political competition and poverty is lower. We find the same patterns when examining both the effects of short-

<sup>5</sup> By “modernization”, we are referring to the prediction of modernization theory that economic growth or education leads to democratization (see [Acemoglu and Robinson, 2018, 26](#)). Within the corruption literature, the modernization approach “views corruption as a product of poverty” ([Fisman and Golden, 2017, 15](#)).

term poverty changes and longer-term poverty levels, and the poverty and corruption data are not endogenous (see Appendix M). Accordingly, our robust results challenge previous literature suggesting that a strong economy allows politicians to get away with corruption (e.g., Manzetti and Wilson, 2007; Klašnja and Tucker, 2013; Zechmeister and Zizumbo-Colunga, 2013; Schleiter and Tavits, 2018). That is not always the case, as our audit-based corruption data from Guatemala show.

## 1. Theoretical Framework

### 1.1. Model Setup

A simple theoretical framework explains why party alignment has a conditional effect on corruption. Our framework focuses on party alignment for two reasons. First, aligned politicians have more possibilities than opposition-party politicians to capture the spoils of the bureaucracy for both clientelistic and corrupt purposes (Greene, 2010; Brollo and Nannicini, 2012; Bueno, 2018; Corvalan, Cox and Osorio, 2018; Velasco Rivera, 2020). Second, there is a competing theoretical narrative, suggesting that such institutional configurations provide voters with corruption-reducing clarity of responsibility (Schwindt-Bayer and Tavits, 2016).

To better understand party alignment’s conditional effect on corruption, let us first consider local-level politician  $i$ ’s maximization problem. 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,  $r_i$ :

$$b_i = g_i + r_i^6 \tag{1}$$

Magaloni, Díaz-Cayeros and Estévez (2007) equate  $r$  merely with clientelism. By contrast,

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<sup>6</sup> 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.

total rents,  $r$ , in our model consists of both money set aside for clientelism,  $c$ , and the personal benefits of public office (corruption),  $p$ :

$$r = c + p, \text{ where } c = \gamma r^7 \quad (2)$$

Under Equation (2), we assume that  $c$  increases with  $r$ , meaning that local-level politician  $i$  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,<sup>8</sup> 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,  $r_{i,2}$ :

$$r_i = r_{i,1} + r_{i,2}^9 \quad (3)$$

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

$$\begin{aligned} s_{i,1} &= W(g_{i,1}) + \beta_i^{1+a} W(\gamma r_{i,1}) + (2a - 1)t(MV) \\ &= W(1 - r_{i,1}) + \beta_i^{1+a} W(\gamma r_{i,1}) + (2a - 1)t(MV) \end{aligned} \quad (4)$$

In Equation (4),  $W(\cdot)$  corresponds to the satisfaction that citizens derive 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);  $a$

<sup>7</sup> Because we cannot directly observe the distinction between  $c$  and  $p$  in Equation (2), we need to introduce  $\gamma \in (0, 1)$ . It denotes the fraction of rents used for clientelistic purposes, which we use for the calculation of the maximization problem in Appendix C.

<sup>8</sup> See, for example, Barro (1973), Ferejohn (1986), Ferraz and Finan (2011), and de Janvry, Finan and Sadoulet (2012).

<sup>9</sup> 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.

corresponds to party alignment, which takes a value of 1 if local-level politician  $i$  is aligned or 0 otherwise;  $t(\cdot)$  captures citizens' satisfaction from clarity of responsibility, measured by local-level politician  $i$ 's margin of victory in the last election ( $MV$ ),<sup>10</sup> such that  $t(\cdot)$  is a positive function,  $t' > 0$ , and  $t'' < 0$ ; and  $\beta_i$  represents that effect of low or decreased poverty on citizens' pre-existing discount rates of clientelistic and other benefits that corrupt politicians may bring through  $W(\gamma r_{1,i})$ .<sup>11</sup>

## 1.2. Clarity of Responsibility and Discount Rates of Corruption-Related Benefits

The model incorporates two independent channels through which clarity of responsibility affects citizens' satisfaction levels with local-level politician  $i$ . The first channel focuses on the direct effects of clarity of responsibility, and the second channel pinpoints how clarity of responsibility interacts with poverty to condition support for corrupt politicians and clientelism. Because citizens' levels of satisfaction with politician  $i$  affect his/her reelection probability ( $\pi_i$ ), citizens' levels of satisfaction also impact politician  $i$ 's incentives to extract rents ( $r$ ) for corrupt ( $p$ ) and clientelistic ( $c$ ) purposes.

### 1.2.1. Channel 1: The Direct Effects of Clarity of Responsibility

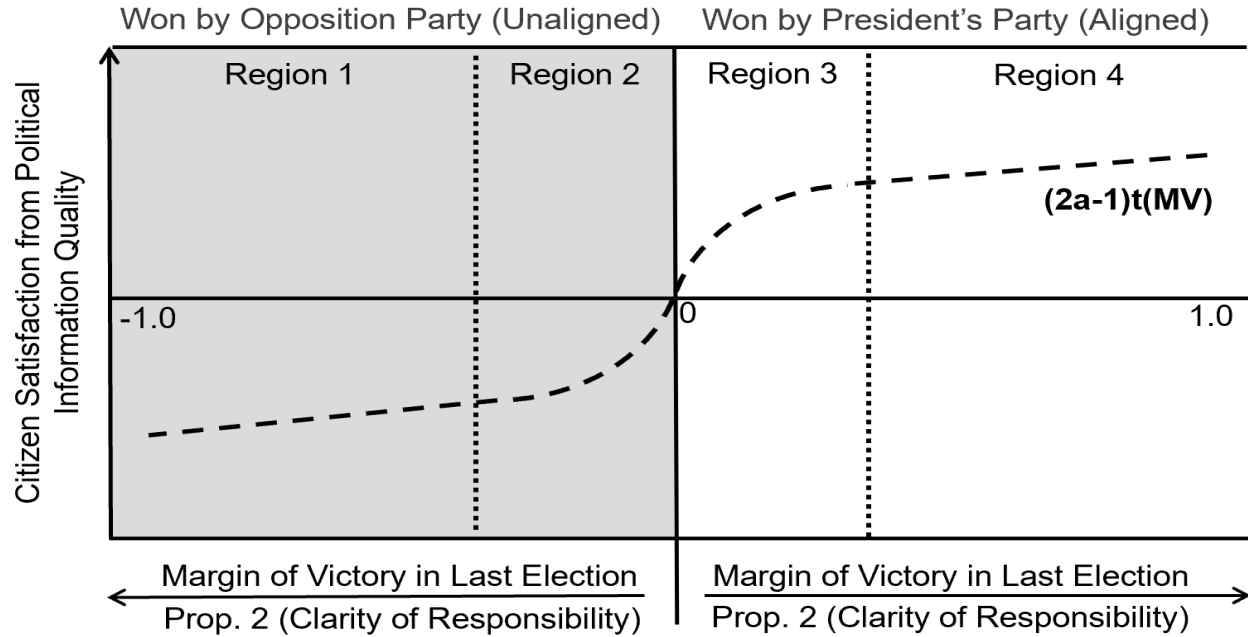
With respect to the first channel, the direct effects of clarity of responsibility on  $s_i$  jointly depend on local-level politician  $i$ 's margin of victory in the last election ( $MV$ ) and party alignment status ( $a$ ). We capture this joint dependency and its ability to be positive when aligned or negative when unaligned with  $(2a - 1)t(MV)$ . It reflects citizens' levels of satisfaction via the quality of political information that they receive. As depicted in Figure

<sup>10</sup> We assume that  $MV$  is exogenous. While there certainly can be strategic voting, the paper's focus on alignment means that voters not only need to be able to predict the election of the local-level politician but also the executive. In practice, this would be very difficult for even an informed electorate. Thus, we believe that treating  $MV$  as exogenous is theoretically justifiable.

<sup>11</sup> Given Equation (1), Equation (4) also captures the inverse benefits that the electorate derives from the local-level politician's rents in the current period,  $r_{i,1}$ .



Figure 1: Margin of Victory, Party Alignment, Information, and Clarity of Responsibility



1, these levels of information quality are highest in Region 4, change precipitously as  $MV$  approaches zero, and are lowest in Region 1. Underpinning these patterns are how parties' campaign incentives vary with levels of  $MV$  (see Appendix D).

Because alignment is a manifestation of single-party control of government, it plays an independent role on politicians' incentives for corruption as well. When local-level politician  $i$  shares the same party as the executive, citizens can easily discern which politician(s), party, or governing coalition is responsible for corruption or effective government.<sup>12</sup> By contrast, citizens' abilities to make such snap judgments are not as robust under divided government (Schwindt-Bayer and Tavits, 2016, 18; Appendix D). That is particularly the case in poor areas: they tend to suffer from political market imperfections, such as voters lacking information about politician performance,<sup>13</sup> identity voting,<sup>14</sup> and politicians' inability to make credible promises to voters (Keefer, 2004, 2007a,b; Keefer and Khemani, 2005; Keefer

<sup>12</sup> There is a large literature on clarity of responsibility, particularly regarding its effects on economic voting (e.g. Powell and Whitten, 1993; Powell, 2000). Tavits (2007) extended this literature, showing how clarity of responsibility affects corruption as well, notably because corruption affects citizens' levels of happiness (Tavits, 2008).

<sup>13</sup> See, for example, Pande (2011), Banerjee et al. (2014), and Lieberman, Posner and Tsai (2014).

<sup>14</sup> See, for example, Chandra (2004) and De La O and Rodden (2008).

and Vlaicu, 2008).

### 1.2.2. Channel 2: Poverty and Voter Demands for Clientelism

The second channel through which clarity of responsibility affects  $s_i$  relates to a primary consequence of political market imperfections: the extent to which citizens value corrupt politicians and clientelism.<sup>15</sup> A large literature establishes that lower poverty leads voters to discount clientelistic benefits more with respect to policy-based, programmatic benefits.<sup>16</sup> Citizens also discount other benefits that corrupt politicians may bring in a similar manner,<sup>17</sup> and we posit that clarity of responsibility amplifies these discounting patterns.

We account for the *additional* discounting brought about by low or decreased poverty on  $W(\gamma r_{i1})$  through  $\beta_i$ . In lower poverty electorates  $\beta_i \in (0, 1)$ , and  $\beta_i = 1$  in higher poverty electorates. In other words, citizens' *a priori* discount rate of  $W(\gamma r_{i1})$  remains unchanged except under the scenario in which poverty is low or has recently decreased.

Especially given information's mixed record in fostering political accountability in poor

<sup>15</sup> Clientelism entails the contingent distribution of material and non-material goods and services in exchange for political support. There are many varieties of clientelism, including vote-buying, (e.g., Auyero, 1999; Stokes, 2005; Finan and Schechter, 2012; Hidalgo and Nichter, 2016); turnout buying (e.g., Nichter, 2008; Larreguy, Marshall and Querubín, 2016); abstention-buying (e.g., Gans-Morse, Mazzuca and Nichter, 2014); double persuasion (e.g., Gans-Morse, Mazzuca and Nichter, 2014); and patronage (e.g., Robinson and Verdier, 2013). In making our argument, we make no distinction between the different forms of clientelism; our argument applies to the phenomenon as a whole.

<sup>16</sup> By programmatic benefits, we mean that the rules concerning their distribution are public, followed, and are not targeted at a particular group or area (Hicken, 2011, 296; Stokes et al., 2013, 7). For an overview of why reducing poverty also leads to a reduction in clientelism, see Stokes et al. (2013, Chapter 6). Qualitative work, notably from Chubb (1982) and Auyero (1999, 2000), provided the basis for the poverty-clientelism relationship. Recent studies from Gonzalez-Ocantos, Kiewiet de Jonge and Nickerson (2014), Jensen and Justesen (2014), Szwarcberg (2015), and Muñoz (2019, 228-229) have provided quantitative confirmation as well.

<sup>17</sup> Here, we are referring to the trade-off hypothesis, commonly known through the Portuguese expression "*rouba mas faz*" [he steals but gets things done]. In short, voters trade-off the value of a corrupt politician against the clientelistic benefits and other benefits (e.g. ideology) the politician can bring (Magaloni, Díaz-Cayeros and Estévez, 2007; Manzetti and Wilson, 2007; Pereira, Rennó and Samuels, 2011; Winters and Weitz-Shapiro, 2013; Pereira and Melo, 2015; Muñoz, Anduiza and Gallego, 2016; Chang and Kerr, 2017; Solaz, De Vries and de Geus, 2019; Leight et al., 2020; Bøttkjær and Justesen, 2021). That is particularly the case when voters are poor and less educated (Keefer, 2007a; Zechmeister and Zizumbo-Colunga, 2013; Del Mar Martínez Rosón, 2016; Nichter and Peress, 2017); and when voters believe that the corruption is self-reinforcing to the extent that there are no clean alternatives in the candidate pool (Charron and Bågenholm, 2016; Pavão, 2018; Agerberg, 2020).

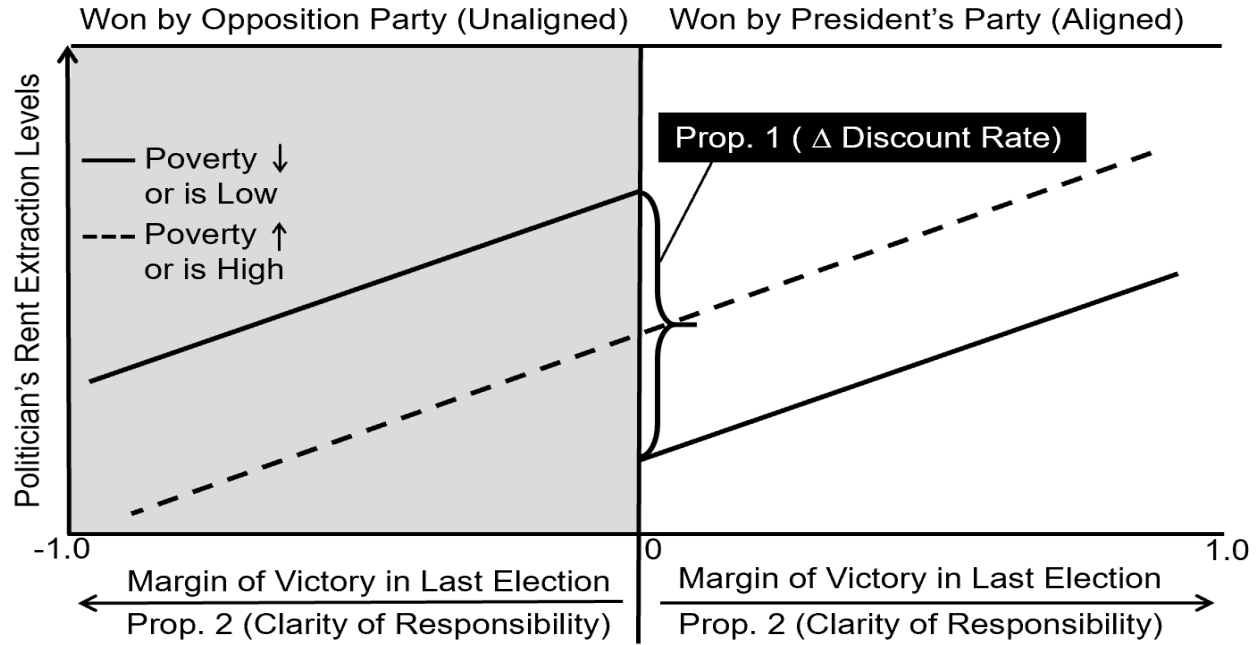
environments,<sup>18</sup> it is crucial to understand how clarity of responsibility fosters different discount rates of corruption-related benefits. Per [Schwindt-Bayer and Tavits \(2016\)](#) and [Figure 1](#), alignment makes identifying clarity of responsibility easier. Accordingly, we suggest that  $a$  magnifies the penalization imposed by low or reduced poverty ( $\beta_i \in (0, 1)$ ) on the pre-existing discount rate,  $W(\gamma r_{i1})$ , such that  $\beta^{1+a} = \beta^{1+1} \implies \beta^2 < \beta^1$ . In words, alignment leads to even higher discount rates for clientelistic and other benefits than the unaligned case due to clarity of responsibility when poverty is low or decreasing. Given that  $\beta = 1$  when poverty is higher, the effects of clarity of responsibility do not travel beyond the lower poverty scenario:  $\beta^{1+a} = \beta^{1+1} \implies \beta^2 = 1^2 = 1 = \beta^1$ .

### 1.3. Solving the Local-Level Politician's Maximization Problem

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](#)). It is necessary to complement  $r_{i,1}$  and  $r_{i,2}$  with  $x_{i,2}$  because politicians trade-off rent extraction in the current period against that of a potential future period ([Niehaus and Sukhtankar, 2013](#)). To that end, since politicians serving in areas with relatively high levels of corruption and clientelism can generally earn more in office than as a private citizen ([Querubín and Snyder, 2013](#); [Fisman, Schulz and Vig, 2014](#)), we specify that  $x_{i,2} < r_{i,2}$ . For its part, the political party of local-level politician  $i$  also wishes to maximize its representation, so its incentives are to ensure that  $r_{i,1}$  are not high enough to potentially cause a corruption scandal that hurts the party brand. Against this backdrop, and given Equations (3) and (4), the maximization

<sup>18</sup> See, for example, [Keefer \(2004, 2007a,b\)](#), [Kosack and Fung \(2014\)](#), [Chong et al. \(2015\)](#), [Fox \(2015\)](#), [Dunning et al. \(2019\)](#).

Figure 2: Graphic Presentation of Propositions 1 and 2



problem for local-level politician  $i$  can be represented as:

$$\begin{aligned} \max_{r_{i,1}} \quad & U(r_{i,1}) + \pi(s_{i,1}) U(r_{i,2}) + (1 - \pi(s_{i,1})) U(x_{i,2}) \\ \text{where } s_{i,1} = \quad & W(g_{i,1}) + \beta_i^{1+a} W(\gamma r_{i,1}) + (2a - 1)t(MV) \end{aligned} \quad (5)$$

**Proposition 1:** *Optimal rents for aligned politicians are less than rents for unaligned politicians at the cutoff (i.e., the margin of victory is zero) when the electorate's economic circumstances are good or have improved.*

The differing discounting rates for aligned and unaligned electorates drives Proposition 1. Specifically, the higher penalization of clientelistic and other benefits in the aligned electorates reduces the reelection probability of aligned local-level politicians with respect to the unaligned ones. Therefore, when the margin of victory approaches 0, or right at the cutoff, this difference in discount rate results in a discontinuity between the optimal rents extracted, where aligned politicians extract less than the unaligned politicians. Refer to the solid line in Figure 2.

*Proof:* See Appendix C.

**Corollary 1** also shows the case when economic circumstances are poor or worsen in a given electorate. In such a case, because citizens do not discount any differently in either the aligned or the non-aligned electorates, there does not exist any discontinuity at the cutoff. The dotted line in Figure 2 captures such a scenario.

*Proof:* See Appendix C.

**Proposition 2:** *Optimal rents for aligned politicians increase with respect to the margin of victory, while they decrease with respect to the margin of victory for the unaligned politicians.*

The direct effect of clarity of responsibility on citizen's levels of satisfaction with their local-level politician underpins Proposition 2, which does not depend on poverty. For the unaligned electorates, the lack of clarity of responsibility negatively affects citizens' satisfaction with local-level politician  $i$  through the quality of information mechanism described in Section 1.2.1 and Appendix D. Unaligned local-level politicians, in turn, react by reducing their optimal rent-seeking behavior in a manner consistent with the margin of victory. The opposite effect takes place in the aligned municipalities. Since the clarity of responsibility from alignment positively affects citizens' satisfaction with local-level politician  $i$  (see Figure 1), it provides aligned politicians with additional opportunity for rent extraction as the margin of victory increases (see Figure 2). Accordingly, our model is consistent with the clientelism and decentralization literatures, which underscore that party alignment fuels greater levels of politically-motivated spending (Greene, 2010; Brollo and Nannicini, 2012; Carozzi and Repetto, 2016; Corvalan, Cox and Osorio, 2018; Lara and Toro, 2019).

*Proof:* See Appendix C.

## 1.4. Summary of the Theoretical Results

A significant strand of the corruption literature argues that clarity of responsibility reduces corruption (e.g., Schwindt-Bayer and Tavits, 2016). By contrast, our model shows

that a prominent manifestation of clarity of responsibility, party alignment, only has a conditional effect on corruption. More specifically, party alignment only reduces corruption under both lower poverty and higher electoral competition. Lower poverty means that the greater clientelistic resources that aligned politicians can share are less valuable to voters, and higher electoral competition makes a potential corruption scandal more costly for politicians. In the next section, we explain our research design to test the model’s predictions using unique, objective data on corruption from Guatemala.

## 2. Research Design

### 2.1. Institutional Context for Guatemala

Guatemala is a poor Central American country with a population of roughly 18 million people, of which 59% live in poverty and 23% live in extreme poverty ([World Bank, 2017](#)). Like many countries in the region, Guatemala officially has a presidential democracy but is not fully democratic. The country emerged from a devastating, 36-year civil war in 1996, and since then Guatemala registered some democratic advances but maintains significant authoritarian enclaves and rather weak institutions ([González, 2014](#)).

Corruption, clientelism, and organized crime present particularly onerous challenges for Guatemala. The country’s 2006-2019 partnership with the United Nations’ International Commission Against Impunity (CICIG) helped uncover some high-level corruption and dismantle some powerful drug-trafficking networks ([Fisman and Golden, 2017](#); [Trejo and Nieto-Matis, 2019](#)). Nevertheless, the country still ranks 144/180 on Transparency International’s (2018) Corruption Perceptions Index, part of the reason for which is likely due to clientelistic pressures. For example, vote buying is a concern in social programs, and CICIG investigations have revealed significant use of state resources in the financing of party campaigns ([Sandberg and Tally, 2015](#); [Meilán, 2016](#)).

General elections for both the national and municipal levels take place concurrently every four years. For departments, which comprise administrative level-2 units akin to a state or province, the president appoints governors from his or her same political party. Accordingly, Guatemala does not have political variation at the department level.

## 2.2. Identification Strategy

Although the lack of political variation at the department level may not be ideal for democracy, it is a boon for our identification strategy. Because there is no political variation in Guatemalan governors, the country is one of the very few in the world where we can directly estimate the effects of mayor-president party alignment on corruption. To causally identify these effects in each of our samples, we employ a series of sharp electoral regression discontinuity designs. They leverage random variation in close elections to as-if randomly assign winning mayors into alignment or non-alignment with the president on the basis of both the mayoral and presidential elections. In line with [Brollo and Nannicini \(2012\)](#), we identify the parameter of theoretical interest, the Local Average Treatment Effect (LATE), as:

$$\begin{aligned} \tau &= \mathbf{E}[r_{it}^{(aligned)} - r_{it}^{(unaligned)} | MV_{it} = 0] = \\ &\lim_{MV \downarrow 0} \mathbf{E}[r_{it} | MV_{it} = MV] - \lim_{MV \uparrow 0} \mathbf{E}[r_{it} | MV_{it} = MV], \text{ such that } MV \in (-h, h) \end{aligned} \quad (6)$$

where  $r_{it}$  reflects the amount of corruption in the aligned/unaligned municipality  $i$  at time  $t$  after a close election; the running variable,  $MV_{it}$ , is the margin of victory for aligned/unaligned mayor  $i$  in the most recent election for time  $t$ ; and  $\pm h$  corresponds to the upper/lower limit of an automatically derived, optimal close-election bandwidth for  $MV$ , following [Calonico, Cattaneo and Titiunik \(2014\)](#). For  $MV_{it} \in (-h, h)$ , we estimate  $\tau$  through a local polynomial regression following [Cattaneo, Idrobo and Titiunik \(2019, 70\)](#):

$$r_i = \alpha + f(MV_i) + \tau D_i + Z_i' \rho + \eta_i$$

$$\text{where } f(MV_i) = \sum_{k=1}^p \beta_k MV_i^k + \sum_{k=1}^p \gamma_k D_i \cdot MV_i^k \quad (7)$$

where  $\alpha$  is the intercept,  $\eta$  is a normally-distributed error term,  $D_i$  is the municipality alignment treatment dummy variable, and  $Z_i$  are the additional covariates that we include to ensure the robustness per [Calonico et al. \(2019\)](#). Following [Gelman and Imbens's \(2019\)](#) advice on avoiding potential bias-variance trade-offs, the estimation relies on polynomials fits of the first and the second order—i.e.,  $p \in (1, 2)$ . We also cluster the standard errors at the municipality level per [Bartalotti and Brummet \(2017\)](#), and follow [Frey \(2019\)](#) by including fixed effects where possible—a falsification test that is very uncommon, even among the most sophisticated regression discontinuity analyses (e.g., [Klašnja and Titiunik, 2017](#)).

### 2.3. Poverty Data and Samples for Estimation

The municipality-level poverty data in this paper come from Guatemala's National Statistics Institute (INE, *Instituto Nacional de Estadística*) poverty maps. The data specifically refer to the percent of people below the poverty and extreme poverty lines. As with most countries in the world, Guatemala does not measure municipal-level poverty rates on a yearly basis. Instead, the country only measures municipal-level poverty rates for the whole country during each census. The latest two years for which poverty map/census data are available are 2002 and 2011.

Given the lack of panel poverty data and inability of regression discontinuity designs to accommodate interactions, we split our sample into the following groups: low-poverty, high-poverty, poverty-increasing, poverty-decreasing, extreme poverty-decreasing, and extreme poverty-increasing municipalities. We construct the low/high poverty measures on the basis of the median. The poverty-decreasing and poverty-increasing samples correspond to municipalities in which poverty decreased or increased from one census measure to the



next. Finally, for comparison with the macro-level predictions of [Schwindt-Bayer and Tavits \(2016\)](#), we also provide estimations using the whole sample—i.e., not dividing the sample by the poverty levels or changes.

As we show in Tables [B5](#) and [B6](#), the low/high poverty samples vary in terms of whether they contain municipalities with increased or decreased poverty rates from one census to the next. The same is true when we analyze these samples by alignment status in Tables [B7](#) and [B6](#). Therefore, the low/high poverty measure and poverty-increasing/decreasing measure capture similar but distinct aspects of economic modernization.

For the analysis by high and low levels of poverty, the sample corresponds to the years 2004-2015. We provide the estimates by poverty or extreme poverty changes for the years 2010-2015 (main analysis), 2011-2015 (Appendix [N](#)), 2009-2015 (Appendix [O](#)), and 2008-2015 (Appendix [P](#)). To accommodate analysis with years other than 2011-2015, we backdate the 2011 poverty rate measure by one, two, or three years. This backdating is justifiable because census poverty measurements for 2011 took place between 2008-2011 ([Instituto Nacional de Estadística de Guatemala, 2014](#)), it is unlikely that estimates fluctuate much from year-to-year, and it is improbable that most citizens are aware or respond to INE's poverty rate announcements. Policy commitments and information are generally not very credible or abundant in a context of poverty like Guatemala, but people generally have a sense of whether their economic conditions are improving ([Banerjee and Duflo, 2007, 2011](#); [Keefer, 2004, 2007a,b](#); [Keefer and Khemani, 2005](#); [Keefer and Vlaicu, 2008](#); [Dunning et al., 2019](#)).

From our 331-municipality cross-section in the panel, poverty data are missing from 32 urban municipalities in 2011.<sup>19</sup> Accordingly, we provide a relevant analysis of these missing data in Appendix [R](#). On the basis of this analysis, we conclude that these missing data do not suggest any potential biases.

<sup>19</sup> According to an email communication with the Guatemalan National Statistics Institute (INE), the 2011 municipal poverty mapping exercise was funded entirely by the World Bank, and funding was not provided to the ascertain the poverty rates for all municipalities.

## 2.4. Electoral Data

We draw the municipal electoral data for this study from Guatemala’s Supreme Electoral Institute (TSE, *Tribunal Supremo Electoral*). After each election the TSE publishes a *Memoria Electoral*, which is an electoral almanac documenting the results of all electoral races in each respective election. For each election, we collected panel data on (i) the names of each winning mayor; (ii) the political party of each winning mayor; (iii) the political party of each second-place candidate; (iv) the number of votes acquired by each winning mayor; (v) the number of votes received by each second-place candidate; (vi) the total number of votes received in the municipalities; and (vii) the number of spoiled ballots. With these data, we first calculate the number of valid votes for each race by subtracting the number of spoiled ballots from the total votes. We then calculate the valid vote shares for the winning and second-place candidates by dividing the number of votes each received by the total number of valid votes. The margin of victory is thus the winning mayor’s share of valid votes received subtracted by those of the second-place candidate. Similar to [Brollo and Nannicini \(2012\)](#), our running variable for the regression discontinuity design is the margin of victory for the aligned/unaligned party mayor. To capture the aligned/unaligned distinction, we follow [Brollo and Nannicini \(2012\)](#) and multiply the margin of victory for the unaligned mayors by negative one (see Figures 1 and 2). If neither the first- nor second-place candidate is from the aligned party, we exclude it from the analysis. Such a strategy allows the empirical analysis to focus on close races in line with our theory and is consistent with the regression discontinuity analyses of [Meyersson \(2014\)](#), [Dell \(2015\)](#), and [Fergusson et al. \(2021\)](#).

Given that the TSE’s funding and capacity are limited ([Meilán, 2016](#)), we take additional steps to ensure that the data are not marred by electoral fraud and are suitable for analysis, etc. In Appendices L.1, L.2, L.3, L.4, L.5, and L.6, we run [McCrary \(2008\)](#) density tests corresponding to our running variable for all of the different samples in the main analyses and appendices. To do so, we use [Cattaneo, Jansson and Ma’s \(2018, 2020\)](#) new method. All tests corresponding to the original electoral term data pass. The failing tests

only correspond to some year-wise perspectives of the electoral data.<sup>20</sup>

## 2.5. Corruption Data

The corruption data for this study come from Guatemala’s Comptroller General (*Contraloría General de Cuentas*). Following Denly’s (2020) approach for discerning the validity of audit data, we examine for potential biases regarding the independence of the auditing agency, the partisan distribution of the audits, and their intensity/dosage in implementation.

With respect to independence, although corruption remains a significant problem in Guatemala, the country’s constitution and many laws protect the integrity of the Comptroller General and its findings. Notably, Article 233 of the current Guatemalan constitution (i.e. from 1985) stipulates that the head of the office (*Controlador de Cuentas*) is elected to four-year, non-reelectable terms by the Congress, not the President. Removing the *Controlador de Cuentas* is also uniquely within the purview of the Congress. It can only remove the *Controlador de Cuentas* by majority vote only for reasons pertaining to “negligence, crime, and lack of aptitude.” In short, Guatemala’s Comptroller General is not a patronage body that serves the interests of the president, making the audit data suitable for this study on alignment and corruption.

Fairness in the intensity/dosage of audit implementation is harder to verify with 100% certainty, especially because auditors need to use discretion when carrying out risk-based audits. Nevertheless, the Comptroller General has a robust code of ethics and Organic Law (*Contraloría General de Cuentas de Guatemala*, 2018). Both of these documents have numerous provisions underpinning its ability to carry out impartial audits, including restrictions on conflicts of interest and sanctions for poorly performing auditors.

<sup>20</sup> For example, a year-wise perspective on the 2010-2015 sample comprise the December 2007 election results twice (for the years 2009 and 2010); the December 2011 election results four times (for the years 2012, 2013, 2014, 2015); and the corruption (i.e. dependent variable) data for each respective year. A term-wise perspective for the same 2010-2015 period, by contrast, comprises the results from the December 2011 and December 2015 elections one time, with the respective corruption (i.e. dependent variable) data aggregated for each electoral term for the respective years in question. Accordingly, there is no concern regarding the original distributions of the electoral data.

Distributionally, each year the Comptroller General audits circa 320 of Guatemala’s 340 municipalities. As shown in Appendix L.9, unaligned municipalities are not more likely to be audited than their aligned counterparts. That is accurate for all of the samples that we examine in this study (see Section 2.3). Accordingly, there are no concerns regarding the partisan distribution of audits.

For each audited municipality from 2004-present, the Comptroller General publishes on its website: the number of overall infractions committed (*sancciones*), and the amount of stolen or misappropriated money in the local currency (Quetzales) associated with these infractions. Both of these variables serve as our study’s dependent variables and correspond most closely with bureaucratic corruption. As Fisman and Golden (2017, 41) explain, bureaucratic corruption takes place because “politicians permit it or fail to exercise adequate oversight to prevent it, all too often because they themselves are benefiting financially and politically.” In the case of these infractions-based measures in Guatemala, they encompasses both what Brollo et al. (2013, 1774) call “broad corruption” and “narrow corruption”.<sup>21</sup> For comparability purposes, we first deflate the money version of the infractions variable and then take its log. We do not transform the number of infractions committed variable. Appendix B provides relevant descriptive statistics and maps.

## 2.6. Other Data

Although most sharp regression discontinuity analyses typically assume that treatment assignment is as good as random within the data-driven bandwidth, we use Calonico et al.’s (2019) method to control for the influence of covariates within the bandwidth. Because more populous municipalities likely have more resources, which makes corruption more feasible, we use covariate data on population from Guatemala’s National Statistics Institute. To similarly control for resource influence, we include data on public goods spending from

<sup>21</sup> *Broad corruption* refers to “irregularities that could also be interpreted as bad administration as rather than as overt corruption.” *Narrow corruption* refers to “severe irregularities that are also more visible to the voters” (Brollo et al., 2013, 1774).

the Guatemalan Ministry of Finance.<sup>22</sup> Corruption also has prominent relationships with reelection and inequality (Alesina and Angeletos, 2005; Ferraz and Finan, 2011; Vuković, 2020), so we include relevant data from the Guatemalan Electoral Institute and Guatemalan National Statistics Institute. Tables B3 and B4 presents descriptive statistics of all covariate data by party alignment status.

### 3. Results

#### 3.1. Corruption Results Disaggregated by Poverty

Figure 3 presents the main results for the infractions dependent variable by electoral term. We show the term-wise results for the (log) amounts of stolen/misappropriated money dependent variable in Figure 4. The figures corresponding to the year-wise results for the same dependent variables, Figures A.1 and A.2, can be found in Appendix A. Appendices E, G, and K contain full tables.

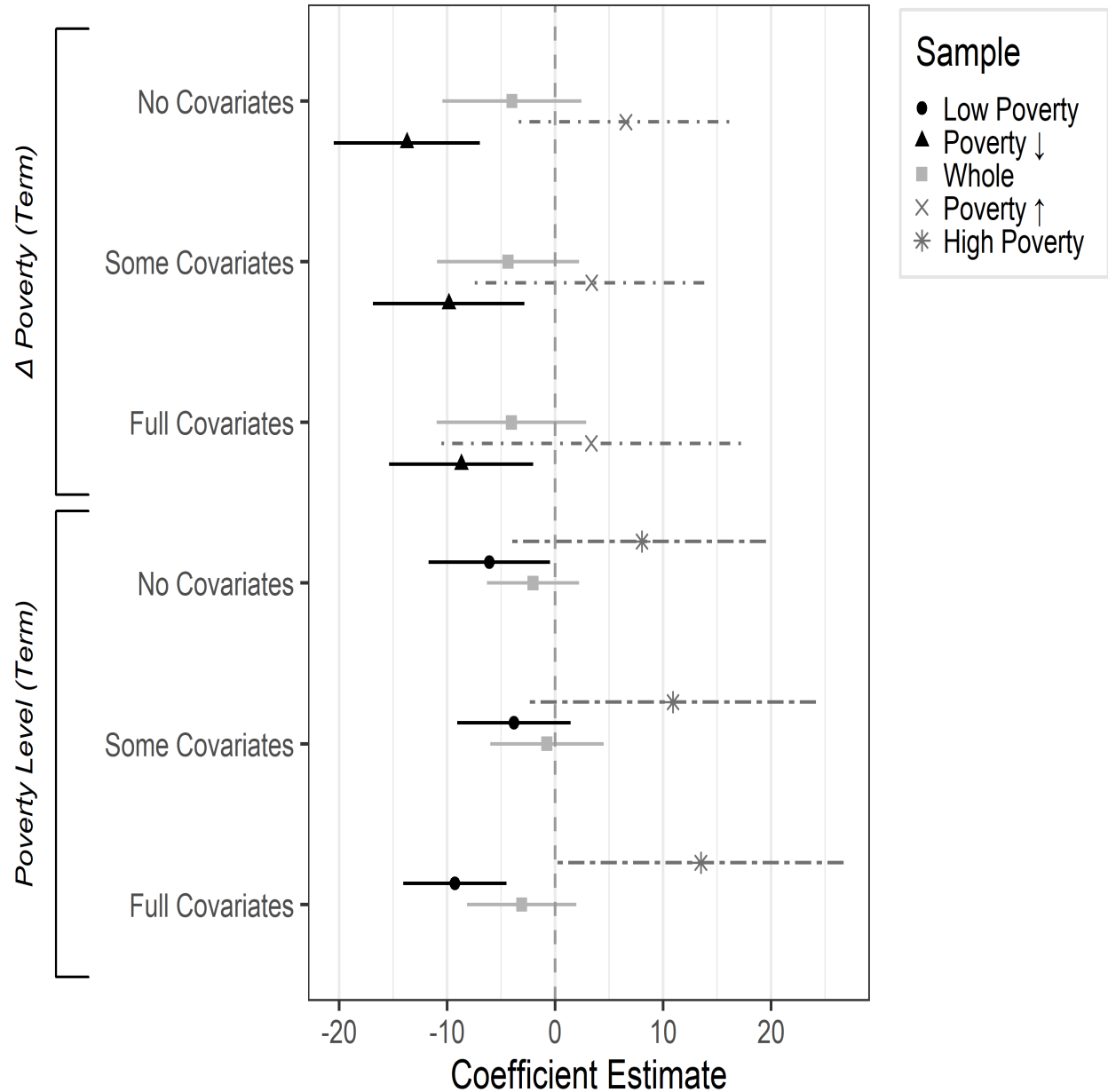
Overall, the results are similar for both yearly and electoral term data: party alignment consistently yields less corruption in the low-poverty and poverty-reducing samples. The results for these samples are not only statistically significant but substantively significant as well. For example, in our base term specification without fixed effects in Figure 3, aligned municipalities commit an average of 13.73 fewer infractions in the poverty-reducing sample and 6.09 fewer infractions in the low-poverty sample. In Appendix E, we undertake the extraordinary falsification test of adding fixed effects to our regression discontinuity estimates and find similar patterns as well. All of the results for the log amounts of stolen/misappropriated money in Figure 4 remain consistent, too.

Controlling for the influence of covariates within the automatically-derived, data-driven

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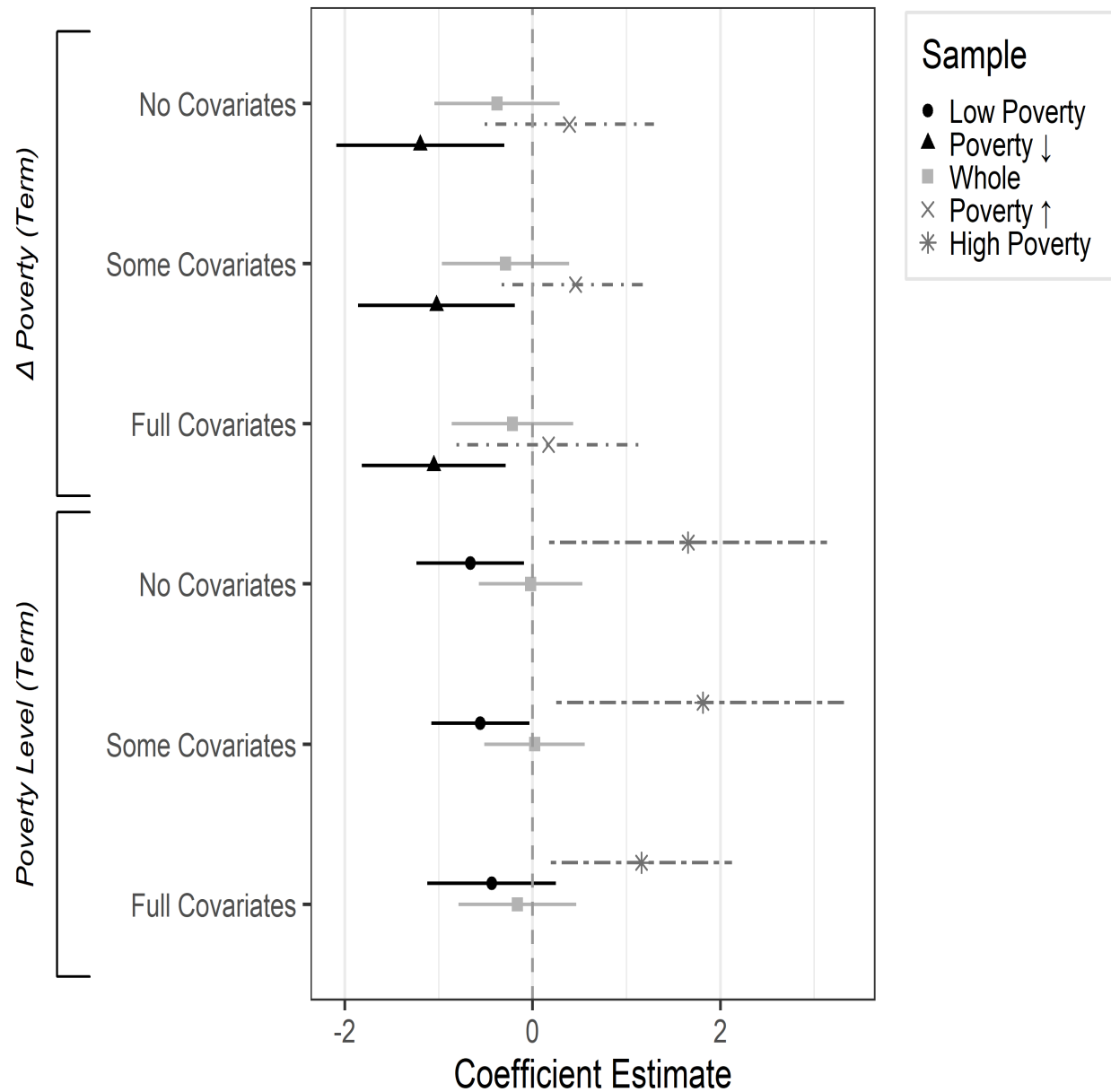
<sup>22</sup> These public goods data are publicly available through the World Bank's (2019) BOOST Initiative. The data aggregate spending on the following categories: Care and natural disaster management; defense and homeland security; defense; education; environmental protection; health; internal security; public order and safety; social protection; sports, culture, recreation, and religion; and urban community services.

Figure 3: Infraction Count by Term for Aligned Municipalities



Note: The above estimates are second-order polynomial fits in line with [Gelman and Imbens \(2019\)](#), with standard errors clustered by municipality and confidence intervals at the 90% level. Per Section 2.3, the poverty levels analyses correspond to 2004-2015, and the poverty change analyses correspond to 2010-2015. “Some Covariates” refer to (log) population and a mayor re-election dummy variable. “Full Covariates” refer to (log) population, a mayor re-election dummy, inequality (gini coefficient), and (log) public goods per capita. Full tables corresponding to the above Figure can be found in Appendices [E](#), [G](#), and [K](#).

Figure 4: Stolen/Misappropriated Money by Term for Aligned Municipalities (Log)



Note: The above estimates are second-order polynomial fits in line with [Gelman and Imbens \(2019\)](#), with standard errors clustered by municipality and confidence intervals at the 90% level. Per Section 2.3, the poverty levels analyses correspond to 2004-2015, and the poverty change analyses correspond to 2010-2015. “Some Covariates” refer to (log) population and a mayor re-election dummy variable. “Full Covariates” refer to (log) population, a mayor re-election dummy, inequality (gini coefficient), and (log) public goods per capita. Full tables corresponding to the above Figure can be found in Appendices [E](#), [G](#), and [K](#).

bandwidth in line with [Calonico et al. \(2019\)](#) also does not alter the interpretation of our results. In Appendix [L.7](#), we further show that these results are not due to outliers. When we change the samples to encompass different years in Appendices [N.1](#), [O.1](#), and [P.1](#), we also find similar results. Given that myriad tests reveal that poverty is not empirically endogenous to corruption (see Appendix [M](#)), the results for the low-poverty and poverty-reducing sample are robust.

The effects of alignment on reducing corruption in the poverty-reducing sample are more pronounced within the final two years of the electoral term. Tables [I13](#) and [I14](#) show the results for the last two years. When compared to the results from the first two years in Tables [J21](#) and [J22](#), it is clear that the final two years of each electoral term are mostly driving the decrease in corruption in the low-poverty and poverty-reducing samples. Overall, these results are consistent with [Ferraz and Finan \(2008\)](#) and [Bobonis, Cámara Fuertes and Schwabe \(2016\)](#), who find that audits in Brazil and Puerto Rico are most effective at reducing corruption closer to elections. More broadly, the results of our analysis are consistent with [Barro \(1973\)](#), [Ferejohn \(1986\)](#), [Ferraz and Finan \(2011\)](#), and [de Janvry, Finan and Sadoulet \(2012\)](#): elections help discipline politicians. In our case, that applies even to aligned politicians, who generally enjoy resource advantages relative to non-aligned politicians (e.g. [Brollo and Nannicini, 2012](#); [Carozzi and Repetto, 2016](#); [Corvalan, Cox and Osorio, 2018](#); [Lara and Toro, 2019](#)).

As predicted by our theory, alignment only reduces corruption in the poverty-reducing and low-poverty samples. Appendix [G.1](#) disaggregates results for the sample in which poverty increased from one census to next, and Appendix [G.2](#) shows the results for the municipalities with poverty higher than the median level. In both Appendices [G.1](#) and [G.2](#), results generally shift in the opposite direction from the low-poverty and poverty-reducing samples (see Figures [3](#) and [4](#)). When poverty is high or increased from one census to the next, there is an uptick in corruption—again, measured by infractions or the log amounts of stolen/misappropriated money associated with those infractions. Theoretically, it is log-



ical that poorer voters may be more forgiving of mayors' corruption, as long as the mayors share their rents with voters through clientelistic or other means means (Fernández-Vázquez, Barberá and Rivero, 2016). However, the year-wise specifications for the poverty-increasing sample fail the McCrary (2008) density tests in Appendices L.1, L.2, L.3, L.4, and L.5, and none of the specifications for the poverty-increasing sample have statistically significant results. The same is true for when we alter the sample in Appendices N.2, O.2, and P.2. Accordingly, we caution against interpreting the results from the high-poverty and poverty-increasing samples as definitive evidence of higher poverty facilitating aligned mayors to extract higher levels of rents.

For purposes of comparison with current predictions of clarity of responsibility theory (see Schwindt-Bayer and Tavits, 2016), all of the aforementioned Figures and Appendix K show the results for the whole sample—i.e., when not disaggregating by poverty. Overall, these findings from the whole sample are inconsistent. Sometimes, alignment yields less corruption; other times, it leads to more corruption. In all instances, though, none of the results are statistically significant. We thus interpret the whole sample results as evidence of the fact that alignment both provides resource advantages and increases clarity of responsibility. When not disaggregating the sample by poverty, these countervailing effects often cancel each other out, which is what the data show here.

### 3.2. Corruption Results Disaggregated by Extreme Poverty

To further assess the extent to which better economic conditions can reduce corruption from aligned politicians, we also examine the extent to which low or decreasing extreme poverty yields similar results as those of low or decreasing poverty. In all specifications, which are detailed in Appendix F, alignment reduces corruption when extreme poverty is low or declines. In our base specification with second-degree polynomial fits, aligned municipalities commit an average 7.1 fewer infractions in the poverty-reducing sample and 4.2 fewer infractions in the low-poverty sample in each term. Results are a bit weaker for the log

amounts of stolen/misappropriated money, as less specifications are statistically significant. Nevertheless, the results with the log amounts as the dependent variable are still suggestive of the same overall pattern: reductions in extreme poverty yields a situation in which aligned politicians reduce their overall corruption levels.

As with the previous subsection, the same results do not hold for the high-extreme-poverty or increasing-extreme-poverty samples (see Appendix H). In nearly all specifications entailing counts of the number of infractions and the (log) amounts associated with those infractions, the coefficient for alignment is positive, indicating that alignment yields an increase in corruption. However, similar to the results for the high-poverty and the poverty-increasing samples, none of the results are statistically significant for the high-extreme-poverty or increasing-extreme-poverty samples, and the year-wise specification does not pass the McCrary (2008) density test (see Appendix L.6).

## 4. Analysis of the Poverty, Alignment, and Close Elections Mechanisms

### 4.1. Alignment as a Mechanism to Signal Politicians' Clarity of Responsibility for Misgovernance to Voters

A premise of the above results is that alignment can act as a mechanism to signal politicians' clarity of responsibility for misgovernance to voters, and that politicians are aware and take mitigating measures (see Appendix D). Although Schwindt-Bayer and Tavits (2016) clearly and comprehensively demonstrate the power of the mechanism, it is necessary to empirically reaffirm with data from Guatemala. We do so with an analysis of municipal corruption levels before and after Guatemala experienced an alignment and party system shock in 2016.

Table 1: Infractions and Stolen/Misappropriated Money Amounts by Alignment Shares

| Term                         | Municipalities<br>Aligned % | Infractions<br>Mean | Amount<br>Mean | Log Amount<br>Mean |
|------------------------------|-----------------------------|---------------------|----------------|--------------------|
| 2008-2011 (Colom)            | 31%                         | 5.33                | 213,240.9 Q    | 12.27              |
| 2012-2015 (Molina/Maldonado) | 36%                         | 6.56                | 215,885.7 Q    | 12.28              |
| 2016-2019 (Morales)          | 0%                          | 12.84               | 429,378.8 Q    | 12.97              |

Note: All amounts adjusted for inflation in the local currency, Quetzales. We exclude the 2004-2007 term since the number of audits taking place from 2004-2006 was minimal.

In Guatemala’s October 25, 2015 run-off election, the people elected a populist outsider, Jimmy Morales, as president. Since not a single candidate from Morales’ party, National Convergence Front (FCN), won a mayoral race during the same general election, it ensured that there were no mayoral-presidential party alignments for the 2016-2019 period.<sup>23</sup> The lack of alignments for the 2016-2019 period limits the ability of the results in the previous sections to travel to other instances of party system instability. By the same token, the shock of electing a populist outsider and its consequent effects on alignment allows us to credibly identify the power of the alignment mechanism and thus support the results presented above.

Both the mean number of municipal-level infractions and amount of misappropriated money increased significantly after the election of Morales (see Table 1). Nevertheless, the (quasi) natural experiment of Morales’ election is probably not sufficient for these descriptive statistics in Table 1 to be interpreted on their own. We therefore supplement these descriptive statistics with the regression analyses presented in Table 2 and the additional tables in Appendix S. Each regression contains the main, time-varying covariates used in our regression discontinuity analyses throughout the paper as well as the poverty indicators used to construct our samples. We exclude the alignment variable because it is collinear with the Morales Term variable, which serves as our main independent variable for the analysis. We also do not interpret the control variables per Cinelli and Hazlett (2020, 45). Given that infractions is a count variable, we estimate those respective regressions with Poisson

<sup>23</sup> New presidents in Guatemala take power in January, and the relevant elections take place late in the previous year.

