Young Politicians and Climate Change Mitigation*

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Abstract

Policies often entail costs today but benefits far into the future, as in the case of climate change mitigation. A key factor shaping how this intertemporal trade-off is addressed is the age of the politicians in power. We study closely contested elections in Brazil and show that when a young politician is in power there is less deforestation and lower greenhouse gas emissions, with no apparent trade-off in terms of local income. Results are partly explained by young mayors turning over the bureaucracy with younger public servants.

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1 Introduction

A fundamental difficulty in policy-making is that policies often have costs today, but benefits extending only far into the future. This is especially evident in climate change and nature conservation, where mitigation requires significant upfront costs, while the benefits—such as avoiding environmental catastrophe—may not be realized for decades. Younger cohorts already express an interest in addressing climate change and say they have personally taken some kind of action to do so across party lines in the U.S. (Tyson et al., 2023; Funk, 2021) and worldwide (Ahlfeldt et al., 2022; Andor et al., 2018). A key constraint in accelerating environmental policy adoption is therefore having elected leaders who are aligned with long-term objectives (Stockemer and Sundström, 2022; Karp et al., 2024). In this paper, we test whether young politicians help mitigate climate change, with a special focus on local governments and deforestation.

We study the effects of having young politicians in power in the case of Brazilian municipalities. The setting is ideal for a few reasons. Brazil contains 60% of the Amazon, the largest tropical forest on the planet. In addition, Brazil has thousands of municipalities (analogous to United States counties) providing plenty of variation and richness to explore. Although mayors in Brazil are not directly responsible for environmental law enforcement, they can impact deforestation, especially when facing strong electoral incentives (Bragança and Dahis, 2022), by favoring campaign donors (Katovich and Moffette, 2024), by allowing the sale of untitled land (Cisneros and Kis-Katos, 2024), or through other implemented agricultural and social programs (Holland, 2016).[1] Moreover, Brazil has monitored deforestation with satellite data since the early 2000s, which produced satellite measurements without misreporting concerns.

Our empirical strategy employs a "politician-characteristic" regression discontinuity (PCRD) design with close elections to recover the local average treatment effect (LATE) of electing young mayors on a variety of outcomes. We first validate our design by showing that municipalities' and elections' characteristics are continuous around the cutoff and that there is no evidence of vote margin manipulation. In our main specification, we define a young candidate as being in the lowest 20^{th} percentile of the candidates' age distribution in each election (approximately 35 years old). Similarly, we define a senior candidate as being above the 80^{th} percentile of the candidates' age distribution in each election (approximately 54 years old).

[1] For example, 118 mayoral candidates were on the national environmental agency's "watch list" for deforestation, illegal burning, exploiting protected native forests, or providing false information to environmental agencies (MongaBay, 2021).

We find that young mayors have better environmental performance with no detectable negative effects on the local economy. Specifically, in our preferred specification, being governed by a young mayor implies a 0.23-0.25 percentage point reduction in the yearly deforestation rate (as a share of the municipality's forest area in 2000). Compared to a mean deforestation rate of 0.45% each year, the effect size amounts to a substantial 51-56% reduction. We also find that when a young mayor is in office, per capita greenhouse gas emissions are reduced by about 44%. Importantly, having a young mayor in office does not significantly affect the municipal gross per capita domestic product.

Our main findings withstand a variety of robustness checks, including alternative definitions of outcomes, samples, and specifications. We vary the definition of *young* to different percentiles of age, change local polynomial degrees, estimate cluster, conventional and robust standard errors in various ways, change kernels, and remove outliers in deforestation and initial forest area. Moreover, we find no evidence of reverse causality, showing that electing a young mayor in the future does not change current deforestation, or attenuation effects, by removing the few observations where a mayor previously classified as young reappeared in the sample as not young and finding similar results. The one exception is that the results are sensitive to medium-level percentage points removed around the cutoff in a doughnut regression discontinuity (RD) exercise.

We then study the effects of being governed by young mayors on other variables. We first find that young mayors in office do not prioritize the agriculture sector. We document a reduction in the agricultural value added. Relatedly, we show that young mayors reduce total greenhouse gas emissions, with an effect on land use emissions. We also report that senior mayors increase agricultural output.

We then turn to documenting three channels through which mayors could impact deforestation and other outcomes. First, we show that municipalities governed by young mayors do not change their pattern of local spending in terms of percentages spent across categories. The opposite is true for senior mayors, who decrease spending towards the environment and increase it for liabilities. Second, we find that farmers do not receive significantly more rural credit when governed by a young mayor but get 31% less credit towards cattle ranching when governed by senior mayors. Finally, we show that young mayors turn over the local bureaucracy towards a younger set of public servants. This effect is not merely a consequence of young mayors being first-time officeholders.

Lastly, we further explore what is driving young mayors to reduce deforestation. We first argue that our results are not driven by other characteristics bundled with age (Marshall, 2024). We find that young mayors are mostly similar in observable characteristics to other winning mayors, such as experience or campaign donations received. The one important exception is political orientation, where at the cutoff young mayors are more frequently left-wing, but we show that results are robust to controlling for any combinations of observable characteristics. Second, our results seem to hold across the board. We find no evidence of heterogeneous treatment effects of being governed by young mayors interacted with any relevant covariate (including political orientation and many others). Third, we estimate a more flexible RD exercise that allows for any combination of ages among the top two candidates to measure the effect of being governed by a younger mayor. The effects of young mayors is present when compared to basically any other age group.

Having established the main results, we close the paper with a discussion of how to interpret the findings. In theory, the relationship between the age of the mayor and long-term environmental policy could be mediated by both *demand* and *supply* channels. Politicians in power could be simply following the preferences expressed by the local median voter (Downs, 1957), and perhaps areas with more support for young politicians are also more likely to have lower deforestation rates.[2] The RD design rules out both of these concerns: our comparisons hold statistically constant an array of characteristics of the municipality and electorate, including the percentage of young voters. Our RD estimates reflect a mix of *supply* channels, albeit locally in areas where there was already substantial support for the young mayor's campaign in the first place.[3] Moreover, determining to what extent different mechanisms explain our findings, such as young politicians having longer life horizons, different discount factors, or less political experience, and whether estimates are driven by age, cohort, or time effects, are left for future research.

We contribute to two main strands of the literature. First, we contribute to the growing literature that studies age and government policy. Alesina et al. (2019b) and Bertrand et al. (2015) argue that younger politicians have more career concerns. Fiva et al. (2025) show that politicians in the Norwegian parliament raise different issues when they are young (e.g., childcare, schools) versus old (e.g., health care). Bertoli et al. (2024) report that countries electing older leaders were less likely to engage in military conflict. To the

[2]Young people voting in young politicians regardless of their valence or agenda is an instance of *descriptive representation* (Pitkin, 1967). In the auxiliary exercises reported in Table A.1, we find that municipalities with more young people also have more young candidates running and that, conditional on municipality fixed effects, in electoral booths where more young people vote, the young candidates receive a larger vote share. The effects for seniors are even stronger.

[3]This point that politicians may diverge from the preferences of the local median voter is made theoretically by the literature on agency and career-concerns models (Besley, 2006) and empirically by the vast literature on politician identity (Chattopadhyay and Duflo, 2004; Beaman et al., 2009). Early papers such as Alesina (1988) and Lee et al. (2004) argued that politicians' proposals would not necessarily converge to the preferences of the median voter in a world without full commitment.

best of our knowledge, we are the first to study the effects of electing young politicians on aspects of climate change mitigation. The papers that most closely resemble ours are McClean (2023) and Baskaran et al. (2024). The former shows that Japanese young mayors spend more on child welfare. The latter argues that Bavarian municipalities with a higher share of young councilors spend more on public goods valued by young inhabitants, such as child care and schools. Our paper has a broader scope, studying the executive branch, employing a standard close elections design, and covering the whole Brazilian Amazon region.

Second, we contribute to the literature that studies the political economy of deforestation (Balboni et al., 2023). At the municipal level, there is evidence that deforestation changes when the mayor is a farmer (Bragança and Dahis, 2022), when the mayor's campaign was financed by donors (Harding et al., 2024; Katovich and Moffette, 2024), when administrative units change borders (Burgess et al., 2012; Edwards et al., 2020; Cisneros et al., 2023), when ethnic fractionalization increases (Alesina et al., 2019a), when public audits of federal funds were conducted (Cisneros and Kis-Katos, 2024), and around elections (Pailler, 2018; Cisneros et al., 2021; Sanford, 2023).[4][5] The effect of electing a donor-funded politician has an effect size of 53-109% compared to the mean deforestation (Harding et al., 2024), comparable to the effect size we estimate of 58% when electing a young politician.

The remainder of the paper is organized as follows. Section 2 describes the setting. Section 3 presents the identification strategy. Section 4 describes the data and summary statistics. Section 5 presents the main results and heterogeneity analyses. Section 6 discusses the findings and concludes.

2 Setting

Brazil contains about 60% of the Amazon forest, the largest tropical forest on the planet. The biome area is contained in the administrative set of 772 municipalities called the *Legal Amazon*, which covers nine states in the Center and North regions of the country and spans nearly 59% of the country's area. This region is historically subject to specific policies and legislation, such as the country's 2012 Forestry Code, and has specific deforestation

[4]For evidence on the impacts of central policies on deforestation in Brazil see examples in Nepstad et al. (2009), Arima et al. (2014), Assunção et al. (2015), Cisneros et al. (2015), Assunção and Rocha (2019), Assunção et al. (2020), Assunção et al. (2023), Burgess et al. (2024).

[5]Mangonnet et al. (2022) find that the Brazilian government systematically designates more protected areas in municipalities controlled by opposition mayors relative to municipalities controlled by mayors in the president's political coalition.

dynamics compared to other biomes (Nepstad et al., 2009). We restrict our attention to this region to hold fixed any macro-conditions that could differ from other parts of the country.

Municipalities are the smallest administrative unit in Brazil. Municipal governments are managed by a mayor elected using the plurality rule in municipalities with less than 200,000 voters and the majority rule in municipalities with more than 200,000 voters. Mayors serve a four-year term and can be reelected once. The Brazilian municipalities also have a local council. Municipal councilors are elected through an open list proportional representation system. Elected mayors and councilors take office on January 1 following the elections held in November. Our sample will consist of sixteen years (2005-2020), spanning four full electoral cycles.

The minimum age to be elected is 21 for mayors and 18 for councilors.[6] The median candidate age in all elections in our data is 44 years, while the median elected candidate age is 48 (see Figure A.1). Other eligibility requirements are being Brazilian, having full electoral rights, having enlisted in the army, living in the relevant geography, and being affiliated with a party.

According to the 1988 Brazilian Constitution, municipalities are responsible for providing an array of public goods and services, such as basic education and health. Jurisdiction over environmental conservation is somewhat an area of institutional ambiguity. Historically, enforcement has been done by the federal government through agencies such as the Brazilian Institute for the Environment and Renewable Resources (*Ibama*), Chico Mendes Institute for Biodiversity Conservation (*ICMBio*), the federal police, and others (Nepstad et al., 2009; Arima et al., 2014; Assunção et al., 2015; Cisneros et al., 2015; Assunção and Rocha, 2019; Assunção et al., 2020; Assunção et al., 2023; Burgess et al., 2024).

However, mayors can still influence deforestation both directly and indirectly. For example, they can directly influence local government's spending in agricultural promotion, infrastructure, and other areas (Bragança and Dahis, 2022). Mayors can make discretionary efforts to attract funding from matching grants with state and federal agencies and parliamentary amendments from representatives (Brollo and Nannicini, 2012; Bracco et al., 2015). Mayors can systematically manipulate forest resources around elections (Pailler, 2018; Cisneros et al., 2021; Sanford, 2023). Recent evidence also suggests they are able to provide patronage to their campaign donors (Katovich and Moffette, 2024). Finally, local governments can also impact sales of untitled land, collude with local sawmills that promote illegal logging, accommodate illegal settlements, and cooperate (or not) with federal

[6] See `https://www.tse.jus.br/eleitor/glossario/termos/elegibilidade`.

raids (Cisneros and Kis-Katos, 2024).

3 Empirical Framework

In this Section, we discuss our "politician characteristic" regression discontinuity (PCRD) design to estimate the effect of having a young mayor in office on deforestation and other outcomes (Bertoli and Hazlett, 2023; Marshall, 2024).[7] First, we define a candidate as "young" if his or her age falls at or below the 20^{th} percentile in the candidates' age distribution within each election year.[8] In our main specifications being "young" essentially means being 35 years old or less.

The ideal experiment would compare municipalities identical in every dimension except that one group is governed by young mayors (treated) and the other group is not (control). Because young candidates can have any age below 35 and the not young ones can have any age above that, estimating a "young mayor" average treatment effect would be averaging across many "age differences" (e.g. the difference between a 52 year old and a 34 year old is 18, while the difference between a 33 year old and a 72 year old is 39). Ideally we would have large enough samples across all age difference combinations such that we could estimate an average treatment effect for each age difference. In reality the ideal experiment is not available and sample sizes for each age difference are relatively small, so we turn to the following PCRD design.

We restrict attention to close elections where in the top two candidates there was a young person and a not young person. Moreover, in order to approximate a comparison within each age difference, we define and control for fifteen "age difference dummies."[9] In sum, we estimate the effect of electing a young mayor on deforestation and other outcomes with the following specification:

$$y^{\tau}_{mt} = \beta \text{YoungWon}_{mt} + f(Margin_{mt}) + \mathbf{AD}_{mt}\delta + \lambda_{t\tau} + \mathbf{Z}^{\tau}_{mt}\gamma + \varepsilon^{\tau}_{mt} \tag{1}$$

where y^{τ}_{mt} is the outcome of interest in municipality m after election year $t \in \{2004, 2008, 2012, 2016\}$

[7] This approach follows an extensive literature applying regression discontinuity (RD) designs in economics (Lee and Lemieux, 2010) and politics (Lee, 2008; Eggers et al., 2015).

[8] Figure A.1 shows that the age distribution for candidates in the Amazon study sample is similar to that of all candidates, although it is more concentrated than that of the whole country.

[9] Specifically, we do the following. For each candidate among the top two we define five age category dummies for ages <35, between 35-44, between 45-54, between 55-64, or ≥65). We then flexibly combine the various age category dummies into fifteen *age difference* dummies for {<35, <35}, {<35, 35-44}, {<35, 45-54}, and so on.

in term year $\tau \in \{1,2,3,4\}$. YoungWon$_{mt}$ is a dummy equal to one if a young candidate won the election (and consequently is in office in years $t+\tau$). Following Gelman and Imbens (2019), we control for flexible local polynomial functions of the margin of victory with $f(Margin_{mt})$. The vector $\mathbf{AD}_{mt}$ stands for the age difference dummies described above. We add time fixed effects $\lambda_{t\tau}$ to control for common yearly shocks such as the weather or national policies. In our preferred specification, given that our sample size is relatively small, we follow Lee and Lemieux (2010) and control for pre-determined variables $\mathbf{Z}^{\tau}_{mt}$ to reduce sampling variance. This vector includes the lagged outcome four years earlier (y^{τ}_{mt-1}), the logarithm of population, the share of young in the population in 2000, and the mayor's characteristics as dummies (male, incumbent, left-wing party, married, and completed college). We select the bandwidth following the data-driven approach proposed by Calonico et al. (2014) and Cattaneo et al. (2015).[10] In the main specification, we employ a triangular kernel for weighting observations as recommended by Cattaneo et al. (2020b). In our main specifications we compute heteroskedasticity-robust standard errors. We report an array of robustness checks in the Appendix. We re-estimate our main specification varying the definition of "young", changing bandwidths, adding higher-order polynomials, removing fixed effects and controls, collapsing the data to the election *mt* level, changing kernels, and varying the choice of standard errors.

On average, the young candidate in our data is 17.5 years younger than its competitor.[11] Still, there could be a concern that our strategy is disproportionately comparing, for example, candidates aged 34 and 36. To avoid those cases, we also present results restricting the sample to only elections with a young and a senior candidate in the top two.[12] The downside to this specification is that there are few such elections and the resulting sample size is small.

In Section 5.5, we leverage the full variation in age in our data to study whether being governed by "younger," and not just "young," mayors has an effect on our outcomes of interest.[13] For example, it could be that a 10-year age difference matters differently if winners and losers are 34 and 44 or if they are 56 and 66 years old. To do that we expand our sample to all elections and define a "younger" dummy for the younger candidate among the top two. We then re-estimate the rest of the PCRD design in Equation (1) with

[10] The approach applies randomization inference to handle cases where the running variable has mass points in its support.

[11] See Figure B.2 for the age gap histogram. The distribution for races where the young candidate won is slightly more spread out than the one in which the not young candidate won.

[12] We define a candidate as senior if his or her age is equal to or above the 80^{th} percentile in the candidate's age distribution within each election year. This translates to an age cutoff of about 54 years.

[13] Bertoli et al. (2024) use a similar design to study the effects of electing older leaders on international conflict.

YoungerWon analogously.

4 Data and Summary Statistics

4.1 Data sources

Deforestation The area deforested each year is provided by the *Instituto Nacional de Pesquisas Espaciais* (INPE) through the *Projeto de Monitoramento do Desmatamento na Amazônia Legal por Satélite* (PRODES). INPE computes deforestation by analyzing satellite images covering only the Legal Amazon, with a resolution of 30 meters x 30 meters pixels. An area is classified as deforested if there is a "suppression of areas of primary forest physiognomy due to anthropic actions" (de Almeida et al., 2021, p.3) and the deforested polygon is larger than 6.25 hectares (625 square meters). The data is yearly using the "PRODES year," which begins on August 1st and ends on July 31st of the following year.[14] The first year with available baseline forest area data in PRODES is 2000. Satellite data is useful because it provides a common metric for all municipalities, despite recent evidence of it containing measurement error (Alix-García and Millimet, 2023; Proctor et al., 2023; Torchiana et al., 2025).

