Young Politicians and Long-Term Policy*

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August 1, 2024

Abstract

Policies often entail costs today but benefits far into the future, as in climate change mitigation. An essential aspect of how this trade-off is faced relates to how young are the politicians in power. We study closely contested elections in Brazil and show that young politicians reduce deforestation and greenhouse gas emissions with no significant effects on local income. We further show that young politicians invest in long-term policy and hire more young bureaucrats. Our results suggest the importance of youth political participation for long-term policy.

JEL: *P18,Q23,Q54*

Keywords: *climate change mitigation, deforestation, young politicians, political selection*

*We are grateful to audiences at URosario, CU Denver, ICDE 2023, AERE@WEAI 2023, ACU, NEUDC 2023, and LACEA for useful comments and feedback. We also want to thank Mauricio Romero, Eduardo Ferraz, Juan Rios, Clark Lundberg, Quoc-Anh Do, and anonymous referees for their helpful comments.

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1 Introduction

A fundamental difficulty in policy-making is that policies often have costs today but benefits only far into the future. This is especially true with climate change and the conservation of natural resources. For example, greenhouse gas emissions are estimated to remain in the atmosphere for decades (IPCC, 2021); therefore, actions to reduce emissions today will benefit future generations. 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 United States (Tyson et al., 2023; Funk, 2021) and worldwide (Ahlfeldt et al., 2022; Andor et al., 2018). A key constraint to accelerating environmental policy adoption is thus having elected leaders aligned with long-term objectives (Stockemer and Sundström, 2022). In this paper, we test whether young politicians affect long-term policy, with a particular focus on local governments and deforestation.

We study the effect of electing young politicians on long-term policy in the case of Brazilian municipalities. The setting is ideal for a few reasons. In particular, the country contains 60% of the Amazon, the largest tropical forest on the planet. In addition, Brazil has thousands of municipalities (analogous to US counties), providing plenty of variation and richness to explore. Although mayors in Brazil are not directly responsible for environmental law enforcement, mayors can affect deforestation under strong electoral incentives (Bragança and Dahis, 2022), favoring campaign donors (Katovich and Moffette, 2024), by allowing the sale of untitled land (Cisneros and Kis-Katos, 2022), or via the agricultural and social programs implemented (Holland, 2016).[1] Brazil has also monitored deforestation with satellite data since the early 2000s, providing data without misreporting concerns.

Our empirical strategy employs a regression discontinuity (RD) 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' 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 the election. This is approximately a candidate less than 35 years old. Similarly, we define a senior candidate as being above the 80^{th} percentile of the candidates' age distribution in the election, approximately 55 years. We show the robustness of our results to the definition of young candidates.

[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, when a young mayor is in office, there is a 0.48 p.p. reduction in the yearly deforestation rate (as a share of the municipality's forest area in 2000). Compared to a mean of 0.72% forest area deforested each year, the effect size amounts to a reduction of almost 67%. We also find that when a young mayor is in office, per capita greenhouse emissions are reduced. Importantly, having a young mayor in office does not significantly affect the municipal gross 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 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 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 results are sensitive to medium-level percentage points removed around the cutoff in a doughnut RD exercise.

We then study the effect of electing 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. Second, we find that young mayors spend a larger share of the municipality's budget on education and reduce future liabilities. The opposite is true when senior politicians are elected. Finally, we show that young mayors turn over the local bureaucracy, in particular hiring more young bureaucrats. Importantly, we show that this is not mechanically driven by young mayors having been elected for the first time.

Having established the main results, we turn to interpreting our 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 (Alesina et al., 2019). First, politicians may simply react to the local demand for environmental protection. Our design could be mechanically comparing areas with more support to this agenda versus other with less, for example areas with younger versus older electorates.[2] This is not the case: the

[2]Young people voting in young politicians regardless of their valence or agenda is an instance of *descriptive representation* (Pitkin, 1967). In 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. Effects for seniors are even stronger.

RD design holds constant local characteristics of the area and its electorate, including the percentage of young voters.

On the other hand, in the tradition of agency models (Besley, 2006) and the vast literature on politician identity (Chattopadhyay and Duflo, 2004; Beaman et al., 2009), even conditional on the electorate's characteristics, our results may be driven by supply channels specific to the elected politician. For example, young politicians may have longer lifespans ahead of them. They may be more patient and have higher discount factors, valuing the future more. They may have been socialized in a more environment-aware culture and, therefore, have more pro-conservation preferences.[3] They may be more inexperienced, more idealistic, or perhaps less co-opted by agribusiness interests. Our RD estimates reflect a mix of such supply channels, albeit locally, in areas where there was already substantial support for the young mayor's campaign in the first place.

Although we do not attempt to explicitly isolate each supply mechanism, we perform three exercises to aid interpretation. First, we show that the effect of a young mayor on deforestation is not heterogeneous by any observable covariate, such as college education, political leaning, or incumbency; while these covariates are important for senior mayors. Second, we find no statistically significant results in an alternative specification in which we exploit the full variation of age differences between candidates and compare outcomes when the *younger* candidate wins. These results suggest a *cohort effect*: young mayors matter because they are part of a new generation, and not because of their lower age per se. Finally, to the extent that age correlates with other politician's characteristics and those variables explain long-term policy, electing a young mayor would be a bundled treatment (Marshall, 2022). We perform horse-races to show that controlling for an array of other characteristics barely affect our estimates.

We contribute to three main strands of the literature. First, we contribute to the growing literature that studies the effects of younger cohorts on government policy. Alesina et al. (2019) and Bertrand et al. (2015) argue that younger politicians have more career concerns. Fiva et al. (2023) show that politicians in the Norwegian parliament raise different issues when they are young (e.g., childcare, schools) versus old (e.g., health care). To the best of our knowledge, we are the first to study the effects of electing young politicians on long-term policy. The paper that most closely resembles ours is by Baskaran et al. (2024), who argue 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

[3] In fact, the Brazilian 1988 Constitution mandated environmental education at all levels of schooling.

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 national level, deforestation can be affected by central government policy (Burgess et al., 2019). At the municipal level, deforestation is higher 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 municipalities split (Burgess et al., 2012), when public audits of federal funds were conducted (Cisneros and Kis-Katos, 2022), and when the election was contested (Sanford, 2021). 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 of 67% of electing a young politician.

Finally, we contribute to the growing environmental justice literature, which has so far focused on the unequal distribution of environmental damages across income and race groups (Hsiang et al., 2019). Our work innovates by highlighting the importance of political representation for younger cohorts, who will be disproportionately impacted by climate change (Thiery et al., 2021).

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. Section 6 discusses how to interpret our findings. Section 7 concludes.

2 Setting

Brazil contains about 60% of the Amazon forest, the largest tropical forest on the planet. We focus on the Legal Amazon municipalities,[4] because this region is where the deforestation data is available. Municipalities are the smallest administrative unit in Brazil, the equivalent of United States counties. The Amazon municipalities represent about 50% of the country's area. Currently, there are 5,572 municipalities in Brazil, of which 772 are in the Amazon region.

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 re-elected once.

[4]Is the area of operation of Superintendence for the Development of the Amazon and is delimited by the law. It was established to promote the sustainable development of the region. This area covers almost 59% of the total Brazilian area. (IBGE, n.d.)

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, next year, after elections in November. We analyze data from elections every four years from 2004 to 2016, covering mayor periods from 2005-2008 to 2017-2019.

The minimum age to be elected mayor is 21 years, while for councilor it is 18.[5] The median candidate age in all elections in our data is 44 years old, 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 a gray area. 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. However, mayors can influence deforestation directly or indirectly, for example, by providing incentives to develop local agriculture or infrastructure projects, and with forbearance (Holland, 2016). Other ways in which mayors can affect deforestation are: allowing the sale of untitled land, colluding with local sawmills that promote illegal logging, accommodating illegal settlements, and cooperating (or not) with federal raids (Cisneros and Kis-Katos, 2022). Another key element of the 1988 Constitution relevant for this research is Article 225, with the mandate to "promote environmental education in all levels of education." Consequently young candidates in our elections sample were in school with this new environmental education mandate.

3 Empirical Framework

In this Section, we discuss the regression discontinuity (RD) design to estimate the effect of having a young mayor in office on deforestation and other outcomes. Consider a municipality m where in the previous election in year t_e the candidate 30 years of age won the election against a candidate 60 years of age. We would like to compare deforestation when the young mayor is in office ($y_{m,t_e+1,30}$), with deforestation if the senior mayor had won ($y_{m,t_e+1,60}$). Unfortunately, we only observe deforestation when the young one is in office

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

($y_{m,t_e+1,30} = y_{m,t_e+1}$). Consequently, we use two strategies to identify the effect of having a young mayor in office. First, we find other municipalities where the top two candidates have a similar age profile to m and include age profile fixed effects ($\delta_{AP(t_e)}$). Ideally, one would have an exact age profile of 30 and 60 years for the top two candidates. In reality we use age bins of size 10 years. For example we find a municipality m' where a 62 years old candidate won the election against a 28 years old candidate and compare y_{m,t_e+1} with y_{m',t_e+1}. Second, we only consider close elections because the winner is quasi-random compared to a case where a candidate won by a landslide victory.

Consequently we study the effect of young mayors on deforestation, using a Regression Discontinuity Design. This quasi-experimental approach compares municipalities where a young candidate barely won the election versus municipalities where the young candidate lost by a small margin. The first step is to define the age limit to define a candidate as young. In the main specification we use the following rule:

$$\text{Young}_{mt} = \begin{cases} 1, & \text{if Age}_{mt_e} <= P_{20}(\text{Age}_{mt_e}) \\ 0, & \text{otherwise} \end{cases}$$

where Age_{mt_e} is the age of the mayor at the time of the previous election (t_e), and $P_{20}(Age_{mt_e})$ refers to the 20^{th} percentile of the age of all politicians in the country running for election that year.[6]

After defining young candidates, we identify mayoral elections in which a young candidate won or obtained second place. Then we estimate the effect of electing a young mayor on deforestation using the following equation:

$$y_{mt} = \beta \text{Young Won}_{mt_e} + f^{+}(Margin^{+}_{mt_e}) + f^{-}(Margin^{-}_{mt_e}) + \delta_{AP(t_e)} + \lambda_t + \gamma Z_{mt} + \varepsilon_{mt} \quad (1)$$

where y_{mt} is the percentage of the forest area deforested in municipality m on year t. The forest area for each municipality is calculated for the baseline year 2000. Young Won_{mt_e} is a dummy equal to one if a young candidate won the previous election (t_e), and consequently is in office at time t. $f^{+}(Margin^{+}_{mt_e})$ and $f^{-}(Margin^{-}_{mt_e})$ are local polynomials of the margin of victory ($+$) or defeat ($-$) of the young candidate in the previous election. $\delta_{AP(t_e)}$ are the age profile fixed effects described above. λ_t are time-fixed effects to control for different yearly shocks, like the weather and national policies. Z_{mt} are municipality time-variant controls such as the logarithm of population and mayor controls such as sex,

[6] 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.

second-term, right-wing, married status and college attendance. Finally, we use Hinkley errors (HC1) (ε_{mt}) in the main specification but present robustness to other error types. The ex post power analysis indicates that this regression has 77.53% power.

In the main specification, we compare young mayors against any mayor that is not classified as young. On average, the young mayor is 17.6 years younger than the rival candidate.[7] Still, there is a concern that the strategy sometimes compares a candidate that is 35 years old against a candidate that is 36 years old. Therefore we also present results using only elections with a young and a senior candidate competing for first place. We define a senior candidate as one that is above the 80th percentile of the age distribution, which is approximately 54 years. However, there are not many elections where the top two candidates are young and senior.

Following the literature, we restrict the use of polynomial order to those of low order (Gelman and Imbens, 2019). We use a linear local polynomial in our main specification. In the case of bandwidth selection, we use the data-driven approach proposed by Calonico et al. (2014) adjusted by mass points. In the main specification, we employ a triangular kernel for weighting observations as recommended by Cattaneo et al. (2020). We present robustness to polynomial degree, bandwidth and kernel in the Appendix.

In addition, to understand the mechanisms driving the results, we estimate the same Equation with different dependent variables – such as economic variables and expenditure type. We also add interactions to compute potential heterogeneous effects of having a young mayor in office.

In Section 6, we explore to what extent cohort effects explain our results. If the main difference between a young and an older candidate was just age itself, one could think of an empirical design with a dummy of *YoungerWon* instead of *YoungWon*. For example, the effect of a 50 year old candidate beating a 60 year old candidate would be similar to that of a 30 year old beating a 40 year old candidate. The difference in each case is 10 years, so the effect on long-term discounting would be similar under certain assumptions. The regression is similar to Equation (1), but using the dummy *YoungerWon*.

[7] See Figure B.2 for the histogram of age gaps. The distribution for races where the young candidate won is slightly more spread out than the one where the not-young candidate won.

4 Data and Summary Statistics

4.1 Data sources

Deforestation. The area deforested each year is provided by the National Institute for Space Research (INPE) through the Measurement of Deforestation by Remote Sensing program (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 categorized 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. 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.