Table 2: Number of Infractions Committed (2008-2019)

|                  | (1)                 | (2)                 | (3)                 | (4)                 | (5)                 | (6)                 |
|------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Morales Term     | 0.786***<br>(0.022) | 0.748***<br>(0.022) | 0.443***<br>(0.046) | 0.787***<br>(0.021) | 0.573***<br>(0.036) | 0.487***<br>(0.049) |
| Poverty Reduced  |                     | -0.071**<br>(0.035) | -0.073**<br>(0.036) |                     |                     |                     |
| Population (log) |                     |                     |                     |                     | 1.571***<br>(0.209) | -0.337<br>(0.301)   |
| Re-elected Mayor |                     |                     |                     |                     | 0.008<br>(0.034)    | 0.002<br>(0.031)    |
| Observations     | 3801                | 3357                | 3357                | 3801                | 3518                | 3518                |
| Municipality FE  | No                  | No                  | No                  | Yes                 | Yes                 | Yes                 |
| Year FE          | No                  | No                  | Yes                 | No                  | No                  | Yes                 |

Note: Poisson regression model, since infractions are a count variable.

Standard errors clustered by municipality in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

and negative binomial models, and the log amounts regressions are estimated with linear regression.

Consistent with our expectations, the Morales Term variable is mostly positive and highly statistically significant throughout. The results are slightly stronger for the number of infractions than the log amounts of stolen/misappropriated money associated with those infractions, but the overwhelming evidence points to increased corruption following the election of populist outsider Morales. In short, party system instability is associated with more corruption. Since the party system instability makes it more difficult to discern clarity of responsibility due to the lack of alignments, mayors take advantage of the institutional configuration and oversee municipalities that commit more corruption.

## 4.2. Analysis of the Poverty Mechanism

For the main results presented in Sections 3.1 and 3.2 to map well to our theory, it is necessary to further demonstrate the power and appropriateness of the poverty mechanism.

To do so, first, we show that poverty is exogenous to corruption. Second, we provide an empirical analysis of corrupt vs. non-corrupt mayors by alignment status in our low-poverty, high-poverty, poverty-reducing and poverty-increasing samples.

If poverty is endogenous to corruption in our empirical analysis, it is not appropriate to interpret the results presented in Sections 3.1 and 3.2 as causal. We therefore test for endogeneity between poverty and corruption in Appendix M. Since endogeneity entails a correlation between the independent variable and the error term, we first directly test for such a relationship using two-stage regression analysis (see Appendix M.2). In the first stage, we separately run a regression of poverty on each of corruption variables: the number of infractions committed and the log amounts of stolen/misappropriated money associated with those infractions. In the second stage, we regress the residuals from the first-stage equation on each corruption variable. In all instances, the results suggest no overall relationship and R-squared values that are essentially 0, indicating that there is no endogeneity between poverty and corruption. Since the lack of endogeneity is so critical to our results, we undertake a second set of regression analyses as well. More specifically, in Appendix M.1 we test whether corruption predicts poverty in a conventional linear regression. Using numerous specifications for both the year-wise and term-wise results, we find no empirical support for the proposition that poverty predicts corruption.

As a final piece of evidence in favor of both our overall results in Sections 3.1 and 3.2 as well as the poverty mechanism, we present descriptive statistics on how poverty and alignment condition behavior by both corrupt and non-corrupt mayors in Appendix Q. To facilitate such analysis, we use the median number of infractions committed and the log amounts of stolen/misappropriated money associated with those infractions to divide the sample into corrupt and non-corrupt mayors. Although the median measures of corrupt and non-corrupt mayors are crude, they help demonstrate how each mechanism melds together to support our theory.

Consider, for example, Panel A of Table Q1, which presents the number of infractions

committed in the poverty-reducing sample. Under such circumstances, approximately 58% of aligned mayors are less corrupt than the median, whereas 42% are more corrupt than the median. For unaligned mayors in the poverty-reducing sample, the results present the opposite pattern: 67% of mayors are more corrupt than the median, and 32% of mayors are less corrupt than the median. We can find results that similarly conform with our theory in Panel A of Table Q2, which presents the distribution of amounts in the poverty-decreasing sample. When the mayor is aligned, 69% of mayors are less corrupt than the median, whereas 31% of mayors are more corrupt than the median. For unaligned mayors the pattern again flips: 56% of mayors are more corrupt than the median, and 44% of mayors are less corrupt than the median. Overall, the combination of poverty and alignment contributes to differential municipal-level corruption patterns. Appendix Q provides even more tables and relevant analysis.

### 4.3. Close Elections as a Mechanism to Temper Rent-Seeking from Aligned Politicians (Placebo Tests)

Proposition 1 in our model suggests that aligned politicians engage in less rent-seeking than their unaligned counterparts as their margin of victory in the most recent election approaches zero. In Section 3, we found causal evidence consistent with Proposition 1 using a series of regression discontinuity designs.

In this subsection, we subject Proposition 1 to further scrutiny by conducting placebo tests that examine corruption activity of aligned and unaligned politicians away from the cutoff. In our regression discontinuity models, Calonico, Cattaneo and Titiunik’s (2014) algorithm usually resulted in data-driven bandwidths for  $MV$  at around 10% on either side of the cutoff. Accordingly, in this section we analyze the data in which  $MV > 10\%$  or  $MV < -10\%$ . Although the analyses in this subsection cannot facilitate the same type of causal interpretation as our earlier regression discontinuity analyses, the analyses show some useful correlations. More specifically, these correlations allow us to discern whether the same

Table 3: Infractions: How Close Elections Matter (2010-2015)

|                   | (1)               | (2)               | (3)               | (4)              | (5)                 | (6)               |
|-------------------|-------------------|-------------------|-------------------|------------------|---------------------|-------------------|
| Alignment         | -0.065<br>(0.045) | -0.061<br>(0.048) | -0.073<br>(0.048) | 0.028<br>(0.056) | 0.039<br>(0.065)    | 0.014<br>(0.065)  |
| Poverty Reduction |                   | -0.019<br>(0.049) | -0.017<br>(0.049) |                  |                     |                   |
| Log Population    |                   |                   |                   |                  | 2.813***<br>(0.500) | -1.017<br>(0.998) |
| Reelected Mayor   |                   |                   |                   |                  | 0.064<br>(0.066)    | 0.065<br>(0.064)  |
| Observations      | 1260              | 1125              | 1125              | 1260             | 1178                | 1178              |

Note: Poisson regression models; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Standard errors clustered by municipality in parentheses.

patterns generally hold away from cutoff. For our argument to find empirical support, the data away from the cutoff should not exhibit the same pattern as those in earlier sections.

Table 3 and the additional tables in Appendix T present the main results from the analysis of infractions outside the close election bandwidth. Under myriad negative binomial and poisson model specifications, alignment does not correlate with the number of infractions committed in less competitive elections. Results are similar when analyzing the log amounts of misappropriated money in Appendix T as well. The effect of alignment is only statistically distinguishable from zero when controlling for poverty reduction without municipal fixed effects. After adding the municipal fixed effects and control variables, the effect of alignment quickly becomes null. In short, the placebo tests we conduct here do not show causal relationships, but they provide support for the existence of a close election mechanism, which Propositions 1 and 2 buttress.

## 5. External Validity

As Findley, Kikuta and Denly (2021) explain, “external validity captures the extent to which inferences drawn from a given study’s sample apply to a broader population [generalizability] or other target populations [transportability].” The previous sections have demonstrated the power of the mechanisms, and the regression discontinuity estimates underpinning the main results of this study are credible from the perspective of causal inference. However, the main regression discontinuity results only apply to a subset of Guatemalan municipalities without further analysis.

Various scholars have proposed methods to ensure that regression discontinuity results extend beyond the as good as random neighborhood around the cutoff (e.g., Angrist and Rokkanen, 2015; Dong and Lewbel, 2015; Wing and Bello-Gomez, 2018), but that is not the goal of this article. Both our theory and empirics suggest that the results do not hold outside of close elections. Accordingly, we focus our generalizability analysis on whether the results hold for different subsets of the close-elections samples and whether the close-election samples are representative of the rest of Guatemalan municipalities.

As we show in Appendix L.10, we find the same patterns as the main analysis when we restrict the sample to municipalities that the Comptroller General audited in all four years of each respective electoral term. The same is true when we examine the average number of infractions and (log) amounts of stolen/missing money per electoral term, taking into account the number of times a municipality was audited in each term (see Appendix L.11). That is accurate for both the low-poverty and poverty-decreasing samples within each subset.

To examine whether the municipalities within the close-election bandwidth are fundamentally different than the rest, we turn to balance tests of the pre-treatment covariates in the close- and noncompetitive election samples. Balance tests are unnecessary for internal validity purposes, notably because balance relates to the sample, and frequentist statisti-



Table 4: Balance Tests for Close-Election and Noncompetitive-Election Samples

| Variable   | (1)                                       |                   | (2)  |                   | T-test             |
|--|---|-------------------|--|-------------------|--------------------|
|  | Close Election (MV ≤ 10%)<br>N/[Clusters] | Mean/SE           | Noncompetitive Election (MV > 10%)<br>N/[Clusters] | Mean/SE           | P-value<br>(1)-(2) |
| Panel A: Whole Sample (Poverty-Change Analysis) [2010-2015]              |   |                   |  |                   |                    |
| Population (log)   | 387<br>[274]                              | 10.230<br>(0.054) | 279<br>[220]                                       | 10.305<br>(0.068) | 0.287              |
| Inequality (Gini)  | 367<br>[263]                              | 25.453<br>(0.307) | 265<br>[217]                                       | 25.438<br>(0.338) | 0.968              |
| Public Goods p/c (log)   | 387<br>[274]                              | 7.210<br>(0.044)  | 279<br>[220]                                       | 7.209<br>(0.105)  | 0.996              |
| Panel B: Poverty-Reducing Sample (Poverty-Change Analysis) [2010-2015]   |   |                   |  |                   |                    |
| Population (log)   | 164<br>[115]                              | 10.312<br>(0.073) | 120<br>[93]  | 10.155<br>(0.075) | 0.063*             |
| Inequality (Gini)  | 164<br>[115]                              | 25.584<br>(0.410) | 120<br>[93]  | 25.467<br>(0.500) | 0.829              |
| Public Goods p/c (log)   | 164<br>[115]                              | 7.025<br>(0.065)  | 120<br>[93]  | 7.136<br>(0.166)  | 0.514              |
| Panel C: Poverty-Increasing Sample (Poverty-Change Analysis) [2010-2015] |   |                   |  |                   |                    |
| Population (log)   | 189<br>[134]                              | 10.173<br>(0.080) | 121<br>[100]                                       | 10.292<br>(0.103) | 0.272              |
| Inequality (Gini)  | 189<br>[134]                              | 25.653<br>(0.464) | 121<br>[100]                                       | 26.055<br>(0.486) | 0.475              |
| Public Goods p/c (log)   | 189<br>[134]                              | 7.296<br>(0.058)  | 121<br>[100]                                       | 7.214<br>(0.174)  | 0.644              |
| Panel D: Whole Sample (Poverty-Level Analysis) [2004-2015]               |   |                   |  |                   |                    |
| Population (log)   | 709<br>[316]                              | 10.164<br>(0.052) | 623<br>[308]                                       | 10.118<br>(0.056) | 0.350              |
| Inequality (Gini)  | 689<br>[315]                              | 22.919<br>(0.255) | 605<br>[306]                                       | 22.564<br>(0.298) | 0.275              |
| Public Goods p/c (log)   | 387<br>[274]                              | 7.573<br>(0.043)  | 279<br>[220]                                       | 7.653<br>(0.047)  | 0.148              |
| Panel E: Low-Poverty Sample (Poverty-Level Analysis) [2004-2015]         |   |                   |  |                   |                    |
| Population (log)   | 333<br>[186]                              | 10.160<br>(0.074) | 314<br>[178]                                       | 10.085<br>(0.074) | 0.272              |
| Inequality (Gini)  | 333<br>[186]                              | 23.628<br>(0.322) | 314<br>[178]                                       | 23.405<br>(0.395) | 0.602              |
| Public Goods p/c (log)   | 150<br>[115]                              | 7.755<br>(0.065)  | 123<br>[104]                                       | 7.860<br>(0.063)  | 0.175              |
| Panel F: High-Poverty Sample (Poverty-Level Analysis) [2004-2015]        |   |                   |  |                   |                    |
| Population (log)   | 376<br>[200]                              | 10.167<br>(0.062) | 309<br>[184]                                       | 10.152<br>(0.073) | 0.829              |
| Inequality (Gini)  | 356<br>[182]                              | 22.255<br>(0.370) | 291<br>[170]                                       | 21.658<br>(0.431) | 0.212              |
| Public Goods p/c (log)   | 237<br>[182]                              | 7.458<br>(0.049)  | 156<br>[133]                                       | 7.489<br>(0.061)  | 0.650              |

Note: Standard errors clustered by municipality. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

cal inference assumes that the sample broadly represents the population of interest (Gill, 1999; Ho et al., 2007; Imai, King and Stuart, 2008; Mutz, Pemantle and Pham, 2019).<sup>24</sup> For external validity purposes, though, that is an assumption that needs to be tested, particularly in regression discontinuity designs that only examine part of the overall sample. As Table 4 shows, all pre-treatment covariates show similar distributions in both the close- and noncompetitive election samples, as denoted by the clustered, robust  $p$ -values that we calculate per Hansen and Bowers (2008). We exclude the reelection variable because it is post-treatment to the election—or what Angrist and Pischke (2008) call a “bad control”.<sup>25</sup> Overall, the results from the balance and other generalizability tests suggests that the data are as-if randomly sampled from the broader population of interest (see Findley, Kikuta and Denly, 2021).

Finally, making transportability inferences is more challenging, because we do not have data for other countries. Nevertheless, the study’s robust results enable us to conjecture that they should hold when using similar *objective* corruption measures to examine poorer countries with democratic institutions and stable party systems. The data also need to include time periods before elections, which discipline corrupt behavior from politicians. Finally, because citizens preferences’ do not immediately respond to reductions in poverty or increasing income (Treisman, 2020), the poverty change data need to have mid-to-long term intervals for corruption levels to possibly change. In other words, it is unlikely that small yearly changes in poverty will have the same effects on corruption that we have documented throughout this paper with mid-to-longer term intervals.

<sup>24</sup>More generally, frequentist statistical inference is based on the idea of a sampling distribution, for which the data are presumed to be random samples of the population (Gill, 1999).

<sup>25</sup> For more on which variables to include in balance tests, see Dunning (2012, 239-242).

## 6. Conclusion

In a recent review, eminent corruption scholars [Golden and Mahdavi \(2015, 414\)](#) suggest that “[t]o understand variations in the frequency of bureaucratic corruption requires a theory of electoral incentives governing strategies of bureaucratic slippage, something that is a long way off.” By showing how party alignment’s conditional effects on corruption is dependent on poverty and electoral competition, we demonstrate that such a theory is no longer “a long way off”. Overall, our findings echo [Weitz-Shapiro’s \(2012, 2014\)](#) work about why politicians opt-out of clientelism in Argentina, but note that our work on the distinct phenomenon of corruption focuses on aligned politicians.

We find causal support for our theory using close-election regression discontinuity designs that measure corruption both through audit infractions and the (log) amounts of misappropriated/stolen money associated with those infractions. Analysis of both dependent variables demonstrate strong support for our theory, though results are marginally stronger for infractions than log amounts. That pattern is likely due to the greater electoral risk associated with stealing large amounts of money vis-à-vis committing lots of small infractions that are less visible to voters. Our results are very similar, albeit somewhat weaker, when party alignment dovetails with significant electoral competition and extreme poverty reduction. From measurement and external validity perspectives, our paper undertakes numerous checks that scholars can follow to credibly analyze corruption outside a context with randomized audits like Brazil, which has heretofore served as the main country in the literature.<sup>26</sup>

For our above theory to hold, it is necessary to have some form of party system stability. When voters succumb to the appeal of populist outsiders who claim to be able to “fix” the corrupt system, it often leads to even more corruption and the gradual death of democracy (e.g., [Levitsky and Ziblatt, 2018](#)). Our analysis adds to this literature, showing that party

<sup>26</sup> See, for example, [Ferraz and Finan \(2008, 2011\)](#), [Brollo et al. \(2013\)](#), [Avis, Ferraz and Finan \(2018\)](#), [Cavalcanti, Daniele and Galletta \(2018\)](#), and [Zamboni and Litschig \(2018\)](#).

system instability fuels local-level corruption by eliminating or decreasing alignment relationships that foster clarity of responsibility. Local-level politicians, in turn, take advantage of these institutional circumstances to oversee more corrupt governments at the local level.

When there is some form of party system stability and party alignment relationships, however, it is possible for alignment to decrease corruption through modernization forces such as poverty reduction. The focus on alignment is critical because aligned politicians are most likely to enjoy significant resource advantages, use these advantages to gain an electoral advantage over opposition parties, and hurt the quality of democracy in the process. What helps temper these pressures are competitive elections, which suggests that they have potential policy relevance for both aid providers as well.

Poverty is not endogenous to corruption in our models (see Appendix [M](#)), but the subgroup analyses that we performed throughout the paper only allowed us to make causal inferences about each subgroup independently. Regression discontinuity designs cannot incorporate interactions, and Guatemala (and most developing countries) only measure local-level poverty intermittently, so subgroup analysis was our only means to test our hypothesis. Nevertheless, our overall results suggest that modernization and political-institutional forces combine to place subnational units within a polity on different starting points, leading to different corruption paths.

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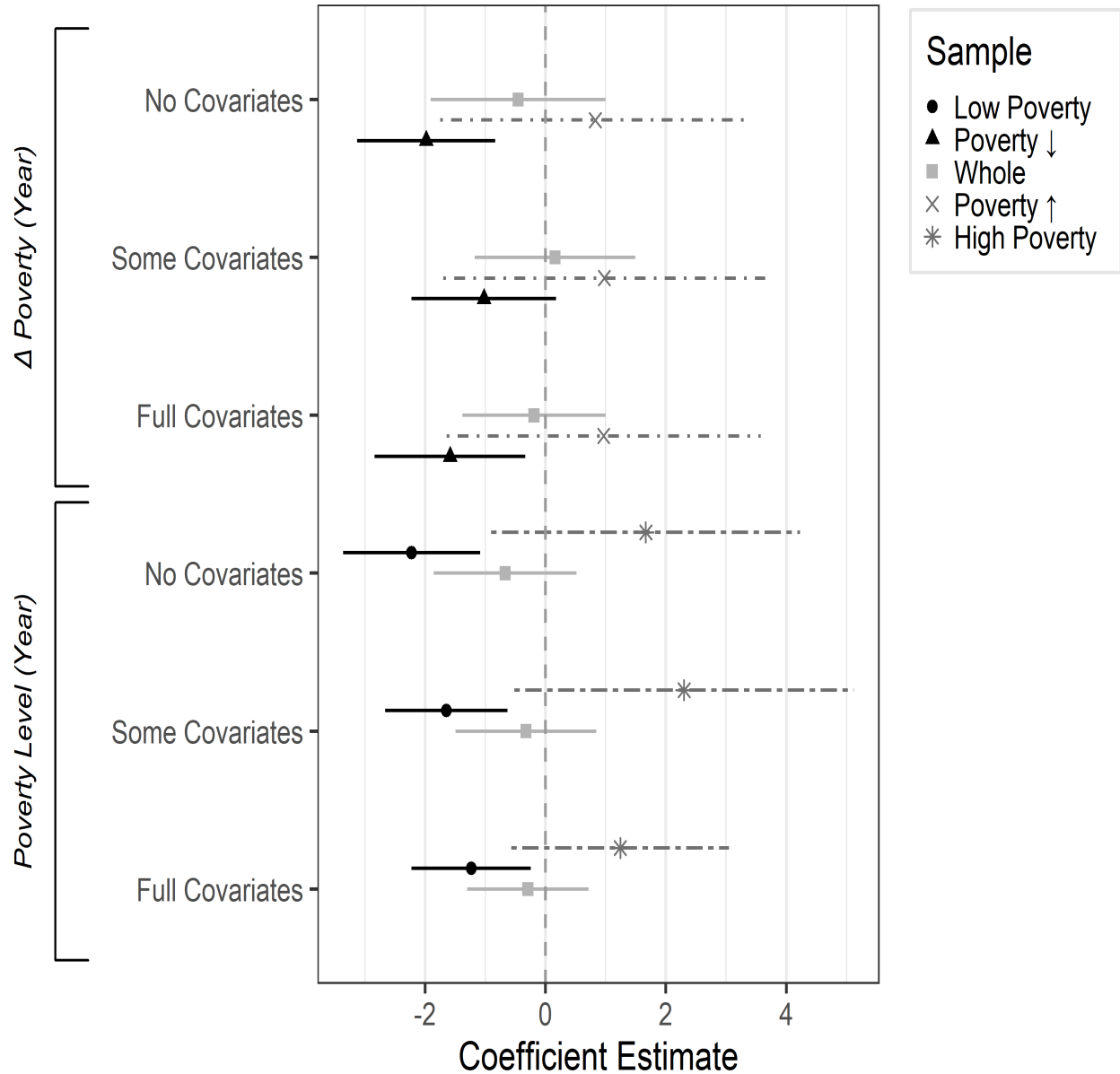
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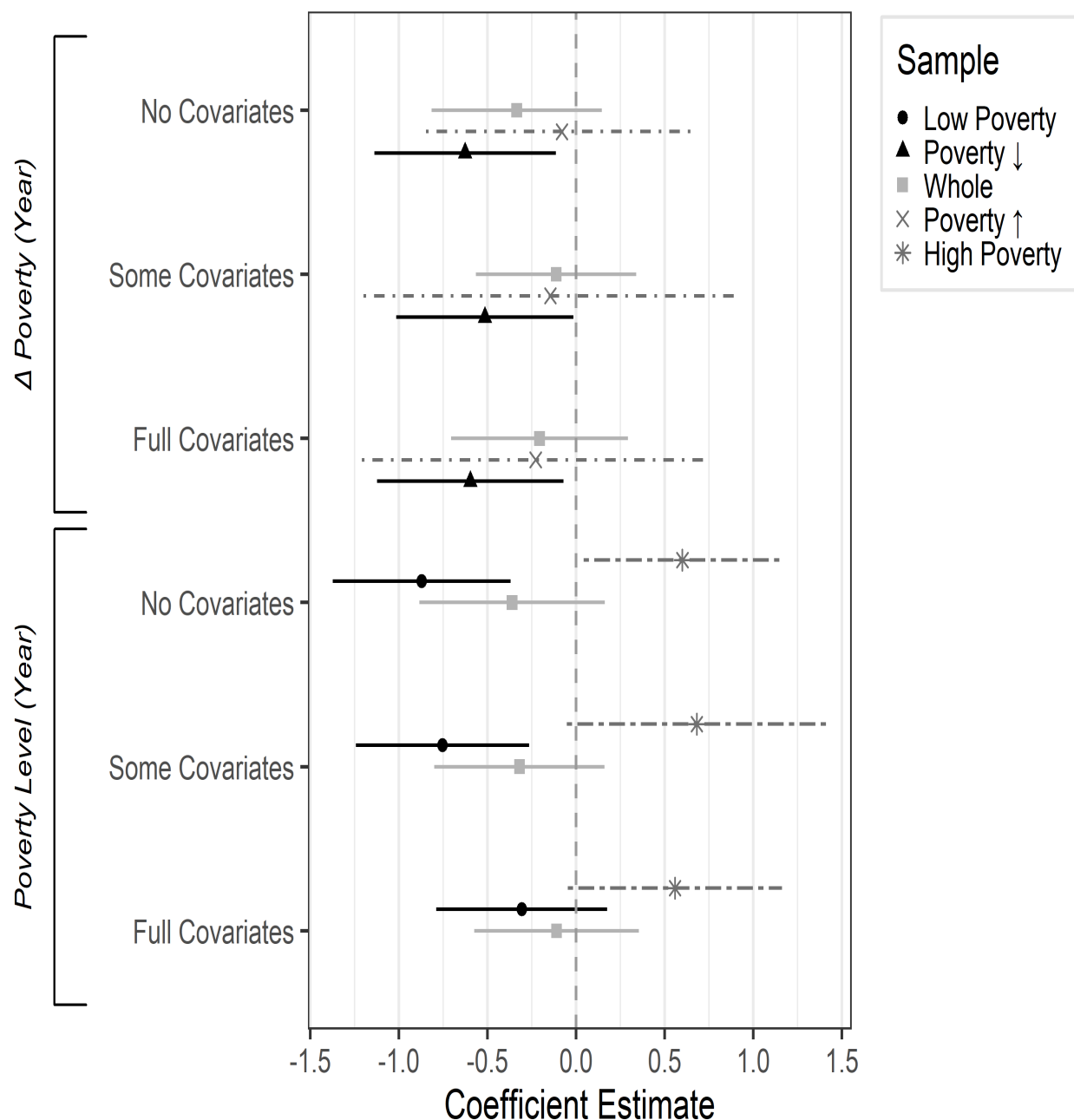
## A. Additional Coefficient Plots for Year-Wise Results

Figure A.1: Infraction Count by Year for Aligned Municipalities



Note: The above estimates are second-order polynomial fits in line with [Gelman and Imbens \(2019\)](#), with standard errors clustered by municipality and confidence intervals at the 90% level. Per Section 2.3, the poverty levels analyses correspond to 2004-2015, and the poverty change analyses correspond to 2010-2015. “Some Covariates” refer to (log) population and a mayor re-election dummy variable. “Full covariates” refer to (log) population, a mayor re-election dummy, inequality (gini coefficient), and (log) public goods per capita. Full tables corresponding to the above Figure can be found in Appendices [E](#), [G](#), and [K](#).

Figure A.2: Stolen/Misappropriated Money by Year for Aligned Municipalities (Log)



Note: The above estimates are second-order polynomial fits in line with [Gelman and Imbens \(2019\)](#), with standard errors clustered by municipality and confidence intervals at the 90% level. Per [Section 2.3](#), the poverty levels analyses correspond to 2004-2015, and the poverty change analyses correspond to 2010-2015. “Some Covariates” refer to (log) population and a mayor re-election dummy variable. “Full covariates” refer to (log) population, a mayor re-election dummy, inequality (gini coefficient), and (log) public goods per capita. Full tables corresponding to the above Figure can be found in [Appendices E, G, and K](#).

## B. Descriptive Statistics and Maps

Table B1: Descriptive Statistics of Infraction Variables (Poverty Increasing/Decreasing Sample)

| Panel A: Infractions (Year Viewpoint)                             |  | Increase  |       | Increase |     | Decrease  |       | Decrease |     |
|---|--|-----------|-------|----------|-----|-----------|-------|----------|-----|
| VARIABLES   |  | Unaligned | N     | Aligned  | N   | Unaligned | N     | Aligned  | N   |
|   |  | Mean      |       | Mean     |     | Mean      |       | Mean     |     |
| Number of Infractions: All Years                                  |  | 9.453     | 1,107 | 6.376    | 348 | 8.704     | 1,043 | 5.443    | 271 |
| Log Amount of Stolen/Misappropriated Money: All Years             |  | 11.53     | 1,106 | 11.40    | 347 | 11.50     | 1,041 | 11.20    | 270 |
| Number of Infractions: First 2 years of Term                      |  | 6         | 184   | 6.286    | 126 | 5.985     | 194   | 5.233    | 90  |
| Log Amount of Stolen/Misappropriated Money: First 2 years of Term |  | 11.21     | 183   | 11.29    | 125 | 11.24     | 193   | 10.91    | 89  |
| Number of Infractions: Last 2 years of Term                       |  | 6.071     | 395   | 6.428    | 222 | 6.438     | 384   | 5.547    | 181 |
| Log Amount of Stolen/Misappropriated Money: Last 2 years of Term  |  | 11.53     | 395   | 11.47    | 222 | 11.56     | 383   | 11.34    | 181 |
| Number of Infractions: Last year of Term                          |  | 6.894     | 198   | 7.387    | 111 | 7.373     | 193   | 6.154    | 91  |
| Log Amount of Stolen/Misappropriated Money: Last year of Term     |  | 11.83     | 198   | 11.89    | 111 | 11.84     | 192   | 11.61    | 91  |

| Panel B: Infractions (Electoral Term)                             |  | Increase  |     | Increase |     | Decrease  |     | Decrease |    |
|---|--|-----------|-----|----------|-----|-----------|-----|----------|----|
| VARIABLES   |  | Unaligned | N   | Aligned  | N   | Unaligned | N   | Aligned  | N  |
|   |  | Mean      |     | Mean     |     | Mean      |     | Mean     |    |
| Number of Infractions: All Years                                  |  | 29.56     | 354 | 19.99    | 111 | 27.10     | 335 | 16.21    | 91 |
| Log Amount of Stolen/Misappropriated Money: All Years             |  | 13.14     | 354 | 12.87    | 111 | 13.12     | 335 | 12.48    | 91 |
| f Number of Infractions: First 2 years of Term                    |  | 12        | 92  | 12.77    | 62  | 12.09     | 96  | 10.47    | 45 |
| Log Amount of Stolen/Misappropriated Money: First 2 years of Term |  | 12.08     | 92  | 12.27    | 62  | 12.21     | 96  | 11.72    | 45 |
| Number of Infractions: Last 2 years of Term                       |  | 12.05     | 199 | 12.86    | 111 | 12.88     | 192 | 11.03    | 91 |
| Log Amount of Stolen/Misappropriated Money: Last 2 years of Term  |  | 12.39     | 199 | 12.43    | 111 | 12.47     | 192 | 12.20    | 91 |
| Number of Infractions: Last year of Term                          |  | 6.894     | 198 | 7.387    | 111 | 7.411     | 192 | 6.154    | 91 |
| Log Amount of Stolen/Misappropriated Money: Last year of Term     |  | 11.83     | 198 | 11.89    | 111 | 11.84     | 192 | 11.61    | 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 B2: Descriptive Statistics of Infraction Variables (Poverty High/Low Sample)

| Panel A: Infractions (Year Viewpoint)                             |  | High      |       | High    |     | Low       |       | Low     |     |
|---|--|-----------|-------|---------|-----|-----------|-------|---------|-----|
|   |  | Unaligned |       | Aligned |     | Unaligned |       | Aligned |     |
| VARIABLES   |  | Mean      | N     | Mean    | N   | Mean      | N     | Mean    | N   |
| Number of Infractions: All Years                                  |  | 6.854     | 1,393 | 5.574   | 432 | 8.139     | 1,265 | 5.638   | 475 |
| Log Amount of Stolen/Misappropriated Money: All Years             |  | 11.32     | 1,390 | 11.34   | 431 | 11.62     | 1,265 | 11.34   | 474 |
| Number of Infractions: First 2 years of Term                      |  | 5.438     | 416   | 5.441   | 204 | 6.063     | 365   | 5.513   | 197 |
| Log Amount of Stolen/Misappropriated Money: First 2 years of Term |  | 11.23     | 414   | 11.24   | 203 | 11.38     | 365   | 11.18   | 196 |
| Number of Infractions: Last 2 years of Term                       |  | 5.882     | 407   | 5.944   | 198 | 6.656     | 372   | 6.117   | 205 |
| Log Amount of Stolen/Misappropriated Money: Last 2 years of Term  |  | 11.50     | 406   | 11.34   | 198 | 11.59     | 372   | 11.48   | 205 |
| Number of Infractions: Last year of Term                          |  | 6.754     | 199   | 6.698   | 96  | 7.521     | 192   | 6.953   | 106 |
| Log Amount of Stolen/Misappropriated Money: Last year of Term     |  | 11.83     | 198   | 11.76   | 96  | 11.83     | 192   | 11.77   | 106 |
| Panel B: Infractions (Electoral Term)                             |  | High      |       | High    |     | Low       |       | Low     |     |
|   |  | Unaligned |       | Aligned |     | Unaligned |       | Aligned |     |
| VARIABLES   |  | Mean      | N     | Mean    | N   | Mean      | N     | Mean    | N   |
| Number of Infractions: All Years                                  |  | 24.60     | 468   | 20.80   | 118 | 28.86     | 409   | 19.35   | 136 |
| Log Amount of Stolen/Misappropriated Money: All Years             |  | 13.13     | 468   | 13.14   | 118 | 13.37     | 409   | 12.94   | 136 |
| Number of Infractions: First 2 years of Term                      |  | 10.88     | 208   | 10.88   | 102 | 12.09     | 183   | 10.97   | 99  |
| Log Amount of Stolen/Misappropriated Money: First 2 years of Term |  | 12.16     | 208   | 12.25   | 102 | 12.32     | 183   | 12.06   | 99  |
| Number of Infractions: Last 2 years of Term                       |  | 11.76     | 208   | 11.87   | 103 | 13.24     | 183   | 12.20   | 99  |
| Log Amount of Stolen/Misappropriated Money: Last 2 years of Term  |  | 12.40     | 208   | 12.35   | 103 | 12.46     | 183   | 12.30   | 99  |
| Number of Infractions: Last year of Term                          |  | 6.716     | 208   | 6.689   | 103 | 7.643     | 182   | 6.980   | 99  |
| Log Amount of Stolen/Misappropriated Money: Last year of Term     |  | 11.80     | 208   | 11.77   | 103 | 11.87     | 182   | 11.76   | 99  |

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 B3: Descriptive Statistics of Covariates (Poverty Increasing/Decreasing Sample)

| Panel A: Year Viewpoint                |  | Increase  |       | Increase |     | Decrease  |       | Decrease |     |
|--|--|-----------|-------|----------|-----|-----------|-------|----------|-----|
|  |  | Unaligned |       | Aligned  |     | Unaligned |       | Aligned  |     |
| VARIABLES                              |  | Mean      | N     | Mean     | N   | Mean      | N     | Mean     | N   |
| Percentage of Mayor Reelected          |  | 0.305     | 1,160 | 0.217    | 332 | 0.326     | 1,110 | 0.0945   | 254 |
| Extreme Poverty Rate                   |  | 25.11     | 1,202 | 25.35    | 348 | 16.32     | 1,148 | 15.53    | 272 |
| Gini coefficient                       |  | 24.95     | 1,202 | 25.29    | 348 | 24.99     | 1,148 | 23.94    | 272 |
| Total Poverty Rate                     |  | 72.70     | 1,202 | 70.96    | 348 | 66.05     | 1,148 | 65.09    | 272 |
| Log Population                         |  | 10.29     | 1,202 | 10.22    | 348 | 10.34     | 1,148 | 10.12    | 272 |
| Log Public Goods Spending (per capita) |  | 6.428     | 582   | 6.144    | 348 | 6.148     | 580   | 6.382    | 272 |

| Panel B: Electoral Term                |  | Increase  |     | Increase |     | Decrease  |     | Decrease |    |
|--|--|-----------|-----|----------|-----|-----------|-----|----------|----|
|  |  | Unaligned |     | Aligned  |     | Unaligned |     | 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 | 10.34     | 335 | 10.10    | 91 |
| Log Public Goods Spending (per capita) |  | 7.308     | 199 | 7.186    | 111 | 6.983     | 193 | 7.260    | 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.

Table B4: Descriptive Statistics of Covariates (Poverty High/Low Sample)

| Panel A: Year Viewpoint                | High<br>Unaligned<br>Mean | N     | High<br>Aligned<br>Mean | N   | Low<br>Unaligned<br>Mean | N     | Low<br>Aligned<br>Mean | N   |
|--|---------------------------|-------|-------------------------|-----|--------------------------|-------|------------------------|-----|
| VARIABLES                              |                           |       |                         |     |                          |       |                        |     |
| Percentage of Mayor Reelected          | 0.270                     | 1,387 | 0.159                   | 390 | 0.365                    | 1,286 | 0.231                  | 450 |
| Extreme Poverty Rate                   | 30.22                     | 1,493 | 31.36                   | 435 | 10.73                    | 1,342 | 10.62                  | 477 |
| Gini coefficient                       | 22.17                     | 1,493 | 21.43                   | 435 | 25.04                    | 1,342 | 25.15                  | 477 |
| Total Poverty Rate                     | 82.25                     | 1,493 | 82.72                   | 435 | 54.01                    | 1,342 | 53.16                  | 477 |
| Log Population                         | 10.31                     | 1,493 | 10.15                   | 435 | 10.21                    | 1,342 | 10.14                  | 477 |
| Log Public Goods Spending (per capita) | 6.009                     | 729   | 5.958                   | 355 | 6.465                    | 650   | 6.494                  | 345 |

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| Panel B: Electoral Term                | High<br>Unaligned<br>mean | N   | High<br>Aligned<br>mean | N   | Low<br>Unaligned<br>mean | N   | Low<br>Aligned<br>mean | N   |
|--|---------------------------|-----|-------------------------|-----|--------------------------|-----|------------------------|-----|
| VARIABLES                              |                           |     |                         |     |                          |     |                        |     |
| Percentage of Mayor Reelected          | 0.275                     | 440 | 0.179                   | 106 | 0.359                    | 396 | 0.248                  | 129 |
| Extreme Poverty Rate                   | 31.61                     | 468 | 33.66                   | 118 | 12.09                    | 409 | 12.54                  | 136 |
| Gini coefficient                       | 22.92                     | 468 | 23.42                   | 118 | 25.83                    | 409 | 26.48                  | 136 |
| Total Poverty Rate                     | 82.84                     | 468 | 83.78                   | 118 | 56.51                    | 409 | 55.45                  | 136 |
| Log Population                         | 10.31                     | 468 | 10.15                   | 118 | 10.20                    | 409 | 10.12                  | 136 |
| Log Public Goods Spending (per capita) | 7.359                     | 209 | 7.462                   | 103 | 7.775                    | 183 | 7.791                  | 99  |

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.

Table B5: Wealth Distribution by Poverty Sub-Sample in 2002

| Poverty-Reducing Sample |           |       | Poverty-Increasing Sample |           |     |
|-------------------------|-----------|-------|---------------------------|-----------|-----|
| Poverty Level           | Frequency | %     | Poverty Level             | Frequency | %   |
| Below Median            | 41        | 28.87 | Below Median              | 93        | 60  |
| Above Median            | 101       | 71.13 | Above Median              | 62        | 40  |
| Total                   | 142       | 100   | Total                     | 155       | 100 |

Note: “Frequency” refers to the number of municipalities that had poverty levels below/above the median poverty level in the poverty mapping for the 2002 census, which serves as a proxy for the wealth distribution of the municipalities. “Poverty-Reducing Sample” refers to the sub-sample of municipalities where poverty decreased from 2002 to 2011, while “Poverty-Increasing Sample” refers to the sub-sample of municipalities where poverty increased between the two poverty measurements.

Table B6: Wealth Distribution by Poverty Sub-Sample in 2011

| Poverty-Reducing Sample |           |       | Poverty-Increasing Sample |           |       |
|-------------------------|-----------|-------|---------------------------|-----------|-------|
| Poverty Level           | Frequency | %     | Poverty Level             | Frequency | %     |
| Below Median            | 91        | 64.08 | Below Median              | 59        | 38.06 |
| Above Median            | 51        | 35.92 | Above Median              | 96        | 61.94 |
| Total                   | 142       | 100   | Total                     | 155       | 100   |

Note: “Frequency” refers to the number of municipalities that had poverty levels below/above the median poverty level in the poverty mapping for the 2011 census, which serves as a proxy for the wealth distribution of the municipalities. “Poverty-Reducing Sample” refers to the sub-sample of municipalities where poverty decreased from 2002 to 2011, while “Poverty-Increasing Sample” refers to the sub-sample of municipalities where poverty increased between the two poverty measurements.

Table B7: Wealth Distribution by Alignment and Poverty Sub-Samples in 2002

| Municipalities Above Median Poverty Level |           |       |       | Municipalities Below Median Poverty Level |           |       |       |
|---|-----------|-------|-------|---|-----------|-------|-------|
| Sample                                    | Alignment | Freq. | %     | Sample                                    | Alignment | Freq. | %     |
| Poverty-Reducing                          | Unaligned | 71    | 70.3  | Poverty-Reducing                          | Unaligned | 25    | 60.98 |
| Poverty-Reducing                          | Aligned   | 30    | 29.7  | Poverty-Reducing                          | Aligned   | 16    | 39.02 |
|   | Total     | 101   | 100   |   | Total     | 41    | 100   |
| Poverty-Increasing                        | Unaligned | 39    | 62.90 | Poverty-Increasing                        | Unaligned | 68    | 73.12 |
| Poverty-Increasing                        | Aligned   | 23    | 37.10 | Poverty-Increasing                        | Aligned   | 25    | 26.88 |
|   | Total     | 62    | 100   |   | Total     | 93    | 100   |

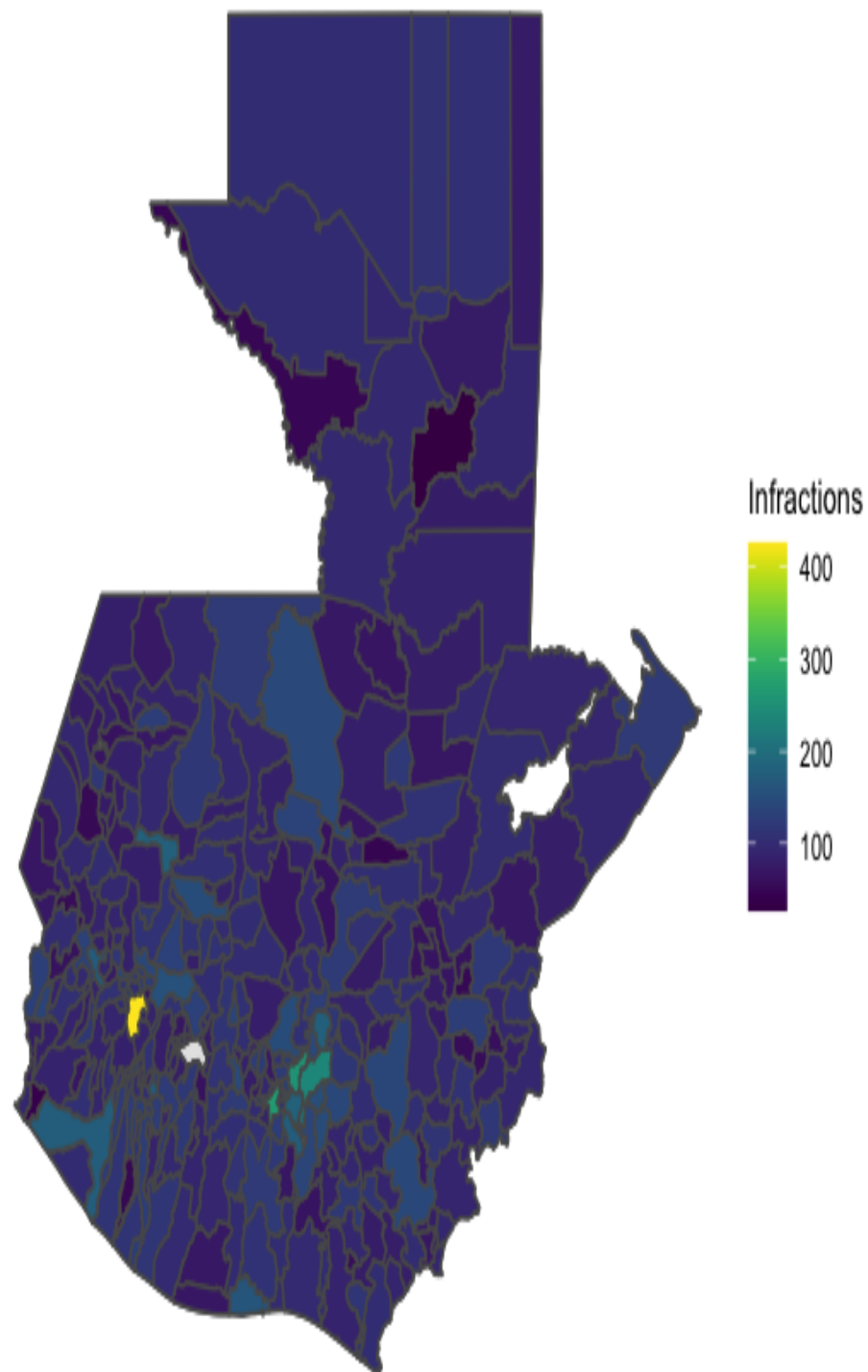
Note: “Municipalities Above Median Poverty Level” refers to the municipalities that have poverty levels above the national median poverty levels in the poverty mapping for the 2002 census, while “Municipalities Below Median Poverty Level” refer to the municipalities below the national median poverty level. “Reducing” refers to the sub-sample of municipalities where poverty decreased from 2002 to 2011, while “Increasing” refers to the sub-sample of municipalities where poverty increased during the same period. “Freq.” is the number of municipalities by alignment status in the Poverty-Increasing/Decreasing Samples.

Table B8: Wealth Distribution by Alignment and Poverty Sub-Samples in 2011

| Municipalities Above Median Poverty Level |           |       |       | Municipalities Below Median Poverty Level |           |       |       |
|---|-----------|-------|-------|---|-----------|-------|-------|
| Sample                                    | Alignment | Freq. | %     | Sample                                    | Alignment | Freq. | %     |
| Poverty-Reducing                          | Unaligned | 37    | 72.55 | Poverty-Reducing                          | Unaligned | 59    | 64.84 |
| Poverty-Reducing                          | Aligned   | 14    | 27.45 | Poverty-Reducing                          | Aligned   | 32    | 35.16 |
|   | Total     | 51    | 100   |   | Total     | 91    | 100   |
| Poverty-Increasing                        | Unaligned | 64    | 66.67 | Poverty-Increasing                        | Unaligned | 43    | 72.88 |
| Poverty-Increasing                        | Aligned   | 32    | 33.33 | Poverty-Increasing                        | Aligned   | 16    | 27.12 |
|   | Total     | 96    | 100   |   | Total     | 59    | 100   |

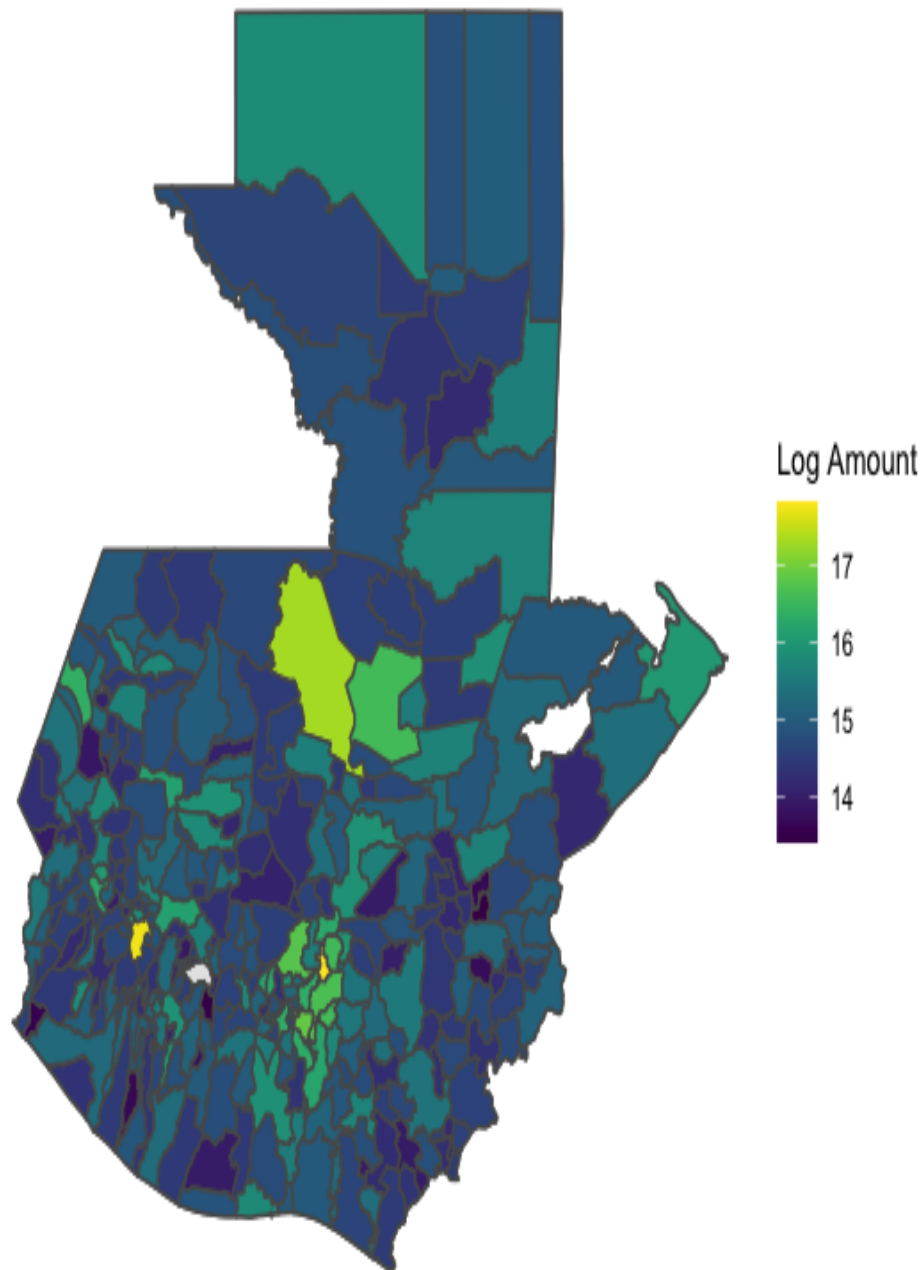
Note: “Municipalities Above Median Poverty Level” refers to the municipalities that have poverty levels above the national median poverty levels in the poverty mapping for the 2011 census, while “Municipalities Below Median Poverty Level” refer to the municipalities below the national median poverty level. “Poverty- Reducing” refers to the sub-sample of municipalities where poverty decreased from 2002 to 2011, while “Poverty-Increasing” refers to sub-sample of municipalities where poverty increased during the same period. “Freq.” is the number of municipalities by alignment status in the Poverty Increasing/Decreasing Samples.

Figure B.3: Total Infractions by Municipality, 2004-2019



Note: The three white areas are lakes.

Figure B.4: Total Misappropriated/Stolen Money by Municipality, 2004-2019



Note: The three white areas are lakes.

