Buying a Blind Eye: Campaign Donations, Regulatory Enforcement, and Deforestation in Colombia

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Abstract

While existing work has demonstrated that campaign donations can buy access to benefits such as favorable legislation and preferential contracting, we highlight another use of campaign contributions: buying reductions in regulatory enforcement. Specifically, we argue that in return for campaign contributions, Colombian mayors who rely on donor-funding (compared to those who do not) choose not to enforce sanctions against illegal deforestation activities. Using a regression discontinuity design, we show that deforestation is significantly higher in municipalities that elect donor-funded as opposed to self-funded politicians. Further analysis shows that only part of this effect can be explained by differences in contracting practices by donor-funded mayors. Instead, evidence of heterogeneity in the effects according to the presence of alternative formal and informal enforcement institutions, and analysis of fire clearance, support the interpretation that campaign contributions buy reductions in the enforcement of environmental regulations.

KEYWORDS: Campaign donations, Deforestation, Regulatory enforcement

1 Introduction

Between 2015 and 2018, tens of thousands of hectares of forest were destroyed in the Colombian municipalities of Calamar and Miraflores, with the rate of devastation tripling over the period.[1] Clearance of the forest was connected in part to the development of a 138km road, constructed between the two municipalities without the required environmental permits or licenses. Responsibility to enforce these environmental regulations lay with the mayors of the municipalities. But rather than enforce the laws, the mayors chose to turn a blind eye, allowing the illegal road construction and related deforestation to proceed. While some ordinary citizens may have appreciated the improved transportation links, the primary beneficiaries of this failure to enforce environmental regulations were local elites and cattle ranchers, looking to capitalise on the forest clearance for financial gain. Indeed, over this same period these two municipalities experienced high levels of vegetation fires, a common practice used by farmers to illegally clear lands for cattle ranching and illicit crop cultivation, and one which mayors also have a responsibility to monitor and prevent.[2] We argue that, given the benefits to be had from forest clearance, campaign donations are used to buy regulatory non-enforcement of this type, as mayors choose not to sanction illegal deforestation in return for campaign contributions.

Previous research has provided evidence that campaign donations can be used to buy benefits such as favourable legislation and preferential access to contracting or public sector jobs (Stratmann, 2005; Boas, Hidalgo and Richardson, 2014; Ruiz, 2017; Colonnelli, Prem and Teso, 2020). But the case described above highlights another use of campaign contributions: buying regulatory non-enforcement. An important strand of the public choice literature has highlighted the phenomenon of state capture by economic elites, recognizing a variety of means by which a rich elite can gain disproportionate influence within a democracy, including through patronage, vote-buying, and lobbying (Acemoglu, Ticchi and Vindigni, 2011). Taking the use of campaign donations as another means by which economic elites can achieve state capture, we argue that donors to mayoral election campaigns in Colombia purchase reductions in the enforcement of environmental regulations.

We support this argument with evidence that mayors in Colombia allow violations of envi-

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[1] See https://www.semana.com/nacion/articulo/trochas-ilegales-acaban-con-la-amazonia-colombiana/649428. Last accessed June 2021.

[2] See for example https://es.mongabay.com/2019/07/incendios-norte-amazonia-deforestacion-colombia/. Last accessed March 2022.

ronmental regulations in return for campaign donations. Using a regression discontinuity design (RDD) on close elections between politicians who receive contributions from private donors and politicians that fund their own mayoral campaigns, we estimate that deforestation between 2012 and 2015 almost doubles in municipalities that elected a donor-funded mayor compared to those that elected a self-funded mayor. Given the central role of deforestation as a key driver of climate change, this is an important finding in itself. The quasi-experimental nature of the research design provides identification, overcoming concerns that differences in deforestation result, for example, from variation in pre-existing enforcement capacity or differences in other pre-term municipal characteristics. As such, although we do not observe variation in enforcement by local mayors directly, the research design allows us to infer that differences in deforestation result from donor-funded mayors pursuing a politically-motivated model of enforcement.

Given existing evidence on campaign donations and contracting, a possible alternative channel is that the estimated effect stems from an increase in infrastructure contracting rather than a reduction in regulatory enforcement. Analyzing the effects of victory by a donor-funded politician on contracting outcomes provides some support for this, because the average value of infrastructure contracts is larger under donor-funded mayors. However, temporal trends show that this channel can only explain part of the estimated increase in deforestation. Moreover, although infrastructure contracts that could increase deforestation primarily relate to roads, we see no evidence of an increase in road density following election of a donor-funded mayor. Further analysis supports the interpretation that campaign contributions buy reductions in the enforcement of environmental regulations.

First, we find that the effect of donor-funded mayors on deforestation is mitigated by the presence of alternative sources of environmental law enforcement. Specifically, exploring heterogeneous effects using pre-term municipal characteristics measuring the extent of protected National Parks (which are subject to higher central government monitoring than most forest areas), and the presence of and distance to offices of Colombia's regional environmental management institutions (Autonomous Regional Corporations, or CARs), we find that both dampen the effect of donor-funded mayors. Similarly, the effect is also attenuated by the number of offices of the Procurator General (*Procuraduría*) and the Attorney General (*Fiscalía*), which we take as additional proxies for the extent of state presence within a municipality. These results, therefore, suggest that tighter institutional oversight beyond that provided by mayors reduces the deforestation linked to

the victory of a donor-funded politician.

Second, we find that the activities of illegal armed actors affect the deforestation dynamics linked to the election of a donor-funded politician. While guerrilla groups such as the Revolutionary Armed Forces of Colombia (FARC) have often obstructed and attacked the business of local elites, paramilitary groups arose out of private security forces created by large landowners and cattle ranchers, and frequently act to protect the interests of these local elites. Exploring heterogeneous effects using pre-term measures of attacks by armed groups, we find that while guerrilla attacks substantially lower the deforestation related to the victory of donor-funded politicians, attacks by paramilitary groups have no such impact. Third, unlike large-scale infrastructure projects, deforestation for cattle ranching and cultivation often makes use of aggressive and frequently illegal practices of clearance by burning. Using data from NASA's Fire Information for Resource Management System (FIRMS), we find a 32.9% increase in average fire intensity in donor-funded municipalities.

These results are consistent with donor-funded mayors selling regulatory non-enforcement. As explained in Section 3, Colombia's local elites have a long history of land appropriation and illegal expansion of the agricultural frontier. In line with existing arguments about local state capture by wealthy elites in Colombia and elsewhere (Sánchez-Talanquer, 2020; Hollenbach and Silva, 2019), our argument suggests that campaign donations create a connection between elites and the ruling mayor. This connection provides elites with a degree of protection when engaging in deforestation activities, as donor-funded mayors turn a blind eye to violations of environmental regulations.

The findings make at least three important contributions. First, they advance the literature on the influence of money in politics. Not only do campaign donations buy favourable legislation and access to preferential contracts, but they also buy the selective non-enforcement of laws. Second, in this way, the results also contribute to the literature on state capture. We provide evidence that campaign donations are used to purchase influence over the local state, which in this instance results in a reduction in regulatory enforcement. Third, the findings make an important contribution to our understanding of the political dynamics of deforestation. In doing so, they have the potential to inform the design of better policies to deal with the urgent challenge of climate change.

Existing work on the impact of corruption on environmental outcomes highlights the role of electoral incentives in ensuring the enforcement of environmental regulations (Aklin et al., 2014).

This is in line with more general arguments about the ability of electoral accountability to generate effective enforcement and reduce the impact of corruption (Hurwicz, 2008; Olken and Pande, 2012). Yet, as Hurwicz (2008) notes, for elections to provide an effective means of "guarding the guardians" requires them to be free. The purchase of reduced regulatory enforcement through campaign donations by local elites subverts this process, highlighting the need to insulate enforcement, and its oversight, from distorted electoral incentives. This emphasises the importance of considering the complex interactions between interest groups, elected officials, and bureaucrats, in order to fully understand the politics of deforestation and natural resource management.

2 Deforestation, donations, and state capture

Deforestation. Increasing awareness of the threat posed by climate change has created an urgency in efforts to understand its drivers. One key factor is deforestation, which is closely linked with global warming.[3] Forests capture up to 45% of terrestrial carbon and remove large amounts of carbon dioxide (Bonan, 2008). However, despite the importance of these ecosystems, they are being destroyed at alarming rates.[4] Limiting deforestation is therefore vital in combating climate change, and accurately understanding the causes of deforestation is crucial to these efforts. Existing research has highlighted activities such as cattle ranching, farming, logging, and urbanisation as leading causes of deforestation (Curtis et al., 2018). Understanding factors influencing the intensity of these activities can therefore facilitate more suitable policy design to effectively manage deforestation (see, for example, Prem, Saavedra and Vargas, 2020).

One such factor is electoral competition, which has been argued to influence deforestation in contrasting ways. On one hand, the mere existence of democracy may limit deforestation. Li and Reuveny (2006) provide evidence that democratic regimes reduce deforestation, along with other forms of environmental degradation. This positive impact of democracy results from various mechanisms, including increased access to information about environmental problems, the greater role of public opinion in policy making, and the aggregation and representation of interest groups. Similarly, Gulzar, Lal and Pasquale (2021) find that local government representation in India substantially reduces deforestation. In contrast, Morjaria (2012) demonstrates that deforestation

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[3]See https://www.nationalgeographic.com/environment/article/deforestation. Last accessed April 2021.
[4]See https://www.wri.org/insights/numbers-value-tropical-forests-climate-change-equation. Last accessed April 2021.

increased following the introduction of multi-party elections in Kenya in 1992, as districts loyal to the central government were allowed increased access to forest land. Likewise, Sanford (2021) provides cross-national evidence that competitive elections are associated with increased deforestation, arguing that deforestation provides short-term, private benefits to voters that politicians exploit to win (re-)election.

Another factor influencing deforestation is corruption. Burgess et al. (2012) argue that the management of logging rules in Indonesia is driven by a process of rent maximisation by local officials. Focusing on Brazil, Pailler (2018) also highlights the role of corruption in encouraging deforestation. Connecting corruption back to electoral competition, she argues that corrupt politicians exploit forest resources to fund their re-election campaigns. This is supported with evidence from Brazilian municipalities demonstrating an increase in deforestation in election years, but only in municipalities where corrupt incumbent mayors are running for re-election. Unlike our argument, however, Pailler (2018) suggests the link between deforestation and campaign finance is due to activities such as granting licenses for firms to engage in deforestation-related activities, rather than a reduction in enforcement. In contrast, Balboni et al. (2021) find evidence of a decrease in forest fires in election years in Indonesia, followed by a steep increase the following year.

Campaign donations. Arguments about re-election incentives connect deforestation firmly to the literature on campaign contributions. It is well-established that campaign donations can buy preferential treatment in the form of favourable legislation or privileged access to contracts or licenses. Although studies have provided mixed evidence concerning the impact of campaign contributions on policy decisions, a meta-analysis by Stratmann (2005) supports the claim that contributions do affect legislative voting behaviour. This is consistent with theoretical models which hypothesise that politicians will grant policy favours in exchange for campaign donations.[5]

Moreover, recent evidence has demonstrated clear effects of campaign donations on preferential access to government contracts. Using an RDD to analyse data from Brazil, Boas, Hidalgo and Richardson (2014) find that firms specialising in public-works projects receive a substantial boost in contracts when they donate to a ruling party candidate who wins the election. Similarly, Ruiz (2017) shows that electing a donor-funded politician more than doubles the probability of donors receiving contracts in Colombia. Linking donations and deforestation more closely, Bulte, Damania

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[5]For examples see: Snyder (1990); Austen-Smith and Wright (1994).

and Lopez (2007) found that wealthy Latin-American farmers bribe politicians with contributions to obtain rural subsidies that are associated with low land productivity and excessive deforestation.

State capture. Tying this literature together, we argue that campaign donations can influence deforestation through an alternative channel: by purchasing reductions in the enforcement of environmental regulations. In this way, campaign donations serve to achieve a form of local state capture, whereby a rich elite exert excessive influence over the local state. Existing literature has highlighted a variety of means by which economic elites gain disproportionate influence within a democracy, including through patronage, vote-buying, and lobbying. For example, Acemoglu, Ticchi and Vindigni (2011) present a model in which the rich generate an inefficient state structure by co-opting bureaucrats through patronage. This allows the rich to capture democratic politics, thereby reducing the amount of redistribution under democracy.

Other studies offer clear examples of state capture in practice. Hollenbach and Silva (2019) provide evidence from Brazil that wealthy elites corrupt local officials and undermine state fiscal capacity to lower their own tax liabilities. Similarly, Sánchez-Talanquer (2020) argues that local elites in Colombia used their influence over mayors to keep land undervalued, thereby limiting their tax burdens. Both cases highlight the use of economic power by wealthy elites to exert disproportionate influence over the local state, to their own benefit. We make a similar argument, that local elites in Colombia use their economic influence to achieve local state capture. By our account, however, this influence is asserted through campaign donations, in return for which donor-funded mayors reduce the enforcement of environmental regulations.[6]

As we discuss in Section 3, local elites in Colombia have strong economic interests in activities such as cattle ranching and cultivation that represent a significant threat to forests. The pursuance of these interests is limited by environmental regulations designed to restrict deforestation, which municipal authorities have a responsibility to enforce. Mayors therefore have the power, as the heads of municipal authorities, to reduce the extent of regulatory enforcement, to benefit local elites. We argue that they do so in return for campaign donations that fund their election to office.

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[6]This argument resonates with the literature on forbearance, or the selective non-enforcement of laws for political ends. A major contribution of recent work on forbearance has been to demonstrate its political use as a form of redistribution to win votes from the poor (Holland, 2017). Within that work, there is also an acknowledgement that forbearance can take more regressive forms, benefiting individuals at the upper end of the income distribution (Holland, 2016). As such, our findings may be taken as evidence of this type of 'forbearance as corruption'.