Election results and candidates information. We have elections' results from 2004 to 2016 from the Superior Electoral Court (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 attendance. In addition, from the political party information, we establish whether the candidate is left or right-wing. 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 A.2 shows the map of the Brazilian Amazon, highlighting the municipalities that enter the regression discontinuity sample by year. Table B.1 reports the threshold for the young definition and Table B.2 the number of municipalities by year that enter each RD sample.

Emissions. We use the emissions data from System for Estimating Greenhouse Gas Emissions and Removals (SEEG) (Sistema de Estimativa de Emissões e Remoções de Gases de Efeito Estufa, Observatório do ClimaSEEG, n.d.).[8] SEEG classifies emissions in different levels depending on the activity that produced the emissions. Emissions are measured in tons of carbon dioxide equivalent (CO_2e), so that different gases are comparable based on their global warming potential. We add these data to proxy environmental behavior by municipality and economic activity.

[8] For more information about methodology used see De Azevedo et al. (2018).

Additional data. We construct measures of bureaucratic turnover from RAIS, the dataset that follows every hire and separation across the whole Brazilian bureaucracy. We also use other datasets such as SICONFI for municipal expenditures, Municipal Agricultural Research, and Agricultural Census. Campaign donations and all other data are pre-processed by the Data Basis project (Dahis et al., 2022) and are available on the organization's website.[9]

4.2 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 regression discontinuity (RD) sample; (3) Amazon municipalities where a young candidate won a close election; (4) Amazon municipalities where a young candidate lost a close election (the "control" group). Columns 5 presents the difference in means between the group of municipalities where the young candidate won (3) versus the group where the young lost (4). Column 6 asses if there is a discontinuity in the characteristics at the close election cutoff. Panel A presents characteristics at the municipality level, while Panel B reports characteristics at the election (municipality-term) level.

The municipalities in our sample are on average slightly poorer, smaller in population, and younger than other municipalities not in the RD sample (inside or outside the Amazon). They had similar levels of forest area in 2000 but somewhat higher deforestation rates during the electoral term. Panel B shows that around 15% of the Brazilian elections had a young candidate among the top two candidates. That percentage is slightly lower in municipalities in the Amazon. By construction, all the elections in the regression discontinuity sample (Columns 3 and 4) have a young candidate in the top two.

Panel B of Table 1 also reports summary statistics on the mayor elected in each election. Country-wide mayors are mostly male. About half are college-educated. Approximately three-quarters are right-wing, 14% are classified as farmers, and about a quarter are in their second term. In the RD sample, young mayors are less likely to be married, farmers, or elected for a second term. Column 6 shows that close to the cutoff young mayors tend to be more educated and less likely right-wing than the not young. We show in Section 6 that such observable differences do not drive our results. Column 6 also shows that close to the cutoff there is statistically significant difference in the amount received in donations per

[9] See `https://basedosdados.org`

capita between young and not young mayors. Table A.2 and Table A.3 present additional summary statistics by municipality-term and candidate level respectively.

5 Results

We first study the effect of having a young mayor in office on deforestation in Section 5.1. We study the effect of a young mayor on other outcomes in Section 5.2. We discuss in detail how young mayors choose to spend local revenues in Section 5.3 and how they turn over the bureaucracy, in particular hiring more young bureaucrats in Section 5.4.

5.1 Effect of having a young mayor in office on deforestation

We find that when a young mayor is in office, there is a reduction in deforestation. Table 2 presents the results of estimating Equation (1). Columns 1, 4 and 7 present the results without controls, while Columns 2-3, 5-6 and 8-9 include controls. In Columns 2, 5 and 8 controls are population and gender. In Columns 3, 6 and 9 we additionally control for party alignment (left or right), second-term, marital status, and college attendance. These last controls are correlated with age, and might capture part of the difference between young and not young mayors. However, as shown in the Table, the coefficients do not vary much. 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 the main specification (Column 3, Panel A) 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, as we will discuss below in the robustness section. Panel A estimates the effect of a young mayor in office when he/she won the election to any other not young candidate. Panel B compares young candidates with senior candidates. Recall that we define young and senior candidate 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. Finally, Panel C compares the senior candidates with any other candidate. All columns show a reduction in deforestation when a young mayor is in office.

Our preferred specification, Column 3 in Panel A, shows that when a young mayor is in office deforestation is 0.48 percentage points smaller compared to municipalities where the young mayor barely lost the election. Compared to the mean of 0.72% of the forest area deforested each year, this is a reduction of almost 67% in the deforestation rate. Figure 1 shows the Regression Discontinuity plot for the main specification. The effect is larger when we restrict the control group to elections with a senior candidate (Column 1, Panel B). This result is explained by the fact that young and senior candidates differ in other dimensions beyond age. We obtain similar coefficient to Panel A once we control for mayor's characteristics. 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 vs. young candidates because the results are symmetric to Panel B.

In Figure 2 we decompose the effects by year of the mayor's term. We find that coefficients are largest in magnitude in year 2, and statistically significant in years 2 and 3. Figure 2 shows that the effects of young mayors in office take some time to materialize. This is in line with the mechanics of the deforestation measure described in Section 4, which shifts deforestation by six months; it attributes deforestation from August 1 of year $t-1$ to July 31 of year t to year t. Figure A.3 shows the results by electoral mandate. Although during 2013-2016 the result does not differ statistically from zero, the direction of the coefficient is constant over time.

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 results presented in Table 2 Columns 7 to 9 are robust and even larger in magnitude than the main results.

An alternative to the main RD specification is to use a difference-in-differences (DD) specification with municipality fixed effects. That is, we compare municipalities that barely elected a young mayor to those where the young candidate barely lost the election, controlling for possible ex-ante differences in deforestation in the municipalities. Table A.4 presents the results of estimating the difference-in-differences specification. Column 1 repeats the main specification, while Column 2 restricts the RD regression to the DD sample. Note that the number of observations is smaller because for the first years we do not have pre-period deforestation data, and also some municipalities had the previous years in the regression with a different treatment status. Columns 3 and 4 present the difference-in-differences results with all controls, and exogenous controls only. 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 of Table A.4

show a reduction in deforestation when the young mayor is in office. We conclude that initial differences between the municipalities that barely elected young mayors are not driving the results.

Table A.5 presents the results when we vary the age limit to define a candidate as young. We still observe a reduction when we use 25th and 15th percentiles of age. When we apply a quadratic and cubic polynomial in the margin of victory, the main results are even larger, (see Table A.6). The main results are also robust to different error estimations (see Table A.7). We use a triangular kernel in main specification following Cattaneo et al. (2020), but we also present robustness to Epanechnikov and Uniform kernels (see Table A.8). The results are robust when we use the same sample as the main specification (Columns 1-3 and 7-9). The coefficient is not statistically significant when using the optimal bandwidth of these kernels due to the wide bandwidth computed (Columns 6, 10, and 11). Table A.9 presents results for a placebo exercise, assigning deforestation four years before as dependent variable. There are no statistical significant effects of the young mayor on previous deforestation, as expected.

Figure A.4 presents the results of the sensitivity analysis in the main specification (Column 3 of Panel A in Table 2). In Figure A.4a we vary the bandwidth between half and twice the optimal bandwidth. The coefficient is statistically significant at 5% up to 17 percentage points of difference in the election. Figure A.4b shows the "Doughnut" results of the main specification when dropping different observations of the closest elections to avoid the results being driven by observations with higher weights in the same way as Barreca et al. (2011). Our result is robust when excluding less than 1 or more than 2.5 percentage points of observations around the cutoff. The coefficient is not statistically different from zero when excluding observations between 1 to 2.5 percentage points around the cutoff.

Figure A.5 presents results when we apply different threshold to drop potential outliers on deforestation and in forest area. The coefficients are constant when we remove forest area (Figure A.5a) and smaller when we drop the areas with more deforestation (Figure A.5b). Table B.3 shows the results excluding mayors in their second-term. Results remain qualitatively unchanged.

5.2 Other outcomes

We now study how having a young mayor in office impacts economic variables and other environmental measures. Table 3 changes the dependent variable on Equation (1) to study the effect of having a young mayor on numerous variables, some as potential mechanisms. Column 1 shows that per capita GDP is not affected when a young mayor is in office. Columns 2 and 3 show the results for GDP by economic sector. We find a reduction in the agricultural sector share and an increase in industry when a young mayor is in office. Although we do not find an increase in the agricultural share for senior mayors (Panel B), Columns 4 and 5 show an increase in agricultural planting area and livestock, measured as the number of bovines.

Columns 6 to 10 of Table 3 study what happens to greenhouse gas emissions per capita. Column 6 shows a large reduction in the emissions per capita when a young mayor is in office. Figure A.6 shows the Regression Discontinuity plot for the result of this Column. Figure A.7 and Figure A.8 show the robustness of the results when we vary bandwidth (Figure A.7a), drop some observations of the closest elections (Figure A.7b), potential outliers in total emissions (Figure A.8a), and in emissions per capita (Figure A.8b).

Part of this reduction is caused by a reduction in emissions associated with deforestation and the agricultural sector (see Table B.4). 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, 2022). The results for young mayors are aligned with the results in Panel B for senior mayors. Panel B shows a statistically significant increase in emissions intensity of the agricultural sector, deforestation, and energy sector when a senior mayor is in office.

Column 11 of Table 3 shows what happens when a young mayor is in office with regard to the number of environmental fines. As there is less deforestation with young mayors, there are also less environmental fines. As Ferreira (2024) mentions, although the low execution of fines is a problem in Brazil, a positive correlation between the imposition of fines and deforestation indicates a well-located enforcement effort. Table B.5 presents the results disaggregating by type of environmental fine. We do not observe a significant effect on fines directly associated with deforestation (Columns 3 and 7). [10]

Table B.7 studies the effect of electing a young mayor on agricultural sector variables. Column 1 shows a reduction in the production value in Panel A and Panel B, but the effect is not statistically significant. Also, we do not find significant effects on productivity (Column 2). Regarding the livestock sector, we find a reduction in the number of cows in municipalities with a young mayor and an increase in municipalities with an senior mayor. [11]

[10] Table B.6 presents same analysis as Table B.5 but using the optimal bandwidth for each specification.

[11] The results are not statistically significant in Column 3 (as they were in Column 5 of Table 3) because there are few observations, given that the Census does not happen yearly. Nonetheless, the sign is consistent

5.3 Local spending

We then study whether young mayors are spending their municipal budget differently and how much they are impacting local governments' liabilities. Column 12 in Table 3 Panel A shows that young mayors do not affect the share of the budget allocated to the environmental sector, while senior mayors (Panel B) reduce it by 0.43 percentage points. This reduction is more than 100% of the mean. There is evidence of more investment by young mayors in long-term policy, such as education (Column 13). Senior mayors invest less in education and more in the agricultural sector (Column 14). In the analysis of municipality liabilities (Column 15), young mayors borrow less, and this reduction is totally driven by the decrease in the amount of long-term liabilities (Column 7 of Table B.8). It means that young mayors commit fewer resources in the long run, although senior mayors spend more today. Table B.9 presents results the analogous to Table 3, selecting the optimal bandwidth for each regression. The conclusions are similar.

5.4 Turnover of bureaucrats

One 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 long-term goals.

We test this possibility in Table 4, estimating Equation (1) on turnover outcomes. In Column 1 we find that having a young mayor in office increases total turnover by about 9 percentage points (significant at the 5% level). In Columns 3 and 4 we decompose this outcome by hires and separations, showing that the effect is more concentrated in hires, although not significantly so. For Columns 5 to 8 we measure the percentage of total hires or total fires 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 / above the twentieth or eightieth percentile. In Column 5 we find a coefficient of 4.25 (significant at 5% level), i.e. young mayors concentrate hires more in young people compared to not young mayors. We do not find significant effects for the other measures.

Maybe 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 construct a new

in the two Columns.

RD sample 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 a third of that of the young mayor in Column 1.

Our findings echo recent work showing that Brazilian mayors can cause significant turnover in education (Akhtari et al., 2022) and health (Toral, 2023). In our case, despite such turnover being potentially driven by patronage (Colonnelli et al., 2020), it is still associated with positive impacts on municipalities' long-term policy outcomes.

6 Interpretation

The results in the previous Section show that when a young mayor is in office there are less environmental damages in the municipality at no clear economic cost. We now turn to interpreting our 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 (Alesina et al., 2019). Our RD design guarantees that we hold demand channels constant, given that municipalities are statistically similar on both sides of the cutoff. Our estimates, therefore, reflect a mix of supply channels, albeit locally, in areas where there was already substantial support for the young mayor's campaign and where the share of young voters was high. Although we do not attempt to explicitly isolate each supply mechanism, we perform three exercises to aid interpretation.