Elections and candidates We have elections results from 2004 to 2016 from the *Tribunal Superior Eleitoral* (TSE), pre-processed by the Data Basis project (Dahis et al., 2022). The dataset contains the elections results of each municipality and information about the candidates, such as age, education, sex, marital status, and college completion. In addition, we classify each candidate's party as left- or right-wing following the methodology in Zucco and Power (2024).[15] Figure A.1 shows the age distribution of all candidates in Brazilian elections and the age distribution of the Brazilian population (see Figure B.1 for a comparison with candidates by election year in the sample). Figure 1 shows the map of the Brazilian Amazon, highlighting the municipalities that enter the sample of close

[14]For example, deforestation in 2006 in the data is forest clearing that occurred between August 1, 2005 and July 31, 2006. The reason for using this time interval is to take as a reference the date with clearest images in terms of clouds, that is, closest to the dry season (de Almeida et al., 2021) and where the satellite can detect the largest extent of the forest.

[15]We classify the following list of parties as left-wing: *Partido Democrático Trabalhista* (PDT), *Partido Trabalhista do Brasil* (PT do B), *Partido Comunista do Brasil* (PC do B), *Partido dos Trabalhadores* (PT), *Partido Socialista Brasileiro* (PSB), *Rede Sustentabilidade* (Rede), *Partido Verde* (PV), *Partido Socialismo e Liberdade* (PSOL), *Partido da Mobilização Nacional* (PMN), *Partido Socialista dos Trabalhadores Unificado* (PSTU). We classify every other party as right-wing.

elections each year. Table B.1 reports the threshold for the young definition and Table B.2 the number of municipalities by year that enter each sample of close elections.

Emissions We use the emissions data from *Sistema de Estimativas de Emissões e Remoções de Gases de Efeito Estufa* (SEEG) (Sistema de Estimativa de Emissões e Remoções de Gases de Efeito Estufa, Observatório do ClimaSEEG, n.d.; De Azevedo et al., 2018). SEEG classifies greenhouse gas emissions in five different sectors depending on the activity that produced the emissions: agriculture, energy, industrial processes, waste and land use. Emissions are measured in tons of carbon dioxide equivalent (CO_2e), so that different gases are comparable based on their global warming potential. The gases measured include carbon dioxide (CO_2), methane (CH_4), fluorinated gases, nitrous oxide (N_2O) and indirect emissions. Emissions generated by deforestation are not included in the agricultural category but rather in the land use category. We add these data to proxy environmental behavior by municipality and economic activity.

Agriculture We source information about agriculture from three sources, the *Produção Agrícola Municipal* (PAM) and *Pesquisa da Pecuária Municipal* (PPM) surveys and the Agricultural Census. The first two are annual surveys covering our whole period while the latter is a census with data available for 1995, 2006, and 2017. They all come from the *Instituto Brasileiro de Geografia e Estatística* (IBGE) and are pre-processed by the Data Basis project (Dahis et al., 2022).

Municipal Revenues and Expenditures We collect annual data about municipal governments' revenues and expenditures from the *Sistema de Informações Contábeis e Fiscais do Setor Público Brasileiro* (SICONFI) dataset. This includes a classification of expenditures by area (e.g. agriculture, education). The data are pre-processed by the Data Basis project (Dahis et al., 2022).

Rural Credit We use the *Matriz de Dados do Crédito Rural* (MDCR) compiled by the Central Bank of Brazil, which constitutes a comprehensive administrative record of rural credit operations at the municipal level.[16] The dataset includes the total value of rural credit (in R$) provided by public and private financial institutions to each municipality.[17] We categorize the credit amounts according to their declared final use, distinguishing be-

[16] The data are available at `https://www.bcb.gov.br/estabilidadefinanceira/micrrural`.

[17] Additional information can be found at `https://www3.bcb.gov.br/mcr`.

tween agriculture and cattle. To account for heterogeneity in municipal size, we normalize the total amount of credit by the municipality's area (in hectares).

Employment We construct annual measures of bureaucratic turnover from the *Relação Anual de Informações Sociais* (RAIS) dataset, which covers the universe of employment relations in the Brazilian formal private and public sectors. The data contain information about every job, person, and employer, such as the wage earned, occupation and economic sector categorizations, age, and gender.

4.2 Sample selection

We select our sample of municipalities with the following procedure. Out of all 5,570 municipalities in Brazil, we restrict attention to the 772 in the Legal Amazon. We impose sequential constraints, each implying further reductions in sample size in parenthesis: they must have data reported in PRODES (760), they must have positive forest area reported in the year 2000 (588), and they must have 90% or more of their area in 2000 be not covered by clouds (575). Over four electoral cycles, out of the 2,300 (575×4) observations remaining, we further require that the term's mean deforestation as a share of 2000 forest area be below the 90^{th} percentile over the whole 2005-2020 period. This reduces the sample to 2,071 elections (410 in 2004, 546 in 2008, 561 in 2012, and 554 in 2016). Finally, out of these, we restrict attention to elections with one young and one not young in the top two. This yields a sample of 375 elections (61 in 2000, 104 in 2008, 96 in 2012, and 114 in 2016).

Finally, the optimal bandwidth for the main RD specification in Table 2 Panel A Column 3 restricts that sample to 188 elections, as reported in Table 1 Panel B in Columns 3 and 4. Hereafter we refer to this sample as the "sample of close elections." We report sample sizes for other specifications in each corresponding Table, Panel, and Column.

4.3 Summary statistics

Table 1 presents summary statistics. Columns 1-4 present the mean and standard deviation for four different groups of municipalities: (1) all Brazilian municipalities except those in the Legal Amazon; (2) municipalities in the Legal Amazon that do not enter the sample of close elections; (3) municipalities where a young candidate won a close election; (4) municipalities where a young candidate lost a close election (the "control" group). Column 5 presents the difference in means between the group of municipalities where the young candidate won versus the group where the young lost. Column 6 assesses if characteristics are discontinuous at the cutoff. Panel A presents data at the municipality level. Panel B reports characteristics of the young candidate at the election (municipality-term) level. Panel C reports other characteristics of the elections.

Panel A shows that the municipalities in the sample of close elections are on average slightly poorer, less populated, and had a higher percentage of people aged 35 years old or less in its population as compared to other municipalities outside the sample of close elections (inside or outside the Amazon). They had similar levels of forest area in 2000. In Column 6 we find that around the cutoff, municipalities where the young candidate won have 4.96 percentage points more people under 35 years old than where the young candidate lost. We will return to this point when interpreting our results below.

Panel B reports summary statistics about the young candidates that barely won and barely lost the election.[18] In Columns 1-4 we see that the characteristics of the young candidates are broadly similar across all groups. Young candidates are on average about 31.5 years old, are 88% male, are about 71% right-wing, and receive R$6.57-8.93 (approximately U$1.5) per capita in campaign donations. The exception is that young candidates in the sample of close elections are about 10 percentage points more likely to be married. By construction of our RD design we would expect all such characteristics to be continuous at the cutoff between Columns 3 and 4. We validate that in Column 6, which shows no statistically significant differences at the cutoff except for a dummy for whether the candidate is an incumbent. In our sample at the cutoff the winner young candidate was 20 percentage points more likely to be incumbent in office. As an extra validity check, we follow Bertoli and Hazlett (2023) and test whether a predicted "Young Won" variable is continuous at the cutoff. We report in Table A.4 that this is indeed the case.

Panel C reports other summary statistics about the elections. In particular, we have that the average age difference between the younger and older candidates in the sample of close elections is about 17.5 years. That difference is reassuringly not discontinuous at the cutoff in Column 6. We also see that average deforestation over the previous 4-year term as a share of forest in 2000 to be 1.97 in Column 3 and 1.33 in Column 4. This is in line with the average in municipalities in the Amazon outside our sample in Column 2 and is consistent with the high rates of deforestation reported by PRODES in the region over our sample period. The difference in Column 6 is also not significant. Finally, in Figure A.2 we cannot reject that the running variable is continuous at the cutoff (McCrary, 2008; Cattaneo et al., 2020a).

[18]In Columns 1 and 2, if there were multiple young candidates running we take averages.

5 Results

We first estimate the effect of being governed by a young mayor on deforestation in Section 5.1. We estimate similar specifications for economic activity and greenhouse gas emissions in Section 5.2. We discuss in detail how municipalities governed by a young mayor spend local revenues and how rural credit is impacted in Section 5.3. We report in Section 5.4 how young mayors turn over the bureaucracy, in particular by hiring more young bureaucrats. We further unpack our results with heterogeneity analyses in Section 5.5.

5.1 Effect of being governed by a young mayor on deforestation

Our first finding is that when a municipality is governed by a young mayor, there is a reduction in deforestation. Table 2 presents the results of estimating Equation (1). Columns 1, 4 and 7 present the results controlling only for deforestation in the previous term, while other columns include more controls. In Columns 2, 5 and 8 we control for the logarithm of population and the mayor's gender. Columns 3, 6 and 9 are our preferred specifications, where we also control for party alignment (left or right), incumbency, marital status, and college completion. These last controls are correlated with age, and might capture part of the difference between young and not young mayors. However, the coefficients do not vary much among columns, as shown in the Table. For each regression in the first three Columns, we recalculate the optimal bandwidth for the given data. In Columns 4-6, we fix the bandwidth to that of our preferred specification (Column 3) so that we compare results with the same margin of victory. In Columns 7-9 we exclude municipalities where a young mayor won in the past, possibly affecting current treatment status. Panel A estimates the effect of a young mayor in office when he or she won the election to any other not young candidate. Panel B restricts the sample to elections with a young and a senior candidate in the top two.[19] Finally, Panel C compares the senior candidates with any other not senior candidate. All columns show a reduction in deforestation when a young mayor is in office. Figure 2 shows the corresponding regression discontinuity plot for our main result in column 3, Panel A.

We start discussing the results from Panel A Column 3. It shows that when a young mayor is in office deforestation is 0.23 percentage points smaller compared to municipalities where the young mayor barely lost the election. Compared to the mean of 0.45% of

[19]As discussed above, we define young and senior candidates as being below the 20^{th} percentile and above the 80^{th} percentile of the candidates' age distribution in the election, respectively. This is approximately below 35 years for young and above 54 years for seniors.

the forest area deforested each year in the control's sample, this is a substantial reduction of about 51% in the deforestation rate. The effect is even larger at 0.55 percentage points in Panel B Column 3 where we restrict the control group to elections with a senior candidate in the top two, although the sample size is about one fourth of the sample size in Panel B. Panel C shows a slight increase in deforestation comparing municipalities with senior mayors with the rest of the municipalities, but statistically we cannot reject the effect being null. Note that we do not include a Panel comparing senior versus young candidates because the results are symmetric to Panel B.

In Figure 3 we decompose the effects by each year within the mayor's term. We find that the first coefficient is statistically significant at 5% level. Figure 3 shows graphically that the effects of young mayors in office start materializing immediately after they take office. However, we run an F-test to see whether the four coefficients are jointly equal and cannot reject the null (p-value 0.80). Moreover, Figure A.3 shows the results by electoral term. Although the confidence intervals are larger in certain terms, we find that the sign of the coefficient is always negative. Again, we cannot statistically reject that these coefficients are the same (p-value 0.39).

Robustness Our results withstand a large set of robustness checks. A first concern from our design is that there might be cases of mayors classified as young in one election but not young in the next election. This could attenuate our estimates to zero. To address this, we exclude from our sample those observations where the mayor was previously classified as young and re-estimate Equation (1). The sample sizes are reduced by 8% from 656 to 604 between columns 3 and 9, but the coefficients in Table 2 Columns 7-9 are remarkably similar to those in Columns 1-3.

Second, we introduce an alternative to the main RD design, which is to use a difference-in-differences (DD) specification with municipality fixed effects. Among our sample of close elections in year t, we restrict attention to those that did not have a young mayor in the previous election $t-1$. We then build the DD sample by stacking each pair of observations (pre and post) for each municipality. Table A.5 presents the results. Column 1 repeats the main specification in Equation (1), while Column 2 restricts the RD regression to the DD sample. Columns 3 and 4 present the DD results with all controls and exogenous controls only, respectively. Note that the number of observations in these two columns is twice that of Column 2 because for each municipality-year we include a pre-period observation. All Columns in Table A.5 show an even larger reduction in deforestation when the young mayor is in office. We interpret this as evidence that any initial differences in deforestation between the municipalities that barely elected young mayors are not driving the results.

Table A.6 presents the results when we vary the age limit to define a candidate as young. We still observe a reduction when we use 15th percentile of age. When we apply a quadratic and cubic polynomial in the margin of victory, the main results are even larger (see Table A.7). The main results are also robust to different error estimations (see Table A.8). We use a triangular kernel in the main specification following Cattaneo et al. (2020b), but we also present robustness to Epanechnikov and Uniform kernels (see Table A.9). The results are broadly robust in all columns as we change kernels and bandwidths.

We assess the possibility of reverse causality in a placebo exercise in Table A.10, where we assign deforestation four years prior as the dependent variable. In Columns 1-3 we allow for the bandwidth to be optimally chosen while in Column 4-6 we set it to the same 11.22 bandwidth as in Table 2 Panel A Column 3. Reassuringly, we find statistically insignificant coefficients in all columns.

Figure A.4 presents the results of the sensitivity analysis for our preferred specification (Table 2 Panel A Column 3). In Figure A.4a we vary the bandwidth between half and twice the optimal bandwidth. The coefficient is always statistically significant at 5% up to 22 percentage points of vote share margin. Figure A.4b implements a "Doughnut" test, where we sequentially remove subsets of data around the cutoff. We report the resulting sample sizes in brackets in the horizontal axis. We find that the coefficient is still negative and statistically significant when removing observations up to 1 percentage point. Beyond that the coefficient turns statistically insignificant and growing confidence intervals.

Figure A.5 presents robustness results when dropping potential outliers based on forest area and outliers based on deforestation thresholds. We sequentially drop subsets of observations below certain baseline forest area levels (e.g. 5, 10, 20 km^2) or above certain deforestation area levels (e.g. 160, 80, 40 km^2). The coefficients are similar when we remove observations up to 20 km^2 in forest area and smaller after that (Figure A.5a). The coefficients remain very similar when removing municipalities with high deforestation (Figure A.5b).

In a final robustness exercise Table B.3 shows the results excluding observations where the mayors were in their second term. Despite a sample about 12% smaller, the results remain qualitatively unchanged. The coefficient in Panel A Column 3 is -0.26, out of an average in the control group of 0.45%.

5.2 Effect of being governed by a young mayor on other outcomes

We are interested in how having a young mayor in office can impact other economic and environmental variables beyond deforestation. We re-estimate Equation (1) and document the effects on economic activity, emissions, and agricultural outcomes in Table 3.

Column 1 shows that per capita GDP is not affected when a young mayor is in office. We estimate a statistically insignificant coefficient of R$3.46 thousand per capita. Columns 2 and 3 show the results for the percentage of GDP by economic sector. We find a 6.23 percentage point reduction in the agricultural sector share and an increase of 6.03 percentage points in industry when a young mayor is in office.[20] Compared to the control group which on average has the GDP composed of 27.7% agriculture and 7.7% industry, these account for a reduction of 22.4% and a substantial increase of 78%, respectively. Columns 4 to 8 study what happens to greenhouse gas emissions per capita when a young mayor holds office. Column 4 shows a reduction in the total emissions of 36.9 CO_2e tons, which is equivalent to a 43.9% decrease if compared to the control mean.[21] As reported in Columns 5 and 6, part of this reduction is explained by a reduction in emissions associated with land use, with a coefficient of about -32.72, or 57.6% of the mean.[22] We find much smaller effects on emissions from energy or waste, which account about one percent or less of total emissions.[23] These effects on agriculture are somewhat corroborated in Columns 9 and 10 with statistically insignificant coefficients, negatively for the impacts of being governed by a young mayor on area planted and positively and small on the number of bovines (in thousands).

We find opposite results in Panel B for senior mayors. Municipalities governed by them do not show statistically significant increases in total emissions per capita in Column 4, but show small changes in emissions from energy and waste. Moreover, we document in Columns 9 and 10 that the area planted grows substantially by 1,013.4 hectares, or about 121% of the control mean, and the number of bovines grows by 67,300 heads, or 66.7% of

[20] IBGE defines the agricultural sector as including agriculture, livestock, fishing, aquaculture, and forestry production. It defines the industry sector as including manufacturing, production and distribution of electricity and gas, water, sewage and urban cleaning, and civil construction (Instituto Brasileiro de Geografia e Estatística , IBGE).

[21] Figure A.6 shows the RD plot for this result. Figure A.7 and Figure A.8 show the robustness of the results when we vary the bandwidth (Figure A.7a), drop some observations around the close elections cutoff (Figure A.7b), drop potential outliers in total emissions (Figure A.8a) and in emissions per capita (Figure A.8b).

[22] Deforestation is not included in the agricultural sector because it is accounted in the Land Use category (Sistema de Estimativa de Emissões e Remoções de Gases de Efeito Estufa, Observatório do ClimaSEEG, 2023).

[23] See Table B.4 for more details.

the control mean.

Column 11 in Table 3 Panel A shows that the coefficient for the number of fines applied by the national environmental agency (Ibama) is small and statistically insignificant. In Panel B we estimate an increase of 4.3 fines, or 45.7% of the control mean and significant at the 1% level, in municipalities governed by senior mayors. Given the effects we estimate on deforestation and other activities discussed above, this suggests that in our sample the intensity of sanctioning per area deforested went slightly up, despite general enforcement being low in Brazil (Ferreira, 2024).[24]

5.3 Local spending and rural credit

Two ways that mayors could potentially directly impact local deforestation and economic outcomes are via local government spending and the supply of rural credit. In this Section we test for these two mechanisms in the data.

