Young Politicians and Long-Term Policy[*]

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Abstract

Policies often entail costs today but benefits only far into the future, as in climate change mitigation. An essential aspect of this trade-off relates to the age of politicians, influencing their life expectancy, career priorities, and educational background. To explore this interplay between young politicians and policies, we concentrate on Brazilian mayors and their influence on environmental outcomes, leveraging data from closely contested elections. We find that electing a young politician causes a reduction in deforestation and greenhouse gas emissions without significant effects on local GDP. We show young politicians invest in long-term policy and hire more young bureaucrats. Our results suggest a cohort effect: young politicians matter not because of their age, but because they are part of a new generation.

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1 Introduction

A fundamental difficulty in policy-making, especially regarding climate change and natural resource conservation, is that policy often has costs today but benefits far into the future. For instance, it is estimated that greenhouse gas emissions stay in the atmosphere for decades (IPCC, 2021); so actions to reduce emissions today will benefit the next 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 U.S. (Funk, 2021; Tyson et al., 2023) and worldwide. 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 study whether young politicians impact long-term policy, in the case of Brazilian mayors and deforestation.

In theory, the relationship between politicians' age and long-term environmental policy could be positive or negative (Alesina et al., 2019). First, a young politician is more likely to be alive to experience the benefits of a policy with long-term benefits. Second, younger politicians have received more information about climate change while in school when compared to previous generations. Consequently, younger politicians would be more likely to reduce deforestation today to diminish future adverse impacts of climate change. On the other hand, younger politicians might have more career concerns, prioritizing short-term economic growth over environmental conservation. Given these opposing channels, the effect of electing young politicians on local deforestation is ex-ante ambiguous.

We empirically study the effect of young politicians on long-term policy in Brazil. Specifically, we study the effect of having a young mayor on deforestation and other outcomes using data from Brazilian municipalities. The setting is ideal for a few reasons. Foremost, the country contains 60% of the Amazon, the largest tropical forest on the planet. In addition, Brazil has thousands of municipalities (analogous to U.S. 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 when under strong electoral incentives (Bragança and Dahis, 2022), allowing the sale of untitled land (Cisneros and Kis-Katos, 2022) or via the agricultural and social programs implemented (Holland, 2016). 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). Brazil has also monitored deforestation with satellite data since the early 2000s, providing data without misreporting concerns.

Our empirical strategy employs a regression discontinuity design (RD) for close elections involving young candidates. The close elections are a natural experiment comparing municipalities that barely elected a young mayor with those where the young candidate barely lost the election. Importantly, young and senior candidates differ in other dimensions besides age. Consequently, the estimated effect is not only the effect of a young mayor, even though we control for observable characteristics. The estimated effect is a combined package of the characteristics of having a young mayor in office (Marshall, 2022). We provide the standard RD validity tests to show the absence of manipulation or discontinuities in covariates around the cutoff.

We find that young mayors have better environmental performance without significantly negatively affecting the local economy. Specifically, when a young mayor is in office, there is a 0.49 p.p. reduction in the yearly deforestation rate (as a share of the municipality's forest area in 2000). Compared to a mean of 0.70% forest area deforested each year, the effect size amounts to a reduction of 70%. We also find that when a young mayor is in office, greenhouse emissions are reduced in levels and intensity. Importantly, having a young mayor in office does not significantly affect the municipal gross domestic product.

Our main findings hold for various robustness checks, including alternative definitions of outcomes, samples, and specifications. We vary the definition of *young* to different percentiles of age, change to regression discontinuity polynomial degrees, estimate conventional and robust standard errors in various ways, change kernels, and remove outliers in deforestation and initial forest area. The one exception is that results are sensitive to medium-level percentage points removed around the cutoff in a doughnut RD exercise. Lastly, we perform a placebo exercise against reverse causality, showing that electing a young mayor in the future does not change deforestation.

Turning to mechanisms, we first find that young mayors do not prioritize the agriculture sector. When a young mayor is in office, there is a reduction in the agricultural sector as measured by a share of total 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. We show that this is not per se driven by young mayors having been elected for the first time.

We rule out alternative hypotheses that could explain our results. First, it could be that young politicians are not intrinsically different but react to the electorate's demand for environmental protection. Because we identify effects from close elections, municipalities' and electorate's observable characteristics are balanced. Second, maybe environmental enforcement was stronger in municipalities governed by young mayors. This explanation is likely not the case because, in Brazil, enforcement is done mostly by federal agencies and is guided by satellite monitoring systems covering the whole Amazon region uniformly (Assunção et al., 2023). Third, young mayors could be disproportionately left-wing or have other observable political traits than the population. But this possibility is not the case in our data.

Lastly, we propose two exercises to test whether our results are capturing (i) *cohort* effects: young mayors are part of a new generation with different preferences about the long-term, or (ii) *age* effects: younger people care more about the future but potentially change as they grow older. First, we show that the effect of a young mayor on deforestation is not heterogeneous by any covariate, such as education, political learning, or incumbency; while for senior mayors, covariates are important. 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. These results suggest that cohort effects dominate: young mayors matter because they are part of a new generation, not because their age per se. This result is consistent with the more recent cohorts having received more climate change-oriented education and being exposed to recent cultural shifts towards environmental protection.

We contribute to three main strands of the literature. First, we contribute to the burgeoning 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. To the best of our knowledge, we are the first to study the effects of electing young politicians on long-term policy and introducing evidence that the underlying channel is of politicians' values and preferences.

Second, we contribute to the literature that studies the political economy of deforestation (Balboni et al., Forthcoming). 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., 2021), 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; Morjaria, 2018). The effect of electing a donor-funded politician has an effect size of 53-109% compared to the deforestation mean (Harding et al., 2021), comparable to the effect size of 70% of electing a young politician.

Finally, we contribute to the 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 highlights the importance of political representation for younger cohorts, who will be disproportionately impacted by climate change (Thiery et al., 2021).

The reminder of the paper is organized as follows. Section 2 discusses the Brazilian context. Section 3 presents the identification strategy. Section 4 describes the data and summary statistics. Section 5 presents the results, Section 6 discusses potential mechanisms, and Section 7 concludes.

2 Institutional Background

Brazil contains 60% of the Amazon rain-forest, the largest tropical forest on the planet. We focus on the Legal Amazon municipalities,[1] because this region is where the deforestation data is available. Municipalities are the smallest administrative unit in Brazil, the equivalent of United States counties. There are currently 5,572 municipalities in Brazil, of which 772 are in the Amazon. However, the Amazon municipalities represent about 50% of the country's area.

Municipal governments are managed by a mayor elected using plurality rule in municipalities with less than 200,000 voters and majority rule in municipalities with more than 200,000 voters. Mayors serve a four-year term, and can be re-elected once. The Brazilian municipalities also have a local council. Municipal councilors are elected through an open list proportional representation system. Elected mayors and councilors take office on January 1st 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 old, while for councilor it is 18.[2] The

[1]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.)

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

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 for the army, living in the relevant geography, and being affiliated to 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. Nevertheless, mayors may influence deforestation directly or indirectly, for example, via incentives to developing local agriculture or with infrastructure projects, and with forbearance (Holland, 2016). Other ways in which mayors can affect deforestation are: allowing the sell of untitled land, colluding with local sawmills that promote the 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

Consider a municipality m where in the previous election of year t_e the 30 years old candidate won the election against a 60 years old candidate. We would like to compare deforestation when the young mayor is in office ($y_{m,t_e+1,30}$), against deforestation if the senior mayor had won ($y_{m,t_e+1,60}$). Unfortunately we only observe the deforestation when the young one is in office ($y_{m,t_e+1,30} = y_{m,t_e+1}$). 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 the exact age profile of 30 and 60 years old 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} against 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.[3]

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

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

[3] Figure A.1 shows that the age distribution for candidates in our amazon study sample is similar to that of all candidates, although it is more concentrated than that of the whole country in 2010.

where y_{mt} is the percentage of the forest area deforested in municipality m on year t. The forest area for each municipality is the forest standing in the 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, second-term, right-wing, married status and college attendance. Finally, we use Hinkley (HC1) errors (ε_{mt}) in the main specification, but present robustness to other error types.

In the main specification, we compare young mayors against any mayor that is not classified as young. On average the young mayor is 17.8 years younger than the rival candidate. 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 compete 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.

If the main difference between a young and an older candidate was just the age, 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. We will use this design in the mechanisms section. The regression is similar to equation (1), but using the *YoungerWon* dummy.

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 the bandwidth selection, we use the data-driven approach proposed by Calonico et al. (2014) adjusted by mass points. We employ in the main specification 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 mechanism 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.

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 in a range of 20x30 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 1st 2005 and July 31st of 2006. The reason for using this time interval is to take as reference the date with most clear images in terms of clouds, that is, closest to the dry season (de Almeida et al., 2021) and where largest extent of the forest can be detected by the satellite.

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 or 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 Brazilian population. Figure A.2 shows the map of the Brazilian Amazon with the distribution of municipalities that enter the regression discontinuity sample by year. While Table B.1 reports the number of municipalities by year that enter the 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.).[4] 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 this data to proxy environmental behavior by municipality and economic activity.

We also use other databases such as SICONFI for municipal expenditures, Municipal Agricultural Research, and Agricultural Census. All data are pre-processed by the Data Basis project Dahis et al. (2022) and are available on the organization's website.[5]

4.2 Summary statistics

Table 1 presents summary statistics of the data we have. 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 design; (3) Amazon municipalities where a young candidate closely won the last election; (4) Amazon municipalities where a young candi-

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

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

date barely lost the last 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 Not young won (4). Column 6 asses if there is a discontinuity in the characteristics at the close election cutoff. Panel A presents characteristics of the municipality, while Panel B characteristics of the mayors.