First, we study heterogeneous effects of young mayors' characteristics on deforestation. We find that young mayors improve environmental performance across the board, whereas senior mayors show significant heterogeneity. In Table 5 we report a version of Equation (1) estimated with heterogeneous treatment effects. Column 1 repeats the main result of Table 2 for ease of comparison. Column 2 studies the heterogeneous effects of having a college degree. We find that college is important to have less deforestation for senior mayors, but not for young mayors. This could be, for instance, due to the fact that the new Brazilian Constitution mandated environmental education throughout all education levels, a change that affected young mayors while in high school. Column 3 shows that young male and female mayors are statistically equally effective at reducing deforestation (although only 11% of young mayors are female; see the bottom row with the mean of the interaction variable). Column 4 studies whether young married mayors have a different effect on deforestation. One could expect that married mayors might have kids and therefore more inclined to protect the environment. Although the coefficient shows a negative sign, as expected, it is not statistically significant in the case of young mayor but it has a positive sign and significant for senior mayors. Column 5 shows that right-wing mayors are less effective at reducing deforestation. For senior mayors the differential effect is statistically significant, but for young mayors is not.

There are also no heterogeneous effects for young mayors, regardless of whether they are farmers, donations received or their experience in office. Column 6 presents the effect of being a young mayor in his second term. Column 7 studies whether young farmer mayors have a differential effect on deforestation. The sign is positive, although the effect is not statistically significant. This result is in line with Bragança and Dahis (2022). Column 8 shows the effect of winning elections the first time the candidate had ever run. Column 9 presents the effect of having more donations during the campaign.

Second, we find no statistically significant results in an alternative specification, where we exploit the full variation of age differences between candidates and compare outcomes when the younger candidate wins. We begin by modifying the treatment dummy *Young Won* to *Younger Won*, i.e. we encode an indicator function for the younger person running having won. This generalizes our previous definition of a young candidate having won and therefore expands our close elections sample to take advantage of the full variation in age differences between the winner and runner-up in elections. We then estimate Equation (1) substituting *Young Won* for *Younger Won*. If age is itself driving our results, we would expect that larger age differences between candidates are associated with larger decreases in deforestation. For instance, we would expect a larger effect when the winner's age is 42 and the runner-up's age is 64 versus when the former's age is 44 versus the latter's age is 48.

We report results in Table 6. Panel A shows results using our benchmark indicator for *Young Won*, whereas Panel B shows results using our alternative indicator for *Younger Won*. In Column 1 Panel A we replicate our main result from Table 2. In Panel B we show that on average the younger mayor having won does not impact deforestation. We allow for age-difference-specific effects in Columns 2 and 3. In particular, in Column 2 we interact our treatment dummies with the age difference between winner and runner-up. We find a statistically null interaction in Panel A but a statistically significant positive 0.01 interaction coefficient in Panel B. In other words, a 10-year age difference is on average associated with a 0.1 increase in deforestation (to be added to the -0.07 coefficient on the younger having won). In Column 3 we allow for more flexibility and fully interact our treatment dummies with a set of age difference bin fixed effects. We find in Panel A that the effect of a young candidate having won is mostly driven by races where the age difference is 10-19. Importantly, in Panel B, we do not find statistically significant reductions in deforestation for any age gap.

Overall, these two results combined suggest a *cohort effect*: young mayors matter because they are part of a new generation, and not because of their lower age per se. We can still not distinguish exactly *why* this new cohort is different. For example, they may have longer lifespans ahead of them. They may be more patient and have higher discount factors, valuing the future more. They may have been socialized in a more environment-aware culture and, so, have more pro-conservation preferences.[12] They may be more inexperienced, more idealistic or, perhaps, less co-opted by agribusiness interests. These are left for future research.

Lastly, to the extent that age correlates with other characteristics of politicians and those variables explain long-term policy, electing a young mayor would be a bundled treatment (Marshall, 2022). We perform horse-races to show that controlling for an array of other characteristics does not impact our estimates. We report coefficients for all controls in Table A.10.

7 Conclusion

In this paper, we study how politicians of different age groups affect environmental conservation and investment in various long-term policies in Brazil. We find evidence that having young mayors in office reduce deforestation and greenhouse-gas emissions. We find roughly opposite effects when a senior mayor is in the office. When exploring heterogeneity and mechanisms, our results suggest a *cohort effect*: young mayors matter because they are part of a new generation and not because of their lower age per se.

Our work highlights the importance of political renovation for environmental conservation. With climate change affecting mainly young generations, these results provide motivation for affirmative action based on age for elected bodies. In addition, it suggests that educating senior cohorts about environmental issues could yield similar positive outcomes. It is important to consider, however, that our results may not extrapolate to contexts where politicians have few levers to influence environmental policy, or where results of policies take longer to materialize, such industrial or energy policy.

Our research opens up several avenues for further exploration. For instance, it remains uncertain whether voters factor in candidates' age considerations when making their electoral choices. Furthermore, it is crucial to extend our analysis to determine whether the

[12] In fact, the Brazilian 1988 Constitution mandated environmental education at all levels of schooling.

observed patterns in Brazil can be generalized to other regions where emissions are primarily driven by sources other than deforestation, such as energy and industrial production. Finally, it will be crucial to understand *why* recent cohorts of politicians are different from previous ones, in terms of lifespan, patience, pro-conservation preferences, experience, among others.

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8 Tables and Figures

Table 1: Summary statistics

Variable	Brazil	Legal Amazon	Young Won	Not Young Won	Young (3) vs. Not Young (4) Difference	RD
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Municipality level						
Area (km2)	723.33	6,485.02	6,491.66	6,906.41	-414.75	1947.15
	(1,498.55)	(13,987.01)	(11,572.66)	(12,873.23)	(1,898.96)	(3,083.90)
GDP per cap. in 2002	5,466.50	3,703.77	3,004.54	3,396.24	-391.70	-9.54
	(6,009.41)	(4,138.13)	(1,769.33)	(2,305.63)	(319.72)	(572.57)
Population in 2002	32,072.88	29,852.95	18,137.75	17,502.44	635.31	-1166.75
	(201,206.06)	(97,420.61)	(17,473.06)	(17,872.80)	(2,751.71)	(6,788.25)
% Young population in 2000 (Census)	58.82	68.57	69.83	70.08	-0.25	2.10
	(6.15)	(5.38)	(5.86)	(5.30)	(0.87)	(1.92)
Forest area in 2000 (km2)	–	4,449.57	4,425.90	5,022.40	-596.49	2622.17
		(13,391.85)	(11,012.53)	(11,616.82)	(1,756.56)	(2,595.00)
N	4,794	605	84	82		
Panel B: Municipality-term level						
% Elections with Young in Top 2	14.76	11.11	100.00	100.00	0.00	0.00
	(35.47)	(31.44)	(0.00)	(0.00)	(0.00)	(0.00)
Deforestation as % of Forest in 2000	–	0.68	0.83	0.71	0.12	-0.41
		(1.21)	(1.12)	(1.20)	(0.16)	(0.28)
College	0.48	0.39	0.47	0.26	0.21***	0.26**
	(0.50)	(0.49)	(0.50)	(0.44)	(0.07)	(0.13)
Male	0.91	0.88	0.88	0.88	0.00	0.07
	(0.29)	(0.33)	(0.33)	(0.32)	(0.05)	(0.09)
Married	0.78	0.72	0.57	0.72	-0.15**	-0.14
	(0.41)	(0.45)	(0.50)	(0.45)	(0.07)	(0.12)
Right-wing	0.77	0.76	0.73	0.71	0.02	-0.22*
	(0.42)	(0.43)	(0.44)	(0.46)	(0.06)	(0.13)
Farmer	0.14	0.15	0.10	0.13	-0.03	-0.04
	(0.34)	(0.35)	(0.30)	(0.34)	(0.05)	(0.09)
Donations per cap.	36.64	41.64	8.39	7.90	0.49	-1.23
	(318.72)	(367.23)	(8.84)	(8.84)	(1.26)	(2.03)
Second term	0.27	0.25	0.09	0.17	-0.08	-0.00
	(0.44)	(0.43)	(0.29)	(0.37)	(0.05)	(0.10)
N	19,176	2,884	98	102		

Notes: Mean and standard deviation (in parentheses) of the municipal and mayor attributes disaggregated by groups. Column 1 includes Brazilian municipalities outside the Legal Amazon. Column 2 contains Legal Amazon municipalities that are not in the RD sample. Columns 3 and 4 municipalities of our main regression sample disaggregated by whether a Young or Not Young candidate won the close election. Columns 5 and 6 show the difference between Young (Column 3) and Not Young (Column 4). Column 5 uses a t-test, and Column 6 uses a regression discontinuity with year fixed effects. Panel A contains information on the municipalities that belong to the main sample. Panel B provides information about the characteristics of those municipalities in the main sample with variation by electoral term. *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 2: Electing a young mayor reduces deforestation

Dependent variable:	Deforestation as % forest 2000								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A:	Margin: Young vs. Not young								
Young won	-0.49**	-0.46**	-0.48**	-0.48**	-0.44**	-0.48**	-0.59***	-0.53***	-0.57***
	(0.20)	(0.19)	(0.19)	(0.20)	(0.19)	(0.19)	(0.21)	(0.21)	(0.21)
Mean Dep. Variable Control	0.73	0.74	0.72	0.72	0.72	0.72	0.76	0.76	0.76
Age Diff.	17.50	17.61	17.57	17.54	17.54	17.57	17.53	17.53	17.57
Bandwidth	12.03	11.39	12.31	12.31	12.31	12.31	12.31	12.31	12.31
N	754	728	755	762	762	755	685	685	678
Panel B:	Margin: Young vs. Senior								
Young won	-0.97***	-0.53*	-0.50	-0.96***	-0.62**	-0.54*	-0.97***	-0.60**	-0.54*
	(0.37)	(0.29)	(0.31)	(0.37)	(0.31)	(0.30)	(0.38)	(0.30)	(0.30)
Mean Dep. Variable Control	0.88	0.79	0.88	0.85	0.85	0.85	0.89	0.89	0.89
Age Diff.	28.17	27.82	27.76	27.94	27.94	28.02	27.73	27.73	27.81
Bandwidth	11.92	15.13	10.82	12.31	12.31	12.31	12.31	12.31	12.31
N	209	246	193	213	213	209	199	199	195
Panel C:	Margin: Senior vs. Not senior								
Senior won	0.06	0.08	0.05	0.03	0.07	0.02	0.03	0.07	0.02
	(0.15)	(0.15)	(0.15)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Mean Dep. Variable Control	0.77	0.79	0.78	0.80	0.80	0.80	0.80	0.80	0.80
Age Diff.	16.71	16.71	16.54	16.75	16.75	16.65	16.75	16.75	16.65
Bandwidth	10.92	11.42	10.89	12.31	12.31	12.31	12.31	12.31	12.31
N	1,737	1,758	1,687	1,868	1,844	1,822	1,868	1,844	1,822
Controls	No	Exo	All	No	Exo	All	No	Exo	All

Notes: This table presents the effect of having a young mayor or a senior mayor on deforestation. The coefficients are estimated using Equation (1). Columns 1 to 3 use the optimal bandwidth of each regression. Columns 4 to 6 are restricted to the optimal bandwidth of Column 3 in Panel A. Columns 1 and 4 do not control for any covariate. Columns 2 and 4 control for population and gender. Columns 3 and 6 control for population, gender, party alignment (left or right), second-term, marital status, and college attendance. Columns 7 to 9 replicate the analysis of Columns 4 to 6, respectively, but excluding from the sample those municipalities whose mayor was classified as young in the past (this restriction is irrelevant when the comparison involves only seniors). Panel A uses the sample of all municipalities with one young candidate in the top two. Panel B restricts the sample to municipalities with exactly one young and one senior candidate in the top two. In Panel C, the sample contains all elections in which a senior candidate was in the top two. Age Diff. is the average difference in age between the top two candidates. All regressions include year and age profile fixed effects. Significance level: $^*p < 0.10$, $^{**}\ p < 0.05$, $^{***}p < 0.01$.