## C. Theoretical Derivation

**Proposition 1.** *Optimal rent levels for aligned politicians are less than rents levels for unaligned politicians at  $MV = 0$  when the electorate's economic circumstances are good or have improved.*

*Proof.* We solve for the following problem for the local-level politician in as in Equation (5):

$$\begin{aligned} \max_{r_{i,1}} & U(r_{i,1}) + \pi(s_i)U(r_{i,2}) + [1 - \pi(s_i)]U(x_{i,2}) \\ \text{where } s_i &= W(1 - r_{i,1}) + \beta_i^{1+a}W(\gamma r_{i,1}) + (2a - 1)t(MV) \end{aligned} \quad (8)$$

Accordingly, we can rewrite the maximization problem as follows:

$$\begin{aligned} \max_{r_{i,1}} & U(r_{i,1}) + \pi(W(1 - r_{i,1}) + \beta_i^{1+a}W(\gamma r_{i,1}) + (2a - 1)t(MV))U(r_{i,2}) \\ & + [1 - \pi(W(1 - r_{i,1}) + \beta_i^{1+a}W(\gamma r_{i,1}) + (2a - 1)t(MV))]U(x_{i,2}) \end{aligned} \quad (9)$$

The corresponding First-Order Condition (F.O.C.) for Equation (9) is:

$$\begin{aligned} 0 = & U'(r_{i,1}) + U(r_{i,2})\pi'(W(1 - r_{i,1}) + \beta_i^{1+a}W(\gamma r_{i,1}) + (2a - 1)t(MV))[-W'(1 - r_{i,1}) \\ & + \gamma\beta_i^{1+a}W'(\gamma r_{i,1})] - U(x_{i,2})\pi'(W(1 - r_{i,1}) + \beta_i^{1+a}W(\gamma r_{i,1}) \\ & + (2a - 1)t(MV))[-W'(1 - r_{i,1}) + \gamma\beta_i^{1+a}W'(\gamma r_{i,1})] \end{aligned} \quad (10)$$

Collecting like terms and bringing them to the other side, Equation (10) can be rewritten as:

$$\begin{aligned} U'(r_{i,1}) = & [U(r_{i,2}) - U(x_{i,2})]\pi'(W(1 - r_{i,1}) + \beta_i^{1+a}W(\gamma r_{i,1}) + (2a - 1)t(MV))[W'(1 - r_{i,1}) - \\ & \gamma\beta_i^{1+a}W'(\gamma r_{i,1})] \end{aligned} \quad (11)$$

Now from the assumption on  $t(\cdot)$ , we know that as  $MV \rightarrow 0$ ,  $t(MV) \rightarrow 0$  since  $t(\cdot)$  increases



with respect to  $MV$ . Thus, as  $MV \rightarrow 0$ , Equation (11) can be written as:

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

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

$$U'(\overline{r}_{i,1}) = [U(r_{i,2}) - U(x_{i,2})]\pi'(W(1 - \overline{r}_{i,1}) + \beta_i^2W(\gamma\overline{r}_{i,1}))[W'(1 - \overline{r}_{i,1}) - \gamma\beta_i^2W'(\gamma\overline{r}_{i,1})] \quad (13)$$

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

$$U'(\underline{r}_{i,1}) = [U(r_{i,2}) - U(x_{i,2})]\pi'(W(1 - \underline{r}_{i,1}) + \beta_i W(\gamma\underline{r}_{i,1}))[W'(1 - \underline{r}_{i,1}) - \gamma\beta_i W'(\gamma\underline{r}_{i,1})] \quad (14)$$

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  $z, k > 0$ .<sup>27</sup>

**Corollary 1:** *Optimal rents extraction levels for aligned and unaligned politicians do not differ at  $MV = 0$  if economic circumstances are poor or worsen.*

This proof follows from replacing  $\beta_i = 1$  in Equation (11) to show that both the aligned and unaligned cases result in the same First-Order Equation. ■ □

**Proposition 2.** *Optimal rent levels for aligned politicians increase with respect to  $MV$ , while they decrease with respect to  $MV$  for the unaligned politicians.*

*Proof.* The proof of this Proposition follows a similar structure as Brollo and Nannicini (2012, Proof of Proposition 2). Per Equation (10), we define the first-order condition as  $g(r_{i,1}, MV) = 0$ , so by implicit differentiation  $\partial r_{i,1} / \partial MV = -(\partial g / \partial MV) / (\partial g / \partial r_{i,1})$ , where

<sup>27</sup>The result follows from similar structural implications as derived in Brollo and Nannicini (2012, Proof of Proposition 1).

$\partial g/\partial r_{i,1} < 0$  due to the maximization of the second-order condition. By extension, therefore:

$$\begin{aligned} \partial g/\partial MV = & [U(r_{i,2}) - U(x_{i,2})]\pi'_{MV}(W(1 - r_{i,1}) + \beta_i^{1+a}W(\gamma r_{i,1}) + \\ & (2a - 1)t(MV))[W'(1 - r_{i,1}) - \gamma\beta_i^{1+a}W'(\gamma r_{i,1})][(2a - 1)t'(MV)] \end{aligned} \quad (15)$$

When  $a = 1$ :

$$\begin{aligned} \partial g/\partial MV = & [U(r_{i,2}) - U(x_{i,2})]\pi'_{MV}(W(1 - r_{i,1}) + \beta_i^2W(\gamma r_{i,1}) + \\ & t(MV))[W'(1 - r_{i,1}) - \gamma\beta_i^2W'(\gamma r_{i,1})]t'(MV) > 0 \end{aligned} \quad (16)$$

Therefore,  $-(\partial g/\partial MV)/(\partial g/\partial r_{i,1}) > 0$  when  $a = 1$ , or  $\partial r_{i,1}/\partial MV > 0$  when  $a = 1$ .

When  $a = 0$ :

$$\begin{aligned} \partial g/\partial MV = & -[U(r_{i,2}) - U(x_{i,2})]\pi'_{MV}(W(1 - r_{i,1}) + \beta_i W(\gamma r_{i,1}) \\ & - t(MV))[W'(1 - r_{i,1}) - \gamma\beta_i W'(\gamma r_{i,1})]t'(MV) < 0 \end{aligned} \quad (17)$$

Therefore,  $\partial r_{i,1}/\partial MV < 0$  when  $a = 0$ . ■

□

## D. Party Alignment's Effects on Clarity of Responsibility and Citizen Satisfaction

Party alignment signals clarity of responsibility for corruption: when local-level and national politicians share the same party, it makes it easier for voters to discern which political party is responsible for corruption. By contrast, under divided government, voters cannot make such snap judgments as easily (Schwindt-Bayer and Tavits, 2016). Consistent with how we represent  $t(\cdot)$  in Equation (4), we make two related arguments to underscore why alignment's effects are conditional on  $MV$ . First, citizens' levels of satisfaction with a local-level politician depend on the quality of political information available. Second, the latter is also at least partly a function of the joint effects of a local-level politician's margin of victory in the last election and party alignment status.

Figure 1 graphically depicts our argument on the information-related satisfaction benefits that citizens derive from clarity of responsibility, denoted by  $(2a - 1)t(MV)$  in Equation (4). Regions 3 and 4 correspond to the positive effects of clarity of responsibility, which the  $(2a - 1)$  term helps capture.<sup>28</sup> In Region 4, where the local-level politician won by a large margin and is aligned, citizens gain satisfaction from knowing that the benefits they received are attributable to one party, which makes understanding and engaging in politics easier. Citizens also derive some satisfaction from information clarity in Region 3, where the politician is still aligned but won by a smaller margin of victory. Nevertheless, the smaller margin of victory indicates that Region 3 is likely more winnable in the next election, which draws more attention from opposition party campaigns in the lead-up to the next election. In turn, the political information environment becomes less clear to citizens in Region 3 than in Region 4, and information clarity likely drops even more precipitously as  $MV \rightarrow 0$ —hence the shape of  $(2a - 1)t(MV)$  in Figure 1. Again, electoral competition is the primary driver of these information flows and intensifies with smaller margins of victory for the incumbent.

<sup>28</sup> When the politicians is aligned ( $a = 1$ ), then  $2(1) - 1 * MV$  must be positive. When the politician is unaligned ( $a = 0$ ), then  $(2(0) - 1) * MV$  must be negative.

When politicians are unaligned, as in Regions 1 and 2, returns to citizen-level satisfaction follow the reverse pattern. More specifically, citizens start to derive negative returns to information in Region 2, where the politician is unaligned and only won the last election by a small margin. The reason is that Region 2 is likely to attract very significant attention from the ruling party at the national level. Given that control of the bureaucracy tends to grant these parties with significant resource advantages over unaligned parties (Greene, 2010; Brollo and Nannicini, 2012; Corvalan, Cox and Osorio, 2018; Lara and Toro, 2019), the aligned party can overwhelm voters with information. At the same time, the unaligned party has an incentive to keep its position, creating a situation of information overload for citizens. The same information overload is unlikely to occur in Region 1, where the local-level politician is unaligned and won by a large margin of victory. Instead, citizens in Region 1 likely do not receive enough high-quality information about the political process, yielding lower levels of citizen satisfaction.<sup>29</sup> Both the national ruling party and other opposition parties have lower incentives to invest in electoral competition, so citizens cannot clearly discern who is responsible for their current situations in Region 1. While such concerns may not be salient when welfare is high, opposition politicians are at disadvantage given their lower levels of access to the spoils of the bureaucracy. Consequently, accurate evaluation of political candidates is most difficult for citizens in Region 1.

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<sup>29</sup>This relative lack of clarity and information leads to higher dissatisfaction in Region 1 than the information-overload encountered in Region 2

## E. When Poverty is Decreasing/Low

### E.1. When Poverty Decreases

Table E9: RDD Estimates for Infraction Count by Year

| Panel A                | (1)                  | (2)                  | (3)               | (4)               | (5)                | (6)                 |
|------------------------|----------------------|----------------------|-------------------|-------------------|--------------------|---------------------|
| RD Estimate            | -1.649***<br>(0.549) | -1.985***<br>(0.698) | -0.802<br>(0.560) | -1.025<br>(0.731) | -0.938*<br>(0.564) | -1.587**<br>(0.761) |
| Observations           | 601                  | 601                  | 569               | 569               | 569                | 569                 |
| Effective Observations | [192,138]            | [198,139]            | [170,112]         | [174,128]         | [170,112]          | [154,104]           |
| Covariates             | None                 | None                 | Some              | Some              | All                | All                 |
| p-value                | 0.00266              | 0.00448              | 0.152             | 0.161             | 0.0963             | 0.0371              |
| Order of Polynomial    | 1                    | 2                    | 1                 | 2                 | 1                  | 2                   |
| Bandwidth              | 0.102                | 0.105                | 0.0943            | 0.0982            | 0.0936             | 0.0851              |
| Panel B                | (1)                  | (2)                  | (3)               | (4)               | (5)                | (6)                 |
| RD Estimate            | -1.219**<br>(0.582)  | -1.453*<br>(0.761)   | -0.522<br>(0.591) | -0.727<br>(0.759) | -0.712<br>(0.608)  | -1.365*<br>(0.779)  |
| Observations           | 601                  | 601                  | 569               | 569               | 569                | 569                 |
| Effective Observations | [182,138]            | [198,139]            | [170,112]         | [174,128]         | [166,112]          | [154,104]           |
| Covariates             | None                 | None                 | Some              | Some              | All                | All                 |
| p-value                | 0.0361               | 0.0563               | 0.378             | 0.338             | 0.242              | 0.0797              |
| Order of Polynomial    | 1                    | 2                    | 1                 | 2                 | 1                  | 2                   |
| Bandwidth              | 0.0992               | 0.110                | 0.0912            | 0.0991            | 0.0905             | 0.0869              |

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 E10: RDD Estimates for Infraction Count by Electoral Term

| Panel A                | (1)                  | (2)                  | (3)                 | (4)                 | (5)                 | (6)                 |
|------------------------|----------------------|----------------------|---------------------|---------------------|---------------------|---------------------|
| RD Estimate            | -10.98***<br>(2.996) | -13.73***<br>(4.113) | -7.952**<br>(3.358) | -9.853**<br>(4.261) | -7.339**<br>(3.245) | -8.692**<br>(4.052) |
| Observations           | 195                  | 195                  | 179                 | 179                 | 179                 | 179                 |
| Effective Observations | [56,45]              | [62,49]              | [46,35]             | [58,45]             | [45,34]             | [57,44]             |
| Covariates             | None                 | None                 | Some                | Some                | All                 | All                 |
| Conventional p-value   | 0.000247             | 0.000845             | 0.0179              | 0.0208              | 0.0237              | 0.0320              |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                   | 2                   |
| Bandwidth              | 0.0958               | 0.106                | 0.0819              | 0.112               | 0.0772              | 0.107               |
| Panel B                | (1)                  | (2)                  | (3)                 | (4)                 | (5)                 | (6)                 |
| RD Estimate            | -3.805*<br>(1.982)   | -5.131*<br>(2.717)   | -1.614<br>(2.118)   | -2.859<br>(2.820)   | -2.344<br>(2.252)   | -4.842<br>(2.976)   |
| Observations           | 195                  | 195                  | 179                 | 179                 | 179                 | 179                 |
| Effective Observations | [57,47]              | [62,49]              | [48,36]             | [53,43]             | [45,34]             | [47,35]             |
| Covariates             | None                 | None                 | Some                | Some                | All                 | All                 |
| Conventional p-value   | 0.0548               | 0.0590               | 0.446               | 0.311               | 0.298               | 0.104               |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                   | 2                   |
| Bandwidth              | 0.0967               | 0.106                | 0.0872              | 0.0987              | 0.0796              | 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 E11: RDD Estimates for Infraction Amount (log) by Year

| Panel A                | (1)                  | (2)                 | (3)                 | (4)                | (5)                 | (6)                |
|------------------------|----------------------|---------------------|---------------------|--------------------|---------------------|--------------------|
| RD Estimate            | -0.773***<br>(0.216) | -0.627**<br>(0.311) | -0.564**<br>(0.256) | -0.515*<br>(0.304) | -0.660**<br>(0.264) | -0.598*<br>(0.320) |
| Observations           | 598                  | 598                 | 566                 | 566                | 566                 | 566                |
| Effective Observations | [206,147]            | [182,136]           | [144,98]            | [170,112]          | [146,102]           | [188,129]          |
| Covariates             | None                 | None                | Some                | Some               | All                 | All                |
| p-value                | 0.000354             | 0.0436              | 0.0274              | 0.0908             | 0.0123              | 0.0619             |
| Order of Polynomial    | 1                    | 2                   | 1                   | 2                  | 1                   | 2                  |
| Bandwidth              | 0.120                | 0.0971              | 0.0730              | 0.0939             | 0.0777              | 0.109              |
| Panel B                | (1)                  | (2)                 | (3)                 | (4)                | (5)                 | (6)                |
| RD Estimate            | -0.731***<br>(0.213) | -0.587*<br>(0.310)  | -0.488*<br>(0.263)  | -0.454<br>(0.312)  | -0.574**<br>(0.267) | -0.588*<br>(0.322) |
| Observations           | 598                  | 598                 | 566                 | 566                | 566                 | 566                |
| Effective Observations | [208,151]            | [182,136]           | [140,86]            | [170,118]          | [144,98]            | [170,118]          |
| Covariates             | None                 | None                | Some                | Some               | All                 | All                |
| p-value                | 0.000613             | 0.0581              | 0.0633              | 0.146              | 0.0315              | 0.0676             |
| Order of Polynomial    | 1                    | 2                   | 1                   | 2                  | 1                   | 2                  |
| Bandwidth              | 0.123                | 0.0972              | 0.0707              | 0.0947             | 0.0732              | 0.0952             |

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 E12: RDD Estimates for Infraction Amount (log) by Term

| Panel A                | (1)                  | (2)                 | (3)                  | (4)                 | (5)                  | (6)                 |
|------------------------|----------------------|---------------------|----------------------|---------------------|----------------------|---------------------|
| RD Estimate            | -1.240***<br>(0.427) | -1.197**<br>(0.544) | -1.080***<br>(0.389) | -1.024**<br>(0.508) | -1.016***<br>(0.371) | -1.053**<br>(0.466) |
| Observations           | 195                  | 195                 | 179                  | 179                 | 179                  | 179                 |
| Effective Observations | [48,37]              | [56,43]             | [45,34]              | [51,38]             | [47,35]              | [51,38]             |
| Covariates             | None                 | None                | Some                 | Some                | All                  | All                 |
| Conventional p-value   | 0.00368              | 0.0280              | 0.00547              | 0.0437              | 0.00615              | 0.0239              |
| Order of Polynomial    | 1                    | 2                   | 1                    | 2                   | 1                    | 2                   |
| Bandwidth              | 0.0739               | 0.0942              | 0.0792               | 0.0903              | 0.0865               | 0.0908              |
| Panel B                | (1)                  | (2)                 | (3)                  | (4)                 | (5)                  | (6)                 |
| RD Estimate            | -0.819**<br>(0.369)  | -0.762<br>(0.470)   | -0.645*<br>(0.381)   | -0.564<br>(0.483)   | -0.730*<br>(0.374)   | -0.697<br>(0.485)   |
| Observations           | 195                  | 195                 | 179                  | 179                 | 179                  | 179                 |
| Effective Observations | [49,39]              | [57,47]             | [45,34]              | [52,40]             | [47,35]              | [53,43]             |
| Covariates             | None                 | None                | Some                 | Some                | All                  | All                 |
| Conventional p-value   | 0.0267               | 0.105               | 0.0904               | 0.243               | 0.0508               | 0.151               |
| Order of Polynomial    | 1                    | 2                   | 1                    | 2                   | 1                    | 2                   |
| Bandwidth              | 0.0795               | 0.0971              | 0.0764               | 0.0955              | 0.0852               | 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.



## E.2. When Poverty is Low

Table E13: RDD Estimates for Infraction Count by Year

| Panel A                | (1)                  | (2)                  | (3)                  | (4)                  | (5)                 | (6)                 |
|------------------------|----------------------|----------------------|----------------------|----------------------|---------------------|---------------------|
| RD Estimate            | -1.991***<br>(0.616) | -2.225***<br>(0.692) | -1.588***<br>(0.541) | -1.646***<br>(0.618) | -1.158**<br>(0.494) | -1.235**<br>(0.603) |
| Observations           | 970                  | 970                  | 906                  | 906                  | 647                 | 647                 |
| Effective Observations | [248,229]            | [343,318]            | [252,225]            | [321,318]            | [197,175]           | [231,229]           |
| Covariates             | None                 | None                 | Some                 | Some                 | All                 | All                 |
| p-value                | 0.00122              | 0.00131              | 0.00331              | 0.00773              | 0.0192              | 0.0407              |
| Order of Polynomial    | 1                    | 2                    | 1                    | 2                    | 1                   | 2                   |
| Bandwidth              | 0.0822               | 0.143                | 0.0923               | 0.156                | 0.104               | 0.152               |
| Panel B                | (1)                  | (2)                  | (3)                  | (4)                  | (5)                 | (6)                 |
| RD Estimate            | -1.792***<br>(0.619) | -1.988***<br>(0.707) | -1.289**<br>(0.545)  | -1.223*<br>(0.626)   | -1.043**<br>(0.487) | -1.011*<br>(0.569)  |
| Observations           | 970                  | 970                  | 906                  | 906                  | 647                 | 647                 |
| Effective Observations | [254,229]            | [343,318]            | [256,225]            | [324,330]            | [203,175]           | [243,266]           |
| Covariates             | None                 | None                 | Some                 | Some                 | All                 | All                 |
| p-value                | 0.00378              | 0.00492              | 0.0180               | 0.0508               | 0.0323              | 0.0755              |
| Order of Polynomial    | 1                    | 2                    | 1                    | 2                    | 1                   | 2                   |
| Bandwidth              | 0.0857               | 0.144                | 0.0948               | 0.163                | 0.110               | 0.179               |

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 E14: RDD Estimates for Infraction Count by Electoral Term

| Panel A                | (1)                 | (2)                 | (3)                  | (4)                  | (5)                  | (6)                  |
|------------------------|---------------------|---------------------|----------------------|----------------------|----------------------|----------------------|
| RD Estimate            | -5.810**<br>(2.826) | -6.086*<br>(3.422)  | -4.698*<br>(2.517)   | -3.821<br>(3.188)    | -7.646***<br>(2.589) | -9.284***<br>(2.909) |
| Observations           | 284                 | 284                 | 267                  | 267                  | 192                  | 192                  |
| Effective observations | [90,75]             | [105,100]           | [88,77]              | [94,86]              | [46,42]              | [67,63]              |
| Covariates             | None                | None                | Some                 | Some                 | All                  | All                  |
| p-value                | 0.0398              | 0.0753              | 0.0620               | 0.231                | 0.00315              | 0.00142              |
| Order of Polynomial    | 1                   | 2                   | 1                    | 2                    | 1                    | 2                    |
| Bandwidth              | 0.111               | 0.171               | 0.120                | 0.141                | 0.0742               | 0.133                |
| Panel B                | (1)                 | (2)                 | (3)                  | (4)                  | (5)                  | (6)                  |
| RD Estimate            | -5.568**<br>(2.393) | -6.486**<br>(2.727) | -5.332***<br>(1.958) | -5.963***<br>(2.262) | -5.948**<br>(2.398)  | -6.227**<br>(2.788)  |
| Observations           | 284                 | 284                 | 267                  | 267                  | 192                  | 192                  |
| Effective observations | [75,65]             | [101,90]            | [69,62]              | [94,87]              | [50,45]              | [68,63]              |
| Covariates             | None                | None                | Some                 | Some                 | All                  | All                  |
| p-value                | 0.0200              | 0.0174              | 0.00647              | 0.00837              | 0.0131               | 0.0255               |
| Order of Polynomial    | 1                   | 2                   | 1                    | 2                    | 1                    | 2                    |
| Bandwidth              | 0.0849              | 0.141               | 0.0858               | 0.142                | 0.0847               | 0.137                |

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 E15: RDD Estimates for Infraction Amount (log) by Year

| Panel A                | (1)                  | (2)                  | (3)                  | (4)                 | (5)               | (6)               |
|------------------------|----------------------|----------------------|----------------------|---------------------|-------------------|-------------------|
| RD Estimate            | -0.735***<br>(0.265) | -0.872***<br>(0.305) | -0.632***<br>(0.244) | -0.754**<br>(0.297) | -0.243<br>(0.244) | -0.307<br>(0.293) |
| Observations           | 969                  | 969                  | 905                  | 905                 | 646               | 646               |
| Effective Observations | [231,212]            | [318,273]            | [221,211]            | [295,267]           | [187,165]         | [228,217]         |
| Covariates             | None                 | None                 | Some                 | Some                | All               | All               |
| p-value                | 0.00555              | 0.00430              | 0.00969              | 0.0112              | 0.319             | 0.295             |
| Order of Polynomial    | 1                    | 2                    | 1                    | 2                   | 1                 | 2                 |
| Bandwidth              | 0.0726               | 0.117                | 0.0811               | 0.122               | 0.0942            | 0.140             |
| Panel B                | (1)                  | (2)                  | (3)                  | (4)                 | (5)               | (6)               |
| RD Estimate            | -0.667***<br>(0.246) | -0.776***<br>(0.300) | -0.554**<br>(0.223)  | -0.596**<br>(0.285) | -0.334<br>(0.236) | -0.392<br>(0.285) |
| Observations           | 969                  | 969                  | 905                  | 905                 | 646               | 646               |
| Effective Observations | [240,225]            | [318,275]            | [250,225]            | [295,267]           | [187,165]         | [228,224]         |
| Covariates             | None                 | None                 | Some                 | Some                | All               | All               |
| p-value                | 0.00672              | 0.00963              | 0.0131               | 0.0368              | 0.158             | 0.169             |
| Order of Polynomial    | 1                    | 2                    | 1                    | 2                   | 1                 | 2                 |
| Bandwidth              | 0.0799               | 0.119                | 0.0913               | 0.122               | 0.0955            | 0.147             |

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 E16: RDD Estimates for Infraction Amount (log) by Term

| Panel A                | (1)                 | (2)                | (3)                 | (4)                | (5)               | (6)               |
|------------------------|---------------------|--------------------|---------------------|--------------------|-------------------|-------------------|
| RD Estimate            | -0.562*<br>(0.299)  | -0.665*<br>(0.348) | -0.506*<br>(0.264)  | -0.557*<br>(0.317) | -0.295<br>(0.291) | -0.437<br>(0.417) |
| Observations           | 284                 | 284                | 267                 | 267                | 192               | 192               |
| Effective observations | [83,73]             | [101,89]           | [80,70]             | [94,86]            | [47,44]           | [62,52]           |
| Covariates             | None                | None               | Some                | Some               | All               | All               |
| p-value                | 0.0600              | 0.0563             | 0.0552              | 0.0784             | 0.311             | 0.295             |
| Order of Polynomial    | 1                   | 2                  | 1                   | 2                  | 1                 | 2                 |
| Bandwidth              | 0.101               | 0.140              | 0.105               | 0.142              | 0.0776            | 0.113             |
| Panel B                | (1)                 | (2)                | (3)                 | (4)                | (5)               | (6)               |
| RD Estimate            | -0.592**<br>(0.300) | -0.678*<br>(0.353) | -0.596**<br>(0.274) | -0.616*<br>(0.334) | -0.344<br>(0.287) | -0.465<br>(0.418) |
| Observations           | 284                 | 284                | 267                 | 267                | 192               | 192               |
| Effective observations | [80,68]             | [95,84]            | [71,63]             | [88,77]            | [47,44]           | [62,52]           |
| Covariates             | None                | None               | Some                | Some               | All               | All               |
| p-value                | 0.0487              | 0.0551             | 0.0294              | 0.0652             | 0.231             | 0.266             |
| Order of Polynomial    | 1                   | 2                  | 1                   | 2                  | 1                 | 2                 |
| Bandwidth              | 0.0914              | 0.125              | 0.0897              | 0.121              | 0.0787            | 0.114             |

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.

## F. When Extreme Poverty is Low/Decreasing

### F.1. When Extreme Poverty Decreases

Table F17: RDD Estimates for Infraction Count by Year

| Panel A                | (1)                  | (2)                 | (3)                | (4)               | (5)                 | (6)                 |
|------------------------|----------------------|---------------------|--------------------|-------------------|---------------------|---------------------|
| RD Estimate            | -1.489***<br>(0.557) | -1.837**<br>(0.724) | -1.152*<br>(0.612) | -1.255<br>(0.763) | -1.278**<br>(0.648) | -1.939**<br>(0.806) |
| Observations           | 670                  | 670                 | 625                | 625               | 625                 | 625                 |
| Effective Observations | [191,162]            | [211,173]           | [160,134]          | [196,161]         | [140,130]           | [172,144]           |
| Covariates             | None                 | None                | Some               | Some              | All                 | All                 |
| p-value                | 0.00746              | 0.0111              | 0.0597             | 0.100             | 0.0485              | 0.0162              |
| Order of Polynomial    | 1                    | 2                   | 1                  | 2                 | 1                   | 2                   |
| Bandwidth              | 0.0959               | 0.104               | 0.0896             | 0.109             | 0.0792              | 0.0930              |
| Panel B                | (1)                  | (2)                 | (3)                | (4)               | (5)                 | (6)                 |
| RD Estimate            | -1.302**<br>(0.585)  | -1.604**<br>(0.756) | -0.992<br>(0.632)  | -1.060<br>(0.781) | -1.147*<br>(0.666)  | -1.524*<br>(0.809)  |
| Observations           | 670                  | 670                 | 625                | 625               | 625                 | 625                 |
| Effective Observations | [191,156]            | [213,173]           | [152,134]          | [200,165]         | [140,130]           | [188,160]           |
| Covariates             | None                 | None                | Some               | Some              | All                 | All                 |
| p-value                | 0.0262               | 0.0338              | 0.117              | 0.175             | 0.0852              | 0.0595              |
| Order of Polynomial    | 1                    | 2                   | 1                  | 2                 | 1                   | 2                   |
| Bandwidth              | 0.0942               | 0.107               | 0.0877             | 0.112             | 0.0785              | 0.101               |

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 F18: RDD Estimates for Infraction Count by Term

| Panel A                | (1)                 | (2)                 | (3)                  | (4)                 | (5)                  | (6)                  |
|------------------------|---------------------|---------------------|----------------------|---------------------|----------------------|----------------------|
| RD Estimate            | -6.891**<br>(2.959) | -7.099**<br>(3.526) | -7.733***<br>(2.867) | -7.943**<br>(3.342) | -9.355***<br>(3.010) | -10.34***<br>(3.838) |
| Observations           | 217                 | 217                 | 194                  | 194                 | 194                  | 194                  |
| Effective Observations | [61,58]             | [79,81]             | [51,48]              | [69,69]             | [42,43]              | [58,54]              |
| Covariates             | None                | None                | Some                 | Some                | All                  | All                  |
| Conventional p-value   | 0.0199              | 0.0441              | 0.00700              | 0.0175              | 0.00188              | 0.00708              |
| Order of Polynomial    | 1                   | 2                   | 1                    | 2                   | 1                    | 2                    |
| Bandwidth              | 0.0976              | 0.155               | 0.0936               | 0.151               | 0.0785               | 0.109                |
| Panel B                | (1)                 | (2)                 | (3)                  | (4)                 | (5)                  | (6)                  |
| RD Estimate            | -3.655*<br>(2.040)  | -4.751*<br>(2.713)  | -3.573<br>(2.258)    | -4.167<br>(2.827)   | -4.639**<br>(2.362)  | -5.992**<br>(2.914)  |
| Observations           | 217                 | 217                 | 194                  | 194                 | 194                  | 194                  |
| Effective Observations | [58,54]             | [67,60]             | [43,44]              | [58,54]             | [42,43]              | [56,54]              |
| Covariates             | None                | None                | Some                 | Some                | All                  | All                  |
| Conventional p-value   | 0.0731              | 0.0799              | 0.114                | 0.141               | 0.0495               | 0.0398               |
| Order of Polynomial    | 1                   | 2                   | 1                    | 2                   | 1                    | 2                    |
| Bandwidth              | 0.0908              | 0.105               | 0.0824               | 0.110               | 0.0767               | 0.103                |

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 F19: RDD Estimates for Infraction Amount (log) by Year

| Panel A                | (1)                | (2)               | (3)               | (4)               | (5)               | (6)               |
|------------------------|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| RD Estimate            | -0.454*<br>(0.237) | -0.487<br>(0.308) | -0.315<br>(0.257) | -0.285<br>(0.317) | -0.363<br>(0.268) | -0.340<br>(0.335) |
| Observations           | 667                | 667               | 622               | 622               | 622               | 622               |
| Effective Observations | [187,156]          | [195,172]         | [144,130]         | [180,160]         | [144,132]         | [196,161]         |
| Covariates             | None               | None              | Some              | Some              | All               | All               |
| p-value                | 0.0555             | 0.113             | 0.221             | 0.368             | 0.174             | 0.310             |
| Order of Polynomial    | 1                  | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.0934             | 0.0987            | 0.0811            | 0.0995            | 0.0835            | 0.108             |
| Panel B                | (1)                | (2)               | (3)               | (4)               | (5)               | (6)               |
| RD Estimate            | -0.443*<br>(0.238) | -0.475<br>(0.308) | -0.294<br>(0.259) | -0.267<br>(0.321) | -0.321<br>(0.266) | -0.396<br>(0.327) |
| Observations           | 667                | 667               | 622               | 622               | 622               | 622               |
| Effective Observations | [187,156]          | [195,172]         | [140,130]         | [180,160]         | [140,130]         | [176,150]         |
| Covariates             | None               | None              | Some              | Some              | All               | All               |
| p-value                | 0.0627             | 0.123             | 0.256             | 0.406             | 0.226             | 0.226             |
| Order of Polynomial    | 1                  | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.0928             | 0.0987            | 0.0805            | 0.0999            | 0.0788            | 0.0954            |

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 F20: RDD Estimates for Infraction Amount (log) by Term

| Panel A                | (1)                | (2)               | (3)                | (4)               | (5)                 | (6)                 |
|------------------------|--------------------|-------------------|--------------------|-------------------|---------------------|---------------------|
| RD Estimate            | -0.710*<br>(0.397) | -0.764<br>(0.488) | -0.618*<br>(0.354) | -0.695<br>(0.492) | -0.692**<br>(0.333) | -0.934**<br>(0.470) |
| Observations           | 217                | 217               | 194                | 194               | 194                 | 194                 |
| Effective Observations | [49,46]            | [60,56]           | [51,48]            | [51,48]           | [53,53]             | [43,44]             |
| Covariates             | None               | None              | Some               | Some              | All                 | All                 |
| Conventional p-value   | 0.0736             | 0.118             | 0.0812             | 0.158             | 0.0378              | 0.0469              |
| Order of Polynomial    | 1                  | 2                 | 1                  | 2                 | 1                   | 2                   |
| Bandwidth              | 0.0715             | 0.0953            | 0.0918             | 0.0925            | 0.0984              | 0.0844              |
| Panel B                | (1)                | (2)               | (3)                | (4)               | (5)                 | (6)                 |
| RD Estimate            | -0.550<br>(0.358)  | -0.565<br>(0.429) | -0.367<br>(0.328)  | -0.367<br>(0.465) | -0.509<br>(0.321)   | -0.636<br>(0.463)   |
| Observations           | 217                | 217               | 194                | 194               | 194                 | 194                 |
| Effective Observations | [49,46]            | [61,59]           | [52,52]            | [53,53]           | [55,53]             | [52,50]             |
| Covariates             | None               | None              | Some               | Some              | All                 | All                 |
| Conventional p-value   | 0.125              | 0.188             | 0.263              | 0.430             | 0.113               | 0.170               |
| Order of Polynomial    | 1                  | 2                 | 1                  | 2                 | 1                   | 2                   |
| Bandwidth              | 0.0723             | 0.0991            | 0.0965             | 0.0992            | 0.101               | 0.0954              |

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.



## F.2. When Extreme Poverty is Low

Table F21: RDD Estimates for Infraction Count by Year

| Panel A                | (1)                  | (2)                  | (3)                 | (4)                 | (5)               | (6)               |
|------------------------|----------------------|----------------------|---------------------|---------------------|-------------------|-------------------|
| RD Estimate            | -1.844***<br>(0.656) | -2.016***<br>(0.701) | -1.264**<br>(0.564) | -1.328**<br>(0.620) | -0.812<br>(0.583) | -0.885<br>(0.760) |
| Observations           | 954                  | 954                  | 886                 | 886                 | 634               | 634               |
| Effective Observations | [224,219]            | [340,343]            | [216,206]           | [315,326]           | [148,148]         | [199,170]         |
| Covariates             | None                 | None                 | Some                | Some                | All               | All               |
| p-value                | 0.00498              | 0.00402              | 0.0250              | 0.0324              | 0.164             | 0.245             |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                 | 2                 |
| Bandwidth              | 0.0785               | 0.159                | 0.0849              | 0.163               | 0.0779            | 0.114             |
| Panel B                | (1)                  | (2)                  | (3)                 | (4)                 | (5)               | (6)               |
| RD Estimate            | -1.798***<br>(0.651) | -1.914***<br>(0.702) | -1.049*<br>(0.552)  | -1.052*<br>(0.623)  | -0.732<br>(0.553) | -0.665<br>(0.819) |
| Observations           | 954                  | 954                  | 886                 | 886                 | 634               | 634               |
| Effective Observations | [224,219]            | [340,343]            | [224,206]           | [315,326]           | [154,149]         | [190,163]         |
| Covariates             | None                 | None                 | Some                | Some                | All               | All               |
| p-value                | 0.00571              | 0.00636              | 0.0573              | 0.0911              | 0.185             | 0.417             |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                 | 2                 |
| Bandwidth              | 0.0804               | 0.160                | 0.0875              | 0.162               | 0.0831            | 0.105             |

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 F22: RDD Estimates for Infraction Count by Term

| Panel A                | (1)                | (2)                | (3)                 | (4)                | (5)                  | (6)                  |
|------------------------|--------------------|--------------------|---------------------|--------------------|----------------------|----------------------|
| RD Estimate            | -3.968<br>(3.127)  | -4.172<br>(3.617)  | -2.367<br>(2.945)   | -2.598<br>(3.622)  | -7.362***<br>(2.815) | -9.000***<br>(3.172) |
| Observations           | 281                | 281                | 263                 | 263                | 188                  | 188                  |
| Effective observations | [85,69]            | [105,104]          | [80,68]             | [93,90]            | [41,41]              | [66,61]              |
| Covariates             | None               | None               | Some                | Some               | All                  | All                  |
| p-value                | 0.204              | 0.249              | 0.422               | 0.473              | 0.00892              | 0.00456              |
| Order of Polynomial    | 1                  | 2                  | 1                   | 2                  | 1                    | 2                    |
| Bandwidth              | 0.106              | 0.179              | 0.111               | 0.157              | 0.0740               | 0.141                |
| Panel B                | (1)                | (2)                | (3)                 | (4)                | (5)                  | (6)                  |
| RD Estimate            | -4.823*<br>(2.541) | -5.305*<br>(2.781) | -4.175**<br>(2.073) | -4.469*<br>(2.310) | -6.156**<br>(2.476)  | -7.063**<br>(2.771)  |
| Observations           | 281                | 281                | 263                 | 263                | 188                  | 188                  |
| Effective observations | [72,63]            | [103,97]           | [63,60]             | [93,93]            | [43,43]              | [64,59]              |
| Covariates             | None               | None               | Some                | Some               | All                  | All                  |
| p-value                | 0.0577             | 0.0565             | 0.0440              | 0.0531             | 0.0129               | 0.0108               |
| Order of Polynomial    | 1                  | 2                  | 1                   | 2                  | 1                    | 2                    |
| Bandwidth              | 0.0841             | 0.161              | 0.0820              | 0.160              | 0.0786               | 0.133                |

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 F23: RDD Estimates for Infraction Amount (log) by Year

| Panel A                | (1)                | (2)                | (3)               | (4)               | (5)                | (6)                |
|------------------------|--------------------|--------------------|-------------------|-------------------|--------------------|--------------------|
| RD Estimate            | -0.466*<br>(0.270) | -0.632*<br>(0.347) | -0.303<br>(0.247) | -0.388<br>(0.331) | -0.0730<br>(0.265) | -0.115<br>(0.283)  |
| Observations           | 953                | 953                | 885               | 885               | 633                | 633                |
| Effective Observations | [269,230]          | [316,287]          | [255,227]         | [294,274]         | [160,149]          | [236,242]          |
| Covariates             | None               | None               | Some              | Some              | All                | All                |
| p-value                | 0.0843             | 0.0681             | 0.220             | 0.242             | 0.783              | 0.685              |
| Order of Polynomial    | 1                  | 2                  | 1                 | 2                 | 1                  | 2                  |
| Bandwidth              | 0.0950             | 0.130              | 0.103             | 0.132             | 0.0854             | 0.171              |
| Panel B                | (1)                | (2)                | (3)               | (4)               | (5)                | (6)                |
| RD Estimate            | -0.441*<br>(0.249) | -0.546*<br>(0.323) | -0.171<br>(0.238) | -0.206<br>(0.292) | -0.0458<br>(0.261) | -0.0920<br>(0.273) |
| Observations           | 953                | 953                | 885               | 885               | 633                | 633                |
| Effective Observations | [281,240]          | [322,294]          | [237,216]         | [294,277]         | [163,149]          | [240,261]          |
| Covariates             | None               | None               | Some              | Some              | All                | All                |
| p-value                | 0.0766             | 0.0911             | 0.472             | 0.482             | 0.860              | 0.736              |
| Order of Polynomial    | 1                  | 2                  | 1                 | 2                 | 1                  | 2                  |
| Bandwidth              | 0.102              | 0.135              | 0.0914            | 0.134             | 0.0859             | 0.185              |

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 F24: RDD Estimates for Infraction Amount (log) by Term

| Panel A                | (1)              | (2)              | (3)              | (4)              | (5)               | (6)               |
|------------------------|------------------|------------------|------------------|------------------|-------------------|-------------------|
| RD Estimate            | 0.334<br>(0.701) | 0.503<br>(0.848) | 0.671<br>(0.801) | 0.835<br>(0.932) | -0.208<br>(0.339) | -0.408<br>(0.439) |
| Observations           | 281              | 281              | 263              | 263              | 188               | 188               |
| Effective observations | [90,72]          | [105,104]        | [80,67]          | [98,107]         | [38,39]           | [56,47]           |
| Covariates             | None             | None             | Some             | Some             | All               | All               |
| p-value                | 0.634            | 0.553            | 0.403            | 0.370            | 0.539             | 0.353             |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                 | 2                 |
| Bandwidth              | 0.113            | 0.177            | 0.109            | 0.191            | 0.0708            | 0.102             |
| Panel B                | (1)              | (2)              | (3)              | (4)              | (5)               | (6)               |
| RD Estimate            | 0.315<br>(0.694) | 0.457<br>(0.830) | 0.615<br>(0.809) | 0.763<br>(0.923) | -0.275<br>(0.325) | -0.440<br>(0.440) |
| Observations           | 281              | 281              | 263              | 263              | 188               | 188               |
| Effective observations | [89,71]          | [105,105]        | [78,66]          | [98,107]         | [41,41]           | [56,47]           |
| Covariates             | None             | None             | Some             | Some             | All               | All               |
| p-value                | 0.650            | 0.582            | 0.447            | 0.409            | 0.398             | 0.318             |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                 | 2                 |
| Bandwidth              | 0.112            | 0.181            | 0.105            | 0.190            | 0.0735            | 0.105             |

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.

## G. When Poverty is Increasing/High

### G.1. When Poverty Increases

Table G1: RDD Estimates for Infraction Count by Year

| Panel A                | (1)              | (2)              | (3)              | (4)              | (5)              | (6)              |
|------------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| RD Estimate            | 0.570<br>(0.942) | 0.824<br>(1.566) | 0.519<br>(1.030) | 0.975<br>(1.627) | 0.547<br>(1.081) | 0.970<br>(1.586) |
| Observations           | 605              | 605              | 562              | 562              | 562              | 562              |
| Effective Observations | [159,198]        | [159,234]        | [130,176]        | [138,222]        | [130,168]        | [138,228]        |
| Covariates             | None             | None             | Some             | Some             | All              | All              |
| p-value                | 0.545            | 0.599            | 0.614            | 0.549            | 0.613            | 0.541            |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                | 2                |
| Bandwidth              | 0.118            | 0.133            | 0.101            | 0.131            | 0.0969           | 0.135            |
| Panel B                | (1)              | (2)              | (3)              | (4)              | (5)              | (6)              |
| RD Estimate            | 0.415<br>(0.983) | 0.521<br>(1.549) | 0.547<br>(1.090) | 0.919<br>(1.599) | 0.593<br>(1.089) | 0.960<br>(1.560) |
| Observations           | 605              | 605              | 562              | 562              | 562              | 562              |
| Effective Observations | [155,194]        | [159,236]        | [130,164]        | [138,224]        | [130,168]        | [138,230]        |
| Covariates             | None             | None             | Some             | Some             | All              | All              |
| p-value                | 0.673            | 0.737            | 0.616            | 0.565            | 0.586            | 0.538            |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                | 2                |
| Bandwidth              | 0.115            | 0.135            | 0.0955           | 0.131            | 0.0965           | 0.136            |

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 G2: RDD Estimates for Infraction Count by Term

| Panel A                | (1)              | (2)              | (3)              | (4)              | (5)               | (6)              |
|------------------------|------------------|------------------|------------------|------------------|-------------------|------------------|
| RD Estimate            | 4.224<br>(3.797) | 6.547<br>(6.035) | 1.230<br>(4.063) | 3.371<br>(6.561) | -2.501<br>(4.456) | 3.318<br>(8.434) |
| Observations           | 196              | 196              | 174              | 174              | 174               | 174              |
| Effective Observations | [55,62]          | [57,76]          | [44,56]          | [46,71]          | [44,55]           | [44,57]          |
| Covariates             | None             | None             | Some             | Some             | All               | All              |
| Conventional p-value   | 0.266            | 0.278            | 0.762            | 0.607            | 0.575             | 0.694            |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                 | 2                |
| Bandwidth              | 0.115            | 0.136            | 0.109            | 0.132            | 0.104             | 0.111            |
| Panel B                | (1)              | (2)              | (3)              | (4)              | (5)               | (6)              |
| RD Estimate            | 1.448<br>(3.180) | 1.881<br>(4.584) | 1.701<br>(3.540) | 3.016<br>(5.265) | 0.936<br>(3.735)  | 2.655<br>(5.101) |
| Observations           | 196              | 196              | 174              | 174              | 174               | 174              |
| Effective Observations | [54,59]          | [59,79]          | [43,53]          | [46,67]          | [41,52]           | [46,71]          |
| Covariates             | None             | None             | Some             | Some             | All               | All              |
| Conventional p-value   | 0.649            | 0.682            | 0.631            | 0.567            | 0.802             | 0.603            |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                 | 2                |
| Bandwidth              | 0.109            | 0.144            | 0.0958           | 0.128            | 0.0923            | 0.133            |

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 G3: RDD Estimates for Infraction Amount (log) by Year

| Panel A                | (1)              | (2)                | (3)               | (4)               | (5)               | (6)               |
|------------------------|------------------|--------------------|-------------------|-------------------|-------------------|-------------------|
| RD Estimate            | 0.305<br>(0.302) | -0.0806<br>(0.466) | 0.255<br>(0.315)  | -0.146<br>(0.641) | 0.265<br>(0.315)  | -0.229<br>(0.596) |
| Observations           | 603              | 603                | 560               | 560               | 560               | 560               |
| Effective Observations | [158,212]        | [164,238]          | [131,184]         | [131,176]         | [131,182]         | [131,184]         |
| Covariates             | None             | None               | Some              | Some              | All               | All               |
| p-value                | 0.312            | 0.863              | 0.419             | 0.820             | 0.399             | 0.701             |
| Order of Polynomial    | 1                | 2                  | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.121            | 0.141              | 0.114             | 0.106             | 0.113             | 0.114             |
| Panel B                | (1)              | (2)                | (3)               | (4)               | (5)               | (6)               |
| RD Estimate            | 0.350<br>(0.285) | 0.176<br>(0.401)   | 0.0991<br>(0.355) | -0.190<br>(0.632) | 0.0759<br>(0.376) | -0.221<br>(0.618) |
| Observations           | 603              | 603                | 560               | 560               | 560               | 560               |
| Effective Observations | [164,238]        | [200,274]          | [129,164]         | [129,176]         | [119,158]         | [131,176]         |
| Covariates             | None             | None               | Some              | Some              | All               | All               |
| p-value                | 0.219            | 0.660              | 0.780             | 0.764             | 0.840             | 0.721             |
| Order of Polynomial    | 1                | 2                  | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.139            | 0.175              | 0.0944            | 0.102             | 0.0888            | 0.108             |

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 G4: RDD Estimates for Infraction Amount (log) by Term

| Panel A                | (1)              | (2)               | (3)              | (4)              | (5)               | (6)              |
|------------------------|------------------|-------------------|------------------|------------------|-------------------|------------------|
| RD Estimate            | 0.602<br>(0.371) | 0.391<br>(0.548)  | 0.413<br>(0.398) | 0.455<br>(0.478) | 0.301<br>(0.389)  | 0.169<br>(0.595) |
| Observations           | 196              | 196               | 174              | 174              | 174               | 174              |
| Effective Observations | [55,61]          | [60,79]           | [44,57]          | [58,88]          | [45,60]           | [48,75]          |
| Covariates             | None             | None              | Some             | Some             | All               | All              |
| Conventional p-value   | 0.104            | 0.476             | 0.299            | 0.341            | 0.439             | 0.776            |
| Order of Polynomial    | 1                | 2                 | 1                | 2                | 1                 | 2                |
| Bandwidth              | 0.114            | 0.147             | 0.113            | 0.196            | 0.116             | 0.149            |
| Panel B                | (1)              | (2)               | (3)              | (4)              | (5)               | (6)              |
| RD Estimate            | 0.516<br>(0.329) | -0.129<br>(0.651) | 0.555<br>(0.346) | 0.502<br>(0.448) | 0.600*<br>(0.334) | 0.530<br>(0.449) |
| Observations           | 196              | 196               | 174              | 174              | 174               | 174              |
| Effective Observations | [57,74]          | [57,63]           | [46,69]          | [58,88]          | [46,73]           | [58,86]          |
| Covariates             | None             | None              | Some             | Some             | All               | All              |
| Conventional p-value   | 0.117            | 0.843             | 0.109            | 0.262            | 0.0720            | 0.238            |
| Order of Polynomial    | 1                | 2                 | 1                | 2                | 1                 | 2                |
| Bandwidth              | 0.133            | 0.118             | 0.131            | 0.193            | 0.137             | 0.188            |

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.