Table 4 Panel A shows that municipalities governed by young mayors do not show a different pattern of local spending when compared to the control group. The shares of the budget allocated to the environmental sector (Column 1), to education (Column 2), or to agriculture (Column 3) do not change. The coefficients are small in magnitude and statistically insignificant. On the other hand in Panel B we find that municipalities governed by senior mayors show a reduction in environmental spending by 0.28 percentage points, a large reduction of equivalent size to the albeit low control mean in this sample.[25] We also find that municipalities governed by senior politicians spend 1.55 percentage points less in education, which amounts to approximately 9% of the control mean. We find no similar effects on agriculture spending.

Column 4 shows that municipalities governed by young mayors borrow less, with a coefficient that is economically meaningful but statistically insignificant. In Table B.8 Column 7 we unpack this result and show that it is driven by decreasing long-term liabilities. We find the opposite pattern for municipalities governed by senior politicians. They show a 5.5 percentage point increase in liabilities, driven mostly by increases in long-term liabilities (see Table B.8 Column 7) and equivalent to 44% of the control mean.[26]

[24] This is indeed what we find in Table B.5, which presents the results disaggregating by type of environmental fine. We do not observe a significant effect on fining intensity directly associated with deforestation (Columns 3 and 7). Table B.6 presents same analysis as Table B.5 but using the optimal bandwidth for each specification.

[25] As opposed to education or health, by law in our period of study municipalities did not have any minimum spending requirements on the environment. They must spend 25% of net tax revenues in education and 15% in health.

[26] Table B.9 and Table B.10 present the results analogous to Table 3 and Table 4 respectively, selecting the

Next, we study whether electing young mayors impacts the total amount of rural credit taken up in the municipality. We find in Table 4 Panel A Columns 5 and 6 that the effects are small and statistically insignificant. The analogous is not true for senior politicians in Panel B, where the effect in Column 6 is -10.31, or 32% of the control mean. It would take further research to unpack and understand these results, given the literature documenting the role of credit in agriculture and deforestation in the Brazilian Amazon (Assunção et al., 2020). Because of data limitations we unfortunately cannot measure whether results are driven by changes in supply, with mayors interfering and making less credit available or better targeted, or in demand, with farmers taking fewer loans endogenously to other changes in the municipality.

5.4 Turnover of bureaucrats

Another mechanism through which young mayors could affect local policy is by employing a younger bureaucracy. Renewing their staff, by firing senior bureaucrats and hiring young ones, can shift the local state capacity and better align the bureaucracy's preferences to the mayor's goals.

We test for this possibility in Table 5, estimating Equation (1) on turnover outcomes. In Column 1 we find that having a young mayor in office increases total turnover by about 9.3 percentage points, or a 19.1% increase relative to the control mean.[27] In Columns 3 and 4 we decompose this outcome by hires and separations, showing that the effect is more concentrated in hires. In Columns 5 to 8 we measure the percentage of total hires or total separations that were young or senior people. They measure to what extent turnover is concentrated across age groups. Following our definition from Section 3, we define a worker as "young" or "senior" if his age is below or above the twentieth or eightieth percentile, respectively. In Column 5 we find a coefficient of about 3.6 percentage points, i.e. young mayors concentrate hires more in young people compared to the control group. The effect is equivalent to about 6.9% of the control group's mean of about 52%. We do not find other statistically significant coefficients in Columns 6-8.

One potential concern is that our effects are not driven by young mayors *per se* but by the fact that young mayors also tend to be elected for the first time, and newly elected politicians turn over the bureaucracy more on average. We test this idea in Column 2. We

optimal bandwidth for each regression. The conclusions are similar.

[27] Municipalities in our sample of close elections had on average 624 public servants, out of which 42.86% were young. An average turnover rate of 48.62% means that on average about 303.39 ($= 0.4862 \times 624$) people turn over public employment in election years in our data.

construct a new sample of close elections with the running variable being the margin of the *new* candidate and estimate the exercise analogous to Equation (1) retaining the bandwidth fixed. We find that new mayors have no statistically significant effect on turnover, and the coefficient is only 1.94, almost a fifth of that of the young mayor in Column 1.

Our findings echo recent work showing that Brazilian mayors can cause significant turnover in the local bureaucracy. For example, Akhtari et al. (2022) find that political party turnover increases the share of personnel that is new to the bureaucracy by 7 percentage points (23% of the mean value). Toral (2024) finds that an incumbent's electoral defeat leads to a 41.9% increase in dismissals of temporary workers in the last three months of their term. In our case, despite such turnover being potentially driven by patronage (e.g. as found by Colonnelli et al. (2020) in Brazil), it is still associated with positive impacts on municipalities' environmental and economic outcomes. Lastly, among several political economy models consistent with these results, one interpretation in line with Egorov and Sonin (2011) is that young mayors have career concerns and hire bureaucrats more likely to support their agenda.

5.5 Heterogeneity analysis

The results in the previous Sections show that municipalities governed by young mayors show signs of better environmental conservation with no clear economic trade-offs. In this Section we further unpack our results with three exercises to aid interpretation.

First, because the RD design does not guarantee that the characteristics of the winning mayor are balanced at the cutoff, we document whether winning mayors are disproportionately of a certain profile in Table 6. As discussed by Marshall (2024), being young may be bundled with other demographic or political characteristics, which themselves could explain the effects of being governed by young mayors we estimate. We test for all mayors' characteristics available and find that only political leaning has a statistically significant coefficient at the cutoff. We find that young mayor winners are 26 percentage points less likely to be classified as right-wing than not young winners. All other characteristics, such as the mayor's gender, education, and campaign donations per capita received are balanced. We explicitly test for whether controlling for all these covariates qualitatively changes our main results in Table A.11 and find that is does not.

Second, beyond what characteristics are more frequently bundled with being young, we study to what extent our main effects are heterogeneous by these characteristics. In Table 7 we report a version of Equation (1) estimated with heterogeneous treatment effects.

Column 1 repeats the main result from Table 2 for ease of comparison. In the following Columns we report coefficients for the treatment variable (*YoungWon* or *SeniorWon*), the variable of interest, and the interaction $Treat \times Interaction$. We find that the effect of being governed by a young mayor on deforestation is essentially the same across the board. The analogous is true for the lack of effects estimated for senior mayors.

In Columns 2-9 we estimate heterogeneous treatment effects for having a college degree, being male, being married, being right-wing, being a farmer, the amount received in campaign donations, being in their second term, and running for the first time. In Panel A we find that the interaction coefficients are almost all small and insignificant. One exception is being married whose coefficient is 0.22 and statistically significant at the 5% level. The findings in Panel B are similar, with no meaningful heterogeneity by characteristics for senior mayors. Overall we do not adjudicate whether this is due to relatively small sample sizes to detect heterogeneous treatment effects or predictions born out of theory.

Finally, we exploit the full variation in age of the winner and the runner-up to assess from what part of the distribution comes the main effects estimated above. We begin by modifying the treatment dummy *Young Won* to *Younger Won*, i.e. we encode an indicator for the younger person running having won. This generalizes our previous definition of a young candidate having won and therefore expands our sample of close elections. We then estimate Equation (1) substituting *Young Won* for *Younger Won* and breaking the sample by combinations of age intervals between the younger and the older candidates.

We report results in Table 8. We report the number of observations in each regression in squared brackets below the coefficient and standard error. Panel A shows results for the full regression. We find that the average effect of being governed by the younger mayor on deforestation is small and statistically insignificant at 0.02. Panel B reports separate regressions for each combination of age intervals between the younger and the older candidate. In Column 1 we select younger candidates in each percentile age category ($\leq$ p20, between p20-40, between p40-p60, and between p60-p80) and allow for older candidates of any other age. We find that the negative effects on deforestation are concentrated in the sample of races between younger candidates below the 20^{th} percentile or below. Other coefficients are small and statistically insignificant, except for the sample of races with the younger candidate aged between p40-p60, which is positive at 0.16. Moreover, when we decompose the sample by specific combinations of ages for the older candidate and re-estimate the coefficient of interest in Columns 2-5 we find similar patterns. The effects are large and negative in races with younger candidates aged below the 20^{th} percentile across all other groups, and smaller but positive for those aged between p40-p60. As expected in Panel B in the first row, the coefficient in Column 2 is mechanically the same as in Table A.11 Panel A Column 3, and the coefficient in Column 5 is the same as in Table A.11 Panel B Column 3.

6 Discussion

In this paper, we study how politicians of different age groups impact environmental and social outcomes. We find evidence that municipalities with young mayors in office show lower rates of deforestation and greenhouse gas emissions, while directing the composition of local economic activity towards manufacturing. When exploring mayors' actions, we find no evidence of changing government spending but find significant bureaucratic turnover in favor of young public servants. Further unpacking and decomposition of results are consistent with a type of youth effect, with young mayors having average effects on deforestation regardless of the age of the runner-up candidate.

Having established the main results and explored *how* mayors acted, we close the paper with a discussion of how to interpret our findings. As elaborated in Section 1, our RD design rule out *demand*-side explanations, such as differences in local economic realities or electorate's tastes, and instead reflect a mix of *supply* channels, albeit locally, in areas where there was already substantial support for the young mayor's campaign in the first place. Our empirical investigation does not attempt to distinguish the reasons *why* young mayors differ from other mayors. We provide a brief discussion about it next, but leave this agenda as an open avenue of future research.

As outlined by Alesina et al. (2019b), young politicians may differ from older ones in a variety of ways. They may have stronger career incentives; they have longer life horizons ahead of them; they may be more energetic, tech-savvy, and productive at work; they may have larger and more dynamic social networks and be less subject to special interests. They may also have different discount factors or attitudes toward risk.[28] They may have different preferences towards nature after being exposed to more climate-related education and news. They may also have fewer children than the average politician.[29] Disentangling to what extent each of these channels explain our findings will require further

[28] A comprehensive meta-analysis by Seaman et al. (2022) examined 37 cross-sectional studies involving over 104,000 participants to assess the relationship between age and temporal discounting. They found no substantial correlation between age and temporal discounting, suggesting that younger, middle-aged, and older adults exhibit similar preferences for immediate versus delayed rewards. Meissner et al. (2023) find that age is positively correlated with risk aversion and negatively correlated with loss aversion.

[29] Görlitz and Tamm (2020) find that men and women experience a considerable increase in risk aversion around the time of first childbirth. This increase already starts as early as two years before they become parents, it is largest shortly after childbirth and it disappears when the child becomes older.

research.

A second avenue of future research is to determine whether our estimates are driven by age, cohort, or time effects. For example, it could be that young mayors matter because they are part of a new generation more attuned to the dangers of climate change, and that effect will last as they age and time passes. These effects could also be driven by age alone, such that electing young mayors at any time would cause similar results but as mayors age they would act differently. There can also be combinations of effects such as younger mayors being quicker to adapt to or embrace new technologies or regulatory tools, while older mayors might be more embedded in pre-existing political norms or relationships. Studying these will require new data, such as opinion surveys, or further structural assumptions. With larger sample sizes one could re-estimate our RD regressions separately by election year and measure how estimates vary over time.

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7 Tables and Figures

Table 1: Summary statistics

Variable	Brazil	Legal Amazon	Young in the Top 2 in Close Elections: Young Won	Young Lost	Young Won (3) vs. Lost (4): Difference	RD
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Characteristics of the municipality						
Area (km2)	723.33	6,333.46	6,916.15	8,008.04	-1091.89	3,117.51
	(1,498.55)	(13,716.16)	(12,224.49)	(14,207.28)	(2,241.87)	(3,292.17)
GDP (000s) per capita in 2002	5.47	3.70	2.97	3.25	-0.29	-0.09
	(6.01)	(4.09)	(1.74)	(1.97)	(0.32)	(0.56)
Population in 2002	32,072.88	29,311.12	16,912.58	19,105.78	-2193.21	2,490.11
	(201,206.06)	(95,420.64)	(15,432.44)	(19,553.55)	(2,983.25)	(6,521.58)
% Young population in 2000	58.82	68.62	69.25	70.93	-1.68*	4.93**
	(6.15)	(5.36)	(6.11)	(5.09)	(0.96)	(1.92)
Forest area in 2000 (km2)	–	4,323.60	4,743.95	6,010.01	-1266.06	3,817.99
		(13,119.07)	(11,668.22)	(12,840.28)	(2,078.99)	(2,713.75)
Number of Observations	4,794	632	74	65		
Panel B: Characteristics of the young candidate						
Age	31.06	31.10	31.64	31.48	0.16	-0.10
	(3.12)	(3.13)	(2.88)	(2.93)	(0.45)	(0.79)
College	0.57	0.46	0.47	0.46	0.01	0.01
	(0.49)	(0.49)	(0.50)	(0.50)	(0.08)	(0.13)
Male	0.88	0.84	0.88	0.87	0.01	-0.01
	(0.32)	(0.36)	(0.33)	(0.34)	(0.05)	(0.09)
Married	0.53	0.50	0.59	0.62	-0.03	0.12
	(0.49)	(0.49)	(0.49)	(0.49)	(0.08)	(0.14)
Right-wing	0.74	0.71	0.71	0.70	0.01	-0.12
	(0.43)	(0.44)	(0.46)	(0.46)	(0.07)	(0.14)
Farmer	0.09	0.13	0.07	0.09	-0.02	0.03
	(0.28)	(0.33)	(0.25)	(0.29)	(0.04)	(0.07)
Campaign Donations (R$ per capita)	4.94	7.25	8.87	6.57	2.30*	-0.86
	(5.61)	(8.42)	(9.67)	(6.86)	(1.35)	(2.20)
Incumbent	0.11	0.12	0.07	0.10	-0.03	0.20**
	(0.31)	(0.32)	(0.25)	(0.30)	(0.04)	(0.08)
Number of Observations	2,872	369	76	89		
Panel C: Characteristics of the election						
Age difference between younger and older	18.29	16.89	17.95	17.44	0.51	-0.25
	(9.87)	(9.60)	(9.98)	(9.87)	(1.55)	(1.37)
Deforestation as % of 2000's forest area in previous term	–	1.59	1.96	1.33	0.63	0.69
		(2.40)	(4.69)	(3.21)	(0.62)	(1.15)
Number of Observations	2,872	369	76	89		

Notes: Mean and standard deviation (in parentheses) for municipal and mayor attributes by group. Column 1 includes municipalities outside the Legal Amazon. Column 2 contains municipalities in the Legal Amazon outside the sample of close elections. Columns 3 and 4 include municipalities in the sample of close elections (defined by the vote share margin in Table 2 Panel A), split by whether a young candidate won or lost. Columns 5 and 6 show the difference between Young Won (Column 3) and Young Lost (Column 4). Column 5 runs a t-test, and Column 6 runs a regression discontinuity with year and age difference fixed effects. Panel A reports characteristics at the municipality level. Panel B reports characteristics at the municipality-election year level. The number of observations between Panel A and Panel B may differ because municipalities can appear in multiple elections. *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 2: Effects on deforestation

Dependent variable:	Deforestation as % of 2000 forest area								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Young vs. Not young									
Young won	-0.23***	-0.22***	-0.23***	-0.25***	-0.22***	-0.23***	-0.24***	-0.22***	-0.21***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)
Mean Dep. Var. Control	0.45	0.46	0.45	0.46	0.46	0.45	0.47	0.47	0.46
Age Difference	17.01	17.24	17.28	17.24	17.24	17.28	17.29	17.29	17.33
Bandwidth	13.21	11.48	11.22	11.22	11.22	11.22	11.22	11.22	11.22
Number of Observations	760	668	660	668	668	660	612	612	604
Panel B: Young vs. Senior									
Young won	-0.23	-0.41**	-0.55***	-0.27	-0.41**	-0.57***	-0.27	-0.45***	-0.61***
	(0.17)	(0.16)	(0.15)	(0.17)	(0.16)	(0.15)	(0.17)	(0.16)	(0.15)
Mean Dep. Var. Control	0.45	0.46	0.46	0.46	0.46	0.46	0.48	0.48	0.48
Age Difference	28.57	28.50	28.13	28.78	28.78	28.86	28.62	28.62	28.70
Bandwidth	13.12	10.86	10.49	11.22	11.22	11.22	11.22	11.22	11.22
Number of Observations	196	176	164	180	180	176	164	164	160
Panel C: Senior vs. Not senior									
Senior won	0.00	-0.01	-0.02	0.03	0.01	0.00	0.03	0.01	0.00
	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Mean Dep. Var. Control	0.36	0.36	0.36	0.36	0.35	0.35	0.36	0.35	0.35
Age Difference	16.59	16.66	16.63	16.63	16.63	16.46	16.63	16.63	16.46
Bandwidth	14.14	15.82	16.52	11.22	11.22	11.22	11.22	11.22	11.22
Number of Observations	1,880	1,956	1,992	1,580	1,556	1,536	1,580	1,556	1,536
Controls	Lagged Deforestation	Pre-determined	All	Lagged Deforestation	Pre-determined	All	Lagged Deforestation	Pre-determined	All

Notes: This table presents the effect of having a young mayor (Panel A and Panel B) or a senior mayor (Panel C) on deforestation. The coefficients are estimated using Equation (1). Columns 1-3 use the optimal bandwidth of each regression. Columns 4-6 use the optimal bandwidth from Panel A Column 3. Columns 1 and 4 control only for deforestation four years prior. Columns 2 and 5 control additionally for the logarithm of population, percentage of young in the population in 2000, and gender. Columns 3 and 6 control additionally for incumbency, party alignment (left or right), marital status, and college completion. Columns 7-9 replicate the analysis in Columns 4-6 but excluding from the sample those municipalities whose mayor was classified as young in the past. Panel A restricts the sample to elections with one young candidate in the top two. Panel B restricts the sample to elections with exactly one young and one senior candidate in the top two. Panel C restricts the sample to elections in which a senior candidate was in the top two. All regressions control for year and age difference fixed effects, and the percentage of the municipality's area unobserved each year. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 3: Effects on other outcomes