Table 3: Electing a young mayor changes other outcomes

	GDP			Agro		Emissions per capita (tCO2)					# Fines	% Government spending			
Dependent variable:	Per cap. (1)	Agro (%) (2)	Industry (%) (3)	Area (ha) (4)	# Bovine (5)	Total (6)	Agro (7)	Land Use (8)	Energy (9)	Waste (10)	Total (11)	Environment (12)	Education (13)	Agro (14)	Liabilities (15)
Panel A:	Margin: Young vs. Not Young														
Young won	1,365.56	-5.65***	3.57**	-181.25	-30.67	-68.55***	-6.08	-62.78***	0.05	0.26***	-0.12	-0.14	2.71**	0.20	-7.90**
	(2,746.19)	(2.05)	(1.70)	(229.21)	(31.82)	(18.68)	(3.93)	(16.11)	(0.32)	(0.07)	(2.55)	(0.17)	(1.07)	(0.14)	(3.86)
Mean Dep. Var. Control	13,420.85	26.84	8.99	898.34	128.22	71.64	23.76	46.39	1.14	0.36	8.68	0.36	19.70	0.60	11.25
Optimal band	12.31	12.31	12.31	12.31	12.31	12.31	12.31	12.31	12.31	12.31	12.31	12.31	12.31	12.31	12.31
N	755	755	755	755	755	710	710	710	710	710	755	330	330	330	301
Panel B:	Margin: Senior vs. Not Senior														
Senior won	6,238.97***	0.00	0.91	726.50***	100.51***	24.90	6.48**	17.42	1.04***	-0.05	5.81**	-0.43***	-2.94***	0.25***	5.71**
	(2,257.17)	(1.38)	(1.26)	(221.48)	(21.50)	(21.72)	(2.61)	(20.76)	(0.29)	(0.04)	(2.35)	(0.11)	(0.79)	(0.09)	(2.48)
Mean Dep. Var. Control	13,135.52	25.83	9.70	916.63	103.77	42.75	18.98	22.34	1.06	0.37	9.59	0.36	19.83	0.54	11.06
Optimal band	10.89	10.89	10.89	10.89	10.89	10.89	10.89	10.89	10.89	10.89	10.89	10.89	10.89	10.89	10.89
N	1,687	1,687	1,687	1,683	1,687	1,574	1,574	1,574	1,574	1,574	1,687	734	734	734	668

Notes: The coefficients are estimated using Equation (1) but changing the variable of interest. The bandwidth used in this Table is the same as Column 3 of Table 2 but can be smaller given that not all variables have observations in all years used in main sample. Column 1 shows the effect on the GDP 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 Agro and Industry sectors respectively by the total nominal GDP of each year. Columns 4 and 5 are calculated using data from Municipal Agricultural Research (Pesquisa Agrícola Municipal). Columns 6 to 10 are computed by dividing the CO2 emissions in tons by the population of each municipality. All emissions data are provided by (Sistema de Estimativa de Emissões e Remoções de Gases de Efeito Estufa, Observatório do ClimaSEEG, n.d.). Data are available until 2018. 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, 2022, p.7). Column 11 uses the number of fines provided by IBAMA. Columns 12 to 14 are calculated by dividing the expenditure per budget by the total budget of the municipality. Column 15 presents results on municipality liabilities as percentage of the municipality expenditure. The amounts of liabilities are deflated using the IPCA index. Panel A takes as a sample all municipalities with at least one young candidate among the top two. In Panel B, the sample contains all elections in which a senior candidate was in the top two. All regressions have year and age profile fixed-effects, and control for mayor gender, party alignment (left or right), second-term, marital status, college attendance and population. Significance level: $*p < 0.10$, $**\ p < 0.05$, $***p < 0.01$.

Table 4: Electing a young mayor increases 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	8.72**		3.01	1.60	4.25**	-0.51	2.79	-0.03
	(4.10)		(2.15)	(2.99)	(1.94)	(0.67)	(1.98)	(0.96)
New Won		2.96						
		(2.60)						
Mean Dep. Var. Control	50.17	46.90	24.11	25.45	54.03	6.48	50.86	9.51
Bandwidth	12.31	12.31	12.31	12.31	12.31	12.31	12.31	12.31
N	656	1,647	642	656	637	637	655	655

Notes: This table shows the effect of having a young mayor 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 and adding interactions. The bandwidth used is the same as in the main regression. All regressions have year and age profile fixed-effects, and control by mayor gender, party alignment (left or right), second-term, marital status, college attendance, and population. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 5: Heterogeneous effects of electing a young mayor

Dependent variable:		Deforestation as % forest 2000							
		Interaction variables as columns							
		College	Male	Married	Right wing	Second term	Farmer	First time running	Donations per cap.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A:		Margin: Young vs. Not Young							
Treat	-0.48***	-0.52**	-1.14**	-0.38*	-0.78***	-0.51**	-0.50***	-0.51**	-0.53***
	(0.19)	(0.23)	(0.53)	(0.22)	(0.28)	(0.20)	(0.19)	(0.23)	(0.20)
Treat X Interaction		0.12	0.74	-0.13	0.41	0.25	0.22	0.16	0.01
		(0.25)	(0.49)	(0.21)	(0.25)	(0.27)	(0.41)	(0.23)	(0.01)
Mean Dep. Var. Control	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72
Mean interact.	-	0.46	0.89	0.57	0.74	0.09	0.10	0.83	8.28
N		755	755	755	755	755	755	755	755
Panel B:		Margin: Senior vs. Not Senior							
Treat	0.05	0.27*	0.00	-0.34*	-0.41*	0.07	0.03	0.05	0.07
	(0.15)	(0.16)	(0.21)	(0.18)	(0.22)	(0.15)	(0.15)	(0.15)	(0.15)
Treat X Interaction		-0.59***	0.05	0.55***	0.64***	-0.18	-0.00	0.04	-0.00
		(0.16)	(0.20)	(0.15)	(0.19)	(0.16)	(0.26)	(0.17)	(0.01)
Mean Dep. Var. Control	0.78	0.78	0.78	0.78	0.78	0.78	0.78	0.78	0.78
Mean interact.	-	0.36	0.88	0.74	0.79	0.25	0.20	0.24	7.29
N		1,687	1,687	1,687	1,687	1,687	1,687	1,687	1,687

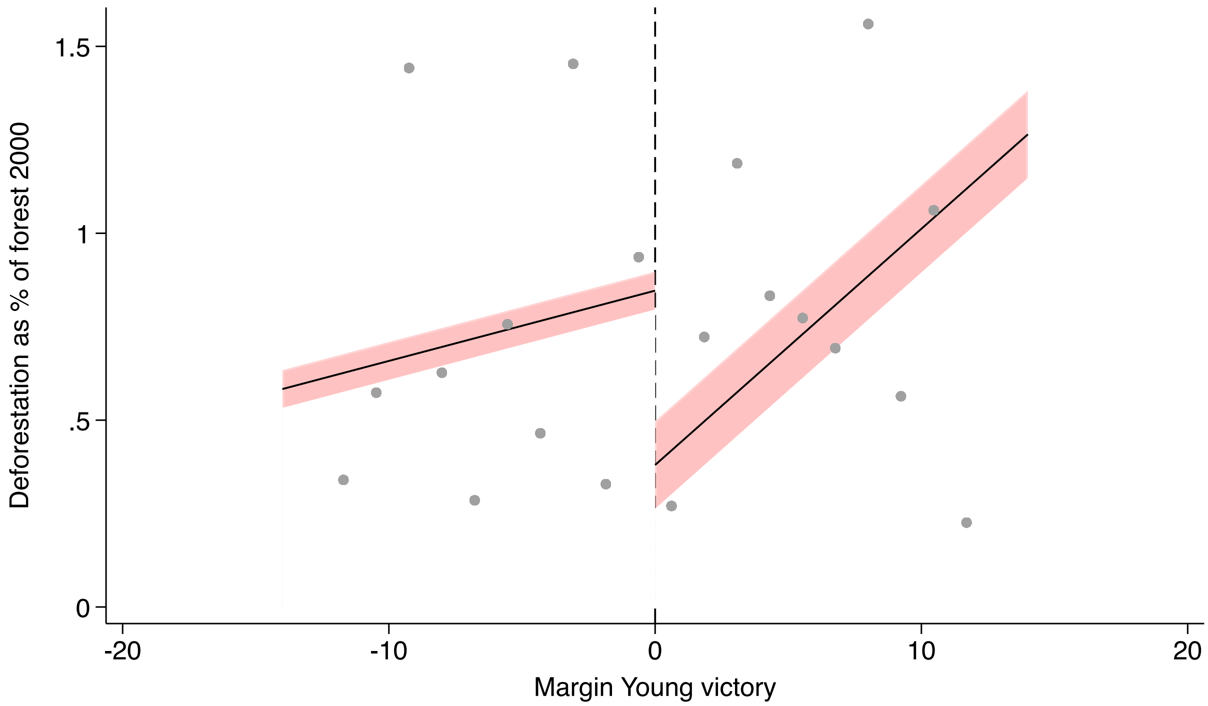
Notes: Heterogeneous effect of having a young or senior mayor on deforestation. The coefficients are estimated using Equation (1) but adding an interaction term between the treatment dummy and the variable of interest. The sample of this Table is the same as Column 3 of Table 2. Column 1 presents the 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 of the main specification sample (1.6%), 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 have year and age profile fixed-effects, and control for mayor gender, party alignment (left or right), second-term, marital status, college attendance, and population. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 6: Distinguishing age and cohort effects

Dependent variable:	Deforestation as % forest 2000		
	(1)	(2)	(3)
Panel A:	Margin: Young vs. Not Young		
Young Won	-0.48***	-0.70***	
	(0.19)	(0.23)	
Young Won × Age Diff.		0.01	
		(0.01)	
Young Won × 0-9			-0.43
			(0.28)
Young Won × 10-19			-0.67***
			(0.24)
Young Won × 20-29			-0.26
			(0.20)
Young Won × 30+			-0.44
			(0.27)
Mean Dep. Var.	0.72	0.72	0.72
N. Obs	755	755	755
R^2	0.21	0.21	0.21
Panel B:	Margin: Younger vs. Not Younger		
Younger Won	0.06	-0.07	
	(0.09)	(0.09)	
Younger Won X Age Diff.		0.01**	
		(0.01)	
Younger Won X 0-9			0.05
			(0.09)
Younger Won × 10-19			-0.02
			(0.11)
Younger Won × 20-29			0.32*
			(0.18)
Younger Won × 30+			0.08
			(0.18)
Mean Dep. Var.	0.69	0.69	0.69
N. Obs	4,200	4,200	4,200
R^2	0.11	0.11	0.11

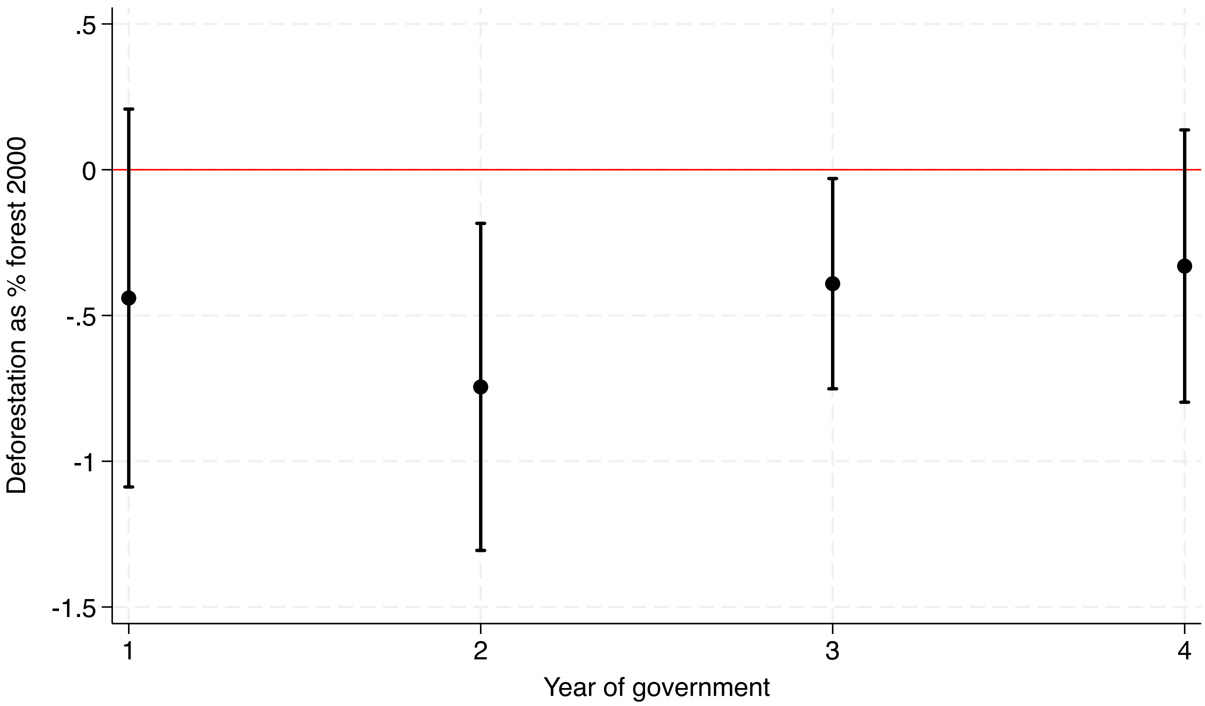
Notes: Effect of having a younger mayor in the mayor office dissagregated by age intervals. The coefficients of Column 2 are estimated by using Equation (1) but adding an interaction term between the treatment dummy and the variable of interest, while Column 3 is computed by splitting the coefficient. Panel A shows the results using the main specification. Panel B displays results using younger between the two most voted candidates as treatment. All regressions have year and age profile fixed-effects, and control for mayor gender, party alignment (left or right), second-term, marital status, and population. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Figure 1: Visual regression discontinuity (RD) results



Notes: Regression Discontinuity plot of the main specification (Column 3 of Panel A in Table 2). Observations are grouped in 10 bins at each side of the winning cutoff. Triangular kernel is used. The regression controls for population, gender, party alignment (left or right), second-term, marital status, college attendance, and it also includes year and age profile fixed effects.

Figure 2: Heterogeneous effects by year within term



Notes: This figure shows the effect disaggregated by year within term using the same sample as the main specification (Column 3 of Panel A in Table 2). These coefficients have been computed interacting the treatment variable with each of the four years of government. Confidence intervals at 95%.

