ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Master Thesis Economics of Sustainability

The Effect of Female Municipal Leaders on Deforestation: Evidence from Brazil

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Date final version: 6 August 2024

Contents

Abstract

This paper investigates the impact of female mayors on deforestation in the Brazilian Legal Amazon. Using a regression discontinuity design, we compare municipalities with female mayors who narrowly defeated a male candidate to those with male mayors who narrowly defeated a female candidate. Contrary to expectations, we find that female-led municipalities do not exhibit lower levels of deforestation. We also find that female municipal leadership is not associated with greater environmental protection efforts by local governments against deforestation. We find inconclusive results regarding whether female mayors are less likely to engage in corruption. Our findings suggest that female mayors do not prioritise reducing deforestation within the Legal Amazon more than male mayors, but our findings could also be explained by obstacles inherent to municipal forest management which do not allow mayors to reflect their policy preferences.

1 Introduction

Approximately half of the planet's remaining forests can be found in tropical regions. Tropical forests are ecosystems of global importance for several reasons (Balboni, et al., 2023). They are strong natural carbon sinks, sequestering more carbon than any other terrestrial ecosystem; they are home to the largest concentration of biodiversity on Earth; and they regulate water cycles for a significant percentage of the world's population. Their ongoing destruction is thus a cause of global concern. Accordingly, a tropical country has received extensive attention from researchers, NGOs, and policymakers around the world given its deforestation rates and the paramount importance of its forests: Brazil.

Brazil contains the majority of the Amazon, the largest rainforest in the world, but also contains other tropical forest biomes that cover more than half of its territory. At the same time, these ecosystems came under increasing pressure from deforestation over the last decade. As a result, the primary source of carbon emissions in the country is land use change and agriculture, and Brazil's ability to meet the commitments made in the Paris Agreement depends on halting deforestation (European Parliament, 2022). In the case of its Amazon biome, continued deforestation also threatens the loss of invaluable biodiversity and the disruption of water cycles on which Brazil's agriculture sector relies (Arraut, et al., 2012; May, et al., 2013). The situation is further aggravated by the fact that the deforested area in the Amazon is approaching the tipping point at which the forest is expected to start degrading into a savannah (Lovejoy & Nombre, 2018).

Given these concerns, extensive research has looked at the causes of deforestation in Brazil. Research has focused on the Brazilian Legal Amazon, a geographic area subjected to consistent monitoring of deforestation for many decades. The region encompasses the whole Amazon biome, and portions of two other biomes: the Cerrado and the Pantanal[1]. Research identified that deforestation within the Legal Amazon often involves forest clearing to allow cattle grazing and agricultural cultivation, among other less prominent land uses (Almeida, et al., 2016). This is compounded by weak property rights prevalent in the Legal Amazon (Araujo, et al., 2009; Assunção,

[1]The Cerrado biome is composed of savannahs and forested areas, while the Pantanal is a tropical wetland.

et al., 2020)[2], and difficulties in adequately enforcing environmental law in the rainforest (Hargrave & Kis-Katos, 2013)[3]. Consequently, most of the deforested land is cleared illegally (Lawson, 2014).

Our paper examines an area of research that has received less attention: the role played by local leaders in deforestation within the Legal Amazon. Forest management is centralised in Brazil, where the national government and federal agencies hold the power and responsibility to design deforestation policies, designate protected areas and Indigenous Reserves, and enforce environmental laws, among other competencies. Nevertheless, lower levels of government, such as the state and municipality, can still affect local deforestation through different channels. Municipal governments can designate local protected areas, attract private investment for forest management programmes, and in collaboration with federal agencies, play a key role in environmental enforcement (Ferroukhi, 2003; Tacconi, et al., 2019). The ability of municipal governments to take these actions critically depends on the support of the municipal leader, the mayor, who influences municipal priorities, legislation, and budget. However, this support may be far from guaranteed as local economic interests often stand opposed to forest conservation. Engagement in corruption is another channel through which mayors can influence deforestation within the Legal Amazon, as identified by a quasi-experimental study (Pailler, 2018)[4].

Given the influence local leadership can have on deforestation, we explore the relationship between mayor gender and local deforestation outcomes in the Legal Amazon. Our research question is motivated by findings that women in leadership have been associated with better environmental outcomes, including forest conservation (Salahodjaev & Jarilkapova, 2020), and have been found to engage less in corruption (Brollo & Troiano, 2016). If these characteristics can be transposed to female mayors throughout the Legal Amazon, we would expect to find that female-led municipalities exhibit lower levels of deforestation.

However, identifying the effect of female leadership on deforestation is not straightforward. A simple comparison of the area deforested in municipalities led by female mayors and municipalities led by male mayors would suffer from endogeneity. This is because municipalities that are more supportive of women in positions of power may also be richer, less dependent on agriculture, more supportive of the environment, or different in many other factors which also influence deforestation. We follow Bruce et al. (2022) to overcome this endogeneity by first restricting our sample to municipalities which held competitive mixed-gender mayoral elections in 2008, 2012 or 2016. We then use research discontinuity (RD) design to compare deforestation between municipalities with female mayors who narrowly defeated a male candidate and municipalities with male mayors who narrowly defeated a female candidate. This approach relies on the assumption that winning or

[2] The Brazilian legal framework protects holders of land "in productive use", but this does not include forested areas, which are thus vulnerable to expropriation and invasion. Furthermore, a large number of long-term landholders in the Legal Amazon still lack land-ownership titles. The resulting weak property rights thus create an incentive to clear forested land and raise cattle or cultivate crops for landowners and potential squatters.

[3] These include the low collection rates of imposed environmental fines, and the difficulty for law enforcement to detect and reach areas being deforested in time.

[4] Pailler (2018) found that mayors manipulate forest resources in election years to increase their chances of re-election.

losing in close elections is as good as random, and thus the two groups of municipalities are similar in observed and unobserved characteristics.

This paper is within the strand of economic literature that investigates the effects of female representatives on policy outcomes. A recent review of the empirical literature conducted by Hessami & Fonseca (2020) concludes that the effect of the gender of a policymaker on outcomes is partially explained by a gender discrepancy in social preferences and priorities[5]. The effect of female leaders is however context-dependent: in developing countries female representation is found to be associated to lower levels of corruption and better public good provision, but more limited effects are identified in developed countries[6]. A few authors explore the role of female policymakers in the Brazilian context. These quasi-experimental studies explore the relationship between female leadership and various outcomes at the municipal level employing an RD design. Brollo and Troiano (2016) find causal evidence that municipalities led by female mayors present lower levels of corruption and health outcomes. Bruce et al. (2022) also find that female-led municipalities have substantially better health outcomes in the context of the COVID-19 pandemic. In contrast to these significant effects, Barbosa (2017) finds that female mayors do not affect education outcomes. These three studies are very closely related to our own work, and our contribution to this literature is examining the effect of female representation on an environmental outcome: deforestation.

That positions our work within the scarce research that focuses on the effect of female leadership on environmental policies. While it has been documented that women are more concerned about the environment than men (Hunter, et al., 2004; Franzen & Vogl, 2013), only a few studies have looked at whether this translates into influence on environmental outcomes when in positions of power. Three cross-country studies have looked at this relationship and identify a correlation between the percentage of women in parliament and the creation of protected areas (Nugent & Shandra, 2009), carbon emissions (Ergas & York, 2012), and forest cover (Salahodjaev & Jarilkapova, 2020). In contrast to these cross-country analyses of national representation, our work looks at the effect of local female leadership within an emerging economy.

In view of the existing literature, we expect to observe that female-led municipalities exhibit lower deforestation than male-led municipalities due to stronger municipal policy action and lower

[5]In terms of social preferences, early lab studies found that women display more aversion towards competition and risk than men (Crosson & Gneezy, 2009), which may affect the way they govern. These results are partly driven by the overconfidence displayed by men, and are also identified outside of the lab (Buser, et al., 2014). A gender gap in rent-extracting behaviour has also been documented by survey studies (Dollar, et al., 2001; Swamy, et al., 2001), which may lead to lower engagement in such activities by female leaders. In terms of priorities, survey-based studies across developed and developing countries find that women favour more redistribution than men (Chattopadhyay & Duflo, 2004; Alesina & Ferrara, 2005; Funk, et al., 2015), potentially influencing their priorities in office.

[6]Beanman et al. (2012), Chattopadhyay & Duflo (2004), Clots-Figueras (2012), and Bhalotra and Clots-Figueras (Bhalotra & Clots-Figueras, 2014) identify positive policy outcomes resulting from female representation in India, including the provision of education and public health. Employing quasi-experimental studies, Bagues and Campa (2021) and Ferreira and Gyourko (2014), and Baltrunaite et al. (2019) find no effect on public expenditure resulting from female representation in Spain, the US and Italy, respectively, but Lippmann (2022) finds that female legislators are more likely policy areas related to women's issues in France. When considering the quality of institutions, Afridi et al. (2017), Beanman et al. (2007) and Baskaran et al. (Baskaran, et al., 2024) identify empirical evidence that female leaders are less likely to engage in corruption in India. Consistently, Decarolis et al. (2023) find that female policymakers in China and Italy are less likely to be investigated for corruption.

corruption in the public administration. We formulate the following hypotheses:

Hypothesis 1: Brazilian municipalities in the Legal Amazon led by a female mayor present lower levels of deforestation.

Hypothesis 1.1: Brazilian municipalities in the Legal Amazon led by a female mayor exhibit higher environmental protection efforts against deforestation.

Hypothesis 1.2: Brazilian municipalities in the Legal Amazon led by a female mayor are less likely to be engaged in corruption.

In our analysis we find evidence against hypothesis 1 and hypothesis 1.1. No differential levels of deforestation are observed between female-led and male-led municipalities. Additional findings suggest that this may be the result of a lack of differentiated policy effort by female mayors. That is, we find that female municipal leadership is not associated with environmental enforcement and expenditure, protected area designation, nor municipal environmental institutions. Regarding hypothesis 1.2, our findings for the different indicators of municipal corruption are inconsistent, and therefore we do not have enough evidence to confirm or reject the hypothesis. Overall, our findings suggest that female mayors do not prioritise reducing deforestation within the Legal Amazon more than male mayors, but our findings could also be explained by obstacles inherent to municipal forest management which do not allow mayors to reflect their policy preferences.

The paper is divided into the following sections: Section 2 describes the policy background of deforestation in Brazil, Section 3 presents our data and empirical approach, Section 4 presents our results, Section 5 checks the robustness of the identified effects, Section 6 discusses our findings and Section 7 concludes.

2 Policy background

Facing increasing deforestation rates at the turn of the century, Brazil's national government introduced strong federal policies aimed at curbing deforestation from 2004. Between 2004-2008, the government improved monitoring and enforcement capabilities using satellite technology[7], strengthened law enforcement for environmental crimes[8], created numerous protected areas[9], restrained access to rural credit for properties not in compliance with environmental regulations[10], and employed differentiated policy action for municipalities added to a 'priority list' due to their high deforesta-

[7]The Real-Time Deforestation Detection System (DETER) was created and operated from 2004 by the National Institute for Space Research (INPE). By creating georeferenced images of forest cover in the Amazon biome in 15-day intervals, DETER allowed the creation of deforestation alerts. The Brazilian Institute of Environment and Renewable Natural Resources (IBAMA), which exercises control over the environmental police, employed these alerts to target law enforcement in the Amazon to deforestation hotspots.

[8]A Presidential Decree passed in 2008 increased the clarity and speed of administrative processes for the investigation and penalisation of environmental infractions.

[9]Between 2003 and 2008, protected areas in Brazil increased from 57 to 103 million hectares (Rochedo, et al., 2018). By 2010, 43% of the Amazon was protected in the form of Conservation Units or Indigenous Reserves (Assunção, et al., 2015).

[10]Subsidised low interest loans are an essential form of support for agricultural production in Brazil. Resolution 3545 passed in 2008 by the Brazilian Central Bank made access to subsidised rural credit in the Amazon conditional on proving of legal land-ownership and compliance with environmental regulations (Assunção, et al., 2020).

tion rates[11] (Assunção, et al., 2015; Cisneros, et al., 2015; Assunção, et al., 2020). Deforestation in the Legal Amazon peaked in 2004, after which it declined substantially until 2012, and Assunção et al. (2015) find that the described policies were an important driver of this trend.

Figure 1: Area deforested in the Legal Amazon annually between 2000 and 2023. Source: INPE Terrabrasilis

In contrast to the strong policy agenda of the late 2000s, environmental protection gradually weakened since 2012 and deforestation increased once again. This is partly attributed to rising political support for the ruralistas, a political bloc representing the interests of large landholders (Fearnside, 2017). Growth in the agribusiness lobbying effort led to an increase in the number of ruralistas in congress from 116 in the previous legislature to 142 in 2011-2014 (Rochedo, et al., 2018). Their increasing influence is evident in the 2012 Forest Code Reform[12], which pardoned all illegal clearings on private land taking place before 2008 (Soares-Filho, et al., 2014). This widespread amnesty may have created the expectation of future ones (Azevedoa, et al., 2017). The number of ruralistas further increased in 2015-2018 to 207, representing 38% of congress members. Their influence during this legislature was magnified due an ongoing political crisis in Brazil, in which President Dilma Rousseff (2011-2016) was impeached due to corruption within her administration, and President Michel Temer (2016-2018) narrowly avoided impeachment on similar allegations by bargaining with the mostly ruralist Congress (Rochedo, et al., 2018). In this political context, the creation of new protected areas came to a standstill, and the budget for the Ministry of the Environment was slashed (Dasgupta, 2017). Other important reversals of deforestation policy include lowering environmental licensing requirements, suspending the designation of Indigenous

[11] Since January 2008, municipalities in the legal Amazon with intense deforestation have been added annually to the list of 'priority municipalities' (Cisneros, et al., 2015). Subjected to differentiated policy action, 'priority municipalities' can only exit the list via substantial reductions in deforestation.

[12] As of 2001, the Forest Code establishes limits to deforestation on private land. It requires landowners to conserve native vegetation by maintaining Legal Reserves on their land. The percentage of land that must be occupied by Legal Reserves is 80% in the Amazon rainforest and 35% in the Cerrado (Soares-Filho, et al., 2014).

Reserves, reducing the size of several protected areas, and facilitating the provision of titles for illegally deforested areas to land grabbers, although some of these actions were later annulled (Crouzeilles, et al., 2017; Rochedo, et al., 2018).