	GDP			Emissions per capita (CO_2e tons)					Agriculture		# Fines
Dependent variable:	Per capita (000s)	Agriculture (%)	Industry (%)	Total	Agriculture	Land Use	Energy	Waste	Area (ha)	# Bovines (000s)	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: Young vs. Not Young											
Young won	3.46	-6.23***	6.03***	-36.87*	-4.83	-32.72*	0.53	0.15***	-175.35	10.27	1.75
	(3.01)	(2.06)	(1.88)	(20.80)	(4.15)	(18.32)	(0.34)	(0.04)	(220.42)	(29.95)	(2.77)
Mean Dep. Var. Control	14.10	27.71	7.72	84.09	25.82	56.74	1.15	0.36	794.31	134.40	6.65
Optimal bandwidth	11.22	11.22	11.22	11.22	11.22	11.22	11.22	11.22	11.22	11.22	11.22
Number of Observations	660	660	660	660	660	660	660	660	660	660	660
Panel B: Senior vs. Not Senior											
Senior won	1.80	1.69	-1.66	20.72	2.85	17.51	0.48*	-0.12***	1013.33***	67.32***	4.34**
	(2.68)	(1.31)	(1.29)	(22.04)	(2.36)	(21.32)	(0.25)	(0.04)	(233.63)	(18.91)	(2.02)
Mean Dep. Var. Control	15.58	26.75	8.77	51.51	20.33	29.68	1.09	0.40	837.01	101.26	9.40
Optimal bandwidth	16.52	16.52	16.52	16.52	16.52	16.52	16.52	16.52	16.52	16.52	16.52
Number of Observations	1,992	1,992	1,992	1,992	1,992	1,992	1,992	1,992	1,988	1,990	1,992

Notes: This table presents the results of having a young mayor (Panel A) or senior mayor (Panel B) on different economic and environmental outcomes. The coefficients are estimated from Equation (1). Each column contains municipalities in the sample of close elections (as defined by the optimal bandwidths in Table 2 Panels A and C), subject to data availability for each outcome. Column 1 shows the effect on the GDP (in thousands) per capita. Columns 2 and 3 present the results in GDP disaggregated by sector share. This share is calculated by dividing the value added of the Agricultural and Industry sectors respectively by the total nominal GDP of each year. Columns 4 to 8 are calculated dividing emissions (CO_2e tons) by population. All emissions data are provided by Sistema de Estimativa de Emissões e Remoções de Gases de Efeito Estufa, Observatório do ClimaSEEG (n.d.). Agricultural emissions "do not include emissions resulting from deforestation, other agro-industrial residues, and energy used in agriculture, which are accounted for in the respective sectors [...] in Land Use, Waste and Energy" (Sistema de Estimativa de Emissões e Remoções de Gases de Efeito Estufa, Observatório do ClimaSEEG, 2023, p.9). Columns 9 and 10 are calculated using data from *Pesquisa Agrícola Municipal* (PAM). Column 11 uses the number of fines provided by Ibama. All regressions include year and age difference fixed effects, and control for gender, party alignment (left or right), incumbency, marital status, college completion, logarithm of population and percentage of young in the population in 2000. Significance level: $*p < 0.10$, $**\ p < 0.05$, $***p < 0.01$.

Table 4: Effects on local spending and rural credit

	% Government spending				Rural Credit	
Dependent variable:	Environment (1)	Education (2)	Agriculture (3)	Liabilities (4)	Agriculture (5)	Cattle (6)
Panel A: Young vs. Not Young						
Young won	-0.03	-0.90	-0.06	-3.19	2.23	-2.41
	(0.06)	(0.67)	(0.10)	(3.29)	(7.46)	(7.42)
Mean Dep. Var. Control	0.22	17.17	0.62	13.03	19.70	43.72
Optimal bandwidth	11.22	11.22	11.22	11.22	11.22	11.22
Number of Observations	620	620	620	577	632	632
Panel B: Senior vs. Not Senior						
Senior won	-0.28***	-0.51	-0.02	3.11*	-2.07	-10.31***
	(0.05)	(0.40)	(0.06)	(1.61)	(6.11)	(3.61)
Mean Dep. Var. Control	0.29	17.00	0.57	12.21	22.49	32.65
Optimal bandwidth	16.52	16.52	16.52	16.52	16.52	16.52
Number of Observations	1,869	1,869	1,869	1,744	1,893	1,893

Notes: This table presents the results of having a young mayor (Panel A) or senior mayor (Panel B) on the allocation of government spending and rural credit. The coefficients are estimated from Equation (1). Each column contains municipalities in the sample of close elections (as defined by the optimal bandwidths in Table 2 Panels A and C), subject to data availability for each outcome. Columns 1 to 3 are calculated by dividing the expenditure per budget by the total budget of the municipality. Column 4 presents results on municipality liabilities as a percentage of municipality expenditure. Credit variables in Columns 5 and 6 are measured in Brazilian reais (R$) per hectare at the municipal level. All regressions include year and age difference fixed effects, and control for logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, and college completion. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 5: Effects on bureaucratic turnover

Dependent variable:	% Turnover		% Hires	% Separations	% Young Hires	% Senior Hires	% Young Separations	% Senior Separations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Young Won	9.27**		3.95**	2.01	3.57*	-0.34	3.03	0.29
	(4.00)		(1.79)	(2.76)	(1.87)	(0.60)	(1.87)	(0.95)
New Won		1.94						
		(2.72)						
Mean Dep. Var. Control	48.62	45.34	23.48	24.42	51.98	6.54	48.64	10.00
Bandwidth	11.22	11.22	11.22	11.22	11.22	11.22	11.22	11.22
Number of Observations	616	1,589	604	616	600	600	615	615

Notes: This table shows the effect of having a young mayor (Columns 1 and 3-8) or a first-time mayor (Column 2) on the number of people either hired or fired (separated) from the public sector. Coefficients are estimated using Equation (1) but changing the dependent variable. Each column contains municipalities in the sample of close elections (as defined by the 11.22 vote share margin bandwidth in Table 2 Panel A). All regressions include year and age difference fixed effects, and control for logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, and college completion. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 6: Characteristics of winning mayors

	Young in the Top 2			
	Young Won	Young Lost	Difference	RD
	(1)	(2)	(3)	(4)
Characteristics of the winner				
Age	31.64	48.92	-17.28***	-17.21***
	(2.88)	(9.16)	(1.09)	(1.56)
College	0.47	0.27	0.20***	0.19
	(0.50)	(0.45)	(0.07)	(0.13)
Male	0.88	0.89	-0.01	-0.04
	(0.33)	(0.32)	(0.05)	(0.09)
Married	0.59	0.71	-0.12	-0.08
	(0.49)	(0.46)	(0.07)	(0.13)
Right-wing	0.71	0.74	-0.03	-0.26**
	(0.46)	(0.44)	(0.07)	(0.13)
Farmer	0.07	0.11	-0.04	-0.06
	(0.25)	(0.32)	(0.05)	(0.08)
Donations per capita (R$ per capita)	8.79	8.14	0.65	-1.23
	(9.48)	(9.29)	(1.48)	(2.26)
Incumbent	0.07	0.16	-0.09*	0.03
	(0.25)	(0.37)	(0.05)	(0.11)

Notes: Mean and standard deviation (in parentheses) of candidates attributes splitting by the type of candidate who won. Column 1 contains municipalities in the sample of close elections (as defined by the 11.22 vote share margin bandwidth in Table 2 Panel A) where the young candidate won. Column 2 contains municipalities in the sample of close elections where the young candidate lost. Column 3 shows the difference between Young Won (Column 1) and Young Lost (Column 2) using a t-test to compare means. Column 4 uses a regression discontinuity with year and age difference fixed effects. *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 7: Heterogeneous effects of electing a young mayor

Dependent variable:	Deforestation as % forest 2000								
		Interaction variables as columns							
		College	Male	Married	Right wing	Farmer	Donations per capita	Second term	First time running
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Young vs. Not Young									
Treat	-0.23***	-0.26***	-0.14	-0.41***	-0.31***	-0.22**	-0.17*	-0.23**	-0.32***
	(0.09)	(0.09)	(0.14)	(0.12)	(0.11)	(0.09)	(0.10)	(0.09)	(0.11)
Treat × Interaction		0.10	-0.10	0.22**	0.11	-0.03	-0.01	-0.00	0.05
		(0.11)	(0.13)	(0.10)	(0.10)	(0.19)	(0.01)	(0.12)	(0.10)
Interaction		0.05	0.07	-0.06	-0.10	0.20**	0.01	-0.02	0.18**
		(0.09)	(0.09)	(0.07)	(0.08)	(0.10)	(0.00)	(0.07)	(0.07)
Mean Dep. Var. Control	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
Mean Interaction	-	0.47	0.88	0.59	0.71	0.07	8.79	0.07	0.84
Number of Observations	660	660	660	660	660	660	660	660	660
Panel B: Senior vs. Not Senior									
Treat	-0.02	0.03	-0.08	-0.03	-0.08	-0.04	0.01	-0.03	0.00
	(0.05)	(0.06)	(0.11)	(0.07)	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)
Treat × Interaction		-0.13**	0.07	0.01	0.08	0.11	-0.00	0.03	0.00
		(0.06)	(0.11)	(0.06)	(0.07)	(0.09)	(0.00)	(0.07)	(0.06)
Interaction		-0.01	-0.09	-0.00	-0.03	0.01	0.01**	-0.04	0.08
		(0.04)	(0.08)	(0.05)	(0.05)	(0.07)	(0.00)	(0.05)	(0.05)
Mean Dep. Var. Control	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36
Mean Interaction	-	0.39	0.87	0.73	0.78	0.19	7.68	0.26	0.26
Number of Observations	1,992	1,992	1,992	1,992	1,992	1,992	1,992	1,992	1,992

Notes: This table presents heterogeneous effects of having a young or senior mayor on deforestation. The coefficients are estimated using Equation (1) but adding an interaction term between the treatment dummy and the variable of interest. Each column contains municipalities in the sample of close elections (as defined by the 11.22 vote share margin bandwidth in Table 2 Panel A). Column 1 presents the results of the main specification with mayor controls. Columns 2 to 9 present the treatment interacted with mayor-related variables. Donations per capita are not available for 12 observations in the main specification sample (1.8%), mean was imputed in those cases. Panel A takes as a sample all municipalities with at least one young candidate among the first two candidates. In Panel B, the sample contains all elections in which a senior candidate was between the top two candidates. All regressions include year and age difference fixed effects, and control for logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, college completion, deforestation four years prior, and percentage of the municipality's area unobserved each year. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 8: Decomposing effects by age interval combinations

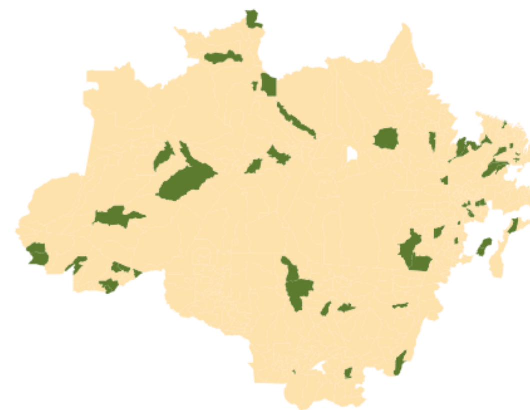
Dependent variable:	Deforestation as % forest 2000				
	Older Age				
	Any Age	$\geq p20$	$\geq p40$	$\geq p60$	$\geq p80$
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
Younger Won	0.02				
	(0.03)				
	[4703]				
Panel B: Age interval combinations					
Younger Age					
$\leq p20$	-0.23***	-0.23***	-0.43***	-0.43***	-0.55***
	(0.07)	(0.07)	(0.09)	(0.11)	(0.15)
	[676]	[660]	[424]	[280]	[164]
$(p20 - p40]$	0.05		0.06	0.07	0.03
	(0.05)		(0.06)	(0.07)	(0.09)
	[1316]		[1192]	[984]	[384]
$(p40 - p60]$	0.16***			0.13**	0.30***
	(0.05)			(0.06)	(0.11)
	[1000]			[896]	[380]
$(p60 - p80]$	-0.02				-0.06
	(0.09)				(0.10)
	[752]				[608]

Notes: Effect of having a younger mayor in the mayor office dissagregated by age interval combinations. Age percentiles are reported in Table B.1. The coefficients are estimated by using Equation (1) restricting the sample to races where the top two candidates were either younger and older in each age interval, respectively. All regressions contain year and age difference fixed effects and control for logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, college completion, deforestation four years prior, and percentage of the municipality's area unobserved each year. Each regression uses its optimal bandwidth. Effective number of observations are in brackets. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Figure 1: Municipalities in the sample of close elections by election year

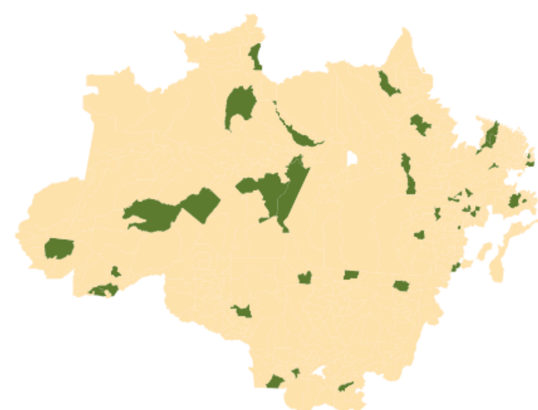
(a) 2004

(b) 2008



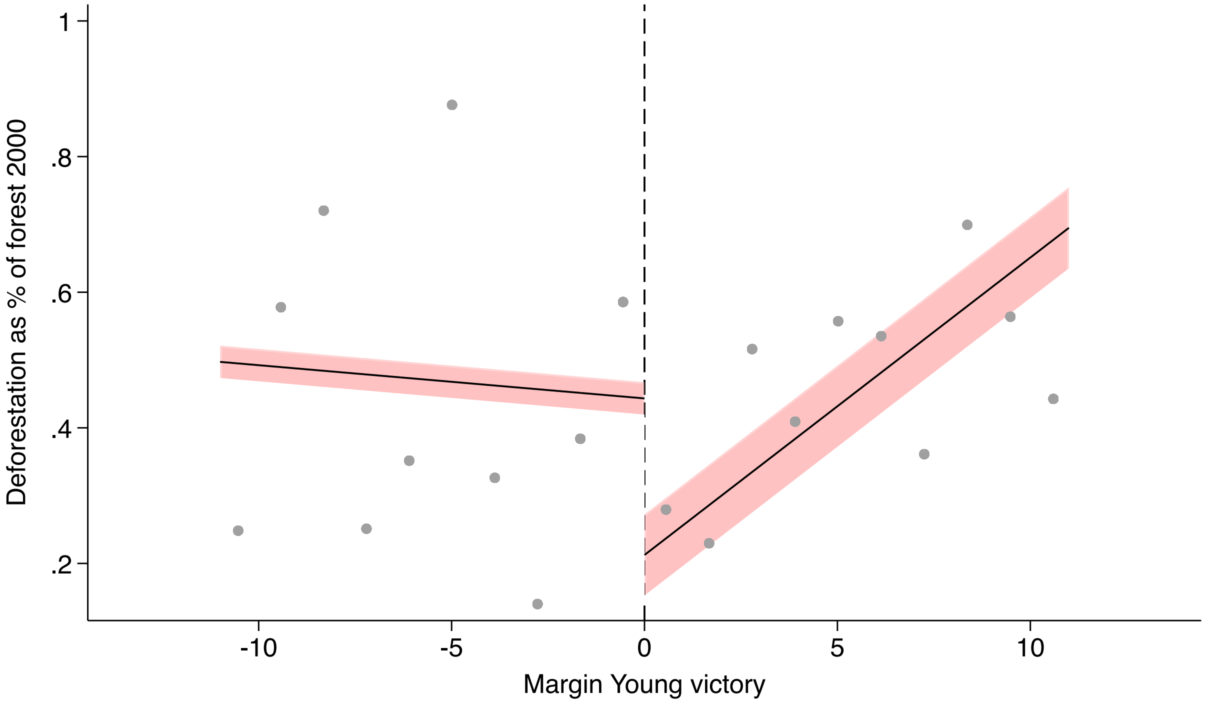
(c) 2012

(d) 2016



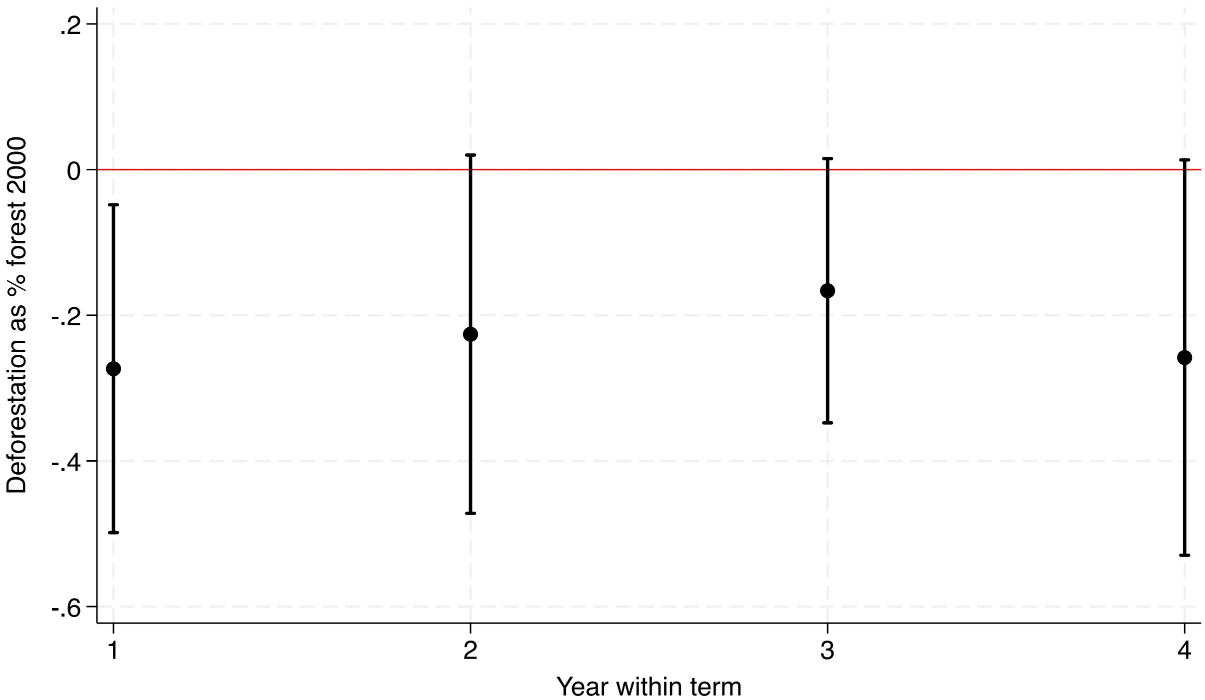
Notes: This figure presents the geographical distribution of the 164 municipalities in the sample of close elections (as defined by the 11.22 vote share margin bandwidth in Table 2 Panel A Column 3) by election year.