Panel A shows that around 15% of elections in Brazil have a young candidate in the top two candidates, and the percentage is similar in Amazon municipalities. By construction, all the elections in the regression discontinuity sample (Columns 3 and 4) have a young candidate in the top two. Municipalities have on average 30,000 inhabitants in all groups, but Amazon municipalities are around ten times as large in terms of area. As stated before, the deforestation data is only available for Amazon municipalities. These municipalities had on average 4,500 km^2 of forest in the year 2000 and deforest each year 0.7% of the forest. These forest variables are similar in treatment and control groups Columns 5 and 6 show.

Panel B of Table 1 presents summary statistics of the mayor characteristics. Only 10% of the mayors are female and 27% are in their second term. 46% of young mayors went to college, while only 27% of not young mayors went to college. As expected, young mayors are less likely to be married. Interestingly young mayors are almost equally likely to be from a right wing party. As we have statistically significant differences between Young and Not young mayors, we control by college, marital status, sex, second-term, and right-wing, in the regressions. Table A.1 and Table A.2 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 in other outcomes in Section 5.2. We discuss in detail two mechanisms behind our main findings: 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

Table 2 presents the results of estimating Equation (1). Column 1 presents the results without controlling for characteristics of the mayor, while Column 2 includes controls. For each regression in these first two Columns, we recalculate the optimal bandwidth for the given data. In Columns 3-4, we fix the bandwidth to that of the main specification (Column 2, Panel A) so that we compare results with the same margin of victory. Panel A estimates the effect of a young mayor in office when he won the election to any other not young candidate. The coefficients of the mayor covariates can be consulted in Table A.3. Panel B compares young candidates against 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 senior candidates against any other candidate. Column 1 in Panel A shows that when a young mayor is in office, deforestation is 0.49 percentage points smaller compared to municipalities where the young mayor barely lost the election. Relative to the mean of 0.70% of the forest area deforested each year, this is a reduction of 70% in the deforestation rate. The reduction is of equal magnitude (70%) when we control by mayor characteristics (Column 2). The ex-post power analysis indicates this regression has 64.38 % power. Figure A.3 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 is null. Note that we do not include a Panel comparing Senior vs Young candidates, because the results are symmetric to Panel B.

Robustness.

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 to the DD sample. We have fewer observations because some municipalities were treatment or control in consecutive periods. Columns 3 and 4 present the diff-in=diffs results with and without mayor controls. Note that the number of observations 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. Note that the number of observations is smaller than twice the observations in the main regression 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.

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. The main results are even larger, when we apply a quadratic and cubic polynomial in the margin of victory (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 (Table A.8).

The results are robust when we use the same sample as the main specification (Columns 1, 2, 5 and 6) and when we control for the mayor characteristics (Columns 4 and 8).The coefficient is not statistically significant when using the optimal bandwidth of these kernels due to the wide bandwidth computed (Columns 3 and 7). Table A.9 presents results for a placebo exercise, assigning deforestation four years ago 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 2 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 up to 19 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 0.5 or more than 2.5 percentage points of observations around the cutoff. But the coefficient is not statistically different from zero when excluding observations between 1 to 2.5.

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.2 shows the results excluding the second-term mandates.

5.2 Other outcomes

We now study what happens to economic variables and other environmental measures when a young mayor is in office. Table 3 varies the dependent variable 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 to 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. While 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 the greenhouse gas emissions intensity of GDP. Column 6 shows a large reduction in the emissions intensity of aggregate GDP 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 intensity (Figure A.8b).

Part of this reduction is caused by a reduction in emissions associated with the agricultural sector. This variable do not include deforestation because deforestation is accounted in Land Use category (Sistema de Estimativa de Emissões e Remoções de Gases de Efeito Estufa, Observatório do ClimaSEEG, 2022), where there is also a reduction. 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 and energy sector when a senior mayor is in office. Furthermore, there is a significant and positive effect on the total emissions when young mayor is in the office. Table B.3 shows the results using other measurements units.

Column 11 of Table 3 shows what happens when a young mayor is in office on the number of environmental fines. As there is less deforestation with young mayors, there are also less environmental fines. Table B.4 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). Table B.5 presents same analysis as Table B.4 but using the optimal bandwidth for each specification.

Table B.6 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. [6]

5.3 Local spending

Lastly, Columns 12 to 15 of Table 3 study whether young mayors are spending their municipal budget differently and how much they are impacting local governments' liabilities. Column 12 of 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). 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.7). It means that young mayors commit fewer resources in the long run. While senior mayors spend more today. Finally, there is a non significant increase in the budget allocated in the agricultural sector. Table B.8 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 "fresh blood" young ones, can shift the local state capacity and better align the bureaucracy's

[6] 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 in the two Columns.

preferences to long-term goals.

We test this possibility in Table 4. We construct measures of bureaucratic turnover from RAIS, following every hire and separation across the whole Brazilian bureaucracy. We then estimate Equation (1) on these main outcomes. In Column 1 we find that having a young mayor in office increases total turnover by about 8 percentage points (significant at the 10% 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. In Column 5 we find a coefficient of 3.74 (significant at 10% level), i.e. young mayors concentrate hires more in young people as compared to not young mayors. We do not find significant effects for the other measures.

It could be that our effects are not driven by young mayors per se but by the fact that young mayors also tend to be people elected for the first time, and maybe newly elected politicians on average turn over the bureaucracy more. We test this idea in Column 2. We construct a new RD sample with the running variable being the margin for the new candidate and estimate the analogous exercise to Equation (1) holding the bandwidth fixed. We find that new mayors have no statistically significant effect on turnover.

Our findings echo recent work showing that Brazilian mayors can cause significant turnover in education (Akhtari et al., 2022) and in 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 Distinguishing Age and Cohort Effects

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. This better environmental performance could in principle be due to *age* effects: maybe young mayors have longer horizons ahead of them, or maybe young people value environmental conservation more but this effect fades out as they grow older. Alternatively, our main results may be explained by *cohort* effects: it could be that more recent cohorts are fundamentally different from older ones. Recent cohorts may have different preferences regarding conservation by having been systematically exposed to climate change education in school or in society.[7] In this Section we investigate to what extent each mechanism drives our results. We perform heterogeneity analysis by mayors' characteristics and introduce a new specification to isolate the effects of age.

First, in Table 5 we report a version of Equation (1) estimated with heterogeneous treatment effects. Overall we find that young mayors improve environmental performance across the board, whereas senior mayors show significant heterogeneity. Column 2 studies the heterogeneous effects of having a college degree. We find that college is important to have lower deforestation for senior mayors, but not for young mayors. This is probably because the new Brazilian Constitution mandated environmental education throughout all education levels. Column 3 shows that young male and female mayors are equally effective (although only 13% of young mayors are female; see the bottom row with the mean of the interaction variable). Column 4 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. Column 5 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 6 presents the effect of being a young mayor in his second-term mandate. Column 7 studies whether young farmer mayors have a differential effect on deforestation. The sign is positive, although

[7] We avoid the notoriously famous age-cohort-time identification problem by including time fixed effects in our specifications and thus safely ruling out the effects of *time*.

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 that the candidate was presented. Column 9 studies the heterogeneous effect of having a young mayor with younger population in the municipality. It shows that having a younger electorate facilitate the reductions in deforestation that young mayors can achieve. Finally, Figure A.9 shows the coefficients by year of election and mandate. We can observe that deforestation is reduced mainly in the second and third period.

Next, we introduce a more direct test to distinguish *age* versus *cohort* effects. 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 candidate aged 35 or younger 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 estimate Equation (1) substituting *Young Won* for *Younger Won*. If age is itself driving our results, we would expect larger age differences between candidates to be 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 -0.09 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 and above 30. Importantly, however, we find no such pattern in Panel B, with no age difference profile interactions being significant.

Overall our results suggest that cohort effects are the key driver behind our main estimates.[8] What seems to matter is electing people from recent cohorts, not electing younger people per se. In particular, it could be that recent cohorts value more environmental conservation than previous ones. This could be for instance because the curricula taught at schools incorporated climate change more, or via a larger cultural shift in recent decades.

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 GDP emissions intensity. We find roughly opposite effects when a senior mayor is in the office. When exploring heterogeneity and mechanisms, our results point to the importance of electing recent cohorts. We speculate that this could be driven by younger cohorts having been exposed to education and broader culture more attuned to climate change.

Our work highlights the importance of political renovation for environmental conservation. With climate change mainly affecting young generations, these results provide motivation for affirmative action based on age for elected bodies. It also suggests that educating the senior cohorts could achieve similar goals. It is important to consider, however, that our results may not extrapolate to contexts where politicians have few levers

[8] Notice that this argument requires an assumption of similar discount factors across cohorts.

to influence environmental policy, or where results of policies take longer to materialize, such industrial or energy policy.

Our work leaves various paths of research open. For example, it is unclear whether voters incorporate the candidates' age trade-offs in their voting decisions. Moreover, it is important to test whether the Brazil result generalizes to other contexts where emissions are driven mainly not by deforestation but by energy and industrial production.