## G.2. When Poverty is High

Table G5: RDD Estimates for Infraction Count by Year

| Panel A                | (1)              | (2)              | (3)              | (4)              | (5)              | (6)              |
|------------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| RD Estimate            | 1.089<br>(1.060) | 1.664<br>(1.561) | 1.486<br>(1.195) | 2.301<br>(1.715) | 0.829<br>(0.771) | 1.241<br>(1.099) |
| Observations           | 906              | 906              | 804              | 804              | 607              | 607              |
| Effective Observations | [220,210]        | [276,276]        | [178,179]        | [227,236]        | [153,165]        | [186,207]        |
| Covariates             | None             | None             | Some             | Some             | All              | All              |
| p-value                | 0.305            | 0.287            | 0.214            | 0.180            | 0.282            | 0.259            |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                | 2                |
| Bandwidth              | 0.0892           | 0.123            | 0.0825           | 0.116            | 0.0956           | 0.134            |
| Panel B                | (1)              | (2)              | (3)              | (4)              | (5)              | (6)              |
| RD Estimate            | 0.996<br>(0.912) | 1.438<br>(1.377) | 1.389<br>(1.030) | 2.185<br>(1.573) | 0.605<br>(0.651) | 1.742<br>(1.187) |
| Observations           | 906              | 906              | 804              | 804              | 607              | 607              |
| Effective Observations | [226,218]        | [276,276]        | [182,183]        | [223,228]        | [166,184]        | [163,177]        |
| Covariates             | None             | None             | Some             | Some             | All              | All              |
| p-value                | 0.275            | 0.296            | 0.178            | 0.165            | 0.352            | 0.142            |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                | 2                |
| Bandwidth              | 0.0927           | 0.123            | 0.0870           | 0.113            | 0.114            | 0.110            |

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 G6: RDD Estimates for Infraction Count by Term

| Panel A                | (1)              | (2)              | (3)              | (4)              | (5)              | (6)               |
|------------------------|------------------|------------------|------------------|------------------|------------------|-------------------|
| RD Estimate            | 5.120<br>(4.747) | 8.026<br>(7.297) | 7.291<br>(5.527) | 10.90<br>(8.057) | 7.115<br>(5.269) | 13.48*<br>(8.065) |
| Observations           | 258              | 258              | 230              | 230              | 181              | 181               |
| Effective observations | [64,61]          | [80,76]          | [51,50]          | [67,65]          | [39,41]          | [47,52]           |
| Covariates             | None             | None             | Some             | Some             | All              | All               |
| p-value                | 0.281            | 0.271            | 0.187            | 0.176            | 0.177            | 0.0946            |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                | 2                 |
| Bandwidth              | 0.0924           | 0.122            | 0.0819           | 0.114            | 0.0795           | 0.105             |
| Panel B                | (1)              | (2)              | (3)              | (4)              | (5)              | (6)               |
| RD Estimate            | 4.130<br>(3.425) | 5.662<br>(5.127) | 6.039<br>(3.968) | 8.339<br>(5.740) | 4.323<br>(3.645) | 10.78<br>(7.324)  |
| Observations           | 258              | 258              | 230              | 230              | 181              | 181               |
| Effective observations | [63,61]          | [80,77]          | [52,51]          | [69,66]          | [45,51]          | [47,53]           |
| Covariates             | None             | None             | Some             | Some             | All              | All               |
| p-value                | 0.228            | 0.269            | 0.128            | 0.146            | 0.236            | 0.141             |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                | 2                 |
| Bandwidth              | 0.0919           | 0.123            | 0.0855           | 0.119            | 0.102            | 0.109             |

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 G7: RDD Estimates for Infraction Amount (log) by Year

| Panel A                | (1)               | (2)               | (3)                | (4)               | (5)              | (6)              |
|------------------------|-------------------|-------------------|--------------------|-------------------|------------------|------------------|
| RD Estimate            | 0.500<br>(0.311)  | 0.599*<br>(0.338) | 0.543*<br>(0.310)  | 0.680<br>(0.446)  | 0.413<br>(0.257) | 0.557<br>(0.367) |
| Observations           | 902               | 902               | 800                | 800               | 603              | 603              |
| Effective Observations | [219,210]         | [337,369]         | [188,187]          | [222,232]         | [149,151]        | [162,173]        |
| Covariates             | None              | None              | Some               | Some              | All              | All              |
| p-value                | 0.108             | 0.0766            | 0.0798             | 0.128             | 0.109            | 0.129            |
| Order of Polynomial    | 1                 | 2                 | 1                  | 2                 | 1                | 2                |
| Bandwidth              | 0.0901            | 0.173             | 0.0900             | 0.114             | 0.0908           | 0.106            |
| Panel B                | (1)               | (2)               | (3)                | (4)               | (5)              | (6)              |
| RD Estimate            | 0.501*<br>(0.293) | 0.559<br>(0.353)  | 0.548**<br>(0.277) | 0.682*<br>(0.412) | 0.345<br>(0.228) | 0.440<br>(0.354) |
| Observations           | 902               | 902               | 800                | 800               | 603              | 603              |
| Effective Observations | [219,210]         | [302,309]         | [181,187]          | [216,220]         | [162,177]        | [159,173]        |
| Covariates             | None              | None              | Some               | Some              | All              | All              |
| p-value                | 0.0874            | 0.113             | 0.0481             | 0.0979            | 0.130            | 0.214            |
| Order of Polynomial    | 1                 | 2                 | 1                  | 2                 | 1                | 2                |
| Bandwidth              | 0.0893            | 0.143             | 0.0883             | 0.107             | 0.110            | 0.104            |

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 G8: RDD Estimates for Infraction Amount (log) by Term

| Panel A                | (1)               | (2)               | (3)               | (4)               | (5)              | (6)                |
|------------------------|-------------------|-------------------|-------------------|-------------------|------------------|--------------------|
| RD Estimate            | 1.266*<br>(0.726) | 1.656*<br>(0.900) | 1.408*<br>(0.800) | 1.814*<br>(0.950) | 0.562<br>(0.408) | 1.159**<br>(0.586) |
| Observations           | 258               | 258               | 230               | 230               | 181              | 181                |
| Effective observations | [68,66]           | [84,80]           | [57,58]           | [74,72]           | [47,53]          | [47,54]            |
| Covariates             | None              | None              | Some              | Some              | All              | All                |
| p-value                | 0.0812            | 0.0657            | 0.0783            | 0.0561            | 0.168            | 0.0481             |
| Order of Polynomial    | 1                 | 2                 | 1                 | 2                 | 1                | 2                  |
| Bandwidth              | 0.101             | 0.135             | 0.0970            | 0.135             | 0.109            | 0.112              |
| Panel B                | (1)               | (2)               | (3)               | (4)               | (5)              | (6)                |
| RD Estimate            | 1.203*<br>(0.690) | 1.532*<br>(0.891) | 1.365*<br>(0.749) | 1.705*<br>(0.917) | 0.511<br>(0.349) | 1.023*<br>(0.571)  |
| Observations           | 258               | 258               | 230               | 230               | 181              | 181                |
| Effective observations | [69,68]           | [87,82]           | [60,59]           | [76,74]           | [54,64]          | [47,54]            |
| Covariates             | None              | None              | Some              | Some              | All              | All                |
| p-value                | 0.0815            | 0.0858            | 0.0683            | 0.0629            | 0.144            | 0.0730             |
| Order of Polynomial    | 1                 | 2                 | 1                 | 2                 | 1                | 2                  |
| Bandwidth              | 0.104             | 0.137             | 0.100             | 0.140             | 0.139            | 0.113              |

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.

## H. When Extreme Poverty is Increasing/High

### H.1. When Extreme Poverty Increases

Table H9: RDD Estimates for Infraction Count by Year and Term

| Panel A                | (1)              | (2)              | (3)              | (4)              | (5)              | (6)              |
|------------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| RD Estimate            | 0.913<br>(0.967) | 1.191<br>(1.772) | 0.920<br>(1.068) | 2.295<br>(2.156) | 0.652<br>(1.276) | 1.576<br>(1.890) |
| Observations           | 536              | 536              | 506              | 506              | 506              | 506              |
| Effective Observations | [148,196]        | [142,192]        | [128,158]        | [128,158]        | [124,144]        | [130,184]        |
| Covariates             | None             | None             | Some             | Some             | All              | All              |
| p-value                | 0.345            | 0.501            | 0.389            | 0.287            | 0.609            | 0.404            |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                | 2                |
| Bandwidth              | 0.140            | 0.135            | 0.115            | 0.116            | 0.0995           | 0.129            |
| Panel B                | (1)              | (2)              | (3)              | (4)              | (5)              | (6)              |
| RD Estimate            | 2.999<br>(4.751) | 3.247<br>(6.555) | 1.366<br>(4.782) | 4.537<br>(7.647) | 0.806<br>(4.067) | 6.185<br>(9.568) |
| Observations           | 174              | 174              | 159              | 159              | 159              | 159              |
| Effective Observations | [49,47]          | [54,67]          | [43,46]          | [45,56]          | [45,58]          | [43,47]          |
| Covariates             | None             | None             | Some             | Some             | All              | All              |
| Conventional p-value   | 0.528            | 0.620            | 0.775            | 0.553            | 0.843            | 0.518            |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                | 2                |
| Bandwidth              | 0.105            | 0.152            | 0.110            | 0.128            | 0.130            | 0.111            |

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 H10: RDD Estimates for Infraction Amount (log) by Year and Term

| Panel A                | (1)              | (2)               | (3)              | (4)                | (5)               | (6)                |
|------------------------|------------------|-------------------|------------------|--------------------|-------------------|--------------------|
| RD Estimate            | 0.157<br>(0.344) | -0.129<br>(0.700) | 0.105<br>(0.360) | -0.0200<br>(0.731) | 0.0987<br>(0.366) | -0.0855<br>(0.668) |
| Observations           | 534              | 534               | 504              | 504                | 504               | 504                |
| Effective Observations | [141,182]        | [135,154]         | [123,152]        | [123,144]          | [123,150]         | [123,150]          |
| Covariates             | None             | None              | Some             | Some               | All               | All                |
| p-value                | 0.648            | 0.854             | 0.771            | 0.978              | 0.787             | 0.898              |
| Order of Polynomial    | 1                | 2                 | 1                | 2                  | 1                 | 2                  |
| Bandwidth              | 0.124            | 0.111             | 0.113            | 0.100              | 0.112             | 0.112              |
| Panel B                | (1)              | (2)               | (3)              | (4)                | (5)               | (6)                |
| RD Estimate            | 0.321<br>(0.441) | 0.237<br>(0.550)  | 0.210<br>(0.461) | 0.116<br>(0.702)   | 0.139<br>(0.456)  | 0.139<br>(0.768)   |
| Observations           | 174              | 174               | 159              | 159                | 159               | 159                |
| Effective Observations | [51,55]          | [64,80]           | [44,51]          | [46,61]            | [45,52]           | [45,57]            |
| Covariates             | None             | None              | Some             | Some               | All               | All                |
| Conventional p-value   | 0.467            | 0.666             | 0.649            | 0.868              | 0.761             | 0.857              |
| Order of Polynomial    | 1                | 2                 | 1                | 2                  | 1                 | 2                  |
| Bandwidth              | 0.120            | 0.191             | 0.117            | 0.142              | 0.118             | 0.129              |

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.2. When Extreme Poverty is High

Table H11: RDD Estimates for Infraction Count by Year and Term

| Panel A                | (1)              | (2)              | (3)              | (4)              | (5)              | (6)              |
|------------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| RD Estimate            | 0.735<br>(1.042) | 0.986<br>(1.318) | 1.120<br>(1.211) | 1.792<br>(1.749) | 0.381<br>(0.696) | 1.263<br>(1.292) |
| Observations           | 922              | 922              | 824              | 824              | 620              | 620              |
| Effective Observations | [232,219]        | [312,329]        | [195,185]        | [246,251]        | [176,199]        | [173,196]        |
| Covariates             | None             | None             | Some             | Some             | All              | All              |
| p-value                | 0.481            | 0.454            | 0.355            | 0.306            | 0.584            | 0.328            |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                | 2                |
| Bandwidth              | 0.0893           | 0.144            | 0.0814           | 0.118            | 0.118            | 0.114            |
| Panel B                | (1)              | (2)              | (3)              | (4)              | (5)              | (6)              |
| RD Estimate            | 4.126<br>(4.866) | 7.773<br>(7.202) | 6.297<br>(5.683) | 10.44<br>(8.168) | 4.910<br>(5.036) | 9.364<br>(7.785) |
| Observations           | 261              | 261              | 234              | 234              | 185              | 185              |
| Effective observations | [62,58]          | [78,76]          | [54,50]          | [66,67]          | [43,44]          | [50,56]          |
| Covariates             | None             | None             | Some             | Some             | All              | All              |
| p-value                | 0.397            | 0.280            | 0.268            | 0.201            | 0.330            | 0.229            |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                | 2                |
| Bandwidth              | 0.0833           | 0.114            | 0.0780           | 0.111            | 0.0817           | 0.111            |

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 H12: RDD Estimates for Infraction Amount (log) by Year and Term

| Panel A                | (1)              | (2)               | (3)              | (4)               | (5)              | (6)              |
|------------------------|------------------|-------------------|------------------|-------------------|------------------|------------------|
| RD Estimate            | 0.157<br>(0.267) | 0.0686<br>(0.353) | 0.131<br>(0.295) | 0.0852<br>(0.331) | 0.243<br>(0.241) | 0.305<br>(0.395) |
| Observations           | 918              | 918               | 820              | 820               | 616              | 616              |
| Effective Observations | [241,235]        | [295,294]         | [194,181]        | [277,305]         | [176,202]        | [159,174]        |
| Covariates             | None             | None              | Some             | Some              | All              | All              |
| p-value                | 0.557            | 0.846             | 0.656            | 0.797             | 0.315            | 0.440            |
| Order of Polynomial    | 1                | 2                 | 1                | 2                 | 1                | 2                |
| Bandwidth              | 0.0946           | 0.131             | 0.0809           | 0.148             | 0.118            | 0.0955           |
| Panel B                | (1)              | (2)               | (3)              | (4)               | (5)              | (6)              |
| RD Estimate            | 0.203<br>(0.350) | 0.320<br>(0.488)  | 0.236<br>(0.424) | 0.310<br>(0.509)  | 0.372<br>(0.412) | 0.895<br>(0.596) |
| Observations           | 261              | 261               | 234              | 234               | 185              | 185              |
| Effective observations | [85,81]          | [93,98]           | [62,63]          | [89,89]           | [50,55]          | [50,56]          |
| Covariates             | None             | None              | Some             | Some              | All              | All              |
| p-value                | 0.562            | 0.512             | 0.578            | 0.543             | 0.366            | 0.133            |
| Order of Polynomial    | 1                | 2                 | 1                | 2                 | 1                | 2                |
| Bandwidth              | 0.127            | 0.157             | 0.103            | 0.167             | 0.105            | 0.110            |

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.



# I. Last Two Years of the Electoral Term

## I.1. When Poverty Decreases

Table I13: RDD Estimates for Infraction Count by Year and Term

| Panel A                | (1)                 | (2)                 | (3)               | (4)               | (5)               | (6)                |
|------------------------|---------------------|---------------------|-------------------|-------------------|-------------------|--------------------|
| RD Estimate            | -1.925**<br>(0.806) | -2.466**<br>(1.068) | -1.133<br>(0.804) | -1.546<br>(1.092) | -1.173<br>(0.850) | -2.057*<br>(1.240) |
| Observations           | 389                 | 389                 | 357               | 357               | 357               | 357                |
| Effective Observations | [114,96]            | [126,99]            | [106,86]          | [114,87]          | [104,84]          | [94,70]            |
| Covariates             | None                | None                | Some              | Some              | All               | All                |
| p-value                | 0.0170              | 0.0210              | 0.159             | 0.157             | 0.167             | 0.0971             |
| Order of Polynomial    | 1                   | 2                   | 1                 | 2                 | 1                 | 2                  |
| Bandwidth              | 0.0997              | 0.112               | 0.0994            | 0.106             | 0.0963            | 0.0869             |
| Panel B                | (1)                 | (2)                 | (3)               | (4)               | (5)               | (6)                |
| RD Estimate            | -3.885**<br>(1.634) | -5.039**<br>(2.158) | -2.335<br>(1.650) | -3.189<br>(2.196) | -2.390<br>(1.917) | -3.532<br>(2.488)  |
| Observations           | 194                 | 194                 | 178               | 178               | 178               | 178                |
| Effective Observations | [57,47]             | [62,49]             | [52,40]           | [57,44]           | [45,34]           | [51,38]            |
| Covariates             | None                | None                | Some              | Some              | All               | All                |
| Conventional p-value   | 0.0174              | 0.0196              | 0.157             | 0.147             | 0.213             | 0.156              |
| Order of Polynomial    | 1                   | 2                   | 1                 | 2                 | 1                 | 2                  |
| Bandwidth              | 0.0976              | 0.110               | 0.0953            | 0.107             | 0.0784            | 0.0902             |

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 I14: RDD Estimates for Infraction Amount (log) by Year and Term

| Panel A                | (1)                  | (2)                  | (3)                  | (4)                 | (5)                  | (6)                 |
|------------------------|----------------------|----------------------|----------------------|---------------------|----------------------|---------------------|
| RD Estimate            | -1.225***<br>(0.373) | -1.296***<br>(0.449) | -0.997***<br>(0.350) | -1.139**<br>(0.453) | -1.011***<br>(0.360) | -1.157**<br>(0.461) |
| Observations           | 388                  | 388                  | 356                  | 356                 | 356                  | 356                 |
| Effective Observations | [96,74]              | [118,96]             | [104,76]             | [110,86]            | [104,84]             | [120,93]            |
| Covariates             | None                 | None                 | Some                 | Some                | All                  | All                 |
| p-value                | 0.00102              | 0.00390              | 0.00441              | 0.0118              | 0.00501              | 0.0120              |
| Order of Polynomial    | 1                    | 2                    | 1                    | 2                   | 1                    | 2                   |
| Bandwidth              | 0.0729               | 0.101                | 0.0912               | 0.101               | 0.0964               | 0.124               |
|                        | (1)                  | (2)                  | (3)                  | (4)                 | (5)                  | (6)                 |
| Panel B                |                      |                      |                      |                     |                      |                     |
| RD Estimate            | -1.165***<br>(0.423) | -1.197**<br>(0.512)  | -0.997**<br>(0.410)  | -1.051**<br>(0.514) | -0.923**<br>(0.386)  | -1.014**<br>(0.513) |
| Observations           | 194                  | 194                  | 178                  | 178                 | 178                  | 178                 |
| Effective Observations | [48,38]              | [61,49]              | [45,34]              | [55,43]             | [53,43]              | [59,46]             |
| Covariates             | None                 | None                 | Some                 | Some                | All                  | All                 |
| Conventional p-value   | 0.00593              | 0.0195               | 0.0150               | 0.0409              | 0.0169               | 0.0481              |
| Order of Polynomial    | 1                    | 2                    | 1                    | 2                   | 1                    | 2                   |
| Bandwidth              | 0.0747               | 0.104                | 0.0806               | 0.102               | 0.0988               | 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.

## I.2. When Poverty Is Low

Table I15: RDD Estimates for Infraction Count by Year and Term (Final 2 Years of Term)

| Panel A                | (1)                | (2)               | (3)                | (4)               | (5)                 | (6)                 |
|------------------------|--------------------|-------------------|--------------------|-------------------|---------------------|---------------------|
| RD Estimate            | -1.608*<br>(0.910) | -1.719<br>(1.094) | -1.173<br>(0.919)  | -1.009<br>(1.102) | 0.243<br>(0.930)    | 0.316<br>(1.023)    |
| Observations           | 406                | 406               | 375                | 375               | 264                 | 264                 |
| Effective Observations | [121,109]          | [143,135]         | [113,101]          | [130,127]         | [76,73]             | [99,114]            |
| Covariates             | None               | None              | Some               | Some              | All                 | All                 |
| p-value                | 0.0773             | 0.116             | 0.202              | 0.360             | 0.794               | 0.757               |
| Order of Polynomial    | 1                  | 2                 | 1                  | 2                 | 1                   | 2                   |
| Bandwidth              | 0.100              | 0.144             | 0.102              | 0.144             | 0.0980              | 0.184               |
| Panel B                | (1)                | (2)               | (3)                | (4)               | (5)                 | (6)                 |
| RD Estimate            | -2.892<br>(1.846)  | -3.091<br>(2.187) | -3.364*<br>(1.825) | -3.277<br>(2.144) | -4.214**<br>(1.864) | -4.307**<br>(2.145) |
| Observations           | 208                | 208               | 192                | 192               | 192                 | 192                 |
| Effective observations | [63,50]            | [76,67]           | [56,47]            | [69,64]           | [51,45]             | [67,63]             |
| Covariates             | None               | None              | Some               | Some              | All                 | All                 |
| p-value                | 0.117              | 0.158             | 0.0653             | 0.126             | 0.0238              | 0.0447              |
| Order of Polynomial    | 1                  | 2                 | 1                  | 2                 | 1                   | 2                   |
| Bandwidth              | 0.0945             | 0.144             | 0.0935             | 0.143             | 0.0861              | 0.135               |

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 I16: RDD Estimates for Infraction Amount (log) by Year and Term

| Panel A                | (1)                  | (2)                  | (3)                 | (4)                 | (5)                | (6)                |
|------------------------|----------------------|----------------------|---------------------|---------------------|--------------------|--------------------|
| RD Estimate            | -0.861***<br>(0.318) | -1.009***<br>(0.356) | -0.816**<br>(0.331) | -0.942**<br>(0.395) | -0.433<br>(0.355)  | -0.603<br>(0.466)  |
| Observations           | 406                  | 406                  | 375                 | 375                 | 264                | 264                |
| Effective Observations | [102,97]             | [143,133]            | [90,89]             | [120,112]           | [82,78]            | [89,92]            |
| Covariates             | None                 | None                 | Some                | Some                | All                | All                |
| p-value                | 0.00682              | 0.00455              | 0.0137              | 0.0171              | 0.223              | 0.196              |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                  | 2                  |
| Bandwidth              | 0.0808               | 0.141                | 0.0764              | 0.122               | 0.113              | 0.138              |
|                        | (1)                  | (2)                  | (3)                 | (4)                 | (5)                | (6)                |
| Panel B                |                      |                      |                     |                     |                    |                    |
| RD Estimate            | -0.530<br>(0.358)    | -0.699<br>(0.428)    | -0.531<br>(0.354)   | -0.607<br>(0.456)   | -0.684*<br>(0.355) | -0.839*<br>(0.481) |
| Observations           | 208                  | 208                  | 192                 | 192                 | 192                | 192                |
| Effective observations | [60,50]              | [73,63]              | [47,44]             | [62,52]             | [47,44]            | [61,50]            |
| Covariates             | None                 | None                 | Some                | Some                | All                | All                |
| p-value                | 0.139                | 0.102                | 0.134               | 0.183               | 0.0543             | 0.0815             |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                  | 2                  |
| Bandwidth              | 0.0900               | 0.129                | 0.0767              | 0.114               | 0.0763             | 0.110              |

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.

### I.3. When Extreme Poverty Decreases

Table I17: RDD Estimates for Infraction Count by Year and Term

| Panel A                | (1)                 | (2)                | (3)               | (4)               | (5)                | (6)                |
|------------------------|---------------------|--------------------|-------------------|-------------------|--------------------|--------------------|
| RD Estimate            | -1.479**<br>(0.722) | -1.910*<br>(1.000) | -1.278<br>(0.844) | -1.519<br>(1.103) | -1.111<br>(0.885)  | -2.093*<br>(1.221) |
| Observations           | 432                 | 432                | 387               | 387               | 387                | 387                |
| Effective Observations | [133,119]           | [133,119]          | [102,96]          | [116,107]         | [96,90]            | [96,90]            |
| Covariates             | None                | None               | Some              | Some              | All                | All                |
| p-value                | 0.0407              | 0.0560             | 0.130             | 0.168             | 0.210              | 0.0865             |
| Order of Polynomial    | 1                   | 2                  | 1                 | 2                 | 1                  | 2                  |
| Bandwidth              | 0.108               | 0.110              | 0.0927            | 0.110             | 0.0893             | 0.0893             |
| Panel B                | (1)                 | (2)                | (3)               | (4)               | (5)                | (6)                |
| RD Estimate            | -2.545<br>(1.609)   | -3.239<br>(2.106)  | -2.588<br>(1.700) | -3.158<br>(2.227) | -3.525*<br>(1.930) | -4.544*<br>(2.409) |
| Observations           | 216                 | 216                | 193               | 193               | 193                | 193                |
| Effective Observations | [59,54]             | [67,60]            | [51,48]           | [58,54]           | [42,43]            | [53,53]            |
| Covariates             | None                | None               | Some              | Some              | All                | All                |
| Conventional p-value   | 0.114               | 0.124              | 0.128             | 0.156             | 0.0678             | 0.0593             |
| Order of Polynomial    | 1                   | 2                  | 1                 | 2                 | 1                  | 2                  |
| Bandwidth              | 0.0935              | 0.110              | 0.0924            | 0.109             | 0.0771             | 0.0992             |

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 I18: RDD Estimates for Infraction Amount (log) by Year and Term

| Panel A                | (1)                 | (2)                 | (3)                | (4)                | (5)                | (6)                |
|------------------------|---------------------|---------------------|--------------------|--------------------|--------------------|--------------------|
| RD Estimate            | -0.908**<br>(0.376) | -1.048**<br>(0.435) | -0.595*<br>(0.344) | -0.779*<br>(0.453) | -0.564*<br>(0.342) | -0.710*<br>(0.420) |
| Observations           | 431                 | 431                 | 386                | 386                | 386                | 386                |
| Effective Observations | [91,86]             | [121,118]           | [102,96]           | [116,107]          | [110,106]          | [138,135]          |
| Covariates             | None                | None                | Some               | Some               | All                | All                |
| p-value                | 0.0156              | 0.0159              | 0.0840             | 0.0857             | 0.0984             | 0.0911             |
| Order of Polynomial    | 1                   | 2                   | 1                  | 2                  | 1                  | 2                  |
| Bandwidth              | 0.0697              | 0.0990              | 0.0938             | 0.108              | 0.102              | 0.147              |
| Panel B                | (1)                 | (2)                 | (3)                | (4)                | (5)                | (6)                |
| RD Estimate            | -0.840**<br>(0.404) | -0.917*<br>(0.472)  | -0.564<br>(0.392)  | -0.742<br>(0.505)  | -0.572<br>(0.351)  | -0.802<br>(0.506)  |
| Observations           | 216                 | 216                 | 193                | 193                | 193                | 193                |
| Effective Observations | [48,44]             | [65,60]             | [46,45]            | [58,54]            | [58,54]            | [60,55]            |
| Covariates             | None                | None                | Some               | Some               | All                | All                |
| Conventional p-value   | 0.0375              | 0.0521              | 0.150              | 0.142              | 0.103              | 0.113              |
| Order of Polynomial    | 1                   | 2                   | 1                  | 2                  | 1                  | 2                  |
| Bandwidth              | 0.0708              | 0.104               | 0.0884             | 0.107              | 0.108              | 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.

## I.4. When Extreme Poverty is Low

Table I19: RDD Estimates for Infraction Count by Year and Term

| Panel A                | (1)                 | (2)                 | (3)                | (4)                | (5)                  | (6)                  |
|------------------------|---------------------|---------------------|--------------------|--------------------|----------------------|----------------------|
| RD Estimate            | -2.018**<br>(0.905) | -2.550**<br>(1.205) | -1.062<br>(0.866)  | -1.245<br>(1.179)  | 0.132<br>(0.834)     | -0.0489<br>(1.200)   |
| Observations           | 400                 | 400                 | 365                | 365                | 258                  | 258                  |
| Effective Observations | [116,100]           | [130,114]           | [109,97]           | [115,106]          | [80,69]              | [86,80]              |
| Covariates             | None                | None                | Some               | Some               | All                  | All                  |
| p-value                | 0.0258              | 0.0343              | 0.220              | 0.291              | 0.874                | 0.967                |
| Order of Polynomial    | 1                   | 2                   | 1                  | 2                  | 1                    | 2                    |
| Bandwidth              | 0.0968              | 0.121               | 0.111              | 0.121              | 0.109                | 0.128                |
| Panel B                | (1)                 | (2)                 | (3)                | (4)                | (5)                  | (6)                  |
| RD Estimate            | -3.649*<br>(1.885)  | -4.337*<br>(2.497)  | -3.196*<br>(1.740) | -3.937*<br>(2.303) | -5.568***<br>(1.805) | -5.743***<br>(2.048) |
| Observations           | 205                 | 205                 | 188                | 188                | 188                  | 188                  |
| Effective observations | [58,48]             | [68,54]             | [54,47]            | [62,53]            | [43,43]              | [64,58]              |
| Covariates             | None                | None                | Some               | Some               | All                  | All                  |
| p-value                | 0.0529              | 0.0824              | 0.0663             | 0.0873             | 0.00204              | 0.00504              |
| Order of Polynomial    | 1                   | 2                   | 1                  | 2                  | 1                    | 2                    |
| Bandwidth              | 0.0909              | 0.119               | 0.100              | 0.122              | 0.0787               | 0.131 height         |

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 I20: RDD Estimates for Infraction Amount (log) by Year and Term

| Panel A                | (1)                 | (2)                 | (3)                 | (4)                | (5)                | (6)               |
|------------------------|---------------------|---------------------|---------------------|--------------------|--------------------|-------------------|
| RD Estimate            | -0.717**<br>(0.313) | -0.826**<br>(0.353) | -0.597**<br>(0.304) | -0.654*<br>(0.392) | -0.375<br>(0.384)  | -0.500<br>(0.501) |
| Observations           | 400                 | 400                 | 365                 | 365                | 258                | 258               |
| Effective Observations | [105,94]            | [142,142]           | [88,86]             | [115,106]          | [74,66]            | [87,84]           |
| Covariates             | None                | None                | Some                | Some               | All                | All               |
| p-value                | 0.0218              | 0.0194              | 0.0499              | 0.0951             | 0.329              | 0.318             |
| Order of Polynomial    | 1                   | 2                   | 1                   | 2                  | 1                  | 2                 |
| Bandwidth              | 0.0876              | 0.153               | 0.0854              | 0.122              | 0.0950             | 0.133             |
| Panel B                | (1)                 | (2)                 | (3)                 | (4)                | (5)                | (6)               |
| RD Estimate            | -0.520<br>(0.401)   | -0.711<br>(0.443)   | -0.507<br>(0.393)   | -0.512<br>(0.479)  | -0.678*<br>(0.411) | -0.826<br>(0.514) |
| Observations           | 205                 | 205                 | 188                 | 188                | 188                | 188               |
| Effective observations | [50,46]             | [71,62]             | [42,41]             | [59,49]            | [39,39]            | [54,47]           |
| Covariates             | None                | None                | Some                | Some               | All                | All               |
| p-value                | 0.195               | 0.109               | 0.197               | 0.285              | 0.0990             | 0.108             |
| Order of Polynomial    | 1                   | 2                   | 1                   | 2                  | 1                  | 2                 |
| Bandwidth              | 0.0785              | 0.134               | 0.0744              | 0.113              | 0.0709             | 0.0985            |

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.



## J. First Two Years

### J.1. When Poverty Decreases

Table J21: RDD Estimates for Infraction Count by Year and Term

| Panel A                | (1)               | (2)               | (3)               | (4)               | (5)               | (6)               |
|------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| RD Estimate            | -0.970<br>(0.752) | -0.958<br>(1.023) | -0.195<br>(0.823) | -0.195<br>(1.022) | -0.604<br>(0.914) | -1.144<br>(1.206) |
| Observations           | 212               | 212               | 212               | 212               | 212               | 212               |
| Effective Observations | [72,42]           | [74,42]           | [62,36]           | [72,42]           | [66,38]           | [72,42]           |
| Covariates             | None              | None              | Some              | Some              | All               | All               |
| p-value                | 0.197             | 0.349             | 0.813             | 0.848             | 0.509             | 0.343             |
| Order of Polynomial    | 1                 | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.103             | 0.105             | 0.0900            | 0.101             | 0.0952            | 0.102             |
| Panel B                | (1)               | (2)               | (3)               | (4)               | (5)               | (6)               |
| RD Estimate            | -1.972<br>(1.503) | -1.945<br>(2.092) | -0.637<br>(1.577) | -0.415<br>(2.094) | -1.373<br>(1.747) | -2.358<br>(2.454) |
| Observations           | 105               | 105               | 105               | 105               | 105               | 105               |
| Effective Observations | [37,21]           | [36,21]           | [36,21]           | [34,21]           | [35,21]           | [36,21]           |
| Covariates             | None              | None              | Some              | Some              | All               | All               |
| Conventional p-value   | 0.189             | 0.352             | 0.686             | 0.843             | 0.432             | 0.336             |
| Order of Polynomial    | 1                 | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.109             | 0.103             | 0.103             | 0.0998            | 0.100             | 0.102             |

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 J22: RDD Estimates for Infraction Amount (log) by Year and Term

| Panel A                | (1)               | (2)              | (3)              | (4)              | (5)               | (6)                |
|------------------------|-------------------|------------------|------------------|------------------|-------------------|--------------------|
| RD Estimate            | 0.146<br>(0.307)  | 0.289<br>(0.354) | 0.299<br>(0.299) | 0.379<br>(0.346) | 0.179<br>(0.362)  | 0.132<br>(0.415)   |
| Observations           | 210               | 210              | 210              | 210              | 210               | 210                |
| Effective Observations | [52,24]           | [60,34]          | [50,24]          | [60,34]          | [50,24]           | [60,34]            |
| Covariates             | None              | None             | Some             | Some             | All               | All                |
| p-value                | 0.635             | 0.415            | 0.318            | 0.273            | 0.621             | 0.751              |
| Order of Polynomial    | 1                 | 2                | 1                | 2                | 1                 | 2                  |
| Bandwidth              | 0.0610            | 0.0868           | 0.0602           | 0.0866           | 0.0587            | 0.0859             |
| Panel B                | (1)               | (2)              | (3)              | (4)              | (5)               | (6)                |
| RD Estimate            | 0.0195<br>(0.390) | 0.165<br>(0.447) | 0.136<br>(0.374) | 0.179<br>(0.435) | 0.0784<br>(0.478) | -0.0730<br>(0.556) |
| Observations           | 105               | 105              | 105              | 105              | 105               | 105                |
| Effective Observations | [26,12]           | [31,17]          | [26,12]          | [33,18]          | [25,12]           | [30,17]            |
| Covariates             | None              | None             | Some             | Some             | All               | All                |
| Conventional p-value   | 0.960             | 0.711            | 0.716            | 0.680            | 0.870             | 0.896              |
| Order of Polynomial    | 1                 | 2                | 1                | 2                | 1                 | 2                  |
| Bandwidth              | 0.0612            | 0.0893           | 0.0612           | 0.0911           | 0.0579            | 0.0868             |

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.

## J.2. When Poverty is Low

Table J23: RDD Estimates for Infraction Count by Year and Term

| Panel A                | (1)                  | (2)                  | (3)                 | (4)                 | (5)                 | (6)                 |
|------------------------|----------------------|----------------------|---------------------|---------------------|---------------------|---------------------|
| RD Estimate            | -2.470***<br>(0.805) | -2.940***<br>(0.936) | -2.052**<br>(0.804) | -2.329**<br>(0.944) | -1.880**<br>(0.751) | -2.213**<br>(0.910) |
| Observations           | 414                  | 414                  | 383                 | 383                 | 383                 | 383                 |
| Effective Observations | [107,94]             | [147,131]            | [100,90]            | [140,133]           | [98,90]             | [134,125]           |
| Covariates             | None                 | None                 | Some                | Some                | All                 | All                 |
| p-value                | 0.00214              | 0.00169              | 0.0107              | 0.0136              | 0.0123              | 0.0150              |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                   | 2                   |
| Bandwidth              | 0.0761               | 0.134                | 0.0846              | 0.153               | 0.0827              | 0.133               |
| Panel B                | (1)                  | (2)                  | (3)                 | (4)                 | (5)                 | (6)                 |
| RD Estimate            | -4.257**<br>(1.794)  | -5.180**<br>(2.127)  | -4.085**<br>(1.624) | -4.699**<br>(1.930) | -3.672**<br>(1.623) | -4.944**<br>(2.048) |
| Observations           | 208                  | 208                  | 192                 | 192                 | 192                 | 192                 |
| Effective observations | [54,47]              | [74,66]              | [49,45]             | [69,64]             | [47,44]             | [67,63]             |
| Covariates             | None                 | None                 | Some                | Some                | All                 | All                 |
| p-value                | 0.0176               | 0.0149               | 0.0119              | 0.0149              | 0.0237              | 0.0158              |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                   | 2                   |
| Bandwidth              | 0.0796               | 0.137                | 0.0833              | 0.145               | 0.0784              | 0.134               |

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 J24: RDD Estimates for Infraction Amount (log) by Year and Term

| Panel A                | (1)               | (2)               | (3)               | (4)               | (5)               | (6)               |
|------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| RD Estimate            | -0.274<br>(0.328) | -0.405<br>(0.393) | -0.149<br>(0.309) | -0.184<br>(0.348) | -0.102<br>(0.307) | -0.182<br>(0.348) |
| Observations           | 413               | 413               | 382               | 382               | 382               | 382               |
| Effective Observations | [117,96]          | [151,131]         | [112,94]          | [144,149]         | [112,94]          | [144,149]         |
| Covariates             | None              | None              | Some              | Some              | All               | All               |
| p-value                | 0.403             | 0.302             | 0.630             | 0.597             | 0.739             | 0.600             |
| Order of Polynomial    | 1                 | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.0877            | 0.138             | 0.0957            | 0.173             | 0.0940            | 0.173             |
| Panel B                | (1)               | (2)               | (3)               | (4)               | (5)               | (6)               |
| RD Estimate            | -0.219<br>(0.350) | -0.233<br>(0.434) | -0.225<br>(0.321) | -0.272<br>(0.384) | -0.156<br>(0.318) | -0.302<br>(0.392) |
| Observations           | 208               | 208               | 192               | 192               | 192               | 192               |
| Effective observations | [63,50]           | [74,66]           | [55,47]           | [69,64]           | [53,45]           | [69,64]           |
| Covariates             | None              | None              | Some              | Some              | All               | All               |
| p-value                | 0.532             | 0.591             | 0.483             | 0.478             | 0.625             | 0.441             |
| Order of Polynomial    | 1                 | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.0929            | 0.137             | 0.0915            | 0.142             | 0.0896            | 0.143             |

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.

### J.3. When Extreme Poverty Decreases

Table J25: RDD Estimates for Infraction Count by Year and Term

| Panel A                | (1)                | (2)               | (3)               | (4)               | (5)               | (6)               |
|------------------------|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| RD Estimate            | -1.331*<br>(0.770) | -1.425<br>(0.971) | -0.791<br>(0.807) | -0.835<br>(0.997) | -0.891<br>(0.836) | -1.331<br>(1.050) |
| Observations           | 238                | 238               | 238               | 238               | 238               | 238               |
| Effective Observations | [58,44]            | [82,56]           | [58,44]           | [82,56]           | [58,44]           | [80,54]           |
| Covariates             | None               | None              | Some              | Some              | All               | All               |
| p-value                | 0.0837             | 0.142             | 0.327             | 0.402             | 0.287             | 0.205             |
| Order of Polynomial    | 1                  | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.0830             | 0.114             | 0.0824            | 0.113             | 0.0818            | 0.106             |
| Panel B                | (1)                | (2)               | (3)               | (4)               | (5)               | (6)               |
| RD Estimate            | -2.661*<br>(1.543) | -2.872<br>(1.957) | -1.601<br>(1.610) | -1.667<br>(2.030) | -1.925<br>(1.675) | -2.818<br>(2.160) |
| Observations           | 118                | 118               | 118               | 118               | 118               | 118               |
| Effective Observations | [29,22]            | [42,28]           | [29,22]           | [41,28]           | [29,22]           | [40,27]           |
| Covariates             | None               | None              | Some              | Some              | All               | All               |
| Conventional p-value   | 0.0847             | 0.142             | 0.320             | 0.411             | 0.251             | 0.192             |
| Order of Polynomial    | 1                  | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.0842             | 0.115             | 0.0845            | 0.112             | 0.0840            | 0.105             |

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 J26: RDD Estimates for Infraction Amount (log) by Year and Term

| Panel A                | (1)                | (2)              | (3)               | (4)              | (5)                  | (6)                |
|------------------------|--------------------|------------------|-------------------|------------------|----------------------|--------------------|
| RD Estimate            | 0.172<br>(0.351)   | 0.264<br>(0.392) | 0.169<br>(0.342)  | 0.271<br>(0.397) | 0.231<br>(0.353)     | 0.114<br>(0.420)   |
| Observations           | 236                | 236              | 236               | 236              | 236                  | 236                |
| Effective Observations | [52,34]            | [70,48]          | [56,42]           | [60,44]          | [54,36]              | [60,44]            |
| Covariates             | None               | None             | Some              | Some             | All                  | All                |
| p-value                | 0.625              | 0.501            | 0.621             | 0.495            | 0.513                | 0.786              |
| Order of Polynomial    | 1                  | 2                | 1                 | 2                | 1                    | 2                  |
| Bandwidth              | 0.0650             | 0.0917           | 0.0714            | 0.0869           | 0.0695               | 0.0867             |
| Panel B                | (1)                | (2)              | (3)               | (4)              | (5)                  | (6)                |
| RD Estimate            | -0.0309<br>(0.384) | 0.166<br>(0.471) | -0.157<br>(0.355) | 0.143<br>(0.473) | -0.000151<br>(0.386) | -0.0117<br>(0.523) |
| Observations           | 118                | 118              | 118               | 118              | 118                  | 118                |
| Effective Observations | [28,22]            | [35,24]          | [33,23]           | [35,24]          | [28,22]              | [33,23]            |
| Covariates             | None               | None             | Some              | Some             | All                  | All                |
| Conventional p-value   | 0.936              | 0.725            | 0.658             | 0.763            | 1                    | 0.982              |
| Order of Polynomial    | 1                  | 2                | 1                 | 2                | 1                    | 2                  |
| Bandwidth              | 0.0769             | 0.0935           | 0.0901            | 0.0922           | 0.0781               | 0.0902             |

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.

## J.4. When Extreme Poverty is Low

Table J27: RDD Estimates for Infraction Count by Year and Term

| Panel A                | (1)                 | (2)                 | (3)               | (4)               | (5)                | (6)                |
|------------------------|---------------------|---------------------|-------------------|-------------------|--------------------|--------------------|
| RD Estimate            | -2.033**<br>(0.931) | -2.577**<br>(1.075) | -1.392<br>(0.941) | -1.607<br>(1.124) | -1.426*<br>(0.863) | -1.741*<br>(1.016) |
| Observations           | 407                 | 407                 | 376               | 376               | 376                | 376                |
| Effective Observations | [97,88]             | [143,124]           | [90,86]           | [126,114]         | [86,86]            | [128,118]          |
| Covariates             | None                | None                | Some              | Some              | All                | All                |
| p-value                | 0.0290              | 0.0165              | 0.139             | 0.153             | 0.0984             | 0.0866             |
| Order of Polynomial    | 1                   | 2                   | 1                 | 2                 | 1                  | 2                  |
| Bandwidth              | 0.0749              | 0.137               | 0.0833            | 0.129             | 0.0794             | 0.135              |
| Panel B                | (1)                 | (2)                 | (3)               | (4)               | (5)                | (6)                |
| RD Estimate            | -3.305<br>(2.056)   | -4.235*<br>(2.404)  | -2.789<br>(1.890) | -3.225<br>(2.266) | -2.105<br>(1.882)  | -3.603<br>(2.367)  |
| Observations           | 205                 | 205                 | 188               | 188               | 188                | 188                |
| Effective observations | [50,46]             | [74,64]             | [45,43]           | [63,58]           | [43,43]            | [64,59]            |
| Covariates             | None                | None                | Some              | Some              | All                | All                |
| p-value                | 0.108               | 0.0782              | 0.140             | 0.155             | 0.263              | 0.128              |
| Order of Polynomial    | 1                   | 2                   | 1                 | 2                 | 1                  | 2                  |
| Bandwidth              | 0.0788              | 0.141               | 0.0833            | 0.129             | 0.0786             | 0.137              |

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 J28: RDD Estimates for Infraction Amount (log) by Year and Term

| Panel A                | (1)                | (2)               | (3)                | (4)               | (5)              | (6)               |
|------------------------|--------------------|-------------------|--------------------|-------------------|------------------|-------------------|
| RD Estimate            | -0.135<br>(0.376)  | -0.323<br>(0.437) | 0.137<br>(0.361)   | 0.0483<br>(0.428) | 0.185<br>(0.360) | 0.0978<br>(0.438) |
| Observations           | 406                | 406               | 375                | 375               | 375              | 375               |
| Effective Observations | [99,92]            | [141,124]         | [94,86]            | [128,118]         | [92,86]          | [128,116]         |
| Covariates             | None               | None              | Some               | Some              | All              | All               |
| p-value                | 0.721              | 0.460             | 0.705              | 0.910             | 0.607            | 0.823             |
| Order of Polynomial    | 1                  | 2                 | 1                  | 2                 | 1                | 2                 |
| Bandwidth              | 0.0804             | 0.133             | 0.0851             | 0.136             | 0.0844           | 0.131             |
| Panel B                | (1)                | (2)               | (3)                | (4)               | (5)              | (6)               |
| RD Estimate            | -0.0912<br>(0.400) | -0.192<br>(0.491) | -0.0704<br>(0.362) | -0.211<br>(0.416) | 0.102<br>(0.361) | -0.190<br>(0.395) |
| Observations           | 205                | 205               | 188                | 188               | 188              | 188               |
| Effective observations | [53,46]            | [70,61]           | [45,43]            | [66,61]           | [43,43]          | [70,70]           |
| Covariates             | None               | None              | Some               | Some              | All              | All               |
| p-value                | 0.820              | 0.695             | 0.846              | 0.612             | 0.778            | 0.630             |
| Order of Polynomial    | 1                  | 2                 | 1                  | 2                 | 1                | 2                 |
| Bandwidth              | 0.0841             | 0.129             | 0.0834             | 0.143             | 0.0807           | 0.170             |

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.



## K. Results for the Whole Sample (i.e. When Poverty Is Not Considered)

### K.1. For Poverty Increasing/Decreasing Sample

Table K29: RDD Estimates for Infraction Count by Year

| Panel A                | (1)                | (2)               | (3)              | (4)              | (5)               | (6)               |
|------------------------|--------------------|-------------------|------------------|------------------|-------------------|-------------------|
| RD Estimate            | -0.0346<br>(0.581) | -0.455<br>(0.885) | 0.110<br>(0.532) | 0.158<br>(0.812) | -0.132<br>(0.634) | -0.193<br>(0.724) |
| Observations           | 1,357              | 1,357             | 1,275            | 1,275            | 1,151             | 1,151             |
| Effective Observations | [451,419]          | [467,461]         | [472,487]        | [486,505]        | [343,333]         | [470,517]         |
| Covariates             | None               | None              | Some             | Some             | All               | All               |
| p-value                | 0.952              | 0.607             | 0.837            | 0.845            | 0.835             | 0.789             |
| Order of Polynomial    | 1                  | 2                 | 1                | 2                | 1                 | 2                 |
| Bandwidth              | 0.132              | 0.149             | 0.170            | 0.178            | 0.120             | 0.212             |
| Panel B                | (1)                | (2)               | (3)              | (4)              | (5)               | (6)               |
| RD Estimate            | 0.0420<br>(0.624)  | -0.143<br>(0.868) | 0.370<br>(0.578) | 0.338<br>(0.713) | 0.0368<br>(0.654) | 0.231<br>(0.846)  |
| Observations           | 1,357              | 1,357             | 1,275            | 1,275            | 1,151             | 1,151             |
| Effective Observations | [421,377]          | [471,473]         | [430,417]        | [536,559]        | [331,322]         | [415,447]         |
| Covariates             | None               | None              | Some             | Some             | All               | All               |
| p-value                | 0.946              | 0.869             | 0.522            | 0.636            | 0.955             | 0.785             |
| Order of Polynomial    | 1                  | 2                 | 1                | 2                | 1                 | 2                 |
| Bandwidth              | 0.118              | 0.153             | 0.142            | 0.219            | 0.114             | 0.169             |

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 K30: RDD Estimates for Infraction Count by Term

| Panel A                | (1)               | (2)               | (3)               | (4)               | (5)                | (6)               |
|------------------------|-------------------|-------------------|-------------------|-------------------|--------------------|-------------------|
| RD Estimate            | -2.232<br>(2.695) | -3.996<br>(3.911) | -2.892<br>(2.848) | -4.365<br>(3.998) | -5.220*<br>(3.141) | -4.038<br>(4.206) |
| Observations           | 440               | 440               | 398               | 398               | 372                | 372               |
| Effective Observations | [132,119]         | [148,142]         | [117,108]         | [134,134]         | [99,93]            | [121,123]         |
| Covariates             | None              | None              | Some              | Some              | All                | All               |
| Conventional p-value   | 0.408             | 0.307             | 0.310             | 0.275             | 0.0966             | 0.337             |
| Order of Polynomial    | 1                 | 2                 | 1                 | 2                 | 1                  | 2                 |
| Bandwidth              | 0.111             | 0.136             | 0.107             | 0.141             | 0.0935             | 0.132             |
| Panel B                | (1)               | (2)               | (3)               | (4)               | (5)                | (6)               |
| RD Estimate            | 0.276<br>(1.954)  | -0.196<br>(2.696) | 1.232<br>(1.989)  | 1.225<br>(2.425)  | -0.758<br>(2.234)  | 0.0322<br>(3.030) |
| Observations           | 440               | 440               | 398               | 398               | 372                | 372               |
| Effective Observations | [135,122]         | [154,157]         | [126,120]         | [160,171]         | [102,101]          | [124,129]         |
| Covariates             | None              | None              | Some              | Some              | All                | All               |
| Conventional p-value   | 0.888             | 0.942             | 0.536             | 0.613             | 0.734              | 0.992             |
| Order of Polynomial    | 1                 | 2                 | 1                 | 2                 | 1                  | 2                 |
| Bandwidth              | 0.115             | 0.152             | 0.122             | 0.194             | 0.100              | 0.142             |

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 K31: RDD Estimates for Infraction Amount (log) by Year

| Panel A                | (1)               | (2)               | (3)                | (4)                | (5)                | (6)                |
|------------------------|-------------------|-------------------|--------------------|--------------------|--------------------|--------------------|
| RD Estimate            | -0.173<br>(0.217) | -0.336<br>(0.292) | -0.0737<br>(0.210) | -0.113<br>(0.275)  | -0.0910<br>(0.211) | -0.207<br>(0.303)  |
| Observations           | 1,352             | 1,352             | 1,270              | 1,270              | 1,146              | 1,146              |
| Effective Observations | [398,353]         | [459,431]         | [389,361]          | [462,477]          | [339,331]          | [375,393]          |
| Covariates             | None              | None              | Some               | Some               | All                | All                |
| p-value                | 0.424             | 0.249             | 0.726              | 0.680              | 0.667              | 0.495              |
| Order of Polynomial    | 1                 | 2                 | 1                  | 2                  | 1                  | 2                  |
| Bandwidth              | 0.106             | 0.141             | 0.119              | 0.164              | 0.117              | 0.142              |
| Panel B                | (1)               | (2)               | (3)                | (4)                | (5)                | (6)                |
| RD Estimate            | -0.139<br>(0.221) | -0.272<br>(0.290) | -0.0318<br>(0.213) | -0.0187<br>(0.255) | -0.0378<br>(0.207) | -0.0905<br>(0.291) |
| Observations           | 1,352             | 1,352             | 1,270              | 1,270              | 1,146              | 1,146              |
| Effective Observations | [386,352]         | [461,443]         | [381,349]          | [513,529]          | [341,333]          | [379,409]          |
| Covariates             | None              | None              | Some               | Some               | All                | All                |
| p-value                | 0.530             | 0.348             | 0.882              | 0.942              | 0.856              | 0.755              |
| Order of Polynomial    | 1                 | 2                 | 1                  | 2                  | 1                  | 2                  |
| Bandwidth              | 0.103             | 0.142             | 0.114              | 0.189              | 0.118              | 0.151              |

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 K32: RDD Estimates for Infraction Amount (log) by Term

| Panel A                | (1)                | (2)               | (3)               | (4)               | (5)               | (6)               |
|------------------------|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| RD Estimate            | -0.0541<br>(0.247) | -0.379<br>(0.405) | 0.0199<br>(0.247) | -0.288<br>(0.412) | -0.203<br>(0.287) | -0.215<br>(0.394) |
| Observations           | 440                | 440               | 398               | 398               | 372               | 372               |
| Effective Observations | [150,144]          | [146,136]         | [136,142]         | [132,132]         | [108,103]         | [125,135]         |
| Covariates             | None               | None              | Some              | Some              | All               | All               |
| Conventional p-value   | 0.827              | 0.350             | 0.936             | 0.484             | 0.480             | 0.586             |
| Order of Polynomial    | 1                  | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.138              | 0.130             | 0.148             | 0.136             | 0.109             | 0.148             |
| Panel B                | (1)                | (2)               | (3)               | (4)               | (5)               | (6)               |
| RD Estimate            | -0.0200<br>(0.253) | -0.200<br>(0.366) | 0.161<br>(0.244)  | 0.0577<br>(0.353) | 0.0716<br>(0.256) | 0.0626<br>(0.358) |
| Observations           | 440                | 440               | 398               | 398               | 372               | 372               |
| Effective Observations | [133,120]          | [147,136]         | [127,124]         | [136,142]         | [110,107]         | [125,135]         |
| Covariates             | None               | None              | Some              | Some              | All               | All               |
| Conventional p-value   | 0.937              | 0.585             | 0.509             | 0.870             | 0.780             | 0.861             |
| Order of Polynomial    | 1                  | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.112              | 0.131             | 0.125             | 0.148             | 0.114             | 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.