3 Context

Deforestation in Colombia. Natural forest covers between half to two-thirds of Colombia's surface area, an amount that includes about 10% of the Amazon rainforest.[7] Part of this forest, equivalent to 17% of the country, is designated as a protected area under the care of the National Parks administration, and is subject to more stringent regulation and monitoring overseen directly by the national government.[8] Yet as elsewhere in the world, deforestation is an increasing problem. From 2001 to 2020, Colombia lost more than 4.6 million hectares of tree cover, equivalent to a 5.7% decrease in the total forest area (Global Forest Watch, 2019).

As in much of Latin America, the most notorious driver of deforestation is cattle ranching (FAO, 2006). Colombia has a long history of cattle production, being the fourth largest cattle breeder in the region and the seventh worldwide, and over 200 thousand hectares of forest are lost each year to pasturing.[9] The impact of cattle ranching on deforestation has been accompanied by the deleterious effects of other activities such as mining, illegal logging and crop production, infrastructure development, and the growth of agro-businesses.

Deforestation in Colombia has also been affected by the country's shifting political environment. Following the December 2014 ceasefire, and the FARC's subsequent disarmament in 2016, deforestation rose in areas previously under FARC control (Prem, Saavedra and Vargas, 2020). That this effect was greater in areas with lower state presence and more land-intensive economic activities highlights the impact of regulatory enforcement and activities such as cattle ranching on deforestation.

Economic interests of local elites. Land-intensive activities of this type are key to the economic interests of Colombian local elites. Since colonial times, Colombian landlords have steadily increased their land ownership and consolidated their power through it (Fernandez, 2012; LeGrand, 1988), resulting in substantial land inequality. This inequality has been exacerbated by violent periods such as 'La Violencia' in the late-1940s, which led to massive forced displacement and land expropriation (Guzmán, Fals Borda and Umaña, 2010; Fernandez, 2012). Moreover, institutional efforts to alter the distribution of land have been instrumentalised by elites to appropriate large land extensions

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[7]Global Forest Watch (2019), IDEAM webpage (last accessed March 2022).
[8]See https://news.mongabay.com/2021/03/colombias-national-parks-at-a-crossroads-as-new-director-installed/. Last accessed June 2021.
[9]For details on the cattle industry in Colombia, see UNODC (2016).

([Ibañez and Muñoz-Mora, 2010](#)).

Land inequality is a factor underpinning the presence of illegal armed actors in Colombia. The foundation of guerrilla groups such as the FARC was justified in part to protect impoverished rural people, and as such these groups presented themselves as enemies of the local elites. In response, the rise of guerrilla groups led to the creation of private security forces used by wealthy landowners and cattle ranchers. These forces represented the precursors to far-right paramilitary groups, which frequently act to protect and promote the interests of local elites.[10] Central to these interests are activities involving intensive land exploitation, such as ranching and cultivation, which are key drivers of deforestation.

Environmental regulatory institutions. Colombia's National Environmental System (*Sistema Nacional Ambiental*, SINA) governs the implementation of a set of general environmental principles.[11] Under SINA, the Ministry of Environment leads and coordinates environmental management, but the key institutional actors responsible for implementing environmental policy are the CARs. As independent corporate entities endowed with fiscal and administrative autonomy, CARs have broad responsibility for managing natural resources and promoting sustainable development within their territories. This remit includes granting required environmental concessions, permits, or licences, overseeing activities involving natural resources, collecting fees and tariffs for the use of renewable resources, and imposing sanctions when environmental protection norms are violated.

Despite the CARs' jurisdiction over the nation's natural resources, their ability to maintain oversight and enforce regulations is often insufficient ([Montes Cortés, 2018](#)). Hence, other institutional actors also play a significant role in environmental protection. The national government, through the Ministry of Environment, the Department of Planning, and the army, contribute to protecting Colombia's natural habitat. Moreover, local governments at both the department and municipality levels are legally required to support CARs and implement national environmental policy within their territories.

Under the Constitution, mayors represent the foremost policing authorities within their municipalities, and are responsible for supervising the National Police assigned to the area under their

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[10]See https://es.insightcrime.org/investigaciones/elites-crimen-organizado-colombia-introduccion/. Last accessed April 2021.

[11]See https://www.minambiente.gov.co/ordenamiento-ambiental-territorial-y-sistema-nacional-ambiental-sina/. Last accessed February 2022. For information on environmental regulatory institutions in Colombia see Blackman, Morgenstern and Topping (2006).

jurisdiction. This includes the specialized Environmental and Natural Resource Police unit created to assist territorial authorities with the enforcement of environmental laws.[12] Furthermore, municipal governments have various legal mechanisms to enforce environmental laws, including the imposition of sanctions, suspension of environmental licenses, permits, or concessions, and power to close or demolish businesses and seize products or equipment. Therefore, mayors have significant responsibilities for enforcing environmental regulations, and have substantial powers to meet these responsibilities.

Colombian Local Elections. Since 1986, mayors in Colombia have been directly elected via a first-past-the-post system for a single four-year term.[13] The mayor's term coincides exactly with the calendar year. For the period we study, the mayoral term starts January 1, 2012 and ends December 31, 2015. Colombian mayoral election campaigns are expensive. For the 2015 municipal elections, the total spent on mayoral campaigns was more than 238 billion pesos (about 82 million US dollars), equivalent to 71% of the nation's entire science and technology budget (MOE, 2018). Despite this cost, public resources available for local election campaigns are scarce, and campaigns are primarily financed by personal resources and private donations (Casas-Zamora and Falguera, 2016). Furthermore, campaigns are frequently highly competitive, and there is a strong correlation between campaign spending and the probability of victory (Gulzar, Robinson and Ruiz, 2020). Consequently, candidates have powerful incentives to secure private contributions. Such campaign contributions can be very valuable to donors, with the election of a donor-funded politician increasing the probability that donors receive municipal contracts (Ruiz, 2017).

As discussed in Ruiz (2017), mayors in Colombia have discretion over around 20% of spending within their municipalities, with resources from property tax revenues funding services including education, healthcare, water, and sanitation. Some of the activities undertaken under the purview of these contracts, especially where they involve infrastructure provision such as road construction, are likely to result in deforestation and other forms of environmental degradation.[14] We explore this empirically in Section 6. But given the strong economic interest that local elites have in land-intensive activities such as forest clearance and cattle ranching, and the crucial role that

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[12]Mayors also have a duty to procure sufficient resources for fire services within their municipalities, in part to stop forest fires from expanding and mitigate illegal deforestation. See https://www.procuraduria.gov.co/portal/Procuradora-apropiacion-recursos-servicio-bomberos.news. Last accessed June 2021.

[13]Mayors cannot serve consecutive terms, but can be reelected to non-consecutive terms.

[14]Examples of such contracts in the data that we employ include works to the road connecting the municipality of Regidor with the township of San Cayetano, and the improvement of rural roads in San Jose del Guaviare.

mayors play in the enforcement of environmental regulations limiting such activities, our central argument is that campaign donations also purchase reductions in regulatory enforcement. In return for campaign contributions, mayors turn a blind eye to the illegal exploitation of land, thereby facilitating deforestation.

4 Data

Combining data from various sources we build a municipality-candidate level dataset to study the effect of a donor-funded politician victory on deforestation. We focus on the 2011 elections and the subsequent 2012-2015 mayoral term.

Election results and campaign donations. Electoral information comes originally from Pachón and Sánchez (2014), who gathered mayoral election results for all municipalities reported by the Registraduría Nacional del Estado Civil, the Colombian electoral authority. Campaign contributions data was collected from the National Electoral Commission by Ruiz (2017), who shows it to be highly reliable with low incentives to misreport. Political parties were obliged to electronically report sources and amounts of campaign expenditure, and then provide physical evidence corroborating this. Moreover, in 2011 the Electoral Commission had the power to penalize candidates with fines, which generated an 89% compliance rate (Ruiz, 2017). The commission subsequently lost this sanctioning power, limiting reporting compliance for the 2015 electoral period, and therefore we focus our analysis on the 2011 elections.[15]

We code candidates as donor-funded if they receive any private donations. Results in the appendix show the findings are robust to various alternative definitions setting thresholds on the share of private funding and the number of private donors and donations (Appendix Table A1). Of the 1,080 municipalities that elected mayors in 2011, our sample is first restricted to the 996 municipalities where the top two candidates reported their campaign financing. Of these, we focus on the 408 races decided between a candidate who received private donations and one who did not, implementing an RDD around the margin of victory of the candidates. These races are arguably representative; they are spread throughout the country, and across a variety of characteristics the municipalities in the sample are not statistically different to those that are excluded (Appendix

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[15]No data on campaign donations is available for elections prior to 2011 because the reporting system was introduced in 2009.

Table A2).

Deforestation. Our measurement of deforestation comes from the Global Forest Change dataset collected by Hansen et al. (2013), who analyse Landsat satellite images to identify changes in forest cover between 2000-2020. These data, comprising pixels of 30 meters by 30 meters (approximately), have been widely used to measure deforestation (Prem, Saavedra and Vargas, 2020; Zhu et al., 2016).

Tree cover is defined as vegetation taller than 5 meters and is coded as a percentage per output grid cell. We adopt a definition that considers any pixel with tree cover superior to 50% of its surface as forest. Hence, deforestation is a pixel change from the status of forest to non-forest. This data is aggregated to the municipal level. Using the baseline coverage levels and the yearly tree-cover loss and gain for each municipality, we recover the yearly coverage in each municipality, allowing us to calculate our deforestation measure.[16] Our primary deforestation variable is defined as the negative of the change in forest area in the municipality during the mayor's term relative to the municipality tree cover in the year before the new mayor's mandate, as follows:

$$\text{(Relative) Deforestation in term} = \frac{-\Delta Coverage_{\text{government term}}}{Coverage_{\text{election year}}}. \tag{1}$$

We calculate the deforestation measure for the 2011 election (2012-2015 government term) and the previous election, the 2007 election (2008-2011 government term).[17] Figure 1 shows that deforestation was a broad phenomenon across the country during the study period. Moreover, deforestation was rapidly consuming the country's tree cover. As shown in Table 1, the 1,080 municipalities that elected a mayor in 2011 lost on average almost 1.2% of their tree-cover during the subsequent mayoral term (2012-2015).

Additional data. Since illegal deforestation is often undertaken using aggressive fire clearance, we use FIRMS data to track fires during the study period.[18] We use detailed contracting data from the SECOP system, which collects information on all government contracts, to investigate whether the estimated effect of donor-funded candidate victory results from an increase in deforestation-related

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[16]The yearly coverage is obtained as $coverage_t = coverage_{2000} + \sum_{i=2001}^{t}(gain_i - loss_i)$.

[17]The main results are robust to an alternative deforestation measure calculated relative to the year 2000. These results are available upon request.

[18]We acknowledge the use of data and/or imagery from NASA's Fire Information for Resource Management System (FIRMS) (https://earthdata.nasa.gov/firms).

Figure 1: Deforestation during term by municipality
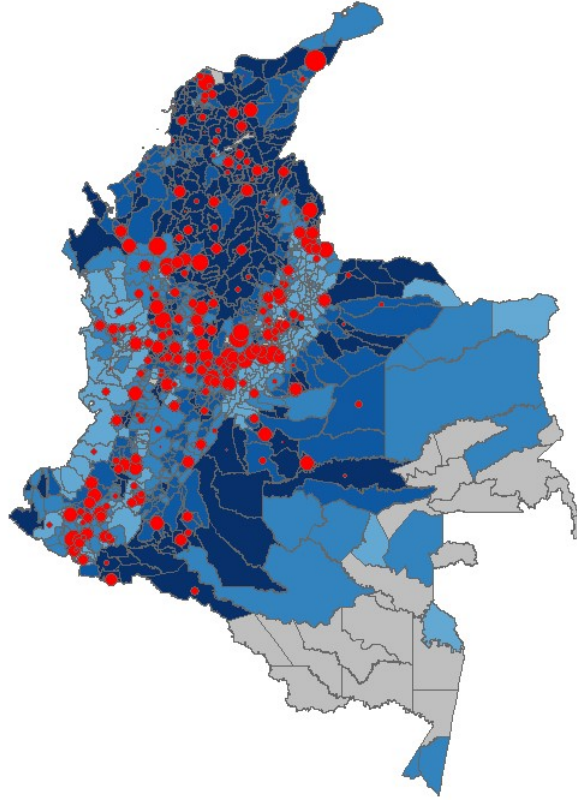
Note: This figure shows the geographical distribution of deforestation and the vote share of privately funded candidates for the 2011 election period. The shades of blue correspond to the quartiles of deforestation during the full term. The bubble size correspond to the quartiles of the margin of victory privately funded candidates.

Table 1: Summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)
	Obs	Mean	Standard Deviation	Minimum	Median	Maximum
A. Elections						
Private income % total	2160	0.19	0.27	0	0	1
Margin of victory donor-funded	408	0.022	0.101	-0.354	0.019	0.383
B. Deforestation						
Deforestation ratio 2008-2011	1080	2.141	2.023	0	1.526	14.565
Deforestation ratio 2012-2015	1080	1.182	1.572	0	0.576	16.625

Note: This table presents summary statistics for the main variables of interest used in the analysis. An observation is a municipality except for the Private income % total that uses as unit of observation the candidate (top two candidates per each municipality).

contracting. To evaluate whether the main effects are mediated by the presence of illegal armed groups we use the violent events data collected by Restrepo, Spagat and Vargas (2004) and updated by Universidad del Rosario.[19] Finally, we use a set of municipal-level covariates taken primarily from data collected by Universidad de Los Andes and their Center For Economic Development Studies.

5   Empirical Strategy

If campaign donations purchase reductions in the enforcement of environmental regulations designed to limit deforestation, we should expect to see more deforestation in municipalities electing donor-funded mayors. However, the victory of a donor-funded candidate is plausibly correlated with a broad range of municipal characteristics, including enforcement capacity. Moreover, deforestation itself may be determined by municipality characteristics. For example, more rural municipalities might have more cattle ranching that may increase deforestation. Due to these identification problems, a straightforward comparison of deforestation across municipalities electing donor-funded as opposed to self-funded mayors may be confounded by local municipality characteristics.