The pace of environmental backsliding increased further with the election of President Jair Bolsonaro in 2018, who is a close ally of ruralistas (Ferrante & Fearnside, 2019). During his campaign, Bolsonaro promoted a pro-deforestation rethoric in the name of economic development. Accordingly, in his first days in office he appointed a ruralista as head of the Environment Ministry, and moved the Environment Ministry's deforestation control sector to the Agricultural Ministry, which was also headed by a ruralista (Ferrante & Fearnside, 2019). Consistent with Bolsonaro's discourse which empowered land grabbers, during his first year in office vandalism and attacks on environmental agencies and Indigenous Reserves spiked (Ferrante & Fearnside, 2019; Souza, et al., 2021). Bolsonaro's administration also drastically reduced the budget of key federal institutions for deforestation monitoring and enforcement, including FUNAI[13], IBAMA[14], ICMBio[15], and INPE[16]. Several institutions were also subjected to the replacement of their directors and technical experts with non-expert military agents, further limiting their ability to combat deforestation. All of these actions created a climate of impunity in which illegal deforestation was perceived to entail a small risk of conviction (Souza, et al., 2021). Given this political landscape, in 2020, the rate of deforestation in the Legal Amazon was at its highest level in over a decade (Terrabrasilis, 2024).

Therefore, our analysis examines the effect of municipal female leadership on deforestation in a period during which federal deforestation policy was first strengthened before being drastically weakened.

3 Data and empirical strategy

3.1 Data

The Legal Amazon encompasses the whole Amazon biome and part of the Cerrado and Pantanal biomes. Politically, it is composed of the states of Acre, Amapá, Amazonas, Pará, Rondônia, Roraima, Tocantins and Mato Grosso, and also by some municipalities in the state of Maranhão (IBGE, 2024). This corresponds to 772 municipalities extending over 61% of the Brazilian territory (see Figure 2). To explore our research question we compile data on electoral outcomes, deforestation, and other characteristics for municipalities in the Legal Amazon.

[13]The National Foundation of Indigenous Peoples (FUNAI) is in charge of protecting and promoting the rights of indigenous peoples in Brazil. FUNAI monitors and inspects indigenous land, and plays a key role in the designation of Indigenous Reserves.

[14]The Brazilian Institute of Environment and Renewable Natural Resources (IBAMA) exercises control over the environmental police and carries out actions for certain national environmental policies.

[15]The Chico Mendez Institute for Biodiversity Conservation (ICMBio) is responsible for managing, protecting, monitoring, and inspecting the 338 Federal Conservation Units throughout Brazil. One of its key actions include monitoring forest fires and fighting and monitoring environmental crime.

[16]The National Institute for Space Research plays a key role in enabling the monitoring of deforestation in Brazil.

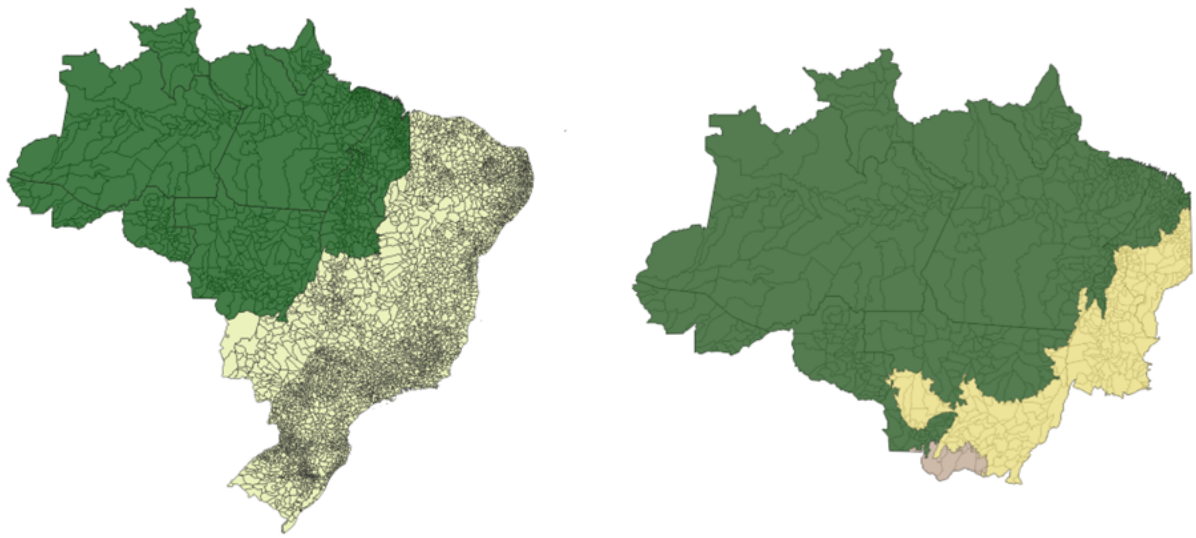

Figure 2: Maps of Brazilian Legal Amazon
Left) Map of Brazilian Municipalities in Legal Amazon. Source: INPE (2024)
Right) Map of biomes within the Legal Amazon. *Notes:* Amazon rainforest in green, Cerrado in yellow, and Pantanal in brown. Source: INPE (2024)

Electoral data: Elections are held in Brazil every two years, in even years, alternating between municipal and general elections (TSE, 2024). In municipal elections, a mayor and a legislative chamber is elected to lead the autonomous government of each Brazilian municipality. Mayors are elected following a plurality rule in municipalities with less than 200,000 voters, and a runoff rule in remaining municipalities[17] (Thomas, 2011).

We obtained electoral data for the 2008, 2012, and 2016 mayoral elections in Legal Amazon municipalities from Brazil's National Electoral Authority (TSE)[18]. For each electoral term, the data contains extensive information on all mayoral election candidates, including their vote share in the election, their gender, and other background characteristics. Taking advantage of the data, we narrow our sample to municipalities holding competitive mixed-gender elections[19]. That is, we keep elections in which a female candidate was elected and a male candidate was the runner-up, or vice versa. We further limit our sample to municipalities in which the elected mayor served the whole electoral term, and we thus exclude those which held extraordinary elections. This gives us an initial sample of 607 mayoral races.

Finally, we note that while the municipal elections in our sample took place in 2008, 2012 and 2016, the elected candidates only took office in January of the following year. This determines our approach for generating deforestation measures and other covariates for each electoral term.

[17]In elections following a plurality rule, the candidate receiving the most votes is elected. In elections following a runoff rule, if no candidate obtains a majority of votes, a runoff election is held between the two candidates who obtained the most votes.

[18]Tribunal Superior Eleitoral.

[19]In those municipalities holding runoff elections, we drop the first voting round and only keep the second round if it is a mixed gender election.

Deforestation outcomes: Deforestation refers to the suppression or removal of primary old-growth vegetation in forest and non-forest formations. In Brazil, annual municipal-level deforestation data is produced by PRODES[20], a satellite-based deforestation monitoring project managed by Brazil's National Institute for Space Research (INPE)[21]. The programme monitors primary vegetation cover for the Brazilian Legal Amazon over 12 month periods with a great level of accuracy (INPE, 2022; INPE, 2023). In particular, for any given year t, PRODES captures forest cover change occurring between 1 August of year $t-1$ and 31 July of year t[22]. However, in producing municipal-level deforestation data, INPE only considers areas where natural vegetation has been completely removed and whose surface exceeds 6.25 ha. That is, smaller patches of deforestation and areas degraded due to selective logging are not accounted for in PRODES figures.

We use 2008-2021 PRODES data to compute the total area deforested per electoral term for each municipality in our sample [23]. This is used to form the dependent variable in our analysis. However, in computing total deforested areas per electoral term, we take into account that PRODES data does not coincide perfectly with annual deforestation cycles, as highlighted by Pailler (2018). That is, deforestation is a long process which starts in the rainy season in December and may finish as late in the dry season as September. This means that for any year t, an important part of annual deforestation is only captured in PRODES year $t+1$. We thus follow Pailler (2018) and compute our deforestation measures by treating the area deforested in any calendar year t as that reflected by PRODES at $t+1$. As a result, the total area deforested for each municipality during a given electoral term captures deforestation registered by PRODES between 1 August of a mayor's first year in office and 31 July of the year after a mayor leaves office.

We also employ PRODES data to further limit our sample. Our relationship of interest can only be investigated in those municipalities with remaining natural vegetation. Therefore, we use remaining forest cover data from PRODES to exclude from our sample those municipalities with less than 4% of their surface covered by forests. This leaves us with a sample of 411 observations.

Finally, for the period 2016-2021 INPE also makes available data on cloud coverage per municipality at the time satellite images were taken for computing PRODES deforestation data. Given the impact of cloud coverage on measurement error for deforestation data (Pailler, 2018; Assunção, et al., 2020), we check that cloud coverage is balanced across our treatment and control municipalities in those years when cloud coverage data is available in Section 4.2.

Baseline covariates: We use data on municipal and mayor baseline characteristics from a range of sources. This data is essential for checking the validity of our empirical analysis, but some characteristics are also used as controls to improve the precision of our estimates. For an accurate

[20] Projeto de Monitoramento do Desmatamento na Amazônia Legal por Satélite.

[21] Instituto Nacional de Pesquisas Espaciais

[22] PRODES years are distributed in this way because August and July fall in the dry season for the Amazon and Cerrado biomes, which allows capturing clearer satellite images on account of lower cloud coverage.

[23] While INPE has monitored deforestation data through PRODES since 1988, the institute notes that due to a technological update, data generated between 1988-2007 and that generated from 2008 onwards is not compatible. It is due to this incompatibility that annual deforestation data between 1988-2007 is no longer available via INPE's Terrabrasilis portal.

description of each variable in our dataset and their source see Table A.1, Table A.2 and Table A.3.

The municipal characteristics we use are environmental, economic and sociodemographic. Environmental characteristics include whether a municipality has been blacklisted due to high deforestation rates; and the percentage of the municipal area covered by protected areas or Indigenous reserves, which are spaces in which deforestation is strictly prohibited. We access the former from the Environment Ministry (MMA)[24] and the latter from INPE. Economic data mainly indicates municipal agricultural activity, which is positively associated with deforestation (Assunção, et al., 2015). In particular, for each municipality we access the percentage GDP coming from the agriculture sector, the area used for crops, and the heads of cattle from several IBGE datasets. Another economic control denoting agricultural activity is issued rural credit (Assunção, et al., 2020), accessed from the Brazilian Central Bank. Sociodemographic data is accessed from IBGE's 2000 census for the 2008 electoral term and from IBGE's 2010 census for the 2012 and 2016 electoral terms. This data covers several variables of interest, including population density, literacy rate and urbanisation rate, among others.

Candidate-level characteristics are accessed from TSE electoral data. These include education level, political party, and campaign contributions. While it is unclear how these characteristics would affect deforestation, they are important for checking whether female and male mayors in our sample only differ in gender.

Policy outcomes: To test hypothesis 1.1 and 1.2, we access data on environmental policy and corruption. Testing the hypotheses means that these variables are used as dependent variables in certain specifications.

We use several measures of municipal environmental policy action: (i) IBAMA provides municipal data on environmental fines and properties embargoed[25] due to environmental transgressions; (ii) INPE data allows us to create a variable representing the surface designated as protected over a given electoral term in a municipality; (iii) Annual Accounts Statements published by the National Treasury (Finbra)[26] allows us to compute municipal environmental expenditure data from 2016 onwards[27]; and (iv) IBGE's municipal surveys (MUNIC)[28] provide data on the presence of environmental councils and funds in each municipality over the 2008 and 2012 electoral terms. For our analysis, these different mechanisms are aggregated at the electoral term level for each municipality.

Regarding the second mechanism, corruption has been shown to be an important determinant of deforestation in Brazil (Pailler, 2018). Moreover, because female mayors have been identified to be less engaged in corruption in Brazil (Brollo & Troiano, 2016), corruption may be an important mechanism for our relationship of interest. Nevertheless, comprehensive data on budget irregularities for Brazilian municipalities over our time period of interest is absent[29]. We thus follow Brollo

[24] Ministério do Meio Ambiente e Mudança do Clima.

[25] Embargoes can be applied to landowners as punishment for illegal deforestation inside private properties (Assunção, et al., 2020). Areas under embargo can no longer be used for production.

[26] Finanças Brasileiras.

[27] While account data between 2008 and 2015 is reported at the municipality level by Finbra, data in this period display a large and varying number of missing observations which make it unusable.

[28] Pesquisa de Informações Básicas Municipais.

[29] We note that Brazil's public corruption fighting body, the Corregedoria-Geral da União, does carry out and

and Troiano (2016) and employ two measures associated with corruption: the number of temporary public workers directly employed in a municipality over an electoral term, and a candidate's total and self-funded campaign contributions. Temporary public employment can be used as a channel for patronage, and campaign contributions may allow private actors to gain influence over mayors. The required municipal employment data is accessed from IBGE's MUNIC surveys for each term, and electoral funding data is accessed from TSE for the 2016 term.

3.2 Regression discontinuity design

Identifying the effect of female leadership on deforestation outcomes is not straightforward. A simple comparison of municipalities led by a female mayor and those led by a male mayor would likely produce biased estimates due to endogeneity, since many factors can influence our outcomes of interest and the mayor's gender simultaneously. For instance, municipalities more supportive of women may be more likely to elect female mayors but may also have economic and demographic characteristics which put less pressure on primary forests. Define Y_{1mt} as the potential deforestation outcomes of municipality m if the mayor is female in mayoral term t, and Y_{0mt} as the potential outcome of the same municipality and term if the mayor is male. The treatment status of municipality m in term t is given by F_{mt}: if the mayor is female $F_{mt} = 1$, and if it is male $F_{mt} = 0$. We want to estimate the causal effect, given by the difference in potential outcomes of female-led municipalities: $E(Y_{1mt}|F_{mt} = 1) - E(Y_{0mt}|F_{mt} = 1)$. However, the second term is unobserved, as we do not know what deforestation outcomes female-led municipalities would have presented under a male mayor in a given mayoral term. Therefore, to identify a suitable counterfactual we use regression discontinuity (RD) design. This identification strategy is well suited to find causal effects where treatment is determined by an observed running variable which shifts treatment status discontinuously upon exceeding a known threshold.