A Appendix

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)
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	-0.04	6.57	-12.04	12.31	200
Margin young vs senior	-0.18	6.02	-10.02	10.72	50
Margin senior vs not senior	-0.02	6.10	-10.86	10.89	450
Panel B: Other variables					
% Environmental expenditure	0.38	0.68	0.00	4.42	330
% Education expenditure	19.87	5.78	0.00	34.84	330
% Health expenditure	10.67	2.37	0.00	16.52	330
% Agro expenditure	0.64	0.68	0.00	3.54	330
GDP (R$ Current prices) per cap.	13,280.46	14,618.73	1,440.19	180,941.36	755
Donations per cap.	8.05	8.67	0.10	50.83	755
Agro as % GDP	25.73	15.03	0.78	72.73	755

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 (1.6% 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$. The Energy Emissions intensity from Brazil was 0.5 for 1 (kgCO2/R$) in the United States in 2019.

Table A.3: Additional summary statistics by candidate

Variable	Brazil	Amazon	Sample	Young in sample
	(1)	(2)	(3)	(4)
College	0.48	0.41	0.38	0.46
	(0.50)	(0.49)	(0.48)	(0.50)
Male	0.89	0.85	0.88	0.87
	(0.31)	(0.35)	(0.33)	(0.34)
Married	0.75	0.70	0.65	0.57
	(0.43)	(0.46)	(0.48)	(0.50)
Right-wing	0.71	0.71	0.70	0.72
	(0.45)	(0.45)	(0.46)	(0.45)
Donations per cap.	5.33	8.17	8.14	8.39
	(5.67)	(9.52)	(8.82)	(8.84)
Pro-Agriculture	0.13	0.13	0.13	0.10
	(0.33)	(0.34)	(0.33)	(0.30)
N	50,773	8,328	625	225

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, 2,687, 197, 97 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. Column 3 presents the running candidates statistics in the municipalities with close elections used in Column 3 of Table 2. Column 4 uses the same data as Column 3 but keeping only the young candidates. Each candidate is one observation.

Table A.4: 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	-0.48**	-0.11	-0.43***	-0.54***
	(0.19)	(0.10)	(0.16)	(0.15)
Mean Dep. Variable Control	0.72	0.43	1.00	1.00
Controls	All	All	All	Exo
Bandwidth	12.31	12.31	–	–
Coef. PT	–	–	2.67	2.50
	–	–	(4.89)	(3.72)
N	755	487	974	974

Notes: This table presents the effect of having 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 is the same as the main specification (Column 3 of Table 2), while Column 2 restricts the sample to those municipalities that not belong to the sample in the previous electoral period and with values in dependent variable and covariates not only during the period of the main specification but four periods before. Column 3 uses the same sample as Column 2 but changes the estimation to a DD approach, doubling the number of observations to take the observations before the arrival of the mayors in the main sample. Column 4 uses the same sample but keeping only exogenous controls. The parallel trends (PT) assumption is tested by computing the regression only in the pre-treatment period. RD estimations include year and age profile fixed effects and control by population, gender, second-term, right wing, and married. DD estimations include municipality and cohort fixed effects. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A.5: Robustness to treatment and dependent variable

Dependent variable:	Deforestation as % forest 2000							
	p25		p20		p15		LEI No 11.692	Born in 1976
	By-election	Whole sample	By-election	Whole sample	By-election	Whole sample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Margin: Young vs. Not Young								
Young Won	-0.32**	-0.07	-0.48**	-0.23	-0.71**	-0.54**	0.32	-0.10
	(0.16)	(0.17)	(0.19)	(0.17)	(0.29)	(0.26)	(0.52)	(0.16)
Mean Dep. Variable Control	0.74	0.88	0.72	0.74	0.85	0.84	0.96	0.63
Bandwidth	12.31	12.31	12.31	12.31	12.31	12.31	12.31	12.31
N	1,077	1,165	755	871	486	550	200	838
Panel B: Margin: Young vs. Not Young								
Young Won	-0.31**	-0.11	-0.48**	-0.22	-0.68**	-0.37	0.32	-0.08
	(0.16)	(0.15)	(0.19)	(0.17)	(0.29)	(0.23)	(0.52)	(0.15)
Mean Dep. Variable Control	0.72	0.84	0.72	0.72	0.84	0.75	0.96	0.60
Optimal bandwidth	13.20	14.38	12.31	13.35	12.66	17.87	12.09	17.36
N	1,143	1,330	755	932	506	717	200	1,063
Panel C: Margin: Senior vs. Not Senior								
Senior Won	-0.07	-0.11	0.05	0.01	0.09	-0.09	0.39	0.12
	(0.14)	(0.14)	(0.15)	(0.14)	(0.15)	(0.15)	(0.26)	(0.17)
Mean Dep. Variable Control	0.77	0.77	0.78	0.68	0.68	0.70	0.64	0.64
Bandwidth	10.89	10.89	10.89	10.89	10.89	10.89	10.89	10.89
N	1,852	1,822	1,687	1,617	1,341	1,165	367	785
Panel D: Margin: Senior vs. Not Senior								
Senior Won	-0.10	-0.12	0.05	0.03	0.29*	0.10	0.63**	0.08
	(0.13)	(0.13)	(0.15)	(0.14)	(0.17)	(0.17)	(0.28)	(0.15)
Mean Dep. Variable Control	0.78	0.79	0.78	0.67	0.71	0.73	0.62	0.59
Optimal bandwidth	12.65	11.96	10.89	10.19	7.89	7.94	9.14	17.36
N	2,066	1,946	1,687	1,521	993	865	301	1,063

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–. Column 8 defines young as those people who were born after 1976 (having 12 years when 1988 changes were implemented in the Constitution). 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 bandwidth restricted to the optimal bandwidth of the main regression. Panels B and D use the optimal bandwidth for each regression. All regressions have year and age profile fixed effects and control by population, gender, second-term, right wing, and married. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A.6: 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	-0.79***	-0.75***	-0.77***	-0.96***	-0.90***	-0.91***	-0.98***	-0.91***	-0.90***	-1.40***	-1.30***	-1.27***
	(0.23)	(0.22)	(0.22)	(0.25)	(0.24)	(0.23)	(0.26)	(0.25)	(0.25)	(0.39)	(0.36)	(0.36)
Mean Dep. Variable Control	0.68	0.69	0.70	0.72	0.72	0.72	0.71	0.71	0.70	0.72	0.72	0.72
Controls	No	Exo	All	No	Exo	All	No	Exo	All	No	Exo	All
Polynomial Order	2	2	2	2	2	2	3	3	3	3	3	3
Bandwidth	15.09	14.58	14.39	12.31	12.31	12.31	20.21	20.10	19.95	12.31	12.31	12.31
N	904	886	865	762	762	755	1,096	1,096	1,083	762	762	755
Panel B:	Margin: Senior vs. Not Senior											
Senior Won	0.23	0.28	0.25	0.40*	0.48**	0.44*	0.38	0.44*	0.41*	0.69**	0.80**	0.75**
	(0.19)	(0.19)	(0.20)	(0.22)	(0.23)	(0.23)	(0.23)	(0.24)	(0.24)	(0.30)	(0.31)	(0.31)
Mean Dep. Variable Control	0.79	0.79	0.79	0.77	0.77	0.78	0.77	0.77	0.78	0.77	0.77	0.78
Controls	No	Exo	All	No	Exo	All	No	Exo	All	No	Exo	All
Polynomial Order	2	2	2	2	2	2	3	3	3	3	3	3
Bandwidth	14.97	14.92	14.19	10.89	10.89	10.89	17.99	17.96	17.48	10.89	10.89	10.89
N	2,168	2,137	2,042	1,733	1,709	1,687	2,408	2,384	2,318	1,733	1,709	1,687

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 3 to 6 and 10 to 12 are restricted to the optimal bandwidth of the main specification of Table 2 (Column 3). Columns 2, 5, 8 and 11 control by gender and population. Columns 3, 6, 9 and 12 control by gender, population, party alignment (left or right), second-term, married status and college attendance. 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 profile fixed effects. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A.7: Robustness to different standard errors

Dependent variable:	Deforestation as % forest 2000		
	(1)	(2)	(3)
Panel A:	Margin: Young vs. Not Young		
Young Won	-0.48	-0.44	-0.48
HC0 Conventional	(-0.871,-0.098)	(-0.812,-0.061)	(-0.859,-0.110)
HC0 Robust	(-1.401,-0.418)	(-1.310,-0.386)	(-1.327,-0.408)
HC1 Conventional	(-0.872,-0.097)	(-0.813,-0.060)	(-0.860,-0.109)
HC1 Robust	(-1.403,-0.416)	(-1.312,-0.384)	(-1.328,-0.406)
HC2 Conventional	(-0.872,-0.097)	(-0.814,-0.059)	(-0.860,-0.109)
HC2 Robust	(-1.404,-0.416)	(-1.313,-0.384)	(-1.329,-0.406)
HC3 Conventional	(-0.873,-0.095)	(-0.815,-0.058)	(-0.861,-0.108)
HC3 Robust	(-1.406,-0.413)	(-1.315,-0.382)	(-1.331,-0.404)
Clustered Municipality Conventional	(-0.962,-0.007)	(-0.887, 0.014)	(-0.925,-0.044)
Clustered Municipality Robust	(-1.789,-0.030)	(-1.650,-0.046)	(-1.656,-0.078)
Clustered Municipality-term Conventional	(-0.831,-0.137)	(-0.774,-0.099)	(-0.820,-0.149)
Clustered Municipality-term Robust	(-1.452,-0.367)	(-1.360,-0.337)	(-1.377,-0.358)
Mean Dep. Variable Control	0.72	0.72	0.72
Controls	No	Exo	All
Bandwidth	12.31	12.31	12.31
N	762	762	755
Panel B:	Margin: Senior vs. Not Senior		
Senior Won	0.06	0.10	0.05
HC0 Conventional	(-0.226, 0.346)	(-0.196, 0.391)	(-0.243, 0.339)
HC0 Robust	(-0.036, 0.823)	(0.010, 0.898)	(-0.033, 0.847)
HC1 Conventional	(-0.227, 0.346)	(-0.196, 0.391)	(-0.243, 0.339)
HC1 Robust	(-0.036, 0.823)	(0.009, 0.899)	(-0.034, 0.848)
HC2 Conventional	(-0.227, 0.346)	(-0.196, 0.392)	(-0.243, 0.339)
HC2 Robust	(-0.037, 0.824)	(0.009, 0.899)	(-0.035, 0.849)
HC3 Conventional	(-0.228, 0.347)	(-0.197, 0.392)	(-0.244, 0.340)
HC3 Robust	(-0.038, 0.825)	(0.008, 0.900)	(-0.036, 0.850)
Clustered Municipality Conventional	(-0.388, 0.507)	(-0.359, 0.555)	(-0.398, 0.494)
Clustered Municipality Robust	(-0.283, 1.070)	(-0.245, 1.153)	(-0.279, 1.093)
Clustered Municipality-term Conventional	(-0.229, 0.349)	(-0.198, 0.394)	(-0.244, 0.340)
Clustered Municipality-term Robust	(-0.037, 0.824)	(0.008, 0.900)	(-0.034, 0.848)
Mean Dep. Variable Control	0.77	0.77	0.77
Controls	No	Exo	All
Bandwidth	10.89	10.89	10.89
N	1,733	1,709	1,687

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. (2020) and is not point-centered. Optimal bandwidths are restricted to the optimal bandwidth of Column 3 in Table 2. Column 2 controls by gender and population. Column 3 controls by gender, population, party alignment (left or right), second-term, married status, and college attendance. 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 profile fixed effects.

Table A.8: 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	-0.45**	-0.40**	-0.44**	-0.41**	-0.38**	-0.18	-0.44**	-0.39**	-0.43**	-0.23	-0.06	-0.35**
	(0.20)	(0.20)	(0.20)	(0.19)	(0.19)	(0.16)	(0.19)	(0.19)	(0.19)	(0.17)	(0.15)	(0.17)
Mean Dep. Variable Control	0.72	0.72	0.72	0.69	0.70	0.70	0.72	0.72	0.72	0.69	0.70	0.68
Controls	No	Exo	All	No	Exo	All	No	Exo	All	No	Exo	All
Bandwidth	12.31	12.31	12.31	14.58	14.13	20.55	12.31	12.31	12.31	16.27	18.68	14.73
N	762	762	755	886	858	1,092	762	762	755	937	1,033	882
Panel B:	Margin: Senior vs. Not Senior											
Senior Won	0.01	0.05	-0.00	0.04	0.07	0.02	-0.04	-0.01	-0.07	0.00	-0.02	-0.01
	(0.14)	(0.14)	(0.14)	(0.15)	(0.15)	(0.15)	(0.13)	(0.14)	(0.14)	(0.14)	(0.13)	(0.14)
Mean Dep. Variable Control	0.77	0.77	0.78	0.77	0.77	0.78	0.77	0.77	0.78	0.79	0.79	0.80
Controls	No	Exo	All	No	Exo	All	No	Exo	All	No	Exo	All
Bandwidth	10.89	10.89	10.89	9.93	10.15	9.99	10.89	10.89	10.89	11.45	13.55	11.51
N	1,733	1,709	1,687	1,602	1,598	1,563	1,733	1,709	1,687	1,786	1,986	1,740

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 do not have controls. Columns 2, 5, 8 and 11 control by gender and population. Columns 3, 6, 9 and 12 control by gender, population, party alignment (left or right), second-term, married status and college attendance. 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 profile fixed effects. Significance level: $^{*}p < 0.10$, $^{**}\ p < 0.05$, $^{***}p < 0.01$.

