Journal of Economic Behavior and Organization 241 (2026) 107375

Contents lists available at ScienceDirect

Journal of Economic Behavior and Organization

journal homepage: www.elsevier.com/locate/jebo

Research Paper

Female legislators and forest conservation in India ⋆

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A R T I C L E I N F O

JEL classification:
D72
H70
J16
Q23
Q28
Q54

Keywords:
Forest conservation
Female legislators
Close elections
Regression discontinuity
India

A B S T R A C T

Forest conservation is a key strategy for addressing climate change. However, the role of women's political representation in shaping conservation outcomes remains understudied. This paper examines the causal impact of female legislators on forest cover in India, leveraging a regression discontinuity design based on close mixed-gender electoral races. We find that electing a female legislator increases annual forest cover growth by 6 percentage points, but this effect is concentrated in constituencies reserved for candidates from historically marginalized groups. When we examine forest cover growth over the entire electoral cycle, the positive impact of female legislators is found for all constituencies, but this effect continues to be driven by constituencies reserved for historically disadvantaged communities. These findings suggest that women in political office can significantly influence environmental outcomes, particularly when institutional structures promote the inclusion of underrepresented groups. We argue that differences in environmental preferences and constraints by legislator identity may explain these effects. Our results underscore the importance of legislator identity in shaping environmental governance.

1. Introduction

Forests have been widely considered major carbon sinks, and much of the recent scientific literature is devoted to understanding the magnitude of this effect (Chambers et al., 2001; Luyssaert et al., 2008; Soepadmo, 1993; Pugh et al., 2019; Pan et al., 2011; Nabuurs et al., 2013; Whitehead, 2011; Jayachandran et al., 2017; Zhu et al., 2018). Multilateral agreements such as the Kyoto Protocol and, most recently, COP-26 have emphasized conservation of forests as one of the important strategies for combating climate change and, more specifically, limiting the rise in global temperature. The literature in economics has also documented the health and productivity

⋆ We are very grateful to the associate editor, two anonymous reviewers, Kathyrn Baragwanath, Robin Burgess, Matteo F. Ferroni, Maitreesh Ghatak, Tarun Jain, Pushkar Maitra, JV Meenakshi, Abhiroop Mukhopadhyay and Rohini Pande for providing us with numerous helpful suggestions and feedback. We also thank participants at the 2023 Delhi Winter School of the Econometric Society; 2024 Inaugural Economics Workshop at Plaksha University; 2024 LSE Environment Week; 2024 NEUDC; 2024 Annual Conference on Economic Growth and Development, ISI Delhi for their comments. Athisii Kayina provided excellent research assistance. We acknowledge financial assistance from the Centre for Climate Change and Sustainability, Ashoka University and the Indian Institute of Management, Indore. All remaining errors are our own.

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https://doi.org/10.1016/j.jebo.2025.107375
Received 7 July 2024; Received in revised form 15 November 2025; Accepted 3 December 2025
Available online 23 December 2025
0167-2681/

benefits of forest conservation. For example, forest cover loss has been shown to influence disease ecology for some tropical diseases (Garg, 2019); increased heat exposure on account of deforestation has been shown to adversely affect cognitive behavior (Masuda et al., 2020) and overall worker productivity (Masuda et al., 2021). Therefore, protecting and promoting the growth of forests is of great policy relevance.

In this paper we specifically study the causal impact of female political leaders on environmental conservation, as proxied by growth in forest cover. In particular, we examine the impact of electing female legislators in state assembly elections in India on subsequent constituency level annual forest cover growth. Additionally, we also examine how forest cover growth may evolve over a legislator's electoral term to understand any long-term or dynamic impacts of legislator identity on the environment. It is well known that India is a federation of states and elections to state assemblies, in general, occur once every five years. Elections follow the "first past the post" electoral rule for deciding the winner, who is termed Member of the Legislative Assembly (MLA) of his/her respective state. Forests belong to the "Concurrent" list of the Indian Constitution, over which not only the federal government but state governments have jurisdiction to enact legislation as well.[1] Therefore, MLAs potentially could exert important influence on environmental and in particular forest conservation policies.

There are three main reasons that motivate us to pursue this research question. Firstly, adverse impacts of climate change such as extreme temperature, erratic rainfall and extreme weather events have been shown to adversely affect child survival, maternal health and violence against women (Banerjee and Maharaj, 2020; Kim et al., 2021; Kumar et al., 2016; Currie and Rossin-Slater, 2013; Sekhri and Storeygard, 2014; Sekhri and Hossain, 2023). Given that there is now a large body of literature in economics that has established that women politicians are responsive to issues that are more likely to affect women and children in the spirit of the citizen-candidate model of Besley and Coate (1997) (Chattopadhyay and Duflo, 2004; Bhalotra and Clots-Figueras, 2014; Bhalotra et al., 2023; Bhalotra and da Fonseca, 2023); it is surprising that the impact of electing female politicians on environmental outcomes has remained largely understudied in the literature. To the best of our knowledge, Jagnani and Mahadevan (2023) is the only study that examines the role of female politicians on the incidence of crop fires in India that, in turn, cause air pollution and adversely affect child health. It is in this context that we attempt to contribute to this nascent literature. However, unlike air pollution, which is often location specific, climate change combating strategies likely generate significant positive externalities across locations and hence result in under-investment. Besides, investing in forest resources is only likely to yield benefits in the future instead of the present. Hence, investment in combating air pollution and climate change are conceptually distinct, and therefore the impact of female politicians in mitigating air pollution need not apply to their role in the promotion of forest resources. Thus, examining the role of female politicians in promoting forest growth is warranted. Secondly, there exists some evidence that women are likely to have greater concern for the environment, including regarding climate change (McCright and Sundström, 2013). Additionally, the *Chipko* movement in India to prevent deforestation was largely women-led. Further evidence from a recent wave (2022) of the World Values Survey for India reveal that a greater proportion of women relative to men favor investing in environmental protection, even at the cost of economic growth. However, whether these preferences of women are indeed translated to women in positions of power is largely understudied. A recent cross-country study suggests that women parliamentarians are more likely to enact more stringent policies to protect the environment (Mavisakalyan and Tarverdi, 2019). But micro-level causal evidence on whether women politicians are indeed more likely to promote forest conservation is largely absent.[2] This provides impetus to pursue our research question. Lastly, Baskaran et al. (2023) shows that women legislators improve economic growth in their constituencies. This raises an interesting scenario, as economic growth and environmental conservation have often been viewed as being at loggerheads with each other. Therefore, ex ante, it is not clear whether women politicians would necessarily promote forest cover growth. However, with increased acknowledgement of the need for sustainable growth, examining whether female legislators indeed can help promote a sustainable growth path is an interesting question.