To overcome these problems, we employ a quasi-experimental Regression Discontinuity Design (RDD). Using the margin of victory as the running variable, we take advantage of the discontinuous change at the threshold between victory of a donor-funded as opposed to a non-donor-funded mayor. This defines the treatment rule:

$$
L_i = \begin{cases} L_i = 1 & \text{if } x_i > 0 \\ L_i = 0 & \text{if } x_i < 0 \end{cases} \tag{2}
$$

where x_i reflects margin of victory for the donor-funded politician, and L_i represents treatment status, as a dummy variable taking the value of one if a donor-funded politician won the election.

Following this, our main analysis estimates a regression of the form:

$$
y_i = \alpha + \beta_1 L_i + \beta_2 f(x_i) + \beta_3 L_i \times f(x_i) + \varepsilon_i \tag{3}
$$

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[19]For details see Prem et al. (2022).

Here y_i is the outcome, measured as the change in deforestation during the elected mayor's term in office. β_1 is our estimate of the effect of electing a donor-funded mayor. $f(x_i)$ is a polynomial in the donor-funded politician margin of victory. Finally, ε_i corresponds to the idiosyncratic error term.

Correctly estimating β_1 requires two key assumptions: (1) there should be no manipulation of election results around the cut-off, and (2) covariates potentially correlated with the treatment and outcome variables must vary smoothly around the cut-off. On the first, results from the Cattaneo, Jansson and Ma (2018) manipulation test based on density discontinuity presented in Figure 2 show no statistically significant evidence of systematic manipulation.[20] On the second, Table 2 shows there is no discontinuity of covariates at the cut-off, suggesting that municipalities are similar except in the treatment status.

Figure 2: Manipulation Test

* P−value for bias−corrected density test = .76
** Triangular kernel
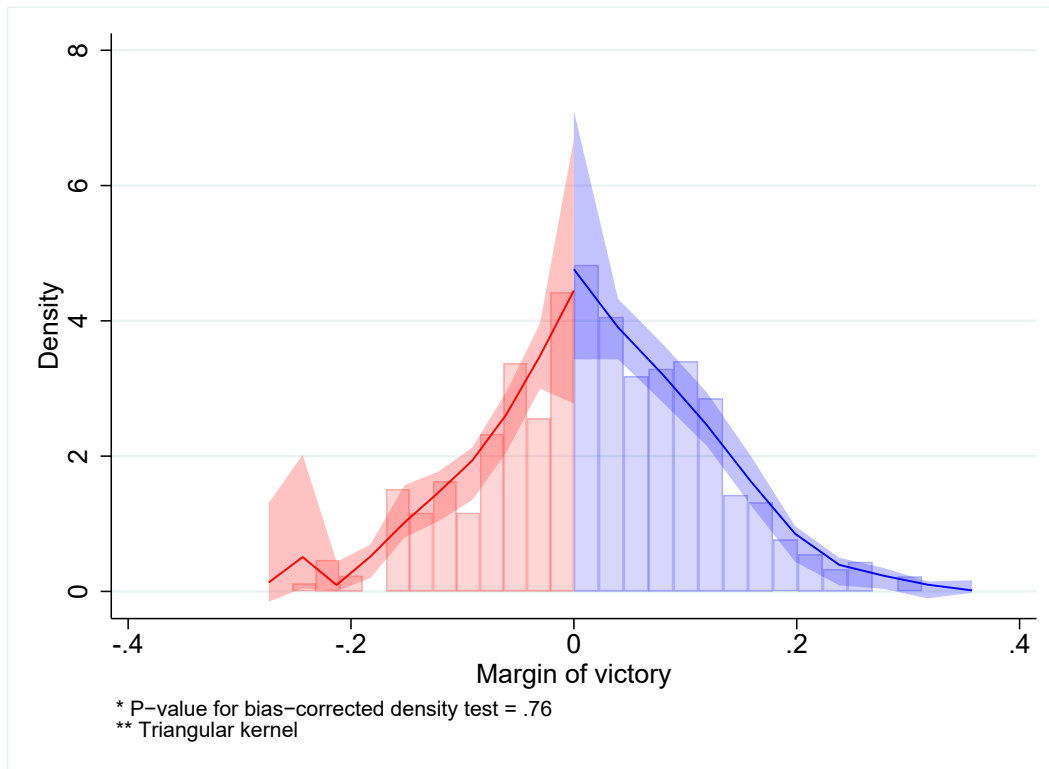
Note: This figure presents the density test suggested by Cattaneo, Jansson and Ma (2018) using a quadratic polynomial and triangular kernel weights. The p-value for the bias corrected density test is 0.76. The p-values using a polynomial of degree one and three are 0.25 and 0.59, respectively.

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[20]Similar results are found using the McCrary (2008) test for sorting around the threshold with a p-value of 0.29.

Table 2: Smooth covariates

	(1) Mean	(2) Std. Dev.	(3) Donor fund. won	(4) Std. Error.	(5) Obs	(6) P-value	(7) Pval Canay
Panel A: Individual covariates							
Women	0.116	0.320	0.119	0.202	132	0.121	0.789
Age	45.245	9.709	-3.551	5.398	126	0.573	0.061
Black	0.044	0.205	-0.023	0.195	126	0.865	0.490
Indigenous Background	0.107	0.309	0.050	0.230	126	0.570	0.423
Left-wing party	0.024	0.154	0.018	0.165	132	0.801	0.664
Right-wing party	0.239	0.427	0.181	0.147	132	0.474	0.816
Illegal Registration of ID.	0.005	0.071	0.013	0.009	132	0.268	1.000
Has political experience	0.361	0.480	0.156	0.181	132	0.336	0.871
Panel B. Policy Outcomes							
Total Income Y(COP M)	47102.906	361239.511	12723.550	8666.063	132	0.704	0.467
Land Taxes (%Y)	3.889	4.695	0.346	2.083	132	0.938	0.303
Industry (%Y)	3.377	5.967	1.378	1.755	132	0.823	0.252
Funct. expen. (%Y)	13.284	5.045	-1.439	4.719	132	0.535	0.758
Investment (%Y)	86.716	5.045	1.439	4.719	132	0.535	0.757
Deficit (%Y)	11.346	9.573	1.049	6.648	132	0.613	0.963
Panel C. Other municipality socio-economic characteristics							
Altitude (meter)	1158.170	1161.175	-227.936	571.983	132	0.885	0.164
Area in Square km	876.992	2982.007	-91.459	578.174	132	0.323	0.713
Forest coverage (10 000 hectares)	5.343	21.979	-0.441	5.031	132	0.307	0.492
Proportion of forest coverage	0.507	0.278	-0.096	0.173	132	0.326	0.337
Agricultural land (10 000 hectares)	3.803	11.146	-0.017	3.132	132	0.921	0.769
Agricultural production (1000 ton)	41.181	173.422	12.826	20.576	132	0.836	0.473
Distance to department capital	78.701	56.010	13.930	25.906	132	0.855	0.112
Distance to Bogota	319.459	189.400	-84.390	183.531	132	0.286	0.609
Pop. density	148.146	675.196	15.406	45.587	132	0.764	0.283
Road density	0.829	0.451	0.256	0.250	132	0.356	0.252
Nighttime lights	1.509	1.158	0.183	0.642	132	0.968	0.800
Literacy rate	83.903	8.484	-0.536	5.141	132	0.818	0.138
Rurality index (0-1)	0.564	0.239	-0.107	0.133	132	0.322	0.225
Unsatisfied basic needs	44.622	20.279	9.368	9.454	132	0.197	0.187
National Parks Area (10 000 sq. hectares)	0.920	7.605	0.961	1.207	132	0.819	0.615
CAR office	0.140	0.347	-0.030	0.205	132	0.545	1.000
Distance to CAR office	0.030	0.033	-0.004	0.015	132	0.363	0.935
Procurator general offices	0.604	6.388	0.044	0.091	132	0.636	1.000
Attorney general offices	4.042	38.057	0.810	0.683	132	0.629	0.570
Paramilitary attacks	1.279	9.780	0.151	1.882	132	0.724	0.173
Guerilla attacks	0.608	2.091	0.424	1.215	132	0.995	0.205
Panel D. Other potential explanations							
Deforestation during previous term	2.141	2.019	0.685	0.641	132	0.334	0.365
Disposable Income (mw)	29004.315	393732.953	1078.397	5317.036	126	0.719	0.305
Municipal category	5.708	0.995	0.095	0.241	132	0.264	1.000
Mayor wages	6.692	2.543	-0.190	0.481	132	0.264	1.000
Council size	10.957	2.907	1.775	1.292	132	0.217	0.081
Total population	41707.711	257110.752	8672.028	9205.110	132	0.926	0.214
Income from royalties	0.070	0.150	0.022	0.159	130	0.487	0.747

Note: The first two columns present the basic statistics (mean and standard deviation) of each covariate. Column (3) reports the RDD's point estimate of the effect of a donor-funded candidate victory on each covariate (as dependant variable), the MSE optimal bandwidth for the main model is used throughout. Bias corrected robust standard errors (column 4). The number of effective observations is detailed in column 5. Column 6 reports the estimated p-value, while column 7 reports the Canay and Kamat (2018) permutation test for the null hypothesis of continuity of the distribution around the cutoff.

We follow Cattaneo, Idrobo and Titiunik (2020) and estimate the RDD specified in equation (3) non-parametrically using polynomials of order one and two, and weight observations accord-

ing to their distance to the cutoff using triangular kernel weights.[21] Additionally, we employ an optimal data-driven bandwidth selection procedure that minimises the asymptotic mean square error (MSE). Since MSE bandwidths produce non-robust confidence intervals, we estimate robust standard errors and confidence intervals but report conventional point estimates within the MSE optimal bandwidth (Cattaneo, Idrobo and Titiunik, 2020).

In further exercises, we perform parametric estimations, including additional interactions, to capture possible heterogeneous effects. In these, we estimate the RDD parametrically within the MSE optimal bandwidth sample, using OLS regression weighted by a triangular kernel, and controlling for a linear polynomial.

6   Results

6.1   Main effects

Figure 3 presents our main estimate of the effect of electing a donor-funded mayor on deforestation. The left and right panels show estimates using linear and quadratic polynomial approximations, respectively. We find a clear discontinuous jump in deforestation around the threshold determining victory of a donor-funded mayor. Moreover, the jump is statistically significant for both the linear and quadratic approaches. This result implies that the amount of deforestation in a municipality during a donor-funded mayor's term in office is significantly higher than that during the term of a self-funded mayor.

Table 3 presents the main result in greater detail. Our coefficient of interest represents the effect on deforestation of electing a donor-funded compared to a self-funded mayor. The estimates in Columns 2 and 4 also include the measure of deforestation for the previous term, 2008-2011. Prior deforestation varies smoothly around the cutoff, as shown in the lower panels of Figure 3, but we employ this measure as a robustness check and improve the precision of the estimates (Lee and Lemieux, 2010). The estimates are positive and significant across all specifications, showing robustness to linear or quadratic polynomials, and the inclusion of the previous deforestation measure. Moreover, the effect of electing a donor-funded politician is substantial, representing an increase in

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[21]Appendix Table A3 presents results using a cubic polynomial.

Figure 3: Effect of electing a donor funded politician on deforestation

Panel A: Deforestation during the incumbency term

Panel B: Deforestation during the previous incumbency term
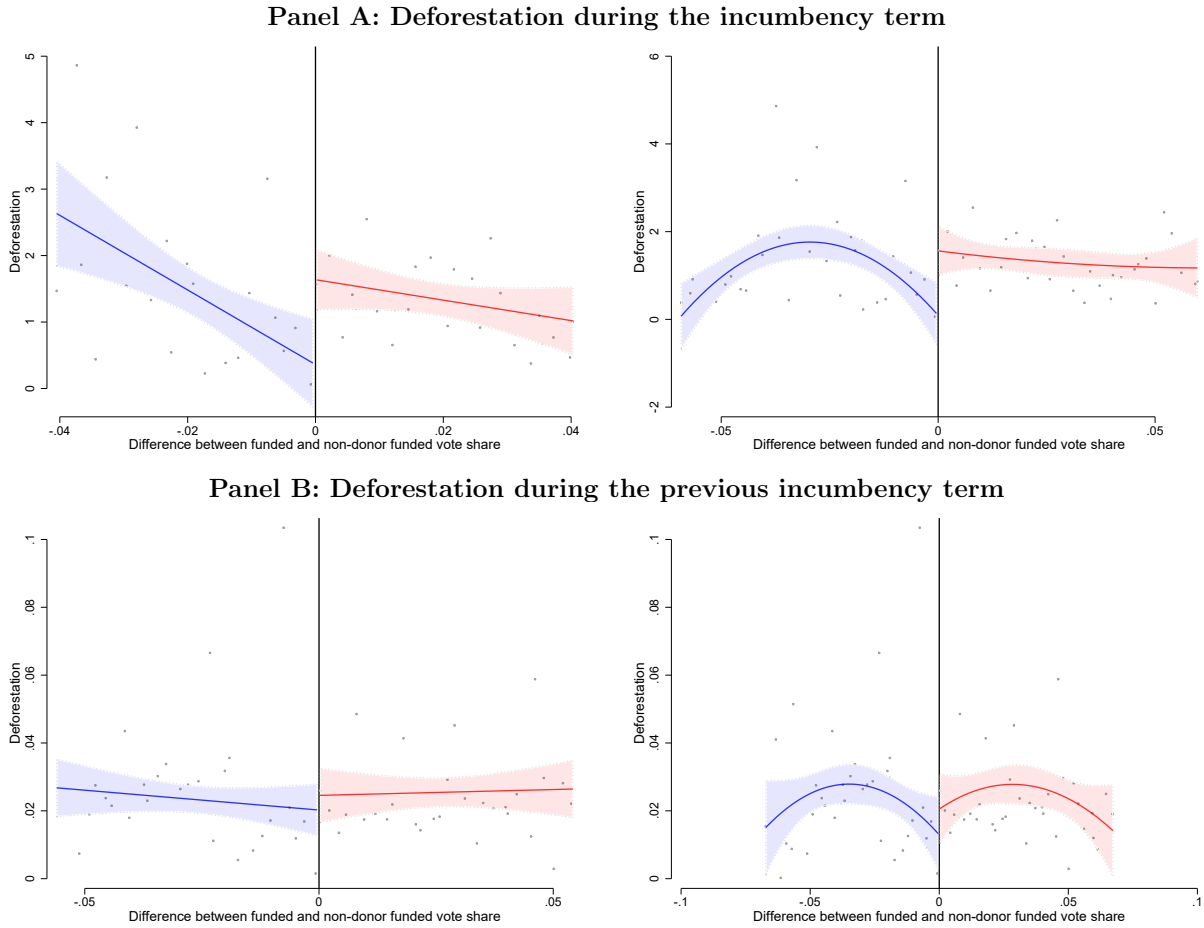
Note: This figure presents a graphical approximation of the regression discontinuity design. We present deforestation during the full incumbency term in the first row, while deforestation during the previous incumbency term is shown in the second row. The observations are shown within MSE optimal bandwidth. From left to right; the first figure uses a linear polynomial approximation, meanwhile, the second uses a quadratic approximation.

deforestation of 92.9% of the self-funded average for the linear specification. The effect size remains reasonably stable across specifications, ranging between 53% and 109% of the self-funded average.