Table A.9: 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	-0.13	-0.11	-0.08	-0.19	-0.10	-0.11
	(0.36)	(0.37)	(0.34)	(0.51)	(0.50)	(0.50)
Mean Dep. Variable Control	1.11	1.12	1.10	1.14	1.14	1.14
Age Diff.	17.19	17.35	17.14	17.37	17.37	17.42
Bandwidth	20.41	19.32	21.98	12.31	12.31	12.31
N	860	818	893	544	544	537
Panel B: Margin	Margin: Senior vs. Not Senior					
Senior Won future election	0.18	0.31	0.30	0.36	0.52	0.53
	(0.55)	(0.59)	(0.59)	(0.69)	(0.73)	(0.73)
Mean Dep. Variable Control	1.27	1.27	1.28	1.29	1.28	1.30
Age Diff.	17.08	16.99	16.99	16.89	16.89	16.73
Bandwidth	16.48	15.92	16.15	10.89	10.89	10.89
N	1,643	1,575	1,572	1,147	1,126	1,105

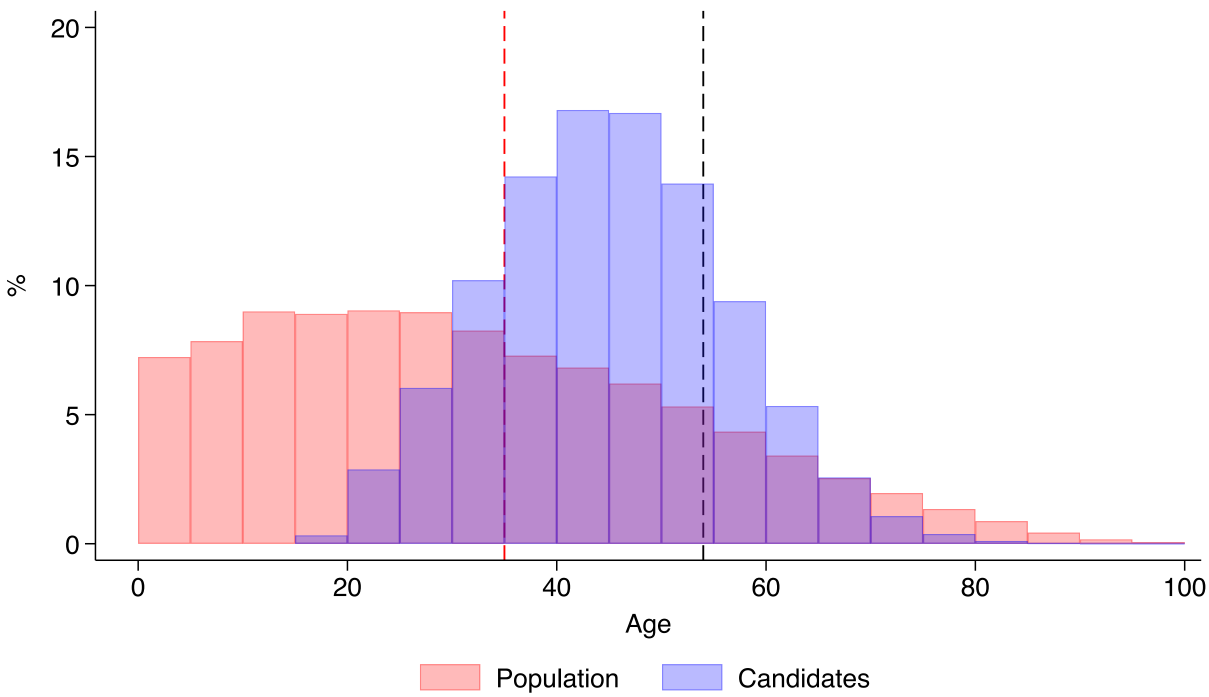
Notes: This table presents the placebo analysis. The coefficients are estimated using Equation (1), but the dependent variable is deforestation of the same municipality four years ago and those observations treated during one period and the next one were removed. Columns 1 to 3 are computed considering 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 do not have controls. Columns 2 and 5 control by population and gender. Columns 3 and 6 control by population, gender, party alignment (left or right), second-term, married status and college attendance. 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 and age profile fixed-effects. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A.10: Results reporting mayor covariates' coefficients

Dependent variable:	Deforestation as % forest 2000					
	(1)	(2)	(3)	(4)	(5)	(6)
	Margin: Young vs. Not Young					
Young Won	-0.47**	-0.42**	-0.42**	-0.43**	-0.48**	-0.48***
	(0.19)	(0.17)	(0.17)	(0.17)	(0.19)	(0.19)
Male		-0.54**	-0.54**	-0.54**	-0.52**	-0.52**
		(0.26)	(0.26)	(0.27)	(0.26)	(0.26)
Married			0.00	0.00	-0.01	-0.01
			(0.10)	(0.11)	(0.11)	(0.11)
College				0.03	0.01	0.01
				(0.12)	(0.13)	(0.12)
Right					-0.26*	-0.26*
					(0.13)	(0.14)
2nd Term						0.00
						(0.16)
Mean Dep. Var.	0.72	0.72	0.72	0.72	0.72	0.72
N. Obs	755	755	755	755	755	755
R^2	0.19	0.20	0.20	0.20	0.21	0.21

Notes: Coefficients of the controls using sample in Table 2 (Column 3). All regressions have year and age profile fixed effects. Columns 2-6 also control by population. Significance level: $^{*}p < 0.10$, $^{**}\ p < 0.05$, $^{***}p < 0.01$.

Figure A.1: Age distribution

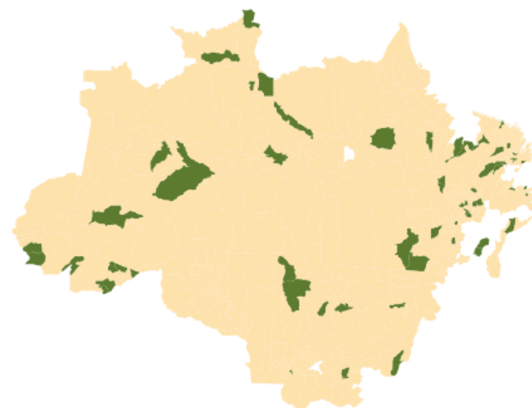


Notes: This histogram presents the age distribution of all candidates in ordinary municipal elections in Brazil during the elections included in the study period: 2004 to 2016 and the Brazilian population according to the 2010 Census. Lines in red and black show the 20th percentile of the age (approximately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

Figure A.2: Municipalities in the RD sample by election year

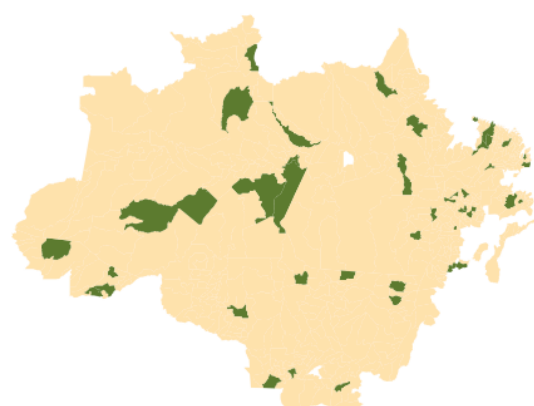
(a) RD sample in 2004 elections

(b) RD sample in 2008 elections



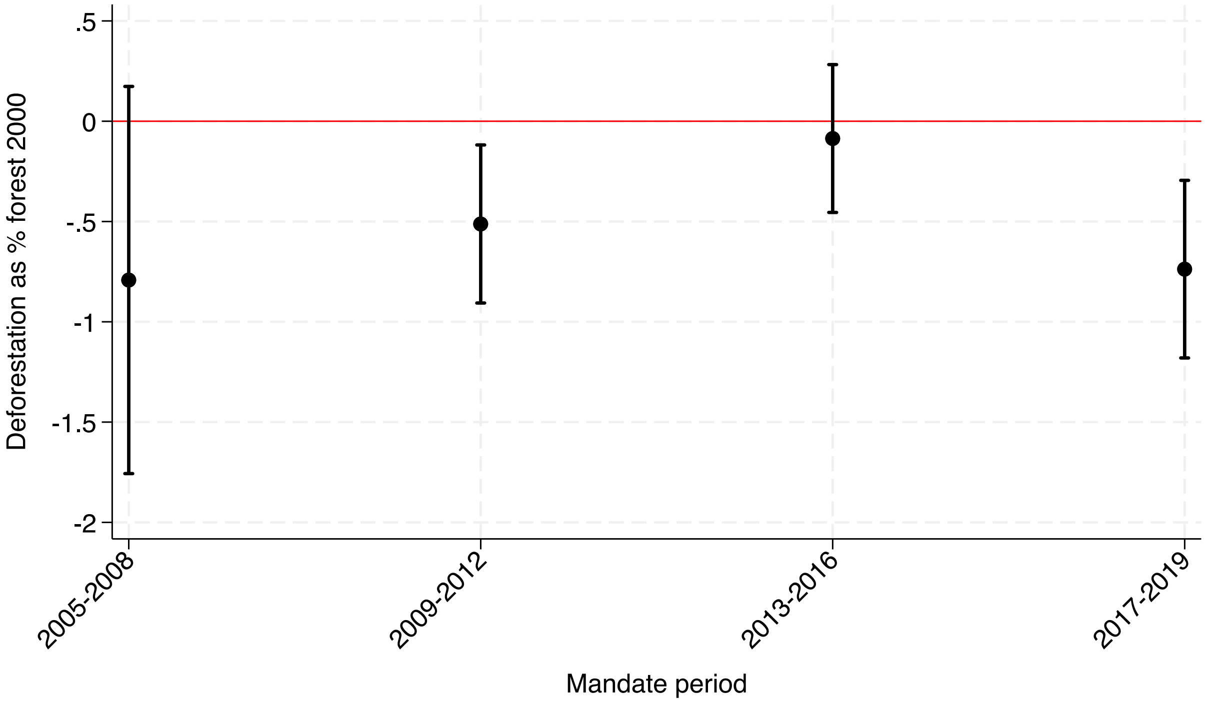
(c) RD sample in 2012 elections

(d) RD sample in 2016 elections



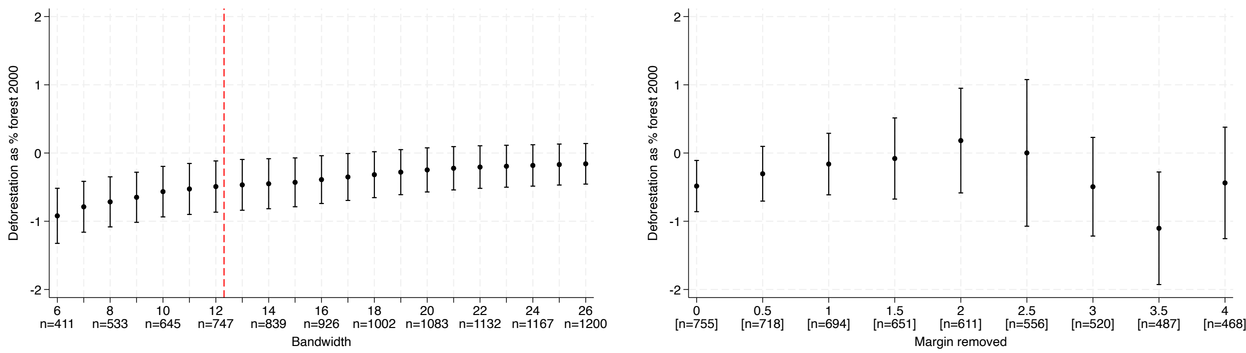
Notes: This figure presents the geographical distribution of the municipalities that belong to the regression discontinuity (RD) sample of the main regression.

Figure A.3: Heterogeneous effects by election year



Notes: This figure shows the effect disaggregated by election year using the same sample as the main specification (Column 3 of Panel A in Table 2). These coefficients have been computed interacting the treatment variable with each of the four years of government. Confidence intervals at 95%.

Figure A.4: Deforestation sensitivity analysis

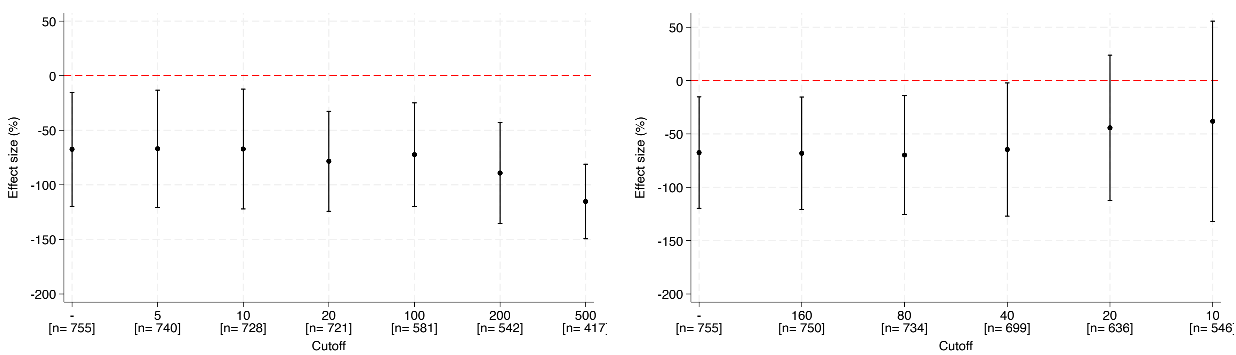


(a) Robustness to bandwidth

(b) Donut'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 have year and age profile fixed effects, and control by population, gender, party alignment (left or right), second-term, married status and college attendance. 95% confidence intervals are shown.