Identifying the impact of female politicians on forest cover growth is not straightforward because simply comparing constituencies that elect a male politician with those that elect a female politician could pick up unobserved differences (such as the preference of the voters for a certain type of politician) between these constituencies, and these could, in turn, be correlated with the dynamics of forest cover changes. To circumvent this problem, we adopt the regression discontinuity design (RDD) strategy through which we compare forest cover growth in constituencies where a female politician won to those where a male politician won in "close" mixed gender electoral races. The intuition behind this estimation strategy is that the victory of a politician of a certain gender in "close" mixed gender race is potentially quasi-random. Hence, a comparison between constituencies where a female politician "closely" won against a male politician and vice-versa can provide credible causal impact of politician gender on the outcome in our analysis. In our RDD framework, the treatment status of an assembly constituency is defined by the gender of the politician who wins the election, which is also a deterministic function of our running variable, the margin of victory between a female and male politician in a mixed gender race. This is, therefore, a sharp RDD set up. Margin of victory in turn is the difference between the vote share

[1] Prior to 1976, forests belonged to the "State" list of the Indian Constitution. This implies that state governments could exclusively enact legislation regarding forest conservation. Although forests now belong to the "Concurrent" list, each state government has a forest department headed by a minister in the state cabinet and which oversees the conservation of forests within the state through various legislations and policy measures. Anecdotal evidence also shows that while parliamentary discussion on environmental and climate change issues is not widespread, state government legislators appear to be more engaged regarding environmental issues (https://india.mongabay.com/2022/08/parliamentary-discussions-related-to-climate-change-are-largely-missing-in-india-finds-study/, accessed on February 1, 2024). This shows the preeminent role that members of the state legislature continue to play in forest governance and conservation.

[2] The only exception to this that we are aware of is, Baragwanath and Zheng (2023) who study the impact of electing female mayors on deforestation in Brazil.

percentage of the female and male politicians who occupy the top two ranks in the race. Hence, constituencies in which a female politician wins belong to the treatment group, and here the margin of victory is non-negative. On the other hand, those in which a male politician wins form our control group, where the margin of victory is negative. Clearly, the margin of victory of 0 defines the threshold/cut-off of our running variable that determines whether assembly constituencies would belong to the treatment or control groups. The credibility of the RDD rests on the inability of politicians to manipulate the margin of victory to alter electoral outcomes (McCrary density test). Another important consideration is that other constituency or candidate characteristics (for which there is no reason to believe that they would be influenced by the current electoral outcome) should be continuous at the threshold of the margin of victory (covariate continuity).[3] As such, RDD techniques have been widely used in the economics and political science literatures to establish the causal effect of politician characteristics, including politician gender, on a variety of outcomes (see for example, Clots-Figueras, 2011; Clots-Figueras, 2012; Bhalotra and Clots-Figueras, 2014; Broockman, 2014; Brollo and Troiano, 2016; Asher and Novosad, 2017; Bhalotra et al., 2018; Baskaran et al., 2023; Amarasinghe et al., 2023; Nishijima and Pal, 2023).

For our analysis, we combine forest cover data for the period 2000–2014 and corresponding state assembly elections data from The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). Our analysis shows that female politicians winning in close races against male politicians improve subsequent annual forest cover growth in their constituencies, but this result is only statistically significant for constituencies that are reserved for politicians belonging to the historically marginalized communities, the Scheduled Castes (SCs) and Scheduled Tribes (STs).[4] For the SC/ST reserved constituencies, the causal impact of electing a female politician on subsequent constituency-level annual forest cover growth is around 6 percentage points. In this regard, our results are similar in spirit to Clots-Figueras (2011), who find that beneficial impacts of electing female politicians are largely driven by such politicians who also belong to marginalized castes. Further, our results are also conceptually similar to Clots-Figueras (2012) who find the beneficial impacts of female politicians being concentrated in sub-samples and not for the whole sample in the analysis.[5] We also find that our results are unlikely to be driven by constituencies that lie at either extreme of the initial distribution of forest cover or for states where forest cover data is likely to have measurement error (such as states in North-East India). Additionally, we examine whether effects of legislator gender on forest cover growth build up over time. This is to examine the possibility that significant impacts on forest cover growth may be observed over a legislator's electoral term despite little impact on subsequent year to year forest cover growth. We find that, over the electoral term, constituencies with female legislators record significant increases in forest cover growth. On exploring the heterogeneity by constituency reservation status, we find that the magnitude of the treatment effect is larger for both reserved and unreserved constituencies when we consider growth of forest cover over the electoral term relative to when yearly growth in forest cover is considered, potentially indicating an accumulation of the positive effects of electing a female MLA over time (albeit nonlinearly). However, the effect appears to be only statistically significant for the sample of reserved constituencies. Although SC/ST reserved constituencies do not dominate the sample of all constituencies, the magnitude of the impact of electing a female politician on subsequent growth of forest cover during the electoral term is plausibly large enough for these constituencies to drive the overall significant increase in this outcome for all constituencies. Therefore, the positive effect of a female legislator on forest cover growth over the electoral term appears to be driven by the sample of SC/ST reserved constituencies.