Our sample of Legal Amazon municipalities with competitive mixed-gender elections, in which female mayoral candidates narrowly won or lost against a male candidate, is thus ideal for applying RD design[30]. Define M_{mt} as the margin of victory of the female candidate in election t of municipality m, which takes values between -1 and 1[31]. In our sample, a female candidate only takes office ($F_{mt} = 1$) in municipality m when she obtains a positive victory margin ($M_{mt} > 0$) in election t, and therefore, our treatment status (F_{mt}) indeed jumps discontinuously from 0 to 1 when the value of the running variable (M_{mt}) exceeds 0 ($F_{mt} = 1$ if $M_{mt} > 0$ and $F_{mt} = 0$ otherwise). Sharp RD design exploits this discontinuity to evaluate the effect of female leadership on deforestation at the vicinity of this threshold $M_{mt} = 0$ (average treatment effect at the threshold). In other words, municipalities in which a man won by a narrow margin are used as counterfactual for municipalities

publish internal audits of municipalities under its Federative Entities Inspection Programme. Brollo and Nannicini (2012) coded reports from this programme published between 2003 and 2009 to identify budget irregularities, and this data was reused in several corruption studies (Brollo Troiano, 2016; Pailler, 2018). Nevertheless, to the best of our knowledge, similar data is not publicly available for audit reports published between 2009 and 2021.

[30] RD design is often used in close election settings (Bruce, et al., 2022; Brollo & Troiano, 2016; Barbosa, 2017).

[31] We compute M_{mt} by first constructing the vote share received by each candidate in a municipal election, and then subtracting the vote share received by the male candidate to the vote share received by the female candidate.

in which a woman won by a narrow margin.

The validity of our RD design relies on the assumption that in close elections, winning or losing can be considered as good as random, and thus, near the $M_{mt} = 0$ threshold, our treatment F_{mt} is as good as randomly assigned[32]. This is often referred to as the continuity assumption as it implies that expected potential deforestation outcomes are continuous across the threshold $M_{mt} = 0$. While untestable, the assumption is more likely to hold under two conditions. First, continuity is observed in other covariates around the threshold, and second, no manipulation is observed in the margin of victory of female candidates. We test these two conditions in Section 4.2.

We now described the three RD design specifications which we use throughout our analysis:

$$\log(Y_{mt}) = \alpha + \beta F_{mt} + f(M_{mt}) + \epsilon_{mt} \qquad (1)$$

Equation 1 is our unadjusted specification, in which m denotes municipality, and t denotes a mayoral term (2008, 2012 or 2016). Y_{mt} is the total area deforested in municipality m in term t. We employ a natural logarithm of deforestation as our dependent variable to smooth variation resulting from heterogenous municipality sizes. F_{mt} is our treatment variable taking value 1 if the mayor of municipality m in term t is a woman, and value 0 if the mayor is a man. β is therefore our treatment effect, which represents the effect of female mayors on deforestation. M_{mt} denotes the margin of victory for female candidates and is our running variable, as it discontinuously determines the gender of mayors. As our running variable, it must be included in all specifications. Finally, ϵ_{mt} is the standard error which we cluster at the municipality level. Equation 1 is our simplest specification, but given our quasi-experimental setting we expect the RD estimate for β to be unbiased. Instead, the purpose for employing additional specifications in our analysis is increasing the precision of our RD estimate.

$$\log(Y_{mt}) = \alpha + \beta F_{mt} + f(M_{mt}) + \tau_t + \epsilon_{mt} \qquad (2)$$

Equation 2 is our fixed-effects adjusted specification. The only additional term compared to equation 1 is τ_t, which are electoral term fixed-effects. Term fixed-effects are expected to improve the precision of the RD estimate as they account for varying macroeconomic conditions and federal policies over our period of study (Assunção, et al., 2015; Fearnside, 2017). Federal state fixed-effects could also be appropriate as they would capture some geographic variability. Nevertheless, fixed-effects should only be added to an RD specification where they are balanced across treatment and control groups, so as to maintain the consistency of the RD estimate (Calonico, et al., 2019). Electoral-term fixed effects are balanced across female-led and male-led municipalities, but state fixed-effects are not, as shown in Table A.4. This is why we only include the term fixed-effects.

[32] Under a random assignment, treatment is independent of unobserved factors near the threshold and our counterfactual is valid as $E[Y_{0mt}|F_{mt} = 1, M_{mt} = 0] = E[Y_{0mt}|F_{mt} = 0, M_{mt} = 0]$.

$$\log(Y_{mt}) = \alpha + \beta F_{mt} + f(M_{mt}) + \mathbf{Z_{mt}} + \tau_t + \epsilon_{mt} \qquad (3)$$

Equation 3 is our covariate adjusted specification. The additional term compared to equation 2 is $\mathbf{Z_{mt}}$, which denotes a range of pre-treatment municipal-level covariates[33]. The purpose of including covariates is again improving the precision of our estimates[34] (Cattaneo, et al., 2020). As in the fixed-effects case, our RD estimate must not vary with the inclusion of covariates (Cattaneo, et al., 2023), which in turn requires covariates to be continuous across the threshold $M_{mt} = 0$ (Calonico, et al., 2019). This is analogous to the RD covariate continuity validity condition discussed in the previous paragraphs, which is tested in Section 4.2.

We estimate all of the described specification treating $f(\cdot)$ as a first order polynomial function, as recommended by Gelman and Imbens (2019) and Cattaneo et al. (2020)[35]. We also use a triangular kernel to estimate all specifications. The kernel function or "weighting scheme" assigns weights to observations according to the proximity of the running variable values of each observation to the threshold (Cattaneo, et al., 2020). A triangular kernel assigns the highest weights at the cutoff and the weights decrease linearly for values away from the threshold[36].

As previously described, RD design allows us to identify the average treatment effect within a close range or "bandwidth" around the threshold $M_{mt} = 0$. We must thus choose a bandwidth, h, to determine the effective number of observations we will use for estimating our described specification (RD only uses observations with $M_{mt} \in [-h, +h]$ for estimation). A common practice is choosing h to minimise the mean squared error (MSE) of the RD point estimator, $\hat{\beta}$ (Imbens & Kalyanaraman, 2012). As the MSE of $\hat{\beta}$ is the sum of the estimator's squared bias and variance[37], by choosing h to minimise the MSE we optimise the bias-variance trade-off associated to the choice of bandwidth (Cattaneo, et al., 2020)[38]. In view of this, we use a data driven procedure developed by Calonico et al. (2014) to identify MSE-optimal bandwidths in our unadjusted specification[39], and an alternative procedure developed by Calonico et al. (2019) to identify MSE-optimal bandwidths in our fixed-effects and covariate adjusted specification.

Finally, we follow best practice for statistical inference by using robust bias-corrected confidence

[33] These are the percentage of municipality covered by forest, heads of cattle per km2, population density, urbanisation rate, percentage of mixed-race population, and the literacy rate.

[34] In RD, covariates cannot correct an identification assumption which is rendered implausible by the conditions discussed in the previous paragraphs (Cattaneo, et al., 2020).

[35] High order polynomials can lead to overfitting and unreliable results near the threshold.

[36] When used in conjunction with bandwidths optimising the mean squared error, triangular kernels lead to point estimators with optimal properties.

[37] $MSE(\hat{\beta}) = \text{Bias}^2(\hat{\beta}) + \text{Variance}(\hat{\beta})$

[38] Choosing a bandwidth presents a trade-off between bias and variance. A larger bandwidth will increase sample size, increasing the precision of estimates, but also raises the risk of bias by including observations further from the threshold. The opposite occurs with a smaller bandwidth: the risk of bias is lower, but so is the number of observations, reducing estimates' precision.

[39] Calonico et al. (2014) propose to choose the bandwidth to minimise a first-order approximation to the MSE of the RD point estimator, which generates an MSE-optimal bandwidth choice. They use a second-generation plug-in rule, where unknown quantities in the MSE-optimal bandwidth are replaced by consistent estimators (Cattaneo & Titiunik, 2022). Their computation includes a regularisation term to avoid small denominators in small samples (Cattaneo, et al., 2020).

intervals to report the variance and p-values of all of our results. Unlike other inference approaches for RD[40], the robust bias corrected approach initially developed by Calonico et al. (2014) is theoretically valid and has some optimality properties.

4 Results

4.1 Sample composition and descriptive statistics

The Legal Amazon has 772 municipalities. For our analysis, we focus on those municipalities which held competitive mixed-gender mayoral elections in 2008, 2012 or 2016[41]. This gives us an initial sample of 607 mayoral races. As our relationship of interest can only be studied for municipalities with pre-existing forest cover, we also exclude municipalities with less than 4% of their surface covered by forests before an election[42]. This removes almost a third of our sample. Dropped municipalities mainly belong to the less forested Cerrado biome, and sit in the Arc of Deforestation, an area covering the Legal Amazon's southeastern limit which has historically been subjected to high deforestation (Assunção, et al., 2020). Our final sample is composed of 411 mayoral races from 270 different municipalities. Figure 3 presents the municipalities included in our final sample in dark green, and those dropped due to low forest cover in orange.

Table 1 reveals additional insight on sample composition by mayoral gender, that is, by treatment (female mayor) and control (male mayor) units. The first panel displays sample composition by mayoral term. It can be observed that for forested Legal Amazon municipalities, the number of competitive mixed-gender mayoral elections increased between 2008 and 2016, since observations from later electoral terms compose a larger share of our sample. The panel also shows that the sample composition of each electoral term is balanced across the gender of mayors, which is a requirement for the use of term fixed-effects in our main specifications. The second panel presents the geographic composition of our sample. The largest states in the Legal Amazon by number of municipalities are Maranhão, Mato Grosso, Pará and Tocantins, each with over 100 municipalities. These large states form most of our sample. The geographic composition of our sample is balanced across treatment units for these larger states, but not for the smaller states of Acre (22 municipalities), Amapá (16 municipalities) and Roraima (15 municipalities).

Table 2 provides summary statistics for baseline and outcome variables by mayoral gender (treatment category). The first two panels present baseline municipality and mayor characteristics. Municipality characteristics include environmental, economic and socio-demographic characteris-

[40] Other inference approaches for RD include the conventional approach and standard bias correction. These approaches present different issues (Calonico, et al., 2014; Cattaneo, et al., 2020). Conventional inference ignores the misspecification error inherent in RD design, leading to invalid inference. Standard bias correction does estimate and remove misspecification error when constructing confidence intervals, but its performance is still inadequate due to a variance term which does not account for the estimation and removal of the misspecification error. Instead, robust-bias correction appropriately recentres and rescales confidence intervals.

[41] We also exclude electoral terms during which an extraordinary election was held, as this indicates the mayor stepped down or was deposed during the term.

[42] Forest cover in the election year was used for the 2008 and 2016 terms, and forest cover in the year preceding an election for the 2012 term.

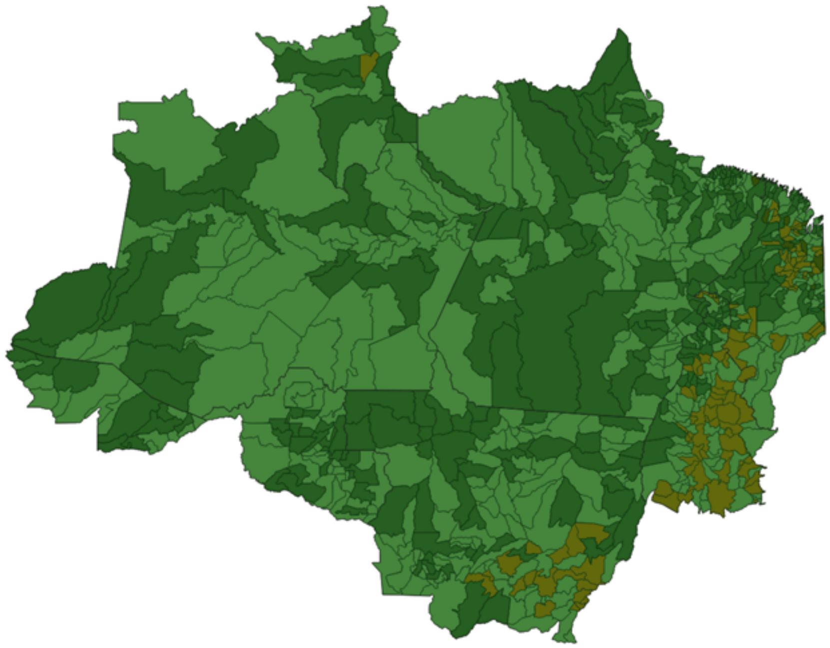

Figure 3: Legal Amazon municipalities holding competitive mixed gender elections in the 2008, 2012 or 2016 mayoral election and with more than 4% forest cover (dark green). *Note*: Municipalities holding competitive mixed gender elections with less than 4% forest cover are depicted in orange. Municipalities which did not hold competitive mixed-gender mayoral elections are depicted in light green.

Table 1: Sample composition by gender of mayor

	Female mayor		Male mayor	
	Mean	Obs.	Mean	Obs.
Electoral term				
2008	0.271	170	0.282	241
2012	0.341	170	0.369	241
2016	0.388	170	0.349	241
Federal state				
Acre	0.024	170	0.046	241
Amazonas	0.076	170	0.066	241
Amapá	0.053	170	0.029	241
Maranhão	0.235	170	0.203	241
Mato Grosso	0.171	170	0.149	241
Pará	0.259	170	0.253	241
Rondônia	0.071	170	0.112	241
Roraima	0.012	170	0.029	241
Tocantins	0.100	170	0.112	241

Notes: Each observation in the *Female mayor* columns represents a municipality holding an election in which the winner is female and the runner-up is male. Conversely, each observation in the *Male mayor* columns represents a municipality holding an election in which the winner is male and the runner-up is female. The *Mean* column represents the average value within the respective sample, and *Obs.* represents the number of observations.

tics, which are all measured before a mayor takes office. Mayor characteristics are also measured before the beginning of an electoral term, and include political affiliation, education level, whether the mayor is the incumbent, and campaign contributions. The last panel contains several outcome variables of interest. Unlike baseline variables, outcome variables are measured over an electoral term for each municipality. Our data is thus structured at a municipality-mandate level. The outcome variables presented in Table 2 include the total area deforested over an electoral term; total fines and area embargoed, which denote environmental policing; the percentage of municipal budget spent on the environment; and cloud coverage at the time PRODES images were taken.

Our sample is composed of 411 observations split among female-led and male-led municipalities. There are more observations for male-led municipalities, suggesting that male candidates win more mixed-gender elections in our sample. We also note that due to data limitations, some variables could only be observed for specific electoral terms. One outcome variable is affected by such limitations: the percentage of the municipal budget spent on the environment, which could only be observed for the 2016 term.

Most of the baseline characteristics presented in Table 2 seem balanced across female-led and male-led municipalities, but we carry out formal discontinuity tests for these characteristics in the following section.