Figure A.5: Sensitivity analysis of deforestation to outliers

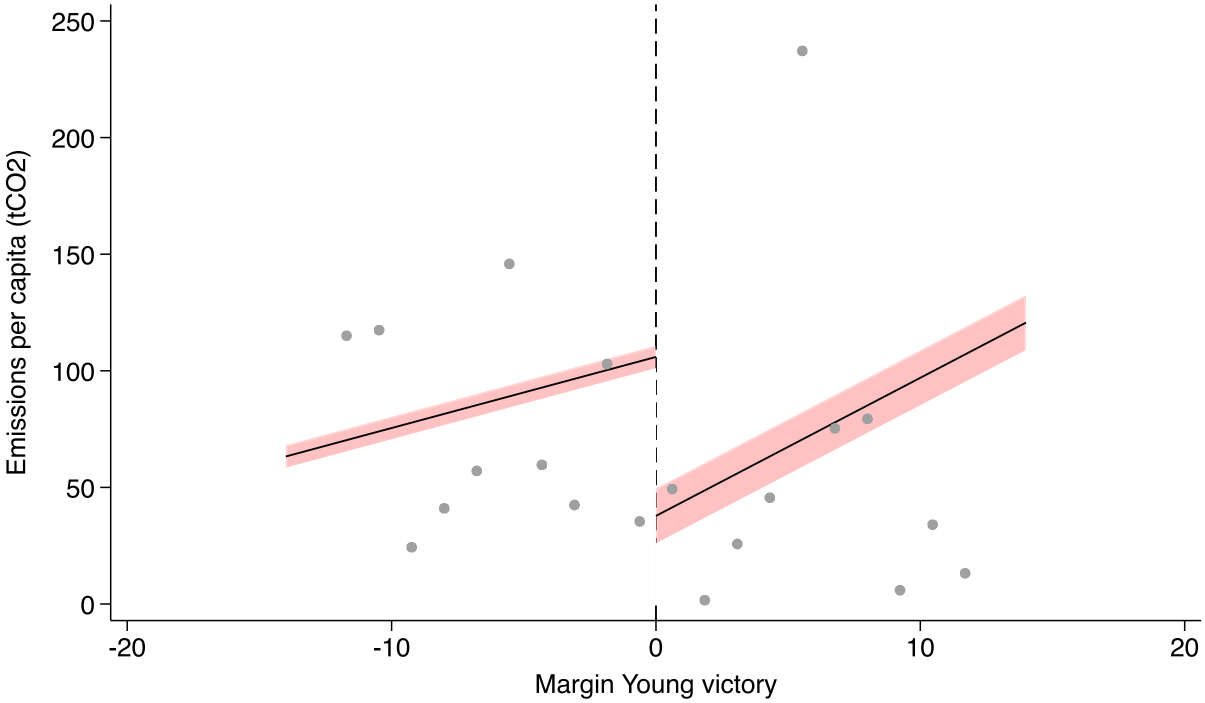


(a) Excluding forest area outliers

(b) Excluding deforestation outliers

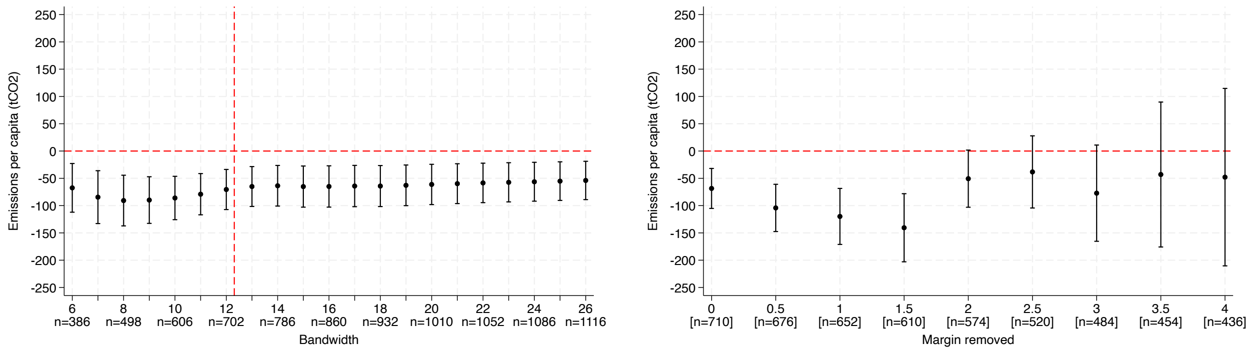
Notes: Results for the main regression (Column 3 of Panel A in Table 2) excluding outliers. Forest area outliers (Figure A.5a) are municipalities with forest area below the cutoff indicated. For deforestation outliers (Figure A.5b) are those with a deforestation rate above the cutoff indicated.

Figure A.6: Visual Regression Discontinuity (RD) in emissions per capita (tCO2)



Notes: Regression Discontinuity plot using the emissions per capita (tCO2) 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 population, gender, left/right leaning of the mayor's party, second-term, married status, college attendance, and it also includes year and age profile fixed effects.

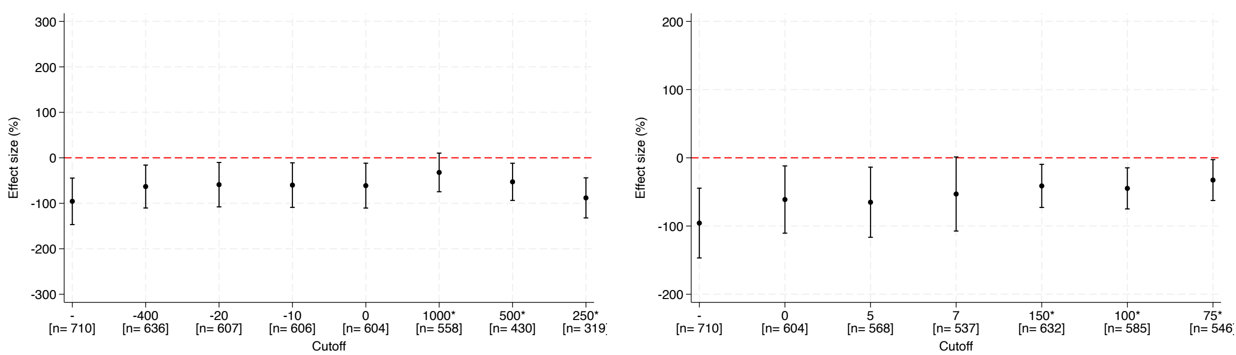
Figure A.7: Sensitivity analysis of emissions per capita (tCO2)



(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 have year and age profile fixed effects, and control by population, gender, party alignment (left or right), second-term, married status and college attendance. 95% confidence intervals are shown.

Figure A.8: Sensitivity analysis of emissions per capita (tCO2) to outliers



(a) Excluding total emissions outliers (b) Excluding emissions per cap. (tCO2) 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 (tCO2) outliers (Figure A.8b) we use the same procedure.

B Online Appendix

Table B.1: Definition of young based on percentile by year

	Percentile				
	30	25	20	15	10
	(1)	(2)	(3)	(4)	(5)
2004	38	36	34	32	30
2008	38	37	35	33	30
2012	38	36	34	32	30
2016	38	37	35	33	30

Notes: Candidate's age percentiles by year.

Table B.2: Observations by year

	Young vs. Not Young	Young vs. Senior	Senior vs. Not Senior
	(1)	(2)	(3)
2005	43	11	126
2006	43	11	126
2007	43	11	126
2008	43	11	126
2009	59	17	103
2010	59	17	103
2011	59	17	103
2012	59	17	103
2013	53	15	108
2014	53	15	108
2015	53	15	108
2016	53	15	108
2017	45	7	113
2018	45	7	113
2019	45	7	113
Total	755	193	1687

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 without second term

Dependent variable:	Deforestation as % forest 2000		
	(1)	(2)	(3)
Panel A:	Margin: Young vs. Not Young		
Young won	-0.59***	-0.57***	-0.62***
	(0.22)	(0.21)	(0.21)
Mean Dep. Variable Control	0.66	0.66	0.65
Age Diff.	17.61	17.61	17.65
Bandwidth	12.31	12.31	12.31
N	663	663	656
Panel B:	Margin: Senior vs. Not Senior		
Senior won	0.06	0.10	0.05
	(0.15)	(0.15)	(0.15)
Mean Dep. Variable Control	0.77	0.77	0.78
Age Diff.	16.65	16.65	16.54
Bandwidth	10.89	10.89	10.89
N	1,733	1,709	1,687

Notes: This table presents the effect of having a young or senior mayor on deforestation by excluding the second-term mandates of the sample. The coefficients are estimated using Equation (1) and the optimal bandwidth used in the main specification (Column 3 in Table 2). Column 1 does not control for any covariate. Column 2 controls by population and gender. Column 3 controls by population, gender, party alignment (left or right), second-term, married status and college attendance. 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 profile fixed effects. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table B.4: Results on emission outcomes

	tCO2 emissions					GDP emission intensity (kgCO2/R$)				
Dependent variable:	Total	Agro	Land Use	Energy	Waste	Total	Agro	Land Use	Energy	Waste
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A:	Margin: Young vs. Not Young									
Young Won	-459642.58*	-63,650.16	-397383.37*	1,008.70	382.25	-8.17***	-1.01***	-7.16***	-0.01	0.01***
	(251,371.44)	(63,754.90)	(211,797.10)	(5,451.32)	(778.66)	(1.96)	(0.25)	(1.85)	(0.01)	(0.00)
Mean Dep. Var. Control	791,877.80	265,640.91	500,275.53	19,096.29	6,865.07	5.32	1.92	3.27	0.09	0.04
Bandwidth	12.31	12.31	12.31	12.31	12.31	12.31	12.31	12.31	12.31	12.31
N	710	710	710	710	710	710	710	710	710	710
Panel B:	Margin: Senior vs. Not Senior									
Senior Won	662,621.98**	210,646.17***	448,015.01	5,479.16	-1,518.36	5.34**	0.42**	4.88**	0.05**	-0.01***
	(313,563.08)	(44,611.25)	(294,210.98)	(4,890.75)	(1,433.94)	(2.48)	(0.19)	(2.42)	(0.02)	(0.00)
Mean Dep. Var. Control	652,337.03	224,298.87	391,803.32	27,367.95	8,866.90	2.83	1.85	0.85	0.09	0.05
Bandwidth	10.89	10.89	10.89	10.89	10.89	10.89	10.89	10.89	10.89	10.89
N	1,574	1,574	1,574	1,574	1,574	1,574	1,574	1,574	1,574	1,574

Notes: Effect of having a young mayor in the office on the emissions outcomes. Coefficients are estimated by using Equation (1) but changing the variable of interest. The bandwidth used in this Table is the optimal one for each regression. Columns 1 to 5 show the total emissions. Columns 6 to 10 are computed by dividing the CO2 emissions in kg 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, 2022, p.7). Data are available until 2018. 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 have year and age profile fixed-effects, and control by mayor gender, left or right-wing of the mayor's party, second-term, married status, college attendance and population. 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	-0.79	0.67	-0.47	-4.89**	-1.06	-3.82**	-2.14
	(0.54)	(2.28)	(1.53)	(1.98)	(0.82)	(1.76)	(1.41)
Mean Dep. Variable Control	2.12	6.57	3.70	3.00	1.14	1.86	1.65
Bandwidth	12.31	12.31	12.31	12.31	12.31	12.31	12.31
N	755	755	755	641	641	641	641
Margin				Senior vs. Not Senior			
Senior Won	1.85***	3.96**	0.99	1.43	-0.06	1.49	0.19
	(0.67)	(1.97)	(1.01)	(1.34)	(0.72)	(0.92)	(0.56)
Mean Dep. Variable Control	2.87	6.72	3.40	3.86	1.83	2.03	1.17
Bandwidth	10.89	10.89	10.89	10.89	10.89	10.89	10.89
N	1,687	1,687	1,687	1,396	1,396	1,396	1,396