## K.2. For Poverty High/Low Sample

Table K33: RDD Estimates for Infraction Count by Year

| Panel A                | (1)               | (2)               | (3)               | (4)                | (5)               | (6)               |
|------------------------|-------------------|-------------------|-------------------|--------------------|-------------------|-------------------|
| RD Estimate            | -0.326<br>(0.476) | -0.671<br>(0.722) | -0.233<br>(0.523) | -0.324<br>(0.712)  | -0.296<br>(0.448) | -0.294<br>(0.613) |
| Observations           | 2,004             | 2,004             | 1,834             | 1,834              | 1,254             | 1,254             |
| Effective Observations | [666,606]         | [700,664]         | [562,515]         | [640,658]          | [369,358]         | [421,465]         |
| Covariates             | None              | None              | Some              | Some               | All               | All               |
| p-value                | 0.493             | 0.353             | 0.657             | 0.649              | 0.509             | 0.631             |
| Order of Polynomial    | 1                 | 2                 | 1                 | 2                  | 1                 | 2                 |
| Bandwidth              | 0.130             | 0.144             | 0.115             | 0.154              | 0.112             | 0.150             |
| Panel B                | (1)               | (2)               | (3)               | (4)                | (5)               | (6)               |
| RD Estimate            | -0.107<br>(0.438) | -0.527<br>(0.718) | 0.128<br>(0.457)  | -0.0374<br>(0.692) | -0.202<br>(0.444) | -0.222<br>(0.565) |
| Observations           | 2,004             | 2,004             | 1,834             | 1,834              | 1,254             | 1,254             |
| Effective Observations | [700,668]         | [690,640]         | [614,584]         | [636,638]          | [369,366]         | [454,509]         |
| Covariates             | None              | None              | Some              | Some               | All               | All               |
| p-value                | 0.807             | 0.462             | 0.779             | 0.957              | 0.650             | 0.694             |
| Order of Polynomial    | 1                 | 2                 | 1                 | 2                  | 1                 | 2                 |
| Bandwidth              | 0.144             | 0.138             | 0.135             | 0.150              | 0.114             | 0.170             |

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 K34: RDD Estimates for Infraction Count by Term

| Panel A                | (1)                | (2)               | (3)               | (4)               | (5)               | (6)               |
|------------------------|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| RD Estimate            | -1.323<br>(2.158)  | -2.044<br>(2.585) | -1.105<br>(2.360) | -0.758<br>(3.186) | -2.631<br>(2.323) | -3.089<br>(3.079) |
| Observations           | 567                | 567               | 522               | 522               | 373               | 373               |
| Effective observations | [191,169]          | [236,238]         | [164,147]         | [186,185]         | [108,102]         | [129,146]         |
| Covariates             | None               | None              | Some              | Some              | All               | All               |
| p-value                | 0.540              | 0.429             | 0.640             | 0.812             | 0.257             | 0.316             |
| Order of Polynomial    | 1                  | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.131              | 0.212             | 0.117             | 0.156             | 0.108             | 0.159             |
| Panel B                | (1)                | (2)               | (3)               | (4)               | (5)               | (6)               |
| RD Estimate            | -0.0818<br>(1.626) | -1.540<br>(2.637) | 0.349<br>(1.683)  | -0.526<br>(2.545) | -1.718<br>(2.383) | -2.156<br>(2.491) |
| Observations           | 567                | 567               | 522               | 522               | 373               | 373               |
| Effective observations | [198,178]          | [198,178]         | [174,158]         | [183,177]         | [102,101]         | [153,169]         |
| Covariates             | None               | None              | Some              | Some              | All               | All               |
| p-value                | 0.960              | 0.559             | 0.836             | 0.836             | 0.471             | 0.387             |
| Order of Polynomial    | 1                  | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.140              | 0.140             | 0.131             | 0.149             | 0.100             | 0.211             |

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 K35: RDD Estimates for Infraction Amount (log) by Year

| Panel A                | (1)               | (2)               | (3)                | (4)               | (5)                | (6)                |
|------------------------|-------------------|-------------------|--------------------|-------------------|--------------------|--------------------|
| RD Estimate            | -0.144<br>(0.193) | -0.362<br>(0.318) | -0.0799<br>(0.182) | -0.320<br>(0.292) | -0.0297<br>(0.190) | -0.111<br>(0.282)  |
| Observations           | 1,999             | 1,999             | 1,829              | 1,829             | 1,249              | 1,249              |
| Effective Observations | [599,537]         | [625,553]         | [585,556]          | [592,556]         | [352,346]          | [400,403]          |
| Covariates             | None              | None              | Some               | Some              | All                | All                |
| p-value                | 0.456             | 0.254             | 0.660              | 0.273             | 0.876              | 0.694              |
| Order of Polynomial    | 1                 | 2                 | 1                  | 2                 | 1                  | 2                  |
| Bandwidth              | 0.111             | 0.116             | 0.125              | 0.126             | 0.102              | 0.129              |
| Panel B                | (1)               | (2)               | (3)                | (4)               | (5)                | (6)                |
| RD Estimate            | -0.120<br>(0.194) | -0.277<br>(0.307) | -0.0630<br>(0.185) | -0.202<br>(0.268) | -0.0232<br>(0.186) | -0.0849<br>(0.267) |
| Observations           | 1,999             | 1,999             | 1,829              | 1,829             | 1,249              | 1,249              |
| Effective Observations | [599,533]         | [637,564]         | [573,523]          | [616,588]         | [359,348]          | [406,431]          |
| Covariates             | None              | None              | Some               | Some              | All                | All                |
| p-value                | 0.538             | 0.367             | 0.733              | 0.450             | 0.901              | 0.750              |
| Order of Polynomial    | 1                 | 2                 | 1                  | 2                 | 1                  | 2                  |
| Bandwidth              | 0.108             | 0.119             | 0.118              | 0.137             | 0.105              | 0.137              |

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 K36: RDD Estimates for Infraction Amount (log) by Term

| Panel A                | (1)                 | (2)                | (3)                | (4)               | (5)                | (6)               |
|------------------------|---------------------|--------------------|--------------------|-------------------|--------------------|-------------------|
| RD Estimate            | -0.00483<br>(0.230) | -0.0220<br>(0.335) | -0.0127<br>(0.241) | 0.0211<br>(0.325) | -0.0485<br>(0.255) | -0.162<br>(0.381) |
| Observations           | 567                 | 567                | 522                | 522               | 373                | 373               |
| Effective observations | [193,174]           | [202,197]          | [167,152]          | [193,188]         | [108,102]          | [119,119]         |
| Covariates             | None                | None               | Some               | Some              | All                | All               |
| p-value                | 0.983               | 0.948              | 0.958              | 0.948             | 0.849              | 0.672             |
| Order of Polynomial    | 1                   | 2                  | 1                  | 2                 | 1                  | 2                 |
| Bandwidth              | 0.134               | 0.154              | 0.122              | 0.162             | 0.108              | 0.129             |
| Panel B                | (1)                 | (2)                | (3)                | (4)               | (5)                | (6)               |
| RD Estimate            | 0.0117<br>(0.231)   | -0.0456<br>(0.343) | 0.0177<br>(0.238)  | 0.0136<br>(0.332) | -0.0244<br>(0.257) | -0.136<br>(0.382) |
| Observations           | 567                 | 567                | 522                | 522               | 373                | 373               |
| Effective observations | [189,169]           | [201,186]          | [168,152]          | [184,183]         | [108,102]          | [119,118]         |
| Covariates             | None                | None               | Some               | Some              | All                | All               |
| p-value                | 0.959               | 0.894              | 0.941              | 0.967             | 0.924              | 0.722             |
| Order of Polynomial    | 1                   | 2                  | 1                  | 2                 | 1                  | 2                 |
| Bandwidth              | 0.130               | 0.146              | 0.122              | 0.154             | 0.107              | 0.128             |

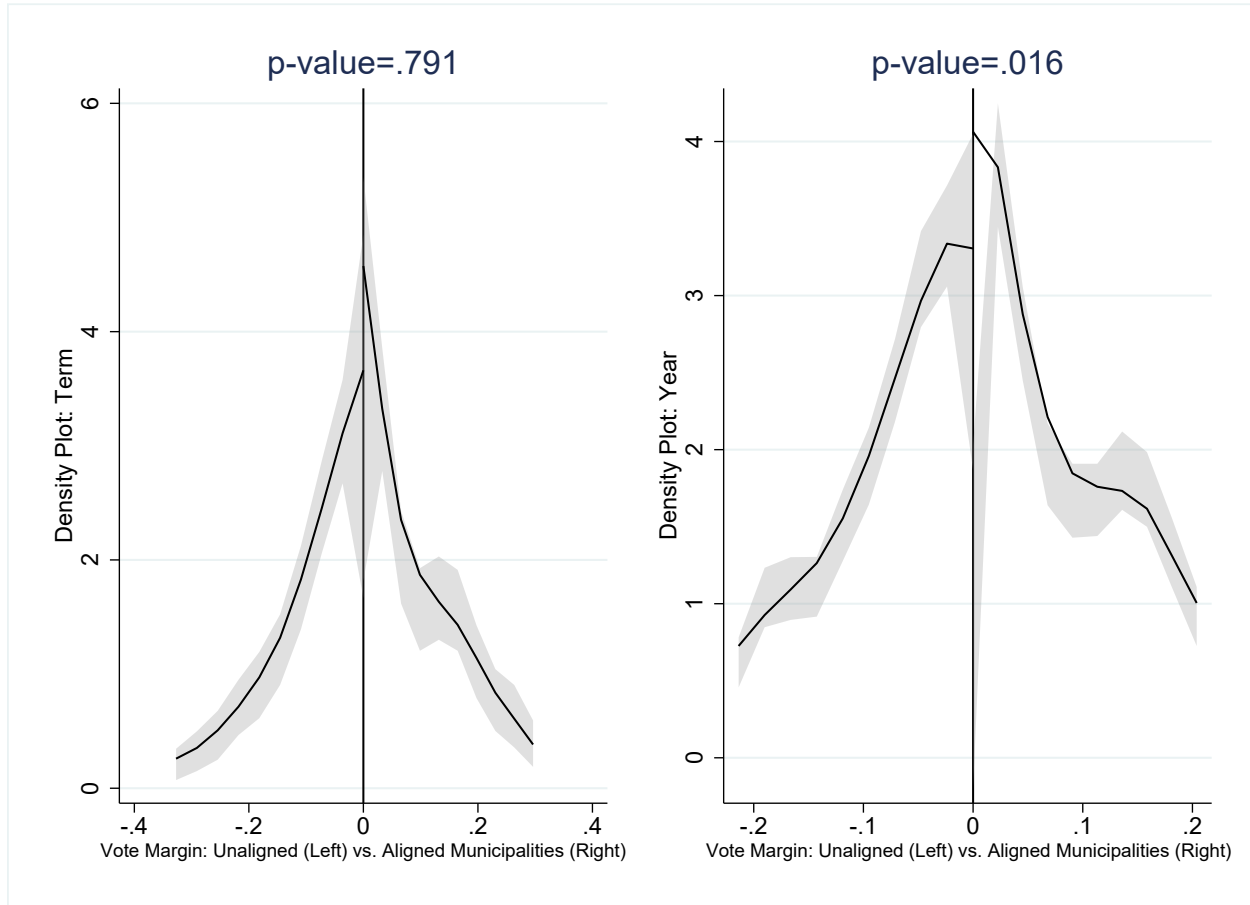
Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Panel A shows results without term fixed effects, while Panel B shows results with term fixed effects. All specifications use standard errors clustered by municipality. Bandwidth corresponds to the margin of 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.



## L. RDD Robustness Checks: Term and Year

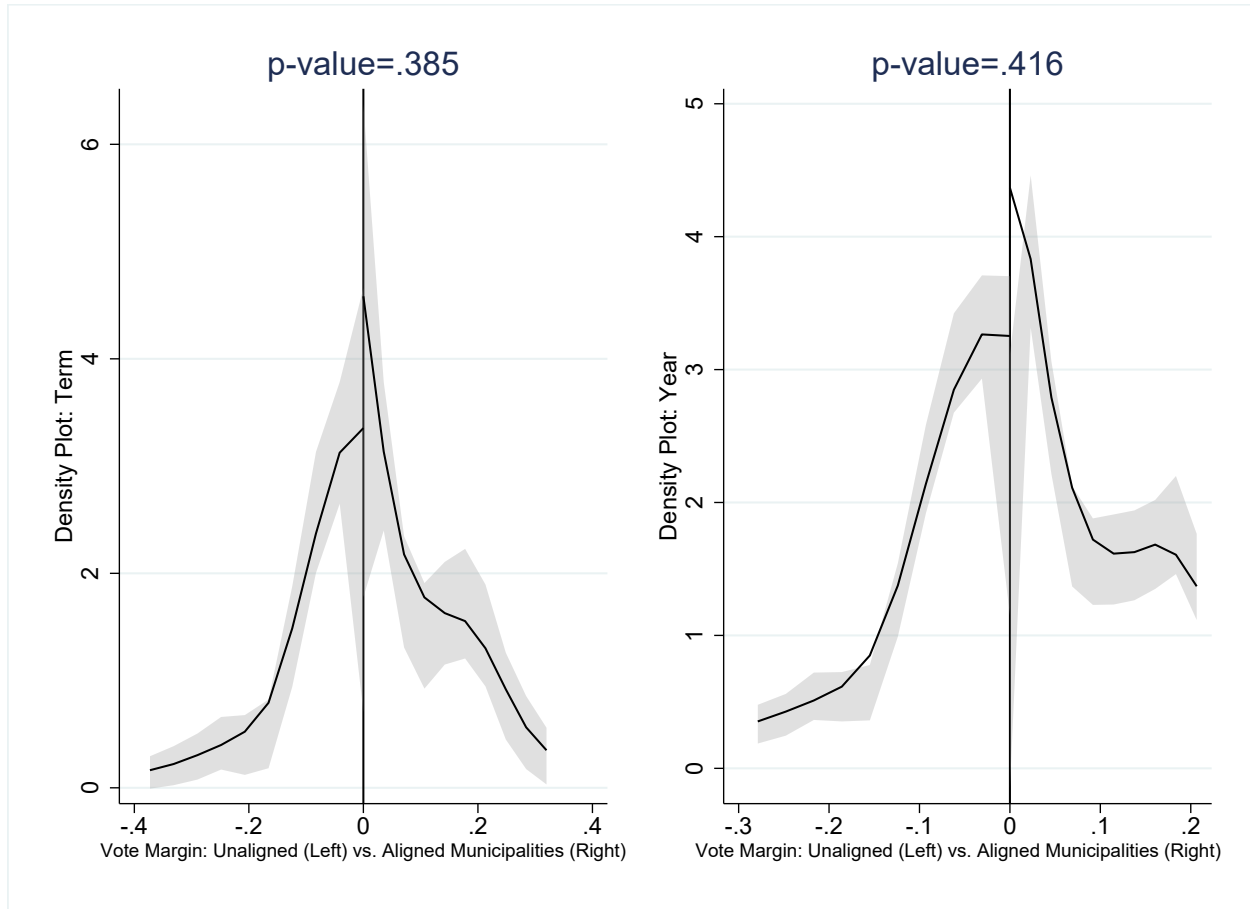
### L.1. Density Plots for Poverty High/Low Sample

Figure L.1: RDD Density Plots for Infraction Count and Amount (Whole Sample)



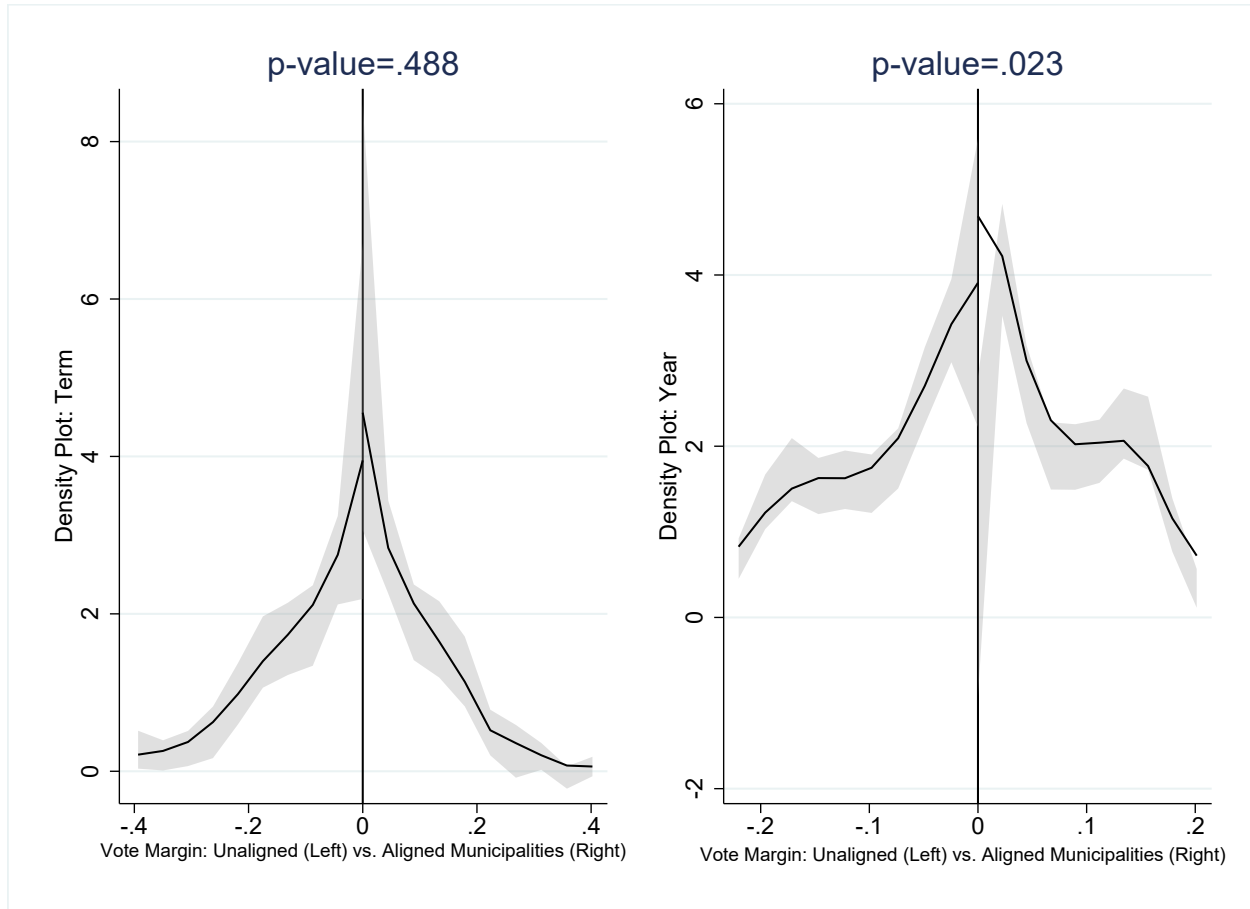
Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. The electoral term are results are not statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis in this sample. The year-wise results for this sample do not pass the [McCrary \(2008\)](#) density tests, indicating a potential problem with using the margin of victory as a running variable for this sample. The above plots provide further evidence via the overlapping confidence intervals (shaded gray areas) on both sides of the cutoff.

Figure L.2: RDD Density Plots for Infraction Count and Amount (Low-Poverty Sample)



Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. Neither the electoral term nor year results are statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis. The above plots provide further evidence via the overlapping confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

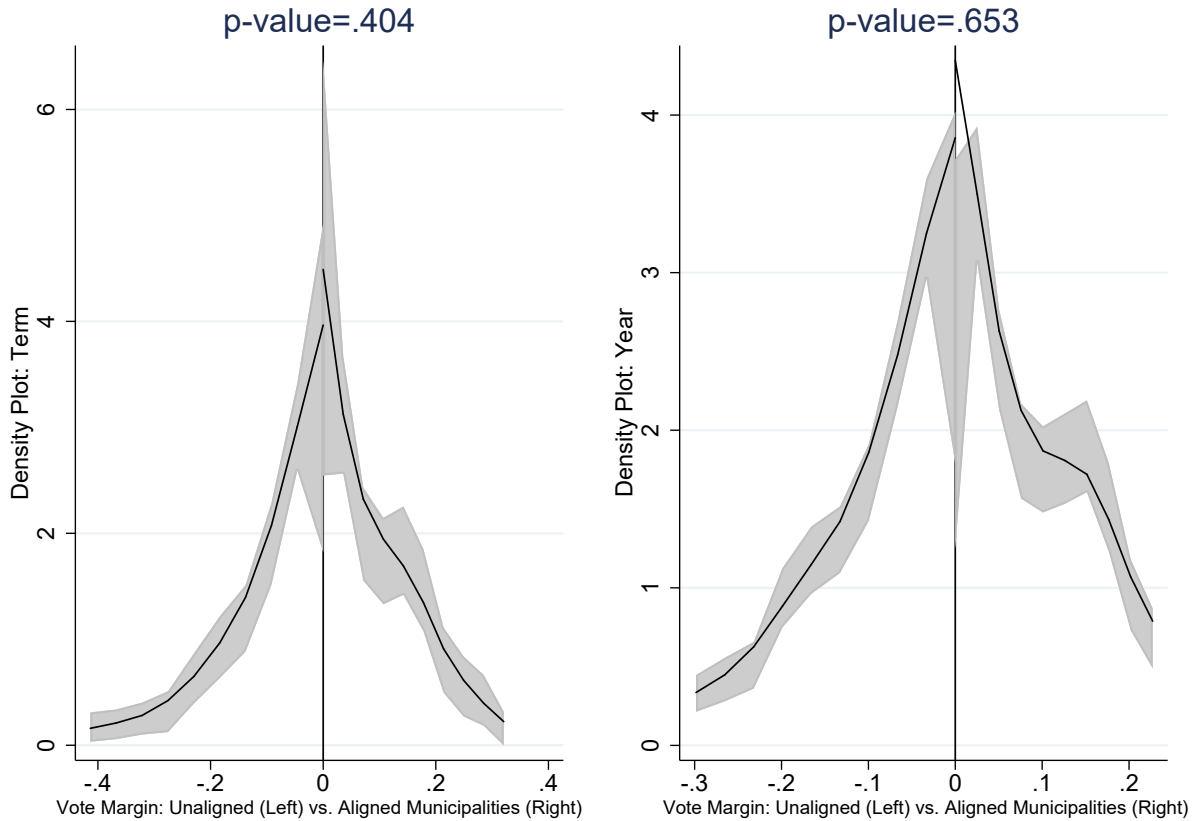
Figure L.3: RDD Density Plots for Infraction Count and Amount (High-Poverty Sample)



Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. The electoral term are results are not statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis in this sample. The year-wise results for this sample do not pass the [McCrary \(2008\)](#) density tests, indicating a potential problem with using the margin of victory as a running variable for this sample. The above plots provide further evidence via the confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

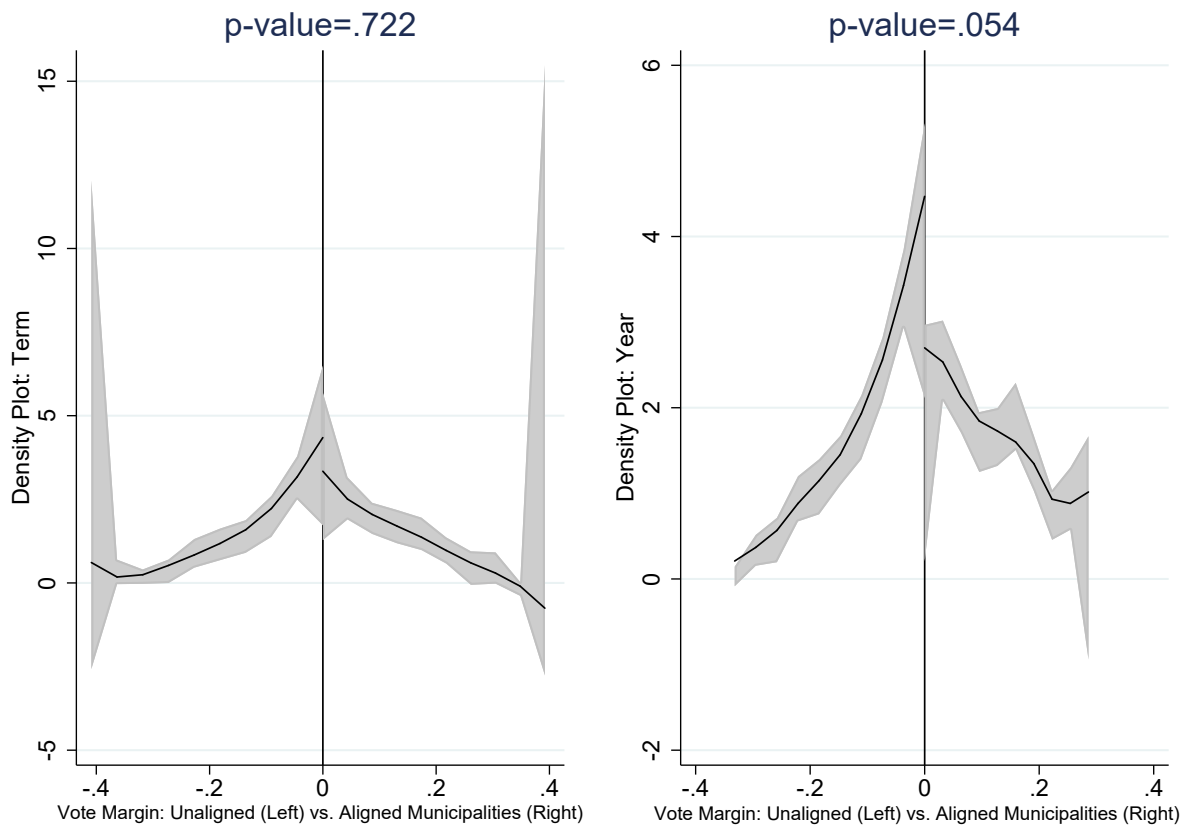
## L.2. Density Plots for Poverty Increasing/Decreasing Sample: 2010-2015 (Main Results)

Figure L.4: RDD Density Plots for Infraction Count and Amount (Whole Sample)



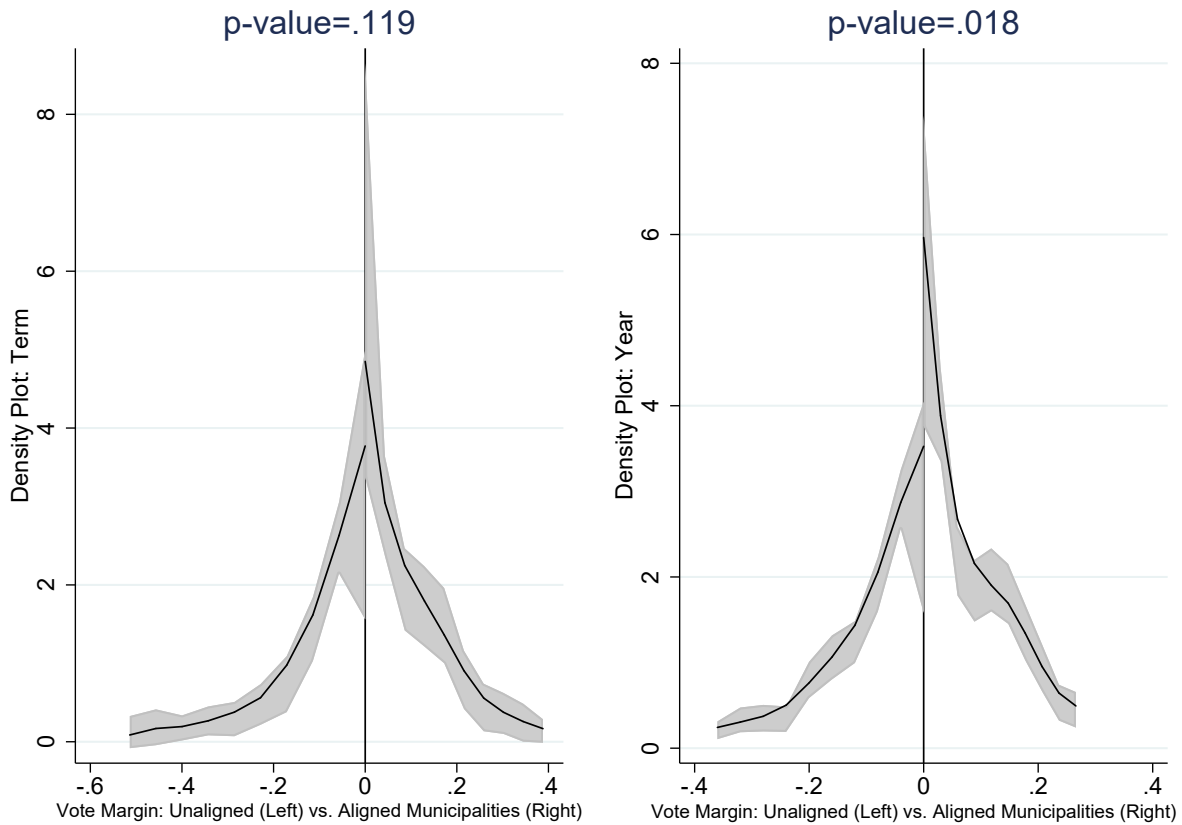
Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. Neither the electoral term nor year results are statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis. The above plots provide further evidence via the overlapping confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

Figure L.5: RDD Density Plots for Infraction Count and Amount (Poverty-Decreasing Sample)



Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. Neither the electoral term nor year results are statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis. The above plots provide further evidence via the overlapping confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

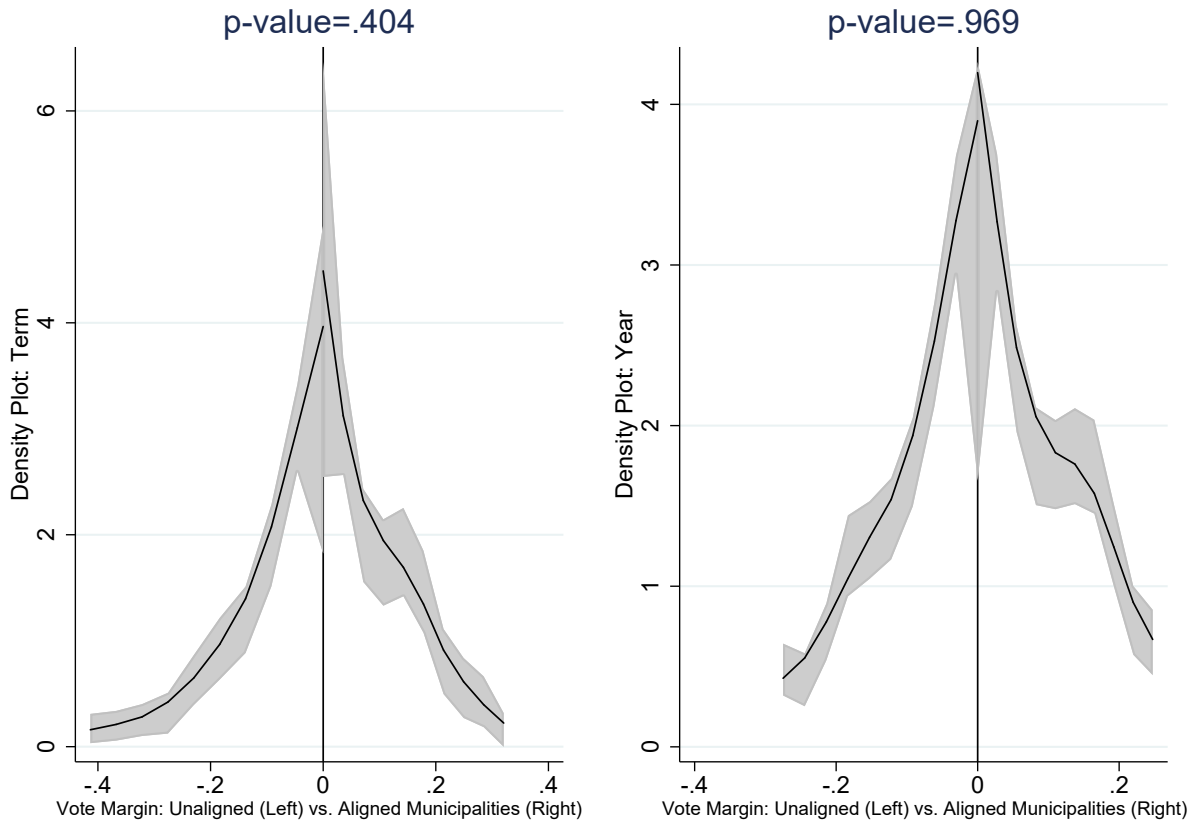
Figure L.6: RDD Density Plots for Infraction Count and Amount (Poverty-Increasing Sample)



Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. The electoral term are results are not statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis in this sample. The year-wise results for this sample do not pass the [McCrary \(2008\)](#) density tests, indicating a potential problem with using the margin of victory as a running variable for this sample. The above plots provide further evidence via the confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

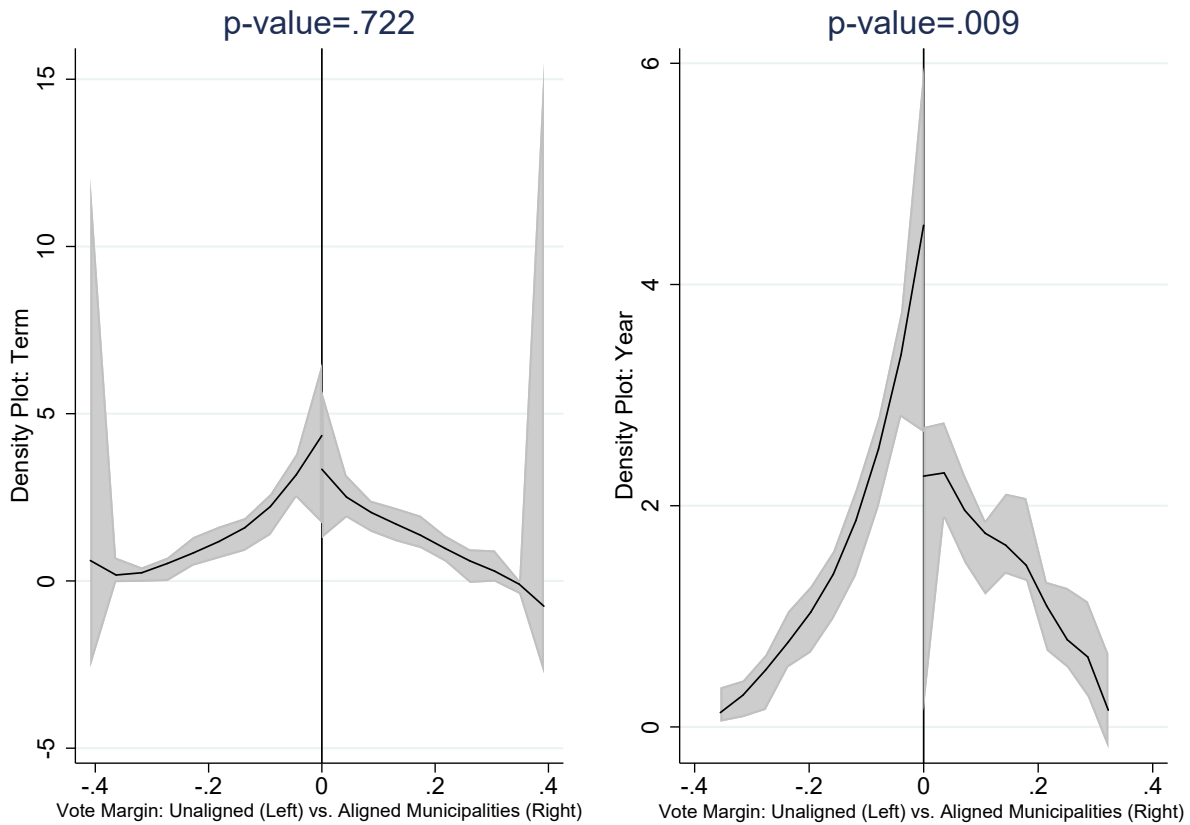
### L.3. Density Plots for Poverty Increasing/Decreasing Sample: 2011-2015

Figure L.7: RDD Density Plots for Infraction Count and Amount (Whole Sample)



Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. Neither the electoral term nor year results are statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis. The above plots provide further evidence via the overlapping confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

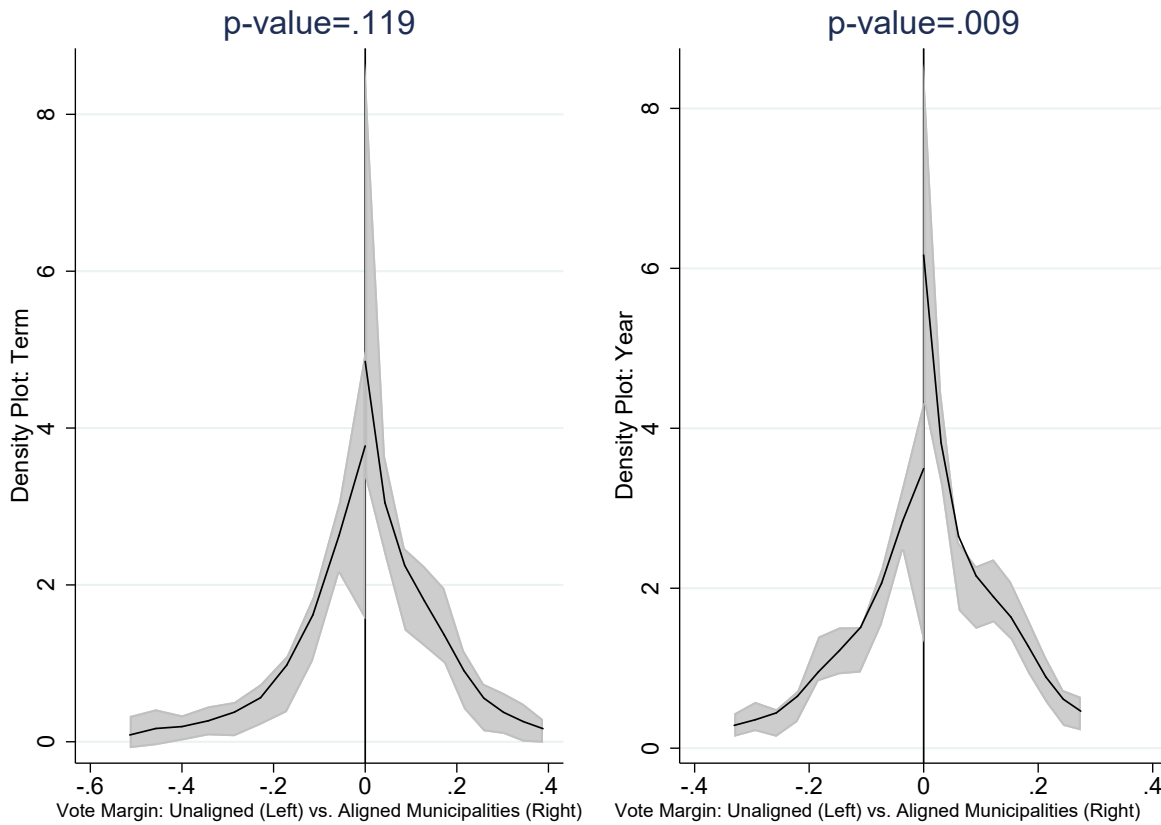
Figure L.8: RDD Density Plots for Infraction Count and Amount (Poverty-Decreasing Sample)



Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. The electoral term are results are not statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis in this sample. The year-wise results for this sample do not pass the [McCrary \(2008\)](#) density tests, indicating a potential problem with using the margin victory data for this sample. The above plots provide further evidence via the confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.



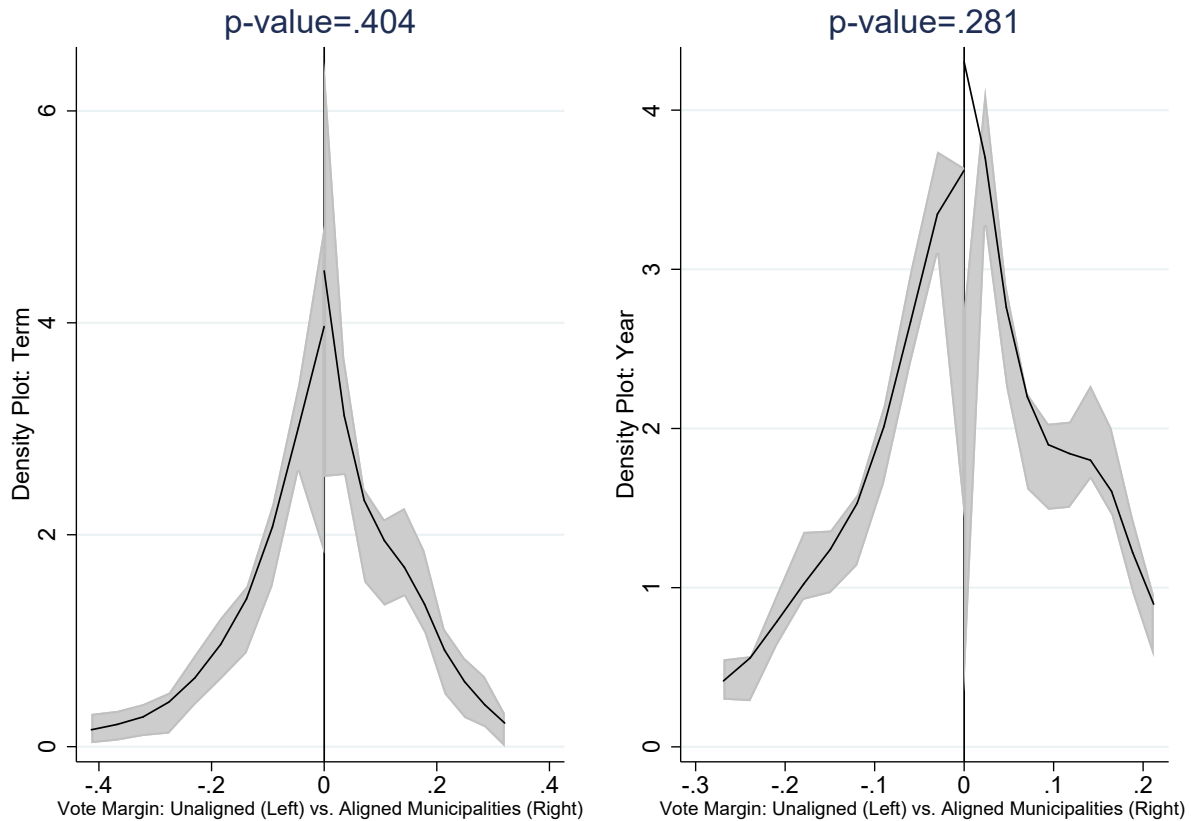
Figure L.9: RDD Density Plots for Infraction Count and Amount (Poverty-Increasing Sample)



Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. The electoral term results are not statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis in this sample. The year-wise results for this sample do not pass the [McCrary \(2008\)](#) density tests, indicating a potential problem with using the margin of victory as a running variable for this sample. The above plots provide further evidence via the overlapping confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

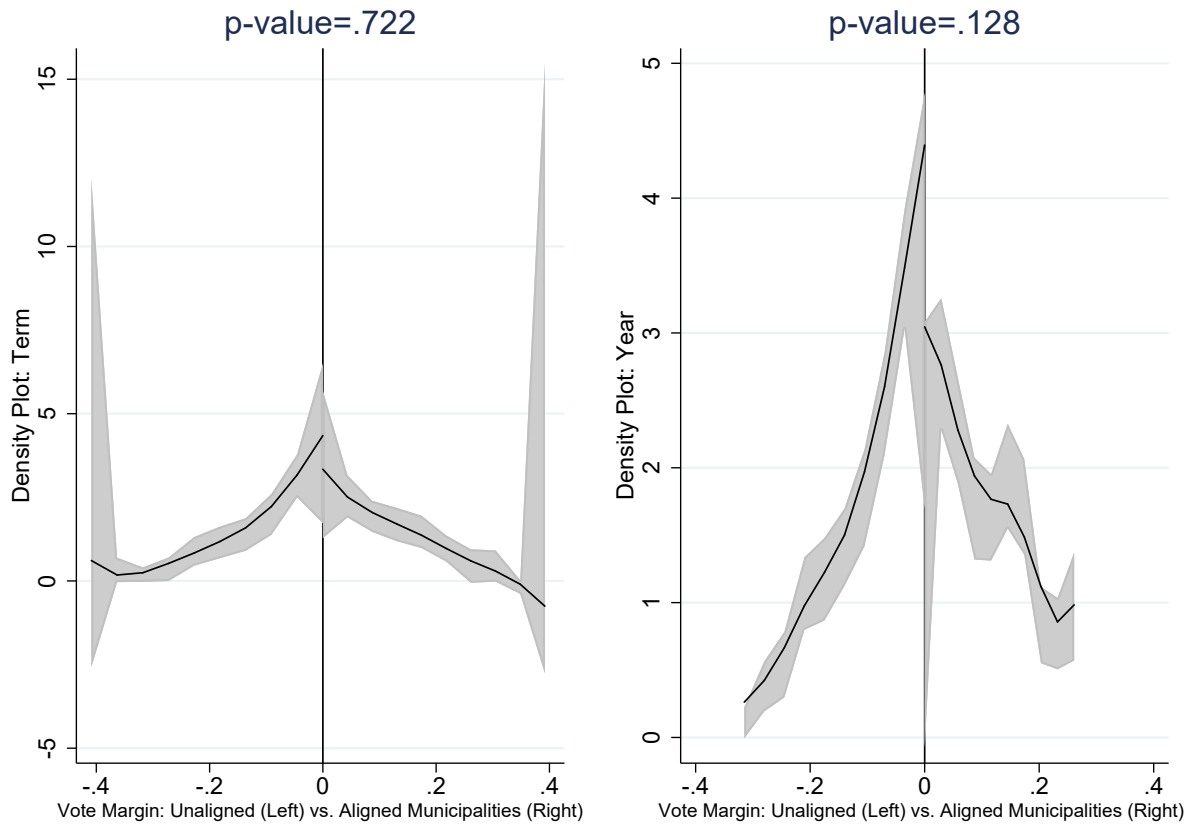
## L.4. Density Plots for Poverty Increasing/Decreasing Sample: 2009-2015

Figure L.10: RDD Density Plots for Infraction Count and Amount (Whole Sample)



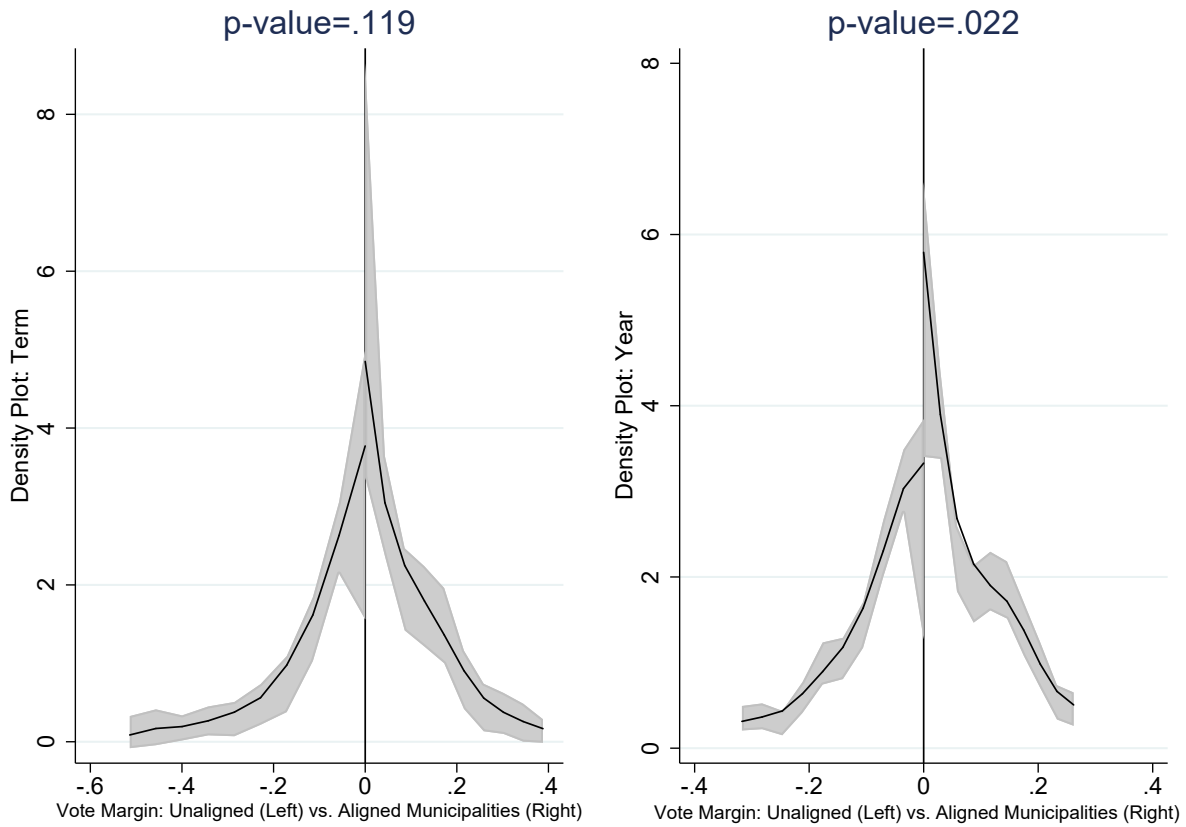
Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. Neither the electoral term nor year results are statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis. The above plots provide further evidence via the overlapping confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

Figure L.11: RDD Density Plots for Infraction Count and Amount (Poverty-Decreasing Sample)



Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. Neither the electoral term nor year results are statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis. The above plots provide further evidence via the overlapping confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