We, then, attempt to explore potential mechanisms that could help support our findings. Since we do not find systematic differences between female and male winners in close mixed gender races especially in SC/ST reserved constituencies, in terms of observed characteristics that could independently influence investments in environmental conservation (Saavedra Pineda et al., 2023; Harding et al., 2024), it appears the difference in the environmental outcomes between constituencies with a female and male legislator is largely on account of their genders. Political representation of SC/STs along with special legal provisions in SC/ST reserved constituencies with regard to environmental conservation (such as the Panchayat Extension to Scheduled Area/PESA and subsequently The Scheduled Tribes and Other Traditional Forest Dwellers (Recognition of Forest Rights) Act/FRA) have been shown to improve forest cover in these constituencies (Gulzar et al., 2024). But the existing literature does not examine whether these impacts could be largely driven by female legislators in these constituencies. Potential reasons why both politician gender and caste could be relevant in influencing environmental outcomes are differences in preferences as well as constraints faced in coping with environmental adversities between men and women as well as between SC/ST and non-SC/ST groups. Gender differences in behavioral traits such as patience, risk aversion, or altruism (Bauer and Chytilová, 2013; Croson and Gneezy, 2009), greater awareness of the adverse impacts of climate change among female legislators (Jagnani and Mahadevan, 2023) in addition to acknowledgement of greater vulnerability of especially women belonging to disadvantaged communities to climate change among female legislators from these communities could be potential mechanisms influencing our results. These mechanisms are also likely to extend to the context of forest cover growth over the electoral term, as it is largely driven by the sample of SC/ST reserved constituencies. Additionally, we also found that the only noticeable difference between female and male legislators in the sample of all constituencies is their age, with the

[3] Additional tests to assess the credibility of RDD have been proposed by Cattaneo et al. (2019).

[4] In this context, it is also important to note that the rationale of studying SC/ST reserved constituencies lies in understanding how political leaders, especially women leaders, from these communities are likely to engage in environmental conservation. Although it is well understood that ST communities live in proximity to forests, the role of SC community members in fostering environmental protection is a thriving area of research in other social science disciplines (for eg: see Sharma, 2012, 2022; Cherechés, 2024). However, the role that politicians from SC/ST communities can potentially play in conserving the environment is relatively unexplored.

[5] There are several examples of female SC/ST politicians who have been important drivers of environmental conservation, including tackling issues centered around human-forest/wildlife interactions such as Droupadi Murmu (accessed on July 26, 2025), Birbaha Hansda, (accessed on February 2, 2024), Chandana Bauri, (accessed on February 2, 2024) to name a few.

former being younger than the latter. We find that the positive effect of electing a female politician on the constituency level growth in forest cover over the electoral term is largely observed for younger, female politicians. This finding is also consistent with Dahis et al. (2023), who shows that younger politicians are more likely to invest in the environment, which yields benefits largely in the future.

Overall, our findings are similar in spirit to Leone (2019) who demonstrate the importance of gender composition of decision makers in collective action bodies aimed at forest conservation (but in the context of Nepal). However, unlike Leone (2019), our study focuses on individuals holding public office and thereby extends the analysis to examine the role of women in politics in influencing environmental conservation. Our results underscore the large potential role of female legislators, especially those from historically marginalized communities, in combating climate change. It is also worth noting that the Indian Parliament recently passed a legislation that would guarantee reservation of one-third of seats in the lower house of the Parliament as well as state assemblies for women (earlier such reservation applied only to the levels of local governments such as city/town municipalities and village councils and not upper levels of government). Additionally, this new law, which is yet to be implemented, also applies to seats that are already reserved for the historically marginalized communities such as the SC/STs. Although this law aims to increase women's representation at higher levels of government, it is acknowledged that greater women's representation in politics is not simply a rights issue but can bring about important changes in policy making and implementation. In this context, our paper is extremely topical and adds to our understanding of how women politicians, and especially those from historically marginalized communities, can influence long term citizen welfare through environmental conservation.

The paper is organized as follows: Section 2 discusses the institutional background; Section 3 describes the data used, while Section 4 describes the empirical strategy; Section 5 presents the main findings; Section 6 provides a discussion of the potential mechanisms and limitations of our analysis, while Section 7 concludes.

2. Institutional background

2.1. Elections & reservation system

India is a parliamentary democracy and a federation of states. Apart from parliamentary elections that usually occur once every five years, legislators are also elected to each state's legislative assembly. Elections to state assemblies also typically occur once every five years. The timing of the elections to state assemblies for each state usually differs, and the timing may not necessarily coincide with that of parliamentary elections. Each state is divided into several assembly constituencies depending on population size and area, and each constituency elects a legislator to the state assembly representing it through the "first past the post" electoral rule. The elected politician is termed a Member of the Legislative Assembly (MLA).

Article 332 of the Constitution of India (1950) provides for the reservation of seats for legislators who belong to the historically marginalized communities, such as the Scheduled Castes (SCs) and Scheduled Tribes (STs) in the legislative assemblies of the states. While the SCs are social groups who have been subjected to societal exclusion and untouchability on account of the traditional institution of the caste system in Hindu society, the STs constitute social groups who reside in geographically remote locations and have their own socio-cultural customs and languages. As historically, individuals from SC/ST communities have remained excluded from socio-economic opportunities, the Indian constitution provided provisions for their protection and socio-economic mobility through provisions of reservations in public sector jobs and educational institutions. Importantly, to guarantee that individuals from SC/ST communities are politically represented so that the interests of these communities are adequately represented in designing legislation and policymaking, the constitution provides for political representation of individuals from SC/ST communities at all levels of governance. For administrative purposes and specifically to receive benefits of reservation in accordance with the constitution, communities are notified as SC/ST by an act of parliament.