Notes: This table displays the effect of having a young or senior mayor on fines restricted to the main specification. 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 have year and age profile fixed-effects, and control by mayor's gender, being left- or right-wing, second-term, married status, college attendance and population. 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	-0.84	-0.06	-0.97	-4.71**	-1.08	-3.37**	-2.15
	(0.52)	(2.08)	(1.36)	(1.96)	(0.82)	(1.68)	(1.37)
Mean Dep. Variable Control	2.39	7.94	4.09	2.85	1.14	1.70	1.54
Optimal band	14.45	14.33	15.67	12.84	12.21	14.56	13.27
N	872	861	911	674	637	743	691
Margin				Senior vs. Not Senior			
Senior Won	1.98***	4.49***	1.05	1.26	-0.23	1.39	0.20
	(0.62)	(1.68)	(1.00)	(1.36)	(0.74)	(0.93)	(0.56)
Mean Dep. Variable Control	3.26	7.40	3.68	4.03	1.89	2.11	1.49
Optimal band	14.83	17.43	10.19	11.47	12.11	11.87	9.14
N	2,111	2,307	1,579	1,444	1,502	1,468	1,215

Notes: This table displays the effect of having a young or senior mayor on fines computing the optimal bandwidth for each regression. 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 have year and age profile fixed-effects, and control by mayor gender, left or right-wing of the mayor's party, second-term, married status, college attendance and population. Significance level: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.7: Effect on agricultural variables

Dependent variable:	Agriculture		Livestock
	Production Value (R$)	Productivity (R$ per Ha.)	N Bovine (Census)
	(1)	(2)	(3)
Panel A:	Margin: Young vs. Not Young		
Young Won	-2894.03	-0.68	-3.21
	(1,942.73)	(0.67)	(30.09)
Mean Dep. Variable Control	5,633.91	6.97	70.94
Bandwidth	12.31	12.31	12.31
N	755	704	88
Panel B:	Margin: Senior vs. Not Senior		
Senior Won	-1129.12	0.17	11.20
	(2,647.56)	(0.56)	(19.25)
Mean Dep. Variable Control	8,661.79	6.98	42.13
Bandwidth	10.89	10.89	10.89
N	1,683	1,543	239

Notes: This table shows the effect of having a young or senior mayor on the Agro variables using the sample restricted to the main specification. Coefficients are estimated using Equation (1) but changing the dependent variable. Column 1 is computed using data from Municipal Agricultural Research (Pesquisa Agrícola Municipal). Column 2 is computed by dividing Column 3 of Table 3 by Column 1 of this table. Column 3 uses Agricultural Census (Censo Agropecuário). 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 have year and age profile fixed-effects, and control by mayor's gender, being left- or right-wing, second-term, married status, college attendance, and population. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table B.8: Results on other municipality outcomes

Dependent variable:	GDP per capita Total	Agro	Industry	% of muni. expenditure Health	Capital	Liabilities Short-term	Long-term
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A:	Margin: Young vs. Not Young						
Young Won	1,365.56	-1818.77	2,297.27**	-0.81*	0.89	0.68	-8.58**
	(2,746.19)	(1,350.39)	(906.79)	(0.48)	(1.03)	(0.69)	(3.80)
Mean Dep. Var. Control	13,668.41	4,006.67	1,336.58	10.68	8.37	4.19	7.37
Bandwidth	12.31	12.31	12.31	12.31	12.31	12.31	12.31
N	755	755	755	330	330	301	301
Panel B:	Margin: Senior vs. Not Senior						
Senior Won	6,238.97***	1,624.54**	1,496.16	0.83**	0.19	-0.01	5.72**
	(2,257.17)	(676.62)	(1,503.16)	(0.40)	(0.70)	(0.63)	(2.38)
Mean Dep. Var. Control	13,376.21	3,375.19	2,245.00	11.18	7.94	4.36	7.83
Bandwidth	10.89	10.89	10.89	10.89	10.89	10.89	10.89
N	1,687	1,687	1,687	734	734	668	668

Notes: Testing of results on different outcomes. Coefficients are estimated by using Equation (1) but changing the variable of interest. The bandwidth used in this Table is the same as Column 3 of Table 2 but can be smaller given that not all variables have observations in all years used in main sample. Columns 1 to 3 present the results in GDP disaggregated by sector measured in per capita terms. This share is calculated by dividing the nominal GDP or the value added by each sector 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. Liabilities amounts are deflated using IPCA. 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 have year and age profile fixed-effects, and control by mayor gender, left or right-wing of the mayor's party, second-term, married status, college attendance and population. Significance level: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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

Dependent variable:	GDP Per cap.	GDP Agro (%)	GDP Industry (%)	Agro Area (Ha)	Agro N Bovine	tCO2 emissions per capita Total	tCO2 emissions per capita Agro	tCO2 emissions per capita Land Use	tCO2 emissions per capita Energy	tCO2 emissions per capita Waste	N Fines Total	% of municipal expenditure Environment	% of municipal expenditure Education	% of municipal expenditure Agro	% of municipal expenditure Liabilities
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A:	Margin: Young vs. Not Young														
Young won	1,470.63	-4.93***	3.54**	-182.43	-44.43*	-66.44***	-7.46	-71.52***	0.15	0.26***	-1.27	-0.14	2.79***	0.19	-6.46**
	(2,638.26)	(1.89)	(1.59)	(228.32)	(25.12)	(18.59)	(4.59)	(16.43)	(0.34)	(0.08)	(2.20)	(0.15)	(1.03)	(0.13)	(3.27)
Mean Dep. Var. Control	14,757.73	27.71	9.35	894.82	122.04	81.36	24.78	43.08	1.14	0.35	8.12	0.33	19.82	0.62	11.32
Optimal band	13.56	14.60	14.78	12.96	17.83	12.71	8.78	11.14	9.80	7.86	16.46	14.04	13.66	13.05	15.52
N	816	879	882	798	1,002	742	542	674	606	492	945	374	370	360	384
Panel B:	Margin: Senior vs. Not Senior														
Senior won	6,508.36***	0.03	0.20	750.28***	122.57***	-3.04	6.73**	7.37	1.18***	-0.05	6.59***	-0.41***	-3.02***	0.17**	6.18**
	(2,286.37)	(1.35)	(1.16)	(223.47)	(23.13)	(17.22)	(2.64)	(19.42)	(0.33)	(0.04)	(2.11)	(0.10)	(0.79)	(0.08)	(2.64)
Mean Dep. Var. Control	13,144.65	25.69	9.18	908.90	107.32	48.33	19.17	22.19	1.04	0.37	10.17	0.34	19.80	0.52	10.94
Optimal band	10.42	11.49	13.85	11.16	8.44	20.65	10.56	12.92	8.56	12.08	15.47	13.02	10.63	14.34	9.37
N	1,627	1,740	2,001	1,701	1,355	2,350	1,522	1,782	1,280	1,698	2,149	822	719	884	589

Notes: Testing of the different mechanisms. Coefficients are estimated by using Equation (1) but changing the variable of interest. The bandwidth used in this Table is the optimal one for each regression. Column 1 shows the effect on the GDP per capita. Columns 2 and 3 present the results in GDP disaggregated by sector share. This share is calculated by dividing the added value of the Agro and Industry sectors respectively by the total nominal GDP of each year. Columns 4 and 5 are computed using data from Municipal Agricultural Research (Pesquisa Agrícola Municipal). Columns 6 to 10 are computed by dividing the CO2 emissions in tons by the population of each municipality. All emissions data are provided by (Sistema de Estimativa de Emissões e Remoções de Gases de Efeito Estufa, Observatório do ClimaSEEG, n.d.). Data are available until 2018. 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, 2022, p.7). Column 11 uses the number of fines provided by IBAMA. Columns 12 to 14 are computed by dividing the expenditure per budget by the municipality's total budget. Column 15 presents results on municipality liabilities as percentage of the municipality expenditure. Liabilities amounts are deflated using IPCA. 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 have year and age profile fixed-effects, and control by mayor gender, left or right-wing of the mayor's party, second-term, married status, college attendance and population. Significance level: $^{*}p < 0.10$, $^{**}\ p < 0.05$, $^{***}p < 0.01$.

Figure B.1: Age distribution by election year

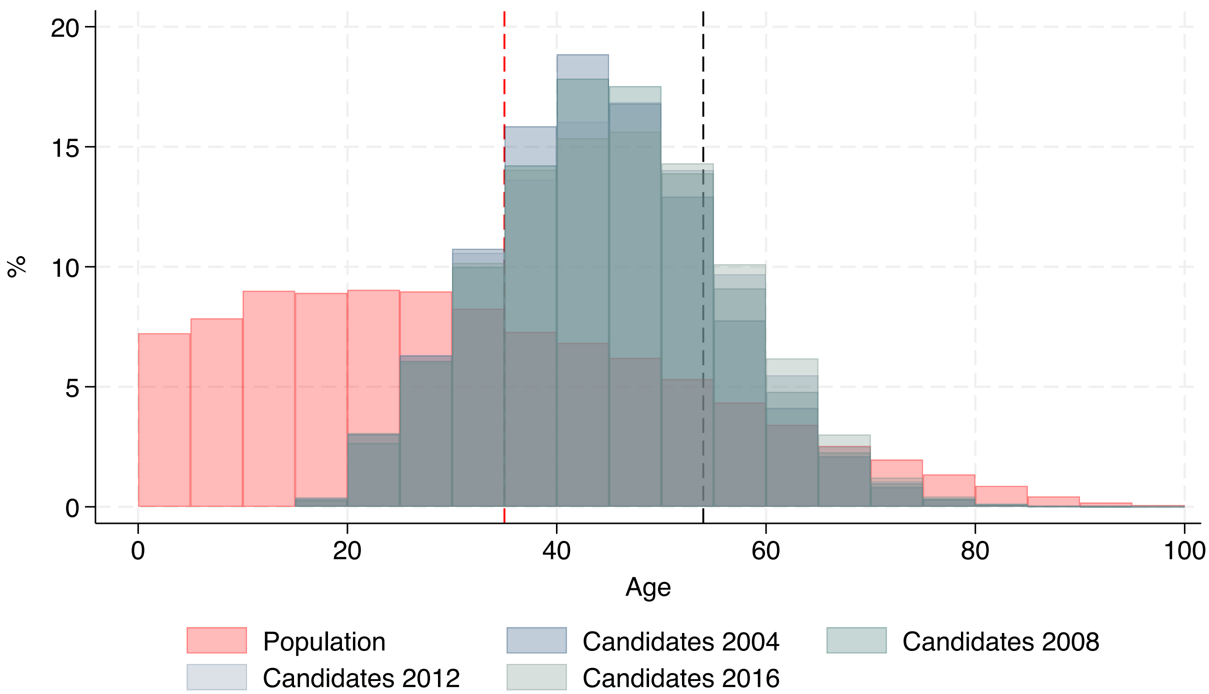
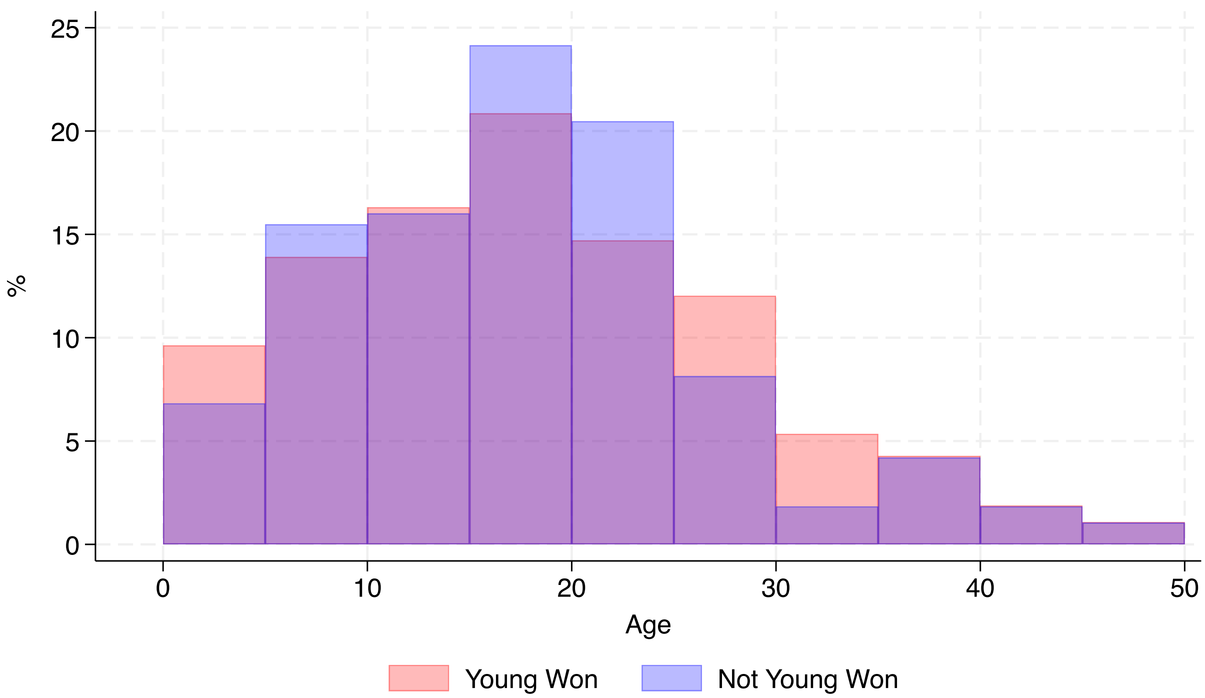


Figure B.2: Age gap distribution



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) divides by those elections where a young candidate won and elections where the winner was not young.