4.2 Validity tests

Our RD approach relies on the identifying assumption that in close mayoral races winning or losing is as good as random, and therefore, our treatment is as good as randomly assigned. While the assumption cannot be tested, it is more likely to hold where two conditions are met: no manipulation and continuity in covariates.

The first condition refers to the fact that no manipulation must be observed in the margin of victory of female candidates (M_{mt}) around the threshold at which treatment is determined: $M_{mt} = 0$. The condition implies that no sorting occurs, which is an essential requirement of the RD identifying assumption. Following Imbens & Lemieux (2008), we check whether the condition holds by looking for bunching of units with a McCrary test (McCrary, 2008). More specifically, the test checks for the presence of a jump in the density of the margin of victory variable at either side of the threshold $M_{mt} = 0$.

The McCrary test returns a very high p-value of 0.866 and we thus fail to reject the null hypothesis that the density of female victory margin is continuous at the threshold. Figure 4 graphs the associated density plot. Consistently, it does not reveal a jump in density at the threshold, and instead shows that the 95% confidence intervals of the fitted density lines of female-led and male-led municipalities overlap at $M_{mt} = 0$.

The lack of evidence found for manipulation is not surprising given the nature of our running variable, as it is hard to manipulate the number of votes received in an election. This may especially apply to Brazil, where the national electoral authority already implemented electronic ballot boxes in 1996 to minimise fraud and enhance the transparency of voting processes (TSE, 2024).

Table 2: Summary statistics by gender of mayor

	Female mayor		Male mayor	
	Mean	Obs.	Mean	Obs.
Municipal characteristics				
Municipal area (km2)	8,956.2	170	7,996.8	241
% forest cover	0.376	170	0.346	241
% of mun. designated as PA	0.203	170	0.163	241
% of mun. designated as IR	0.098	170	0.092	241
Presence of mun. env. fund	0.413	104	0.382	157
Presence of mun. env. council	0.558	104	0.484	157
Blacklisted municipality	0.094	170	0.083	241
Permanent public employees	728.1	170	859.7	237
Temporary public employees	305.3	170	392.7	237
GDP per capita (thousand R$)	10.593	170	11.640	241
% GDP from agri-sector	0.253	170	0.243	241
Heads of cattle per km2	31.318	170	39.185	241
% mun. area destined for crops	0.038	170	0.028	240
Total rural credit (milion R$)	130.914	124	122.062	173
Population	24,074.8	170	34,301.3	241
Population density	15.774	168	16.359	240
Urbanisation rate	0.517	170	0.544	241
% mixed-race population	0.645	170	0.632	241
% Indigenous population	0.028	170	0.028	241
% male population	0.520	170	0.519	241
% population under 15	0.344	170	0.344	241
% population 15 to 60	0.582	170	0.584	241
Literacy rate	0.810	168	0.820	240
Mayor characteristics				
Candidate is the incumbent mayor	0.124	170	0.253	241
Candidate completed higher education	0.641	170	0.344	241
Candidate completed highschool	0.918	170	0.714	241
Candidate from DEM	0.041	170	0.058	241
Candidate from PMDB	0.212	170	0.195	241
Candidate from PSDB	0.171	170	0.112	241
Candidate from PT	0.088	170	0.104	241
Campaign contr. (thousands R$)	112.4	66	123.3	84
Self-funded contr. (thousands R$)	25.9	66	51.0	84
Deforestation outcomes				
Total deforested area (km2)	57.791	170	57.464	241
Total environmental fines	41.694	170	39.282	241
Total area embargoed (km2)	17.961	170	15.916	241
% of environmental expenditure	0.010	64	0.008	83
Average cloud coverage	0.031	170	0.023	241

Notes: Each observation in the *Female mayor* columns represents a municipality holding an election in which the winner is female and the runner-up is male. Conversely, each observation in the *Male mayor* columns represents a municipality holding an election in which the winner is male and the runner-up is female. The *Mean* column represents the average value within the respective sample, and *Obs.* represents the number of observations. The first two panels represent baseline characteristics measured before a mayor takes office. The last panel represents outcomes of interest measured over an electoral term.

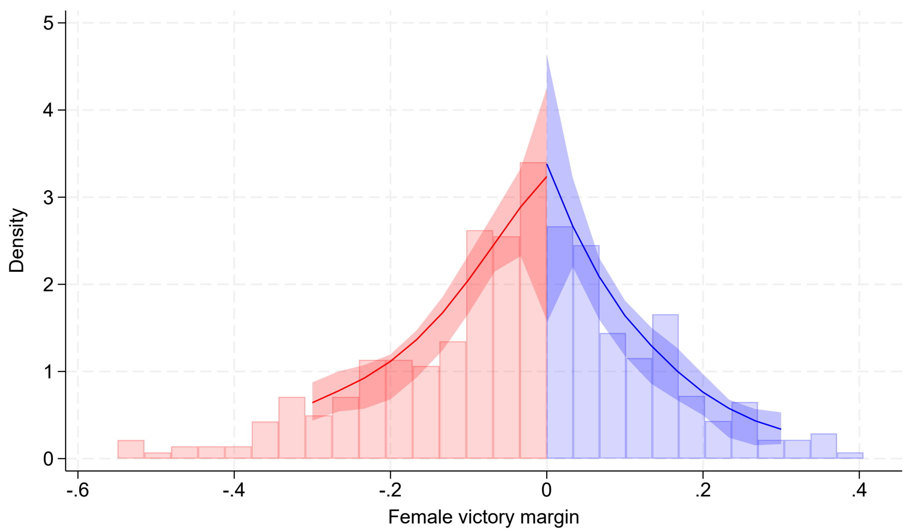

Figure 4: Density plot of female victory margin *Notes*: The histogram bins represent the density of observations within given values of female victory margin. Observations in red represent municipalities in which the election winner is male, and observations in blue represent municipalities in which the election winner is female. The shaded areas around the fitted lines represent 95% confidence intervals.

The second condition refers to covariates displaying continuity around the threshold $M_{mt} = 0$. That is, if winning or losing is as good as random in close elections, we would expect female-led and male-led municipalities to be similar in terms of observable characteristics. This implies that all covariates not affected by the gender of the mayor should be continuous around the threshold $M_{mt} = 0$. To test the condition we follow Cattaneo, et al. (2020) and look for discontinuities at the threshold for an array of baseline covariates. These include those listed in the first two panels of Table 2 and baseline values of outcome variables (measured in the year before a mayor takes office).

We analyse the continuity of each covariate separately in the same way as we later analyse the outcome variables. This requires replacing the dependent variable of the unadjusted specification of equation 1 with each of our covariates and identifying unique optimal bandwidths [43]. Results from these regression are displayed in Table 3. We also display a similar continuity test for electoral term indicators in Table A.4. Graphs for all tested covariates are presented in Figure A.1, Figure A.2, and Figure A.3.

The first panel of Table 3 shows that no discontinuity is observed in municipal characteristics around the threshold $M_{mt} = 0$. The second panel, however, reveals a discontinuity in the mayor's level of education. A larger percentage of mayors in female-led municipalities are found to have completed higher education and high-school compared to male-led municipalities. These discontinuities are significant at the 1% level. We note however, that the education level of mayors may

[43] These optimal bandwidths are different for each covariate, and therefore are also different from that used for our outcome of interest (Cattaneo, et al., 2020). This is because the estimated regression function for each covariate is different, exhibiting different curvature and shape.

Table 3: Formal Continuity-Based Analysis for Covariates

Variable	MSE-Optimal BW	RD Estimator	Robust p-value	Robust Conf. Int.	Eff. num. of obs.
Municipal characteristics					
Municipal area (km2)	0.138	2837	0.452	[-5868, 13168]	250
% forest cover	0.129	-0.031	0.689	[-0.202, 0.134]	242
% of mun. designated as PA	0.118	0.048	0.476	[-0.131, 0.280]	233
% of mun. designated as IR	0.148	-0.004	0.868	[-0.129, 0.109]	267
Presence of mun. env. fund	0.109	0.226	0.219	[-0.144, 0.628]	143
Presence of mun. env. council	0.122	0.180	0.383	[-0.220, 0.574]	152
Blacklisted municipality	0.138	-0.030	0.752	[-0.193, 0.140]	249
Permanent public employees	0.140	161.2	0.469	[-312.7, 679.3]	251
Temporary public employees	0.103	-24.0	0.655	[-313.7, 197.1]	210
GDP per capita (thousand R$)	0.101	-0.003	0.110	[-0.007, 0.001]	208
% GDP from agri-sector	0.123	-0.050	0.321	[-0.144, 0.047]	237
Heads of cattle per km2	0.118	1.779	0.643	[-14.08, 22.80]	233
% mun. area destined for crops	0.133	-0.001	0.834	[-0.031, 0.025]	242
Log of rural credit (R$)	0.138	-1.035	0.394	[-4.340, 1.710]	249
Log of population	0.141	-0.214	0.436	[-0.850, 0.367]	257
Population density	0.126	-6.069	0.516	[-41.56, 20.88]	240
Urbanisation rate	0.206	0.003	0.886	[-0.097, 0.083]	311
% mixed-race population	0.140	-0.021	0.543	[-0.098, 0.051]	254
% Indigenous population	0.178	0.008	0.881	[-0.050, 0.058]	297
% male population	0.122	-0.005	0.384	[-0.012, 0.005]	236
% population under 15	0.129	0.000	0.954	[-0.032, 0.030]	241
% population 15 to 60	0.130	-0.009	0.505	[-0.037, 0.018]	243
Literacy rate	0.129	-0.030	0.200	[-0.080, 0.017]	240
Mayor characteristics					
Candidate is the incumbent	0.140	-0.058	0.774	[-0.318, 0.237]	254
Candidate completed higher education	0.119	0.347***	0.009	[0.091, 0.654]	235
Candidate completed highschool	0.122	0.332***	0.002	[0.138, 0.586]	236
Candidate from DEM	0.138	-0.042	0.342	[-0.166, 0.058]	249
Candidate from PMDB	0.116	-0.150	0.126	[-0.428, 0.053]	233
Candidate from PSDB	0.124	0.101	0.286	[-0.089, 0.303]	239
Candidate from PT	0.120	-0.003	0.900	[-0.166, 0.189]	235
Baseline deforestation outcomes (measured in election year)					
Log of deforested area (km2)	0.137	-0.303	0.580	[-1.623, 0.907]	249
Environmental fines	0.210	-0.826	0.955	[-18.66, 19.77]	312
Area embargoed (km2)	0.166	-138.63	0.345	[-458.2, 160.1]	281
% of environmental expenditure	0.124	0.005	0.324	[-0.006, 0.017]	201
Placebo covariates					
Average cloud coverage	0.190	0.020	0.599	[-0.044, 0.077]	107

Notes: This table presents RD estimates of the association between female mayors and municipal characteristics, mayor characteristics, baseline deforestation outcomes, and one placebo covariate. Each RD local linear regression uses a polynomial of order 1 and an MSE-optimal bandwidth calculated following Calonico, et al. (2014). Following the same study, the table reports robust-bias corrected p-values and 95% confidence intervals. The standard errors of each regression are clustered at the municipality level. Coefficients significantly different from zero at 99% (***), 95% (**) and 90% (*) confidence level.

need to be considered as a characteristic which changes with treatment instead of a baseline characteristic. This is because among all 772 municipalities in the Legal Amazon, on average female mayors have a higher education level than male mayors in each electoral term between 2008 and 2020. Considering mayors' level of education as a mechanism is consistent with Bruce et al. (2022), and implies that the significant effect identified does not threaten our identification strategy. Instead, the higher education of female mayors may be the underlying cause of any effect we may identify in our main analysis. The remaining mayor characteristics in the second panel do display continuity. The third panel shows that baseline deforestation outcomes also seem to be continuous across female-led and male-led municipalities.

The final panel of Table 3 checks for discontinuity in one important placebo covariate which is not affected by treatment. The placebo covariate represents the average level of cloud coverage at the time deforestation was measured via satellite, and therefore, the covariate is closely associated with deforestation measurement error (Pailler, 2018; Assunção, et al., 2020). Therefore, continuity in this covariate would suggest that measurement error is evenly spread across female-led and male-led municipalities. On account of data limitations we only have access to average cloud coverage during the 2016 electoral term, but we do find continuity across the threshold $M_{mt} = 0$ for this term.

To sum up, the results identified from our McCrary and covariate continuity tests do not find evidence of sorting nor discontinuous changes in factors other than the gender of the mayor in the vicinity of the threshold $M_{mt} = 0$. This in turn strengthens the argument for the validity of the results presented in the following sections.

4.3 Deforestation outcomes

This section describes the main results of our analysis of the effect of female mayors on deforestation. Our deforestation outcome is the logarithm of the total area deforested over an electoral term in a given municipality[44], based on INPE's PRODES. We first report in Table 4 the effect on our deforestation outcome for the full sample, before exploring the heterogeneity of the identified effect in different sample subsets in Table 5.

Table 4 reports the estimated effect of female leadership on deforestation for unadjusted, fixed-effects adjusted, and covariate adjusted specifications. Our estimates are similar across specifications and point to around 40% lower deforestation over an electoral term for female-led municipalities compared to male-led municipalities in close elections[45]. However, the results are not significant at conventional levels. We observe that the robust confidence interval narrows with the addition of term fixed effects and covariates, but even for our most precise specification, the covariate adjusted one, the identified effect remains insignificant. This suggests that the gender of the mayor has no effect on deforestation in our full sample.

[44]Total area deforested in a given municipality between 1 August of the year in which a mayor takes office and 31 July of the year after the electoral term ended.

[45]Since total area deforested is in logarithmic scale, the percentage difference in area deforested between female-led and male-led municipalities is given by $(exp(\beta) - 1) * 100$, where β is the RD estimate of the treatment variable F_{mt}.

Table 4: Impact of female leadership on deforestation – RD estimates.

	Unadjusted specification	FE adjusted specification	Covariate adjusted specification
Dep. variable: Logarithm of total area deforested over electoral term			
RD estimator	-0.543	-0.520	-0.472
Robust p-value	0.301	0.324	0.235
Robust conf. int.	[-1.921, 0.593]	[-1.900, 0.627]	[-1.611, 0.395]
MSE-optimal BW	0.127	0.126	0.114
Eff. number obs.	241	241	228
Term fixed effects		x	x
Covariate list			x
Number of obs.	411	411	408

Notes: The table presents RD estimates of the effect of female mayors on the logarithm of the total area deforested over an electoral term in Brazilian municipalities. The first column includes no covariates, the second adds electoral term fixed effects, and the third adds a list of baseline covariates: percentage of municipality covered by forest, heads of cattle per km2, population density, urbanisation rate, percentage of mixed-race population, and the literacy rate. Our full sample is used for estimation. Each RD local linear regression uses a polynomial of order 1 and an MSE-optimal bandwidth calculated following Calonico, et al. (2014). Following the same study, the table reports robust-bias corrected p-values and 95% confidence intervals. The standard errors of each regression are clustered at the municipality level. Coefficients significantly different from zero at 99% (***), 95% (**) and 90% (*) confidence level.