Specifically, with regard to state legislatures, the number of seats reserved in each state is roughly proportional to the population of SC/STs in that state. Although reservation for SC/STs was initially envisaged for the first 10 years after the constitution came into force in 1950, reservations have continued through subsequent constitutional amendments. For SC/ST reserved constituencies, only individuals from these communities can contest elections, but any legally registered voter, irrespective of their caste group, can cast their votes in these constituencies as in unreserved constituencies. In general, SC/ST constituencies have a higher proportion of individuals belonging to these social groups. According to the 2011 census of India, unlike unreserved constituencies, SC/ST reserved constituencies are more likely to be poorer, have lower literacy rates, and have poorer access to infrastructure and services. They may also be more dependent on agriculture, collection of forest produce, or engaged in other informal jobs with no or limited social security. This potentially stems from the higher concentration of SC/ST communities in the SC/ST reserved constituencies, who have faced social exclusion and marginalization historically. The number of assembly constituencies, including those reserved for the SC/STs, changes through redrawing of electoral boundaries or delimitation conducted by the Delimitation Commission to ensure equal representation as population size grows and its composition changes. The last redrawing of assembly constituency boundaries took place starting with assembly elections in 2008. However, assembly constituency boundaries had remained unchanged between 1976 and 2008, which corresponds to our period of analysis in this paper.

2.2. Environmental policy at the state level & role of MLAs

States of India play a key role in influencing sustainable development outcomes in India by enacting legislation, designing the institutional framework for implementing policies, and suitably directing government expenditures. State governments also facilitate the implementation of development projects of the federal government through institution design and cost sharing. Since 1976, forests have belonged to the concurrent list of the Indian constitution, implying that both federal and state governments can enact legislation to govern forest protection. Although federal laws take precedence over state laws in case of conflict between the legislations, state governments have been granted significant autonomy to design forest laws tailored to their specific ecological and socio-economic needs.

In terms of forest related legislations, almost all states in India adopted the Joint Forest Management (JFM) framework since 1990, which envisaged forest conservation through joint engagement of local individuals dependent on forests with the government forest departments, under the broad guidance of the Government of India. The efficacy of implementation has varied across states, with West Bengal, Tamil Nadu, Madhya Pradesh, and Odisha being some of the states with the strongest implementation framework. Following JFM initiatives, various state governments have subsequently introduced legislation that aims to address forest conservation in their specific contexts, recognizing that a uniform forest protection policy would not be successful in achieving the desired objective.[6] State legislations regarding tree cover and forests often target specific locations within their jurisdiction, especially arid/drought prone locations or locations that have a significant proportion of the population dependent on forests for their livelihoods.[7]

Across assembly constituencies, irrespective of reservation status, MLAs have access to numerous avenues through which they can foster sustainable development. Firstly, MLAs can play an important role in actively participating in debates, formulating legislation, and asking questions during question time to members of the state government about various development issues, including environmental conservation. They can also collect feedback from their constituents about their grievances and needs and convey these to members of the state government in an attempt to lobby for funding of various sustainable development projects for their specific constituencies. Another way in which MLAs can direct development works in their constituencies is through the utilization of the MLA Local Area Development (MLA-LAD) funds, which are provided to each MLA annually for facilitating development works catering to the specific needs of their constituencies. The set of permissible expenses includes not only infrastructure development (like street lighting and roads) but also explicit environmental works such as tree plantations. Additionally, MLAs can also ensure that the benefits of various federal and state welfare schemes and sustainable development works, including environmental conservation measures, get appropriately delivered to their constituents, thereby ensuring better implementation. Specifically with regard to forest conservation, MLAs can direct that afforestation funds aimed at compensating for the loss of tree cover on account of developmental works be appropriately channelled and utilized in their constituencies. They can visit project sites and take stock of survival rates of trees and demand progress reports of utilization of afforestation funds to ensure transparency and appropriate utilization. MLAs can ensure better environmental conservation by actively participating in tree planting, raising awareness about environmental conservation, and advocating against ecologically harmful development projects. Therefore, while state level legislation applies to all assembly constituencies within the state, the nature and quality of implementation and delivery of programmes could vary across constituencies. This is particularly found to be true for developing countries, where a significant difference between legislation and de facto implementation may be common.[8]

Constituencies specifically reserved for SC/ST politicians receive the same amount of discretionary funding in the form of MLA-LADs as unreserved constituencies, and there is no constitutional mandate that SC/ST politicians should target developmental works only towards their SC/ST constituents. However, in practice, SC/ST politicians may be more aware of the community's needs and be better able to lobby for or target government spending that benefits SC/ST communities. Additionally, since SC/ST reserved constituencies have a higher proportion of individuals from these communities, government spending in SC/ST constituencies is likely to benefit citizens from these communities. As many members of SC/ST communities depend on informal wage labor in agriculture and collection of forest produce, SC/ST legislators are likely to be in a position to better enforce legislation that aims to protect forests without compromising an individual's access to livelihoods, promote agro-forestry as a means of conserving green cover and enhancing livelihood options, and promote local self-governance of green cover/forests in their constituencies.

Lastly, specific MLA characteristics, and in particular MLA gender, have been demonstrated to influence development outcomes in the economics literature. For example, female politicians elected to state legislatures have been demonstrated to increase spending on public goods like health and education (Clots-Figueras, 2011, 2012; Bhalotra and Clots-Figueras, 2014), facilitate faster economic growth (Baskaran et al., 2023), and curb air pollution (Jagnani and Mahadevan, 2023). Additionally, Clots-Figueras (2011) shows that the beneficial impacts of electing a female politician to state legislatures largely accrue for SC/ST reserved constituencies and hence highlights the importance of taking into account both gender and caste of MLAs in exploring their roles in fostering development.

Therefore, MLA-specific characteristics could have a significant influence on how policies, including those aimed at environmental conservation, are implemented in their constituencies.

[6] Some examples of state-based legislation include the West Bengal Forest Policy (2004), Madhya Pradesh Forest Policy (2005), Tamil Nadu Afforestation Project (1997), and Green Tamil Nadu Mission (2002).

[7] See, for example, the Tamil Nadu Tree Cultivation in Private Lands, the Maharashtra Village Forest Rules, and the Social Forestry Programme for the Sunderbans of the government of West Bengal.

[8] There are several qualitative examples that demonstrate how specific MLAs advance environmental protection in their own constituencies even under the overarching umbrella of statewide legislation that aims at forest protection. MLAs have been found to do so on their own initiative to foster better implementation of state level policies through usage of their MLA-LAD funds/other local area development funds, through general awareness/activism, and by actively lobbying for environmental conservation needs for the health and livelihood of their constituents. Examples of MLAs include Bethi Subhash Reddy (accessed on July 4, 2025), Gudem Mahipal Reddy (accessed on July 4, 2025), Pamin Lepcha (accessed on July 4, 2025), Bharati Lavekar (accessed on July 4, 2025), Nirmala Sawant (accessed on July 4, 2025) and Sayantika Banerjee (accessed on July 4, 2025), who have invested in forest/green cover conservation in their specific constituencies.