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8 Tables and Figures

Table 1: Summary statistics

Variable	Brazil	Legal Amazon	Young	Not Young	Young (3) vs Not Young (4) Difference	RD
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Municipality						
% Elections with Young in Top 2	14.70	10.46	100.00	100.00	0.00	0.00
	(35.41)	(30.61)	(0.00)	(0.00)	(0.00)	(0.00)
Population (000s)	35.72	33.00	20.00	21.46	-1.46	-8.81
	(219.89)	(106.46)	(19.54)	(20.02)	(2.71)	(6.97)
Area (km2)	723.33	6,499.36	6,820.10	7,070.92	-250.82	519.21
	(1,498.43)	(13,614.51)	(12,711.96)	(14,333.97)	(1,856.00)	(1,294.71)
Forest Area in 2000 (km2)	-	4,468.03	4,942.02	5,145.57	-203.55	1045.89
		(12,963.82)	(11,245.31)	(14,082.99)	(1,748.37)	(1,109.27)
Deforestation as % of Forest	-	0.68	0.85	0.69	0.17	-0.18
		(1.21)	(1.15)	(1.16)	(0.16)	(0.15)
N	19,176	2,870	104	110		
Panel B: Mayor						
College	0.48	0.39	0.46	0.27	0.19***	0.25*
	(0.50)	(0.49)	(0.50)	(0.45)	(0.06)	(0.13)
Male	0.91	0.88	0.87	0.88	-0.01	0.07
	(0.29)	(0.33)	(0.34)	(0.32)	(0.05)	(0.09)
Right-wing	0.77	0.76	0.74	0.70	0.04	-0.21*
	(0.42)	(0.43)	(0.44)	(0.46)	(0.06)	(0.12)
Married	0.78	0.72	0.58	0.73	-0.15**	-0.16
	(0.41)	(0.45)	(0.50)	(0.45)	(0.06)	(0.12)
Second term	0.27	0.25	0.11	0.15	-0.04	0.02
	(0.44)	(0.43)	(0.31)	(0.36)	(0.05)	(0.09)
N	19,176	2,870	104	110		

Notes: Mean and standard deviation (in parenthesis) of the municipality and mayor attributes disaggregated by groups. Column 1 includes municipalities that are neither in our main specification sample nor in the Legal Amazon. Column 2 contains all municipalities belonging to Legal Amazon that are not in our main sample. Columns 3 and 4 municipalities of our main regression sample disaggregated by Young and Not Young groups. Columns 5 and 6 show the results for differences testing 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 and controlling by the logarithm of the population. Panel A contains information with variation across municipalities and electoral terms in the case of deforestation from PRODES and population and just by municipalities in the rest of the variables. Panel B provides information about the candidates and elections of the sample. *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 2: Electing a young mayor reduces deforestation and emissions

Dependent variable:	Deforestation as % forest 2000			
	(1)	(2)	(3)	(4)
Panel A:	Margin: Young vs Not young			
Young Won	-0.49**	-0.49**	-0.49**	-0.49**
	(0.19)	(0.19)	(0.20)	(0.19)
Mean Dep. Variable Control	0.70	0.70	0.70	0.70
Age Diff.	17.45	17.49	17.45	17.49
Bandwidth	13.16	13.09	13.09	13.09
N	812	805	812	805
Panel B:	Margin: Young vs Senior			
Young Won	-1.11***	-0.48	-0.93**	-0.53*
	(0.39)	(0.32)	(0.37)	(0.30)
Mean Dep. Variable Control	0.91	0.91	0.85	0.85
Age Diff.	27.59	27.65	27.87	27.94
Bandwidth	9.37	9.86	13.09	13.09
N	181	177	221	217
Panel C:	Margin: Senior vs Not senior			
Senior Won	0.07	0.07	0.05	0.05
	(0.14)	(0.15)	(0.14)	(0.14)
Mean Dep. Variable Control	0.79	0.80	0.77	0.78
Age Diff.	16.68	16.62	16.72	16.62
Bandwidth	11.66	11.43	13.09	13.09
N	1,798	1,736	1,970	1,928
Mayor Controls	No	Yes	No	Yes

Notes: This table presents the effect of having a young mayor or senior mayor on deforestation. Coefficients are estimated using Equation (1). Columns 1 and 2 use the optimal bandwidth of each regression. Columns 3 and 4 are restricted to the optimal bandwidth of Column 2 in Panel A. Even columns control for gender, party alignment (left or right), second-term, married status and college attendance. 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, and control for population. Significance level: $*p < 0.10$, $**\ p < 0.05$, $***p < 0.01$.

Table 3: 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	1431.75	-5.94***	4.07**	-180.65	-36.01	-67.82***	-6.83*	-61.30***	0.07	0.24***	-0.48	-0.14	2.74***	0.19	-7.77**
	(2700.41)	(1.99)	(1.67)	(230.03)	(30.58)	(18.72)	(3.86)	(16.23)	(0.32)	(0.07)	(2.45)	(0.16)	(1.04)	(0.13)	(3.70)
Mean Dep. Var. Control	14,599.31	27.42	9.32	888.83	127.48	79.11	23.65	53.91	1.18	0.36	8.43	0.33	19.98	0.62	10.55
Bandwidth	13.09	13.09	13.09	13.09	13.09	13.09	13.09	13.09	13.09	13.09	13.09	13.09	13.09	13.09	13.09
N	805	805	805	805	805	754	754	754	754	754	805	364	364	364	332
Panel B:	Margin: Senior vs Not Senior														
Senior Won	5839.14***	-0.13	0.85	769.72***	95.78***	21.70	5.82**	14.95	0.99***	-0.05	5.82**	-0.43***	-2.75***	0.23**	5.37**
	(2217.61)	(1.35)	(1.24)	(224.78)	(21.17)	(21.26)	(2.56)	(20.32)	(0.28)	(0.04)	(2.32)	(0.10)	(0.77)	(0.09)	(2.43)
Mean Dep. Var. Control	13,059.85	25.77	9.79	905.30	102.93	42.72	18.80	22.46	1.09	0.37	9.50	0.35	19.96	0.54	10.94
Bandwidth	11.43	11.43	11.43	11.43	11.43	11.43	11.43	11.43	11.43	11.43	11.43	11.43	11.43	11.43	11.43
N	1,736	1,736	1,736	1,732	1,736	1,620	1,620	1,620	1,620	1,620	1,736	759	759	759	691

Notes: Coefficients are estimated by using Equation (1) but changing the variable of interest. The bandwidth used in this Table is the same as Column 2 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 computed using data from Municipal Agricultural Research (Pesquisa Agrícola Municipal). Columns 6 to 10 are computed by dividing the CO2 emissions in tons by 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 the IPCA index. Panel A takes as 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, married status, college attendance and population. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 4: Electing a young mayor increases turnover

Dependent variable:	% Turnover		% Hires	% Separations	% Young Hires	% Senior Hires	% Young Separations	% Senior Separations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Young Won	8.08*		2.96	0.85	3.74*	-0.54	2.48	-0.23
	(4.27)		(2.17)	(2.98)	(2.00)	(0.68)	(2.05)	(1.03)
New Won		2.97						
		(3.37)						
Mean Dep. Var.	49.64	46.75	23.91	24.90	53.67	6.51	50.98	9.51
Bandwidth	13.43	13.43	13.43	13.43	13.43	13.43	13.43	13.43
N	728	1,769	715	728	710	710	727	727
R^2	0.17	0.16	0.18	0.11	0.14	0.058	0.11	0.058

Notes: This table shows the effect of having a young 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, 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 5: Heterogeneous effects

Dependent variable:	Deforestation as % forest 2000								
		Interaction variables as columns							
		College	Male	Right wing	Married	Second term	Farmer	First time in election	% Young population
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A:	Margin: Young vs Not Young								
Treated	-0.48***	-0.51**	-1.02**	-0.76***	-0.43**	-0.50**	-0.50***	-0.57**	-0.38*
	(0.18)	(0.23)	(0.51)	(0.28)	(0.21)	(0.19)	(0.19)	(0.24)	(0.20)
Treated × Interaction		0.09	0.61	0.38	-0.06	0.15	0.25	0.24	-0.06**
		(0.25)	(0.48)	(0.25)	(0.21)	(0.29)	(0.39)	(0.24)	(0.03)
Mean Dep. Var. Control	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69
Mean Interaction	-	0.45	0.88	0.75	0.57	0.11	0.10	0.81	0.16
N	812	812	812	812	812	812	812	812	812
Panel B:	Margin: Senior vs Not Senior								
Treated	0.07	0.28*	0.03	-0.39*	-0.32*	0.11	0.06	-0.01	-0.01
	(0.14)	(0.16)	(0.21)	(0.22)	(0.17)	(0.15)	(0.15)	(0.14)	(0.14)
Treated × Interaction		-0.55***	0.05	0.63***	0.54***	-0.25	-0.07	0.26	0.02*
		(0.16)	(0.19)	(0.19)	(0.15)	(0.15)	(0.26)	(0.17)	(0.01)
Mean Dep. Var. Control	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80
Mean Interaction	-	0.35	0.88	0.79	0.75	0.24	0.20	0.26	-0.20
N	1,736	1,736	1,736	1,736	1,736	1,736	1,736	1,736	1,736

Notes: Heterogeneous effect of having a young or senior mayor on deforestation. Coefficients are estimated by 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 2 of Table 2. Column 1 presents the results of the main specification with mayor controls. Columns 2 to 8 present the treatment interacted with mayor related variables. Column 9 interacts with the standardize percentage of young (35 or under) population in the municipality. This variable is standardized with the mean of 70%. Panel A takes as sample all municipalities with at least one young candidate among the two first 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, married 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	-0.49***	-0.69***	
	(0.18)	(0.23)	
Young Won × Age Diff.		0.01	
		(0.01)	
Young Won × 0-9			-0.43
			(0.27)
Young Won × 10-19			-0.69***
			(0.24)
Young Won × 20-29			-0.27
			(0.19)
Young Won × 30+			-0.43*
			(0.26)
Mean Dep. Var.	0.70	0.70	0.70
N	805	805	805
R^2	0.21	0.21	0.21
Panel B:	Margin: Younger vs Not Younger		
Younger Won	0.04	-0.09	
	(0.09)	(0.09)	
Younger Won × Age Diff.		0.01**	
		(0.01)	
Younger Won × 0-9			0.04
			(0.09)
Younger Won × 10-19			-0.04
			(0.11)
Younger Won × 20-29			0.27
			(0.18)
Younger Won × 30+			0.06
			(0.18)
Mean Dep. Var.	0.70	0.70	0.70
N	4,236	4,236	4,236
R^2	0.11	0.11	0.11

Notes: Effect of having a younger mayor in the mayor office dissagregated by age intervals. 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 spiting 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, married status, and population. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

A Appendix

Table A.1: Additional summary statistics

Variable	Mean	Std Dev	Min	Max	N
	(1)	(2)	(3)	(4)	(5)
Panel A: Municipality term					
Margin young vs not young	-0.16	7.21	-13.03	13.02	214
Margin young vs senior	-0.66	5.43	-9.30	9.08	46
Margin senior vs not senior	0.11	6.28	-11.29	11.31	463
Panel B: Other variables					
% Environmental expenditure	0.36	0.66	0.00	4.42	364
% Education expenditure	19.89	5.74	0.00	34.84	364
% Health expenditure	10.62	2.31	0.00	16.52	364
% Agro expenditure	0.65	0.68	0.00	3.54	364
GDP (R$ Current prices) per cap.	14,015.80	16,114.39	1,440.19	180,941.36	805
Agro as % GDP	26.44	15.70	0.78	72.73	805

Notes: Summary statistics (mean, standard deviation, minimum, maximum, and number of observations) of variables we use. 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: 1R$ $\sim$ 0.2 USD$. The Energy Emissions intensity from Brazil was 0.5 for 1 (kgCO2/R$) in the United States in 2019.