Figure 2: Visual regression discontinuity (RD) results



Notes: Regression Discontinuity plot of the main specification (Table 2 Panel A Column 3). Observations are grouped in 10 bins at each side of the winning cutoff. Triangular kernel is used. The regression controls for the logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, college completion, deforestation four years prior, the percentage of the municipality's area unobserved each year, and includes year and age difference fixed effects. The red area represents the 95% confidence interval.

Figure 3: Heterogeneous effects by year within term



Notes: This figure shows the effect disaggregated by year within term using the sample of close elections (as defined by the 11.22 vote share margin bandwidth in Table 2 Panel A Column 3). These coefficients have been computed interacting the treatment variable with each of the four years of government. The regression controls for the logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, college completion, deforestation four years prior, the percentage of the municipality's area unobserved each year, and includes year and age difference fixed effects. The bars represent the 95% confidence intervals.

A Appendix Tables and Figures

Table A.1: Descriptive representation by age groups

	Young Candidates		Senior Candidates		% Votes in Any Young		% Votes in Any Senior	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Young Voters	0.010***	0.531***			0.007***	0.067***		
	(0.002)	(0.041)			(0.001)	(0.001)		
% Senior Voters			0.026***	0.171**			0.049***	0.103***
			(0.005)	(0.068)			(0.004)	(0.002)
Young Candidates					17.600***	0.189***	-5.020***	-0.096***
					(0.056)	(0.002)	(0.059)	(0.002)
Senior Candidates					-1.174***	-0.058***	13.589***	0.036***
					(0.022)	(0.001)	(0.058)	(0.001)
ln(Voters)	0.050***	8.615***	0.327***	14.789***	-0.064	-0.478***	0.796***	0.575***
	(0.013)	(0.567)	(0.023)	(1.069)	(0.097)	(0.092)	(0.188)	(0.095)
% Male Voters	-0.002	-0.475***	-0.026***	-0.404***	-0.019**	-0.121***	0.055***	0.028***
	(0.004)	(0.071)	(0.008)	(0.093)	(0.008)	(0.007)	(0.016)	(0.009)
% High-School Voters	0.005	1.116***	0.050***	1.821***	0.015	0.032***	0.056***	0.046***
	(0.009)	(0.218)	(0.016)	(0.372)	(0.011)	(0.011)	(0.020)	(0.012)
% College Voters	0.004	-0.621	0.044	-0.689	-0.076***	0.219***	-0.338***	0.290***
	(0.022)	(0.629)	(0.043)	(1.136)	(0.022)	(0.022)	(0.040)	(0.024)
Number of Observations	3,412	3,412	3,412	3,412	178,011	177,966	178,011	177,966
R-squared	0.024	0.519	0.205	0.591	0.656	0.300	0.636	0.334
Municipality FE	-	-	-	-	✓	✓	✓	✓
Office	Mayor	Representative	Mayor	Representative	Mayor	Representative	Mayor	Representative

Notes: The sample includes data from the *Minas Gerais* state for the years 2000, 2004, 2008, 2012, 2016, and 2020. Columns 1 to 4 have data at the municipality-year level. Columns 5-8 have data at the electoral booth-year level. In this exercise, people 35 years or under are labeled *young*. Those 55 years of age or older are labeled *senior*. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A.2: Additional summary statistics

Variable	Mean	Std Dev	Min	Max	N
	(1)	(2)	(3)	(4)	(5)
Panel A: Municipality term					
Margin Young vs. Not Young	-0.41	6.13	-11.09	11.16	165
Margin Young vs. Senior	-0.66	5.87	-10.02	10.12	41
Margin Senior vs. Not Senior	-0.08	8.55	-16.43	16.51	498
Panel B: Other variables					
% Environmental expenditure	0.24	0.51	0.00	4.42	620
% Education expenditure	17.20	5.89	0.00	34.07	620
% Health expenditure	9.85	3.04	0.00	18.77	620
% Agro expenditure	0.65	0.71	0.00	4.85	620
GDP (R$ Current prices, 000s) per capita	14.60	15.68	1.44	180.94	660
Donations per capita	8.44	9.25	0.10	50.83	660
Agriculture as % GDP	25.55	14.95	0.78	72.72	660

Notes: Summary statistics (mean, standard deviation, minimum, maximum, and number of observations) of variables that we use. For donations per capita variable, 12 observations are not available, and the mean was imputed in those cases (1.8% of the main specification sample). Panel A contains information with variation across the municipality-election term, so there is one observation per municipality for four years. Panel B provides information about variables measured by municipality-year; nonetheless, the sample is restricted due to data availability. Exchange rate: 1 BRL $\sim$ 0.2 USD$.

Table A.3: Additional summary statistics by candidate

Variable	Brazil	Amazon	Sample	Young in sample
	(1)	(2)	(3)	(4)
College	0.48	0.41	0.39	0.47
	(0.50)	(0.49)	(0.49)	(0.50)
Male	0.89	0.85	0.88	0.88
	(0.31)	(0.35)	(0.33)	(0.32)
Married	0.75	0.70	0.65	0.58
	(0.43)	(0.46)	(0.48)	(0.49)
Right-wing	0.71	0.71	0.71	0.70
	(0.45)	(0.45)	(0.45)	(0.46)
Donations per capita (R$ per capita)	5.33	8.15	8.44	8.79
	(5.67)	(9.48)	(9.36)	(9.48)
Pro-Agriculture	0.13	0.13	0.12	0.08
	(0.33)	(0.34)	(0.32)	(0.27)
Number of Observations	50,773	8,431	522	187

Notes: Summary statistics (mean and standard deviation in parentheses) of candidates running for mayoral elections. Observations are at candidate-year level and include 2004, 2008, 2012 and 2016 elections. Donations per capita variables has less observations due to the lack on data reported in the original dataset (observations are 18,018, 2,700, 184, 86 for Columns 1, 2, 3 and 4, respectively). Column 1 shows the statistics using as sample all candidates running for any of the Brazilian municipalities removing those from the Legal Amazon. Column 2 restricts the sample to those municipalities belonging to the Legal Amazon that are not in the main sample of close elections (as defined by the 11.22 vote share margin bandwidth in Table 2 Panel A Column 3). Column 3 presents the running candidates statistics in the municipalities with close elections. Column 4 uses the same data as Column 3 but keeping only the young candidates. Each candidate is one observation.

Table A.4: Predicted "Young Won"

Dependent variable:	Predicted Young Won	
	(1)	(2)
Young Won	0.002	0.003
	(0.002)	(0.003)
Bandwidth	20.46	11.22
Number of Observations	254	163

Notes: We predict the variable "Young Won" based on our variables of interest and test whether that prediction is discontinuous at the RD cutoff (Bertoli and Hazlett, 2023). The list of predictors is logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, and college completion. It also includes year and age difference fixed effects. The coefficients are estimates using Equation 1 using the predicted "Young Won" and controls for the logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, college completion, deforestation four years prior, the percentage of the municipality's area unobserved each year, and includes year and age difference fixed effects. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Robustness using a difference-in-differences approach

Dependent variable:	Deforestation as % forest 2000			
	RD		DD	
	(1)	(2)	(3)	(4)
	Margin: Young vs. Not young			
Young Won	-0.23***	-0.27***	-1.80***	-1.67***
	(0.07)	(0.07)	(0.68)	(0.61)
Mean Dep. Var. Control	0.45	0.45	1.89	1.89
Controls	All	All	All	Pre-determined
Bandwidth	11.22	11.22	–	–
Coefficient Parallel Pre-Trends	–	–	15.51	7.33
	–	–	(19.16)	(5.75)
Number of Observations	660	576	1,152	1,152

Notes: This table presents the effect of being governed by a young mayor using two different approaches: regression discontinuity (RD) and difference-in-differences (DD). Coefficients in Columns 1 and 2 are estimated using Equation (1). Column 1 replicates Table 2 Panel A Column 3, while Column 2 restricts observations to those municipalities that will enter the DD specification, because they do not switch treatment status. Columns 3 and 4 estimate the DD specification, expanding the sample to include a period before the election. The parallel trends assumption is tested by computing the regression only in the pre-treatment period. RD estimations include year and age difference fixed effects and control for deforestation four years prior, logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, and college attendance. DD estimations also include municipality fixed effects. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A.6: Robustness to treatment and dependent variable

Dependent variable:	Deforestation as % forest 2000						
	p25		p20		p15		LEI No 11.692
	By-election	Whole sample	By-election	Whole sample	By-election	Whole sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A:	Margin: Young vs. Not Young						
Young Won	-0.09	-0.04	-0.23***	-0.09	-0.20**	-0.30***	-0.64***
	(0.06)	(0.06)	(0.07)	(0.07)	(0.09)	(0.09)	(0.12)
Mean Dep. Var. Control	0.42	0.40	0.45	0.44	0.47	0.47	0.53
Bandwidth	11.22	11.22	11.22	11.22	11.22	11.22	11.22
Number of Observations	912	996	660	740	420	468	176
Panel B:	Margin: Young vs. Not Young						
Young Won	-0.08	-0.03	-0.23***	-0.09	-0.19**	-0.29***	-1.10***
	(0.06)	(0.06)	(0.07)	(0.06)	(0.08)	(0.09)	(0.12)
Mean Dep. Var. Control	0.41	0.40	0.45	0.43	0.47	0.47	0.45
Optimal bandwidth	12.39	12.20	11.22	14.42	11.77	11.96	7.43
Number of Observations	992	1,060	660	908	420	476	108
Panel C:	Margin: Senior vs. Not Senior						
Senior Won	-0.08*	-0.05	-0.02	-0.05	-0.02	-0.03	-0.10
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.11)
Mean Dep. Var. Control	0.37	0.36	0.36	0.35	0.35	0.34	0.32
Bandwidth	16.52	16.52	16.52	16.52	16.52	16.52	16.52
Number of Observations	2,216	2,196	1,992	1,948	1,612	1,444	476
Panel D:	Margin: Senior vs. Not Senior						
Senior Won	-0.08*	-0.04	-0.02	-0.04	-0.01	-0.04	0.15
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.13)
Mean Dep. Var. Control	0.37	0.35	0.36	0.35	0.33	0.33	0.41
Optimal bandwidth	16.82	15.85	16.52	15.36	14.53	20.02	9.84
Number of Observations	2,240	2,132	1,992	1,880	1,512	1,620	312

Notes: This table presents the results when we vary the definition of young and senior to other percentiles. The coefficients are estimated using Equation (1). Columns 1 to 6 use different thresholds for defining Young based on percentiles. Column 7 uses the definition of young displayed in LEI No 11.692 "Programa Nacional de Inclusão de Jovens" where young is all people up to 29 years and we set old as the retirement age –65 years old–. From 1 to 6, odd columns compute percentiles using the percentile by electoral term in the same form as main specification, while even columns compute the percentile using the whole sample of candidates. Panels A and B take as sample all municipalities with at least one young candidate among the first two candidates. In Panels C and D, the sample contains all elections in which almost a senior candidate was between the first two candidates. Panels A and C use the sample of close elections in our main regression (as defined by the optimal bandwidths in Table 2 Panels A and C). Panels B and D use the optimal bandwidth for each regression. All regressions include year and age difference fixed effects and control for deforestation four years prior, logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), married, college completion, and percentage of the municipality's area unobserved each year. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A.7: Robustness to polynomial order

Dependent variable:	Deforestation as % forest 2000											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A:	Margin: Young vs. Not Young											
Young Won	-0.31***	-0.29***	-0.29***	-0.38***	-0.33***	-0.34***	-0.37***	-0.33***	-0.32***	-0.48***	-0.45***	-0.44***
	(0.09)	(0.09)	(0.09)	(0.11)	(0.10)	(0.10)	(0.11)	(0.10)	(0.11)	(0.14)	(0.14)	(0.14)
Mean Dep. Var. Control	0.44	0.43	0.42	0.46	0.46	0.45	0.43	0.43	0.43	0.46	0.46	0.45
Polynomial Order	2	2	2	2	2	2	3	3	3	3	3	3
Bandwidth	18.42	17.15	15.58	11.22	11.22	11.22	20.53	20.66	20.34	11.22	11.22	11.22
Number of Observations	964	928	856	668	668	660	1,036	1,036	1,024	668	668	660
Controls	Lagged Deforestation	Pre-determined	All	Lagged Deforestation	Pre-determined	All	Lagged Deforestation	Pre-determined	All	Lagged Deforestation	Pre-determined	All
Panel B:	Margin: Senior vs. Not Senior											
Senior Won	0.12	0.10	0.09	0.09	0.08	0.08	0.15*	0.11	0.12	0.19**	0.18**	0.18**
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)
Mean Dep. Var. Control	0.36	0.35	0.36	0.37	0.36	0.36	0.35	0.35	0.35	0.37	0.36	0.36
Polynomial Order	2	2	2	2	2	2	3	3	3	3	3	3
Bandwidth	14.28	14.72	14.77	16.52	16.52	16.52	22.20	26.10	23.19	16.52	16.52	16.52
Number of Observations	1,892	1,896	1,884	2,036	2,012	1,992	2,388	2,544	2,384	2,036	2,012	1,992
Controls	Lagged Deforestation	Pre-determined	All	Lagged Deforestation	Pre-determined	All	Lagged Deforestation	Pre-determined	All	Lagged Deforestation	Pre-determined	All

Notes: This table presents results using a second-order polynomial and third-order polynomial. Columns 1 to 3 and 7 to 9 are computed considering the optimal bandwidth using the second- and third-order polynomial, respectively. Columns 4 to 6 and 10 to 12 are restricted to the optimal bandwidth of the main specification of Table 2 (Column 3). Columns 1, 4, 7 and 10 control only for deforestation four years prior. Columns 2, 5, 8 and 11 control for logarithm of population, percentage of young in the population in 2000, gender, and deforestation four years prior. Columns 3, 6, 9 and 12 control for logarithm of population, percentage of young in the population in 2000, gender, deforestation four years prior, incumbency, party alignment (left or right), marital status, and college completion. Panel A takes as a sample all municipalities with at least one young candidate among the first two candidates. In Panel B, the sample contains all elections in which almost a senior candidate was between the first two candidates. All regressions include year and age difference fixed effects and control for the percentage of the municipality's area unobserved each year. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A.8: Robustness to different standard errors

Dependent variable:	Deforestation as % forest 2000		
	(1)	(2)	(3)
Panel A:	Margin: Young vs. Not Young		
Young Won	-0.25	-0.22	-0.23
Clustered Municipality-term Conventional	(-0.457,-0.039)	(-0.419,-0.025)	(-0.420,-0.042)
Clustered Municipality-term Robust	(-0.652,-0.049)	(-0.593,-0.022)	(-0.595,-0.044)
Clustered Municipality Conventional	(-0.457,-0.039)	(-0.419,-0.024)	(-0.421,-0.041)
Clustered Municipality Robust	(-0.651,-0.050)	(-0.591,-0.023)	(-0.594,-0.044)
HC0 Conventional	(-0.394,-0.101)	(-0.364,-0.079)	(-0.372,-0.089)
HC0 Robust	(-0.558,-0.143)	(-0.509,-0.105)	(-0.521,-0.118)
HC1 Conventional	(-0.395,-0.101)	(-0.364,-0.079)	(-0.373,-0.089)
HC1 Robust	(-0.559,-0.142)	(-0.510,-0.104)	(-0.521,-0.117)
HC2 Conventional	(-0.395,-0.101)	(-0.365,-0.079)	(-0.373,-0.089)
HC2 Robust	(-0.559,-0.142)	(-0.510,-0.104)	(-0.522,-0.117)
HC3 Conventional	(-0.396,-0.100)	(-0.365,-0.078)	(-0.374,-0.088)
HC3 Robust	(-0.560,-0.141)	(-0.511,-0.103)	(-0.523,-0.116)
Mean Dep. Var. Control	0.46	0.46	0.46
Bandwidth	11.22	11.22	11.22
Number of Observations	668	668	660
Controls	Lagged Deforestation	Pre-determined	All
Panel B:	Margin: Senior vs. Not Senior		
Senior Won	-0.02	-0.02	-0.02
Clustered Municipality-term Conventional	(-0.160, 0.129)	(-0.161, 0.125)	(-0.165, 0.121)
Clustered Municipality-term Robust	(-0.102, 0.286)	(-0.119, 0.266)	(-0.125, 0.263)
Clustered Municipality Conventional	(-0.160, 0.128)	(-0.161, 0.125)	(-0.166, 0.121)
Clustered Municipality Robust	(-0.102, 0.286)	(-0.120, 0.267)	(-0.125, 0.264)
HC0 Conventional	(-0.121, 0.089)	(-0.124, 0.087)	(-0.128, 0.084)
HC0 Robust	(-0.051, 0.235)	(-0.071, 0.218)	(-0.076, 0.214)
HC1 Conventional	(-0.121, 0.089)	(-0.124, 0.088)	(-0.128, 0.084)
HC1 Robust	(-0.051, 0.235)	(-0.071, 0.218)	(-0.076, 0.214)
HC2 Conventional	(-0.121, 0.089)	(-0.124, 0.088)	(-0.129, 0.084)
HC2 Robust	(-0.051, 0.235)	(-0.072, 0.218)	(-0.076, 0.214)
HC3 Conventional	(-0.121, 0.090)	(-0.124, 0.088)	(-0.129, 0.084)
HC3 Robust	(-0.051, 0.235)	(-0.072, 0.219)	(-0.076, 0.215)
Mean Dep. Var. Control	0.36	0.36	0.36
Bandwidth	16.52	16.52	16.52
Number of Observations	2,036	2,012	1,992
Controls	Lagged Deforestation	Pre-determined	All

Notes: This table presents in parenthesis the conventional and robust confidence intervals at 95% of confidence varying the kind of error correction used. Clustered errors are by municipality level. Robust bias-corrected is proposed by Cattaneo et al. (2020b) and is not point-centered. Bandwidths are restricted to the optimal bandwidth from Table 2 Panel A Column 3. Column 1 controls for deforestation four years prior. Column 2 controls for logarithm of population, percentage of young in the population in 2000, gender, and deforestation four years prior. Column 3 controls by logarithm of population, percentage of young in the population in 2000, gender, deforestation four years prior, incumbency, party alignment (left or right), marital status, and college completion. Panel A takes as a sample all municipalities with at least one young candidate among the first two candidates. In Panel B, the sample contains all elections in which almost a senior candidate was between the first two candidates. All regressions have year age difference fixed effects and control for the percentage of the municipality's area unobserved each year.