In Figure 4, we explore the resilience of the results to variation in bandwidth size. Following best practice, we report results for a range of bandwidths around the MSE optimal bandwidth, from half to double the size. Overall the results are encouraging, with the effect remaining robust to a considerable range of bandwidths. It is not surprising that the results do not hold for very small bandwidths, for which the estimates are unlikely to have sufficient power. However, the effect remains reassuringly robust up to bandwidths of 0.08, where races are far less competitive and municipalities less comparable.

Table 3: Donor funded politician and deforestation during term in office

	(1)	(2)	(3)	(4)
Donor Funded	1.099***	0.627**	1.290**	0.972**
Robust p-value	0.008	0.019	0.026	0.021
CI 95%	[0.339, 2.220]	[0.127, 1.442]	[0.158, 2.471]	[0.158, 1.940]
Previous deforestation		✓		✓
Observations	408	408	408	408
Bandwidth obs.	132	174	191	198
Mean	1.183	1.183	1.183	1.183
Effect size (%)	92.90	53.00	109.05	82.16
Bandwidth	0.041	0.053	0.060	0.064
(Local) polynomial order	1	1	2	2

Note: Columns 1 and 2 present the local linear estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. Columns 3 and 4 presents the quadratic estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The Effect Size (%) is computed as the point estimate over the mean x 100. Columns (2) and (4) include as covariate the measure of deforestation in the previous term (2008-2011). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 4: Different bandwidth sizes: Effect of electing a donor-funded politician on deforestation
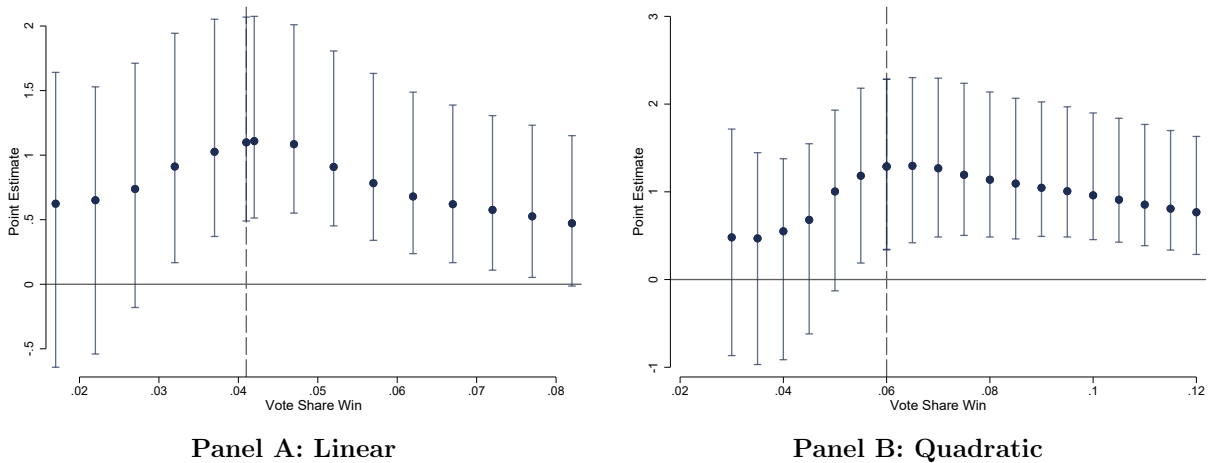
Panel A: Linear

Panel B: Quadratic

Note: Estimates of average treatment effects at the cut-off, using triangular kernel weights. Optimal MSE bandwidths displayed in the dotted line. Following Cattaneo, Idrobo and Titiunik (2020), we display estimates between half and double the optimal bandwidth. Robust 90% confidence intervals estimated following Calonico, Cattaneo and Titiunik (2014).

Overall, these main effects provide compelling evidence that deforestation in Colombia increases in municipalities that elect donor-funded mayors.[22] This in itself is an important finding. Defor-

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[22]Results hold with OLS regressions using all 996 municipalities that elected mayors in 2011 (Appendix Table A4).

estation is a key driver of climate change, and efforts to limit it are key to long-term environmental sustainability. Consequently, evidence highlighting political determinants of deforestation are crucial to the formulation of effective environmental protection policies.

6.2 Mechanisms

We argue that there are two primary channels through which the election of a donor-funded mayor could result in greater deforestation: contracting and regulatory non-enforcement. These channels are not mutually exclusive. Indeed, as highlighted by the example of the Calamar-Miraflores road discussed in the introduction, they may operate hand-in-hand, with contracts for infrastructure projects being accompanied by the selective non-enforcement of environmental regulations pertaining to the ensuing construction work. Nevertheless, we explore the extent to which each is driving the estimated effects.

6.2.1 Contracting

To examine the contracting channel we explore its implied temporal sequence, whereby any impact of electing a donor-funded mayor on contracting precedes the subsequent deforestation. First, in Table 4 we break down the main result by each year of the mayoral term. The positive effect is significant in all but the third year, and intensifies during the final year of the term.[23] Although the estimated coefficient is substantially larger for the final year, in comparison to the average for self-funded mayors the difference is less stark. For year one, deforestation in municipalities with a donor-funded mayor is about 92.4% higher vis-a-vis municipalities that elected self-funded mayors, while for the last year it is 107.7% higher.[24] It seems implausible that deforestation in year one, at least, derives from the contracting channel, since insufficient time would have passed for contacts to have been awarded and environmentally harmful work to have commenced. We explore this further by estimating the effect of electing donor-funded mayors on contracting outcomes.

Since infrastructure construction is a major state-related source of deforestation, we test whether

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[23]Estimating a non-parametric differences-in-differences model we also see a large and significant increase in deforestation for the last year of the term (Appendix Figure A1).

[24]Similar results hold with a quadratic polynomial, although the relative effect size is more consistent across years one to three and then greater in year four (Appendix Table A5).

Table 4: Donor funded politician and deforestation by year of government

	(1)	(2)	(3)	(4)
		Year of government		
	1	2	3	4
Donor Funded	0.195***	0.220**	0.117	0.490***
Robust p-value	0.003	0.029	0.224	0.006
CI 95%	[0.077, 0.376]	[0.027, 0.504]	[-0.095, 0.404]	[0.164, 0.959]
Observations	408	408	408	408
Bandwidth obs.	132	139	187	130
Mean	0.211	0.306	0.211	0.455
Effect size (%)	92.42	71.90	55.45	107.69
Bandwidth	0.041	0.043	0.059	0.040
(Local) polynomial order	1	1	1	1

Note: Local linear estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. Each column shows the deforestation rate, defined as lost coverage$_t$/$coverage_{\text{election year}}$, for a given year of government. The Effect size (%) is computed as the point estimate over the mean x 100. *** p<0.01, ** p<0.05, * p<0.1.

there is a differential increase in the number and average value of infrastructure contracts. As Table 5 shows, we find no evidence that donor-funded mayors commission more infrastructure projects, but their election is related to an increase in the average value of infrastructure contracts, with the estimated effect corresponding to an increase of 109% over municipalities electing self-funded mayors.[25] It is worth noting that contracts awarded to campaign donors have been found to involve significant over-costs (Ruiz, 2017), which suggests that the estimated increased average value of infrastructure contracts may not actually result in larger projects that could induce greater deforestation, but instead may simply increase the cost of similar projects to those undertaken in municipalities run by self-funded mayors. This possibility is reinforced by the fact that we see no significant increase in road density following election of donor-funded mayors, despite roads being a major component of infrastructure contracts, and the type of infrastructure project most likely to result in deforestation. We also look at contracts for mining and environmental work, both of which may be related to deforestation, but find no significant differences in their number or average value between municipalities electing self-funded and donor-funded mayors.

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[25]Results are equivalent with a quadratic polynomial (Appendix Table A6).

Table 5: Donor funded politician and contracts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Infrastructure			*Environmental*		*Mining*
	Number	*Log Avg. value*	Road construction	*Number*	*Log Avg. value*	*Number*	*Log Avg. value*
Donor Funded	-30.151	1.091**	-0.015	-4.904	0.486	0.209	-0.307
Robust p-value	0.357	0.017	0.346	0.742	0.150	0.637	0.672
CI 95%	[-127.980, 46.163]	[0.219, 2.258]	[-0.060, 0.021]	[-55.157, 39.293]	[-0.197, 1.294]	[-0.774, 1.265]	[-1.785, 1.150]
Observations	401	400	401	401	366	401	145
Bandwidth obs.	226	165	211	211	174	216	96
Mean	140.896	4.818	0.015	18.197	3.795	0.976	3.618
Effect Mean(%)	-21.40	109	-100	-26.95	48.6	21.41	-30.7
Bandwidth	0.077	0.049	0.071	0.073	0.062	0.074	0.112
(Local) polynomial order	1	1	1	1	1	1	1

Note: Local linear estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The average value of contracts was transformed using inverse hyperbolic sine. The contracts are catalogued in each category by analysing their reported object. For columns 1, 3, 4, and 6, the effect size (%) is computed as the point estimate over the mean x 100, while for the rest of the columns is the point estimate x 100. *** p<0.01, ** p<0.05, * p<0.1.

Given the implied temporal sequence, we analyse the impact of electing a donor-funded politician on the value of infrastructure contracts by year of the mayoral term. Results in Appendix Table A7 show that the estimated coefficient is only significant in year three. Given the larger magnitude of the estimated effect on deforestation in year four, this finding is consistent with the claim that donor-funded mayors contribute to deforestation in part by awarding larger contracts for infrastructure projects. Therefore the contracting channel may explain part of the estimated effect of donor-funded mayors on deforestation that occurs in the final year of the mayoral term.[26]

In a final test of the contracting mechanism, we explore the extent to which infrastructure contracts relate to activities that can plausibly influence deforestation. Coding all infrastructure contracts, we find that only 27% were for activities that might affect deforestation, of which the vast majority were for road construction.[27] These findings therefore suggest that the contracting channel alone cannot account for the overall effect of electing a donor-funded mayor on deforestation.

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[26]Mediation analysis using sequential g-estimation (Acharya, Blackwell and Sen, 2016) finds almost no impact of infrastructure contracting as a potential mediator, suggesting that preferential contracting alone cannot explain the effect of electing a donor-funded mayor on deforestation (Appendix Figures A2 and A3).

[27]Many contracts were related to projects such as the construction of schools, hospitals, and sports centres, all in the pre-existing urban areas of municipalities. Table A8 presents estimates of the effect of electing a donor-funded mayor on infrastructure contracts separately for contacts that were and were not related to deforestation. Effects are slightly larger for contracts related to deforestation.

6.2.2 Regulatory non-enforcement

We argue that these effects also result from donor-funded mayors rewarding donors with selective non-enforcement of environmental regulations. It is difficult to directly observe selective regulatory non-enforcement. One benefit of the RDD we employ is that, given the balance on pre-term municipal characteristics, we can be confident the observed differences in deforestation do not result from variation in previous enforcement capacity. However, the problem remaining is that we observe the outcome, deforestation, rather than directly observing compliance with or enforcement of environmental regulations. Our approach is therefore to explore a series of further implications of this mechanism. First, that selective non-enforcement of environmental regulations by mayors should be offset by alternative formal enforcement institutions. Second, that selective non-enforcement should be offset by informal enforcement actors. And third, that illegal deforestation is more likely to be accompanied by fires.

Alternative formal enforcement institutions. If donor-funded mayors turn a blind eye to their donors' illegal deforestation activities, the effect of electing donor-funded mayors on deforestation should be mitigated by the presence of alternative sources of environmental law enforcement. Where other enforcement institutions are present, selective non-enforcement by mayors should determine deforestation levels to a lesser extent. We investigate whether the effect of electing a donor-funded mayor is conditional on either of two alternative enforcement institutions: the CARs and the National Parks administration. We also test whether the main effect is attenuated by the number of offices of the Procurator General (*Procuraduría*) and of the Attorney General (*Fiscalía*), which we take as additional proxies for the extent of state presence within the municipality. Importantly, all measures capturing the presence of these alternative formal enforcement institutions vary smoothly at the cutoff (see Table 2).

As detailed in Section 3, part of Colombia's natural forest is designated protected area under the care of the National Parks administration, and is subject to more stringent regulation and monitoring overseen directly by the national government.[28] This means that in areas designated as National Parks, responsibility for enforcement of environmental regulations falls less heavily on local municipal officials. Table 6 column 1 presents results from an analysis interacting donor-funded politician victory with a measure of area in square kilometres designated as National Parks

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[28]Bonilla-Mejía and Higuera-Mendieta (2019) show that protected area designation reduces deforestation.

in the municipality. Consistent with our interpretation, the estimated coefficient on the interaction term is negative and significant, indicating that an increase in National Parks area reduces the additional deforestation linked to electing a donor-funded mayor.