Table A.2: Additional summary statistics by candidate

Variable	Brazil	Amazon	Sample	Young in sample
	(1)	(2)	(3)	(4)
College	0.47	0.40	0.37	0.46
	(0.50)	(0.49)	(0.48)	(0.50)
Male	0.88	0.86	0.87	0.86
	(0.32)	(0.35)	(0.33)	(0.34)
Married	0.74	0.69	0.66	0.57
	(0.44)	(0.46)	(0.48)	(0.50)
Right	0.71	0.71	0.70	0.71
	(0.45)	(0.45)	(0.46)	(0.45)
N	60,181	9,025	686	243

Notes: Summary statistics (mean and standard deviation in parentheses) of the candidates running for mayoral elections. Observations are at candidate-year level and include 2004, 2008, 2012 and 2016 elections. Column 1 shows the statistics using as sample all candidates running for any of the Brazilian municipalities. Column 2 restricts the sample to the municipalities belonging to the Legal Amazon. Column 3 presents the running candidates statistics in the municipalities with close elections used in Column 2 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.3: Results showing mayor controls' coefficients

Dependent variable:	Deforestation as % forest 2000	
	(1)	(2)
	Margin: Young vs Not Young	
Young Won	-0.49***	-0.49***
	(0.19)	(0.18)
Male		-0.49*
		(0.25)
Right		-0.23*
		(0.13)
2nd Term		0.10
		(0.17)
Married		-0.02
		(0.11)
College		0.03
		(0.13)
Mean Dep. Var.	0.70	0.70
N	812	805
R^2	0.19	0.21

Notes: Results of the main regression showing mayor controls' coefficients. All regressions have year and age profile fixed-effects. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

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	-0.49**	-0.11	-0.47***	-0.39**
	(0.19)	(0.10)	(0.15)	(0.16)
Mean Dep. Variable Control	0.70	0.42	0.96	0.96
Major Controls	Yes	Yes	No	Yes
Bandwidth	13.09	13.09	-	-
N	805	515	1,030	1,030

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 main specification (Column 2 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 removing the mayor controls. 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 definition

Dependent variable:	Deforestation as % forest 2000						
	p25		p20		p15		LEI No 11.692
	By-election	All sample	By-election	All sample	By-election	All sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A:	Margin: Young vs Not Young						
Young Won	-0.33**	-0.11	-0.49**	-0.26	-0.64**	-0.49*	0.30
	(0.16)	(0.16)	(0.19)	(0.17)	(0.28)	(0.26)	(0.52)
Mean Dep. Variable Control	0.72	0.85	0.70	0.72	0.81	0.81	0.92
Bandwidth	13.09	13.09	13.09	13.09	13.09	13.09	13.09
N	1,148	1,244	805	929	513	585	210
Panel B:	Margin: Young vs Not Young						
Young Won	-0.33**	-0.14	-0.49**	-0.27	-0.65**	-0.29	0.33
	(0.16)	(0.15)	(0.19)	(0.17)	(0.29)	(0.22)	(0.52)
Mean Dep. Variable Control	0.72	0.84	0.70	0.73	0.82	0.77	0.96
Optimal bandwidth	12.92	14.35	13.09	12.86	12.84	20.32	12.14
N	1,137	1,330	805	915	510	774	196
Panel C:	Margin: Senior vs Not Senior						
Senior Won	-0.05	-0.08	0.07	0.03	0.12	-0.02	0.35
	(0.13)	(0.13)	(0.15)	(0.14)	(0.15)	(0.14)	(0.26)
Mean Dep. Variable Control	0.79	0.78	0.80	0.70	0.71	0.71	0.64
Bandwidth	11.43	11.43	11.43	11.43	11.43	11.43	11.43
N	1,908	1,878	1,736	1,673	1,382	1,388	370
Panel D:	Margin: Senior vs Not Senior						
Senior Won	-0.07	-0.08	0.07	0.06	0.31*	0.16	0.60**
	(0.13)	(0.13)	(0.15)	(0.14)	(0.17)	(0.16)	(0.28)
Mean Dep. Variable Control	0.77	0.79	0.80	0.66	0.71	0.73	0.61
Optimal bandwidth	12.98	12.27	11.43	10.41	7.90	7.71	9.34
N	2,109	1,967	1,736	1,565	997	992	316

Notes: This table presents the results when we vary the definition of young and senior to other percentiles. Coefficients are estimated by 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–. 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 two first candidates. In Panels C and D, the sample contains all elections in which almost a senior candidate was between the two first candidates. Panels A and C use bandwidth restricted to 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)
Panel A:	Margin: Young vs Not Young							
Young Won	-0.83***	-0.81***	-0.92***	-0.88***	-1.01***	-0.94***	-1.37***	-1.26***
	(0.23)	(0.22)	(0.24)	(0.23)	(0.27)	(0.26)	(0.36)	(0.34)
Mean Dep. Variable Control	0.69	0.70	0.70	0.70	0.71	0.70	0.70	0.70
Major Controls	No	Yes	No	Yes	No	Yes	No	Yes
Poly Order	2	2	2	2	3	3	3	3
Bandwidth	14.84	14.29	13.09	13.09	18.97	19.05	13.09	13.09
N	881	851	812	805	1,025	1,021	812	805
Panel B:	Margin: Senior vs Not Senior							
Senior Won	0.24	0.25	0.36*	0.40*	0.37	0.40	0.62*	0.69*
	(0.18)	(0.19)	(0.21)	(0.22)	(0.23)	(0.24)	(0.29)	(0.30)
Mean Dep. Variable Control	0.79	0.80	0.79	0.80	0.76	0.77	0.79	0.80
Major Controls	No	Yes	No	Yes	No	Yes	No	Yes
Poly Order	2	2	2	2	3	3	3	3
Bandwidth	15.85	14.65	11.43	11.43	18.28	17.73	11.43	11.43
N	2,218	2,100	1,778	1,736	2,426	2,326	1,778	1,736

Notes: This table presents results using a second-order polynomial. Columns 1 and 2 are computed considering the optimal bandwidth using the second-order polynomial. Columns 3 and 4 are restricted to the optimal bandwidth of the main specification of Table 2 (Column 2). Columns 2 and 4 control by gender, left or right-wing of the mayor's party, second-term, married status and college attendance. Panel A takes as sample all municipalities with at least one young candidate among the two first candidates. In Panel B, the sample contains all elections in which almost a senior candidate was between the two first candidates. All regressions include year and age profile fixed-effects and control by population. 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)	(4)
Panel A:	Margin: Young vs Not Young			
Young Won	-0.49**	-0.49**	-0.49**	-0.49**
HC0 Conv.	(-0.871,-0.108)	(-0.863,-0.117)	(-0.872,-0.108)	(-0.863,-0.117)
HC0 Robust	(-0.998,-0.155)	(-0.988,-0.164)	(-1.348,-0.410)	(-1.288,-0.399)
HC1 Conv.	(-0.871,-0.107)	(-0.863,-0.116)	(-0.873,-0.107)	(-0.864,-0.116)
HC1 Robust	(-0.998,-0.153)	(-0.988,-0.162)	(-1.349,-0.408)	(-1.289,-0.397)
HC2 Conv.	(-0.871,-0.106)	(-0.864,-0.115)	(-0.873,-0.107)	(-0.864,-0.115)
HC2 Robust	(-0.998,-0.153)	(-0.988,-0.162)	(-1.350,-0.408)	(-1.290,-0.397)
HC3 Conv.	(-0.872,-0.104)	(-0.864,-0.113)	(-0.875,-0.105)	(-0.865,-0.114)
HC3 Robust	(-0.999,-0.151)	(-0.988,-0.160)	(-1.352,-0.405)	(-1.292,-0.395)
Mean Dep. Variable Control	0.70	0.70	0.701	0.70
Major Controls	No	Yes	No	Yes
Bandwidth HC0	13.12	13.05	13.09	13.09
Bandwidth HC1	13.16	13.09	13.09	13.09
Bandwidth HC2	13.18	13.10	13.09	13.09
Bandwidth HC3	13.23	13.15	13.09	13.09
N	812	805	812	805
Panel B:	Margin: Senior vs Not Senior			
Senior Won	0.07	0.07	0.08	0.07
HC0 Conv.	(-0.205, 0.351)	(-0.215, 0.355)	(-0.204, 0.356)	(-0.215, 0.355)
HC0 Robust	(-0.199, 0.442)	(-0.208, 0.449)	(-0.068, 0.769)	(-0.050, 0.810)
HC1 Conv.	(-0.205, 0.351)	(-0.215, 0.355)	(-0.205, 0.356)	(-0.215, 0.355)
HC1 Robust	(-0.199, 0.442)	(-0.209, 0.448)	(-0.068, 0.770)	(-0.050, 0.811)
HC2 Conv.	(-0.205, 0.351)	(-0.216, 0.355)	(-0.205, 0.356)	(-0.216, 0.355)
HC2 Robust	(-0.200, 0.442)	(-0.209, 0.448)	(-0.069, 0.770)	(-0.051, 0.811)
HC3 Conv.	(-0.206, 0.351)	(-0.216, 0.355)	(-0.206, 0.357)	(-0.216, 0.356)
HC3 Robust	(-0.201, 0.442)	(-0.210, 0.448)	(-0.070, 0.771)	(-0.052, 0.812)
Mean Dep. Variable Control	0.79	0.80	0.789	0.80
Major Controls	No	Yes	No	Yes
Bandwidth HC0	11.65	11.41	11.43	11.43
Bandwidth HC1	11.66	11.43	11.43	11.43
Bandwidth HC2	11.68	11.44	11.43	11.43
Bandwidth HC3	11.72	11.48	11.43	11.43
N	1,798	1,736	1,778	1,736