Table A.9: Robustness to kernels

Dependent variable:	Deforestation as % forest 2000											
Kernel:	Epanechnikov						Uniform					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A:	Margin: Young vs. Not Young											
Young Won	-0.24***	-0.21***	-0.21***	-0.21***	-0.20***	-0.20***	-0.21***	-0.19***	-0.18**	-0.20***	-0.16**	-0.18**
	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Mean Dep. Var. Control	0.46	0.46	0.45	0.44	0.45	0.44	0.46	0.46	0.45	0.46	0.45	0.45
Bandwidth	11.22	11.22	11.22	13.46	12.65	12.17	11.22	11.22	11.22	11.80	12.36	11.41
Number of Observations	668	668	660	768	736	692	668	668	660	684	712	660
Controls	Lagged Deforestation	Pre-determined	All	Lagged Deforestation	Pre-determined	All	Lagged Deforestation	Pre-determined	All	Lagged Deforestation	Pre-determined	All
Panel B:	Margin: Senior vs. Not Senior											
Senior Won	-0.03	-0.03	-0.04	-0.04	-0.03	-0.04	-0.04	-0.04	-0.04	0.00	-0.07	-0.05
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
Mean Dep. Var. Control	0.37	0.36	0.36	0.36	0.36	0.36	0.37	0.36	0.36	0.37	0.36	0.36
Bandwidth	16.52	16.52	16.52	18.63	16.20	17.04	16.52	16.52	16.52	11.93	17.51	15.59
Number of Observations	2,036	2,012	1,992	2,204	1,984	2,032	2,036	2,012	1,992	1,648	2,100	1,928
Controls	Lagged Deforestation	Pre-determined	All	Lagged Deforestation	Pre-determined	All	Lagged Deforestation	Pre-determined	All	Lagged Deforestation	Pre-determined	All

Notes: This table presents results of Table 2 using different kernels. Columns 1 to 6 use an Epanechnikov kernel, while Columns 7 to 12 use a Uniform kernel. Columns 1-3 and Columns 7-9 are restricted to the optimal bandwidth of the main specification of Table 2 (Column 3). Columns 4 to 6, and 10-12 are computed considering the optimal bandwidth using their respective kernels. Columns 1, 4, 7 and 10 control only for deforestation four years prior. Columns 2, 5, 8 and 11 control for logarithm of population, percentage of young in the population in 2000, gender, and deforestation four years prior. Columns 3, 6, 9 and 12 control for logarithm of population, percentage of young in the population in 2000, gender, deforestation four years prior, incumbency, party alignment (left or right), marital status, and college completion. Panel A takes as sample all municipalities with at least one young candidate among the first two candidates. In Panel B, the sample contains all elections in which almost a senior candidate was between the first two candidates. All regressions include year and age difference fixed effects and control for the percentage of the municipality's area unobserved each year. Significance level: $^{*}p < 0.10$, $^{**}\ p < 0.05$, $^{***}p < 0.01$.

Table A.10: Placebo results

Dependent variable:	Deforestation as % forest 2000					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	Margin: Young vs. Not Young					
Young Won future election	0.28	0.40	0.39	0.69	0.87	0.91
	(0.91)	(0.96)	(0.94)	(1.22)	(1.21)	(1.21)
Mean Dep. Var. Control	1.14	1.11	1.14	1.33	1.33	1.33
Age Difference	17.21	17.16	17.26	17.24	17.24	17.28
Bandwidth	19.63	17.41	18.53	11.22	11.22	11.22
Number of Observations	1,000	932	960	668	668	660
Panel B: Margin	Margin: Senior vs. Not Senior					
Senior Won future election	0.12	0.24	0.22	0.18	0.30	0.23
	(0.64)	(0.65)	(0.71)	(0.77)	(0.79)	(0.79)
Mean Dep. Var. Control	1.65	1.65	1.66	1.76	1.76	1.78
Age Difference	16.47	16.47	16.51	16.76	16.76	16.63
Bandwidth	24.78	24.68	20.44	16.52	16.52	16.52
Number of Observations	2,520	2,492	2,248	2,036	2,012	1,992
Controls	–	Pre-determined	All	–	Pre-determined	All

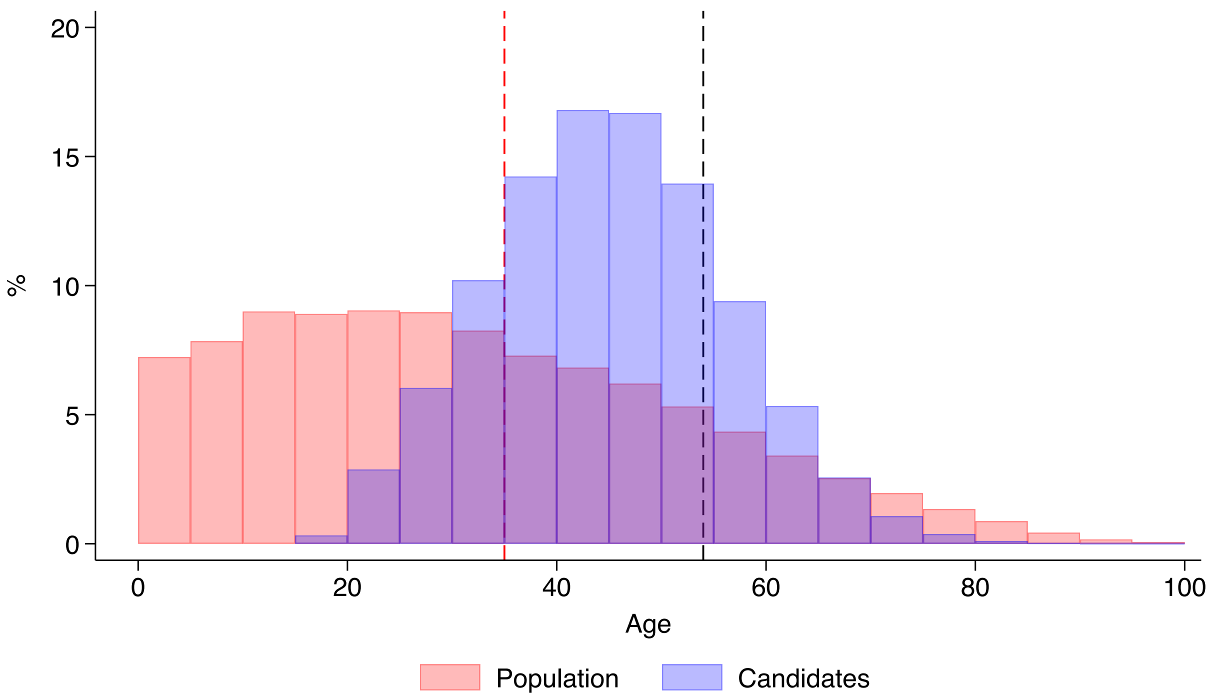
Notes: This table presents the placebo analysis. The coefficients are estimated using Equation (1), but the dependent variable is deforestation four years prior. Columns 1 to 3 are computed considering the optimal bandwidth. Columns 4 to 6 are restricted to the optimal bandwidth of the main regression (Column 3 of Table 2). Columns 1 and 4 include no controls because data on deforestation is unavailable for 1997-2000. Columns 2 and 5 control for logarithm of population, percentage of young in the population in 2000, and gender. Columns 3 and 6 control for logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, and college completion. Panel A takes as a sample all municipalities with at least one young candidate among the first two candidates. In Panel B, the sample contains all elections in which almost a senior candidate was between the first two candidates. All regressions include year and age difference fixed effects. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A.11: Results reporting mayor covariates' coefficients

Dependent variable:	Deforestation as % forest 2000								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Margin: Young vs. Not Young								
Young Won	-0.24***	-0.23***	-0.22***	-0.21**	-0.21**	-0.20**	-0.22***	-0.23***	-0.23***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)
Deforestation four years prior		-0.01**	-0.01**	-0.01**	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unobserved municipality area (%)			-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% Young population in 2000				-0.01	-0.01**	-0.01**	-0.01**	-0.01**	-0.01**
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Male					-0.02	-0.01	0.02	0.02	0.01
					(0.06)	(0.06)	(0.07)	(0.07)	(0.07)
Married						0.05	0.05	0.05	0.05
						(0.05)	(0.05)	(0.05)	(0.05)
College							0.10*	0.10	0.10
							(0.06)	(0.06)	(0.06)
Right-wing								-0.04	-0.04
								(0.05)	(0.05)
Incumbent									-0.02
									(0.05)
Mean Dep. Var.	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
Number of Observations	660	660	660	660	660	660	660	660	660

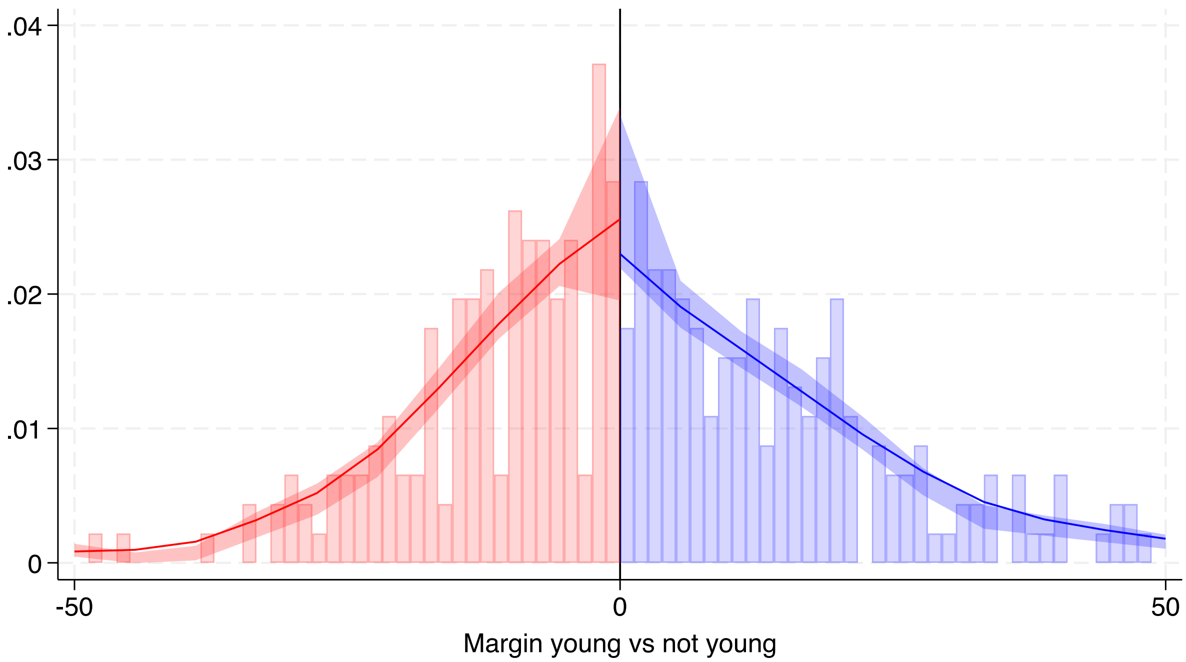
Notes: Coefficients of the controls using the sample of close elections in Table 2 Panel A Column 3. All regressions include year and age difference fixed effects. Columns 4-9 also control for the logarithm of population. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.1: Age distribution



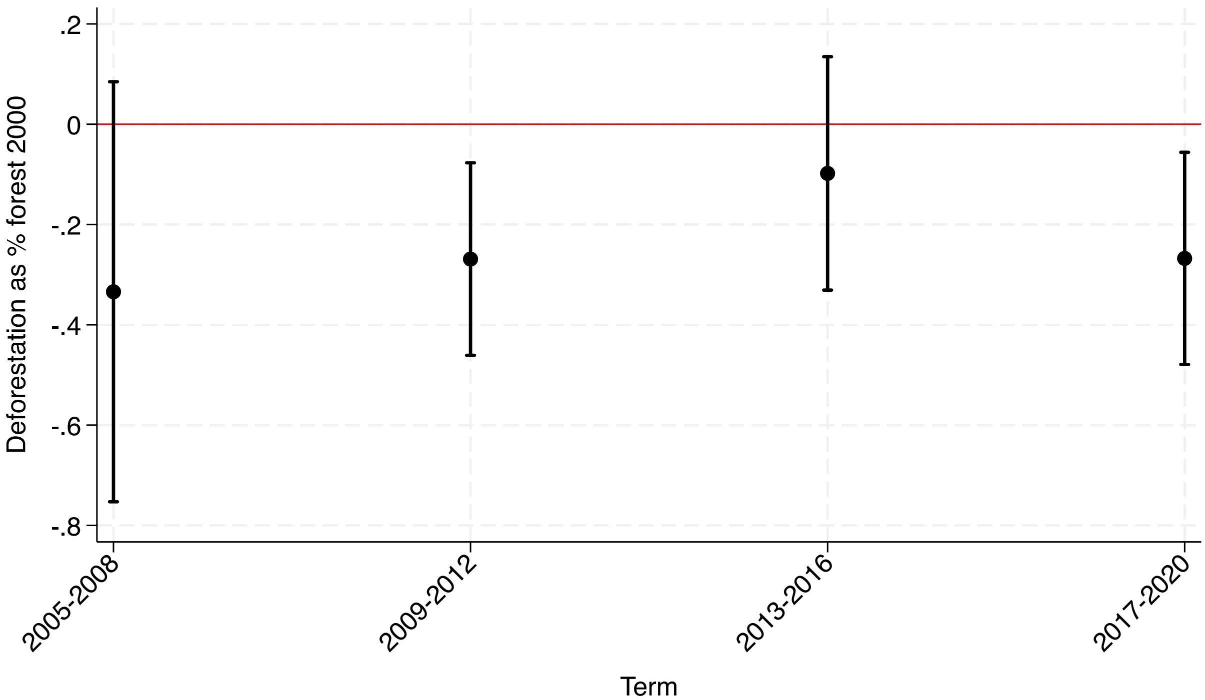
Notes: This histogram presents the age distribution of all candidates in ordinary municipal elections in Brazil during the elections included in the study period: 2004 to 2016 and the Brazilian population according to the 2010 Census. Lines in red and black show the 20th percentile of the age (approximately 35 years old) and the 80th percentile (approximately 54 years old) by election.

Figure A.2: Manipulation test



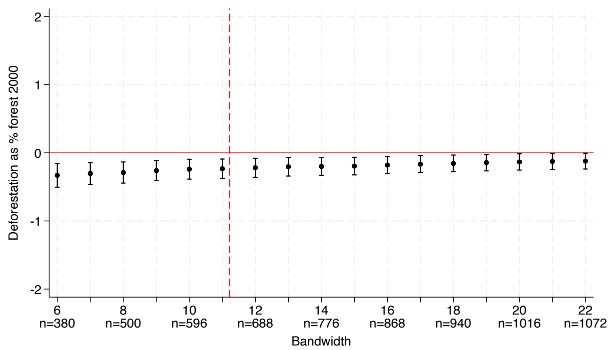
Notes: This figure presents the results from the manipulation test of the running variable in regression discontinuity designs based on McCrary (2008). The test implemented is proposed by Cattaneo et al. (2020a) and uses local polynomial density estimation. It includes the full sample of elections described in Section 3.