Table 6: Heterogeneous Effects: State Presence

		(1)	(2)	(3)	(4)	(5)
				Measure Z		
		National Parks Area	CAR office	Distance to CAR	Procurator offices	Attorney offices
A	Donor funded	1.117**	1.195**	-0.149	1.024**	1.325***
		(0.439)	(0.466)	(0.518)	(0.427)	(0.496)
	Z	0.210**	0.487	0.0003	1.195***	0.215**
		(0.105)	(0.592)	(0.0079)	(0.175)	(0.0992)
B	Z × Donor funded	-0.279*	-1.610*	0.0371**	-2.434***	-0.450**
		(0.144)	(0.966)	(0.0153)	(0.245)	(0.162)
Observations		408	408	408	408	408
Bandwidth obs.		132	132	132	132	132
R-squared		0.051	0.062	0.209	0.053	0.067
Bandwidth		0.041	0.041	0.041	0.041	0.041
(Local) polynomial order		1	1	1	1	1
A + B		0.838	-0.416	-0.111	-1.410	0.875
Effect size (%)		93.09	-35.04	-15.12	-72.136	102.267
Ho: A + B = 0						
F-statistic		4.39	0.24	0.05	34.5	4.7
P-value		0.04	0.62	0.83	0.05	0.30

Note: OLS regression weighted by a triangular kernel within the MSE optimal bandwidth sample and controlling for a linear polynomial. Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The dependent variable is deforestation during the full term. National Parks area is defined as the total area with national parks in the municipality, CAR office is a dummy that takes the value one if there was at least on CAR office in the municipality, Distance to CAR is the distance to the closest CAR, Procurator offices is the number of offices of the Procurator General (*Procuraduría*), and Attorney offices is the number of offices of the Attorney General (*Fiscalía*). The Effect size (%) is computed as $100x(A+B)/(constant+\beta_Z)$. *** p<0.01, ** p<0.05, * p<0.1.

Section 3 also detailed the CARs significant role in monitoring and enforcing environmental regulations across Colombia. While CARs delegate much of this responsibility to territorial governments, their own offices still play an important role in enforcement. Therefore, we study how the presence of and distance to CAR offices mediate the effects of victory by donor-funded mayors on deforestation. Columns 2 and 3 in Table 6 show estimates where the indicator of donor-funded politician victory is interacted with a dummy for the presence of a CAR office in the municipality, and with the distance to the closest CAR office from the centroid of the municipality, respectively. Once again, the results support the regulatory non-enforcement channel. The presence of CAR offices significantly diminishes the effect of a donor-funded victory on deforestation. Meanwhile,

the greater the distance to the CAR offices, the greater the increase in deforestation when a donor-funded politician is elected.

We also explore whether there is heterogeneity in the main effects according to the number of offices of the Procurator General (*Procuraduría*) and of the Attorney General (*Fiscalía*). As shown in Table 6, the coefficients on the interaction terms between both these additional measures and victory by a donor-funded politician are negative and significant. These findings, therefore, add further weight to the idea that the presence of alternative formal enforcement institutions mitigates the impact of selective regulatory non-enforcement by donor-funded mayors.

Informal enforcement institutions. Landowners and cattle ranchers benefit from selective regulatory enforcement by exploiting land with greater intensity. The activities of these local elites have long been affected by the dynamics of internal conflict in Colombia. As such, we posit that an additional source of alternative regulatory enforcement comes from informal institutions, in particular illegal armed groups.

As discussed in Section 3, the lasting presence of illegal armed actors in Colombia is closely connected to conflict over land, with the actions of guerrilla groups such as the FARC often justified by a desire to push back against inequality exacerbated by land expropriation by local elites. Partly in response, far-right paramilitary groups have frequently acted to protect and promote the economic interests of these elites. Given this history, we consider these armed groups as representing informal institutions for the enforcement of environmental protection. Specifically, because guerrilla groups have often obstructed and attacked the business of elites, we expect their presence to limit illegal deforestation by local elites, thereby offsetting selective non-enforcement of environmental regulations by donor-funded mayors. The presence of paramilitary groups, on the other hand, should have no such effect.

Taking pre-term attacks by these two types of armed groups as proxies for their presence in a municipality, we study how this affects our main result. As with formal institutions, the measures capturing presence of these informal enforcement institutions also vary smoothly at the cutoff (see Table 2). Table 7 presents estimated effects of the impact of a donor-funded politician on deforestation, conditional on number of attacks by each type of group in the municipality.[29] The results are consistent with the historical alignment of armed groups with local elites. While

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[29]Results hold with a quadratic polynomial (Appendix Table A9).

attacks by guerrilla groups mitigate the increase in deforestation linked to a donor-funded victory, paramilitary attacks have no such impact. Taking attacks by guerrilla groups as a proxy for the presence of informal institutions providing checks on illegal deforestation by local elites, therefore, these findings provide further evidence in support of the regulatory non-enforcement mechanism.[30]

Table 7: Heterogeneous Effects: Armed Conflict

		(1)	(2)
		Attacks measure Z	
		Paramilitary	Guerrilla
A	Donor funded	0.704*	1.133***
		(0.422)	(0.427)
	Z	0.116	0.574***
		(0.139)	(0.187)
B	Z × Donor funded	0.123	-0.623**
		(0.153)	(0.241)
	Observations	408	408
	Bandwidth obs.	132	132
	R-squared	0.116	0.131
	Bandwidth	0.041	0.041
	(Local) polynomial order	1	1
	A + B	0.827	0.510
	Effect size (%)	90.17	42.86
	Ho: A + B = 0		
	F-statistic	4.60	1.37
	P-value	0.03	0.24

Note: OLS regression weighted by a triangular kernel within the MSE optimal bandwidth sample and controlling for a quadratic polynomial. Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The dependent variable is deforestation during the full term. Paramilitary (Guerrilla) attacks is the number of paramilitary (guerrilla) attacks during the previous term (2008-2011). The Effect size (%) is computed as $100x(A + B)/(constant + \beta_Z)$. *** p<0.01, ** p<0.05, * p<0.1.

Fires. In Colombia and elsewhere, fire clearance of forest areas for cattle ranching and cultivation is widespread, and this environmentally harmful practice is regulated by the law.[31] Moreover, intensive fire clearance practices are much more likely to be employed for illegal land grabbing linked to cattle ranching and cultivation than for government-contracted infrastructure projects.

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[30]These results could also reflect underlying elite preferences for infrastructure projects across areas with paramilitaries/guerrillas, although evidence of a differential increase in deforestation in FARC-controlled areas following the ceasefire suggest otherwise (Prem, Saavedra and Vargas, 2020).

[31]See for example, https://news.mongabay.com/2019/09/as-the-amazon-burns-colombias-forests-decimated-for-cattle-and-coca/ and https://theecologist.org/2020/aug/17/deforestation-colombia. Last accessed June 2021.

Therefore, we check for an increase in the intensity of forest fires in municipalities governed by donor-funded mayors. A differential increase in fire intensity would strongly indicate unregulated land exploitation through fire clearance. Following the same RDD approach described above, we test for a discontinuous jump in fire intensity, measured as average fire brightness, when a donor-funded mayor is elected. Table 8 presents results consistent with our interpretation; we find an increase in average fire intensity of 32.9% when a donor-funded mayor is elected. Results are robust to selecting linear or quadratic polynomials (Table A10) and hold across a range of bandwidths (Figure A4).[32]

Table 8: Donor funded politician and fire intensity

	(1)	(2)
Donor Funded	80.976*	75.464**
Robust p-value	0.059	0.041
CI 95%	[-3.381, 181.446]	[3.189, 156.092]
Previous fire intensity		✓
Observations	408	408
Bandwidth obs.	195	198
Mean	246.141	246.141
Effect size (%)	32.90	30.66
Bandwidth	0.061	0.063
(Local) polynomial order	1	1

Note: Local linear estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. Column (2) includes as covariate the measure of fire intensity from the previous term (2009-2011), being 2009 the first year with data availability. Fire intensity is measured as the average brightness of fires in a municipality. The Effect size (%) is computed as the point estimate over the mean x 100. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Disaggregating the estimates of fire intensity shows this effect is concentrated in the final year (Appendix Table A11). This behaviour may be consistent with an increase in illegal deforestation towards the end of the term as perpetrators seek to maximise extraction before their preferred mayor leaves office, due to the potential increased risk of punishment under a future mayor. Indeed, this fits with additional evidence that municipalities electing donor-funded mayors see a significant increase in the chamber of commerce registration of agro-cattle firms, which are known for the use of fire clearance practices, and that this effect is concentrated in the final year of the mayoral term

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[32]Mediation analysis suggests around 20% of the estimated effect of donor-funded mayors on deforestation operates through fire clearance (Appendix Figure A2).

(Tables A12 and A13).[33] Moreover, it suggests that the increase in deforestation in the final year of the mayoral term (shown in Table 4) is not solely due to an increase in the average value of infrastructure contracts.[34]

6.3 Alternative explanations

This section addresses two alternative mechanisms that could plausibly explain increased deforestation following the election of donor-funded mayors: variation in agricultural pressure, and candidate characteristics.[35]

6.3.1 Agricultural pressure

Deforestation could reflect the level of pressure from local agricultural interests to access potential agricultural land. By this mechanism, donations are used to buy access to land, rather than buy reductions in regulatory enforcement. This is unlikely because powers to grant land access via environmental concessions or licenses rests with CARs, not with mayors themselves. The environmental role of municipal governments lies primarily in the local enforcement of regulations through policing and sanctioning regulatory violations. Nevertheless, we explore the potential impact of agricultural pressure empirically, in several ways.

First, in Table 2, we show there is no discontinuity at the cutoff for a variety of measures capturing pre-term levels of agricultural pressure, including hectares of forest coverage and agricultural land, and levels of agricultural production. Second, our main results and the heterogeneous effects based on National Parks area and CAR presence are all robust to the inclusion of controls for the aforementioned agricultural pressure measures (Appendix Tables A14 and A15). Third, the results also hold when we weight observations using pre-term forest coverage or municipality area, thus giving the same weight to each square kilometer (Appendix Table A16). Finally, we find no evidence of differential effects of electing a donor-funded mayor on deforestation according to pre-term

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[33]For reports on the use of fire clearance by agro-businesses, see: https://www.eltiempo.com/vida/medio-ambiente/opinion-480690, and https://es.mongabay.com/2019/07/incendios-norte-amazonia-deforestacion-colombia/. Last accessed June 2021.

[34]This temporal pattern is also consistent with fire clearance being used in the final year to make way for infrastructure projects contracted in year three.

[35]We are grateful to anonymous reviewers for suggesting these.

measures of agricultural pressure (Appendix Table A17).

6.3.2 Candidate characteristics

While our research design identifies the effect of candidates being supported by donors, it is possible that donations are directed towards candidates with particular characteristics, as opposed to donations inducing particular behavior (i.e., regulatory non-enforcement) from candidates. This raises a second possible alternative mechanism: that donors support candidates who are more sceptical of environmental regulation and less willing to enforce regulations strictly. Several empirical results help rule this out.

First, Table 2 shows that covariates measuring candidate characteristics are all smooth at the cut-off, suggesting donations are not targeted to candidates based on these characteristics. This includes ideology, which likely captures much of the variation in candidates' attitudes towards environmental regulation. It also includes measures of candidates' prior political experience, and of whether they have previously registered to vote illegally. These are intended to capture prior history of, or greater proclivity for, malfeasance in office, respectively. Second, we show our main results are robust to controlling for these measures (Appendix Table A14).

Third, we find no evidence that deforestation is affected by the election of a right-wing politician (Appendix Table A18), which shows that electing more conservative candidates does not itself lead to greater deforestation, as this alternative mechanism would imply.[36] Finally, we find no evidence of differential effects of electing a donor-funded mayor on deforestation according to candidates' ideology, prior experience, or history of illegally registering to vote (Appendix Table A19). This suggests that even among conservative candidates, or those with a proclivity for malfeasance, donor-supported candidates cause more deforestation.

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[36] We also see no evidence that deforestation is affected by the election of a candidate with prior political experience (Appendix Table A20). The number having registered to vote illegally is too small to estimate the effect of electing a candidate who has done this.

7   Conclusions

We provide evidence that in Colombia, the election of mayors who rely on campaign donations significantly increases deforestation. In line with existing literature, we show that this may be due in part to differential contracting practices, because the average value of infrastructure contracts increases with the election of a donor-funded mayor. But temporal dynamics demonstrate that the more standard contracting story only partially explains the estimated effects. Instead, we provide evidence consistent with the argument that campaign donations also influence deforestation through another unexplored channel: by purchasing regulatory non-enforcement. Donor-funded mayors turn a blind eye to activities resulting in illegal deforestation in return for campaign contributions.

The RDD alleviates endogeneity concerns and gives us confidence that the estimated effect of electing a donor-funded politician on deforestation is identified. This finding is important in itself, because it provides clear evidence of the political dynamics affecting deforestation, a central driver of environmental degradation and climate change. One key benefit of the RDD is to rule out the possibility that this variation is due to differences in pre-existing institutional enforcement capacity across municipalities. Disaggregating by year shows this effect is present across the mayoral term, and that differential contracting practices can only explain the effect observed in the final year, and even then only partially so. We argue that the remainder of the overall effect results from the selective non-enforcement of environmental regulations by mayors rewarding their donors.

Although we cannot observe enforcement by mayors directly, we present a range of additional evidence consistent with this interpretation. First, we demonstrate that the effect of victory by a donor-funded politician on deforestation is attenuated by the presence of alternative formal enforcement institutions (which are beyond the mayor's control). Second, we show that the effect is also mitigated by the presence of illegal armed groups that serve as informal enforcement actors. Finally, because illegal deforestation frequently makes use of aggressive fire-clearance practices, we show that fire intensity is significantly higher in municipalities that elect donor-funded mayors. Taken together, this range of evidence supports our interpretation that campaign donors in Colombia purchase regulatory non-enforcement by mayors, allowing them to exploit land in a way that increases deforestation. Although the available evidence is compelling, future work could bolster these findings with qualitative evidence garnered through enforcement process tracing (Bozçağa and Holland, 2018).