Notes: This table presents in parenthesis the conventional and robust confidence intervals varying the kind of error correction used. Robust bias-corrected is proposed by Cattaneo et al. (2020) and is not point centered. Optimal bandwidths differ slightly from the main regressions due to different biases and weighting. Columns 1 and 2 are computed considering the optimal bandwidth for each regression. Columns 3 and 4 are restricted to the optimal bandwidth of column 2 in Table 2. Columns 2 and 4 control by gender, left or right-wing of the mayor's party, second-term, married status and college attendance. Panel A takes as sample all municipalities with at least one young candidate among the two first candidates. In Panel B, the sample contains all elections in which almost a senior candidate was between the two first candidates. All regressions have year age profile fixed-effects and control by population. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A.8: Robustness to kernels

Dependent variable:	Deforestation as % forest 2000							
Kernel:	Epanechnikov				Uniform			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:	Margin: Young vs Not Young							
Young Won	-0.46**	-0.46**	-0.23	-0.33*	-0.47**	-0.45**	-0.05	-0.45**
	(0.20)	(0.20)	(0.16)	(0.18)	(0.18)	(0.19)	(0.15)	(0.21)
Mean Dep. Variable Control	0.70	0.70	0.72	0.69	0.70	0.70	0.72	0.65
Major Controls	No	Yes	No	Yes	No	Yes	No	Yes
Bandwidth	13.09	13.09	19.67	17.11	13.09	13.09	19.71	9.56
N	812	805	1,052	957	812	805	1,056	617
Panel B:	Margin: Senior vs Not Senior							
Senior Won	0.04	0.03	0.06	0.06	0.03	0.01	0.04	-0.04
	(0.14)	(0.14)	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)	(0.13)
Mean Dep. Variable Control	0.79	0.80	0.76	0.77	0.79	0.80	0.80	0.78
Major Controls	No	Yes	No	Yes	No	Yes	No	Yes
Bandwidth	11.43	11.43	10.48	10.34	11.43	11.43	11.77	13.28
N	1,778	1,736	1,673	1,612	1,778	1,736	1,806	1,957

Notes: This table presents results of Table 2 using different kernels. Columns 1 to 4 use Epanechnikov kernel, while Columns 5 to 8 use a Uniform kernel. Columns 1 and 3, and 5-6 are restricted to the optimal bandwidth of the main specification of Table 2 (Column 2). Columns 3 and 4, and 7-8 are computed considering the optimal bandwidth using their respective kernels. Even columns control by gender, left or right-wing of the mayor's party, second-term, married status and college attendance. Panel A takes as sample all municipalities with at least one young candidate among the two first candidates. In Panel B, the sample contains all elections in which almost a senior candidate was between the two first candidates. All regressions include year and age profile fixed-effects and control by population. 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)
Panel A:	Margin: Young vs Not Young			
Young Won future election	-0.53	-0.50	-0.56	-0.51
	(0.38)	(0.38)	(0.49)	(0.48)
Mean Dep. Variable Control	1.16	1.17	1.19	1.19
Major Controls	No	Yes	No	Yes
Bandwidth	19.05	19.10	13.09	13.09
N	794	790	592	585
Panel B: Margin	Margin: Senior vs Not Senior			
Senior Won future election	0.05	0.16	0.17	0.25
	(0.46)	(0.48)	(0.52)	(0.54)
Mean Dep. Variable Control	1.27	1.27	1.29	1.30
Major Controls	No	Yes	No	Yes
Bandwidth	14.86	14.37	11.43	11.43
N	1,961	1,880	1,610	1,572

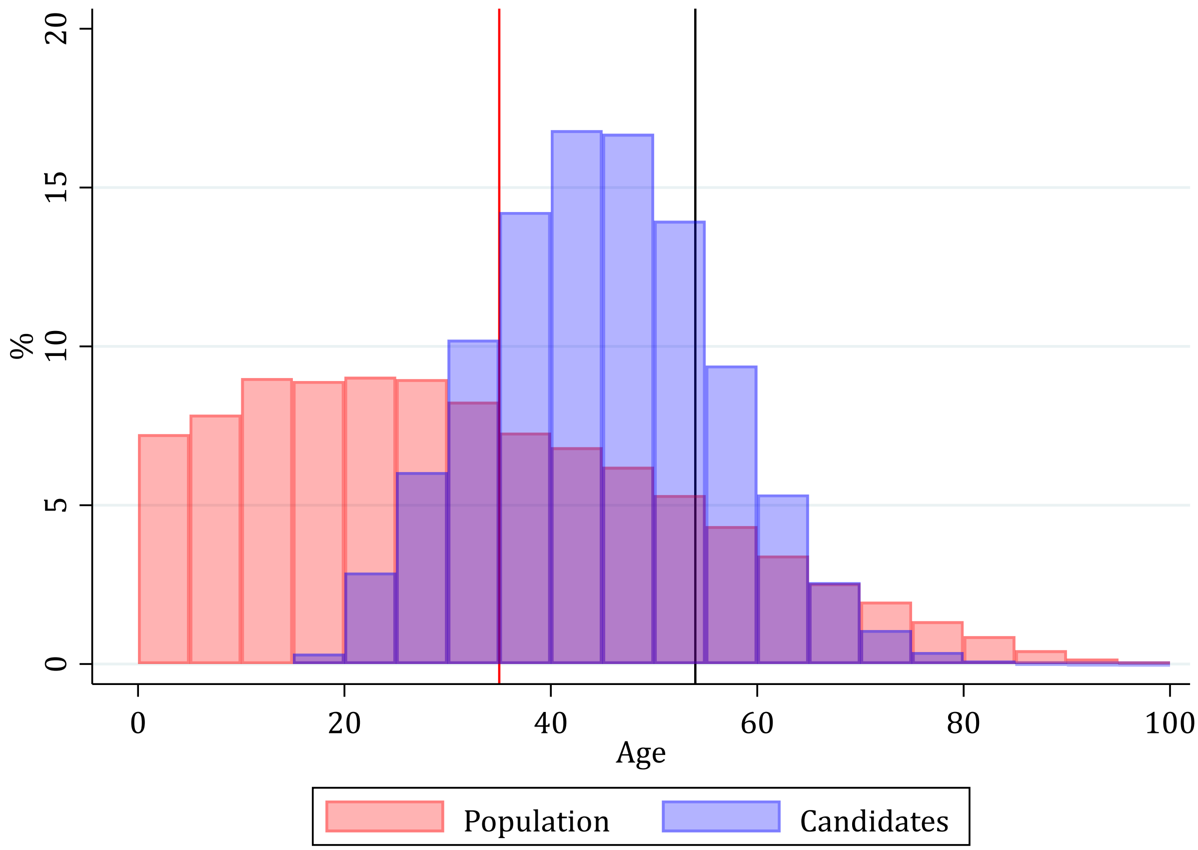
Notes: This table presents the placebo analysis. Coefficients are estimated using Equation Equation 1, but dependent variable is deforestation of the same municipality four years ago and those observations treated during one period and the next one were removed. Columns 1 and 2 are computed considering the optimal bandwidth. Columns 3 and 4 are restricted to the optimal bandwidth of the main regression (Column 2 of Table 2). Columns 2 and 4 control by gender, left or right-wing of the mayor's party, second-term, married status and college attendance. Panel A takes as sample all municipalities with at least one young candidate among the two first candidates. In Panel B, the sample contains all elections in which almost a senior candidate was between the two first candidates. All regressions have year and age profile fixed-effects, and control by population. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A.10: Results using Younger as treatment

Dependent variable:	Deforestation as % forest 2000			
	(1)	(2)	(3)	(4)
Panel A:	Margin: Younger vs Not Younger			
Younger Won	0.04	0.04	0.06	0.06
	(0.08)	(0.09)	(0.08)	(0.08)
Mean Dep. Variable Control	0.69	0.70	0.70	0.71
Age Diff.	11.05	11.03	11.03	11.04
Bandwidth	11.20	11.06	13.09	13.09
N	4,365	4,250	4,896	4,819

Notes: This table presents the effect of having a younger mayor on deforestation. Younger is a dummy that takes the value of one when, comparing two most voted candidates, the younger won. Coefficients are estimated using Equation (1). Columns 1 and 2 use the optimal bandwidth of each regression. Columns 3 and 4 are restricted to the optimal bandwidth of column 2 in Panel A. Columns 2 and 4 control by gender, left or right-wing of the mayor's party, second-term, married status and college attendance. All regressions include year and age profile fixed-effects and 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 color red and black show the 20th percentile of the age (approx. 35 years old) and 80th percentile (approx. 54 years old) by election.