Figure A.3: Heterogeneous effects by election term

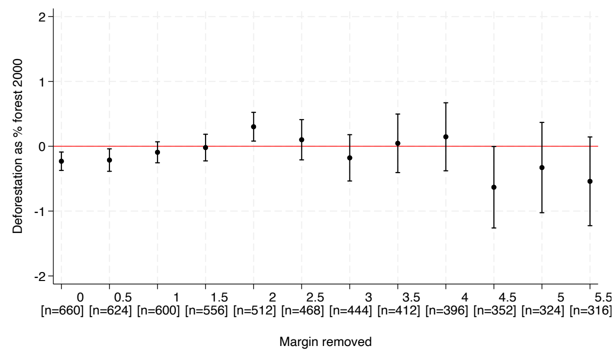


Notes: This figure shows the effect in Table 2 Panel A Column 3 disaggregated by election term. The coefficients are computed interacting the treatment variable with each election term. The regression controls for deforestation four years prior, logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, college completion, percentage of the municipality's area unobserved each year and it also includes year and age difference fixed effects. Confidence intervals at 95%.

Figure A.4: Deforestation sensitivity analysis



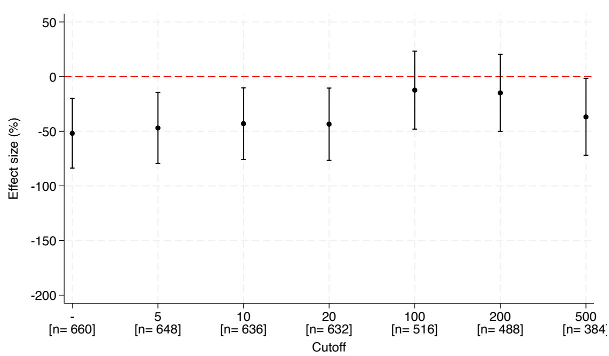
(a) Robustness to bandwidth



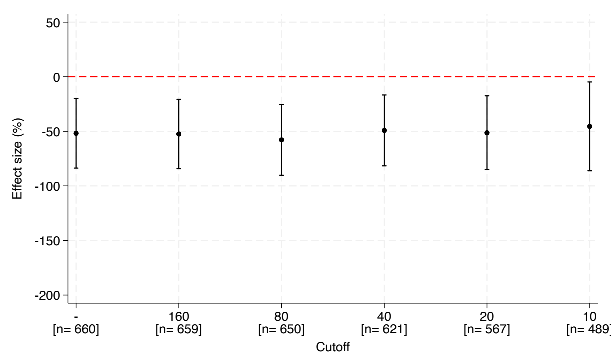
(b) Doughnut's Robustness

Notes: Sensitivity analysis of the main specification (Column 3 of Panel A in Table 2). On the one hand, in Figure A.4a we check the sensitivity of the result by varying the bandwidth between half and twice the optimal bandwidth. The red line represents the optimal bandwidth. On the other hand, in Figure A.4b by dropping different observations of the closest election, leaving a "doughnut" to check how the results are interpreted in the same way as proposed in Barreca et al. (2011). Regressions were estimated using Equation (1). They include year and age difference fixed effects, and control for deforestation four years prior, logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, college completion, and percentage of the municipality's area unobserved each year. 95% confidence intervals are shown.

Figure A.5: Sensitivity analysis of deforestation to outliers



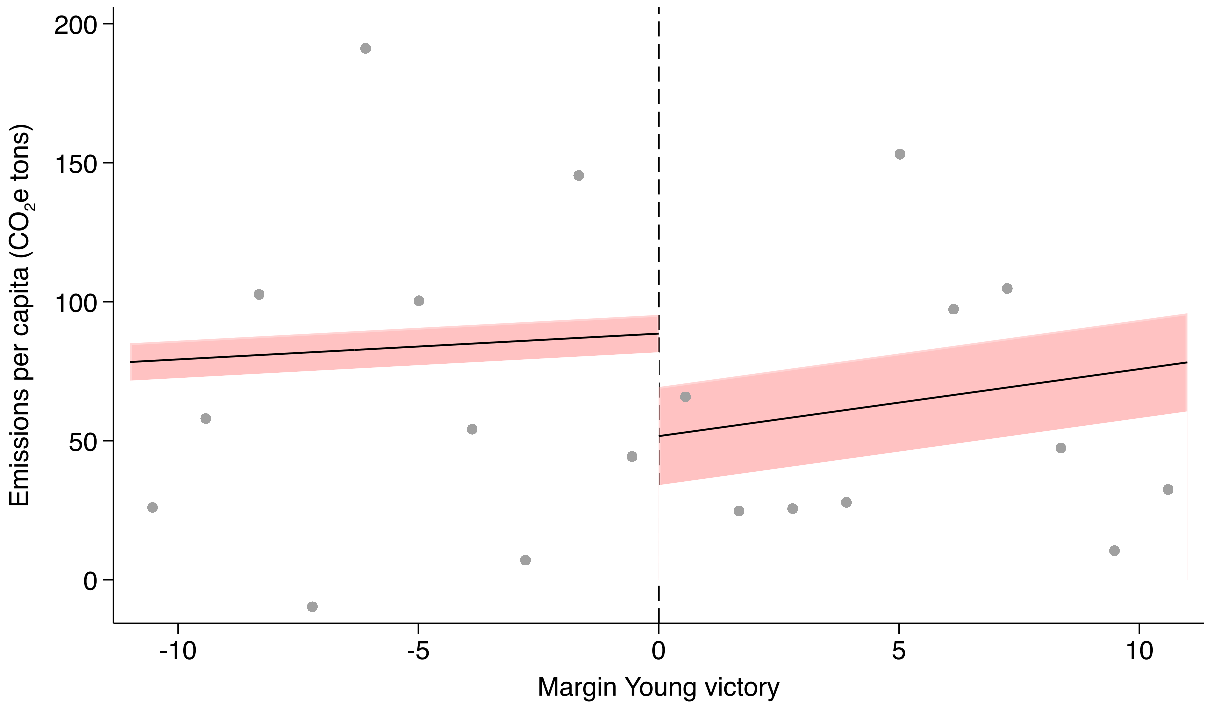
(a) Excluding forest area outliers



(b) Excluding deforestation outliers

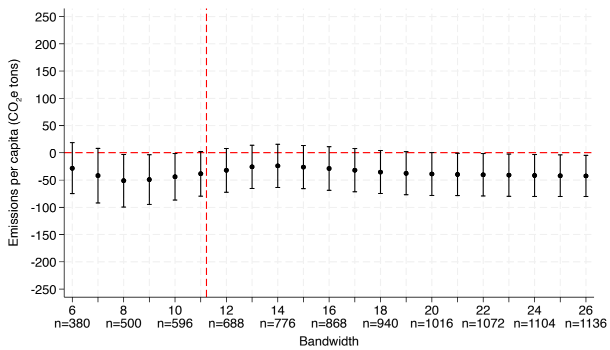
Notes: Results for the main regression (Table 2 Panel A Column 3) excluding outliers. Forest area outliers (Figure A.5a) are municipalities with forest area (km^2) below the cutoff indicated. Deforestation outliers (Figure A.5b) are those with a deforestation area (km^2) above the cutoff indicated. Regressions were estimated using Equation (1). They include year and age difference fixed effects, and control for deforestation four years prior, logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, college completion, and percentage of the municipality's area unobserved each year.

Figure A.6: Visual Regression Discontinuity (RD) in emissions per capita (CO_2e tons)

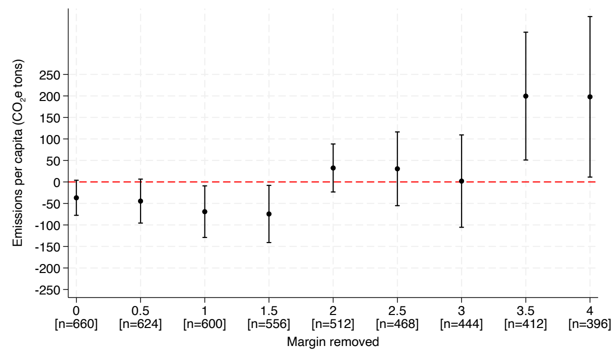


Notes: Regression Discontinuity plot using the emissions per capita (CO_2e tons) as dependent variable (Column 6 of Panel A in Table 3). Observations are grouped into 10 bins on each side of the winning cutoff. The regression controls for logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, college completion, and it also includes year and age difference fixed effects.

Figure A.7: Sensitivity analysis of emissions per capita (CO_2e tons)



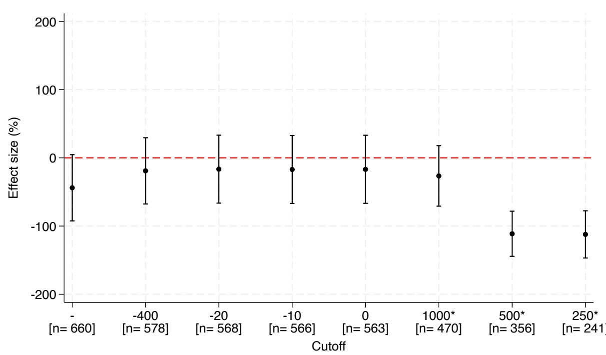
(a) Robustness to bandwidth



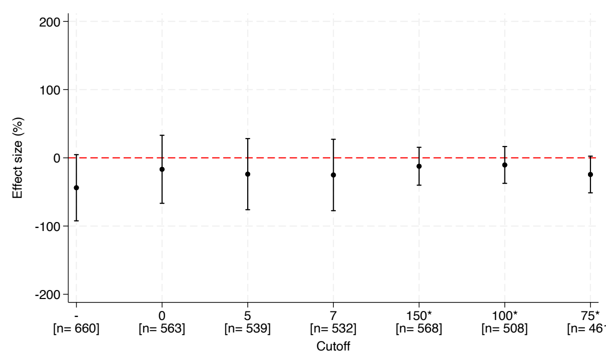
(b) Doughnut's Robustness

Notes: Sensitivity analysis of Column 6 of Panel A in Table 3. On the one hand, we check the sensitivity of the result in Figure A.7a by varying the bandwidth between half and twice the optimal bandwidth. The red line represents the optimal bandwidth. By the other hand, in Figure A.7b by dropping different observations of the closest election leaving a "doughnuts hole" to check how the results in the same way as is proposed in Barreca et al. (2011). Regressions were estimated using Equation Equation 1. They include year and age difference fixed effects, and control for logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, and college completion. 95% confidence intervals are shown.

Figure A.8: Sensitivity analysis of emissions per capita (CO_2e tons) to outliers



(a) Excluding total emissions (CO_2e tons) outliers



(b) Excluding emissions per capita (CO_2e tons) outliers

Notes: Results for Column 6 of Panel A in Table 3 excluding outliers. Given that the distribution of the total emissions involves both positive and negative values, to compute the outliers it is necessary to cut observations above and below some threshold. In Figure A.8a we drop the total emission values smaller than the cutoff indicated in the first results and below when cutoff is indicated next to a star (∗) (values in thousands). For emissions per capita (CO_2e tons) outliers (Figure A.8b) we use the same procedure. Regressions were estimated using Equation (1). They include year and age difference fixed effects, and control for logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, and college completion.

B Online Appendix

Table B.1: Age percentiles by election year

	Year			
	2004	2008	2012	2016
	(1)	(2)	(3)	(4)
p10	30	30	30	30
p15	32	33	32	33
p20	34	35	34	35
p25	36	37	36	37
p30	38	38	38	38
p40	40	42	41	42
p60	46	47	47	48
p80	52	54	54	55

Notes: Candidate's age percentiles by election year.

Table B.2: Number of observations by year

	Young vs. Not Young	Young vs. Senior	Senior vs. Not Senior
	(1)	(2)	(3)
2005	26	7	113
2006	26	7	113
2007	26	7	113
2008	26	7	113
2009	50	13	118
2010	50	13	118
2011	50	13	118
2012	50	13	118
2013	48	14	131
2014	48	14	131
2015	48	14	131
2016	48	14	131
2017	41	7	136
2018	41	7	136
2019	41	7	136
2020	41	7	136
Total	660	164	1992

Notes: Number of municipalities by year used in Column 3 of Table 2. Column 1 corresponds to Panel A sample, columns 2 and 3 refers to Panel B and C respectively.

Table B.3: Results excluding mayors' second term

Dependent variable:	Deforestation as % forest 2000		
	(1)	(2)	(3)
Panel A:	Margin: Young vs. Not Young		
Young won	-0.29***	-0.26***	-0.24***
	(0.08)	(0.08)	(0.08)
Mean Dep. Var. Control	0.47	0.47	0.45
Age Difference	17.13	17.13	17.18
Bandwidth	11.22	11.22	11.22
Number of Observations	592	592	584
Panel B:	Margin: Senior vs. Not Senior		
Senior won	-0.02	-0.02	-0.02
	(0.05)	(0.05)	(0.05)
Mean Dep. Var. Control	0.37	0.36	0.36
Age Difference	16.76	16.76	16.63
Bandwidth	16.52	16.52	16.52
Number of Observations	2,036	2,012	1,992

Notes: This table presents the effect of having a young (Panel A) or senior (Panel B) mayor on deforestation by excluding the second term mandates from the sample. The coefficients are estimated using Equation (1) and the optimal bandwidth used in the main specification (Table 2 Panel A Column 3). Column 1 only controls by deforestation four years prior. Column 2 controls by deforestation four years prior, logarithm of population, percentage of young in the population in 2000, and gender. Column 3 controls by deforestation four years prior, logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, and college completion. Panel A takes as a sample all municipalities with at least one young candidate among the first two candidates. In Panel B, the sample contains all elections in which almost a senior candidate was between the first two candidates. All regressions include year and age difference fixed effects and control for the percentage of the municipality's area unobserved each year. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table B.4: Results on emission outcomes

	CO_2e tons emissions					GDP emission intensity (CO_2e tons/R$)				
Dependent variable:	Total	Agriculture	Land Use	Energy	Waste	Total	Agriculture	Land Use	Energy	Waste
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A:	Margin: Young vs. Not Young									
Young Won	327,771.38	20,974.95	305,545.71	1,295.18	-44.46	-915.36	-907.54***	-17.61	8.12	1.66
	(238,282.66)	(59,319.12)	(211,629.88)	(4,373.51)	(679.29)	(2,025.64)	(226.79)	(1,974.13)	(8.85)	(2.95)
Mean Dep. Var. Control	864,775.08	281,653.00	559,614.92	16,803.99	6,703.17	5,342.99	1,925.01	3,308.84	71.20	37.94
Bandwidth	11.22	11.22	11.22	11.22	11.22	11.22	11.22	11.22	11.22	11.22
Number of Observations	660	660	660	660	660	660	660	660	660	660
Panel B:	Margin: Senior vs. Not Senior									
Senior Won	466,551.98	136,966.20***	349,824.57	-14,021.89**	-6,216.92***	4,881.22*	291.13*	4,585.03*	18.27	-13.21**
	(327,722.48)	(37,896.94)	(313,090.85)	(5,534.20)	(1,421.39)	(2,654.95)	(154.58)	(2,623.05)	(14.01)	(5.60)
Mean Dep. Var. Control	546,540.56	224,698.29	280,423.66	31,402.07	10,016.54	2,070.32	1,669.82	282.91	72.38	45.22
Bandwidth	16.52	16.52	16.52	16.52	16.52	16.52	16.52	16.52	16.52	16.52
Number of Observations	1,992	1,992	1,992	1,992	1,992	1,992	1,992	1,992	1,992	1,992

Notes: Effect of having a young (Panel A) or senior (Panel B) mayor in the office on the emissions outcomes. The coefficients are estimated by using Equation (1) but changing the variable of interest. Bandwidths are restricted to the optimal bandwidth from Table 2 Panel A Column 3. Columns 1 to 5 show the total emissions. Columns 6 to 10 are computed by dividing the emissions (CO_2e) in tons by the GDP of each year. All emissions data are provided by Sistema de Estimativa de Emissões e Remoções de Gases de Efeito Estufa, Observatório do ClimaSEEG (n.d.). Agro emissions "do not include emissions resulting from deforestation, other agro-industrial residues and energy used in agriculture, which are accounted for in the respective sectors [...] in Land Use, Waste and Energy" (Sistema de Estimativa de Emissões e Remoções de Gases de Efeito Estufa, Observatório do ClimaSEEG, 2023, p.9). Panel A takes as sample all municipalities with at least one young candidate among the first two candidates. In Panel B, the sample contains all elections in which a senior candidate was between the top two candidates. All regressions include year and age difference fixed effects, and control for logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, and college completion. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table B.5: Effect on fines

Dependent variable:	Fines for crime in			Fines divided by previous deforestation			
	Non flora	Flora	Deforestation	Total	Non flora	Flora	Deforestation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Margin: Young vs. Not Young							
Young Won	-0.77	2.52	-0.18	-6.58***	-1.92**	-4.67***	-2.42*
	(0.57)	(2.50)	(1.71)	(2.04)	(0.85)	(1.80)	(1.47)
Mean Dep. Var. Control	1.98	4.67	3.40	3.01	1.06	1.95	1.70
Bandwidth	11.22	11.22	11.22	11.22	11.22	11.22	11.22
Number of Observations	660	660	660	552	552	552	552
Margin: Senior vs. Not Senior							
Senior Won	1.34**	3.00*	1.21	-0.29	-1.22	0.93	-0.15
	(0.65)	(1.57)	(1.04)	(1.56)	(0.86)	(1.05)	(0.73)
Mean Dep. Var. Control	2.91	6.48	3.64	4.47	2.14	2.32	1.40
Bandwidth	16.52	16.52	16.52	16.52	16.52	16.52	16.52
Number of Observations	1,992	1,992	1,992	1,592	1,592	1,592	1,592