3. Data

The data used in our analysis comes from The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). The SHRUG platform combines datasets on a number of socio-economic, demographic, environmental, and political variables and makes them available to researchers at fine geographic units (such as the village/town or assembly constituency) that are also consistent over time. For our analysis, we extract and combine data on forest cover available in the SHRUG platform for the period 2000–2014 with corresponding state assembly elections data at the assembly constituency level. While the forest cover data is obtained from the Vegetation Continuous Field (VCF) (Dimiceli et al., 2015), the assembly elections data have been contributed by Jensenius and Verniers (2017). To the best of our knowledge, the VCF data has been sparsely used in the economics literature, and the only known study to use it is Asher et al. (2020) who also provide a detailed description and potential advantages of the VCF over other existing forest cover data sources.[9] The outcome variable we use in our analysis is the annual growth of forest cover in a constituency. Annual growth of forest cover in a constituency in any given period is then given by the difference in the logarithm of forest cover in that period and that in the immediately preceding period. Formulation of the growth in forest cover in this way results in a straightforward interpretation of the regression coefficients in percentage points form. Another outcome variable we use in our analysis is the growth rate of the forest over the whole electoral term of a legislator. This outcome variable is calculated as the logarithm of the forest cover in the final year of one's term as an MLA, net of the logarithm of the forest cover in the year following one's election.[10]

Since we study the election of female legislators on subsequent constituency level growth in forest cover, the electoral data we use starts at a period earlier than 2000. In particular, the earliest year of state assembly election in our data is 1996. On the other hand, care must also be taken to ensure that during the period of our analysis, constituency boundaries have not changed. Since assembly constituency boundaries remained unchanged between 1976 and 2008, we have used assembly elections data up to 2007 in our analysis. Once elected, legislators usually serve a five-year term.[11] Therefore, even though the last year of elections data used comes from 2007 for some states, it is possible to use forest cover data for years beyond that (up to 2011 in our analysis).[12]

The elections data contain rich constituency level information such as electorate size, valid votes, turnout percentage, and number of candidates contesting from the constituency, as well as whether the constituency had a female legislator and whether the winner's party was aligned with the state's ruling party in previous elections, if the winner is an incumbent, and the winner's political party affiliation in any given electoral cycle. Since the predetermined values of many of these variables should not be impacted by the margin of victory in upcoming elections, we use the past values of most of these covariates for our covariate continuity test. We also use information on candidate characteristics such as their net asset ownership, education, age, and number of criminal accusations filed against the candidate for our covariate continuity analysis. This information has been contributed to the SHRUG by Prakash et al. (2019). Given that the declaration of information on candidate characteristics through affidavits was made mandatory for elections held from 2004 onwards (following a Supreme Court order in 2003) and the need to restrict the electoral data for elections held up to 2007, these candidate level information is only available for one election in each state (Prakash et al., 2019). Therefore, unlike other constituency characteristics, lagged values of these variables could not be constructed.

Table 1 here provides the descriptive statistics for all the relevant variables used in our analysis for all constituencies as well as for those where mixed gender elections have been held (Panel A).[13] In addition, similar descriptive statistics have also been provided for constituencies that are reserved for SC/ST politicians and among those constituencies where mixed gender elections have occurred (Panel B). Panel A of Table 1 shows that 14 % of all constituencies are reserved for SC candidates, while 11 % of all constituencies are reserved for ST candidates.[14] Panel A also shows that among all constituencies where mixed gender elections have taken place 19 % and 10 % are found to be reserved for SC and ST candidates, respectively.

Before providing a detailed description of the summary statistics, it may be important to take note of the occurrence of mixed gender elections during our study period. Appendix Table A.1 reports the occurrence of mixed gender elections during the period for which election data is available in the SHRUG platform, which corresponds to 1974–2007; as well as during our study period, which is elections held during 1996–2007. For the entire period available in the SHRUG platform, around 9 % elections in all constituencies and 10 % elections in SC/ST reserved constituencies were mixed gender elections (Panel A of Appendix Table A.1). On the other hand, Panel B of Appendix Table A.1 shows that while 12 % elections in all constituencies have been mixed gender races from 1996 onwards, the corresponding figure is around 15 % for SC/ST reserved constituencies.

[9] For instance, Asher et al. (2020) note that the VCF provides information on annual tree cover in the form of the percentage of each pixel under forest at 250 m resolution using high resolution satellite imagery. Additionally, unlike other sources of forest cover that have been used in the literature before, such as the Normalized Differenced Vegetation Index (NDVI), VCF is better able to differentiate between forests and other plantations as it uses thermal signatures (Asher et al., 2020).

[10] It is also to be noted that pockets of forest cover are common throughout India, despite areas of dense forests being largely geographically concentrated (Asher et al., 2020).

[11] Our sample also excludes constituencies where bye-elections have taken place. Less than 3 % of assembly-electoral year observations correspond to bye-elections. Therefore, dropping them is unlikely to result in significant distortion to the representativeness of the sample.

[12] See Prakash et al. (2019) who follow a similar strategy.

[13] Mixed gender elections refer to those where the winner and the runner up are of opposite genders. We report summary statistics for mixed gender constituencies as observations from this subsample constitute the analysis sample for the RDD exercise.

[14] It is to be noted that in SC/ST reserved constituencies, while the candidates running for the state assembly election must be from the SC/ST communities, the voters can belong to any caste group.

Table 1
Descriptive Statistics.