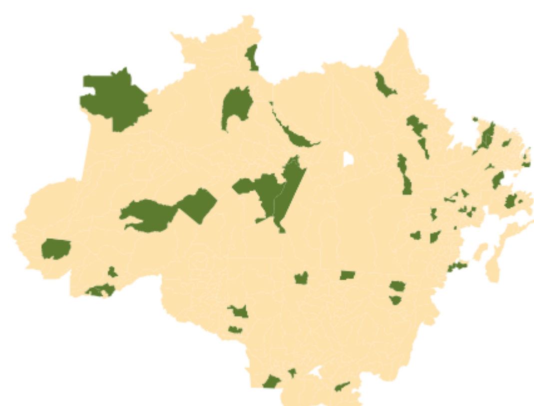
Figure A.2: Municipalities sample by election year

(a) Sample in 2004 elections

(b) Sample in 2008 elections

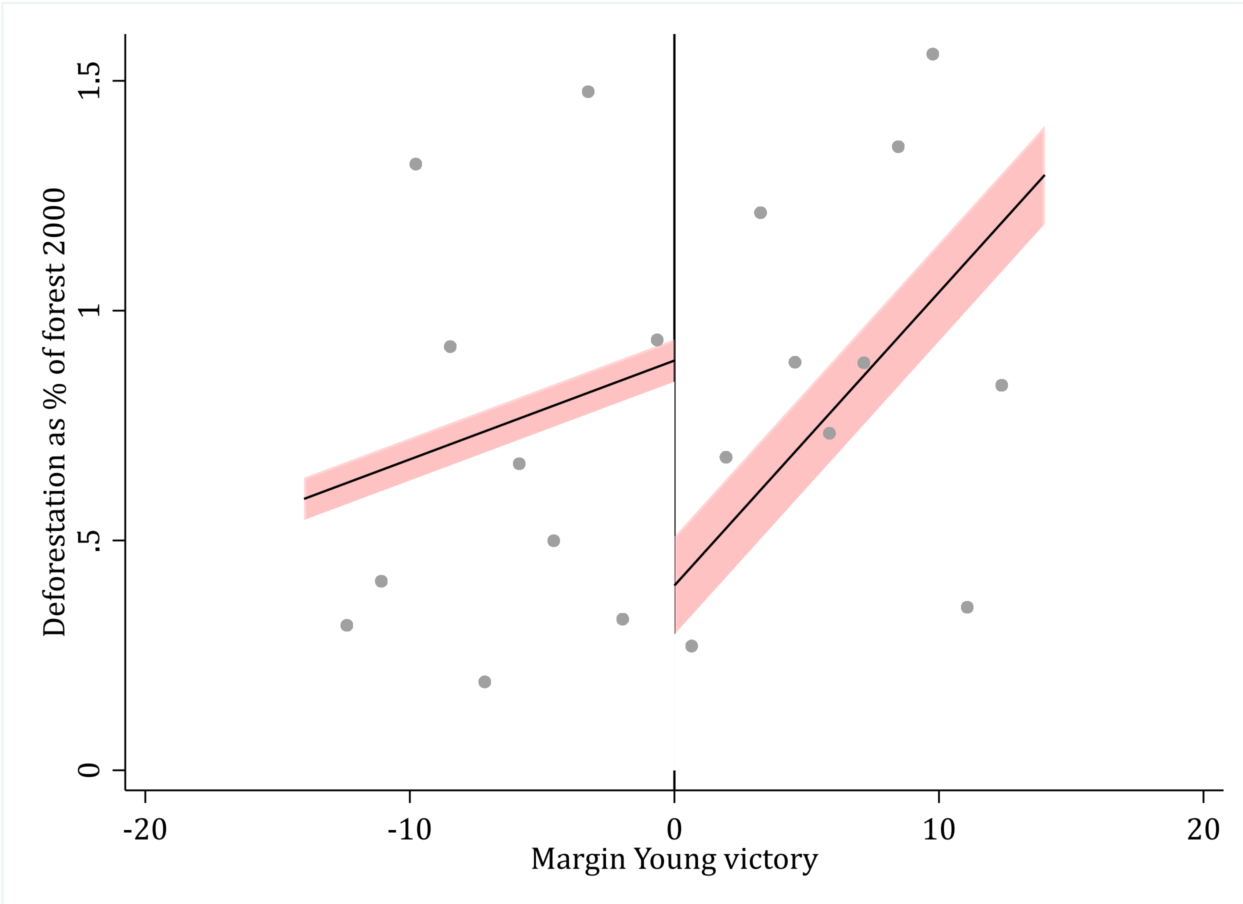
(c) Sample in 2012 elections

(d) Sample in 2016 elections



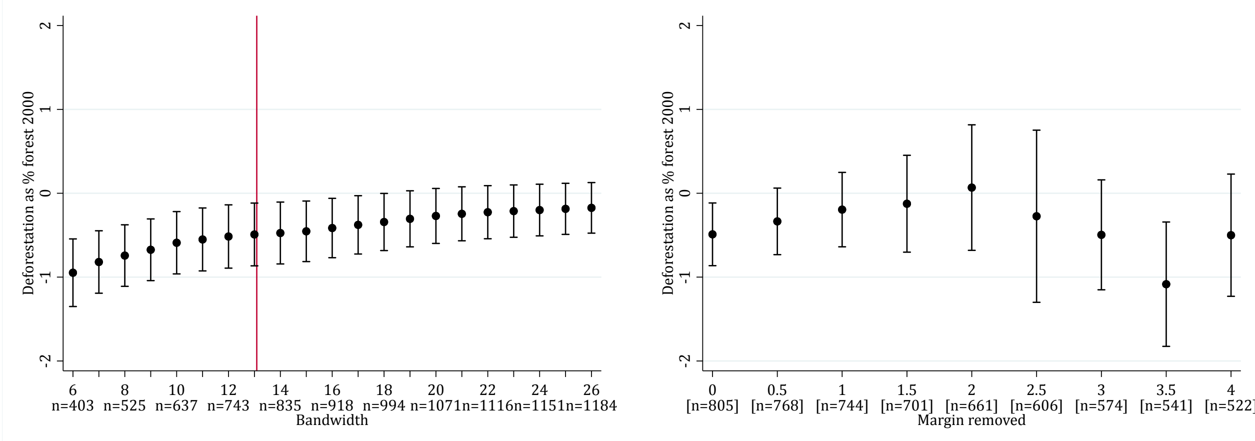
Notes: This figure presents the geographical distribution of municipalities belonging to the regression discontinuity sample of the main regression.

Figure A.3: Visual Regression Discontinuity (RD) results



Notes: Regression Discontinuity plot of the main specification (Column 2 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, 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.4: Deforestation sensitivity analysis

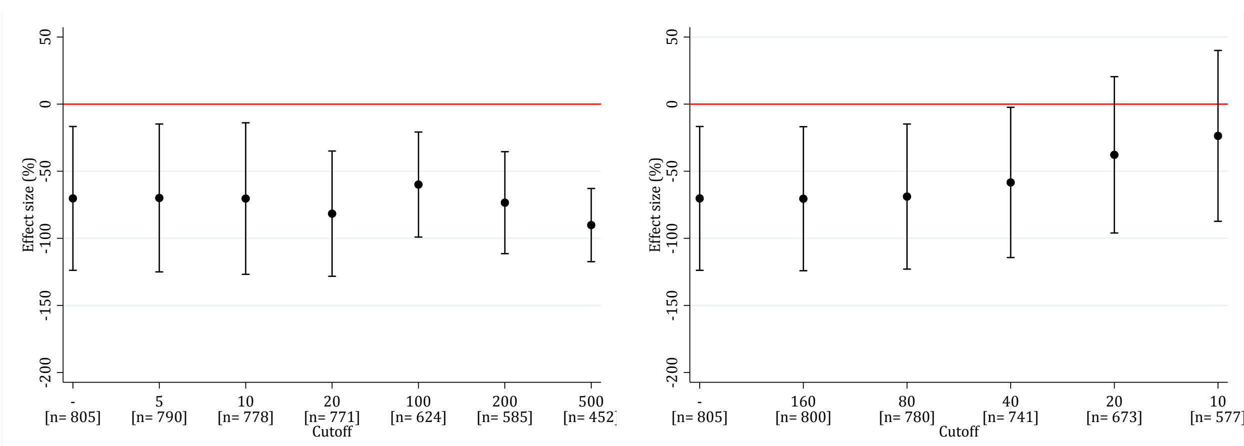


(a) Robustness to bandwidth

(b) Donut's Robustness

Notes: Sensitivity analysis of the main specification (Column 2 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. By the other hand, in Figure A.4b by dropping different observations of the closest election leaving a "doughnut" 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, left or right-wing of the mayor's party, second-term, married status and college attendance. 95% confidence intervals are shown.