The findings make a number of important contributions. First, they advance the literature on the influence of money in politics, moving beyond a focus on favorable legislation and preferential contracting to acknowledge that campaign donations may also influence regulatory enforcement. In doing so, they contribute to the work on state capture by highlighting campaign finance as another means by which economic elites may exert disproportionate influence over the local state. And finally, the findings increase our understanding of the political dynamics of deforestation, and of environmental degradation more broadly. This matters, because learning how political competition and incentives influence the implementation of environmental regulations is vital if we are to effectively counter the challenge of climate change.

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APPENDIX (For Online Publication)

List of Figures

List of Tables

Figure A1: Donor-funded politician on deforestation: Non-parametric DiD

Note: We perform a non-parametric difference-in-differences interacting the treatment by the year dummy. 90% confidence intervals. The year zero represents the first year of government and the year -1, is the election year. We use the full sample 408 of races between donor-funded and non-donor-funded top candidate.

Figure A2: Mediation analysis
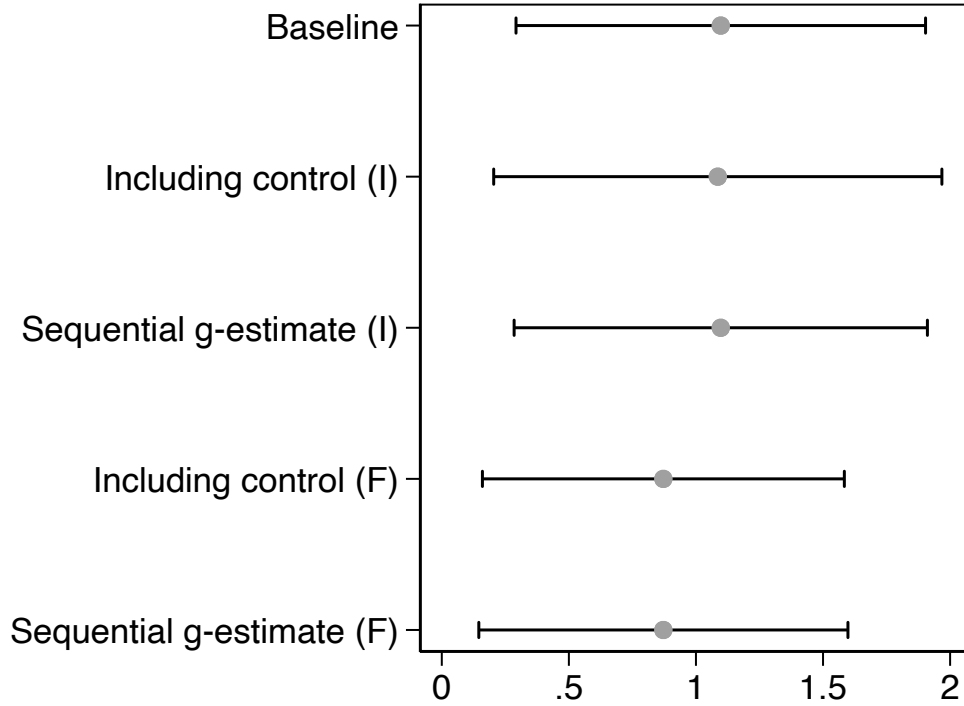
Note: This figure presents the mediation analysis for expenditures in infrastructure and fires. *Baseline* presents the point estimate and the 95% confidence interval for our baseline specification from column 1 Table 3. *Including control (I)* presents the point estimate and the 95% confidence interval for the main specification but adding the hyperbolic sine transformation of the average value of expenditures on infrastructure after the election as a control. *Sequential g-estimate (I)* presents the point estimate and the 95% confidence interval for the sequential g-estimate suggested by Acharya, Blackwell and Sen (2016) using as a mediator the hyperbolic sine transformation of the average value of expenditures on infrastructure after the election. *Including control (F)* presents the point estimate and the 95% confidence interval for the main specification but adding the number of fires after the election as a control. *Sequential g-estimate (F)* presents the point estimate and the 95% confidence interval for the sequential g-estimate suggested by Acharya, Blackwell and Sen (2016) using as a mediator the number of fires after the election. In the case of the *Sequential g-estimate (I)*, we construct the confidence intervals using a non-parametric bootstrap procedure that includes the two estimation stages as suggested by the authors.

Figure A3: Mediation: Sensitivity analysis
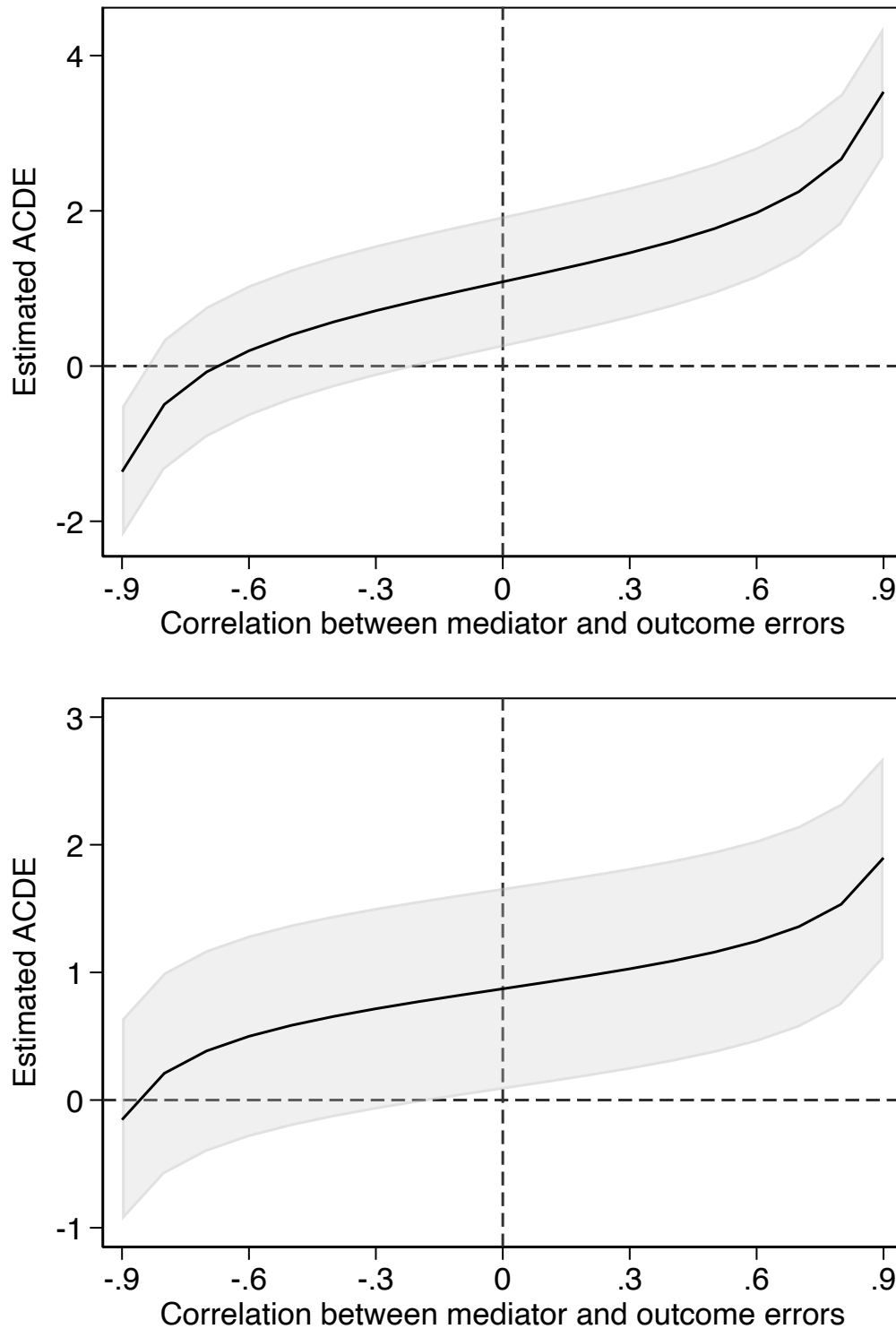
Note: This figure presents the sensitivity analysis for the mediation analysis for expenditures on infrastructure (Panel A) and fires (Panel B) as suggested by Acharya, Blackwell and Sen (2016). We construct the confidence intervals using a non-parametric bootstrap procedure that includes the two estimation stages as suggested by the authors.

Figure A4: Different bandwidth sizes. Donor funded politician and fire intensity
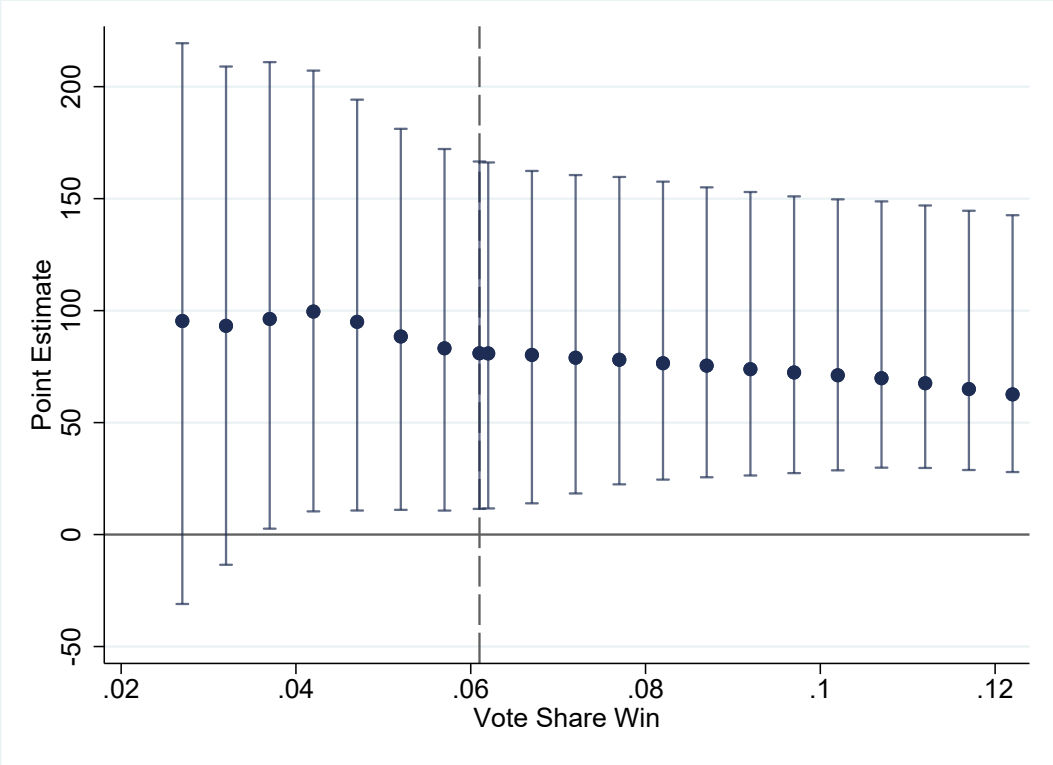
Note: Estimates of average treatment effects at the cut-off, using triangular kernel weights. Optimal MSE bandwidths displayed in the dotted line. Following Cattaneo, Idrobo and Titiunik (2020), we display estimates between half and double the optimal bandwidth. Robust 90% confidence intervals estimated following Calonico, Cattaneo and Titiunik (2014).

Table A1: More stringent donor-funded politician definition

	(1)	(2)	(3)	(4)	(5)	(7)	(8)	(9)
	Share privately funded >				Donors >		Donations >	
	5%	10%	15%	20%	2	4	3	5
Donor Funded	1.071***	0.954**	0.937**	1.135**	1.032**	1.075**	1.166***	1.016**
Robust p-value	0.009	0.023	0.045	0.023	0.012	0.035	0.006	0.048
CI 95%	[0.306, 2.185]	[0.153, 2.100]	[0.027, 2.254]	[0.185, 2.465]	[0.268, 2.155]	[0.087, 2.427]	[0.385, 2.319]	[0.010, 2.366]
Observations	394	370	324	293	388	278	371	270
Bandwidth obs.	135.000	121.000	106.000	94.000	131.000	96.000	118.000	83.000
Mean	1.183	1.183	1.183	1.183	1.183	1.183	1.183	1.183
Effect Mean(%)	90.53	80.64	79.20	95.94	87.24	90.87	98.56	85.88
Bandwidth	0.042	0.040	0.038	0.039	0.043	0.044	0.041	0.041
(Local) polynomial order	1	1	1	1	1	1	1	1

Note: All columns present the local linear estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. Columns 1 to 4 define donor funded politicians if they share of the budget privately funded was higher than 5% (column 1), 10% (column 2), 15% (column 3), and 20% (column 4). Columns 5 and 6 define donor-funded politician based on receiving donations from at least 2 (4) private donors, while columns 8 and 9 define it based on receiving 3 (5) donations. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The Effect Size (%) is computed as the point estimate over the mean x 100. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A2: Difference between RD sample and rest of the country