All Constituencies				Mixed Gender Constituencies		
Variable	Mean	Standard Deviation	Observations	Mean	Standard	Observations Deviation
Panel A:						
Forest Cover in t (%)	12.91	13.25	39,881	11.49	10.70	4967
Growth of forest cover in t	0.03	0.37	35,929	0.02	0.37	4564
Log of Electorate Size in $t-1$	11.53	0.75	25,090	11.67	0.57	2331
Log of Valid Votes in $t-1$	11.02	0.74	25,026	11.15	0.65	2331
Number of Candidates in $t-1$	9.01	6.75	25,092	9.23	6.38	2332
Turnout Percentage in $t-1$	61.58	13.99	25,090	61.27	13.18	2331
Female Legislator in $t-1$	0.04	0.21	25,092	0.27	0.44	2332
Winner's Party Aligned with State Ruling Party in $t-1$	0.58	0.49	25,092	0.62	0.48	2332
Winner is Incumbent in t	0.16	0.36	25,092	0.14	0.35	2332
Winner is from Congress in t	0.34	0.47	29,241	0.33	0.47	2562
Winner is from BJP in t	0.13	0.34	29,241	0.15	0.36	2562
SC Reserved Constituency	0.14	0.35	25,092	0.19	0.39	2332
ST Reserved Constituency	0.11	0.31	25,092	0.10	0.30	2332
Winner's Log Net Assets in t	15.05	1.59	1475	14.97	1.45	172
Winner's Education (yrs.) in t	11.79	2.50	2376	11.42	2.88	312
Winner's Age (yrs.) in t	48.64	10.15	3452	47.42	10.50	442
Winner's Number of Crimes in t	3.14	8.66	2518	2.04	7.54	325
Panel B: SC/ST Constituencies						
Forest Cover in t (%)	17.91	18.37	10,310	12.12	12.15	1577
Growth of forest cover in t	0.02	0.33	9248	0.02	0.35	1446
Log of Electorate Size in $t-1$	11.22	1.01	6450	11.61	0.64	672
Log of Valid Votes in $t-1$	10.66	0.92	6394	11.04	0.66	671
Number of Candidates in $t-1$	6.64	4.15	6450	7.28	4.23	672
Turnout Percentage in $t-1$	58.65	17.76	6450	58.49	14.22	672
Female Legislator in $t-1$	0.05	0.21	6450	0.27	0.44	672
Winner's Party Aligned with State Ruling Party in $t-1$	0.63	0.48	6450	0.64	0.47	672
Winner is Incumbent in t	0.18	0.38	6450	0.12	0.33	672
Winner is from Congress in t	0.35	0.48	7482	0.30	0.46	731
Winner is from BJP in t	0.13	0.34	7482	0.16	0.36	731
Winner's Log Net Assets in t	14.26	1.60	301	14.43	1.29	49
Winner's Education (yrs.) in t	11.59	2.55	539	10.79	3.04	88
Winner's Age (yrs.) in t	46.83	10.16	758	45.38	10.26	126
Winner's Number of Crimes in t	1.55	5.69	587	0.58	2.40	93

Note: Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). Mixed gender constituencies refer to those where the winner and the runner up are of opposite genders. Data corresponds to all election years available in the SHRUG platform 1974 - 2007 and years of forest cover from 2000 to 2011.

From Table 1 we find that the average percentage of a constituency under forest cover for the period of our study is 12.9 %, while in mixed gender constituencies it is around 11.5 %. On the other hand, around 17.9 % of the area of an SC/ST reserved constituency is under forest cover, on average. However, among SC/ST reserved constituencies, those in which mixed gender elections have occurred have around 12 % of their average area under forest cover. In this regard the level of forest cover, measured in terms of the percentage of a constituency under forest, does not appear to be remarkably different between all constituencies and those in which mixed gender elections have taken place, including in mixed gender constituencies that are reserved for SC/ST candidates. We next focus on growth of forest cover, as it is our key outcome variable of interest. We find that the average annual growth rate of forest cover at the level of the assembly constituencies during our study period is 2–3 %. In this regard, all constituencies, as well as SC/ST reserved constituencies and mixed gender constituencies, including those that are reserved for SC/ST politicians, appear to be largely similar. Additionally, computing summary statistics for the growth rate of forest cover over the electoral term for all mixed gender constituencies and those specifically reserved for SC/STs for our study period, we find that the average forest cover growth over the electoral term is 4 % for the former and 7 % for the latter type of constituencies.

Table 1 further reports summary statistics of other constituency level and candidate characteristics. For constituency level characteristics, the lagged values of these variables from past elections have been used. Here the averages are computed for the entire period of time for which election data is available in the SHRUG platform. We find that the lagged logarithm of the electorate size and the number of valid votes is 11.67 and 11.15, on average, for all mixed gender constituencies over time. The corresponding figures for SC/ST reserved constituencies where mixed gender elections have occurred are 11.61 and 11.04 respectively. These are also close in magnitude to those for all constituencies as well as for all SC/ST reserved constituencies, irrespective of whether mixed gender elections have taken place during the said period. Further, we find that the average number of candidates who have run for office in the last election is around 9 for all mixed gender constituencies; while it is around 7 for SC/ST reserved constituencies where mixed gender elections have occurred. The lagged turnout percentage is around 61 % in all constituencies and 58 % in SC/ST reserved constituencies in which mixed gender elections have taken place. In mixed gender constituencies, 27 % of all constituencies as well as SC/ST reserved constituencies are found to have a female legislator in the last assembly election. This is the only variable that is found to be different between the mixed gender constituencies and all constituencies irrespective of their reservation status. Lastly, 62 % of all mixed gender constituencies and 64 % of all mixed gender SC/ST reserved constituencies elected legislators whose party was aligned with the state's ruling party in the last election. For this variable, the numbers for all constituencies are comparable to those for mixed-gender constituencies.[15] Additionally, Table 1 reports that 14 % winning candidates in the current election are incumbents for all mixed gender constituencies, while 12 % winners are found to be incumbents in mixed gender constituencies that are reserved for SC/ST politicians. We also examine what fraction of winners belong to two of the major national political parties, the Congress and the Bharatiya Janata Party (BJP), that have a robust presence across various Indian states. We find that while 33 % of the winners in mixed gender constituencies were from the Congress and 15 % from the BJP during the current electoral cycle, the corresponding figures for SC/ST reserved constituencies where mixed gender elections have occurred are around 30 % and 16 % respectively. These figures are not vastly different from those found overall for all constituencies and SC/ST reserved constituencies in Table 1. Restricting the sample to election years in our study period, that is, from 1996 onwards, changes these findings somewhat, as it reflects the gradually changing political landscape of India, where incumbency slightly increases and the importance of the Congress party decreases (Appendix Table A.2).