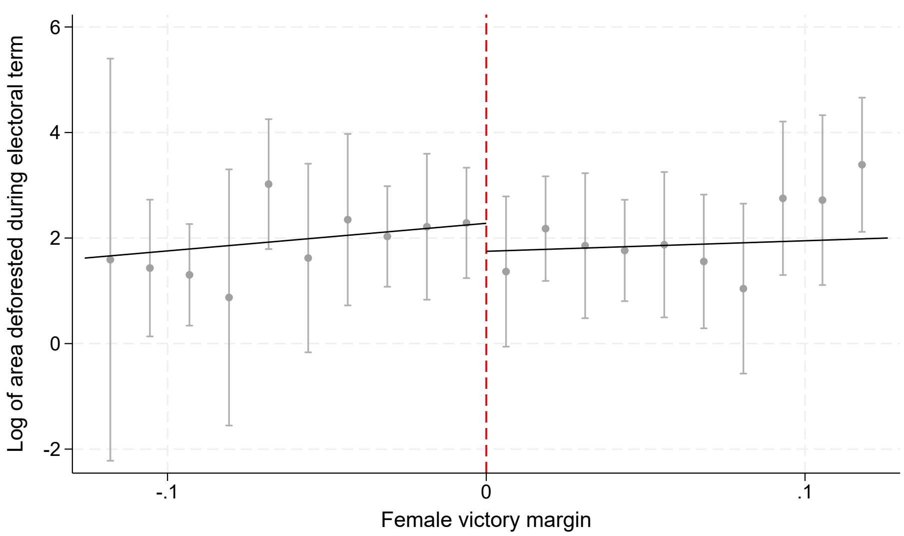

Figure 5: Impact of female mayors on the logarithm of the total area deforested over an electoral term in Brazilian municipalities. *Notes:* The figure shows graphically the effect of female leadership on deforestation. The table is analogous to the unadjusted RD regression from Table 4, and uses the same bandwidth. The plot is generated following Cattaneo et al. (2020). Each dot represents the local sample mean of observations within set values of female victory margin, and the presented range for each dot represents the 95% confidence interval of the local sample mean. A linear specification is used for generating the global polynomial fit.

We plot the unadjusted specification from Table 4 in Figure 5 above. The table does not reveal a large discontinuity in the linear fits of the data at threshold, and the 95% confidence intervals of local sample means of observations near the threshold overlap. This graphical evidence again suggests that there is no difference in deforestation between female-led and male-led municipalities.

We now examine whether female leadership has an effect on deforestation in municipalities with specific characteristics. The use of interaction terms is common for examining the heterogeneity of an effect in economic literature. However, unlike other empirical approaches, the use of interaction terms in RD requires introducing additional restrictive assumptions. Instead, we examine the heterogeneity of the treatment effect by running our RD specifications on subsets of our sample with specific characteristics (Cattaneo, et al., 2023). Accordingly, Table 5 displays results from running the term fixed-effects specification from Table 4 on several such subsets. In particular, we look at whether the effect of female leadership on deforestation differs by electoral term in Panel A and by a range of municipal characteristics in Panel B.

Table 5: Impact of female leadership on deforestation – Heterogeneity of RD estimates.

	Panel A: Electoral terms		
Dep. variable: Logarithm of total area deforested over electoral term			
	2008	2012	2016
RD estimator	-0.087	-0.227	-0.901
Robust *p*-value	0.913	0.901	0.295
Robust conf. int.	[-2.119, 2.368]	[-2.519, 2.218]	[-3.104, 0.943]
MSE-optimal BW	0.098	0.119	0.175
Eff. number obs.	58	83	105
Covariates and FE			
Number of obs.	114	147	150

	Panel B: Municipal characteristics			
Dep. variable: Logarithm of total area deforested over electoral term				
	Over 30% of mun. is covered by forests	Over 50% of rural pop.	Agriculture accounts for over 20% of GDP	Over 20 heads of cattle per km2
RD estimator	-0.288	-0.922	-0.562	-0.849
Robust *p*-value	0.512	0.412	0.323	0.138
Robust conf. int.	[-1.634, 0.814]	[-2.479, 1.016]	[-1.903, 0.627]	[-2.015, 0.279]
MSE-optimal BW	0.139	0.090	0.115	0.133
Eff. number obs.	111	93	138	126
Covariates and FE	x	x	x	x
Number of obs.	192	180	245	221

Notes: The table presents RD estimates of the effect of female mayors on the logarithm of the total area deforested over an electoral term in Brazilian municipalities for different sub-samples. Panel A presents estimates for each electoral term. Panel B presents estimates for municipalities with different baseline characteristics: over 30% of surface covered by forest, over 50% of population living in rural areas, over 20% of GDP coming from agriculture, or over 20 heads of cattle per km2. Regressions in panel B control for term fixed effects and a list of baseline covariates: percentage of municipality covered by forest, heads of cattle per km2, population density, urbanisation rate, percentage of mixed-race population, and the literacy rate. Each RD local linear regression uses a polynomial of order 1 and an MSE-optimal bandwidth calculated following Calonico, et al. (2014). Following the same study, the table reports robust-bias corrected p-values and 95% confidence intervals. The standard errors of each regression are clustered at the municipality level. Coefficients significantly different from zero at 99% (***), 95% (**) and 90% (*) confidence level.

Panel A shows that the effect on deforestation is negative across all electoral terms in our sample, but the effect increases in absolute terms between 2008 and 2016. Nevertheless, the estimates are all insignificant, just as our full-sample results. Panel B looks at whether the effect of female mayors on deforestation is different in municipalities with high forest coverage, a large rural population, or an important agricultural sector. The importance of agriculture is proxied by the contribution of the sector to municipal GDP and by the heads of cattle per square kilometre. All of these characteristics create different municipal priorities and deforestation pressure, which may influence mayors' approach to deter deforestation. Despite this consideration, all estimates are insignificant, suggesting that female mayors have no effect on deforestation also in municipalities with the presented characteristics. Nevertheless, we note that one shortcoming of our subset analysis are small sample sizes which limit our inference capability. For instance, only 93 effective observations are used for estimation in the subset with a large rural population.

To sum up, we do not find an effect from female leadership on deforestation following a competitive mixed-gender election. This is the case for our full sample, as well as for subsets with high forest coverage, a large rural population, or an important agricultural sector.

4.4 Deforestation mechanisms

In this section we explore whether the election of a female mayor has an impact on two mechanisms influencing deforestation within the Legal Amazon: policy action and corruption. This allows us to test hypotheses 1.1 and 1.2. According to hypothesis 1.1, we expect to observe stronger municipal policy action aimed at reducing deforestation in female-led municipalities. According to hypothesis 1.2, we expect to find female mayors to be less engaged in corruption within our sample. The hypotheses are tested in Table 6 and Table 7, and plots are available in Figure A.4 and Figure A.5.

Table 6 presents the effect of female mayors on several municipal policy outcomes measured over an electoral term: (i) environmental fines and embargoed area; (ii) change in protected areas; (iii) municipal environmental spending; and (iv) the creation and removal of municipal environmental councils or funds. We note that due to data limitations, some outcomes are only observed in one or two electoral terms, which restricts the number of observations which can be used for estimation

Given hypothesis 1.1, we expect to observe positive discontinuities in variables denoting environmental enforcement, protection and expenditure, as this would indicate stronger deforestation policy action in female-led municipalities. However, we find no such effect. That is, no discontinuity in policy outcomes is identified between female-led and male-led municipalities in our sample. While most point estimates are large and economically relevant, they are all statistically insignificant at conventional levels. These findings provide evidence against hypothesis 1.1.

Table 7 estimates the relationship between female mayors and two variables associated with corruption: the average number of temporary employees during a mayoral term, which may indicate patronage; and campaign contributions, which may indicate mayoral influence from private actors (Brollo & Troiano, 2016). Campaign contributions are only observed for the 2016 electoral term.

The first columns of Table 7 present the effect of female mayors on the number of permanent

Table 6: Impact of female leadership on deforestation policy – RD estimates.

	Env. fines	Embargoed area (km2)	Δ Protected area (km2)
RD estimator	-23.008	-12.360	4.340
Robust p-value	0.542	0.697	0.262
Robust conf. int.	[-101.927, 53.594]	[-76.057, 50.861]	[-2.416, 8.870]
MSE-optimal BW	0.160	0.161	0.094
Eff. number obs.	278	279	196
Term fixed effects	x	x	x
Number of obs.	411	411	411
	% of mun. budget spent on environment	Δ Mun. env. council	Δ Mun. env. fund
RD estimator	0.011	-0.153	-0.337
Robust p-value	0.240	0.657	0.106
Robust conf. int.	[-0.008, 0.030]	[-0.572, 0.361]	[-0.763, 0.073]
MSE-optimal BW	0.116	0.103	0.120
Eff. number obs.	81	131	150
Term fixed effects		x	x
Number of obs.	147	261	261

Notes: The table presents RD estimates of the effect of female mayors on several municipal outcomes associated to deforestation. Each outcome is measured at the municipality level over the duration of an electoral term. Outcomes are the total number of environmental fines, area embargoed, change in area designated as protected, the percentage of the municipal budget spent on the environment, the change in a dummy indicating the presence of an environmental council, and the change in a dummy indicating the presence of an environmental fund. Some of these outcomes are only observed for one or two electoral terms, and the most complete sample is used for estimation accordingly. Term fixed-effects are included where appropriate. Each RD local linear regression uses a polynomial of order 1 and an MSE-optimal bandwidth calculated following Calonico, et al. (2014). Following the same study, the table reports robust-bias corrected p-values and 95% confidence intervals. The standard errors of each regression are clustered at the municipality level. Coefficients significantly different from zero at 99% (***), 95% (**) and 90% (*) confidence level.

and temporary public employees. Temporary employment in the local government is a channel often used for patronage. This is however not the case for permanent employment, due to the more stringent entrance requirements of such roles. Based on hypothesis 1.2, we thus expect to observe no discontinuity in permanent employees, and a negative discontinuity in temporary employees. We instead find that neither effect is significant, suggesting that female mayors do not affect either type of public employment.

The last two columns of Table 7 look for discontinuities in total and self-funded campaign contributions between female and male mayors for the 2016 term. Large campaign contributions, and especially large self-funded contributions can indicate payments from private actors aiming to gain influence over a future local official (Pailler, 2018). Therefore, based on our hypothesis 1.2 we expect to observe a negative discontinuity in total and self-funded campaign contributions between female-led and male-led municipalities.

Despite the reduced sample size, we indeed find a large, negative and significant discontinuity in total campaign contributions. This effect is shown to be mainly explained by a discontinuity in self-funded campaign contributions. It suggests that in Legal Amazon municipalities holding competitive mixed gender elections in 2016, female mayors contributed R$44,334 ($7824) less to

Table 7: Impact of female leadership on corruption indicators – RD estimates.

	Av. permanent employees	Av. temporary employees	Total campaign contributions (thousand R$)	Self-funded contributions (thousand R$)
RD estimator	50.362	-52.269	-49.033*	-44.592***
Robust p-value	0.907	0.504	0.068	0.003
Robust conf. int.	[-512.677, 577.862]	[-346.942, 170.449]	[-120.411, 4.311]	[-77.181, -15.524]
MSE-optimal BW	0.136	0.105	0.115	0.167
Eff. number obs.	238	212	83	103
Term fixed effects	x	x		
Number of obs.	400	400	150	150

Notes: The table presents RD estimates of the effect of female mayors on several municipal outcomes associated to corruption. The average number of permanent and temporary employees are measured at the municipality level over the duration of an electoral term, and regressions include term fixed-effects. Total and self-funded campaign contributions are measured in the election year for each mayor, and are only observed in 2016. Note that self-funded contributions are a subset of total contributions. Each RD local linear regression uses a polynomial of order 1 and an MSE-optimal bandwidth calculated following Calonico, et al. (2014). Following the same study, the table reports robust-bias corrected p-values and 95% confidence intervals. The standard errors of each regression are clustered at the municipality level. Coefficients significantly different from zero at 99% (***), 95% (**) and 90% (*) confidence level.

their own campaigns than male mayors during the election. This is a very large effect given that even for males, the mean self-funded campaign contributions in our sample is R$51,011 ($8948) in the 2016 election, as shown in Table 2. This effect could indicate that female mayors are less engaged in corruption, but it is also compatible with other explanations, such as differing levels of wealth among female and male mayors prior to the election.

To conclude, we have only weak evidence supporting our hypothesis 1.2. While we find that female mayors have lower self-funded campaign contributions, the relationship could only be examined in the 2016 term and the effect is compatible with explanations other than corruption. The fact that no difference is observed in temporary employees further weaken any claims that evidence of corruption was identified. Since the two indicators of corruption tested are incompatible, we determine that we cannot confirm nor reject hypothesis 1.2. As a result, we are also not able to provide any additional insight on the relationship between corruption and deforestation.

5 Robustness

In this section we carry out one sensitivity test following Cattaneo, et al. (2020) to determine the credibility of the evidence identified in the previous section.

The test examines the sensitivity of our main results to the choice of bandwidth. That is, we examine whether our results remain consistent when we add or remove units from the effective number of observations used in RD analyses. Changing the bandwidth is of course expected to affect our estimates: a larger bandwidth leads to a more biased estimate and a larger variance, while a smaller bandwidth leads to a less biased estimate and a larger variance. However, if we observe large changes in point estimators and p-values, the credibility of our results will be lower.