	(1)	(2)	(3)	(4)	(5)	(6)
	In sample		Rest of the country		p-value difference	Standardized difference
	Mean	Std. Dev.	Mean	Std. Dev.		
A. Individual covariates						
Women	0.136	0.344	0.093	0.290	0.115	0.137
Age	43.492	9.328	45.057	9.782	0.092	-0.164
Black	0.079	0.271	0.041	0.199	0.057	0.160
Asian	0.111	0.316	0.111	0.315	0.997	-0.000
Left-wing party	0.053	0.225	0.024	0.154	0.060	0.149
Right-wing party	0.152	0.360	0.252	0.434	0.011	-0.252
Illegal registration of ID.	0.008	0.087	0.007	0.086	0.981	0.002
Has political experience	0.348	0.478	0.371	0.483	0.621	-0.046
B. Policy Outcomes						
Total income Y(COP M)	2.0e+04	2.1e+04	5.1e+04	3.9e+05	0.351	-0.115
Land taxes (%Y)	3.508	3.890	3.941	4.803	0.321	-0.099
Industry (%Y)	3.054	6.380	3.413	5.907	0.518	-0.058
Funct. expen. (%Y)	13.030	5.259	13.316	5.006	0.541	-0.056
Investment (%Y)	86.970	5.259	86.684	5.006	0.541	0.056
Deficit (%Y)	11.239	10.189	11.369	9.508	0.884	-0.013
C. Other municipality socio-economic characteristics						
Altitude (meter)	960.114	899.361	1186.192	1193.095	0.036	-0.214
Area in square km	772.886	1488.967	892.197	3142.693	0.668	-0.049
Distance to department capital	84.502	54.130	77.844	56.357	0.202	0.121
Distance to Bogota	338.659	201.668	316.599	187.932	0.211	0.113
Literacy rate	83.997	7.463	83.881	8.631	0.883	0.014
Rurality index (0-1)	0.539	0.219	0.567	0.242	0.201	-0.123
Unsatisfied basic needs	43.599	17.666	44.786	20.620	0.529	-0.062
National Parks Area (1,000 sq. hct)	0.568	2.838	0.974	8.070	0.566	-0.067
CAR office	0.136	0.344	0.143	0.351	0.827	-0.020
Distance to CAR office	0.033	0.028	0.029	0.033	0.260	0.111
Comptroller general offices	0.053	0.334	0.695	6.890	0.285	-0.132
Attorney general offices	0.894	1.792	4.560	41.051	0.305	-0.126
Paramilitary attacks	1.394	7.212	1.271	10.141	0.893	0.014
Guerrilla attacks	0.652	2.268	0.602	2.066	0.800	0.023
D. Other potential explanations						
Deforestation during previous term	2.359	2.046	2.110	2.019	0.185	0.122
Disposable Income (mw)	6255.348	1.1e+04	3.2e+04	4.2e+05	0.489	-0.087
Municipal category	5.902	0.460	5.679	1.048	0.016	0.275
Total population	1.9e+04	2.0e+04	4.5e+04	2.7e+05	0.281	-0.133
Income from royalties	0.102	0.186	0.066	0.145	0.009	0.222

Note: The first two columns present the basic statistics (mean and standard deviation) of each covariate for the regression discontinuity sample within the optimal bandwidth, while columns 3 and 4 present them for the rest of the country. Column 5 presents the p-value of the differences in means, while column 6 presents the standardized difference between the two groups.

Table A3: Donor funded politician and deforestation during term in office: Cubic polynomial

	(1)	(2)
	Loc. Linear Pol-3	
Donor Funded	1.326**	0.989**
Robust p-value	0.025	0.035
CI 95%	[0.164, 2.477]	[0.071, 1.903]
Previous deforestation		✓
Observations	408	408
Bandwidth obs.	274.000	274.000
Mean	1.183	1.183
Effect Mean(%)	112.09	83.60
Bandwidth	0.100	0.101
(Local) polynomial order	3	3

Note: Columns 1 and 2 present the cubic estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The Effect Size (%) is computed as the point estimate over the mean x 100. Columns (2) and (4) include as covariate the measure of deforestation in the previous term (2008-2011). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: Donor funded politician and deforestation: OLS

Controls used:	(1) Baseline (No controls)	(2) Pre-term deforestation	(3) Politician characteristics	(4) Development characteristics	(5) Forest coverage	(6) Agricultural preasure
Donor Funded	0.428***	0.266***	0.248***	0.222**	0.257***	0.276***
	(0.095)	(0.080)	(0.081)	(0.089)	(0.080)	(0.080)
Observations	996	996	995	996	996	996
R-squared	0.021	0.312	0.317	0.356	0.315	0.325
Mean DV	1.182	1.182	1.182	1.182	1.182	1.182

Note: OLS regression for deforestation in the mayor's term. Donor Funded is a dummy that takes the value one if the mayor was donor funded. Column 2 to 6 add as control deforestation in the pre-electoral period. Column 3 adds as controls politician characteristics such as political ideology, political experience, and previous electoral illegal behavior. Column 4 adds municipality characteristics such as population density, rural population, and nighttime lights. Column 5 adds forest coverage. Column 6 adds the total agricultural production and the hectares use for agricultural production. Robust standard errors are presented in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Donor funded politician and deforestation ratio - Quadratic Polynomial

	(1)	(2)	(3)	(4)
		Year of government		
	1	2	3	4
Donor Funded	0.002***	0.002*	0.002	0.005**
Robust p-value	0.009	0.074	0.166	0.048
CI 95%	[0.001, 0.004]	[-0.000, 0.005]	[-0.001, 0.006]	[0.000, 0.009]
Observations	408	408	408	408
Bandwidth obs.	188	200	209	187
Mean	0.012	0.012	0.012	0.012
Effect size (%)	16.67	16.67	16.67	41.67
Bandwidth	0.059	0.066	0.070	0.059
(Local) polynomial order	2	2	2	2

Note: Local quadratic estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. Each column shows the deforestation rate, defined as lost $\text{coverage}_t / coverage_{\text{election year}}$, for a given year of government. The Effect size (%) is computed as the point estimate over the mean x 100. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Donor funded politician and contracts: Quadratic polynomial

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Infrastructure			*Environmental*		*Mining*
	Number	*Log Avg. value*	Road construction	*Number*	*Log Avg. value*	*Number*	*Log Avg. value*
Donor Funded	-54.930	1.206**	-0.013	-20.619	0.502	0.278	1.592
Robust p-value	0.373	0.021	0.646	0.446	0.293	0.598	0.111
CI 95%	[-204.554, 76.718]	[0.190, 2.374]	[-0.051, 0.032]	[-101.749, 44.742]	[-0.418, 1.385]	[-0.895, 1.553]	[-0.451, 4.344]
Observations	401	400	406	401	366	401	145
Bandwidth obs.	227	246	252	229	205	268	66
Mean	140.896	4.818	0.013	18.197	3.795	0.976	3.618
Effect Mean(%)	-38.99	120	-86.67	-113.31	50	28.48	159
Bandwidth	0.077	0.089	0.074	0.080	0.076	0.101	0.067
(Local) polynomial order	2	2	2	2	2	2	2

Note: Local linear estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The average value of contracts was transformed using inverse hyperbolic sine. The contracts are catalogued in each category by analysing their reported object. For columns 1, 3, 4, and 6, the effect size (%) is computed as the point estimate over the mean x 100, while for the rest of the columns is the point estimate x 100. *** p<0.01, ** p<0.05, * p<0.1.

x

Table A7: Donor funded politician and avg. value of infrastructure contracts per year

	Year of government			
	1	2	3	4
Donor Funded	0.520	0.484	1.391***	0.760
Robust p-value	0.245	0.252	0.008	0.116
CI 95%	[-0.410, 1.610]	[-0.404, 1.538]	[0.385, 2.597]	[-0.217, 1.968]
Observations	381	386	386	389
Bandwidth obs.	179	195	193	179
Mean	4.204	5.092	5.284	5.508
Effect size (%)	52	48	139	76
Bandwidth	0.060	0.070	0.068	0.058
(Local) polynomial order	1	1	1	1

Note: Local linear estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The average value of contracts was transformed using inverse hyperbolic sine. The contracts are catalogued in each category by analysing their reported object. The effect size (%) is computed as the point estimate x 100. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A8: Donor funded politician and infrastructure contracts by relation to deforestation

	(1) No deforestation related		(3) Deforestation related	
	Number	Avg. value	Number	Avg. value
Donor Funded	-18.177	0.617*	2.201	0.911*
Robust p-value	0.165	0.077	0.733	0.052
CI 95%	[-54.796, 9.383]	[-0.073, 1.415]	[-11.740, 16.685]	[-0.010, 2.057]
Observations	401	392	401	378
Bandwidth obs.	185	234	211	173
Mean	42.171	5.211	14.343	5.091
Effect Mean(%)	-43.10	11.84	15.35	17.89
Bandwidth	0.059	0.085	0.073	0.059
(Local) polynomial order	1	1	1	1

Note: Local linear estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The average value of contracts was transformed using inverse hyperbolic sine. The contracts are catalogued in each category by analysing their reported object. The Effect size (%) is computed as the point estimate over the mean x 100. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A9: Heterogeneous Effects: Armed Conflict - Quadratic Polynomial

		(1)	(2)
		*Measure Z*	
		*Attacks*	
		Paramilitary	Guerrilla
A	Donor funded	0.337	0.733**
		(0.364)	(0.367)
	Z	-0.0783	0.435*
		(0.144)	(0.227)
B	Z × Donor funded	0.168	-0.554**
		(0.156)	(0.241)
	Observations	408	408
	Bandwidth obs.	191	191
	R-squared	0.108	0.166
	Bandwidth	0.0600	0.0600
	(Local) polynomial order	2	2
	A + B	0.505	0.179
	Effect size	30.50	8.68
	Ho: A + B = 0		
	F-statistic	2.43	0.21
	P-value	0.12	0.64

Note: OLS regression weighted by a triangular kernel within the MSE optimal bandwidth sample and controlling for a quadratic polynomial. Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The dependent variable is deforestation during the full term. Paramilitary (Guerrilla) attacks is the number of paramilitary (guerrilla) attacks during the previous term (2008-2011). The Effect size (%) is computed as $100x(A + B)/(constant + \beta_Z)$. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Donor funded politician and fire intensity - Quadratic polynomial

	(1)	(2)
Donor Funded	92.839**	77.625
Robust p-value	0.044	0.145
CI 95%	[2.659, 187.461]	[-26.568, 180.535]
Previous intensity		✓
Observations	408	408
Bandwidth obs.	312	217
Mean	246.141	246.141
Effect size (%)	37.72	31.54
Bandwidth	0.124	0.073
(Local) polynomial order	2	2

Note: Local quadratic estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. Column (2) includes as covariate the measure of fire intensity from the previous term (2009-2011), being 2009 the first year with data availability. Fire intensity is measured as the average brightness of fires in a municipality. The Effect size (%) is computed as the point estimate over the mean x 100. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A11: Donor funded politician and fire intensity by year of government

	(1)	(2)	(3)	(4)
	*Year of government*			
	1	2	3	4
Donor Funded	31.434	55.882	1.715	110.844**
Robust p-value	0.461	0.225	0.978	0.018
CI 95%	[-65.426, 144.208]	[-42.699, 181.289]	[-110.545, 107.437]	[20.741, 224.285]
Observations	408	408	408	408
Bandwidth obs.	232	200	215	237
Mean	189.663	183.108	185.204	198.902
Effect size (%)	16.57	30.52	0.93	55.73
Bandwidth	0.078	0.066	0.073	0.082
(Local) polynomial order	1	1	1	1

Note: Local linear estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. Fire intensity is measured as the average brightness of fires in a municipality. The Effect size (%) is computed as the point estimate over the mean x 100. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A12: Donor funded politician and agro-cattle firms entry by year

	Year of government			
	1	2	3	4
Donor Funded	1.093	1.831	1.340	2.569**
Robust p-value	0.314	0.243	0.496	0.019
CI 95%	[-1.151, 3.585]	[-1.308, 5.169]	[-1.893, 3.910]	[0.495, 5.653]
Observations	408	408	408	408
Bandwidth obs.	190	198	232	161
Mean	0.211	0.306	0.211	0.455
Effect size (%)	518.01	598.37	635.07	564.62
Bandwidth	0.060	0.063	0.077	0.048
(Local) polynomial order	1	1	1	1

Note: Local linear estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The dependent variable is the number of firms registered in agro-cattle business during that year. The Effect Size (%) is computed as the point estimate over the mean x 100. *** p<0.01, ** p<0.05, * p<0.1.

Table A13: Donor funded politician and agro-cattle firms entry by year - Quadratic

	Year of government			
	1	2	3	4
Donor Funded	1.116	1.749	1.168	2.671**
Robust p-value	0.415	0.346	0.505	0.030
CI 95%	[-1.515, 3.671]	[-1.788, 5.097]	[-2.152, 4.370]	[0.278, 5.574]
Observations	408	408	408	408
Bandwidth obs.	245	271	267	246
Mean	0.211	0.306	0.211	0.455
Effect size (%)	528.91	571.57	553.55	587.03
Bandwidth	0.084	0.099	0.097	0.085
(Local) polynomial order	2	2	2	2

Note: Local quadratic estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The dependent variable is the number of firms registered in agro-cattle business during that year. The Effect Size (%) is computed as the point estimate over the mean x 100. *** p<0.01, ** p<0.05, * p<0.1.

Table A14: Donor funded politician and deforestation during term in office: Adding covariates

Covariates:	(1) Ideology	(2) Experience Politician characteristics	(3) Illegal registration of ID	(4) Campaign	(5) Development Municipality characteristics	(6) Forest coverage	(7) Agricultural land
Donor Funded	1.145***	1.132***	1.109***	0.996**	0.869**	1.070**	1.096***
Robust p-value	0.007	0.007	0.007	0.022	0.018	0.011	0.007
CI 95%	[0.371, 2.296]	[0.366, 2.259]	[0.352, 2.232]	[0.171, 2.184]	[0.177, 1.880]	[0.286, 2.216]	[0.341, 2.196]
Observations	408	408	408	408	406	408	408
Bandwidth obs.	130	130	132	122	132	129	136
Mean	1.183	1.183	1.183	1.183	1.183	1.183	1.183
Effect Mean(%)	96.79	95.69	93.74	84.19	73.46	90.45	92.65
Bandwidth	0.040	0.040	0.041	0.036	0.041	0.039	0.042
(Local) polynomial order	1	1	1	1	1	1	1

Note: All columns present the local linear estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. Column 1 adds as a covariate dummies for whether the candidate is from a right-wing party and other for whether the candidate is from a left-wing party. Column 2 adds as covariates dummies for whether the candidate has held a political office before. Column 3 adds dummies for whether the candidate has an illegal registration of ID. Column 4 adds as covariates the number of donors, number of donations, and the amount spent in the campaign and privately funded. Column 5 adds as covariates the share of rural population, the nighttime luminosity, the roads' density, and population density. Column 6 adds as a control the total forest coverage in the municipality. Finally, column 7 adds the share of the municipality with agricultural land and the total agricultural production over the size of the municipality. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The Effect Size (%) is computed as the point estimate over the mean x 100. *** p<0.01, ** p<0.05, * p<0.1.