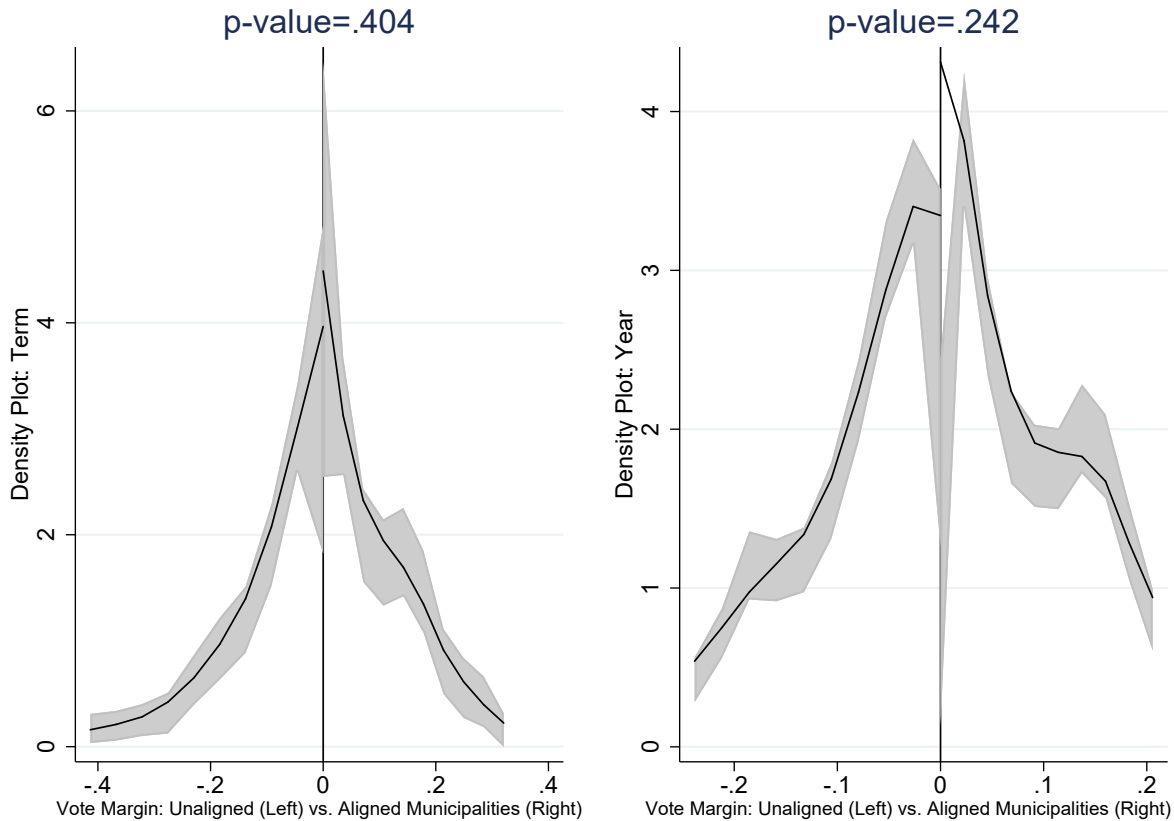
Figure L.12: RDD Density Plots for Infraction Count and Amount (Poverty-Increasing Sample)



Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. The electoral term are results are not statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis in this sample. The year-wise results for this sample do not pass the [McCrary \(2008\)](#) density tests, indicating a potential problem with using the margin of victory as a running variable for this sample. The above plots provide further evidence via the confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

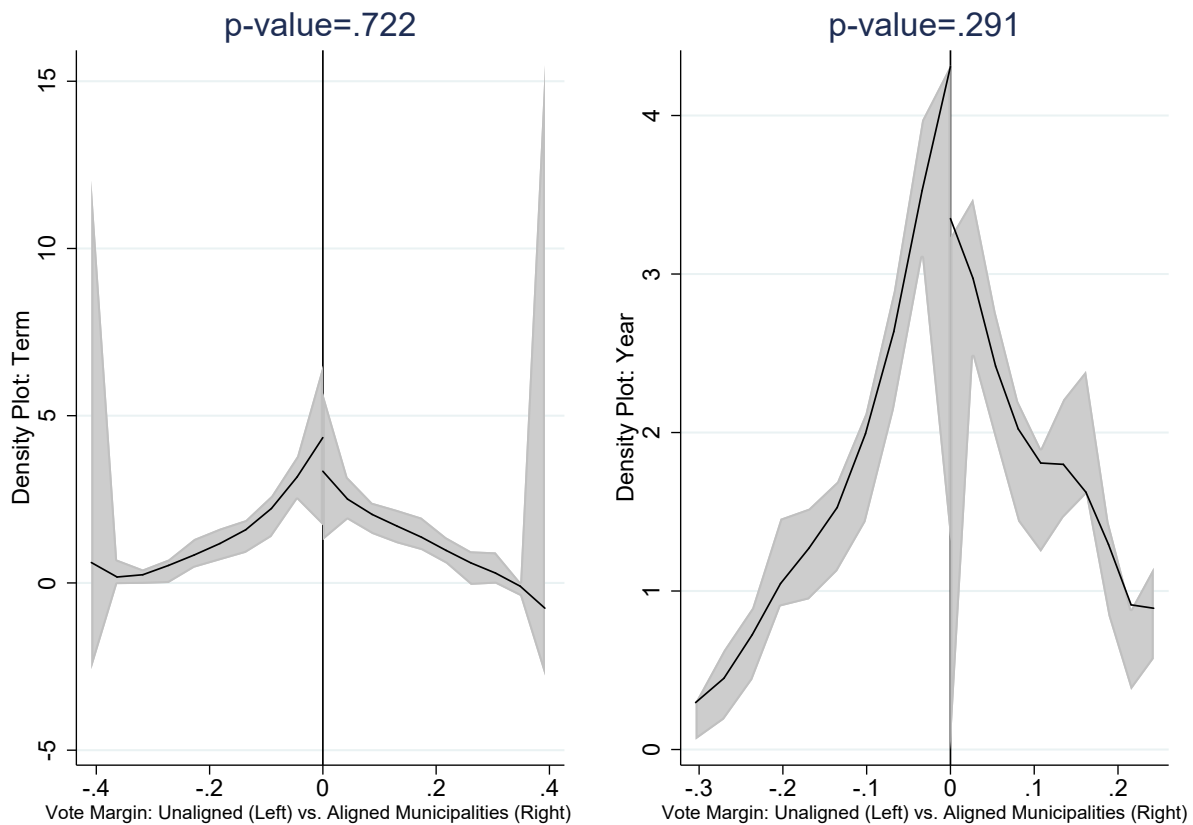
## L.5. Density Plots for Poverty Increasing/Decreasing Sample: 2008-2015

Figure L.13: RDD Density Plots for Infraction Count and Amount (Whole Sample)



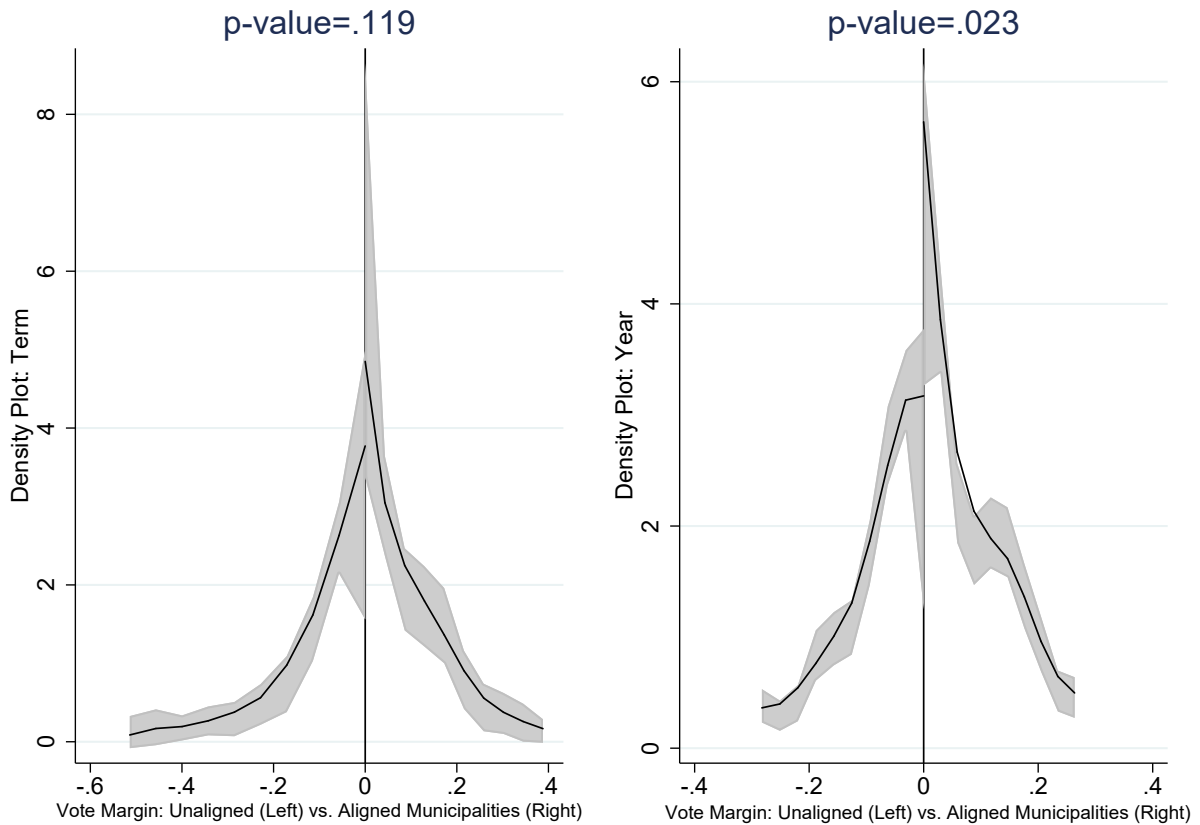
Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. Neither the electoral term nor year results are statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis. The above plots provide further evidence via the overlapping confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

Figure L.14: RDD Density Plots for Infraction Count and Amount (Poverty-Decreasing Sample)



Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. Neither the electoral term nor year results are statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis. The above plots provide further evidence via the overlapping confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

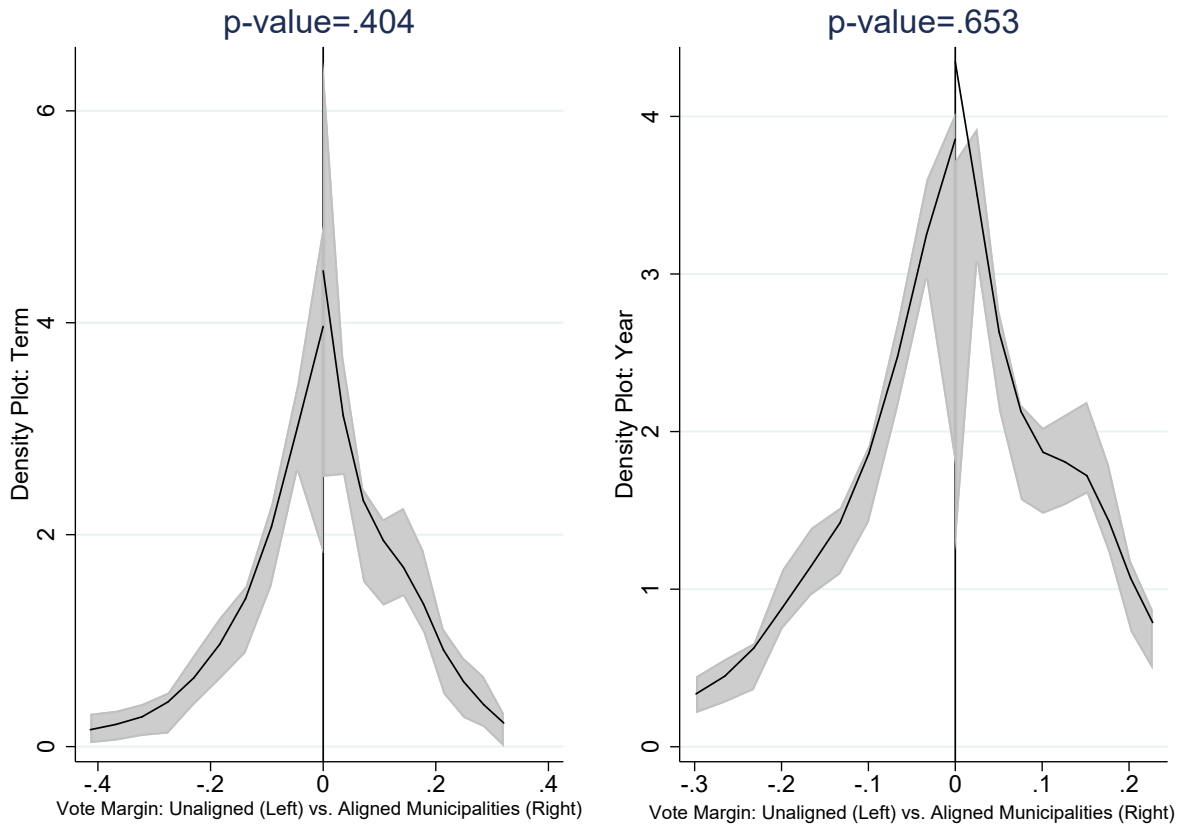
Figure L.15: RDD Density Plots for Infraction Count and Amount (Poverty-Increasing Sample)



Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. The electoral term are results are not statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis in this sample. The year-wise results for this sample do not pass the [McCrary \(2008\)](#) density tests, indicating a potential problem with using the margin victory as the running for this sample. The above plots provide further evidence via the confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

## L.6. Extreme Poverty Density Plots for 2010-2015: Year and Term

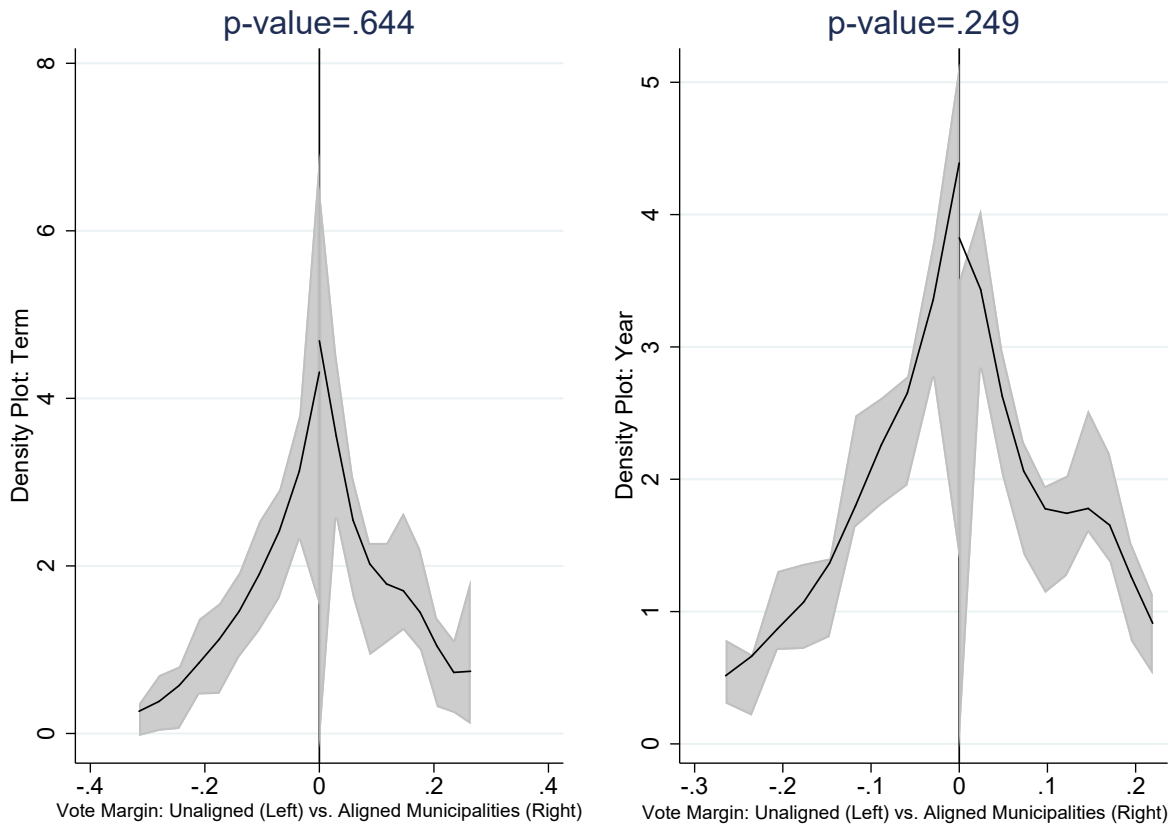
Figure L.16: RDD Density Plots for Infraction Count and Amount (Whole Sample)



Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. Neither the electoral term nor year results are statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis. The above plots provide further evidence via the overlapping confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

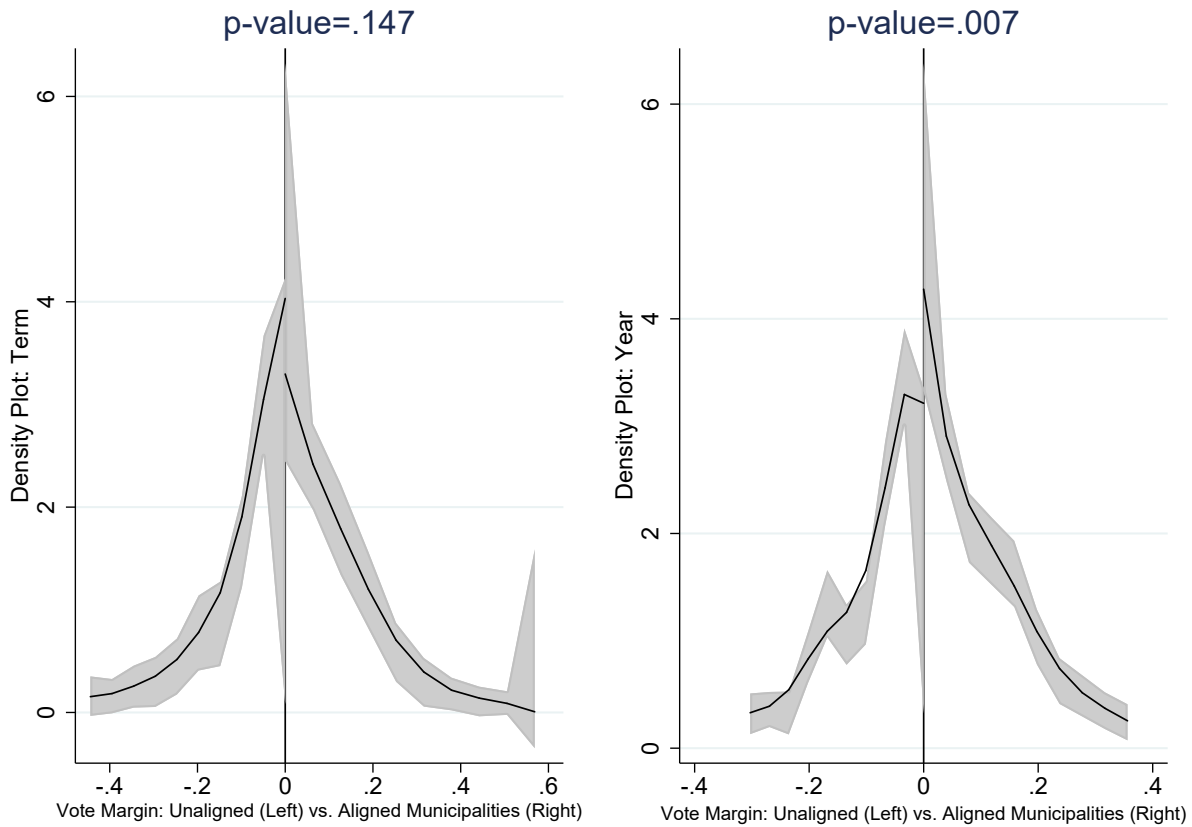


Figure L.17: RDD Density Plots for Infraction Count and Amount (Extreme Poverty-Decreasing Sample)



Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. Neither the electoral term nor year results are statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis. The above plots provide further evidence via the overlapping confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

Figure L.18: RDD Density Plots for Infraction Count and Amount (Extreme Poverty-Increasing Sample)



Note: “Term” refers to the margin of victory for mayors in each electoral term. “Year” refers to the same margin of victory variable but corresponding to a year-wise perspective. Following [Cattaneo, Jansson and Ma \(2018\)](#), all [McCrary \(2008\)](#) density tests are fit with second-order polynomials. The electoral term are results are not statistically significant at the conventional threshold ( $p < .05$ ), indicating that the running variable, margin of victory, is suitable for regression discontinuity analysis in this sample. The year-wise results for this sample do not pass the [McCrary \(2008\)](#) density tests, indicating a potential problem with using the margin victory as a running variable for this sample. The above plots provide further evidence via the confidence intervals (shaded gray areas) on both sides of the cutoff—i.e., with the cutoff being the margin of victory is zero.

## L.7. RDD Estimates Eliminating Outliers

### L.7.1. When Poverty is Decreasing

Table L1: RDD Estimates for Infraction Count by Term and Year

| Panel A                | (1)                  | (2)                  | (3)                 | (4)                 | (5)                  | (6)                  |
|------------------------|----------------------|----------------------|---------------------|---------------------|----------------------|----------------------|
| RD Estimate            | -10.97***<br>(3.076) | -14.04***<br>(4.137) | -8.391**<br>(3.264) | -10.76**<br>(4.199) | -9.023***<br>(3.359) | -9.964**<br>(3.981)  |
| Observations           | 192                  | 192                  | 176                 | 176                 | 176                  | 176                  |
| Effective Observations | [54,42]              | [61,48]              | [46,34]             | [57,44]             | [42,29]              | [56,43]              |
| Covariates             | None                 | None                 | Some                | Some                | All                  | All                  |
| p-value                | 0.000363             | 0.000686             | 0.0101              | 0.0104              | 0.00723              | 0.0123               |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                    | 2                    |
| Bandwidth              | 0.0906               | 0.105                | 0.0849              | 0.112               | 0.0702               | 0.105                |
| Panel B                | (1)                  | (2)                  | (3)                 | (4)                 | (5)                  | (6)                  |
| RD Estimate            | -1.532***<br>(0.543) | -2.009***<br>(0.699) | -0.855<br>(0.539)   | -1.202*<br>(0.703)  | -1.224**<br>(0.587)  | -2.020***<br>(0.722) |
| Observations           | 592                  | 592                  | 560                 | 560                 | 560                  | 560                  |
| Effective Observations | [180,138]            | [195,139]            | [168,126]           | [181,129]           | [144,102]            | [148,104]            |
| Covariates             | None                 | None                 | Some                | Some                | All                  | All                  |
| p-value                | 0.00478              | 0.00408              | 0.113               | 0.0874              | 0.0370               | 0.00516              |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                    | 2                    |
| Bandwidth              | 0.0985               | 0.106                | 0.0959              | 0.103               | 0.0788               | 0.0825               |

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. Results are winsorized at top/bottom 1% level. 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 L2: RDD Estimates for Infraction Amount (log) by Term and Year

| Panel A                | (1)                  | (2)                 | (3)                  | (4)                 | (5)                  | (6)                 |
|------------------------|----------------------|---------------------|----------------------|---------------------|----------------------|---------------------|
| RD Estimate            | -1.188***<br>(0.418) | -1.192**<br>(0.542) | -1.081***<br>(0.385) | -1.024**<br>(0.508) | -1.017***<br>(0.349) | -1.031**<br>(0.464) |
| Observations           | 191                  | 191                 | 176                  | 176                 | 176                  | 176                 |
| Effective Observations | [48,39]              | [55,45]             | [46,34]              | [51,38]             | [53,43]              | [52,40]             |
| Covariates             | None                 | None                | Some                 | Some                | All                  | All                 |
| Conventional p-value   | 0.00446              | 0.0278              | 0.00495              | 0.0438              | 0.00357              | 0.0261              |
| Order of Polynomial    | 1                    | 2                   | 1                    | 2                   | 1                    | 2                   |
| Bandwidth              | 0.0762               | 0.0954              | 0.0811               | 0.0903              | 0.0983               | 0.0944              |
| Panel B                | (1)                  | (2)                 | (3)                  | (4)                 | (5)                  | (6)                 |
| RD Estimate            | -0.591***<br>(0.200) | -0.451*<br>(0.259)  | -0.364<br>(0.225)    | -0.342<br>(0.254)   | -0.508**<br>(0.230)  | -0.430<br>(0.272)   |
| Observations           | 588                  | 588                 | 558                  | 558                 | 558                  | 558                 |
| Effective Observations | [187,136]            | [171,120]           | [130,75]             | [160,111]           | [142,93]             | [186,128]           |
| Covariates             | None                 | None                | Some                 | Some                | All                  | All                 |
| p-value                | 0.00311              | 0.0819              | 0.105                | 0.179               | 0.0275               | 0.114               |
| Order of Polynomial    | 1                    | 2                   | 1                    | 2                   | 1                    | 2                   |
| Bandwidth              | 0.101                | 0.0904              | 0.0646               | 0.0898              | 0.0723               | 0.107               |

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. Results are winsorized at top/bottom 1% level. 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.

**L.7.2. When Poverty is Low**

Table L3: RDD Estimates for Infraction Count by Term and Year

| Panel A                | (1)                  | (2)                  | (3)                  | (4)                 | (5)                  | (6)                  |
|------------------------|----------------------|----------------------|----------------------|---------------------|----------------------|----------------------|
| RD Estimate            | -5.363*<br>(2.831)   | -5.548<br>(3.556)    | -4.403*<br>(2.568)   | -3.244<br>(3.281)   | -6.989***<br>(2.490) | -8.569***<br>(2.930) |
| Observations           | 282                  | 282                  | 265                  | 265                 | 191                  | 191                  |
| Effective Observations | [93,75]              | [103,98]             | [87,75]              | [94,84]             | [47,43]              | [67,62]              |
| Covariates             | None                 | None                 | Some                 | Some                | All                  | All                  |
| p-value                | 0.0582               | 0.119                | 0.0864               | 0.323               | 0.00499              | 0.00345              |
| Order of Polynomial    | 1                    | 2                    | 1                    | 2                   | 1                    | 2                    |
| Bandwidth              | 0.113                | 0.161                | 0.118                | 0.139               | 0.0761               | 0.136                |
| Panel B                | (1)                  | (2)                  | (3)                  | (4)                 | (5)                  | (6)                  |
| RD Estimate            | -1.932***<br>(0.603) | -2.135***<br>(0.691) | -1.448***<br>(0.525) | -1.530**<br>(0.599) | -1.064**<br>(0.492)  | -1.137*<br>(0.625)   |
| Observations           | 966                  | 966                  | 903                  | 903                 | 646                  | 646                  |
| Effective Observations | [266,228]            | [342,317]            | [268,241]            | [328,333]           | [212,189]            | [231,228]            |
| Covariates             | None                 | None                 | Some                 | Some                | All                  | All                  |
| p-value                | 0.00137              | 0.00201              | 0.00581              | 0.0106              | 0.0306               | 0.0688               |
| Order of Polynomial    | 1                    | 2                    | 1                    | 2                   | 1                    | 2                    |
| Bandwidth              | 0.0886               | 0.144                | 0.103                | 0.168               | 0.120                | 0.152                |

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. Results are winsorized at top/bottom 1% level. 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 L4: RDD Estimates for Infraction Amount (log) by Term and Year

| Panel A                | (1)                 | (2)                 | (3)                 | (4)                 | (5)               | (6)               |
|------------------------|---------------------|---------------------|---------------------|---------------------|-------------------|-------------------|
| RD Estimate            | -0.563*<br>(0.296)  | -0.664*<br>(0.349)  | -0.525**<br>(0.261) | -0.556*<br>(0.317)  | -0.306<br>(0.287) | -0.442<br>(0.415) |
| Observations           | 282                 | 282                 | 265                 | 265                 | 190               | 190               |
| Effective observations | [85,73]             | [101,89]            | [83,71]             | [94,86]             | [47,44]           | [62,52]           |
| Covariates             | None                | None                | Some                | Some                | All               | All               |
| p-value                | 0.0572              | 0.0571              | 0.0443              | 0.0794              | 0.286             | 0.287             |
| Order of Polynomial    | 1                   | 2                   | 1                   | 2                   | 1                 | 2                 |
| Bandwidth              | 0.104               | 0.139               | 0.110               | 0.141               | 0.0791            | 0.114             |
| Panel B                | (1)                 | (2)                 | (3)                 | (4)                 | (5)               | (6)               |
| RD Estimate            | -0.605**<br>(0.241) | -0.732**<br>(0.287) | -0.499**<br>(0.229) | -0.603**<br>(0.281) | -0.143<br>(0.223) | -0.118<br>(0.267) |
| Observations           | 962                 | 962                 | 898                 | 898                 | 641               | 641               |
| Effective Observations | [238,221]           | [317,269]           | [241,211]           | [294,275]           | [196,172]         | [227,217]         |
| Covariates             | None                | None                | Some                | Some                | All               | All               |
| p-value                | 0.0121              | 0.0107              | 0.0294              | 0.0318              | 0.523             | 0.658             |
| Order of Polynomial    | 1                   | 2                   | 1                   | 2                   | 1                 | 2                 |
| Bandwidth              | 0.0766              | 0.118               | 0.0895              | 0.124               | 0.103             | 0.145             |

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. Results are winsorized at top/bottom 1% level. 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.

## L.8. RDD Estimates at Varying Cutoffs (Placebo Tests)

### L.8.1. When Poverty is Decreasing

Table L5: RDD Estimates for Infraction Count and Amount (log) by Term

| Panel A                | (-5%)            | (5%)               | (-10%)            | (10%)                | (-15%)            | (15%)            |
|------------------------|------------------|--------------------|-------------------|----------------------|-------------------|------------------|
| RD Estimate            | 1.956<br>(5.234) | -9.964<br>(6.869)  | -2.710<br>(5.727) | -13.20***<br>(4.559) | 0.322<br>(7.178)  | 4.946<br>(6.476) |
| Observations           | 195              | 195                | 195               | 195                  | 195               | 195              |
| Effective Observations | [44,77]          | [42,22]            | [35,80]           | [44,28]              | [24,66]           | [18,16]          |
| Covariates             | None             | None               | None              | None                 | None              | None             |
| Conventional p-value   | 0.709            | 0.147              | 0.636             | 0.00378              | 0.964             | 0.445            |
| Order of Polynomial    | 2                | 2                  | 2                 | 2                    | 2                 | 2                |
| Bandwidth              | 0.133            | 0.0693             | 0.141             | 0.0898               | 0.141             | 0.0545           |
| Panel B                | (-5%)            | (5%)               | (-10%)            | (10%)                | (-15%)            | (15%)            |
| RD Estimate            | 0.104<br>(0.517) | -1.037*<br>(0.614) | -0.791<br>(0.604) | -0.688<br>(0.657)    | -2.054<br>(2.228) | 0.837<br>(0.815) |
| Observations           | 195              | 195                | 195               | 195                  | 195               | 195              |
| Effective Observations | [36,66]          | [60,27]            | [32,60]           | [40,26]              | [17,26]           | [20,16]          |
| Covariates             | None             | None               | None              | None                 | None              | None             |
| Conventional p-value   | 0.840            | 0.0916             | 0.190             | 0.295                | 0.356             | 0.305            |
| Order of Polynomial    | 2                | 2                  | 2                 | 2                    | 2                 | 2                |
| Bandwidth              | 0.101            | 0.0901             | 0.108             | 0.0818               | 0.0794            | 0.0561           |

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.

**L.8.2. When Poverty is Low**

Table L6: RDD Estimates for Infraction Count and Amount (log) by Term

| Panel A                | (-5%)              | (5%)              | (-10%)           | (10%)             | (-15%)            | (15%)               |
|------------------------|--------------------|-------------------|------------------|-------------------|-------------------|---------------------|
| RD Estimate            | 3.339<br>(4.211)   | 8.435<br>(5.933)  | 2.210<br>(5.145) | -1.888<br>(5.337) | 1.996<br>(7.231)  | 11.49***<br>(3.702) |
| Observations           | 284                | 284               | 284              | 284               | 284               | 284                 |
| Effective observations | [66,132]           | [133,73]          | [34,136]         | [105,58]          | [16,65]           | [42,36]             |
| Covariates             | None               | None              | None             | None              | None              | None                |
| p-value                | 0.428              | 0.155             | 0.668            | 0.724             | 0.783             | 0.00191             |
| Order of Polynomial    | 2                  | 2                 | 2                | 2                 | 2                 | 2                   |
| Bandwidth              | 0.179              | 0.154             | 0.165            | 0.137             | 0.109             | 0.0883              |
| Panel B                | (-5%)              | (5%)              | (-10%)           | (10%)             | (-15%)            | (15%)               |
| RD Estimate            | 0.739**<br>(0.376) | -0.876<br>(0.561) | 0.336<br>(0.466) | -0.778<br>(0.789) | 0.0217<br>(0.577) | 0.521<br>(0.491)    |
| Observations           | 284                | 284               | 284              | 284               | 284               | 284                 |
| Effective observations | [60,112]           | [95,47]           | [34,136]         | [81,50]           | [17,73]           | [47,38]             |
| Covariates             | None               | None              | None             | None              | None              | None                |
| p-value                | 0.0495             | 0.119             | 0.472            | 0.324             | 0.970             | 0.289               |
| Order of Polynomial    | 2                  | 2                 | 2                | 2                 | 2                 | 2                   |
| Bandwidth              | 0.139              | 0.0997            | 0.161            | 0.110             | 0.117             | 0.0971              |

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.



## L.9. RDD Estimates for Number of Audits in a Term

### L.9.1. For Poverty Decreasing/Increasing Sample

Table L7: RDD Estimates for the Poverty-Decreasing Sample

|                        | (1)             | (2)             | (3)                | (4)              | (5)             | (6)                  |
|------------------------|-----------------|-----------------|--------------------|------------------|-----------------|----------------------|
| RD Estimate            | 0<br>(6.42e-09) | 0<br>(9.83e-09) | 0.0251<br>(0.0188) | -0<br>(5.69e-09) | 0<br>(1.73e-09) | -0.00990<br>(0.0131) |
| Observations           | 195             | 195             | 179                | 179              | 179             | 179                  |
| Effective observations | [37,29]         | [59,48]         | [66,49]            | [53,42]          | [53,43]         | [57,44]              |
| Covariates             | None            | None            | Some               | Some             | All             | All                  |
| p-value                | 1               | 1               | 0.181              | 1                | 1               | 0.449                |
| Order of Polynomial    | 1               | 2               | 1                  | 2                | 1               | 2                    |
| Bandwidth              | 0.0505          | 0.102           | 0.137              | 0.0972           | 0.0988          | 0.109                |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Variable of interest is the number of times a municipality gets audited in the term. All specifications use standard errors clustered by municipality, and term fixed effects. 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

Table L8: RDD Estimates for Poverty-Increasing Sample

|                        | (1)                | (2)                | (3)                | (4)                | (5)                | (6)                |
|------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| RD Estimate            | 0.0690<br>(0.0700) | 0.0969<br>(0.0971) | 0.0685<br>(0.0699) | 0.0965<br>(0.0972) | 0.0711<br>(0.0699) | 0.0936<br>(0.0928) |
| Observations           | 196                | 196                | 196                | 196                | 196                | 196                |
| Effective observations | [57,69]            | [63,83]            | [57,69]            | [63,82]            | [57,69]            | [67,84]            |
| Covariates             | None               | None               | Some               | Some               | All                | All                |
| p-value                | 0.324              | 0.319              | 0.327              | 0.321              | 0.309              | 0.313              |
| Order of Polynomial    | 1                  | 2                  | 1                  | 2                  | 1                  | 2                  |
| Bandwidth              | 0.123              | 0.158              | 0.123              | 0.158              | 0.123              | 0.165              |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Variable of interest is the number of times a municipality gets audited in the term. All specifications use standard errors clustered by municipality, and term fixed effects. 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population, while (5) and (6) use log of population and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

Table L9: RDD Estimates for Whole Sample

|                        | (1)                | (2)                | (3)                  | (4)                  | (5)                  | (6)                   |
|------------------------|--------------------|--------------------|----------------------|----------------------|----------------------|-----------------------|
| RD Estimate            | 0.0387<br>(0.0338) | 0.0528<br>(0.0439) | 0.00824<br>(0.00685) | 0.00643<br>(0.00406) | 0.00239<br>(0.00193) | 0.00643*<br>(0.00360) |
| Observations           | 441                | 441                | 399                  | 399                  | 399                  | 399                   |
| Effective observations | [130,117]          | [157,165]          | [132,129]            | [139,150]            | [117,108]            | [137,148]             |
| Covariates             | None               | None               | Some                 | Some                 | All                  | All                   |
| p-value                | 0.252              | 0.229              | 0.229                | 0.113                | 0.215                | 0.0740                |
| Order of Polynomial    | 1                  | 2                  | 1                    | 2                    | 1                    | 2                     |
| Bandwidth              | 0.106              | 0.159              | 0.133                | 0.156                | 0.106                | 0.154                 |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Variable of interest is the number of times a municipality gets audited in the term. All specifications use standard errors clustered by municipality, and term fixed effects. 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

**L.9.2. For Poverty Low/High Sample**

Table L10: RDD Estimates for the Low Poverty Sample

|                        | (1)              | (2)              | (3)                 | (4)                 | (5)      | (6)      |
|------------------------|------------------|------------------|---------------------|---------------------|----------|----------|
| RD Estimate            | 0.130<br>(0.111) | 0.159<br>(0.150) | -0.0155<br>(0.0114) | -0.0251<br>(0.0169) | 0<br>(0) | 0<br>(0) |
| Observations           | 284              | 284              | 267                 | 267                 | 192      | 192      |
| Effective observations | [85,73]          | [101,95]         | [60,59]             | [73,65]             | [50,45]  | [53,45]  |
| Covariates             | None             | None             | Some                | Some                | All      | All      |
| p-value                | 0.241            | 0.289            | 0.174               | 0.136               | 0.991    | 0.391    |
| Order of Polynomial    | 1                | 2                | 1                   | 2                   | 1        | 2        |
| Bandwidth              | 0.103            | 0.150            | 0.0738              | 0.0920              | 0.0844   | 0.0885   |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Variable of interest is the number of times a municipality gets audited in the term. All specifications use standard errors clustered by municipality, and term fixed effects. 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

Table L11: RDD Estimates for High Poverty Sample

|                        | (1)                | (2)                | (3)                | (4)                | (5)                 | (6)                 |
|------------------------|--------------------|--------------------|--------------------|--------------------|---------------------|---------------------|
| RD Estimate            | 0.0617<br>(0.0869) | 0.00677<br>(0.118) | 0.0458<br>(0.0863) | -0.0120<br>(0.119) | -0.0180<br>(0.0502) | -0.0365<br>(0.0252) |
| Observations           | 258                | 258                | 258                | 258                | 207                 | 207                 |
| Effective observations | [82,77]            | [79,73]            | [82,77]            | [78,73]            | [62,66]             | [50,50]             |
| Covariates             | None               | None               | Some               | Some               | All                 | All                 |
| p-value                | 0.478              | 0.954              | 0.595              | 0.920              | 0.721               | 0.146               |
| Order of Polynomial    | 1                  | 2                  | 1                  | 2                  | 1                   | 2                   |
| Bandwidth              | 0.129              | 0.119              | 0.129              | 0.117              | 0.127               | 0.0903              |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Variable of interest is the number of times a municipality gets audited in the term. All specifications use standard errors clustered by municipality, and term fixed effects. 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population, while (5) and (6) use log of population and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

Table L12: RDD Estimates for Whole Sample

|                        | (1)                | (2)               | (3)                | (4)                | (5)                  | (6)                  |
|------------------------|--------------------|-------------------|--------------------|--------------------|----------------------|----------------------|
| RD Estimate            | 0.0860<br>(0.0651) | 0.110<br>(0.0722) | 0.0474<br>(0.0458) | 0.0596<br>(0.0541) | -0.00646<br>(0.0233) | 0.000883<br>(0.0134) |
| Observations           | 568                | 568               | 523                | 523                | 399                  | 399                  |
| Effective observations | [177,154]          | [238,239]         | [173,158]          | [216,218]          | [123,117]            | [83,77]              |
| Covariates             | None               | None              | Some               | Some               | All                  | All                  |
| p-value                | 0.187              | 0.129             | 0.300              | 0.271              | 0.781                | 0.947                |
| Order of Polynomial    | 1                  | 2                 | 1                  | 2                  | 1                    | 2                    |
| Bandwidth              | 0.114              | 0.216             | 0.129              | 0.206              | 0.119                | 0.0680               |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Variable of interest is the number of times a municipality gets audited in the term. All specifications use standard errors clustered by municipality, and term fixed effects. 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

## L.10. RDD Estimates for Municipalities with no Missing Audits in a Term

### L.10.1. For Poverty Low/High Sample

Table L13: RDD Estimates for Infraction Count and Amount (log) by Term: Low Poverty Sample

| Panel A                | (1)                 | (2)                 | (3)                 | (4)                | (5)                  | (6)                  |
|------------------------|---------------------|---------------------|---------------------|--------------------|----------------------|----------------------|
| RD Estimate            | -6.805**<br>(2.880) | -7.250**<br>(3.362) | -4.977*<br>(2.580)  | -4.062<br>(3.239)  | -8.685***<br>(2.579) | -10.29***<br>(2.884) |
| Observations           | 279                 | 279                 | 263                 | 263                | 190                  | 190                  |
| Effective Observations | [87,75]             | [105,108]           | [87,75]             | [93,87]            | [45,42]              | [67,62]              |
| Covariates             | None                | None                | Some                | Some               | All                  | All                  |
| p-value                | 0.0181              | 0.0311              | 0.0537              | 0.210              | 0.000759             | 0.000358             |
| Order of Polynomial    | 1                   | 2                   | 1                   | 2                  | 1                    | 2                    |
| Bandwidth              | 0.111               | 0.185               | 0.120               | 0.145              | 0.0747               | 0.136                |
| Panel B                | (1)                 | (2)                 | (3)                 | (4)                | (5)                  | (6)                  |
| RD Estimate            | -0.601**<br>(0.302) | -0.691*<br>(0.358)  | -0.546**<br>(0.263) | -0.568*<br>(0.319) | -0.354<br>(0.287)    | -0.505<br>(0.406)    |
| Observations           | 279                 | 279                 | 263                 | 263                | 190                  | 190                  |
| Effective Observations | [82,73]             | [99,88]             | [81,71]             | [93,84]            | [46,44]              | [62,54]              |
| Covariates             | None                | None                | Some                | Some               | All                  | All                  |
| p-value                | 0.0468              | 0.0532              | 0.0381              | 0.0753             | 0.219                | 0.214                |
| Order of Polynomial    | 1                   | 2                   | 1                   | 2                  | 1                    | 2                    |
| Bandwidth              | 0.103               | 0.139               | 0.109               | 0.140              | 0.0805               | 0.117                |

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 for 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

Table L14: RDD Estimates for Infraction Count and Amount (log) by Term: High Poverty Sample

| Panel A                | (1)               | (2)               | (3)                | (4)                | (5)                | (6)                |
|------------------------|-------------------|-------------------|--------------------|--------------------|--------------------|--------------------|
| RD Estimate            | 4.771<br>(4.698)  | 7.751<br>(7.372)  | 7.377<br>(5.423)   | 11.49<br>(8.219)   | 8.957*<br>(5.290)  | 15.27*<br>(8.153)  |
| Observations           | 249               | 249               | 222                | 222                | 175                | 175                |
| Effective Observations | [62,60]           | [77,74]           | [49,49]            | [64,62]            | [39,40]            | [46,50]            |
| Covariates             | None              | None              | Some               | Some               | All                | All                |
| p-value                | 0.310             | 0.293             | 0.174              | 0.162              | 0.0904             | 0.0611             |
| Order of Polynomial    | 1                 | 2                 | 1                  | 2                  | 1                  | 2                  |
| Bandwidth              | 0.0934            | 0.122             | 0.0833             | 0.113              | 0.0789             | 0.104              |
| Panel B                | (1)               | (2)               | (3)                | (4)                | (5)                | (6)                |
| RD Estimate            | 0.741*<br>(0.433) | 1.001*<br>(0.579) | 0.982**<br>(0.439) | 1.269**<br>(0.551) | 0.706**<br>(0.359) | 0.951**<br>(0.471) |
| Observations           | 249               | 249               | 222                | 222                | 175                | 175                |
| Effective Observations | [62,60]           | [77,75]           | [49,50]            | [66,64]            | [44,50]            | [51,57]            |
| Covariates             | None              | None              | Some               | Some               | All                | All                |
| p-value                | 0.0874            | 0.0838            | 0.0254             | 0.0212             | 0.0490             | 0.0438             |
| Order of Polynomial    | 1                 | 2                 | 1                  | 2                  | 1                  | 2                  |
| Bandwidth              | 0.0926            | 0.124             | 0.0848             | 0.117              | 0.0983             | 0.130 height       |

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 for 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.