Table 8: Bandwidth sensitivity test

	MSE-Optimal BW			25% larger BW			25% smaller BW		
Variable	RD est.	p-value	Eff. obs.	RD est.	p-value	Eff. obs.	RD est.	p-value	Eff. obs.
Main result									
Log of deforestation (FE and covariates)	-0.472	0.235	228	-0.574	0.425	256	-0.532	0.129	184
Policy mechanisms									
Env. fines	-23.0	0.542	278	-21.2	0.624	309	-18.6	0.925	235
Area embargoed (km2)	-12.4	0.697	279	-12.1	0.709	309	-11.5	0.626	236
Protected area (km2)	4.340	0.262	196	4.152	0.263	233	3.508	0.228	161
% env. expenditure	0.011	0.240	81	0.012	0.333	94	0.013*	0.081	65
Δ Mun. env. council	-0.153	0.657	131	-0.175	0.688	154	-0.109	0.435	113
Δ Mun. env. fund	-0.337	0.106	150	-0.338	0.144	170	-0.326	0.228	119
Corruption indicators									
Permanent employees	-52.3	0.504	212	-87.8	0.521	236	-124.5*	0.087	176
Temorary employees	50.4	0.907	238	36.7	0.613	275	154.4	0.704	202
Total campaign contr. (thousand R$)	-49.0*	0.068	83	-32.3	0.119	96	-67.0	0.379	66
Self-funded contr. (thousand R$)	-44.6***	0.003	103	-44.7***	0.009	110	-44.9**	0.033	87

Notes: This table presents RD estimates of the effect of female mayors deforestation outcomes, policy mechanisms and corruption indicators. Each row represents one RD local linear regression run for three different bandwidths: the MSE-optimal bandwidth computed following Calonico et al. (2014), a bandwidth 25% larger than the MSE-optimal one, and a bandwidth 25% smaller than the MSE-optimal one. Each RD local linear regression uses a polynomial of order 1 and reports robust-bias corrected p-values. The standard errors of each regression are clustered at the municipality level. Coefficients significantly different from zero at 99% (***), 95% (**) and 90% (*) confidence level.

To implement the sensitivity test, we simply re-estimate the results identified for deforestation outcomes, policy outcomes, and corruption indicators using a different bandwidth. Cattaneo, et al. (2020) recommend investigating the sensitivity to bandwidth choice only within small ranges around the chosen optimal bandwidth, and therefore, we re-estimate all our main results for a bandwidth 25% larger and one which is 25% smaller than the MSE-optimal bandwidth. The results of the test are displayed in Table 8.

Table 8 shows that our main results remain roughly consistent when different bandwidths are used in their estimation. The estimated effect on deforestation presents some variability in its p-value, but the RD estimate remains consistent. The effect of female leaders on policy mechanisms display a particularly small variability in RD estimates and p-values when alternative bandwidths are used. When it comes to corruption indicators, however, we observe significant variability both in estimates' size and p-value, with the exception of self-funded campaign contributions.

Overall, we determine that with the exception of some corruption indicators, our main results do not seem to be driven by the choice of bandwidth. This renders additional credibility to our finding that female mayors do not affect deforestation outcomes nor policy in the Legal Amazon.

6 Discussion

Our analysis has revealed that female municipal leadership has no effect on deforestation outcomes in the Brazilian Legal Amazon, and we thus reject hypothesis 1. Additional findings suggest that the absence of an effect on deforestation may be the result of a lack of differentiated policy effort by female mayors. That is, we find that female municipal leadership is not associated with higher environmental protection efforts against deforestation, and we thus also reject hypothesis 1.1.

Our findings stand in contrast to cross-country studies which identify female representation in national government to be associated with positive conservation outcomes (Nugent & Shandra, 2009; Salahodjaev & Jarilkapova, 2020). This suggests that this relationship cannot be transposed to municipal leaders in the Legal Amazon. However, our findings also stand opposed to empirical studies which find that female mayors take differentiated policy actions and achieve better health outcomes in Brazil (Bruce, et al., 2022; Brollo & Troiano, 2016). One important consideration which could explain these contrasts is the presence of factors which constrain municipal forest conservation efforts in Brazil.

Two main factors constrain local conservation efforts. First, the lack of access to financial resources. Unlike national governments, most Brazilian municipalities do not collect taxes and instead rely on government transfers for most of their expenses. However, while large earmarked transfers are made to municipalities for health and education, no equivalent transfers are made for environmental purposes (Ferroukhi, 2003). Second, voters may not actively demand forest management policies from municipal governments. This could be the case if forest conservation was less pressing compared to other issues for voters. It could also be the result of a lack of clearly defined municipal responsibilities in the area of forest management, unlike is the case for health and education (Ferroukhi, 2003). We also highlight that local interests may even be strongly opposed to forest conservation in municipalities with large agriculture sectors. Put together, limited resources and low voter interest may leave mayors little space to reflect their environmental concerns in municipal policies. This is consistent with the low percentage of municipal budgets spent on the environment. Finbra data reveals that during the 2016 electoral term, Legal Amazon municipalities spent less than 1% of their budget on the environment, compared to 36% on education and 24% on health.

One associated consideration is that while mayors have significant influence over municipal government actions, their power can be curtailed by the municipal legislature. This may be more likely if mayoral policy preferences enjoy low voter support and compete with other priorities for financial resources, as may be the case for forest management policies.

In view of these considerations, our findings could still be consistent with female mayors being more concerned about the environment, as it has been often documented in the literature. That is, while mayors have different channels through which they can reduce municipal deforestation, it is possible that their forest management preferences could not be reflected in the municipal government due to the obstacles presented by municipal action in this policy area.

Regarding hypothesis 1.2, our findings are inconclusive. Brollo and Troiano (2016) found empirical evidence that female mayors are less likely to engage in corruption in Brazil, but given our results, we cannot confirm nor deny that this also applies in the Legal Amazon. Because of this, we are also not able to provide additional insight on the effect of corruption on deforestation. One limitation which we encountered in this part of our analysis was the limited data availability on indicators of corruption. Given the prevalence of illegal deforestation within the Legal Amazon and the scarce empirical evidence on the role of corruption on deforestation, this is an important area for future research.

Finally, we note that our findings present several limitations. First, they may not persist in countries other than Brazil, since attitudes towards women, forest management, and restraints on municipal action are likely to play a key role for the observed effect, and are also highly context-dependent. Another limitation stems naturally from our identification strategy. While the internal validity of our RD approach is high given that treatment can be considered as good as randomly assigned, its external validity is more limited. This is because we only compare municipalities in which mayors narrowly won a close election. As a result, our findings may not apply in settings of lower electoral competition.

7 Conclusion

In this paper we looked at the effect of municipal female-leadership on deforestation within the Legal Amazon between 2008 and 2020. To overcome endogeneity, we used an RD approach to compare deforestation outcomes between municipalities in which a female-mayor narrowly won an election against a male candidate and municipalities in which a male mayor won against a female candidate. We found that the total area deforested over an electoral term does not differ significantly with the gender of mayors, suggesting that female-leadership does not affect deforestation within the Legal Amazon. This result may be explained by a lack of differentiated policy effort by female mayors since we find that municipal female-leadership has no effect on environmental enforcement, expenditure, protection, and institutions within their municipalities. We also explored the relationship between female mayors and municipal corruption in the Legal Amazon, but our results for the different indicators examined are inconsistent and we thus cannot comment on this relationship. Our findings suggest that female mayors do not prioritise reducing deforestation within the Legal Amazon more than male mayors, but our findings could also be explained by obstacles inherent to municipal forest management which do not allow mayors to reflect their policy preferences. Further research could focus on exploring factors limiting municipal action on deforestation and exploring the relationship between female leadership and corruption in the Legal Amazon.

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Appendix

A.1 Tables

Table A1: Data Description: Electoral Outcomes and Deforestation

Variable	Description	Source
Panel A: Electoral Outcomes		
Candidate vote share	Percentage of valid votes received by mayor	TSE
Candidate gender	Gender of mayor	TSE
Panel B: Deforestation		
Area deforested PRODES	Squared kilometres of primary vegetation removed between 1 August and 31 July (available from 2008)	INPE Terrabrasilis
Cloud coverage	Percentage of municipality covered by clouds or shadows when the satellite images used in mapping PRODES deforestation were captured (only available from 2016)	INPE Terrabrasilis
Forest cover	Percentage of municipality's surface covered by forests before a mayor takes office (years 2008, 2011 and 2016)	INPE Terrabrasilis for 2016; Assunção, et al. (2020) for 2008 and 2011

Notes: All variables are aggregated at municipality level.

Table A2: Data Description: Baseline Covariates

Variable	Description	Source
Panel A: Environmental characteristics		
% Protected areas	Percentage of municipality designated as a protected area	INPE Terrabrasilis
% Indigenous reserves	Percentage of municipality designated as an Indigenous Reserve	INPE Terrabrasilis
Blacklist	Indicator for whether a municipality is blacklisted	MMA
Panel B: Sociodemographic characteristics		
Population	Total population at last census	IBGE 2000 or 2010 census
Population density	Inhabitants per km2 at last census	IBGE 2000 or 2010 census
Urb. rate	% of urban population at last census	IBGE 2000 or 2010 census
% mixed-race	% of mixed-race population at last census	IBGE 2000 or 2010 census
% Indigenous	% of Indigenous population at last census	IBGE 2000 or 2010 census
% male	% of male population at last census	IBGE 2000 or 2010 census
% under 15	% of population under 15 at last census	IBGE 2000 or 2010 census
% over 60	% of population over 60 at last census	IBGE 2000 or 2010 census
Literacy rate	% of literate population at last census	IBGE 2000 or 2010 census
Panel C: Economic characteristics		
GDP per capita	Municipal GDP per capita	IBGE PIB dos Municipios
% GDP from agri-sector	Percentage of GDP coming from agriculture	IBGE PIB dos Municipios
% crop area	Percentage of municipal surface used for planting crops	IBGE Produção Agrícola Municipal
Heads of cattle per km2	Heads of cattle per squared kilometre	IBGE Pesquista Pecuaria Municipal
Rural credit	Total rural credit issued in a PRODES year	Banco Central do Brasil
Panel D: Candidate characteristics		
Incumbent	Mayor served in the previous term	TSE
Candidate education	Level of education of mayor	TSE
Candidate party	Political party of mayor	TSE

Notes: All variables are measured before a mayor takes office.

Table A3: Data Description: Policy Outcomes

Variable	Description	Source
Panel A: Environmental policy		
Environmental fines	Number of environmental fines between 1 of August and 31 July	IBAMA Consulta de Autuações Ambientais e Embargos
Embargoed area	Squared kilometres of embargoed properties between 1 of August and 31 July	IBAMA Consulta de Autuações Ambientais e Embargos
% environmental expenditure	Percentage of total expenditure composed of environmental expenditure (data is only reliable from 2017 onwards)	Siconfi-Finbra: Contais Anuais
Change in protected area	Change in protected areas within municipality (km2)	INPE Terrabrasilis
Environmental council	Indicator for whether a municipal environmental council exists	IBGE MUNIC
Environmental fund	Indicator for whether a municipal environmental fund exists	IBGE MUNIC
Panel B: Corruption		
Permanent employees	Number of permanent employees directly employed by municipal government	IBGE MUNIC
Temporary employees	Number of temporary employees directly employed by municipal government	IBGE MUNIC
Total campaign contributions	Total campaign contributions of mayor in election year	TSE
Self-funded campaign contributions	Self-funded campaign contributions of mayor in election year	TSE

Notes: All variables are aggregated at municipality-term level.

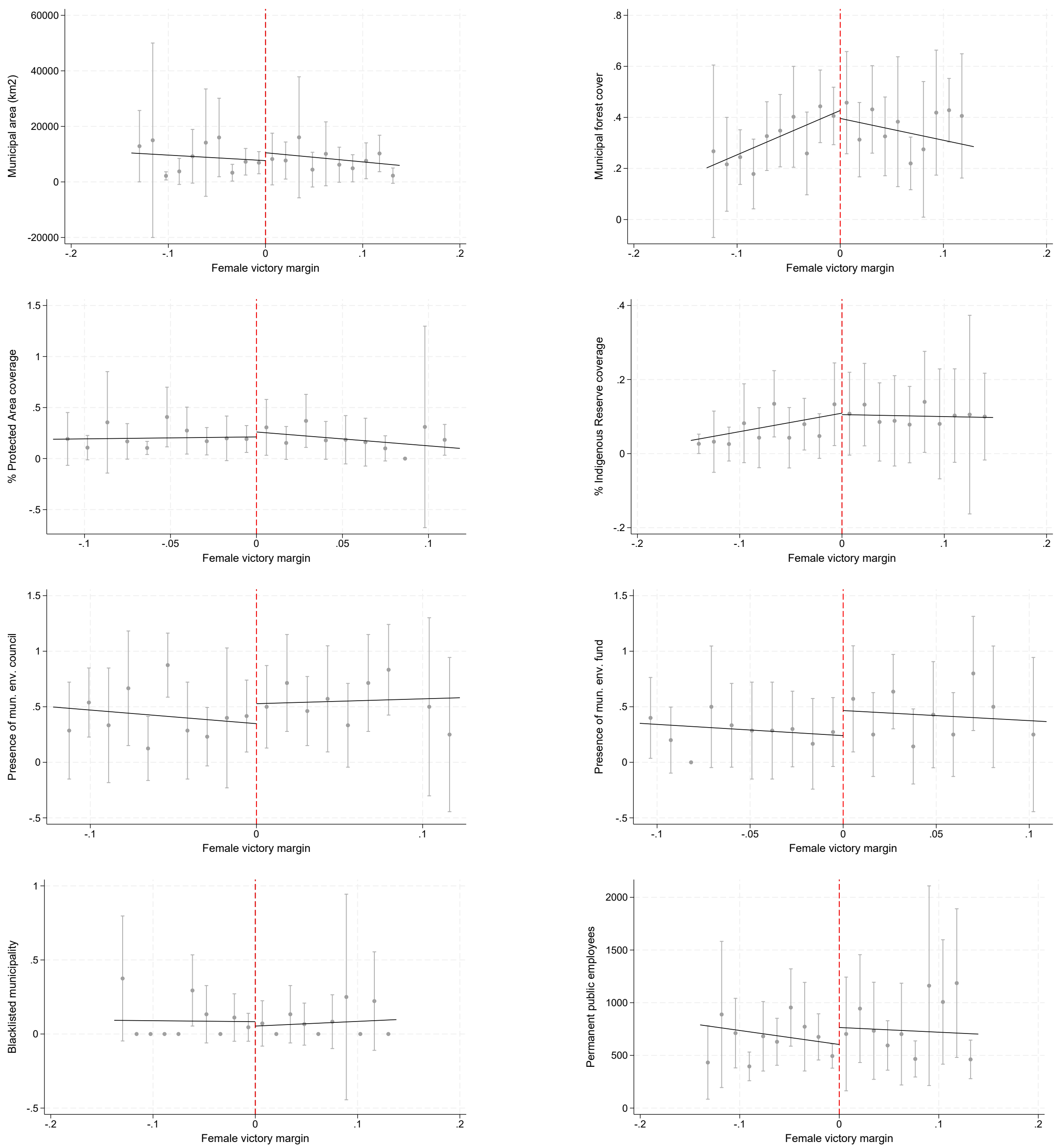
Table A4: Formal Continuity-Based Analysis for term fixed-effects