Table A15: Heterogeneous effects by state presence controlling for agricultural pressure

		(1)	(2)	(3)
			Measure Z	
		National Parks Area	CAR office	Distance to CAR
A	Donor funded	0.986**	1.155**	-0.300
		(0.474)	(0.509)	(0.568)
	Z	0.215**	1.286**	0.000
		(0.102)	(0.600)	(0.009)
B	Z × Donor funded	-0.273*	-2.675**	0.038**
		(0.139)	(1.025)	(0.017)
	Observations	408	408	408
	Bandwidth obs.	131	131	131
	R-squared	0.055	0.073	0.215
	Bandwidth	.041	.041	.041
	(Local) polynomial order	1	1	1
	A + B	0.713	-1.520	-0.262
	Effect size (%)	97.805	-79.208	-53.144
	Ho: A + B = 0			
	F-statistic	2.644	3.614	0.223
	P-value	0.106	0.060	0.637

Note: OLS regression weighted by a triangular kernel within the MSE optimal bandwidth sample and controlling for a linear polynomial. Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The dependent variable is deforestation during the full term. National Parks area is defined as the total area with national parks in the municipality, CAR office is a dummy that takes the value one if there was at least on CAR office in the municipality, and Distance to CAR is the distance to the closest CAR. All specifications control for the share of of the municipality with agricultural land and total agricultural production over the size of the municipality. The Effect size (%) is computed as $100x(A+B)/(constant+\beta_Z)$. *** p<0.01, ** p<0.05, * p<0.1.

Table A16: Donor funded politician and deforestation during term in office: Using different weights

Weights	(1) Forest coverage	(2) Municipality area
Donor funded	1.311**	1.164**
	(0.564)	(0.519)
Observations	408	408
Bandwidth obs.	132	132
R-squared	0.157	0.139
Bandwidth	.041	.041
(Local) polynomial order	1	1

Note: OLS regression within the MSE optimal bandwidth sample and controlling for a linear polynomial. In column 1, we weight the observations using the forest coverage in the municipality in 2011, while in column 2, we use the area of the municipality as weight. Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A17: Heterogeneous effects by agricultural presence

		(1)	(2)	(3)	(4)
			Measure Z		
		Agricultural Area	Sh Agricultural Area	Agricultural production	Sh Agricultural production
A	Donor funded	0.945**	0.943**	1.445**	0.908**
		(0.412)	(0.428)	(0.616)	(0.413)
	Z	0.922**	-0.024	-1.831	-0.130
		(0.431)	(0.021)	(1.783)	(0.113)
B	Z × Donor funded	-0.200	0.336	3.806	-0.186
		(0.957)	(0.995)	(3.677)	(0.345)
	Observations	408	408	408	408
	Bandwidth obs.	132	132	132	132
	R-squared	0.102	0.058	0.056	0.051
	Bandwidth	.041	.041	.041	.041
	(Local) polynomial order	1	1	1	1

Note: OLS regression weighted by a triangular kernel within the MSE optimal bandwidth sample and controlling for a quadratic polynomial. The variables used for heterogeneous effects (Z) are: the total agricultural area, the share of the municipality with agricultural area, total agricultural production, and the share of total agricultural production over the size of the municipality. In all cases, we standardize the Z variable by it's average and standard deviation. Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A18: Right-wing politician and deforestation during term in office

	(1)	(2)	(3)	(4)
	Loc. Linear Pol-1		*Loc. Linear Pol-2*	
Right-wing Politician	0.101	0.059	0.126	-0.131
Robust p-value	0.805	0.966	0.786	0.607
CI 95%	[-0.815, 1.050]	[-0.648, 0.620]	[-0.912, 1.205]	[-0.977, 0.570]
Previous deforestation		✓		✓
Observations	482	482	482	482
Bandwidth obs.	264	245	349	294
Mean	1.183	1.183	1.183	1.183
Effect Mean(%)	8.54	4.99	10.65	-11.07
Bandwidth	0.081	0.073	0.121	0.096
(Local) polynomial order	1	1	2	2

Note: Columns 1 and 2 present the local linear estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. Columns 3 and 4 presents the quadratic estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The Effect Size (%) is computed as the point estimate over the mean x 100. Columns (2) and (4) include as covariate the measure of deforestation in the previous term (2008-2011). *** p<0.01, ** p<0.05, * p<0.1.

Table A19: Heterogeneous effects by candidate characteristics

		Measure Z		
		Political experience	Right-wing	Illegal registration of ID
A	Donor funded	1.435***	1.139**	0.975**
		(0.510)	(0.483)	(0.421)
	Z	0.434	0.056	-0.420
		(0.406)	(0.547)	(0.263)
B	Z × Donor funded	-1.361	-0.696	0.000
		(0.834)	(0.989)	(0.000)
	Observations	408	408	408
	Bandwidth obs.	132	132	132
	R-squared	0.073	0.057	0.041
	Bandwidth	.041	.041	.041
	(Local) polynomial order	1	1	1
	A + B	0.074	0.443	0.975
	Effect size (%)	6.839	54.490	271.588
	Ho: A + B = 0			
	F-statistic	0.012	0.264	5.371
	P-value	0.911	0.609	0.022

Note: OLS regression weighted by a triangular kernel within the MSE optimal bandwidth sample and controlling for a linear polynomial. Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The dependent variable is deforestation during the full term. Political experience is a dummy for whether the candidate has held political office previously. Right-wing is a dummy for the candidate being from a right-wing party. Illegal registration of ID is a dummy for whether the candidate had an illegal registration of an ID. Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A20: Politically experienced politician and deforestation during term in office

	(1)	(2)	(3)	(4)
	Loc. Linear Pol-1		*Loc. Linear Pol-2*	
Politically Experienced	0.154	0.102	-0.010	0.034
Robust p-value	0.544	0.891	0.820	0.873
CI 95%	[-0.535, 1.016]	[-0.680, 0.782]	[-1.175, 0.931]	[-0.883, 0.749]
Previous deforestation		✓		✓
Observations	479	479	479	479
Bandwidth obs.	282	221	275	291
Mean	1.183	1.183	1.183	1.183
Effect Mean(%)	13.02	8.62	-0.84	2.87
Bandwidth	0.084	0.065	0.081	0.091
(Local) polynomial order	1	1	2	2

Note: Columns 1 and 2 present the local linear estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. Columns 3 and 4 presents the quadratic estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The Effect Size (%) is computed as the point estimate over the mean x 100. Columns (2) and (4) include as covariate the measure of deforestation in the previous term (2008-2011). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A21: Heterogeneous Effects: State Presence - Quadratic Polynomial

		(1)	(2)	(3)	(4)	(5)
				Measure Z		
		National Parks Area	CAR office	Distance to CAR	Procurator offices	Attorney offices
A	Donor funded	0.679*	0.750*	-0.234	0.624*	0.830**
		(0.366)	(0.386)	(0.429)	(0.361)	(0.405)
	Z	0.348	1.532*	-0.00279	1.062***	-0.0685
		(0.240)	(0.798)	(0.0101)	(0.310)	(0.143)
B	Z × Donor funded	-0.329*	-2.072***	0.0267**	-1.695***	-0.285**
		(0.176)	(0.660)	(0.0133)	(0.574)	(0.118)
Observations		408	408	408	408	408
Bandwidth obs.		191	191	191	191	191
R-squared		0.069	0.083	0.201	0.068	0.087
Bandwidth		0.060	0.060	0.060	0.060	0.060
(Local) polynomial order		2	2	2	2	2
A + B		0.350	-1.322	-0.207	-1.071	0.545
Effect size (%)		17.56	-41.28	-12.05	-38.988	30.569
Ho: A + B = 0						
F-statistic		.99	6.09	0.24	3.83	4.7
P-value		0.32	0.01	0.62	0.05	0.11

Note: OLS regression weighted by a triangular kernel within the MSE optimal bandwidth sample and controlling for a quadratic polynomial. Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The dependent variable is deforestation during the full term. National Parks area is defined as the total area with national parks in the municipality, CAR office is a dummy that takes the value one if there was at least on CAR office in the municipality, Distance to CAR is the distance to the closest CAR, Comptroller offices is the number of offices of the Comptroller General (*Procuraduría*), and Attorney offices is the number of offices of the Attorney General (*Fiscalía*). The Effect size (%) is computed as $100x(A + B)/(constant + \beta_Z)$. *** p<0.01, ** p<0.05, * p<0.1.

Table A22: Donor funded politician and infrastructure contracts by year of government - Quadratic polynomial

	Year of government			
	1	2	3	4
Donor Funded	0.561	0.195	1.431**	0.886
Robust p-value	0.418	0.918	0.028	0.114
CI 95%	[-0.752, 1.812]	[-1.209, 1.344]	[0.161, 2.785]	[-0.230, 2.136]
Observations	381	386	386	389
Bandwidth obs.	210	217	268	265
Mean	4.204	5.092	5.284	5.508
Effect size (%)	13.34	3.83	27.08	16.09
Bandwidth	0.075	0.076	0.108	0.105
(Local) polynomial order	2	2	2	2

Note: Local quadratic estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The average value of contracts was transformed using inverse hyperbolic sine. The contracts are catalogued in each category by analysing their reported object. The Effect size (%) is computed as the point estimate over the mean x 100. *** p<0.01, ** p<0.05, * p<0.1.

Table A23: Donor funded politician and fire intensity by year of government - Quadratic polynomial

	Year of government			
	1	2	3	4
Donor Funded	51.029	118.096*	4.267	122.898*
Robust p-value	0.451	0.100	0.952	0.068
CI 95%	[-90.214, 203.103]	[-25.585, 292.761]	[-145.384, 154.528]	[-9.357, 256.419]
Observations	408	408	408	408
Bandwidth obs.	238	204	233	267
Mean	189.663	183.108	185.204	198.902
Effect size (%)	26.91	64.50	2.30	61.79
Bandwidth	0.082	0.068	0.079	0.097
(Local) polynomial order	2	2	2	2

Note: Local quadratic estimates of average treatment effects at cut-off estimated with triangular kernel weights and optimal MSE bandwidth. 95% robust confidence intervals and robust p-values are computed following Calonico, Cattaneo and Titiunik (2014). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. Fire intensity is measured as the average brightness of fires in a municipality. The Effect size (%) is computed as the point estimate over the mean x 100. *** p<0.01, ** p<0.05, * p<0.1.

Table A24: Heterogeneous effects: Guerrilla presence and ceasefire

		(1)	(2)	(3)	(4)
		Attacks measure Z			
		Paramilitary		Guerrilla	
		2012-14	2015	2012-14	2015
A	Donor funded	0.302	0.402**	0.629**	0.504***
		(0.244)	(0.196)	(0.273)	(0.180)
	Z	0.078	0.038	0.303***	0.271***
		(0.094)	(0.055)	(0.086)	(0.103)
B	Z × Donor funded	0.114	0.010	-0.343***	-0.280**
		(0.102)	(0.062)	(0.114)	(0.130)
Observations		408	408	408	408
Bandwidth obs.		132	132	132	132
R-squared		0.156	0.063	0.092	0.162
Bandwidth		.041	.041	.041	.041
(Local) polynomial order		1	1	1	1
A + B		0.416	0.412	0.286	0.224
Effect size (%)		67.752	135.974	39.722	47.558
Ho: $A + B = 0$					
F-statistic		3.216	5.536	1.202	1.269
P-value		0.075	0.020	0.275	0.262

Note: OLS regression weighted by a triangular kernel within the MSE optimal bandwidth sample and controlling for a quadratic polynomial. The dependent variable is deforestation between 2012-2014 (columns 1 and 3) and deforestation in 2015 (columns 2 and 4). Bandwidth obs. denotes number of observations in the optimal MSE bandwidth. The dependent variable is deforestation during the full term. Paramilitary (Guerrilla) attacks is the number of paramilitary (guerrilla) attacks during the previous term (2008-2011). The Effect size (%) is computed as $100x(A + B)/(constant + \beta_Z)$. *** p<0.01, ** p<0.05, * p<0.1.

Table A25: Descriptive statistics for donor-funded politicians

Dependent variable	Mean	Std. Dev.
	(1)	(2)
Total privately funded	15.653	17.060
Sh privately funded	0.399	0.270
Number of donors	6.484	5.964
Number of donations	8.340	8.243

Note: There are a total of 408 Mayors in our base sample, 164 which are not donor-funded, while 244 are donor-funded. These descriptive statistics are for donor-funded politicians. "Total privately funded" is the total amount of private donations in millions of Colombian pesos. "Sh privately funded" is the % of total campaign funds from private donations.

Table A26: Private donations and deforestation: OLS

	(1)	(2)	(3)	(4)	(5)	(6)
Share of private donations	0.862**	0.590**				
	(0.350)	(0.298)				
Number of private donations			0.017**	0.007		
			(0.007)	(0.006)		
Number of private donors					0.029***	0.019**
					(0.010)	(0.009)
Deforestation pre-term		0.395***		0.401***		0.400***
		(0.042)		(0.044)		(0.044)
Observations	408	408	408	408	408	408
R-squared	0.025	0.295	0.006	0.284	0.009	0.287
Mean DV	1.210	1.210	1.210	1.210	1.210	1.210

Note: This table presents an OLS regression for deforestation in the mayor's term. Share of private donations is the share of the mayor's electoral budget that privately funded and Number of private donations (private donors) is the number of private donations (donors) that the mayor received. Robust standard errors are presented in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.