Table L15: RDD Estimates for Infraction Count and Amount (log) by Term: Whole Sample

| Panel A                | (1)                | (2)                | (3)                 | (4)                | (5)                | (6)               |
|------------------------|--------------------|--------------------|---------------------|--------------------|--------------------|-------------------|
| RD Estimate            | -1.595<br>(2.257)  | -2.275<br>(2.666)  | -0.993<br>(2.389)   | -0.611<br>(3.060)  | -2.431<br>(2.397)  | -3.004<br>(3.190) |
| Observations           | 554                | 554                | 511                 | 511                | 365                | 365               |
| Effective Observations | [181,164]          | [229,232]          | [162,145]           | [193,193]          | [104,100]          | [124,139]         |
| Covariates             | None               | None               | Some                | Some               | All                | All               |
| p-value                | 0.480              | 0.394              | 0.678               | 0.842              | 0.310              | 0.346             |
| Order of Polynomial    | 1                  | 2                  | 1                   | 2                  | 1                  | 2                 |
| Bandwidth              | 0.123              | 0.206              | 0.118               | 0.172              | 0.104              | 0.154             |
| Panel B                | (1)                | (2)                | (3)                 | (4)                | (5)                | (6)               |
| RD Estimate            | -0.0257<br>(0.217) | -0.0578<br>(0.340) | -0.00773<br>(0.245) | 0.00205<br>(0.324) | -0.0393<br>(0.246) | -0.181<br>(0.378) |
| Observations           | 554                | 554                | 511                 | 511                | 365                | 365               |
| Effective Observations | [196,186]          | [196,187]          | [157,141]           | [182,181]          | [101,100]          | [114,114]         |
| Covariates             | None               | None               | Some                | Some               | All                | All               |
| p-value                | 0.906              | 0.865              | 0.975               | 0.995              | 0.873              | 0.632             |
| Order of Polynomial    | 1                  | 2                  | 1                   | 2                  | 1                  | 2                 |
| Bandwidth              | 0.147              | 0.149              | 0.113               | 0.156              | 0.100              | 0.123             |

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 for 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

**L.10.2. For Poverty Decreasing/Increasing Sample**

Table L16: RDD Estimates for Infraction Count and Amount (log) by Term: Poverty Decreasing Sample

| Panel A                | (1)                  | (2)                  | (3)                  | (4)                 | (5)                  | (6)                 |
|------------------------|----------------------|----------------------|----------------------|---------------------|----------------------|---------------------|
| RD Estimate            | -10.47***<br>(2.901) | -11.88***<br>(3.380) | -7.475**<br>(3.000)  | -9.517**<br>(3.976) | -7.106**<br>(3.181)  | -8.573**<br>(4.046) |
| Observations           | 191                  | 191                  | 175                  | 175                 | 175                  | 175                 |
| Effective Observations | [62,48]              | [73,69]              | [53,43]              | [64,46]             | [45,34]              | [57,43]             |
| Covariates             | None                 | None                 | Some                 | Some                | All                  | All                 |
| p-value                | 0.000305             | 0.000439             | 0.0127               | 0.0167              | 0.0255               | 0.0341              |
| Order of Polynomial    | 1                    | 2                    | 1                    | 2                   | 1                    | 2                   |
| Bandwidth              | 0.105                | 0.160                | 0.0992               | 0.132               | 0.0807               | 0.107               |
| Panel B                | (1)                  | (2)                  | (3)                  | (4)                 | (5)                  | (6)                 |
| RD Estimate            | -1.232***<br>(0.417) | -1.197**<br>(0.546)  | -1.080***<br>(0.388) | -1.029**<br>(0.512) | -1.006***<br>(0.359) | -1.043**<br>(0.465) |
| Observations           | 191                  | 191                  | 175                  | 175                 | 175                  | 175                 |
| Effective Observations | [49,39]              | [56,43]              | [45,34]              | [48,36]             | [52,38]              | [52,38]             |
| Covariates             | None                 | None                 | Some                 | Some                | All                  | All                 |
| p-value                | 0.00315              | 0.0282               | 0.00541              | 0.0444              | 0.00505              | 0.0249              |
| Order of Polynomial    | 1                    | 2                    | 1                    | 2                   | 1                    | 2                   |
| Bandwidth              | 0.0761               | 0.0937               | 0.0794               | 0.0883              | 0.0929               | 0.0922              |

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 for 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

Table L17: RDD Estimates for Infraction Count and Amount (log) by Term: Poverty Increasing Sample

| Panel A                | (1)              | (2)              | (3)              | (4)                | (5)                | (6)              |
|------------------------|------------------|------------------|------------------|--------------------|--------------------|------------------|
| RD Estimate            | 3.711<br>(3.905) | 5.885<br>(6.069) | 1.914<br>(3.806) | 4.417<br>(6.699)   | -1.893<br>(4.518)  | 1.605<br>(8.688) |
| Observations           | 193              | 193              | 172              | 172                | 172                | 172              |
| Effective Observations | [52,60]          | [56,76]          | [45,64]          | [45,69]            | [43,55]            | [43,55]          |
| Covariates             | None             | None             | Some             | Some               | All                | All              |
| p-value                | 0.342            | 0.332            | 0.615            | 0.510              | 0.675              | 0.853            |
| Order of Polynomial    | 1                | 2                | 1                | 2                  | 1                  | 2                |
| Bandwidth              | 0.113            | 0.137            | 0.122            | 0.131              | 0.104              | 0.106            |
| Panel B                | (1)              | (2)              | (3)              | (4)                | (5)                | (6)              |
| RD Estimate            | 0.479<br>(0.388) | 0.136<br>(0.633) | 0.109<br>(0.453) | -0.0331<br>(0.611) | -0.0270<br>(0.414) | 0.218<br>(0.484) |
| Observations           | 193              | 193              | 172              | 172                | 172                | 172              |
| Effective Observations | [52,58]          | [55,73]          | [41,52]          | [47,75]            | [43,55]            | [57,87]          |
| Covariates             | None             | None             | Some             | Some               | All                | All              |
| p-value                | 0.217            | 0.830            | 0.810            | 0.957              | 0.948              | 0.652            |
| Order of Polynomial    | 1                | 2                | 1                | 2                  | 1                  | 2                |
| Bandwidth              | 0.107            | 0.131            | 0.0939           | 0.147              | 0.106              | 0.189            |

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 for 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

Table L18: RDD Estimates for Infraction Count and Amount (log) by Term: Whole Sample

| Panel A                | (1)                | (2)               | (3)                | (4)               | (5)               | (6)               |
|------------------------|--------------------|-------------------|--------------------|-------------------|-------------------|-------------------|
| RD Estimate            | -2.966<br>(2.773)  | -4.793<br>(3.964) | -2.962<br>(2.862)  | -4.506<br>(4.091) | -5.248<br>(3.197) | -3.998<br>(4.392) |
| Observations           | 433                | 433               | 393                | 393               | 367               | 367               |
| Effective Observations | [128,116]          | [145,139]         | [116,108]          | [132,132]         | [98,93]           | [117,117]         |
| Covariates             | None               | None              | Some               | Some              | All               | All               |
| p-value                | 0.285              | 0.227             | 0.301              | 0.271             | 0.101             | 0.363             |
| Order of Polynomial    | 1                  | 2                 | 1                  | 2                 | 1                 | 2                 |
| Bandwidth              | 0.105              | 0.134             | 0.109              | 0.139             | 0.0930            | 0.128             |
| Panel A                | (1)                | (2)               | (3)                | (4)               | (5)               | (6)               |
| RD Estimate            | -0.0990<br>(0.245) | -0.494<br>(0.411) | -0.0395<br>(0.245) | -0.396<br>(0.421) | -0.270<br>(0.287) | -0.315<br>(0.394) |
| Observations           | 433                | 433               | 393                | 393               | 367               | 367               |
| Effective Observations | [149,146]          | [143,133]         | [133,138]          | [128,125]         | [105,101]         | [122,131]         |
| Covariates             | None               | None              | Some               | Some              | All               | All               |
| p-value                | 0.685              | 0.229             | 0.872              | 0.347             | 0.348             | 0.424             |
| Order of Polynomial    | 1                  | 2                 | 1                  | 2                 | 1                 | 2                 |
| Bandwidth              | 0.142              | 0.128             | 0.145              | 0.130             | 0.106             | 0.144             |

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 for 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

## L.11. RDD Estimates for Average Infractions per Audit in a Term

### L.11.1. For Poverty Low/High Sample

Table L19: RDD Estimates for Infraction Count and Amount (log) by Term: Low Poverty Sample

| Panel A                | (1)                  | (2)                  | (3)                  | (4)                  | (5)                  | (6)                  |
|------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| RD Estimate            | -1.880***<br>(0.625) | -2.178***<br>(0.711) | -1.665***<br>(0.552) | -1.846***<br>(0.630) | -1.911***<br>(0.647) | -2.306***<br>(0.726) |
| Observations           | 284                  | 284                  | 267                  | 267                  | 192                  | 192                  |
| Effective Observations | [73,65]              | [99,89]              | [71,65]              | [94,85]              | [46,42]              | [67,63]              |
| Covariates             | None                 | None                 | Some                 | Some                 | All                  | All                  |
| p-value                | 0.00264              | 0.00220              | 0.00255              | 0.00338              | 0.00315              | 0.00148              |
| Order of Polynomial    | 1                    | 2                    | 1                    | 2                    | 1                    | 2                    |
| Bandwidth              | 0.0817               | 0.133                | 0.0899               | 0.139                | 0.0742               | 0.134                |
| Panel B                | (1)                  | (2)                  | (3)                  | (4)                  | (5)                  | (6)                  |
| RD Estimate            | -0.628**<br>(0.303)  | -0.770**<br>(0.349)  | -0.597**<br>(0.288)  | -0.705**<br>(0.340)  | -0.296<br>(0.290)    | -0.439<br>(0.415)    |
| Observations           | 284                  | 284                  | 267                  | 267                  | 192                  | 192                  |
| Effective Observations | [78,65]              | [95,84]              | [73,65]              | [88,81]              | [47,44]              | [62,52]              |
| Covariates             | None                 | None                 | Some                 | Some                 | All                  | All                  |
| p-value                | 0.0385               | 0.0275               | 0.0386               | 0.0384               | 0.308                | 0.290                |
| Order of Polynomial    | 1                    | 2                    | 1                    | 2                    | 1                    | 2                    |
| Bandwidth              | 0.0886               | 0.124                | 0.0911               | 0.125                | 0.0778               | 0.114                |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Panel A shows results for average infraction count per audit in a term, while Panel B shows results for average log infraction amount per audit. 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

Table L20: RDD Estimates for Infraction Count and Amount (log) by Term: High Poverty Sample

| Panel A                | (1)              | (2)              | (3)                | (4)                | (5)              | (6)                |
|------------------------|------------------|------------------|--------------------|--------------------|------------------|--------------------|
| RD Estimate            | 1.126<br>(1.050) | 1.791<br>(1.570) | 1.780<br>(1.225)   | 2.606<br>(1.756)   | 1.694<br>(1.319) | 3.320<br>(2.054)   |
| Observations           | 257              | 257              | 229                | 229                | 181              | 181                |
| Effective Observations | [60,59]          | [78,74]          | [50,49]            | [63,64]            | [39,41]          | [46,52]            |
| Covariates             | None             | None             | Some               | Some               | All              | All                |
| p-value                | 0.283            | 0.254            | 0.146              | 0.138              | 0.199            | 0.106              |
| Order of Polynomial    | 1                | 2                | 1                  | 2                  | 1                | 2                  |
| Bandwidth              | 0.0886           | 0.120            | 0.0797             | 0.112              | 0.0799           | 0.104              |
| Panel B                | (1)              | (2)              | (3)                | (4)                | (5)              | (6)                |
| RD Estimate            | 0.712<br>(0.444) | 1.032<br>(0.628) | 0.931**<br>(0.466) | 1.343**<br>(0.617) | 0.559<br>(0.395) | 1.167**<br>(0.577) |
| Observations           | 257              | 257              | 229                | 229                | 181              | 181                |
| Effective Observations | [64,63]          | [79,77]          | [51,52]            | [63,64]            | [47,53]          | [47,53]            |
| Covariates             | None             | None             | Some               | Some               | All              | All                |
| p-value                | 0.109            | 0.100            | 0.0456             | 0.0297             | 0.157            | 0.0430             |
| Order of Polynomial    | 1                | 2                | 1                  | 2                  | 1                | 2                  |
| Bandwidth              | 0.0954           | 0.124            | 0.0874             | 0.112              | 0.109            | 0.109              |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Panel A shows results for average infraction count per audit in a term, while Panel B shows results for average log infraction amount per audit. 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

Table L21: RDD Estimates for Infraction Count and Amount (log) by Term: Whole Sample

| Panel A                | (1)                 | (2)               | (3)                 | (4)                | (5)                | (6)               |
|------------------------|---------------------|-------------------|---------------------|--------------------|--------------------|-------------------|
| RD Estimate            | -0.414<br>(0.515)   | -0.636<br>(0.713) | -0.322<br>(0.551)   | -0.377<br>(0.704)  | -0.700<br>(0.585)  | -0.869<br>(0.762) |
| Observations           | 567                 | 567               | 522                 | 522                | 373                | 373               |
| Effective Observations | [170,150]           | [200,182]         | [146,135]           | [184,181]          | [106,102]          | [129,146]         |
| Covariates             | None                | None              | Some                | Some               | All                | All               |
| p-value                | 0.422               | 0.373             | 0.559               | 0.593              | 0.231              | 0.254             |
| Order of Polynomial    | 1                   | 2                 | 1                   | 2                  | 1                  | 2                 |
| Bandwidth              | 0.109               | 0.142             | 0.103               | 0.153              | 0.105              | 0.160             |
| Panel B                | (1)                 | (2)               | (3)                 | (4)                | (5)                | (6)               |
| RD Estimate            | -0.00214<br>(0.228) | -0.117<br>(0.352) | -0.00496<br>(0.237) | -0.0504<br>(0.340) | -0.0478<br>(0.253) | -0.163<br>(0.377) |
| Observations           | 567                 | 567               | 522                 | 522                | 373                | 373               |
| Effective Observations | [193,172]           | [198,179]         | [167,152]           | [183,176]          | [106,102]          | [119,118]         |
| Covariates             | None                | None              | Some                | Some               | All                | All               |
| p-value                | 0.992               | 0.740             | 0.983               | 0.882              | 0.850              | 0.665             |
| Order of Polynomial    | 1                   | 2                 | 1                   | 2                  | 1                  | 2                 |
| Bandwidth              | 0.132               | 0.141             | 0.122               | 0.147              | 0.106              | 0.128             |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Panel A shows results for average infraction count per audit in a term, while Panel B shows results for average log infraction amount per audit. 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

**L.11.2. For Poverty Decreasing/Increasing Sample**

Table L22: RDD Estimates for Infraction Count and Amount (log) by Term: Poverty Decreasing Sample

| Panel A                | (1)                  | (2)                  | (3)                 | (4)               | (5)                 | (6)                 |
|------------------------|----------------------|----------------------|---------------------|-------------------|---------------------|---------------------|
| RD Estimate            | -1.582***<br>(0.552) | -2.133***<br>(0.737) | -0.928<br>(0.577)   | -1.155<br>(0.765) | -0.918<br>(0.632)   | -1.581**<br>(0.797) |
| Observations           | 195                  | 195                  | 179                 | 179               | 179                 | 179                 |
| Effective Observations | [64,51]              | [61,49]              | [56,43]             | [57,44]           | [50,38]             | [47,35]             |
| Covariates             | None                 | None                 | Some                | Some              | All                 | All                 |
| p-value                | 0.00417              | 0.00379              | 0.108               | 0.131             | 0.146               | 0.0473              |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                 | 1                   | 2                   |
| Bandwidth              | 0.115                | 0.104                | 0.103               | 0.106             | 0.0898              | 0.0861              |
| Panel B                | (1)                  | (2)                  | (3)                 | (4)               | (5)                 | (6)                 |
| RD Estimate            | -0.861**<br>(0.367)  | -0.807*<br>(0.470)   | -0.786**<br>(0.374) | -0.698<br>(0.465) | -0.812**<br>(0.372) | -0.760<br>(0.467)   |
| Observations           | 195                  | 195                  | 179                 | 179               | 179                 | 179                 |
| Effective Observations | [50,39]              | [57,47]              | [44,33]             | [52,40]           | [45,34]             | [53,43]             |
| Covariates             | None                 | None                 | Some                | Some              | All                 | All                 |
| p-value                | 0.0190               | 0.0862               | 0.0356              | 0.134             | 0.0289              | 0.103               |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                 | 1                   | 2                   |
| Bandwidth              | 0.0810               | 0.0975               | 0.0750              | 0.0952            | 0.0808              | 0.0987              |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Panel A shows results for average infraction count per audit in a term, while Panel B shows results for average log infraction amount per audit. 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.



Table L23: RDD Estimates for Infraction Count and Amount (log) by Term: Poverty Increasing Sample

| Panel A                | (1)              | (2)                | (3)               | (4)              | (5)               | (6)              |
|------------------------|------------------|--------------------|-------------------|------------------|-------------------|------------------|
| RD Estimate            | 0.437<br>(0.740) | 0.341<br>(1.151)   | 0.416<br>(0.776)  | 0.675<br>(1.302) | -0.150<br>(0.930) | 0.595<br>(1.367) |
| Observations           | 196              | 196                | 174               | 174              | 174               | 174              |
| Effective Observations | [62,81]          | [67,84]            | [46,64]           | [47,73]          | [44,55]           | [46,72]          |
| Covariates             | None             | None               | Some              | Some             | All               | All              |
| p-value                | 0.555            | 0.767              | 0.592             | 0.604            | 0.872             | 0.663            |
| Order of Polynomial    | 1                | 2                  | 1                 | 2                | 1                 | 2                |
| Bandwidth              | 0.155            | 0.164              | 0.121             | 0.138            | 0.104             | 0.134            |
| Panel A                | (1)              | (2)                | (3)               | (4)              | (5)               | (6)              |
| RD Estimate            | 0.458<br>(0.336) | -0.0541<br>(0.631) | 0.541*<br>(0.319) | 0.448<br>(0.440) | 0.538*<br>(0.312) | 0.458<br>(0.423) |
| Observations           | 196              | 196                | 174               | 174              | 174               | 174              |
| Effective Observations | [57,70]          | [57,67]            | [47,73]           | [58,88]          | [47,74]           | [58,88]          |
| Covariates             | None             | None               | Some              | Some             | All               | All              |
| p-value                | 0.172            | 0.932              | 0.0900            | 0.308            | 0.0854            | 0.279            |
| Order of Polynomial    | 1                | 2                  | 1                 | 2                | 1                 | 2                |
| Bandwidth              | 0.124            | 0.122              | 0.138             | 0.189            | 0.142             | 0.197            |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Panel A shows results for average infraction count per audit in a term, while Panel B shows results for average log infraction amount per audit. 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

Table L24: RDD Estimates for Infraction Count and Amount (log) by Term: Whole Sample

| Panel A                | (1)                | (2)               | (3)               | (4)                | (5)                 | (6)                |
|------------------------|--------------------|-------------------|-------------------|--------------------|---------------------|--------------------|
| RD Estimate            | -0.0877<br>(0.479) | -0.709<br>(0.793) | 0.0681<br>(0.514) | -0.197<br>(0.748)  | -0.521<br>(0.606)   | -0.385<br>(0.816)  |
| Observations           | 441                | 441               | 399               | 399                | 373                 | 373                |
| Effective Observations | [158,165]          | [150,143]         | [134,133]         | [139,150]          | [103,101]           | [123,129]          |
| Covariates             | None               | None              | Some              | Some               | All                 | All                |
| p-value                | 0.855              | 0.372             | 0.895             | 0.792              | 0.390               | 0.637              |
| Order of Polynomial    | 1                  | 2                 | 1                 | 2                  | 1                   | 2                  |
| Bandwidth              | 0.160              | 0.137             | 0.140             | 0.157              | 0.101               | 0.141              |
| Panel B                | (1)                | (2)               | (3)               | (4)                | (5)                 | (6)                |
| RD Estimate            | -0.112<br>(0.262)  | -0.297<br>(0.373) | 0.0404<br>(0.254) | -0.0874<br>(0.366) | -0.00504<br>(0.254) | -0.0338<br>(0.358) |
| Observations           | 441                | 441               | 399               | 399                | 373                 | 373                |
| Effective Observations | [127,117]          | [146,135]         | [120,113]         | [134,133]          | [109,107]           | [125,135]          |
| Covariates             | None               | None              | Some              | Some               | All                 | All                |
| p-value                | 0.670              | 0.426             | 0.873             | 0.811              | 0.984               | 0.925              |
| Order of Polynomial    | 1                  | 2                 | 1                 | 2                  | 1                   | 2                  |
| Bandwidth              | 0.103              | 0.129             | 0.114             | 0.139              | 0.114               | 0.147              |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Panel A shows results for average infraction count per audit in a term, while Panel B shows results for average log infraction amount per audit. 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. Columns (1) and (2) do not use any additional covariates, (3) and (4) use log of population and dummy for reelection, while (5) and (6) use log of population, dummy for reelection and log of real public good spending (per capita). Per [Gelman and Imbens \(2019\)](#), estimations only rely on polynomials of the first and second order.

## M. Potential Endogeneity between Poverty and Corruption

### M.1. Regression of Poverty Rate on Corruption

#### M.1.1. For Poverty Decreasing/Increasing Sample

Table M1: Term-wise Regression of Poverty Rate on Count of Infraction

|                                       | (1)                 | (2)                 | (3)                  |
|---------------------------------------|---------------------|---------------------|----------------------|
| Infraction Count                      | 0.00908<br>(0.0546) | 0.0100<br>(0.0544)  | 0.0432<br>(0.0470)   |
| Population (log)                      |                     | 3.609<br>(14.55)    | 11.62<br>(16.32)     |
| Public Good Spending per capita (log) |                     | 0.216**<br>(0.0876) | 0.261***<br>(0.0966) |
| Constant                              | 72.60***<br>(0.642) | 34.39<br>(148.5)    | -47.96<br>(166.9)    |
| Observations                          | 632                 | 632                 | 566                  |
| R-squared                             | 0.275               | 0.276               | 0.297                |
| Number of Municipalities              | 333                 | 333                 | 327                  |
| Municipality FE                       | Yes                 | Yes                 | Yes                  |
| Term FE                               | Yes                 | Yes                 | Yes                  |
| Electoral Controls                    | No                  | No                  | Yes                  |

Note: Standard errors in parentheses; \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. All specifications use standard errors clustered by municipality. Dependent variable is the average total poverty rate in the municipality in the given term. All columns use baseline Term and Municipality fixed-effects. Column (2) includes log of population and log of per capita real public goods spending as covariates. Column (3) also adds additional electoral covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.

Table M2: Term-wise Regression of Poverty Rate on Amount of Infraction

|                                       | (1)                 | (2)              | (3)               |
|---------------------------------------|---------------------|------------------|-------------------|
| Infraction Amount (log)               | 0.290<br>(0.344)    | 0.253<br>(0.371) | 0.154<br>(0.418)  |
| Population (log)                      |                     | 3.198<br>(14.65) | 9.758<br>(16.57)  |
| Public Good Spending per capita (log) |                     | 0.147<br>(0.178) | 0.219<br>(0.177)  |
| Constant                              | 69.33***<br>(3.961) | 36.17<br>(149.2) | -30.27<br>(169.3) |
| Observations                          | 632                 | 632              | 566               |
| R-squared                             | 0.277               | 0.277            | 0.295             |
| Number of Municipalities              | 333                 | 333              | 327               |
| Municipality FE                       | Yes                 | Yes              | Yes               |
| Term FE                               | Yes                 | Yes              | Yes               |
| Electoral Controls                    | No                  | No               | Yes               |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . All specifications use standard errors clustered by municipality. Dependent variable is the average total poverty rate in the municipality in the given term. Infraction amount (log) is the log of real infraction in the term. All columns use baseline Term and Municipality fixed-effects. Column (2) includes log of population and log of per capita real public goods spending as covariates. Column (3) also adds additional electoral covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.

Table M3: Year-wise Regression of Poverty Rate on Count of Infraction

|                                       | (1)                 | (2)                  | (3)                 |
|---------------------------------------|---------------------|----------------------|---------------------|
| Infraction Count                      | 0.0465<br>(0.0807)  | 0.0509<br>(0.0808)   | 0.0677<br>(0.0759)  |
| Population (log)                      |                     | 4.819<br>(13.14)     | 0.272<br>(14.16)    |
| Public Good Spending per capita (log) |                     | -0.138**<br>(0.0669) | -0.0990<br>(0.0701) |
| Constant                              | 66.52***<br>(0.923) | 18.16<br>(133.9)     | 62.78<br>(144.2)    |
| Observations                          | 1,819               | 1,819                | 1,694               |
| R-squared                             | 0.016               | 0.016                | 0.027               |
| Number of Municipalities              | 333                 | 333                  | 327                 |
| Municipality FE                       | Yes                 | Yes                  | Yes                 |
| Year FE                               | Yes                 | Yes                  | Yes                 |
| Electoral Controls                    | No                  | No                   | Yes                 |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . All specifications use standard errors clustered by municipality. Dependent variable is the total poverty rate in the municipality in the given year. All columns use baseline Year and Municipality fixed-effects. Column (2) includes log of population and log of per capita real public goods spending as covariates. Column (3) also adds additional electoral covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.

Table M4: Year-wise Regression of Poverty Rate on Amount of Infraction

|                                       | (1)                 | (2)                 | (3)               |
|---------------------------------------|---------------------|---------------------|-------------------|
| Infraction Amount (log)               | 0.217<br>(0.179)    | 0.238<br>(0.182)    | 0.117<br>(0.179)  |
| Population (log)                      |                     | 4.373<br>(13.16)    | -0.381<br>(14.27) |
| Public Good Spending per capita (log) |                     | -0.267**<br>(0.113) | -0.189<br>(0.156) |
| Constant                              | 64.47***<br>(1.933) | 21.19<br>(134.0)    | 68.93<br>(145.2)  |
| Observations                          | 1,814               | 1,814               | 1,689             |
| R-squared                             | 0.017               | 0.018               | 0.027             |
| Number of Municipalities              | 333                 | 333                 | 327               |
| Municipality FE                       | Yes                 | Yes                 | Yes               |
| Year FE                               | Yes                 | Yes                 | Yes               |
| Electoral Controls                    | No                  | No                  | Yes               |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . All specifications use standard errors clustered by municipality. Dependent variable is the total poverty rate in the municipality in the given year. Infraction amount (log) is the log of real infraction in the year. All columns use baseline Year and Municipality fixed-effects. Column (2) includes log of population and log of per capita real public goods spending as covariates. Column (3) also adds additional electoral covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.

**M.1.2. For Poverty Low/High Sample**

Table M5: Term-wise Regression of Poverty Rate on Count of Infraction

|                                       | (1)                 | (2)                | (3)                |
|---------------------------------------|---------------------|--------------------|--------------------|
| Infraction Count                      | 0.0907<br>(0.0623)  | 0.0377<br>(0.0408) | 0.0531<br>(0.0387) |
| Population (log)                      |                     | 0.177<br>(11.14)   | 4.154<br>(12.28)   |
| Public Good Spending per capita (log) |                     | -3.733<br>(2.739)  | -5.189*<br>(2.886) |
| Constant                              | 64.33***<br>(0.753) | 98.84<br>(121.3)   | 69.19<br>(132.5)   |
| Observations                          | 963                 | 632                | 566                |
| R-squared                             | 0.146               | 0.281              | 0.305              |
| Number of Municipalities              | 333                 | 333                | 327                |
| Municipality FE                       | YES                 | YES                | YES                |
| Term FE                               | YES                 | YES                | YES                |
| Electoral Controls                    |                     |                    | YES                |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . All specifications use standard errors clustered by municipality. Dependent variable is the average total poverty rate in the municipality in the given term. All columns use baseline Term and Municipality fixed-effects. Column (2) includes log of population and log of per capita real public goods spending as covariates. Column (3) also adds additional electoral covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.

Table M6: Term-wise Regression of Poverty Rate on Amount of Infraction

|                                       | (1)                 | (2)               | (3)                |
|---------------------------------------|---------------------|-------------------|--------------------|
| Infraction Amount (log)               | -0.301<br>(0.317)   | 0.524<br>(0.442)  | 0.386<br>(0.518)   |
| Population (log)                      |                     | -0.645<br>(11.18) | 2.496<br>(12.50)   |
| Public Good Spending per capita (log) |                     | -3.857<br>(2.721) | -5.084*<br>(2.981) |
| Constant                              | 68.95***<br>(3.939) | 102.1<br>(121.3)  | 81.01<br>(134.4)   |
| Observations                          | 963                 | 632               | 566                |
| R-squared                             | 0.143               | 0.283             | 0.304              |
| Number of Municipalities              | 333                 | 333               | 327                |
| Municipality FE                       | YES                 | YES               | YES                |
| Term FE                               | YES                 | YES               | YES                |
| Electoral Controls                    |                     |                   | YES                |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . All specifications use standard errors clustered by municipality. Dependent variable is the average total poverty rate in the municipality in the given term. Infraction amount (log) is the log of real infraction in the term. All columns use baseline Term and Municipality fixed-effects. Column (2) includes log of population and log of per capita real public goods spending as covariates. Column (3) also adds additional electoral covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.



Table M7: Year-wise Regression of Poverty Rate on Count of Infraction

|                                       | (1)                 | (2)               | (3)               |
|---------------------------------------|---------------------|-------------------|-------------------|
| Infraction Count                      | 0.0731<br>(0.109)   | 0.143<br>(0.138)  | 0.163<br>(0.145)  |
| log_pop                               |                     | 7.300<br>(18.38)  | 0.541<br>(20.78)  |
| Public Good Spending per capita (log) |                     | -0.304<br>(0.216) | -0.291<br>(0.277) |
| Constant                              | 65.31***<br>(0.647) | -7.204<br>(186.7) | 59.25<br>(211.2)  |
| Observations                          | 3,121               | 2,177             | 1,929             |
| R-squared                             | 0.016               | 0.019             | 0.030             |
| Number of Municipalities              | 333                 | 333               | 327               |
| Municipality FE                       | YES                 | YES               | YES               |
| Year FE                               | YES                 | YES               | YES               |
| Electoral Controls                    |                     |                   | YES               |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . All specifications use standard errors clustered by municipality. Dependent variable is the total poverty rate in the municipality in the given year. All columns use baseline Year and Municipality fixed-effects. Column (2) includes log of population and log of per capita real public goods spending as covariates. Column (3) also adds additional electoral covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.

Table M8: Year-wise Regression of Poverty Rate on Amount of Infraction

|                                       | (1)                 | (2)                | (3)               |
|---------------------------------------|---------------------|--------------------|-------------------|
| Infraction Amount (log)               | 0.0627<br>(0.116)   | 0.418**<br>(0.208) | 0.325<br>(0.221)  |
| log_pop                               |                     | 7.138<br>(18.36)   | 0.0528<br>(20.89) |
| Public Good Spending per capita (log) |                     | -0.385<br>(0.238)  | -0.376<br>(0.325) |
| Constant                              | 64.84***<br>(1.331) | -9.130<br>(186.7)  | 61.68<br>(212.4)  |
| Observations                          | 3,115               | 2,172              | 1,924             |
| R-squared                             | 0.015               | 0.020              | 0.030             |
| Number of Municipalities              | 333                 | 333                | 327               |
| Municipality FE                       | YES                 | YES                | YES               |
| Year FE                               | YES                 | YES                | YES               |
| Electoral Controls                    |                     |                    | YES               |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . All specifications use standard errors clustered by municipality. Dependent variable is the total poverty rate in the municipality in the given year. Infraction amount (log) is the log of real infraction in the year. All columns use baseline Year and Municipality fixed-effects. Column (2) includes log of population and log of per capita real public goods spending as covariates. Column (3) also adds additional electoral covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.

## M.2. Two-Stage Regression of Residuals on Corruption

### M.2.1. For Poverty Decreasing/Increasing Sample

Table M9: Term-wise Regression of Residuals on Count of Infraction

|                          | (1)                 | (2)                 | (3)                |
|--------------------------|---------------------|---------------------|--------------------|
| Infraction Count         | 0.00252<br>(0.0296) | 0.00276<br>(0.0296) | 0.0116<br>(0.0288) |
| Constant                 | -0.0447<br>(0.525)  | -0.0491<br>(0.525)  | -0.218<br>(0.538)  |
| Observations             | 632                 | 632                 | 566                |
| R-squared                | 0.000               | 0.000               | 0.001              |
| Number of Municipalities | 333                 | 333                 | 327                |
| Municipality FE          | Yes                 | Yes                 | Yes                |
| Term FE                  | Yes                 | Yes                 | Yes                |
| Controls                 | No                  | Some                | All                |

Note: Standard errors in parentheses; \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Results here show the second stage regression result of residuals on infraction count. Residuals from the first stage are obtained by regressing average total poverty in a term on covariates. All three specifications included Term and Municipality fixed-effects in the first stage. Column (2) includes log population and log of per capita real public good spending. Column (3) adds additional covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.

Table M10: Term-wise Regression of Residuals on Log Amounts of Stolen/Misappropriated Money

|                          | (1)               | (2)               | (3)               |
|--------------------------|-------------------|-------------------|-------------------|
| Infraction Amount (log)  | 0.200<br>(0.264)  | 0.163<br>(0.263)  | 0.0993<br>(0.287) |
| Constant                 | -2.411<br>(3.192) | -1.973<br>(3.170) | -1.205<br>(3.487) |
| Observations             | 632               | 632               | 566               |
| R-squared                | 0.001             | 0.001             | 0.000             |
| Number of Municipalities | 333               | 333               | 327               |
| Municipality FE          | Yes               | Yes               | Yes               |
| Year FE                  | Yes               | Yes               | Yes               |
| Controls                 | No                | Some              | All               |

Note: Standard errors in parentheses; \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Results here show the second stage regression result of residuals on log of real infraction amount. Residuals from the first stage are obtained by regressing average total poverty in a term on covariates. All three specifications included Term and Municipality fixed-effects in the first stage. Column (2) includes log population and log of per capita real public good spending. Column (3) adds additional covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.

Table M11: Year-wise Regression of Residuals on Count of Infraction

|                          | (1)                | (2)                | (3)                |
|--------------------------|--------------------|--------------------|--------------------|
| Infraction Count         | 0.0401<br>(0.0689) | 0.0434<br>(0.0688) | 0.0564<br>(0.0659) |
| Constant                 | -0.252<br>(0.418)  | -0.271<br>(0.418)  | -0.358<br>(0.405)  |
| Observations             | 1,819              | 1,819              | 1,694              |
| R-squared                | 0.000              | 0.000              | 0.001              |
| Number of municipalities | 333                | 333                | 327                |
| Municipality FE          | Yes                | Yes                | Yes                |
| Year FE                  | Yes                | Yes                | Yes                |
| Controls                 | No                 | Some               | All                |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Results here show the second stage regression result of residuals on infraction count. Residuals from the first stage are obtained by regressing average total poverty in a year on covariates. All three specifications included Year and Municipality fixed-effects in the first stage. Column (2) includes log population and log of per capita real public good spending. Column (3) adds additional covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.

Table M12: Year-wise Regression of Residuals on Amount of Infraction

|                         | (1)               | (2)               | (3)               |
|-------------------------|-------------------|-------------------|-------------------|
| Infraction Amount (log) | 0.196<br>(0.165)  | 0.206<br>(0.164)  | 0.0988<br>(0.160) |
| Constant                | -2.119<br>(1.775) | -2.223<br>(1.766) | -1.075<br>(1.724) |
| Observations            | 1,814             | 1,814             | 1,689             |
| R-squared               | 0.001             | 0.001             | 0.000             |
| Number of municipality  | 333               | 333               | 327               |
| Municipality FE         | Yes               | Yes               | Yes               |
| Year FE                 | Yes               | Yes               | Yes               |
| Controls                | No                | Some              | All               |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Results here show the second stage regression result of residuals on log of real infraction amount. Residuals from the first stage are obtained by regressing average total poverty in a year on covariates. All three specifications included Year and Municipality fixed-effects in the first stage. Column (2) includes log population and log of per capita real public good spending. Column (3) adds additional covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.

**M.2.2. For Poverty Low/High Sample**

Table M13: Term-wise Regression of Residuals on Count of Infraction

|                          | (1)                | (2)                | (3)                |
|--------------------------|--------------------|--------------------|--------------------|
| Infraction Count         | 0.0338<br>(0.0441) | 0.0308<br>(0.0370) | 0.0431<br>(0.0340) |
| Constant                 | -0.619<br>(0.808)  | -0.718<br>(0.862)  | -1.027<br>(0.810)  |
| Observations             | 963                | 632                | 566                |
| R-squared                | 0.002              | 0.002              | 0.003              |
| Number of Municipalities | 333                | 333                | 327                |
| Municipality FE          | YES                | YES                | YES                |
| Term FE                  | YES                | YES                | YES                |
| Controls                 | NO                 | SOME               | ALL                |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Results here show the second stage regression result of residuals on infraction count. Residuals from the first stage are obtained by regressing average total poverty in a term on covariates. All three specifications included Term and Municipality fixed-effects in the first stage. Column (2) includes log population and log of per capita real public good spending. Column (3) adds additional covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.

Table M14: Term-wise Regression of Residuals on Log Amounts of Stolen/Misappropriated Money

|                          | (1)               | (2)               | (3)               |
|--------------------------|-------------------|-------------------|-------------------|
| Infraction Amount (log)  | -0.284<br>(0.290) | 0.516<br>(0.426)  | 0.374<br>(0.484)  |
| Constant                 | 3.706<br>(3.776)  | -6.800<br>(5.612) | -4.932<br>(6.387) |
| Observations             | 963               | 632               | 566               |
| R-squared                | 0.001             | 0.005             | 0.002             |
| Number of Municipalities | 333               | 333               | 327               |
| Municipality FE          | YES               | YES               | YES               |
| Term FE                  | YES               | YES               | YES               |
| Controls                 | NO                | SOME              | ALL               |

Note: Standard errors in parentheses; \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Results here show the second stage regression result of residuals on log of real infraction amount. Residuals from the first stage are obtained by regressing average total poverty in a term on covariates. All three specifications included Term and Municipality fixed-effects in the first stage. Column (2) includes log population and log of per capita real public good spending. Column (3) adds additional covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.



Table M15: Year-wise Regression of Residuals on Count of Infraction

|                          | (1)               | (2)               | (3)               |
|--------------------------|-------------------|-------------------|-------------------|
| Infraction Count         | 0.0789<br>(0.104) | 0.141<br>(0.136)  | 0.159<br>(0.146)  |
| Constant                 | -0.476<br>(0.611) | -0.790<br>(0.748) | -0.907<br>(0.814) |
| Observations             | 2,476             | 2,177             | 1,929             |
| R-squared                | 0.001             | 0.002             | 0.002             |
| Number of Municipalities | 333               | 333               | 327               |
| Municipality FE          | YES               | YES               | YES               |
| Year FE                  | YES               | YES               | YES               |
| Controls                 | NO                | SOME              | ALL               |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Results here show the second stage regression result of residuals on infraction count. Residuals from the first stage are obtained by regressing average total poverty in a year on covariates. All three specifications included Year and Municipality fixed-effects in the first stage. Column (2) includes log population and log of per capita real public good spending. Column (3) adds additional covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.

Table M16: Year-wise Regression of Residuals on Amount of Infraction

|                          | (1)               | (2)                 | (3)               |
|--------------------------|-------------------|---------------------|-------------------|
| Infraction Amount (log)  | 0.305<br>(0.189)  | 0.396**<br>(0.197)  | 0.299<br>(0.206)  |
| Constant                 | -3.485<br>(2.153) | -4.485**<br>(2.227) | -3.402<br>(2.326) |
| Observations             | 2,471             | 2,172               | 1,924             |
| R-squared                | 0.002             | 0.003               | 0.002             |
| Number of Municipalities | 333               | 333                 | 327               |
| Municipality FE          | YES               | YES                 | YES               |
| Year FE                  | YES               | YES                 | YES               |
| Controls                 | NO                | SOME                | ALL               |

Note: Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Results here show the second stage regression result of residuals on log of real infraction amount. Residuals from the first stage are obtained by regressing average total poverty in a year on covariates. All three specifications included Year and Municipality fixed-effects in the first stage. Column (2) includes log population and log of per capita real public good spending. Column (3) adds additional covariates, including dummy for mayor being reelected, number of valid votes cast in last election, dummy for mayor being aligned with national party and dummy for mayor's gender.

## N. Results for 2011-2015

### N.1. Results When Poverty Decreases

Table N1: RDD Estimates for Infraction Count by Year

| Panel A                | (1)                 | (2)                | (3)               | (4)               | (5)               | (6)               |
|------------------------|---------------------|--------------------|-------------------|-------------------|-------------------|-------------------|
| RD_Estimate            | -1.431**<br>(0.614) | -1.458*<br>(0.777) | -0.536<br>(0.600) | -0.544<br>(0.794) | -0.788<br>(0.609) | -1.209<br>(0.831) |
| Observations           | 513                 | 513                | 497               | 497               | 497               | 497               |
| Effective Observations | [159,110]           | [177,116]          | [151,92]          | [155,106]         | [151,92]          | [141,87]          |
| Covariates             | None                | None               | Some              | Some              | All               | All               |
| p-value                | 0.0197              | 0.0605             | 0.371             | 0.493             | 0.196             | 0.146             |
| Order of Polynomial    | 1                   | 2                  | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.0971              | 0.112              | 0.0912            | 0.0978            | 0.0922            | 0.0874            |
| Panel B                | (1)                 | (2)                | (3)               | (4)               | (5)               | (6)               |
| RD_Estimate            | -1.130*<br>(0.664)  | -1.192<br>(0.844)  | -0.337<br>(0.645) | -0.345<br>(0.833) | -0.597<br>(0.682) | -1.088<br>(0.887) |
| Observations           | 513                 | 513                | 497               | 497               | 497               | 497               |
| Effective Observations | [155,102]           | [181,117]          | [143,87]          | [164,106]         | [143,92]          | [143,87]          |
| Covariates             | None                | None               | Some              | Some              | All               | All               |
| p-value                | 0.0887              | 0.158              | 0.602             | 0.679             | 0.381             | 0.220             |
| Order of Polynomial    | 1                   | 2                  | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.0945              | 0.115              | 0.0888            | 0.103             | 0.0898            | 0.0890            |

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 N2: RDD Estimates for Infraction Count by Electoral Term

| Panel A                | (1)                  | (2)                  | (3)                 | (4)                 | (5)                | (6)                |
|------------------------|----------------------|----------------------|---------------------|---------------------|--------------------|--------------------|
| RD_Estimate            | -12.58***<br>(3.767) | -15.62***<br>(5.100) | -9.410**<br>(4.142) | -11.76**<br>(5.457) | -5.226*<br>(3.146) | -6.466*<br>(3.749) |
| Observations           | 195                  | 195                  | 179                 | 179                 | 179                | 179                |
| Effective Observations | [57,48]              | [67,53]              | [48,36]             | [59,46]             | [46,35]            | [57,44]            |
| Covariates             | None                 | None                 | Some                | Some                | All                | All                |
| p-value                | 0.000837             | 0.00219              | 0.0231              | 0.0311              | 0.0967             | 0.0846             |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                  | 2                  |
| Bandwidth              | 0.0990               | 0.125                | 0.0884              | 0.116               | 0.0826             | 0.110              |
| Panel B                | (1)                  | (2)                  | (3)                 | (4)                 | (5)                | (6)                |
| RD_Estimate            | -3.000<br>(2.053)    | -3.570<br>(2.724)    | -0.873<br>(2.141)   | -1.569<br>(2.905)   | -1.190<br>(2.257)  | -3.025<br>(3.113)  |
| Observations           | 195                  | 195                  | 179                 | 179                 | 179                | 179                |
| Effective Observations | [54,41]              | [63,51]              | [48,36]             | [57,44]             | [47,35]            | [52,38]            |
| Covariates             | None                 | None                 | Some                | Some                | All                | All                |
| p-value                | 0.144                | 0.190                | 0.683               | 0.589               | 0.598              | 0.331              |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                  | 2                  |
| Bandwidth              | 0.0892               | 0.113                | 0.0885              | 0.105               | 0.0852             | 0.0935             |

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 N3: RDD Estimates for Infraction Amount (log) by Year

| Panel A                | (1)                  | (2)               | (3)                | (4)               | (5)                 | (6)               |
|------------------------|----------------------|-------------------|--------------------|-------------------|---------------------|-------------------|
| RD Estimate            | -0.643***            | -0.473            | -0.465*            | -0.387            | -0.527*             | -0.459            |
| RD_Estimate            | -0.633**<br>(0.248)  | -0.476<br>(0.329) | -0.465*<br>(0.269) | -0.387<br>(0.333) | -0.535*<br>(0.275)  | -0.454<br>(0.341) |
| Observations           | 510                  | 510               | 494                | 494               | 494                 | 494               |
| Effective Observations | [159,111]            | [155,110]         | [128,85]           | [155,106]         | [129,85]            | [172,112]         |
| Covariates             | None                 | None              | Some               | Some              | All                 | All               |
| p-value                | 0.0106               | 0.148             | 0.0841             | 0.245             | 0.0518              | 0.183             |
| Order of Polynomial    | 1                    | 2                 | 1                  | 2                 | 1                   | 2                 |
| Bandwidth              | 0.0991               | 0.0961            | 0.0759             | 0.0995            | 0.0798              | 0.114             |
| Panel B                | (1)                  | (2)               | (3)                | (4)               | (5)                 | (6)               |
| RD_Estimate            | -0.687***<br>(0.243) | -0.526<br>(0.325) | -0.485*<br>(0.270) | -0.472<br>(0.325) | -0.543**<br>(0.276) | -0.530<br>(0.336) |
| Observations           | 510                  | 510               | 494                | 494               | 494                 | 494               |
| Effective Observations | [167,111]            | [155,97]          | [128,83]           | [151,92]          | [128,85]            | [155,106]         |
| Covariates             | None                 | None              | Some               | Some              | All                 | All               |
| p-value                | 0.00475              | 0.105             | 0.0725             | 0.146             | 0.0495              | 0.115             |
| Order of Polynomial    | 1                    | 2                 | 1                  | 2                 | 1                   | 2                 |
| Bandwidth              | 0.101                | 0.0938            | 0.0741             | 0.0939            | 0.0758              | 0.0981            |

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 N4: RDD Estimates for Infraction Amount (log) by Term

| Panel A                | (1)                  | (2)                | (3)                  | (4)                | (5)                 | (6)                |
|------------------------|----------------------|--------------------|----------------------|--------------------|---------------------|--------------------|
| RD_Estimate            | -1.492***<br>(0.502) | -1.306*<br>(0.678) | -1.215***<br>(0.426) | -1.200*<br>(0.619) | -0.861**<br>(0.395) | -0.975*<br>(0.505) |
| Observations           | 195                  | 195                | 179                  | 179                | 179                 | 179                |
| Effective Observations | [49,39]              | [51,40]            | [52,38]              | [47,35]            | [56,43]             | [46,35]            |
| Covariates             | None                 | None               | Some                 | Some               | All                 | All                |
| p-value                | 0.00293              | 0.0542             | 0.00431              | 0.0527             | 0.0293              | 0.0537             |
| Order of Polynomial    | 1                    | 2                  | 1                    | 2                  | 1                   | 2                  |
| Bandwidth              | 0.0772               | 0.0860             | 0.0931               | 0.0864             | 0.103               | 0.0846             |
| Panel B                | (1)                  | (2)                | (3)                  | (4)                | (5)                 | (6)                |
| RD_Estimate            | -0.783**<br>(0.370)  | -0.558<br>(0.544)  | -0.597<br>(0.389)    | -0.481<br>(0.566)  | -0.687*<br>(0.383)  | -0.619<br>(0.565)  |
| Observations           | 195                  | 195                | 179                  | 179                | 179                 | 179                |
| Effective Observations | [57,48]              | [55,43]            | [53,42]              | [52,38]            | [56,44]             | [52,38]            |
| Covariates             | None                 | None               | Some                 | Some               | All                 | All                |
| p-value                | 0.0341               | 0.305              | 0.125                | 0.395              | 0.0727              | 0.274              |
| Order of Polynomial    | 1                    | 2                  | 1                    | 2                  | 1                   | 2                  |
| Bandwidth              | 0.0981               | 0.0907             | 0.0969               | 0.0931             | 0.104               | 0.0943             |

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.

## N.2. Results When Poverty Increases

Table N5: RDD Estimates for Infraction Count by Year

| Panel A                | (1)              | (2)              | (3)              | (4)              | (5)              | (6)              |
|------------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| RD_Estimate            | 0.717<br>(1.062) | 1.155<br>(1.927) | 0.450<br>(1.389) | 1.251<br>(2.235) | 0.497<br>(1.381) | 1.174<br>(2.130) |
| Observations           | 517              | 517              | 495              | 495              | 495              | 495              |
| Effective Observations | [120,163]        | [126,193]        | [92,137]         | [114,164]        | [96,137]         | [115,177]        |
| Covariates             | None             | None             | Some             | Some             | All              | All              |
| p-value                | 0.499            | 0.549            | 0.746            | 0.576            | 0.719            | 0.581            |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                | 2                |
| Bandwidth              | 0.114            | 0.124            | 0.0856           | 0.116            | 0.0863           | 0.120            |
| Panel B                | (1)              | (2)              | (3)              | (4)              | (5)              | (6)              |
| RD_Estimate            | 0.600<br>(1.084) | 0.899<br>(1.908) | 0.466<br>(1.395) | 1.182<br>(2.224) | 0.536<br>(1.387) | 0.975<br>(1.971) |
| Observations           | 517              | 517              | 495              | 495              | 495              | 495              |
| Effective Observations | [120,162]        | [126,193]        | [92,137]         | [114,168]        | [96,137]         | [115,190]        |
| Covariates             | None             | None             | Some             | Some             | All              | All              |
| p-value                | 0.580            | 0.638            | 0.738            | 0.595            | 0.699            | 0.621            |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                | 2                |
| Bandwidth              | 0.113            | 0.125            | 0.0852           | 0.116            | 0.0860           | 0.125            |

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 N6: RDD Estimates for Infraction Count by Electoral Term

| Panel A                | (1)              | (2)              | (3)              | (4)              | (5)               | (6)               |
|------------------------|------------------|------------------|------------------|------------------|-------------------|-------------------|
| RD_Estimate            | 5.162<br>(4.621) | 8.191<br>(6.961) | 0.791<br>(5.001) | 2.865<br>(7.448) | -3.459<br>(4.541) | -1.699<br>(7.943) |
| Observations           | 196              | 196              | 174              | 174              | 174               | 174               |
| Effective Observations | [54,58]          | [57,73]          | [43,55]          | [46,71]          | [43,52]           | [44,56]           |
| Covariates             | None             | None             | Some             | Some             | All               | All               |
| p-value                | 0.264            | 0.239            | 0.874            | 0.700            | 0.446             | 0.831             |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                 | 2                 |
| Bandwidth              | 0.104            | 0.132            | 0.101            | 0.133            | 0.0954            | 0.109             |
| Panel B                | (1)              | (2)              | (3)              | (4)              | (5)               | (6)               |
| RD_Estimate            | 1.258<br>(3.039) | 1.534<br>(4.616) | 1.182<br>(3.710) | 2.385<br>(5.300) | 0.327<br>(3.846)  | 1.961<br>(5.141)  |
| Observations           | 196              | 196              | 174              | 174              | 174               | 174               |
| Effective Observations | [54,60]          | [59,77]          | [41,52]          | [46,67]          | [40,50]           | [46,71]           |
| Covariates             | None             | None             | Some             | Some             | All               | All               |
| p-value                | 0.679            | 0.740            | 0.750            | 0.653            | 0.932             | 0.703             |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                 | 2                 |
| Bandwidth              | 0.111            | 0.139            | 0.0913           | 0.128            | 0.0891            | 0.132             |

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 N7: RDD Estimates for Infraction Amount (log) by Year

| Panel A                | (1)              | (2)                | (3)              | (4)               | (5)              | (6)               |
|------------------------|------------------|--------------------|------------------|-------------------|------------------|-------------------|
| RD_Estimate            | 0.248<br>(0.347) | 0.0581<br>(0.459)  | 0.177<br>(0.367) | -0.472<br>(0.670) | 0.193<br>(0.366) | -0.476<br>(0.669) |
| Observations           | 515              | 515                | 493              | 493               | 493              | 493               |
| Effective Observations | [123,167]        | [162,227]          | [108,154]        | [109,155]         | [109,154]        | [109,155]         |
| Covariates             | None             | None               | Some             | Some              | All              | All               |
| p-value                | 0.475            | 0.899              | 0.630            | 0.481             | 0.597            | 0.477             |
| Order of Polynomial    | 1                | 2                  | 1                | 2                 | 1                | 2                 |
| Bandwidth              | 0.115            | 0.166              | 0.103            | 0.109             | 0.104            | 0.109             |
| Panel B                | (1)              | (2)                | (3)              | (4)               | (5)              | (6)               |
| RD_Estimate            | 0.249<br>(0.348) | -0.0624<br>(0.489) | 0.189<br>(0.366) | -0.477<br>(0.671) | 0.215<br>(0.365) | -0.480<br>(0.672) |
| Observations           | 515              | 515                | 493              | 493               | 493              | 493               |
| Effective Observations | [123,167]        | [146,216]          | [109,154]        | [109,155]         | [109,154]        | [109,155]         |
| Covariates             | None             | None               | Some             | Some              | All              | All               |
| p-value                | 0.474            | 0.898              | 0.606            | 0.477             | 0.556            | 0.475             |
| Order of Polynomial    | 1                | 2                  | 1                | 2                 | 1                | 2                 |
| Bandwidth              | 0.115            | 0.155              | 0.104            | 0.109             | 0.105            | 0.110             |

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 N8: RDD Estimates for Infraction Amount (log) by Term

| Panel A                | (1)              | (2)               | (3)               | (4)               | (5)                | (6)                 |
|------------------------|------------------|-------------------|-------------------|-------------------|--------------------|---------------------|
| RD_Estimate            | 0.463<br>(0.533) | 0.236<br>(0.679)  | 0.0207<br>(0.554) | -0.183<br>(0.713) | -0.0501<br>(0.448) | -0.00795<br>(0.581) |
| Observations           | 196              | 196               | 174               | 174               | 174                | 174                 |
| Effective Observations | [48,52]          | [57,75]           | [38,50]           | [46,73]           | [44,55]            | [55,81]             |
| Covariates             | None             | None              | Some              | Some              | All                | All                 |
| p-value                | 0.385            | 0.729             | 0.970             | 0.798             | 0.911              | 0.989               |
| Order of Polynomial    | 1                | 2                 | 1                 | 2                 | 1                  | 2                   |
| Bandwidth              | 0.0820           | 0.134             | 0.0853            | 0.136             | 0.106              | 0.165               |
| Panel B                | (1)              | (2)               | (3)               | (4)               | (5)                | (6)                 |
| RD_Estimate            | 0.219<br>(0.426) | -0.603<br>(0.714) | 0.585<br>(0.371)  | -0.394<br>(0.703) | 0.621*<br>(0.370)  | -0.441<br>(0.696)   |
| Observations           | 196              | 196               | 174               | 174               | 174                | 174                 |
| Effective Observations | [53,56]          | [53,58]           | [47,73]           | [44,58]           | [47,73]            | [44,57]             |
| Covariates             | None             | None              | Some              | Some              | All                | All                 |
| p-value                | 0.608            | 0.398             | 0.115             | 0.575             | 0.0933             | 0.526               |
| Order of Polynomial    | 1                | 2                 | 1                 | 2                 | 1                  | 2                   |
| Bandwidth              | 0.0961           | 0.103             | 0.142             | 0.114             | 0.141              | 0.111               |

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.