Lastly, the average of the logarithm of the winner's net assets, years of education, age, and the number of crimes that the winner has been charged with in the current election is around 14.97, 11.42 years, 47.42 years, and 2, respectively, for mixed gender constituencies. The corresponding figures for mixed gender constituencies among SC/ST reserved constituencies are 14.43, 10.79 years, 45.38 years, and around 1, respectively. Additionally mixed gender constituencies appear to be similar, on average, to all constituencies in these variables, including for the sample of SC/ST reserved constituencies.

4. Empirical strategy

Our intention is to study the impact of the gender of the legislator on subsequent growth in forest cover in the constituency. Since both our outcome and treatment variables are at the level of the constituency, and we intend to exploit close races between female and male politicians to establish the causal impact of legislator gender on our outcome; the empirical strategy that we adopt is the sharp regression discontinuity design (RDD).

The basic sharp regression discontinuity (RD) equation is as follows:

$$gy_{i,s,t} = \alpha + \beta T_{i,s,t-1} + f(margin_{i,s,t-1}) + \varepsilon_{i,s,t} \tag{1}$$

Here, $gy_{i,s,t}$ represents the growth in forest cover between the years t and $t-1$. If we denote $y_{i,s,t}$ as the forest cover in assembly constituency i in state s in year t; then $gy_{i,s,t} = ln(y_{i,s,t}) - ln(y_{i,s,t-1})$ represents the growth in the forest cover in the constituency between the periods t and $t-1$.[16] In an alternative specification, we also use growth of forest cover over an entire electoral term as the dependent variable (further discussion on this outcome is provided in Section 5 subsequently). $T_{i,s,t-1}$ is the treatment variable that assumes the value 1 if the winner in the constituency i in state s in the preceding election held is a woman (treatment group) and 0 if a man is the winner (control group). $margin_{i,s,t-1}$ is the margin of victory in the preceding election between a male and a female politician and is the running/forcing variable in our estimation framework. Here, $margin_{i,s,t-1}$ is the difference between the percentage of votes obtained by the female and the male candidates. Clearly, $margin_{i,s,t-1}$ assumes non-negative values if the female candidate is the winner and is negative when the male candidate is the winner in a mixed gender race. In other words, $T_{i,s,t-1}$ assumes the value 1 if $margin_{i,s,t-1} \geq 0$ and 0 if $margin_{i,s,t-1} < 0$. Our treatment variable here is, therefore, a deterministic function of our running variable. Clearly the threshold or cutoff, c, in the running variable, $margin_{i,s,t-1}$, that determines whether a unit of observation (here, an assembly constituency) is in the treatment or the control group is $c = 0$. $f(margin_{i,s,t-1})$ is the p-th order polynomial in $margin_{i,s,t-1}$. In practice, we estimate local linear regressions, allowing for the possibility that the slopes of the fitted regression lines can be different on either side of the cut-off.[17] $\varepsilon_{i,s,t}$ is the regression disturbance term, which is clustered at the assembly constituency level.[18]

[15] For these lagged constituency characteristics, limiting the sample to include election years starting only from 1996 yields largely similar mean and standard deviation values across the different types of constituencies as Appendix Table A.2 shows.

[16] From the first order Taylor series expansion of $ln(y_{i,s,t})$ around $ln(y_{i,s,t-1})$, we obtain $ln(y_{i,s,t}) - ln(y_{i,s,t-1}) \approx (y_{i,s,t} - y_{i,s,t-1})/y_{i,s,t-1} = gy_{i,s,t}$ i.e., the yearly growth rate of forest cover. This definition of growth as the outcome variable has been used in other studies in the literature, such as Prakash et al. (2019), Baskaran et al. (2023).

[17] Gelman and Imbens (2019) explain that using higher order polynomials in the running variable for RDD estimation can lead to misleading results and recommend using local linear or at most quadratic polynomial functions for estimation and inference.

[18] To prevent the impact of the legislator who was elected in the last election from influencing our outcome variable, we exclude growth in forest cover corresponding to the year of election, as it would be computed as the difference between the logarithm of forest cover in the year of the election and the logarithm of forest cover in the year preceding the year of the election and the latter measure would correspond to the previously elected politician.

β is the coefficient of interest. It attempts to capture the causal effect of a female legislator on yearly growth in forest cover in that constituency. Identification of the causal effect is achieved by comparing constituencies that elected a female politician vis-a-vis those that elected a male politician in a “close" race. In general, constituencies where a female politician won and those where a male politician was elected may not represent appropriate treatment-control groups, as several unobserved factors, including preference for a politician of a certain type, may be influencing our outcome of interest. For example, it could be possible that constituencies with greater environmental awareness are also more likely to elect female politicians. In this situation, it would be difficult to establish whether any difference in our outcome of interest is on account of politician gender or due to the role of other systematic (unobserved) differences across these types of constituencies. On the other hand, a female candidate winning an election against a male candidate or vice-versa with a “narrow" margin of victory can be taken as quasi-random and hence comparing between such constituencies can credibly establish the causal impact of politician gender on our outcome of interest, under relatively simple assumptions. Formally we compare constituencies where a female politician won to those in which a male politician won in a neighborhood h around the cut-off; that is, constituencies where the margin of victory lies between $(c - h, c + h)$ using local linear regression. Therefore, it is to be noted that the treatment effect that we identify in this framework is a local average treatment effect (LATE). The neighborhood h around the cut-off is called the bandwidth.