Figure A.5: Sensitivity analysis of deforestation to outliers

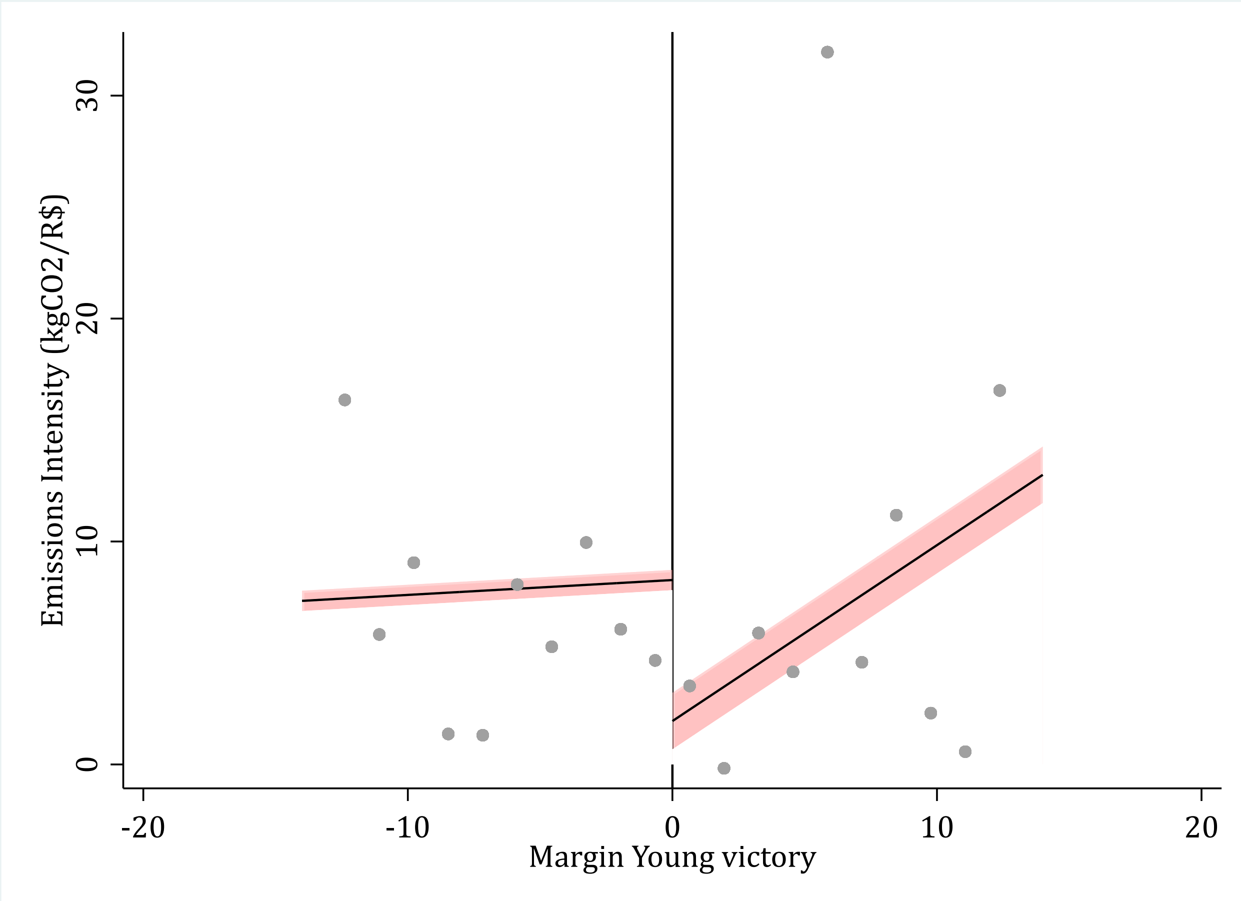


(a) Excluding forest area outliers

(b) Excluding deforestation outliers

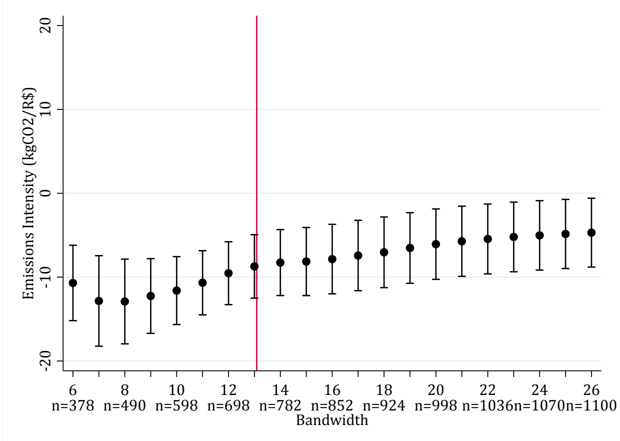
Notes: Results for the main regression (Column 2 of Panel A in Table 2) excluding outliers. Forest area outliers (Figure A.5a) are municipalities with forest area below the cutoff indicated. For deforestation outliers (Figure A.5b) are those with a deforestation rate above the cutoff indicated.

Figure A.6: Visual Regression Discontinuity (RD) in emissions intensity

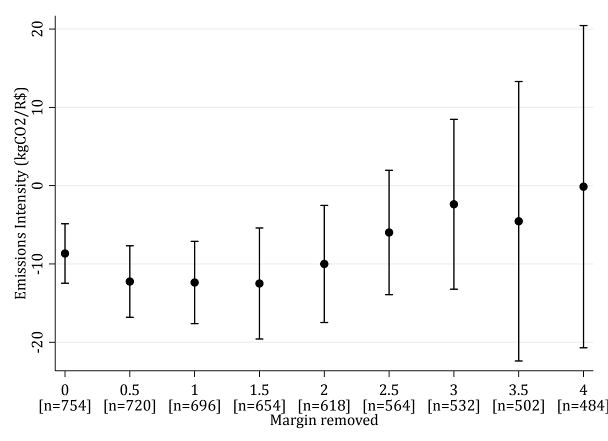


Notes: Regression Discontinuity plot using the emissions intensity as dependent variable (Column 6 of Panel A in Table 3). Observations are grouped in 10 bins at each side of the winning cutoff. The regression controls for population, gender, left/right leaning of the mayor's party, second-term, married status, college attendance, and it also includes year and age profile fixed effects.

Figure A.7: Sensitivity analysis of emissions intensity



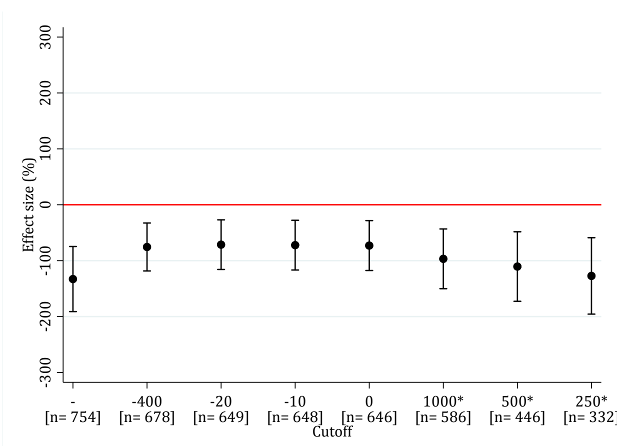
(a) Robustness to bandwidth



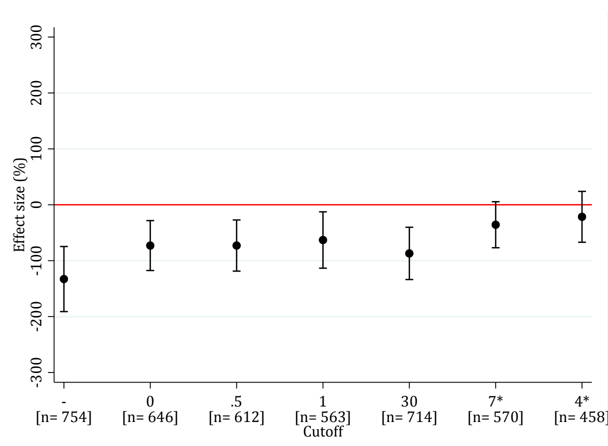
(b) Donut's Robustness

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, left or right-wing of the mayor's party, second-term, married status and college attendance. 95% confidence intervals are shown.

Figure A.8: Sensitivity analysis of emissions intensity to outliers



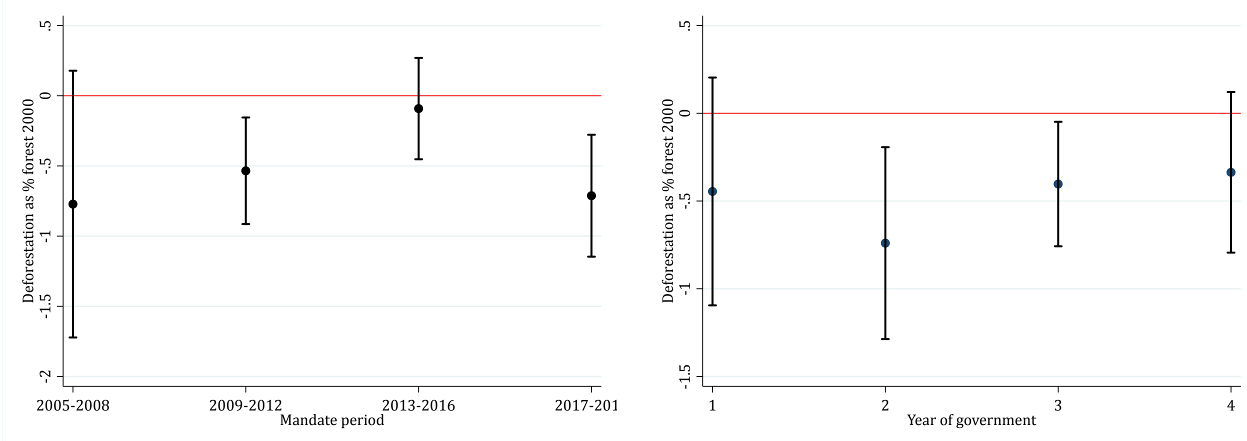
(a) Excluding total emissions outliers



(b) Excluding emissions intensity 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 is necessary to cut observations above and below some threshold. In (Figure A.8a) we drop total emissions 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 intensity outliers (Figure A.8b) we use the same procedure.

Figure A.9: Heterogeneous effects by election and term year

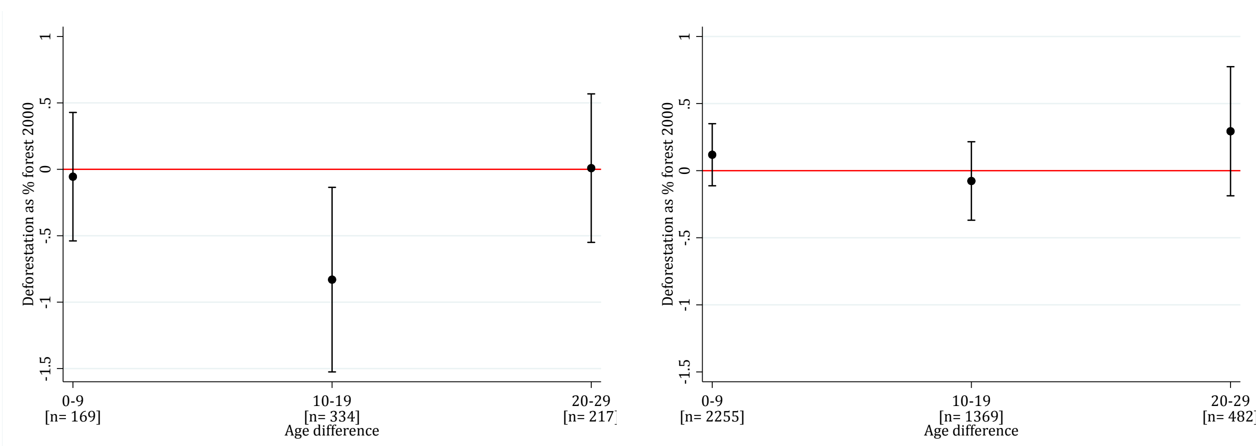


(a) Effect by election year

(b) Effect by year of mandate

Notes: This figure shows the effect dissagregated by election year (Panel A) and year of mandate (Panel B) using the same sample as the main specification (Column 2 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.10: Treatment effects by age difference



(a) Young (Panel A)

(b) YoungerWon (Panel A)

Notes: This figure shows the coefficient of the treatment when the main sample is reduced to the intervals displayed in x-axis. Figure A.10a shows results for main specification and Figure A.10b when we use younger as treatment as in Table A.10.