## O. Results for 2009-2015

### O.1. Results When Poverty Decreases

Table O1: RDD Estimates for Infraction Count by Year

| Panel A                | (1)                  | (2)                  | (3)               | (4)               | (5)               | (6)                 |
|------------------------|----------------------|----------------------|-------------------|-------------------|-------------------|---------------------|
| RD_Estimate            | -1.865***<br>(0.566) | -2.038***<br>(0.647) | -0.836<br>(0.558) | -1.049<br>(0.705) | -0.877<br>(0.535) | -1.495**<br>(0.753) |
| Observations           | 687                  | 687                  | 639               | 639               | 639               | 639                 |
| Effective Observations | [187,139]            | [261,189]            | [171,121]         | [204,150]         | [189,138]         | [175,124]           |
| Covariates             | None                 | None                 | Some              | Some              | All               | All                 |
| p-value                | 0.000993             | 0.00164              | 0.134             | 0.137             | 0.101             | 0.0473              |
| Order of Polynomial    | 1                    | 2                    | 1                 | 2                 | 1                 | 2                   |
| Bandwidth              | 0.0873               | 0.139                | 0.0858            | 0.103             | 0.0956            | 0.0875              |
| Panel B                | (1)                  | (2)                  | (3)               | (4)               | (5)               | (6)                 |
| RD_Estimate            | -1.299**<br>(0.614)  | -1.294*<br>(0.673)   | -0.480<br>(0.605) | -0.613<br>(0.774) | -0.593<br>(0.577) | -1.082<br>(0.781)   |
| Observations           | 687                  | 687                  | 639               | 639               | 639               | 639                 |
| Effective Observations | [183,136]            | [267,238]            | [167,121]         | [208,150]         | [189,138]         | [189,131]           |
| Covariates             | None                 | None                 | Some              | Some              | All               | All                 |
| p-value                | 0.0345               | 0.0547               | 0.428             | 0.429             | 0.304             | 0.166               |
| Order of Polynomial    | 1                    | 2                    | 1                 | 2                 | 1                 | 2                   |
| Bandwidth              | 0.0868               | 0.160                | 0.0840            | 0.108             | 0.0957            | 0.0915              |

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 O2: RDD Estimates for Infraction Count by Electoral Term

| Panel A                | (1)                  | (2)                  | (3)                  | (4)                 | (5)                  | (6)                 |
|------------------------|----------------------|----------------------|----------------------|---------------------|----------------------|---------------------|
| RD_Estimate            | -9.326***<br>(2.315) | -11.25***<br>(3.058) | -5.849***<br>(2.216) | -7.433**<br>(3.096) | -6.417***<br>(2.259) | -8.011**<br>(3.155) |
| Observations           | 195                  | 195                  | 179                  | 179                 | 179                  | 179                 |
| Effective Observations | [62,49]              | [62,49]              | [59,46]              | [57,44]             | [55,43]              | [57,44]             |
| Covariates             | None                 | None                 | Some                 | Some                | All                  | All                 |
| p-value                | 5.63e-05             | 0.000234             | 0.00830              | 0.0163              | 0.00449              | 0.0111              |
| Order of Polynomial    | 1                    | 2                    | 1                    | 2                   | 1                    | 2                   |
| Bandwidth              | 0.107                | 0.110                | 0.115                | 0.110               | 0.101                | 0.108               |
| Panel B                | (1)                  | (2)                  | (3)                  | (4)                 | (5)                  | (6)                 |
| RD_Estimate            | -4.786**<br>(2.216)  | -5.611**<br>(2.735)  | -2.363<br>(2.180)    | -2.769<br>(2.965)   | -2.725<br>(2.131)    | -5.190*<br>(2.876)  |
| Observations           | 195                  | 195                  | 179                  | 179                 | 179                  | 179                 |
| Effective Observations | [56,43]              | [70,53]              | [52,42]              | [57,44]             | [52,38]              | [50,36]             |
| Covariates             | None                 | None                 | Some                 | Some                | All                  | All                 |
| p-value                | 0.0308               | 0.0403               | 0.278                | 0.350               | 0.201                | 0.0712              |
| Order of Polynomial    | 1                    | 2                    | 1                    | 2                   | 1                    | 2                   |
| Bandwidth              | 0.0924               | 0.132                | 0.0965               | 0.108               | 0.0938               | 0.0895              |

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 O3: RDD Estimates for Infraction Amount (log) by Year

| Panel A                | (1)                  | (2)               | (3)               | (4)               | (5)               | (6)               |
|------------------------|----------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| RD_Estimate            | -0.634***<br>(0.243) | -0.510<br>(0.322) | -0.321<br>(0.269) | -0.313<br>(0.320) | -0.409<br>(0.279) | -0.384<br>(0.336) |
| Observations           | 684                  | 684               | 636               | 636               | 636               | 636               |
| Effective Observations | [205,164]            | [201,146]         | [146,89]          | [181,124]         | [146,96]          | [189,131]         |
| Covariates             | None                 | None              | Some              | Some              | All               | All               |
| p-value                | 0.00911              | 0.114             | 0.232             | 0.327             | 0.143             | 0.253             |
| Order of Polynomial    | 1                    | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.0998               | 0.0923            | 0.0642            | 0.0892            | 0.0686            | 0.0942 height     |
| Panel B                | (1)                  | (2)               | (3)               | (4)               | (5)               | (6)               |
| RD_Estimate            | -0.606**<br>(0.244)  | -0.475<br>(0.329) | -0.221<br>(0.289) | -0.244<br>(0.347) | -0.276<br>(0.285) | -0.298<br>(0.344) |
| Observations           | 684                  | 684               | 636               | 636               | 636               | 636               |
| Effective Observations | [213,164]            | [197,146]         | [146,89]          | [175,124]         | [146,89]          | [181,124]         |
| Covariates             | None                 | None              | Some              | Some              | All               | All               |
| p-value                | 0.0128               | 0.149             | 0.445             | 0.482             | 0.333             | 0.387             |
| Order of Polynomial    | 1                    | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.102                | 0.0909            | 0.0607            | 0.0875            | 0.0633            | 0.0888            |

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 O4: RDD Estimates for Infraction Amount (log) by Term

| Panel A                | (1)                | (2)               | (3)               | (4)               | (5)               | (6)               |
|------------------------|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| RD_Estimate            | -0.736*<br>(0.394) | -0.600<br>(0.508) | -0.468<br>(0.444) | -0.349<br>(0.513) | -0.575<br>(0.428) | -0.451<br>(0.496) |
| Observations           | 195                | 195               | 179               | 179               | 179               | 179               |
| Effective Observations | [56,47]            | [56,45]           | [44,32]           | [52,40]           | [45,34]           | [52,42]           |
| Covariates             | None               | None              | Some              | Some              | All               | All               |
| p-value                | 0.0614             | 0.238             | 0.291             | 0.496             | 0.179             | 0.364             |
| Order of Polynomial    | 1                  | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.0966             | 0.0950            | 0.0732            | 0.0953            | 0.0797            | 0.0965            |
| Panel B                | (1)                | (2)               | (3)               | (4)               | (5)               | (6)               |
| RD_Estimate            | -0.641*<br>(0.388) | -0.452<br>(0.517) | -0.222<br>(0.487) | -0.138<br>(0.567) | -0.364<br>(0.475) | -0.280<br>(0.550) |
| Observations           | 195                | 195               | 179               | 179               | 179               | 179               |
| Effective Observations | [59,48]            | [56,43]           | [40,28]           | [52,40]           | [44,32]           | [52,40]           |
| Covariates             | None               | None              | Some              | Some              | All               | All               |
| p-value                | 0.0988             | 0.383             | 0.649             | 0.807             | 0.443             | 0.611             |
| Order of Polynomial    | 1                  | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.101              | 0.0938            | 0.0679            | 0.0948            | 0.0731            | 0.0953            |

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.

## O.2. Results When Poverty Increases

Table O5: RDD Estimates for Infraction Count by Year

| Panel A                | (1)              | (2)               | (3)              | (4)              | (5)              | (6)              |
|------------------------|------------------|-------------------|------------------|------------------|------------------|------------------|
| RD_Estimate            | 0.364<br>(0.868) | 0.363<br>(1.326)  | 0.192<br>(0.997) | 0.426<br>(1.466) | 0.230<br>(1.026) | 0.457<br>(1.436) |
| Observations           | 692              | 692               | 628              | 628              | 628              | 628              |
| Effective Observations | [189,225]        | [203,280]         | [151,190]        | [161,257]        | [147,186]        | [161,260]        |
| Covariates             | None             | None              | Some             | Some             | All              | All              |
| p-value                | 0.675            | 0.784             | 0.847            | 0.772            | 0.823            | 0.750            |
| Order of Polynomial    | 1                | 2                 | 1                | 2                | 1                | 2                |
| Bandwidth              | 0.117            | 0.148             | 0.0961           | 0.133            | 0.0935           | 0.136            |
| Panel B                | (1)              | (2)               | (3)              | (4)              | (5)              | (6)              |
| RD_Estimate            | 0.147<br>(0.939) | 0.0928<br>(1.300) | 0.228<br>(1.025) | 0.368<br>(1.445) | 0.238<br>(1.047) | 0.407<br>(1.426) |
| Observations           | 692              | 692               | 628              | 628              | 628              | 628              |
| Effective Observations | [182,207]        | [207,287]         | [147,186]        | [161,257]        | [144,186]        | [161,260]        |
| Covariates             | None             | None              | Some             | Some             | All              | All              |
| p-value                | 0.875            | 0.943             | 0.824            | 0.799            | 0.820            | 0.775            |
| Order of Polynomial    | 1                | 2                 | 1                | 2                | 1                | 2                |
| Bandwidth              | 0.108            | 0.155             | 0.0935           | 0.134            | 0.0920           | 0.137            |

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 O6: RDD Estimates for Infraction Count by Electoral Term

| Panel A                | (1)              | (2)              | (3)              | (4)              | (5)               | (6)              |
|------------------------|------------------|------------------|------------------|------------------|-------------------|------------------|
| RD_Estimate            | 3.284<br>(2.876) | 4.093<br>(5.435) | 0.953<br>(3.204) | 1.501<br>(5.748) | -1.100<br>(3.988) | 1.156<br>(5.900) |
| Observations           | 196              | 196              | 174              | 174              | 174               | 174              |
| Effective Observations | [60,79]          | [59,78]          | [46,64]          | [46,72]          | [43,55]           | [46,72]          |
| Covariates             | None             | None             | Some             | Some             | All               | All              |
| p-value                | 0.254            | 0.451            | 0.766            | 0.794            | 0.783             | 0.845            |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                 | 2                |
| Bandwidth              | 0.149            | 0.143            | 0.122            | 0.135            | 0.103             | 0.134            |
| Panel B                | (1)              | (2)              | (3)              | (4)              | (5)               | (6)              |
| RD_Estimate            | 1.225<br>(3.432) | 1.268<br>(4.723) | 0.804<br>(3.726) | 1.247<br>(5.148) | 0.0901<br>(3.937) | 1.012<br>(5.131) |
| Observations           | 196              | 196              | 174              | 174              | 174               | 174              |
| Effective Observations | [54,58]          | [61,81]          | [42,52]          | [46,73]          | [40,50]           | [47,73]          |
| Covariates             | None             | None             | Some             | Some             | All               | All              |
| p-value                | 0.721            | 0.788            | 0.829            | 0.809            | 0.982             | 0.844            |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                 | 2                |
| Bandwidth              | 0.107            | 0.153            | 0.0932           | 0.136            | 0.0900            | 0.137            |

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 O7: RDD Estimates for Infraction Amount (log) by Year

| Panel A                | (1)              | (2)                | (3)                | (4)               | (5)                | (6)               |
|------------------------|------------------|--------------------|--------------------|-------------------|--------------------|-------------------|
| RD_Estimate            | 0.295<br>(0.258) | -0.0951<br>(0.416) | 0.0979<br>(0.287)  | -0.367<br>(0.455) | 0.119<br>(0.286)   | -0.262<br>(0.429) |
| Observations           | 690              | 690                | 626                | 626               | 626                | 626               |
| Effective Observations | [202,280]        | [202,280]          | [153,205]          | [160,248]         | [153,205]          | [164,260]         |
| Covariates             | None             | None               | Some               | Some              | All                | All               |
| p-value                | 0.254            | 0.819              | 0.733              | 0.420             | 0.677              | 0.541             |
| Order of Polynomial    | 1                | 2                  | 1                  | 2                 | 1                  | 2                 |
| Bandwidth              | 0.146            | 0.148              | 0.112              | 0.131             | 0.112              | 0.140             |
| Panel B                | (1)              | (2)                | (3)                | (4)               | (5)                | (6)               |
| RD_Estimate            | 0.250<br>(0.274) | -0.378<br>(0.449)  | -0.0480<br>(0.325) | -0.443<br>(0.484) | -0.0878<br>(0.357) | -0.379<br>(0.454) |
| Observations           | 690              | 690                | 626                | 626               | 626                | 626               |
| Effective Observations | [191,266]        | [191,263]          | [146,186]          | [160,234]         | [131,175]          | [160,251]         |
| Covariates             | None             | None               | Some               | Some              | All                | All               |
| p-value                | 0.361            | 0.400              | 0.883              | 0.361             | 0.806              | 0.404             |
| Order of Polynomial    | 1                | 2                  | 1                  | 2                 | 1                  | 2                 |
| Bandwidth              | 0.135            | 0.132              | 0.0938             | 0.123             | 0.0830             | 0.132             |

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 O8: RDD Estimates for Infraction Amount (log) by Term

| Panel A                | (1)              | (2)               | (3)              | (4)                 | (5)              | (6)                  |
|------------------------|------------------|-------------------|------------------|---------------------|------------------|----------------------|
| RD_Estimate            | 0.475<br>(0.302) | 0.180<br>(0.517)  | 0.388<br>(0.311) | -0.00515<br>(0.520) | 0.387<br>(0.310) | -0.000242<br>(0.515) |
| Observations           | 196              | 196               | 174              | 174                 | 174              | 174                  |
| Effective Observations | [60,79]          | [59,77]           | [47,74]          | [48,75]             | [47,74]          | [48,75]              |
| Covariates             | None             | None              | Some             | Some                | All              | All                  |
| p-value                | 0.115            | 0.728             | 0.212            | 0.992               | 0.211            | 1                    |
| Order of Polynomial    | 1                | 2                 | 1                | 2                   | 1                | 2                    |
| Bandwidth              | 0.148            | 0.141             | 0.142            | 0.151               | 0.142            | 0.151                |
| Panel B                | (1)              | (2)               | (3)              | (4)                 | (5)              | (6)                  |
| RD_Estimate            | 0.384<br>(0.322) | -0.188<br>(0.634) | 0.305<br>(0.352) | -0.0460<br>(0.544)  | 0.320<br>(0.348) | -0.0877<br>(0.544)   |
| Observations           | 196              | 196               | 174              | 174                 | 174              | 174                  |
| Effective Observations | [57,74]          | [57,64]           | [46,64]          | [47,75]             | [46,64]          | [47,73]              |
| Covariates             | None             | None              | Some             | Some                | All              | All                  |
| p-value                | 0.233            | 0.766             | 0.386            | 0.933               | 0.357            | 0.872                |
| Order of Polynomial    | 1                | 2                 | 1                | 2                   | 1                | 2                    |
| Bandwidth              | 0.133            | 0.118             | 0.121            | 0.144               | 0.121            | 0.139                |

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.

## P. Results for 2008-2015

### P.1. Results When Poverty Decreases

Table P1: RDD Estimates for Infraction Count by Year

| Panel A                | (1)                  | (2)                  | (3)                 | (4)                 | (5)                | (6)                 |
|------------------------|----------------------|----------------------|---------------------|---------------------|--------------------|---------------------|
| RD_Estimate            | -1.963***<br>(0.548) | -2.114***<br>(0.616) | -1.157**<br>(0.523) | -1.394**<br>(0.701) | -1.045*<br>(0.538) | -1.756**<br>(0.758) |
| Observations           | 776                  | 776                  | 712                 | 712                 | 712                | 712                 |
| Effective Observations | [224,179]            | [296,277]            | [224,171]           | [228,173]           | [228,173]          | [200,151]           |
| Covariates             | None                 | None                 | Some                | Some                | All                | All                 |
| p-value                | 0.000343             | 0.000593             | 0.0268              | 0.0468              | 0.0522             | 0.0206              |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                  | 2                   |
| Bandwidth              | 0.0946               | 0.163                | 0.103               | 0.108               | 0.107              | 0.0899              |
| Panel B                | (1)                  | (2)                  | (3)                 | (4)                 | (5)                | (6)                 |
| RD_Estimate            | -1.375**<br>(0.559)  | -1.578**<br>(0.689)  | -0.802<br>(0.546)   | -0.890<br>(0.736)   | -0.826<br>(0.560)  | -1.362*<br>(0.774)  |
| Observations           | 776                  | 776                  | 712                 | 712                 | 712                | 712                 |
| Effective Observations | [228,191]            | [284,217]            | [224,173]           | [228,173]           | [228,177]          | [208,151]           |
| Covariates             | None                 | None                 | Some                | Some                | All                | All                 |
| p-value                | 0.0139               | 0.0219               | 0.142               | 0.227               | 0.140              | 0.0784              |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                  | 2                   |
| Bandwidth              | 0.0995               | 0.135                | 0.104               | 0.111               | 0.112              | 0.0935              |

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 P2: RDD Estimates for Infraction Count by Electoral Term

| Panel A                | (1)                  | (2)                  | (3)                 | (4)                 | (5)                  | (6)                  |
|------------------------|----------------------|----------------------|---------------------|---------------------|----------------------|----------------------|
| RD_Estimate            | -8.090***<br>(2.207) | -9.698***<br>(2.703) | -4.888**<br>(2.121) | -6.034**<br>(2.862) | -5.559***<br>(2.141) | -7.524***<br>(2.835) |
| Observations           | 195                  | 195                  | 179                 | 179                 | 179                  | 179                  |
| Effective Observations | [58,48]              | [69,53]              | [59,46]             | [57,44]             | [53,43]              | [54,43]              |
| Covariates             | None                 | None                 | Some                | Some                | All                  | All                  |
| p-value                | 0.000247             | 0.000334             | 0.0212              | 0.0350              | 0.00942              | 0.00796              |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                    | 2                    |
| Bandwidth              | 0.101                | 0.129                | 0.118               | 0.108               | 0.0995               | 0.100                |
| Panel B                | (1)                  | (2)                  | (3)                 | (4)                 | (5)                  | (6)                  |
| RD_Estimate            | -5.724**<br>(2.253)  | -6.714**<br>(2.844)  | -3.531<br>(2.211)   | -3.921<br>(2.990)   | -3.666<br>(2.306)    | -6.608**<br>(2.798)  |
| Observations           | 195                  | 195                  | 179                 | 179                 | 179                  | 179                  |
| Effective Observations | [60,48]              | [69,53]              | [58,46]             | [58,45]             | [52,40]              | [52,38]              |
| Covariates             | None                 | None                 | Some                | Some                | All                  | All                  |
| p-value                | 0.0111               | 0.0182               | 0.110               | 0.190               | 0.112                | 0.0182               |
| Order of Polynomial    | 1                    | 2                    | 1                   | 2                   | 1                    | 2                    |
| Bandwidth              | 0.102                | 0.129                | 0.113               | 0.112               | 0.0957               | 0.0925               |

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 P3: RDD Estimates for Infraction Amount (log) by Year

| Panel A                | (1)                 | (2)               | (3)               | (4)               | (5)               | (6)               |
|------------------------|---------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| RD_Estimate            | -0.548**<br>(0.233) | -0.423<br>(0.314) | -0.332<br>(0.266) | -0.299<br>(0.316) | -0.362<br>(0.280) | -0.329<br>(0.334) |
| Observations           | 773                 | 773               | 709               | 709               | 709               | 709               |
| Effective Observations | [232,191]           | [216,163]         | [160,103]         | [200,143]         | [160,103]         | [208,151]         |
| Covariates             | None                | None              | Some              | Some              | All               | All               |
| p-value                | 0.0187              | 0.178             | 0.213             | 0.345             | 0.196             | 0.326             |
| Order of Polynomial    | 1                   | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.100               | 0.0897            | 0.0629            | 0.0889            | 0.0644            | 0.0921            |
| Panel B                | (1)                 | (2)               | (3)               | (4)               | (5)               | (6)               |
| RD_Estimate            | -0.532**<br>(0.232) | -0.393<br>(0.320) | -0.233<br>(0.282) | -0.241<br>(0.332) | -0.267<br>(0.284) | -0.274<br>(0.340) |
| Observations           | 773                 | 773               | 709               | 709               | 709               | 709               |
| Effective Observations | [240,193]           | [208,163]         | [156,103]         | [188,139]         | [160,103]         | [192,143]         |
| Covariates             | None                | None              | Some              | Some              | All               | All               |
| p-value                | 0.0219              | 0.220             | 0.408             | 0.468             | 0.348             | 0.420             |
| Order of Polynomial    | 1                   | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.104               | 0.0874            | 0.0590            | 0.0858            | 0.0611            | 0.0878            |

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 P4: RDD Estimates for Infraction Amount (log) by Term

| Panel A                | (1)                | (2)               | (3)               | (4)               | (5)               | (6)               |
|------------------------|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| RD_Estimate            | -0.612*<br>(0.348) | -0.326<br>(0.472) | -0.394<br>(0.429) | -0.248<br>(0.499) | -0.445<br>(0.413) | -0.326<br>(0.475) |
| Observations           | 195                | 195               | 179               | 179               | 179               | 179               |
| Effective Observations | [62,49]            | [57,48]           | [44,31]           | [53,43]           | [45,34]           | [52,42]           |
| Covariates             | None               | None              | Some              | Some              | All               | All               |
| p-value                | 0.0792             | 0.490             | 0.358             | 0.620             | 0.281             | 0.493             |
| Order of Polynomial    | 1                  | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.110              | 0.0992            | 0.0721            | 0.0995            | 0.0763            | 0.0962            |
| Panel B                | (1)                | (2)               | (3)               | (4)               | (5)               | (6)               |
| RD_Estimate            | -0.645*<br>(0.349) | -0.442<br>(0.462) | -0.354<br>(0.439) | -0.270<br>(0.499) | -0.409<br>(0.429) | -0.319<br>(0.480) |
| Observations           | 195                | 195               | 179               | 179               | 179               | 179               |
| Effective Observations | [62,49]            | [56,43]           | [40,28]           | [52,40]           | [43,29]           | [52,38]           |
| Covariates             | None               | None              | Some              | Some              | All               | All               |
| p-value                | 0.0648             | 0.339             | 0.420             | 0.589             | 0.341             | 0.507             |
| Order of Polynomial    | 1                  | 2                 | 1                 | 2                 | 1                 | 2                 |
| Bandwidth              | 0.106              | 0.0940            | 0.0682            | 0.0946            | 0.0706            | 0.0933            |

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.

## P.2. Results When Poverty Increases

Table P5: RDD Estimates for Infraction Count by Year

| Panel A                | (1)               | (2)                | (3)              | (4)              | (5)              | (6)              |
|------------------------|-------------------|--------------------|------------------|------------------|------------------|------------------|
| RD_Estimate            | 0.283<br>(0.800)  | 0.279<br>(1.227)   | 0.137<br>(0.915) | 0.324<br>(1.346) | 0.168<br>(0.954) | 0.374<br>(1.335) |
| Observations           | 781               | 781                | 695              | 695              | 695              | 695              |
| Effective Observations | [226,279]         | [242,319]          | [172,216]        | [184,287]        | [172,208]        | [184,291]        |
| Covariates             | None              | None               | Some             | Some             | All              | All              |
| p-value                | 0.724             | 0.820              | 0.881            | 0.810            | 0.860            | 0.779            |
| Order of Polynomial    | 1                 | 2                  | 1                | 2                | 1                | 2                |
| Bandwidth              | 0.124             | 0.153              | 0.0980           | 0.134            | 0.0951           | 0.136            |
| Panel B                | (1)               | (2)                | (3)              | (4)              | (5)              | (6)              |
| RD_Estimate            | 0.0379<br>(0.876) | -0.0117<br>(1.201) | 0.178<br>(0.971) | 0.264<br>(1.312) | 0.159<br>(0.988) | 0.284<br>(1.306) |
| Observations           | 781               | 781                | 695              | 695              | 695              | 695              |
| Effective Observations | [214,240]         | [250,327]          | [164,204]        | [184,287]        | [160,200]        | [184,291]        |
| Covariates             | None              | None               | Some             | Some             | All              | All              |
| p-value                | 0.966             | 0.992              | 0.855            | 0.840            | 0.872            | 0.828            |
| Order of Polynomial    | 1                 | 2                  | 1                | 2                | 1                | 2                |
| Bandwidth              | 0.112             | 0.156              | 0.0907           | 0.134            | 0.0899           | 0.137            |

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 P6: RDD Estimates for Infraction Count by Electoral Term

| Panel A                | (1)              | (2)              | (3)              | (4)              | (5)               | (6)               |
|------------------------|------------------|------------------|------------------|------------------|-------------------|-------------------|
| RD_Estimate            | 2.000<br>(3.324) | 2.333<br>(5.142) | 0.535<br>(3.647) | 1.155<br>(5.401) | 0.0550<br>(3.905) | -0.424<br>(5.610) |
| Observations           | 196              | 196              | 174              | 174              | 174               | 174               |
| Effective Observations | [57,70]          | [60,79]          | [43,55]          | [46,72]          | [43,52]           | [47,73]           |
| Covariates             | None             | None             | Some             | Some             | All               | All               |
| p-value                | 0.547            | 0.650            | 0.883            | 0.831            | 0.989             | 0.940             |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                 | 2                 |
| Bandwidth              | 0.124            | 0.150            | 0.0988           | 0.135            | 0.0943            | 0.139             |
| Panel B                | (1)              | (2)              | (3)              | (4)              | (5)               | (6)               |
| RD_Estimate            | 0.854<br>(3.622) | 0.949<br>(4.934) | 0.697<br>(3.863) | 0.998<br>(5.280) | -0.148<br>(4.086) | -1.052<br>(5.608) |
| Observations           | 196              | 196              | 174              | 174              | 174               | 174               |
| Effective Observations | [54,59]          | [63,82]          | [41,52]          | [46,72]          | [40,50]           | [46,73]           |
| Covariates             | None             | None             | Some             | Some             | All               | All               |
| p-value                | 0.814            | 0.847            | 0.857            | 0.850            | 0.971             | 0.851             |
| Order of Polynomial    | 1                | 2                | 1                | 2                | 1                 | 2                 |
| Bandwidth              | 0.110            | 0.156            | 0.0917           | 0.135            | 0.0892            | 0.135             |

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 P7: RDD Estimates for Infraction Amount (log) by Year

| Panel A                | (1)              | (2)               | (3)                | (4)               | (5)                | (6)               |
|------------------------|------------------|-------------------|--------------------|-------------------|--------------------|-------------------|
| RD_Estimate            | 0.315<br>(0.244) | -0.136<br>(0.405) | 0.112<br>(0.275)   | -0.258<br>(0.405) | 0.0997<br>(0.285)  | 0.0636<br>(0.368) |
| Observations           | 779              | 779               | 693                | 693               | 693                | 693               |
| Effective Observations | [237,315]        | [233,307]         | [175,228]          | [187,291]         | [175,220]          | [219,331]         |
| Covariates             | None             | None              | Some               | Some              | All                | All               |
| p-value                | 0.196            | 0.738             | 0.683              | 0.525             | 0.727              | 0.863             |
| Order of Polynomial    | 1                | 2                 | 1                  | 2                 | 1                  | 2                 |
| Bandwidth              | 0.149            | 0.141             | 0.112              | 0.139             | 0.107              | 0.174             |
| Panel B                | (1)              | (2)               | (3)                | (4)               | (5)                | (6)               |
| RD_Estimate            | 0.196<br>(0.274) | -0.427<br>(0.453) | -0.0590<br>(0.348) | -0.330<br>(0.408) | -0.0601<br>(0.342) | 0.0592<br>(0.366) |
| Observations           | 779              | 779               | 693                | 693               | 693                | 693               |
| Effective Observations | [225,267]        | [225,271]         | [151,192]          | [183,287]         | [151,196]          | [219,331]         |
| Covariates             | None             | None              | Some               | Some              | All                | All               |
| p-value                | 0.473            | 0.345             | 0.865              | 0.418             | 0.860              | 0.871             |
| Order of Polynomial    | 1                | 2                 | 1                  | 2                 | 1                  | 2                 |
| Bandwidth              | 0.122            | 0.123             | 0.0802             | 0.134             | 0.0818             | 0.174             |

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 P8: RDD Estimates for Infraction Amount (log) by Term

| Panel A                | (1)              | (2)                | (3)              | (4)               | (5)              | (6)                 |
|------------------------|------------------|--------------------|------------------|-------------------|------------------|---------------------|
| RD_Estimate            | 0.452<br>(0.310) | 0.111<br>(0.509)   | 0.387<br>(0.326) | 0.0247<br>(0.509) | 0.368<br>(0.327) | -0.00815<br>(0.510) |
| Observations           | 196              | 196                | 174              | 174               | 174              | 174                 |
| Effective Observations | [57,70]          | [57,74]            | [46,64]          | [47,73]           | [46,63]          | [47,73]             |
| Covariates             | None             | None               | Some             | Some              | All              | All                 |
| p-value                | 0.145            | 0.827              | 0.236            | 0.961             | 0.261            | 0.987               |
| Order of Polynomial    | 1                | 2                  | 1                | 2                 | 1                | 2                   |
| Bandwidth              | 0.125            | 0.132              | 0.121            | 0.139             | 0.120            | 0.139               |
| Panel B                | (1)              | (2)                | (3)              | (4)               | (5)              | (6)                 |
| RD_Estimate            | 0.412<br>(0.316) | -0.0330<br>(0.566) | 0.338<br>(0.349) | 0.0141<br>(0.517) | 0.284<br>(0.357) | -0.0905<br>(0.528)  |
| Observations           | 196              | 196                | 174              | 174               | 174              | 174                 |
| Effective Observations | [57,70]          | [57,67]            | [44,57]          | [47,73]           | [44,55]          | [46,72]             |
| Covariates             | None             | None               | Some             | Some              | All              | All                 |
| p-value                | 0.192            | 0.954              | 0.332            | 0.978             | 0.426            | 0.864               |
| Order of Polynomial    | 1                | 2                  | 1                | 2                 | 1                | 2                   |
| Bandwidth              | 0.124            | 0.121              | 0.111            | 0.138             | 0.106            | 0.135               |

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.

## Q. Corruption Levels for the Poverty-Reducing, Poverty-Increasing, and Whole Samples (Dichotomous View)

### Q.1. Dichotomous Corruption Results for the 2012-2015 Electoral Term

Table Q1: Corrupt Mayors Defined by Count of Infractions (Term 2012-2015)

| Panel A     | Mayor Not Corrupt | Mayor Corrupt   | Total            |
|-------------|-------------------|-----------------|------------------|
| Aligned     | 26<br>(57.78%)    | 19<br>(42.22%)  | 45<br>(100.00%)  |
| Not-Aligned | 32<br>(32.99%)    | 65<br>(67.01%)  | 97<br>(100.00%)  |
| Panel B     | Mayor Not Corrupt | Mayor Corrupt   | Total            |
| Aligned     | 25<br>(39.68%)    | 38<br>(60.32%)  | 63<br>(100.00%)  |
| Not-Aligned | 46<br>(50.00%)    | 46<br>(50.00%)  | 92<br>(100.00%)  |
| Panel C     | Mayor Not Corrupt | Mayor Corrupt   | Total            |
| Aligned     | 54<br>(45.38%)    | 65<br>(54.62%)  | 119<br>(100.00%) |
| Not-Aligned | 90<br>(42.06%)    | 124<br>(57.94%) | 214<br>(100.00%) |

Note: “Mayor Not Corrupt” and “Mayor Corrupt” are defined as the count of municipalities with the total number of infractions being above/below the median for the 2012-2015 electoral term. Panel A reports the results by alignment status for the poverty-decreasing sample, Panel B presents results by alignment status for the poverty-increasing sample, and Panel C provides the same results but for the whole sample.

Table Q2: Corrupt Mayors Defined by Amount (log) of Infraction for the 2012-2015 Electoral Term

| Panel A     | Mayor Not Corrupt | Mayor Corrupt   | Total            |
|-------------|-------------------|-----------------|------------------|
| Aligned     | 31<br>(68.89%)    | 14<br>(31.11%)  | 45<br>(100.00%)  |
| Not-Aligned | 43<br>(44.33%)    | 54<br>(55.67%)  | 97<br>(100.00%)  |
| Panel B     | Mayor Not Corrupt | Mayor Corrupt   | Total            |
| Aligned     | 29<br>(46.03%)    | 34<br>(53.97%)  | 63<br>(100.00%)  |
| Not-Aligned | 48<br>(52.17%)    | 44<br>(47.83%)  | 92<br>(100.00%)  |
| Panel C     | Mayor Not Corrupt | Mayor Corrupt   | Total            |
| Aligned     | 65<br>(54.62%)    | 54<br>(45.38%)  | 119<br>(100.00%) |
| Not-Aligned | 101<br>(47.20%)   | 113<br>(52.80%) | 214<br>(100.00%) |

Note: “Mayor Not Corrupt” and “Mayor Corrupt” are defined as the count of municipalities with the log amount of stolen/misappropriated money associated with audit infractions being above/below the median for the 2012-2015 electoral term. Panel A reports the results by alignment status for the poverty-decreasing sample, Panel B presents results by alignment status for the poverty-increasing sample, and Panel C provides the same results but for the whole sample.

## Q.2. Dichotomous Corruption Results for the 2008-2011 Electoral Term

Table Q3: Corrupt Mayors Defined by Count of Infraction for the 2008-2011 Electoral Term

| Panel A     | Mayor Not Corrupt | Mayor Corrupt   | Total            |
|-------------|-------------------|-----------------|------------------|
| Aligned     | 25<br>(54.35%)    | 21<br>(45.65%)  | 46<br>(100.00%)  |
| Not-Aligned | 44<br>(45.83%)    | 52<br>(54.17%)  | 96<br>(100.00%)  |
| Panel B     | Mayor Not Corrupt | Mayor Corrupt   | Total            |
| Aligned     | 26<br>(54.17%)    | 22<br>(45.83%)  | 48<br>(100.00%)  |
| Not-Aligned | 47<br>(43.93%)    | 60<br>(56.07%)  | 107<br>(100.00%) |
| Panel C     | Mayor Not Corrupt | Mayor Corrupt   | Total            |
| Aligned     | 54<br>(51.92%)    | 50<br>(48.08%)  | 104<br>(100.00%) |
| Not-Aligned | 107<br>(46.93%)   | 121<br>(53.07%) | 228<br>(100.00%) |

Note: “Mayor Not Corrupt” and “Mayor Corrupt” are defined as the count of municipalities with the total number of infractions being above/below the median for the 2008-2011 electoral term. Panel A reports the results by alignment status for the poverty-decreasing sample, Panel B presents results by alignment status for the poverty-increasing sample, and Panel C provides the same results but for the whole sample.

Table Q4: Corrupt Mayors Defined by Amount (log) of Infraction for the 2008-2011 Electoral Term

|             | Mayor Not Corrupt | Mayor Corrupt   | Total            |
|-------------|-------------------|-----------------|------------------|
| Aligned     | 28<br>(60.87%)    | 18<br>(39.13%)  | 46<br>(100.00%)  |
| Not-Aligned | 46<br>(47.92%)    | 50<br>(52.08%)  | 96<br>(100.00%)  |
|             | Mayor Not Corrupt | Mayor Corrupt   | Total            |
| Aligned     | 22<br>(45.83%)    | 26<br>(54.17%)  | 48<br>(100.00%)  |
| Not-Aligned | 54<br>(50.47%)    | 53<br>(49.53%)  | 107<br>(100.00%) |
|             | Mayor Not Corrupt | Mayor Corrupt   | Total            |
| Aligned     | 52<br>(50.00%)    | 52<br>(50.00%)  | 104<br>(100.00%) |
| Not-Aligned | 112<br>(49.12%)   | 116<br>(50.88%) | 228<br>(100.00%) |

Note: ‘Mayor Not Corrupt’ and ‘Mayor Corrupt’ are defined as the count of municipalities with the log amount of stolen/misappropriated money associated with audit infractions being above/below the median for the 2008-2011 electoral term. Panel A reports the results by alignment status for the poverty-decreasing sample, Panel B presents results by alignment status for the poverty-increasing sample, and Panel C provides the same results but for the whole sample.

## R. Poverty Rates For Different Samples

Table R1: Total Poverty Rates from 2002 & 2011 Waves

| Sample                                | Mean Total Poverty-2002 (%) | Mean Total Poverty-2011 (%) |
|---------------------------------------|-----------------------------|-----------------------------|
| Whole Sample                          | 63.87<br>(21.46)            | 69.51<br>(16.87)            |
| Whole Sample (including missing 2011) | 63.87<br>(21.46)            | 65.84<br>(20.21)            |
| Municipalities Both in 2002 & 2011    | 67.34<br>(18.91)            | 69.51<br>(16.87)            |
| Municipalities Only in 2002           | 33.59<br>(18.55)            | NA<br>NA                    |
| Poverty-Reducing Sample               | 76.12<br>(13.25)            | 64.72<br>(15.90)            |
| Poverty-Increasing Sample             | 59.30<br>(19.76)            | 73.75<br>(16.67)            |
| Low-Poverty Sample                    | 46.30<br>(15.67)            | 59.41<br>(15.97)            |
| High-Poverty Sample                   | 81.34<br>(7.82)             | 77.61<br>(12.72)            |

Note: Standard deviations are in parentheses. Total poverty rates are from the 2002 and 2011 census. “Whole Sample (including missing 2011)” (row 2) included values from 2002 for the 32 municipalities with missing information in 2011. “Municipalities only in 2002” (row 4) refer to the 34 municipalities that had data in the 2002 census only.

As shown in Tables [R1](#) and [R2](#), the 34 urban municipalities for which there are only poverty and extreme poverty data in 2002 exhibit less poverty and extreme poverty than the 299 other municipalities in the whole sample. Additionally, the literatures on poverty traps (e.g., [Sachs, 2005](#); [Banerjee and Duflo, 2011](#)), clientelism (e.g., [Scott, 1972](#); [Keefer, 2007a](#)), and modernization itself (e.g., [Lerner, 1958](#); [Lipset, 1959, 1960](#); [Rostow, 1960](#); [Gershenkron, 1962](#); [Inglehart and Welzel, 2005](#)) indicate that more rural areas are less likely to undergo modernization processes. In short, the results that we find in this article based on more rural areas are less likely from a theoretical perspective. Accordingly, we conjecture that the inclusion of the missing poverty data from the less-poor, urban municipalities would, if anything, reinforce our results.

In all likelihood, though, the missing data would not change much of anything. First, if the data actually existed (and they do not according to email communication Guatemala’s National Statistical Office), the data would be divided between the low-poverty and high-

Table R2: Extreme Poverty Rates from 2002 &amp; 2011 Waves

| Sample                                | Mean Total Poverty-2002 (%) | Mean Total Poverty-2011 (%) |
|---------------------------------------|-----------------------------|-----------------------------|
| Whole Sample                          | 19.79<br>(14.27)            | 20.84<br>(15.47)            |
| Whole Sample (including missing 2011) | 19.79<br>(14.27)            | 19.28<br>(15.51)            |
| Municipalities Both in 2002 & 2011    | 21.42<br>(14.01)            | 20.84<br>(15.47)            |
| Municipalities Only in 2002           | 5.59<br>(6.61)              | NA<br>NA                    |
| Poverty-Reducing Sample               | 26.99<br>(13.66)            | 13.92<br>(8.49)             |
| Poverty-Increasing Sample             | 15.33<br>(11.69)            | 28.31<br>(17.78)            |
| Low-Poverty Sample                    | 8.22<br>(4.50)              | 15.66<br>(11.08)            |
| High-Poverty Sample                   | 31.29<br>(10.96)            | 25.09<br>(17.21)            |

Standard deviations are in parentheses. Total poverty rates are from the 2002 and 2011 census. “Whole Sample (including missing 2011)” (row 2) included values from 2002 for the 32 municipalities with missing information in 2011. “Municipalities only in 2002” (row 4) refer to the 34 municipalities that had data in the 2002 census only.

poverty sample, or the poverty-increasing sample and the poverty-decreasing sample. Second, the data in each sample would be further attenuated based on whether Calonico, Cattaneo and Titiunik’s (2014) algorithm for regression discontinuity analysis classified the municipality-year as having a close election. In technical terms, the observation would have to be an “effective observation”, and the likelihood of any particular observation being an effective observation is circa 50-60% in our models. Therefore, adding the missing the observations would likely only add a minimal number of observations to each sample, thereby making the missing data rather insignificant from a statistical power perspective.



## S. Additional Results for Morales Term Regressions

### S.1. When Poverty is Low/High

Table S1: Number of Infractions Committed (2008-2019) [Poisson]

|                  | (1)                 | (2)                 | (3)                 | (4)                 | (5)                 | (6)                 |
|------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Morales Term     | 0.786***<br>(0.022) | 0.788***<br>(0.022) | 0.468***<br>(0.043) | 0.787***<br>(0.021) | 0.573***<br>(0.036) | 0.487***<br>(0.049) |
| Low Poverty      |                     | 0.003<br>(0.037)    | 0.012<br>(0.037)    |                     |                     |                     |
| Population (log) |                     |                     |                     |                     | 1.571***<br>(0.209) | -0.337<br>(0.301)   |
| Re-elected Mayor |                     |                     |                     |                     | 0.008<br>(0.034)    | 0.002<br>(0.031)    |
| Observations     | 3801                | 3790                | 3790                | 3801                | 3518                | 3518                |
| Municipality FE  | no                  | no                  | no                  | yes                 | yes                 | yes                 |
| Year FE          | no                  | no                  | yes                 | no                  | no                  | yes                 |

Note: Poisson regression model, since infractions are a count variable.

Standard errors clustered by municipality in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table S2: Number of Infractions Committed (2008-2019) [Negative Binomial]

|                  | (1)                 | (2)                 | (3)                 | (4)                 | (5)                 | (6)                 |
|------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Morales Term     | 0.786***<br>(0.022) | 0.788***<br>(0.022) | 0.469***<br>(0.043) | 0.777***<br>(0.020) | 0.568***<br>(0.032) | 0.497***<br>(0.050) |
| Low Poverty      |                     | 0.014<br>(0.035)    | 0.024<br>(0.036)    |                     |                     |                     |
| Population (log) |                     |                     |                     |                     | 1.493***<br>(0.192) | -0.286<br>(0.290)   |
| Re-elected Mayor |                     |                     |                     |                     | 0.019<br>(0.031)    | 0.001<br>(0.030)    |
| Observations     | 3801                | 3790                | 3790                | 3801                | 3518                | 3518                |
| Municipality FE  | no                  | no                  | no                  | yes                 | yes                 | yes                 |
| Year FE          | no                  | no                  | yes                 | no                  | no                  | yes                 |

Note: Negative binomial regression model, since infractions are a count variable.

Standard errors clustered by municipality in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table S3: Log Amounts of Misappropriated Funds (2008-2019)

|                  | (1)                 | (2)                 | (3)                 | (4)                 | (5)                 | (6)              |
|------------------|---------------------|---------------------|---------------------|---------------------|---------------------|------------------|
| Morales Term     | 0.263***<br>(0.081) | 0.261***<br>(0.081) | 0.352***<br>(0.134) | 0.270***<br>(0.079) | -0.055<br>(0.115)   | 0.107<br>(0.280) |
| Low Poverty      |                     | 0.077<br>(0.074)    | 0.091<br>(0.074)    |                     |                     |                  |
| Population (log) |                     |                     |                     |                     | 2.472***<br>(0.488) | 0.816<br>(0.841) |
| Re-elected Mayor |                     |                     |                     |                     | 0.020<br>(0.094)    | 0.010<br>(0.095) |
| Observations     | 3796                | 3785                | 3785                | 3796                | 3513                | 3513             |
| $R^2$            | 0.004               | 0.005               | 0.035               | 0.005               | 0.012               | 0.042            |
| Municipality FE  | no                  | no                  | no                  | yes                 | yes                 | yes              |
| Year FE          | no                  | no                  | yes                 | no                  | no                  | yes              |

Note: linear regression model.

Standard errors clustered by municipality in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## S.2. When Poverty Decreases/Increases

Table S4: Number of Infractions Committed (2008-2019) [Negative Binomial]

|                  | (1)                 | (2)                 | (3)                 | (4)                 | (5)                 | (6)                 |
|------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Morales Term     | 0.786***<br>(0.022) | 0.747***<br>(0.022) | 0.442***<br>(0.046) | 0.777***<br>(0.020) | 0.568***<br>(0.032) | 0.497***<br>(0.050) |
| Poverty Reduced  |                     | -0.060*<br>(0.034)  | -0.063*<br>(0.035)  |                     |                     |                     |
| Population (log) |                     |                     |                     |                     | 1.493***<br>(0.192) | -0.286<br>(0.290)   |
| Re-elected Mayor |                     |                     |                     |                     | 0.019<br>(0.031)    | 0.001<br>(0.030)    |
| Observations     | 3801                | 3357                | 3357                | 3801                | 3518                | 3518                |
| Municipality FE  | no                  | no                  | no                  | yes                 | yes                 | yes                 |
| Year FE          | no                  | no                  | yes                 | no                  | no                  | yes                 |

Note: Negative binomial regression model, since infractions are a count variable.

Standard errors clustered by municipality in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table S5: Log Amounts of Misappropriated Funds (2007-2018)

|                  | (1)                 | (2)                | (3)               | (4)                 | (5)                 | (6)              |
|------------------|---------------------|--------------------|-------------------|---------------------|---------------------|------------------|
| Morales Term     | 0.263***<br>(0.081) | 0.218**<br>(0.086) | 0.254*<br>(0.148) | 0.270***<br>(0.079) | -0.055<br>(0.115)   | 0.107<br>(0.280) |
| Poverty Reduced  |                     | -0.051<br>(0.077)  | -0.054<br>(0.077) |                     |                     |                  |
| Population (log) |                     |                    |                   |                     | 2.472***<br>(0.488) | 0.816<br>(0.841) |
| Re-elected Mayor |                     |                    |                   |                     | 0.020<br>(0.094)    | 0.010<br>(0.095) |
| Observations     | 3796                | 3352               | 3352              | 3796                | 3513                | 3513             |
| $R^2$            | 0.004               | 0.003              | 0.034             | 0.005               | 0.012               | 0.042            |
| Municipality FE  | no                  | no                 | no                | yes                 | yes                 | yes              |
| Year FE          | no                  | no                 | yes               | no                  | no                  | yes              |

Note: linear regression model.

Standard errors clustered by municipality in parentheses; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## T. Additional Close Election Mechanism Regressions

### T.1. When Poverty is Low/High

Table T1: Infractions: How Much Do Close Elections Matter (2004-2015)?

|                 | (1)              | (2)               | (3)                | (4)              | (5)                 | (6)               |
|-----------------|------------------|-------------------|--------------------|------------------|---------------------|-------------------|
| Alignment       | 0.004<br>(0.039) | -0.005<br>(0.041) | -0.036<br>(0.042)  | 0.016<br>(0.047) | 0.047<br>(0.051)    | -0.014<br>(0.053) |
| Low Poverty     |                  | 0.055<br>(0.039)  | 0.078**<br>(0.039) |                  |                     |                   |
| Log Population  |                  |                   |                    |                  | 0.213***<br>(0.072) | 0.106*<br>(0.062) |
| Reelected Mayor |                  |                   |                    |                  | 0.032<br>(0.047)    | 0.038<br>(0.045)  |
| Observations    | 2088             | 2078              | 2078               | 2088             | 1924                | 1924              |
| Municipality FE | no               | no                | no                 | yes              | yes                 |                   |
| Year FE         | no               | no                | yes                | no               | no                  |                   |

Note: poisson regressions; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Note: standard errors clustered by municipality in parentheses.

Table T2: Infractions: How Much Do Close Elections Matter (2004-2015)? [Negative Binomial]

|                 | (1)              | (2)               | (3)                | (4)              | (5)                 | (6)               |
|-----------------|------------------|-------------------|--------------------|------------------|---------------------|-------------------|
| Alignment       | 0.004<br>(0.039) | -0.005<br>(0.041) | -0.036<br>(0.042)  | 0.016<br>(0.047) | 0.047<br>(0.051)    | -0.014<br>(0.053) |
| Low Poverty     |                  | 0.055<br>(0.039)  | 0.078**<br>(0.039) |                  |                     |                   |
| Log Population  |                  |                   |                    |                  | 0.213***<br>(0.072) | 0.106*<br>(0.062) |
| Reelected Mayor |                  |                   |                    |                  | 0.032<br>(0.047)    | 0.038<br>(0.045)  |
| Observations    | 2088             | 2078              | 2078               | 2088             | 1924                | 1924              |
| Municipality FE | no               | no                | no                 | yes              | yes                 |                   |
| Year FE         | no               | no                | yes                | no               | no                  |                   |

Note: negative binomial regressions; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ 

Note: standard errors clustered by municipality in parentheses.

Table T3: Log Amounts of Misappropriated Funds (2004-2015)

|                 | (1)               | (2)                | (3)                | (4)               | (5)               | (6)                |
|-----------------|-------------------|--------------------|--------------------|-------------------|-------------------|--------------------|
| Alignment       | -0.140<br>(0.118) | -0.164<br>(0.122)  | -0.174<br>(0.121)  | -0.159<br>(0.120) | -0.163<br>(0.124) | -0.099<br>(0.137)  |
| Low Poverty     |                   | 0.190**<br>(0.094) | 0.206**<br>(0.094) |                   |                   |                    |
| Log Population  |                   |                    |                    |                   | 0.445<br>(0.606)  | 1.989<br>(1.638)   |
| Reelected Mayor |                   |                    |                    |                   | 0.173<br>(0.114)  | 0.281**<br>(0.119) |
| Observations    | 2083              | 2073               | 2073               | 2083              | 1919              | 1428               |
| $R^2$           | 0.001             | 0.005              | 0.037              | 0.001             | 0.003             | 0.166              |
| Municipality FE | no                | no                 | no                 | yes               | yes               | yes                |
| Year FE         | no                | no                 | yes                | no                | no                | yes                |

Note: Linear regression models; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ 

Standard errors clustered by municipality in parentheses

## T.2. When Poverty Decreases/Increases

Table T4: Infractions: How Much Do Close Elections Matter (2010-2015)?

|                   | (1)               | (2)               | (3)               | (4)              | (5)                 | (6)               |
|-------------------|-------------------|-------------------|-------------------|------------------|---------------------|-------------------|
| Alignment         | -0.065<br>(0.045) | -0.061<br>(0.048) | -0.073<br>(0.047) | 0.030<br>(0.056) | 0.040<br>(0.065)    | 0.014<br>(0.065)  |
| Poverty Reduction |                   | -0.019<br>(0.049) | -0.019<br>(0.048) |                  |                     |                   |
| Log Population    |                   |                   |                   |                  | 2.719***<br>(0.479) | -1.017<br>(0.998) |
| Reelected Mayor   |                   |                   |                   |                  | 0.065<br>(0.066)    | 0.065<br>(0.064)  |
| Observations      | 1260              | 1125              | 1125              | 1260             | 1178                | 1178              |
| Municipality FE   | no                | no                | no                | yes              | yes                 |                   |
| Year FE           | no                | no                | yes               | no               | no                  |                   |

Note: negative binomial regressions; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Note: standard errors clustered by municipality in parentheses.

Note: model with municipality and year fixed effects would not converge.

Table T5: Log Amounts of Misappropriated Funds (2007-2018)

|                   | (1)                 | (2)                 | (3)                 | (4)               | (5)                 | (6)               |
|-------------------|---------------------|---------------------|---------------------|-------------------|---------------------|-------------------|
| Alignment         | -0.264**<br>(0.125) | -0.267**<br>(0.132) | -0.279**<br>(0.133) | -0.049<br>(0.132) | -0.036<br>(0.162)   | -0.038<br>(0.155) |
| Poverty Reduction |                     | -0.042<br>(0.103)   | -0.043<br>(0.103)   |                   |                     |                   |
| Log Population    |                     |                     |                     |                   | 5.704***<br>(1.316) | 2.581<br>(2.389)  |
| Reelected Mayor   |                     |                     |                     |                   | 0.265<br>(0.174)    | 0.279*<br>(0.161) |
| Observations      | 1256                | 1121                | 1121                | 1256              | 1174                | 1077              |
| $R^2$             | 0.007               | 0.008               | 0.079               | 0.000             | 0.039               | 0.198             |
| Municipality FE   | no                  | no                  | no                  | yes               | yes                 | yes               |
| Year FE           | no                  | no                  | yes                 | no                | no                  | yes               |

Note: Linear regression models; \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Standard errors clustered by municipality in parentheses