Notes: This table displays the effect of having a young (Panel A) or senior (Panel B) mayor on fines. The coefficients are estimated by using Equation (1) but changing the variable of interest. Bandwidths are restricted to the optimal bandwidth from Table 2 Panel A Column 3. These data are provided by Ibama. Columns 1 to 2 present the number of fines disaggregated by crimes against flora and the rest. Column 3 shows results for fines imposed by deforestation crimes. Columns 4 to 7 present results by dividing the number of fines by deforestation in the previous year measured in hectares. All regressions include year and age difference fixed effects, and control for logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, and college completion. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table B.6: Effect on fines using optimal bandwidth

Dependent variable:	Fines for crime in			Fines divided by previous deforestation			
	Non flora	Flora	Deforestation	Total	Non flora	Flora	Deforestation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Margin	Young vs. Not Young						
Young Won	-0.65	1.75	-0.37	-6.12***	-1.96**	-3.80**	-2.47*
	(0.52)	(1.92)	(1.33)	(2.02)	(0.85)	(1.70)	(1.36)
Mean Dep. Var. Control	2.25	6.40	3.77	2.87	1.06	1.62	1.48
Optimal bandwidth	15.33	17.22	18.21	12.22	10.97	14.52	13.77
Number of Observations	856	924	944	580	540	683	640
Margin	Senior vs. Not Senior						
Senior Won	1.34**	2.99*	0.14	0.09	-1.40	1.33	-0.04
	(0.67)	(1.59)	(1.10)	(1.65)	(0.93)	(1.11)	(0.68)
Mean Dep. Var. Control	3.49	6.74	3.93	4.77	2.20	2.52	1.73
Optimal bandwidth	14.59	15.24	9.97	11.25	11.99	11.59	9.57
Number of Observations	1,872	1,912	1,408	1,241	1,289	1,261	1,089

Notes: This table displays the effect of having a young (Panel A) or senior (Panel B) mayor on fines. The coefficients are estimated by using Equation (1) but changing the variable of interest. Optimal bandwidths are computed for each column. These data are provided by Ibama. Columns 1 to 2 present the number of fines disaggregated by crimes against flora and the rest. Column 3 shows results for fines imposed by deforestation crimes. Columns 4 to 7 present results by dividing the number of fines by deforestation in the previous year measured in hectares. All regressions include year and age difference fixed effects, and control for logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, and college completion. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table B.7: Effect on agricultural outcomes

Dependent variable:	Agriculture Production Value (R$)	Agriculture Productivity (R$ per Ha.)	Livestock N Bovine (000s) (Census)
	(1)	(2)	(3)
Panel A:	Margin: Young vs. Not Young		
Young Won	-3276.20	-0.46	12.20
	(2,089.66)	(0.72)	(30.20)
Mean Dep. Var. Control	6,122.49	7.74	84.45
Bandwidth	11.22	11.22	11.22
Number of Observations	660	619	67
Panel B:	Margin: Senior vs. Not Senior		
Senior Won	4,280.39**	-1.68***	14.52
	(1,996.16)	(0.59)	(19.78)
Mean Dep. Var. Control	8,602.78	7.65	42.12
Bandwidth	16.52	16.52	16.52
Number of Observations	1,988	1,838	249

Notes: This table shows the effect of having a young (Panel A) or senior (Panel B) mayor on the agricultural outcomes. The coefficients are estimated by using Equation (1) but changing the variable of interest. Bandwidths are restricted to the optimal bandwidth from Table 2 Panel A Column 3. Column 1 is computed using data from *Pesquisa Agrícola Municipal* (PAM). Column 2 is computed by dividing Column 3 of Table 3 by Column 1 of this table. Column 3 uses Agricultural Census to measure the number of heads of cattle (in thousands). Census data is provided every ten years, so we only can use 2006 and 2017 data. Panel A takes as sample all municipalities with at least one young candidate among the first two candidates. In Panel B, the sample contains all elections in which almost a senior candidate was between the first two candidates. All regressions include year and age difference fixed effects, and control for logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, and college completion. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table B.8: Results on other municipality outcomes

Dependent variable:	GDP per capita (000s)			% Government spending			
	Total	Agriculture	Industry	Health	Capital	Short-term Liabilities	Long-term Liabilities
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A:	Margin: Young vs. Not Young						
Young Won	3.46	-1.79	3.21***	0.29	0.98	-0.13	-5.11
	(3.01)	(1.40)	(1.09)	(0.31)	(1.18)	(1.21)	(3.25)
Mean Dep. Var. Control	14.47	4.30	1.30	9.91	10.85	6.29	7.82
Bandwidth	11.22	11.22	11.22	11.22	11.22	11.22	11.22
Number of Observations	660	660	660	620	620	578	578
Panel B:	Margin: Senior vs. Not Senior						
Senior Won	1.80	1.47*	-0.53	0.91***	-2.21***	1.60***	1.54
	(2.68)	(0.89)	(1.78)	(0.24)	(0.63)	(0.52)	(1.52)
Mean Dep. Var. Control	15.80	4.28	2.57	10.32	11.88	5.76	6.59
Bandwidth	16.52	16.52	16.52	16.52	16.52	16.52	16.52
Number of Observations	1,992	1,992	1,992	1,869	1,870	1,744	1,746

Notes: Testing of results on different outcomes. The coefficients are estimated by using Equation (1) but changing the variable of interest. Bandwidths are restricted to the optimal bandwidth from Table 2 Panel A Column 3. Sample may vary due to data availability for each outcome. Columns 1 to 3 present the results in GDP (in thousands) disaggregated by sector measured in per capita terms. This share is calculated by dividing the nominal GDP (in thousands) or the value added by each sector (in thousands) by the population in 2004. Columns 4 and 5 are computed by dividing the expenditure per budget by the municipality's total budget. Columns 6 and 7 show results disaggreating by the type of liability. Panel A takes as a sample all municipalities with at least one young candidate among the first two candidates. In Panel B, the sample contains all elections in which a senior candidate was between the top two candidates. All regressions include year and age difference fixed effects, and control for logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, and college completion. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table B.9: Effect on other outcomes using their optimal bandwidth

Dependent variable:	GDP			Emissions per capita (CO_2e tons)					Agriculture		# Fines
	Per capita (000s)	Agriculture (%)	Industry (%)	Total	Agriculture	Land Use	Energy	Waste	Area (ha)	# Bovine (000s)	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: Young vs. Not Young											
Young won	3.20	-4.97***	5.79***	-28.23	-4.99	-20.69	0.39	0.14***	-172.64	-22.30	1.08
	(2.90)	(1.85)	(1.73)	(20.26)	(4.51)	(18.00)	(0.33)	(0.04)	(224.99)	(19.67)	(2.14)
Mean Dep. Var. Control	14.03	28.16	8.09	80.08	25.81	63.69	1.11	0.36	793.14	125.76	6.46
Optimal bandwidth	12.32	14.50	13.87	15.78	9.08	13.67	12.74	8.68	13.55	22.24	17.71
Number of Observations	700	820	776	860	560	764	732	532	760	1,072	932
Panel B: Senior vs. Not Senior											
Senior won	4.01	-1.25	-1.64	22.06	3.64	18.66	0.59**	-0.12***	824.41***	74.73***	4.27**
	(2.96)	(1.69)	(1.32)	(22.83)	(2.70)	(22.22)	(0.27)	(0.05)	(244.06)	(20.42)	(2.06)
Mean Dep. Var. Control	15.98	25.24	8.89	45.88	20.60	24.28	1.09	0.41	928.18	103.59	9.61
Optimal bandwidth	10.86	9.10	15.36	14.89	11.02	14.71	13.38	15.28	11.00	11.61	14.73
Number of Observations	1,512	1,296	1,920	1,888	1,520	1,872	1,768	1,912	1,516	1,570	1,880

Notes: This table presents the results of having a young mayor (Panel A) or senior mayor (Panel B) on different economic and environmental outcomes. The coefficients are estimated from Equation (1). Each column contains municipalities included in the sample of close elections, defined according to their respective optimal bandwidths and subject to data availability for each outcome. Column 1 shows the effect on the GDP (in thousands) per capita. Columns 2 and 3 present the results in GDP disaggregated by sector share. This share is calculated by dividing the value added of the Agricultural and Industry sectors respectively by the total nominal GDP of each year. Columns 4 to 8 are calculated dividing emissions (CO_2e tons) by population. All emissions data are provided by Sistema de Estimativa de Emissões e Remoções de Gases de Efeito Estufa, Observatório do ClimaSEEG (n.d.). Agricultural emissions "do not include emissions resulting from deforestation, other agro-industrial residues, and energy used in agriculture, which are accounted for in the respective sectors [...] in Land Use, Waste and Energy" (Sistema de Estimativa de Emissões e Remoções de Gases de Efeito Estufa, Observatório do ClimaSEEG, 2023, p.9). Columns 9 and 10 are calculated using data from *Pesquisa Agrícola Municipal* (PAM). Column 11 uses the number of fines provided by Ibama. All regressions include year and age difference fixed effects, and control for percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, college completion, and logarithm of population. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table B.10: Effects on local spending and rural credit using their optimal bandwidth

	% Government spending				Rural Credit	
Dependent variable:	Environment (1)	Education (2)	Agriculture (3)	Liabilities (4)	Agriculture (5)	Cattle (6)
Panel A: Young vs. Not Young						
Young won	-0.03	-0.90	-0.05	-2.07	2.62	-2.44
	(0.06)	(0.57)	(0.09)	(2.39)	(7.51)	(7.36)
Mean Dep. Var. Control	0.22	17.44	0.61	13.09	19.86	43.72
Optimal bandwidth	12.11	16.25	13.89	19.12	10.98	11.54
Number of Observations	651	827	734	863	620	632
Panel B: Senior vs. Not Senior						
Senior won	-0.34***	-0.81*	-0.00	4.32**	4.01	-9.95**
	(0.07)	(0.45)	(0.06)	(1.92)	(6.48)	(4.10)
Mean Dep. Var. Control	0.37	16.88	0.57	12.43	23.13	34.78
Optimal bandwidth	8.48	11.76	14.93	10.98	10.41	11.59
Number of Observations	1,139	1,478	1,775	1,331	1,384	1,483

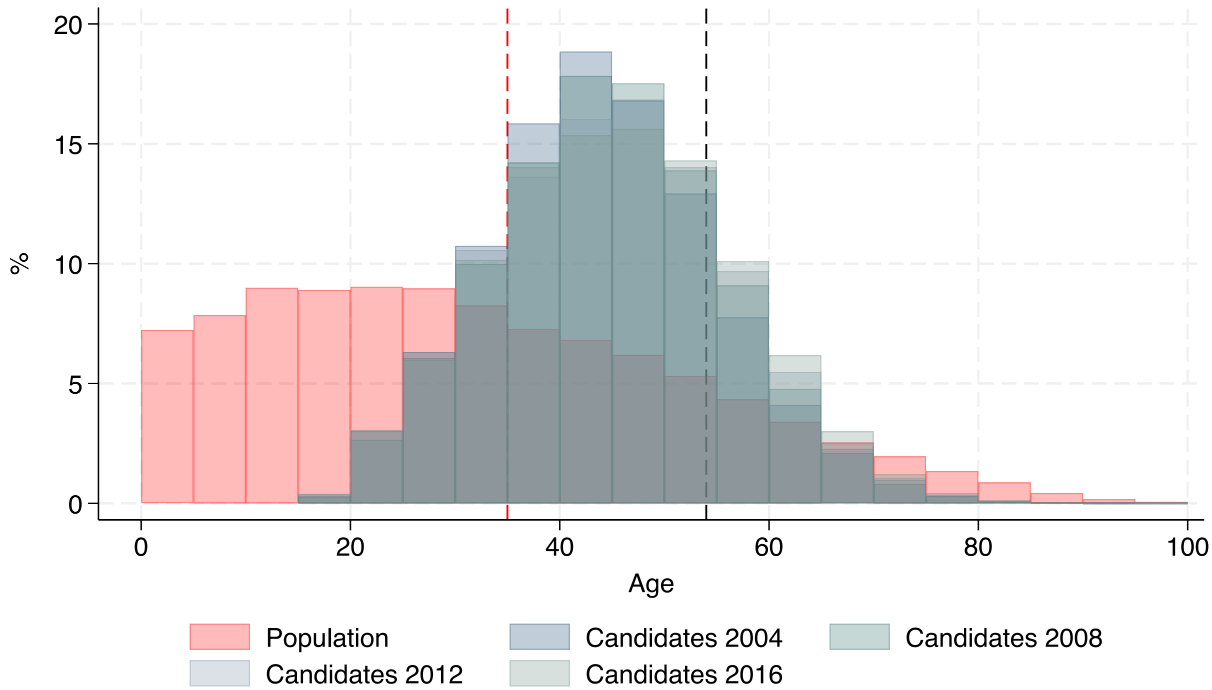
Notes: This table presents the results of having a young mayor (Panel A) or senior mayor (Panel B) on the allocation of government spending and rural credit. The coefficients are estimated by using Equation (1) but changing the variable of interest. Each column contains municipalities included in the sample of close elections, defined according to their respective optimal bandwidths and subject to data availability for each outcome. Columns 1 to 3 are calculated by dividing the expenditure per budget by the total budget of the municipality. Column 4 presents results on municipality liabilities as a percentage of municipality expenditure. Credit variables in Columns 5 and 6 are measured in Brazilian reais (R$) per hectare at the municipal level. All regressions include year and age difference fixed effects, and control for logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, and college completion. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table B.11: Additional robustness tests

Dependent variable:	Deforestation as % forest 2000						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A:	Margin: Young vs. Not Young						
Young won	-0.23***	-0.23***	-0.15*	-0.24***	-0.21***	-0.26*	-0.23**
	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.15)	(0.10)
Mean Dep. Var. Control	0.45	0.45	0.45	0.45	0.42	0.61	0.45
Bandwidth	11.22	11.22	11.22	11.22	11.22	11.22	11.22
Number of Observations	660	660	660	660	582	748	165

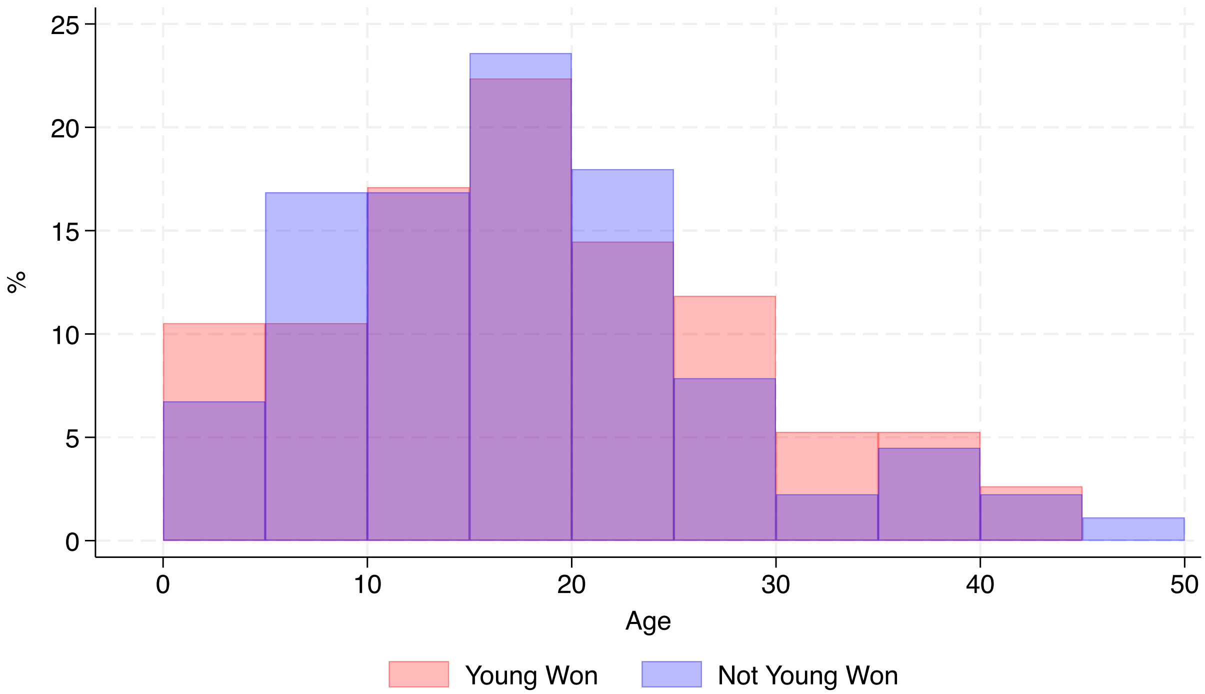
Notes: This table presents the results of our main specification (Column 3 in Table Equation 1) removing different fixed effects, observations and changing the unit of observation. Bandwidths are restricted to the optimal bandwidth from Table 2 Panel A Column 3. Column 1 replicates the main result. Column 2 shows the result in column 1 after removing the age difference fixed effects. Column 3 removes the year fixed effect from the main specification (Column 1), while column 4 excludes deforestation four years prior. Column 5 discards observations before 2008. Column 6 removes the constraint of having during the term a mean in deforestation smaller than 90% of the deforestation during the period. Finally, column 7 shows the result for the main specification at electoral term level. All regressions control for logarithm of population, percentage of young in the population in 2000, gender, incumbency, party alignment (left or right), marital status, college completion, and percentage of the municipality's area unobserved each year. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Figure B.1: Age distribution by election year



Notes: This histogram displays the age distribution of all candidates in regular municipal elections in Brazil, separated by election year from 2004 to 2016, alongside the age distribution of the Brazilian population based on the 2010 Census.

Figure B.2: Age gap distribution



Notes: This histogram presents the age gap in absolute value between the winner and the runner up in the elections in 2004, 2008, 2012, and 2016 using the optimal bandwidth (Column 3 in Table 2). On one hand the red color displays the distribution of the age difference in those elections where the young candidate won. By the other hand, the blue color shows the distribution when the winner was not young.