B Online Appendix

Table B.1: Observations by year

	Young vs Not Young	Young vs Senior	Senior vs Not Senior
	(1)	(2)	(3)
2005	47	10	132
2006	47	10	132
2007	47	10	132
2008	47	10	132
2009	59	15	103
2010	59	15	103
2011	59	15	103
2012	59	15	103
2013	57	14	112
2014	57	14	112
2015	57	14	112
2016	57	14	112
2017	51	7	116
2018	51	7	116
2019	51	7	116
Total	805	177	1,736

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

Table B.2: Results without second term

Dependent variable:	Deforestation as % forest 2000			
	(1)	(2)	(3)	(4)
Panel A:	Margin: Young vs Not Young			
Young Won	-0.60***	-0.67***	-0.56***	-0.57***
	(0.22)	(0.21)	(0.22)	(0.21)
Mean Dep. Variable Control	0.66	0.65	0.64	0.63
Age Diff.	17.47	17.51	17.36	17.39
Bandwidth	11.76	10.92	13.09	13.09
N	648	614	705	698
Panel B:	Margin: Senior vs Not Senior			
Senior Won	0.10	0.12	0.05	0.07
	(0.16)	(0.17)	(0.15)	(0.16)
Mean Dep. Variable Control	0.77	0.78	0.74	0.75
Age Diff.	17.09	17.00	16.95	16.83
Bandwidth	11.55	11.49	13.09	13.09
N	1,382	1,336	1,524	1,482

Notes: This table presents the effect of having a young or senior mayor on deforestation excluding of the sample the second-term mandates. Coefficients are estimated by using Equation (1). Columns 1 and 2 use the optimal bandwidth of each regression. Columns 3 and 4 are restricted to the optimal bandwidth of Column 2 in Panel A of Table 2. Columns 2 and 4 control by gender, left or right-wing of the mayor's party, second-term, married status and college attendance. Panel A takes as sample all municipalities with at least one young candidate among the two first candidates. In Panel B, the sample contains all elections in which almost a senior candidate was between the two first candidates. All regressions include year and age profile fixed-effects, and control by population. Significance level: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table B.3: Results on emission outcomes

Dependent variable:	tCO2 emissions Total	Agro	Land Use	Energy	Waste	GDP emission intensity (kgCO2/R$) 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	-482,456.07*	-77,033.33	-409173.88*	3,252.18	498.96	-8.66***	-1.07***	-7.59***	-0.01	0.01***
	(246,450.94)	(61,413.84)	(209,302.78)	(5,594.60)	(771.92)	(1.94)	(0.24)	(1.84)	(0.01)	(0.00)
Mean Dep. Var. Control	790,236.68	263,631.01	500,315.83	19,370.95	6,918.89	6.52	1.90	4.50	0.09	0.04
Bandwidth	13.09	13.09	13.09	13.09	13.09	13.09	13.09	13.09	13.09	13.09
N	754	754	754	754	754	754	754	754	754	754
Panel B:	Margin: Senior vs Not Senior									
Senior Won	583,972.97*	200,639.34***	380,590.16	4,447.24	-1,703.77	4.75*	0.37**	4.35*	0.04**	-0.01***
	(309,504.29)	(43,848.24)	(290,399.74)	(4,862.41)	(1,427.94)	(2.45)	(0.19)	(2.38)	(0.02)	(0.00)
Mean Dep. Var. Control	652,156.09	222,301.54	393,211.63	27,812.81	8,830.10	2.93	1.84	0.95	0.10	0.05
Bandwidth	11.43	11.43	11.43	11.43	11.43	11.43	11.43	11.43	11.43	11.43
N	1,620	1,620	1,620	1,620	1,620	1,620	1,620	1,620	1,620	1,620

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 two first 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.4: 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	-0.87	0.39	-0.64	-4.60**	-0.96	-3.63**	-2.18
	(0.54)	(2.19)	(1.47)	(1.98)	(0.83)	(1.76)	(1.40)
Mean Dep. Variable Control	2.02	6.41	3.52	2.84	1.09	1.75	1.56
Bandwidth	13.09	13.09	13.09	13.09	13.09	13.09	13.09
N	805	805	805	684	684	684	684
Margin	Senior vs Not Senior						
Senior Won	1.84***	3.98**	0.98	1.21	-0.18	1.39	0.10
	(0.66)	(1.94)	(1.01)	(1.35)	(0.73)	(0.92)	(0.58)
Mean Dep. Variable Control	2.85	6.65	3.37	3.79	1.80	1.99	1.15
Bandwidth	11.43	11.43	11.43	11.43	11.43	11.43	11.43
N	1,736	1,736	1,736	1,445	1,445	1,445	1,445

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.5: 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	-0.91*	-0.45	-1.02	-4.66**	-1.19	-3.37**	-2.16
	(0.52)	(2.02)	(1.37)	(1.99)	(0.82)	(1.71)	(1.33)
Mean Dep. Variable Control	2.44	7.66	4.13	2.87	1.18	1.72	1.51
Optimal band	14.18	15.47	15.68	12.88	11.29	14.57	14.62
N	847	900	903	670	607	735	735
Margin	Senior vs Not Senior						
Senior Won	1.93***	4.50***	1.06	1.20	-0.23	1.36	0.20
	(0.62)	(1.70)	(1.00)	(1.35)	(0.73)	(0.93)	(0.56)
Mean Dep. Variable Control	3.30	7.36	3.69	4.03	1.84	2.12	1.49
Optimal band	14.59	16.58	10.19	11.46	11.85	11.78	9.17
N	2,100	2,235	1,583	1,445	1,466	1,461	1,223

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.6: 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	-2,933.78	-0.63	-1.04
	(1,905.15)	(0.66)	(29.05)
Mean Dep. Variable Control	5,598.06	7.24	74.16
Bandwidth	13.09	13.09	13.09
N	805	754	98
Panel B:	Margin: Senior vs Not Senior		
Senior Won	-345.88	0.10	11.74
	(2,720.48)	(0.55)	(18.88)
Mean Dep. Variable Control	8,550.23	6.92	41.48
Bandwidth	11.43	11.43	11.43
N	1,732	1,592	248

Notes: This table shows the effect of having a young or senior mayor on Agro variables using the sample restricted to 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 the 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 two first candidates. In Panel B, the sample contains all elections in which almost a senior candidate was between the two first 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.7: Results on other municipality outcomes

	GDP per capita			% of muni. expenditure		Liabilities	
Dependent variable:	Total	Agro	Industry	Health	Capital	Short-term	Long-term
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A:	Margin: Young vs Not Young						
Young Won	1,431.75	-1,782.43	2,407.78***	-0.88*	0.83	0.85	-8.63**
	(2,700.41)	(1,334.04)	(878.51)	(0.46)	(0.99)	(0.66)	(3.64)
Mean Dep. Var. Control	14,822.00	4,754.84	1,508.41	10.57	8.32	4.22	6.62
Bandwidth	13.09	13.09	13.09	13.09	13.09	13.09	13.09
N	805	805	805	364	364	332	332
Panel B:	Margin: Senior vs Not Senior						
Senior Won	5,839.14***	1,573.45**	1,317.44	0.83**	0.13	0.07	5.30**
	(2,217.61)	(663.11)	(1,476.78)	(0.39)	(0.69)	(0.62)	(2.34)
Mean Dep. Var. Control	13,298.22	3,346.11	2,239.52	11.15	7.98	4.35	7.70
Bandwidth	11.43	11.43	11.43	11.43	11.43	11.43	11.43
N	1,736	1,736	1,736	759	759	691	691

Notes: Testing of the 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 2 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 sample all municipalities with at least one young candidate among the two first 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.8: 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	1409.70	-5.12***	4.05**	-181.49	-46.33*	-67.97***	-8.34*	-74.81***	0.13	0.25***	-1.49	-0.14	2.71**	0.20	-6.91**
	(2815.60)	(1.84)	(1.64)	(229.78)	(25.77)	(18.69)	(4.57)	(16.45)	(0.33)	(0.08)	(2.17)	(0.16)	(1.07)	(0.14)	(3.37)
Mean Dep. Var. Control	13,741.05	27.60	9.39	888.83	124.05	81.87	24.96	43.97	1.16	0.35	8.23	0.33	19.74	0.60	10.95
Optimal band	11.75	15.66	13.92	13.20	17.42	13.03	8.90	11.12	11.20	7.80	17.44	13.17	12.32	12.23	14.93
N	729	903	835	805	971	752	536	670	674	484	971	364	334	331	381
Panel B:	Margin: Senior vs Not Senior														
Senior won	6839.49***	-0.06	0.29	750.96***	122.01***	-3.67	7.09***	6.29	1.19***	-0.06	6.47***	-0.43***	-3.06***	0.19**	6.00**
	(2330.37)	(1.31)	(1.17)	(223.02)	(22.97)	(17.02)	(2.69)	(19.14)	(0.33)	(0.04)	(2.12)	(0.11)	(0.80)	(0.09)	(2.60)
Mean Dep. Var. Control	13,196.72	25.96	9.28	909.23	107.02	49.18	19.30	26.09	1.07	0.37	9.90	0.37	19.86	0.53	10.93
Optimal band	9.68	12.28	13.46	11.18	8.57	21.12	9.93	13.30	8.30	12.28	15.02	10.55	10.42	12.95	9.69
N	1,522	1,822	1,965	1,709	1,374	2,380	1,462	1,826	1,252	1,700	2,134	716	710	823	601

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 two first 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: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.