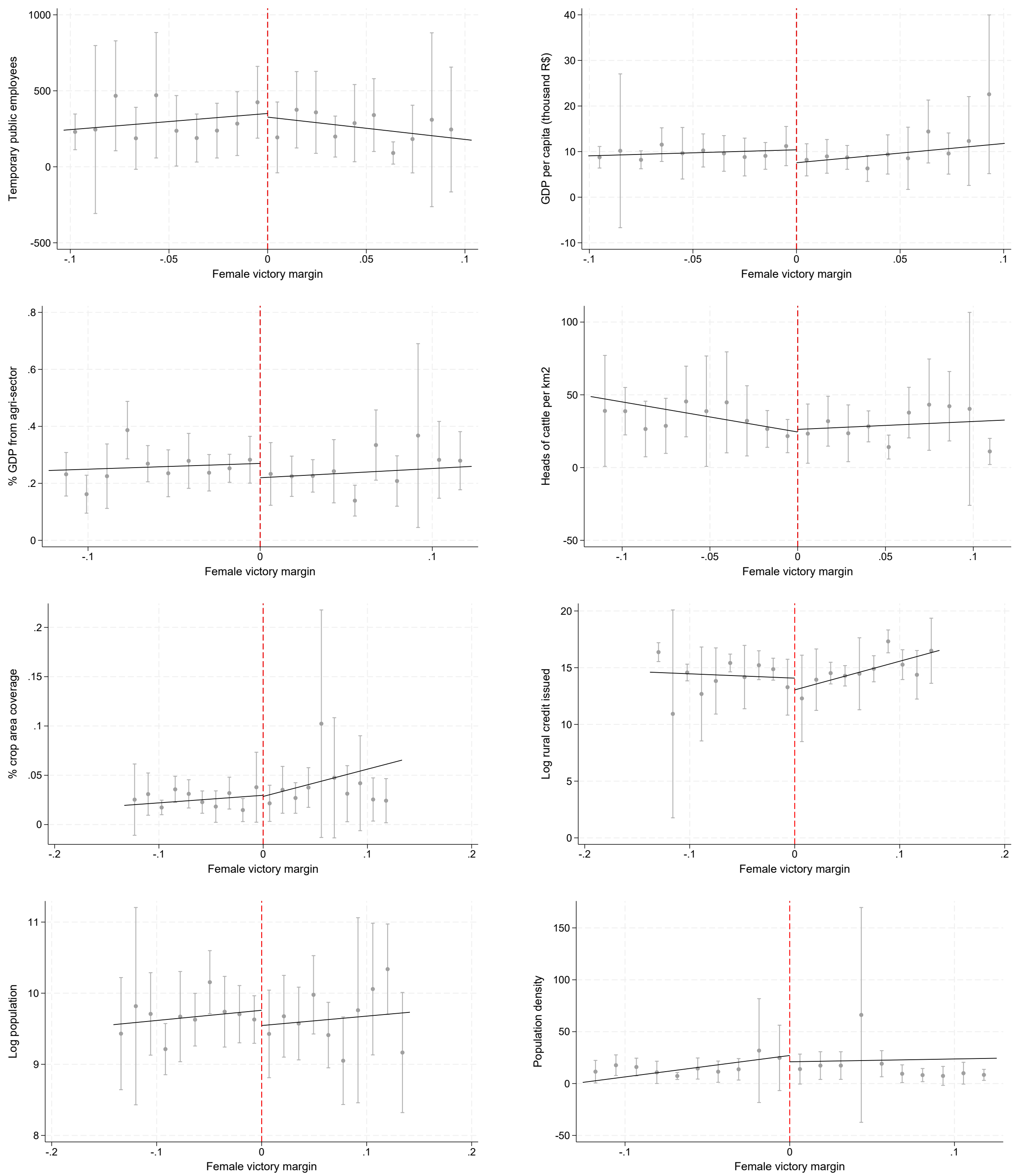
Variable	MSE-Optimal Bandwidth	RD Estimator	Robust Inference p-value	Robust Inference Conf. Int.	Eff. Number of Observations
Electoral term					
2008	0.1381	0.1128	0.3508	[-0.1412, 0.3978]	250
2012	0.1308	0.0559	0.6275	[-0.2255, 0.3738]	243
2016	0.1168	-0.1651	0.1877	[-0.4896, 0.0960]	233
Federal state					
Acre	0.0832	-0.0319	0.2111	[-0.0914, 0.0202]	184
Amazonas	0.1668	0.0237	0.8000	[-0.1035, 0.1342]	282
Amapá	0.1529	0.0068	0.8763	[-0.1459, 0.1711]	271
Maranhão	0.1432	0.1948	0.1038	[-0.0411, 0.4429]	260
Mato Grosso	0.1243	0.0086	0.8227	[-0.1955, 0.2460]	241
Pará	0.1350	-0.2510**	0.0491	[-0.5533, -0.0011]	245
Rondônia	0.1666	-0.0330	0.6221	[-0.1562, 0.0934]	282
Roraima	0.1439	-0.0518	0.1504	[-0.1482, 0.0228]	260
Tocantins	0.1137	0.0686	0.4536	[-0.0944, 0.2113]	229

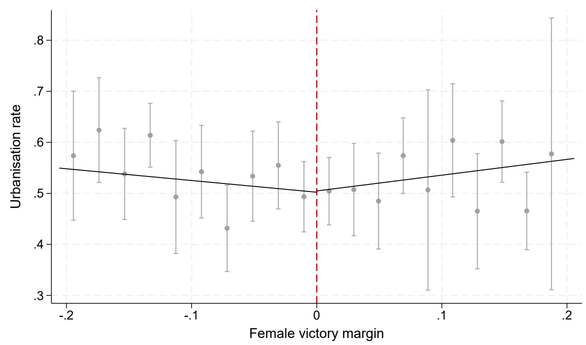
Notes: This table presents RD estimates of the association between female mayors and dummies representing electoral terms and federal states. Each RD local linear regression uses a polynomial of order 1 and an MSE-optimal bandwidth calculated following Calonico et al. (2014). Following the same study, the table reports robust-bias corrected p-values and 95% confidence intervals. The standard errors of each regression are clustered at the municipality level. Coefficients significantly different from zero at 99% (***), 95% (**) and 90% (*) confidence level.

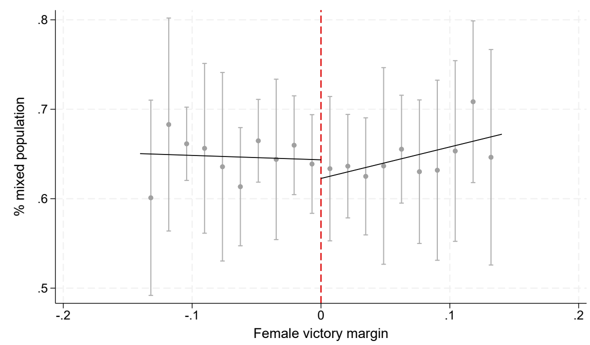
A.2 Figures

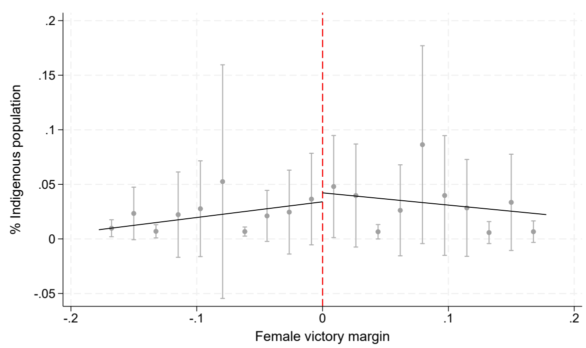
Figure A1: Continuity test plots for municipal characteristics
Notes: The figures show graphically the association between female leadership and baseline municipal characteristics. The figures are analogous to the to Table 3, and use the same bandwidths for each characteristic. The plots are generated following Cattaneo et al. (2020). Each dot represents the local sample mean of observations within set values of female victory margin, and the presented range for each dot represents the 95% confidence interval of the local sample mean. A linear specification is used for generating the global polynomial fit.

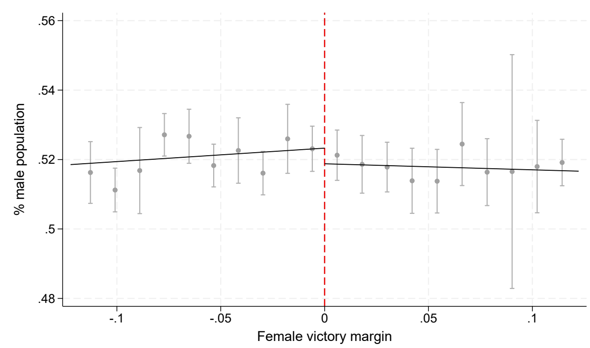


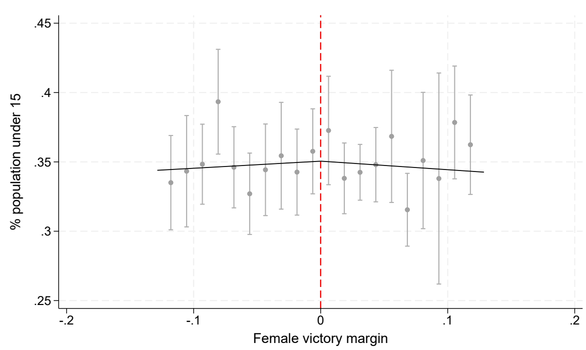

Temporary public employees
Female victory margin
GDP per capita (thousand R$)
Female victory margin
% GDP from agri-sector
Female victory margin
Heads of cattle per km2
Female victory margin
% crop area coverage
Female victory margin
Log rural credit issued
Female victory margin
Log population
Female victory margin
Population density
Female victory margin

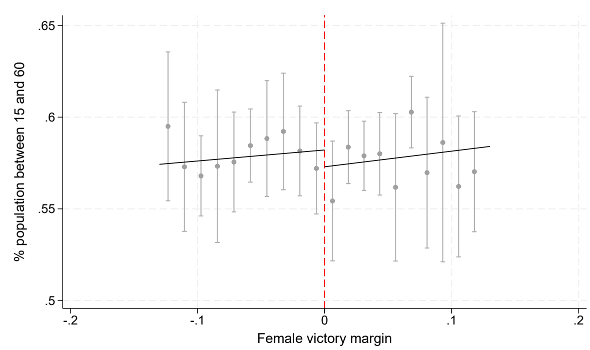

Urbanisation rate
.3 .4 .5 .6 .7 .8
-.2 -.1 0 .1 .2
Female victory margin


% mixed population
.5 .6 .7 .8
-.2 -.1 0 .1 .2
Female victory margin


% Indigenous population
-.05 0 .05 .1 .15 .2
-.2 -.1 0 .1 .2
Female victory margin


% male population
.48 .5 .52 .54 .56
-.1 -.05 0 .05 .1
Female victory margin


% population under 15
.25 .3 .35 .4 .45
-.2 -.1 0 .1 .2
Female victory margin


% population between 15 and 60
.5 .55 .6 .65
-.2 -.1 0 .1 .2
Female victory margin

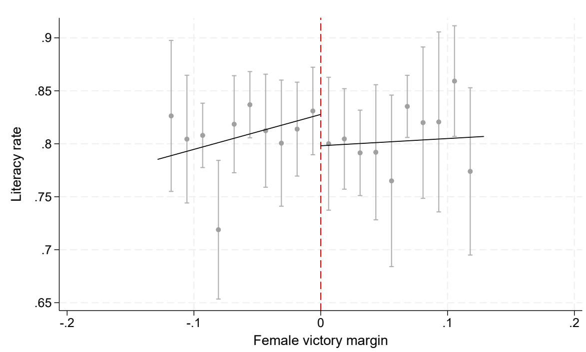

Literacy rate
.65 .7 .75 .8 .85 .9
-.2 -.1 0 .1 .2
Female victory margin

Figure A2: Continuity test plots for mayor characteristics

Notes: The figures show graphically the association between female leadership and mayor characteristics measured in the election year. The figures are analogous to the to Table 3, and use the same bandwidths for each characteristic. The plots are generated following Cattaneo et al. (2020). Each dot represents the local sample mean of observations within set values of female victory margin, and the presented range for each dot represents the 95% confidence interval of the local sample mean. A linear specification is used for generating the global polynomial fit.

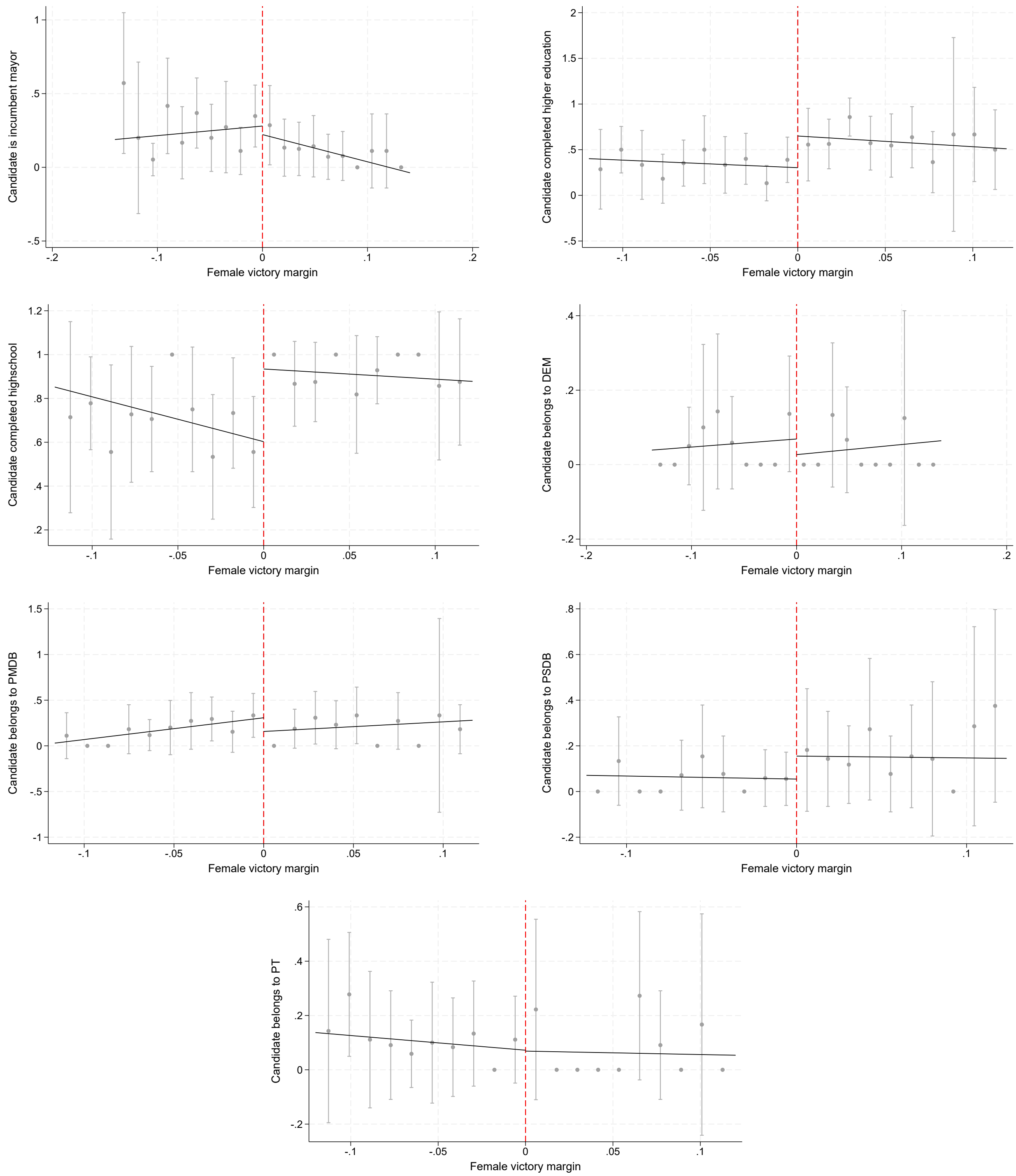


Figure A3: Continuity test plots for baseline deforestation outcomes and placebo characteristics
Notes: The figures show graphically the association between female leadership and baseline deforestation outcomes measured in the election year, and the association between female leadership and cloud coverage measured over the 2016 electoral term. The figures are analogous to the to Table 3, and use the same bandwidths for each variable. The plots are generated following Cattaneo et al. (2020). Each dot represents the local sample mean of observations within set values of female victory margin, and the presented range for each dot represents the 95% confidence interval of the local sample mean. A linear specification is used for generating the global polynomial fit.

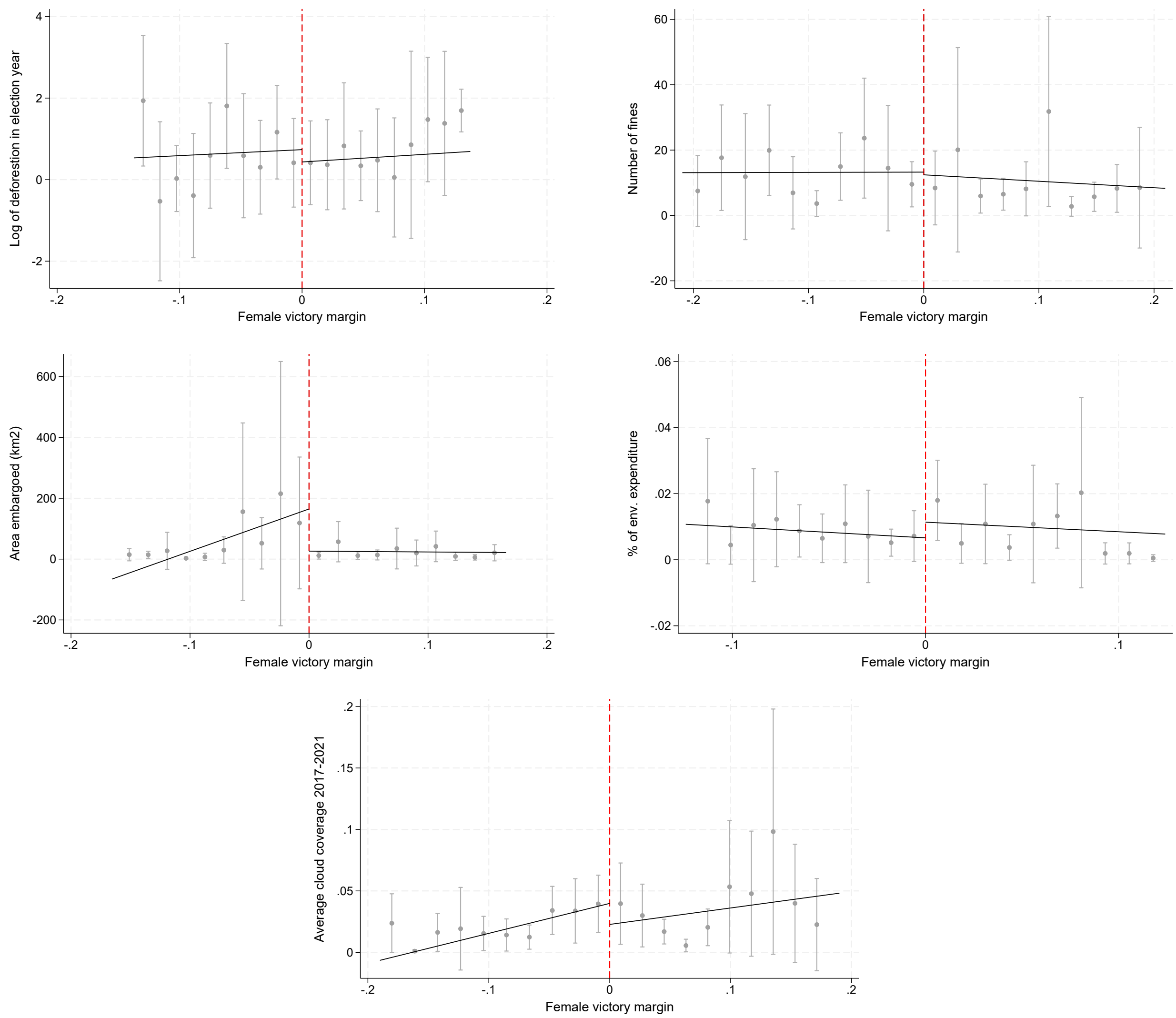


Figure A4: Impact of female mayors on deforestation policy mechanisms

Notes: The figures show graphically the effect of female leadership on several deforestation policy mechanisms. The figures are analogous to the to Table 4, and use the same bandwidths for each mechanism. The plots are generated following Cattaneo et al. (2020). Each dot represents the local sample mean of observations within set values of female victory margin, and the presented range for each dot represents the 95% confidence interval of the local sample mean. A linear specification is used for generating the global polynomial fit.

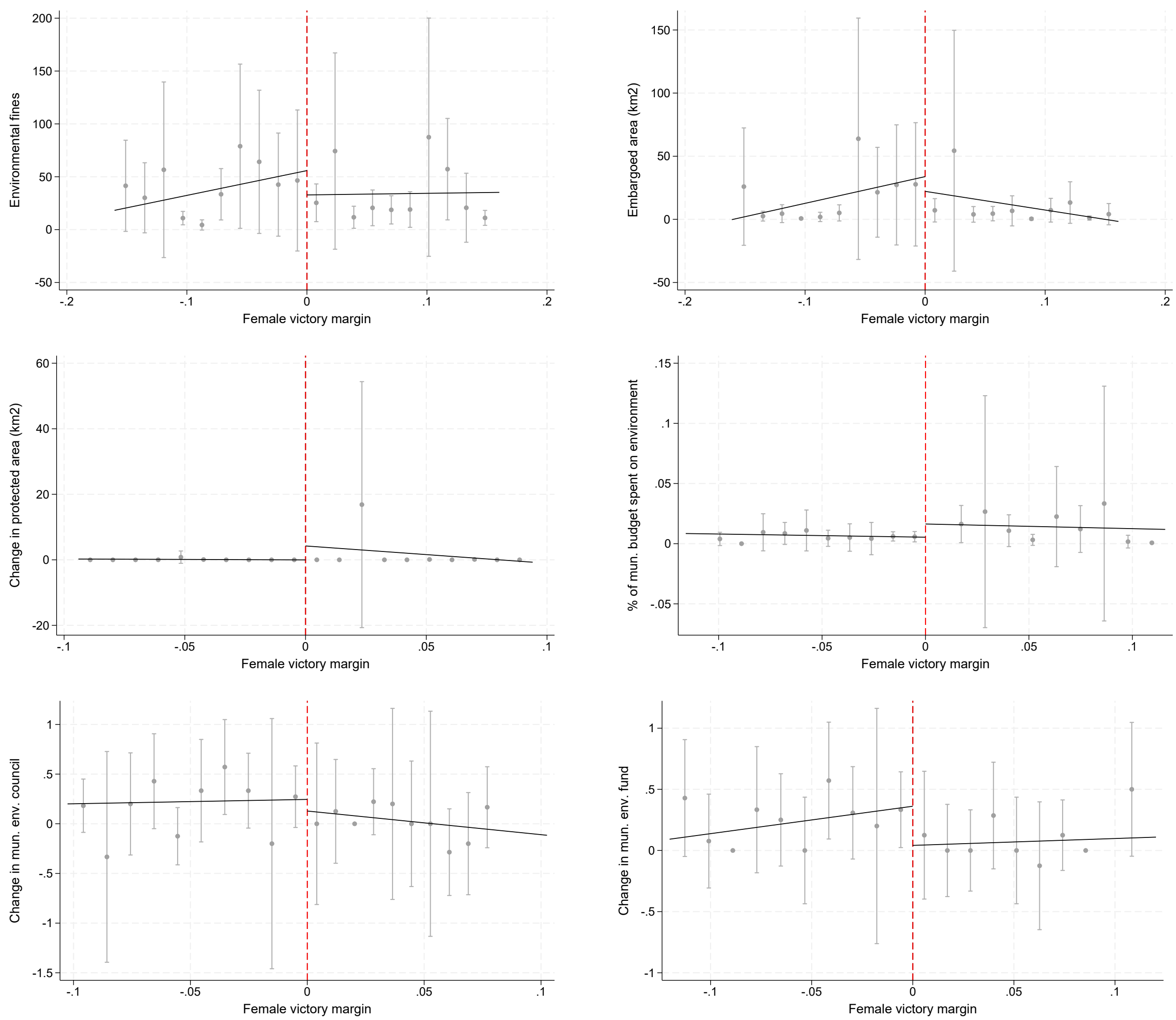
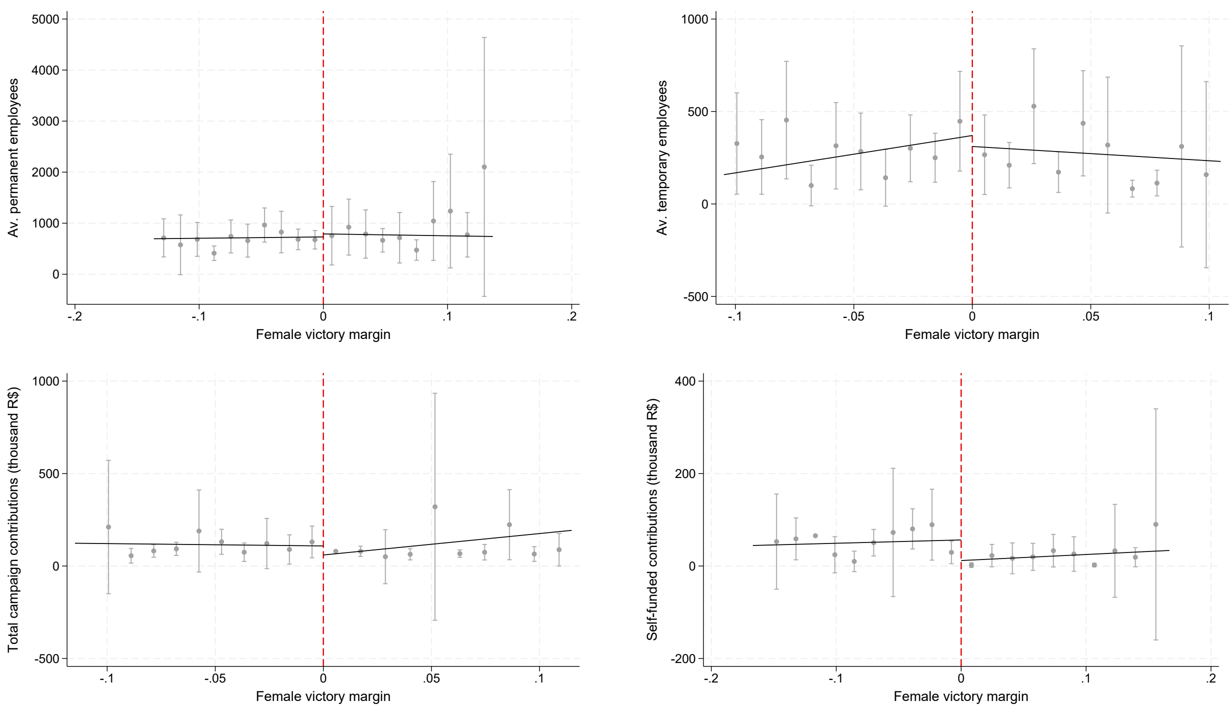


Figure A5: Impact of female mayors on corruption indicators
Notes: The figures show graphically the effect of female leadership on several corruption indicators. The figures are analogous to the to Table 5, and use the same bandwidths for each indicator. The plots are generated following Cattaneo et al. (2020). Each dot represents the local sample mean of observations within set values of female victory margin, and the presented range for each dot represents the 95% confidence interval of the local sample mean. A linear specification is used for generating the global polynomial fit.



A.3 Processing of geospatial data

Some data sources required spatial processing to render the municipal-level values required for our analysis. These data sources include cloud coverage at the time of deforestation measurement, Protected Area coverage and Indigenous Reserves coverage. Shapefiles were downloaded and processed for each of these from the source listed in Table X. Rendering this spatial data in a municipal-level format required downloading data on municipal limits from Terrabrasilis. The data was processed in the QGIS 3.38.0 software. Spatial projections were set to SIRGAS 2000 (EPSG4674). All geometries were fixed (fix geometries tool).

The same approach was followed in processing geospatial data as in Assunção et al. (2023). The main spatial data files were intersected with municipal boundaries (intersection tool). The area of features in the vector output was calculated in squared metres and transformed to squared kilometres. The resulting areas of features were summed up in Stata to calculate total areas by municipality.