We choose the optimal bandwidth h such that it minimizes the mean squared error (MSE) and a triangular kernel, following Cattaneo et al. (2019). Since the bias and variance characteristics of the RDD point estimator are unknown when selecting ad hoc bandwidths (even though they may be intuitively appealing), Cattaneo et al. (2019) advise against using ad hoc bandwidths and recommend using data-driven optimal bandwidths instead. Intuitively, Cattaneo et al. (2019) note that the algorithm of the data driven optimal bandwidths will produce larger optimal bandwidths when asymptotic variance is likely to be large, as larger bandwidths would reduce variability, while the possibility of larger asymptotic bias would result in smaller optimal bandwidths, as such bandwidths would reduce bias.

However, it is important to acknowledge that a challenge with the MSE optimal bandwidths is that these bandwidth choices have been developed for point estimation purposes. It is possible that the optimal bandwidths may not be small enough to exclude the leading bias terms from the standard distribution approximations needed to construct statistical inference. [19] Therefore, without accounting for the leading bias term, the t-statistic and the confidence interval constructed using the MSE optimal bandwidths will typically produce wrong statistical inferences (Cattaneo et al., 2019). One theoretically justified but ad hoc approach is to employ these conventional confidence intervals with a smaller or “undersmoothed" bandwidth than the MSE-optimal one used for the point estimator construction. The theoretical rationale for this is that, when the bandwidth is smaller than the MSE-optimal value, the bias term will be insignificant in the approximation of the distribution for large samples. In other words, the use of conventional t-statistics and confidence intervals will be more appropriate with a smaller bandwidth. The primary disadvantage of this undersmoothing procedure is the absence of explicit and transparent criteria for reducing the bandwidth below the MSE-optimal value. Additionally, this approach results in a reduction in statistical power due to the fact that a smaller bandwidth results in a smaller number of observations that are utilized for estimation and inference (Cattaneo et al., 2019).

In this paper we implement a robust bias correction approach, as proposed by Calonico et al. (2014) and recommended by Cattaneo et al. (2019), to generate standard errors and confidence intervals. The robust bias correction approach generates valid inferences even when the MSE-optimal bandwidth for point estimation is implemented, necessitating no undersmoothing. In this approach, the bias term is removed from the RDD point estimator while constructing the t-statistic and the confidence interval. A new asymptotic variance is employed that takes into account the impact of the bias correction procedure on the variability of the bias-corrected point estimator. Thus, compared to the conventional confidence interval, the robust bias-corrected confidence interval is both recentered (bias-corrected) and rescaled (variance is readjusted).[20] In a recent article, Stommes et al. (2023) emphasize the importance of employing robust bias-corrected standard error in order to draw accurate statistical inference in applied econometric research that relies on RDD estimation. In a different paper, De Magalhaes et al. (2020) find that compared to local linear regression with conventional inference, RDD estimation with bias-correction and robust inference does a better job of reproducing experimental estimates. We, therefore, follow these recent recommendations in the choice of data-driven optimal bandwidth and robust and bias-corrected standard errors. Additionally, we verify the robustness of our point estimation by employing the coverage error (CER) optimal bandwidth. Calonico et al. (2018) introduce CER optimal bandwidth, where the selection of this bandwidth minimizes the approximation to the coverage error of the confidence interval of the RD treatment effect.[21]

For the RDD to yield a credible causal estimate of the impact of female politicians on our outcome of interest, some of the key assumptions that need to be satisfied include the inability of agents to manipulate the margin of victory and consequently their treatment status (McCrary density test) as well as continuity of all other factors that are unlikely to be affected by the current electoral outcome at the cutoff (covariate continuity). We provide evidence to this end along with various additional tests of validity and falsification as suggested by Cattaneo et al. (2019) for sharp RDD that potentially support the validity of our RDD strategy.

[19] Please see Cattaneo et al. (2019) for a detailed technical discussion.

[20] Mathematical details can be found in Cattaneo et al. (2019) and the references therein.

[21] The coverage error is the discrepancy between the nominal level of the confidence interval and its empirical coverage. As an illustration, if a 95 % confidence interval includes the correct parameter 80 % of the time, the coverage error is 15 percentage points. For details, please see Cattaneo et al. (2019) and the references therein.

5. Results

5.1. Annual growth of forest cover

We present our main results in Table 2 here. As mentioned in the last section, we perform our RDD point estimation using the MSE optimal bandwidth in Panel A and perform inference by relying on the robust bias-corrected confidence interval. We find that female politicians who won in a close race against a male politician have a positive impact on the annual growth in forest cover in their constituencies, but this effect is not found to be statistically significant. However, heterogeneity appears to be present in terms of the impact of female politicians on forest cover change when we examine constituencies that have been reserved for the historically marginalized communities, the SC/ST, and those that are unreserved. While no impact on forest cover growth can be found in unreserved constituencies (the point estimate is also small), electing a female politician in a close race against a male politician significantly increases annual forest cover growth by 6 percentage points in reserved constituencies.[22] Constituencies narrowly won by male politicians show a positive average annual increase in forest cover (as can be seen from the control means in Table 2), indicating baseline afforestation. The additional 6 percentage point increase in constituencies led by female politicians suggests that female leadership is associated with increased afforestation. Among SC/ST reserved constituencies falling within the optimal bandwidth, those won by male candidates and therefore constituting our control group exhibit an average annual forest cover growth rate of 4 %. Accordingly, within the optimal bandwidth, the estimated treatment effect corresponds to a 150 % premium in the yearly growth in forest cover on account of electing female legislators, relative to the mean of this outcome in the control group. However, this magnitude should be interpreted with caution because the control mean does not exactly reflect the average growth rate in constituencies won by male candidates at the cut-off. Notably, comparable figures can be found from other studies that employ close election RDD in the context of other outcome variables.[23] Another alternative way of interpreting the RDD treatment effect obtained for SC/ST reserved constituencies led by women is by comparing it to the overall annual average forest cover growth rate during the time period that largely corresponds to our study period. In particular, the forest cover is found to have exhibited an average annual growth rate of approximately 4.8 % during the period from 2001 to 2017 in India (Balaji et al., 2022). The RDD estimate can then be viewed as capturing the premium in the average annual forest cover growth rate led by female politicians in closely contested elections. Specifically, this premium is 1.25 times higher than the mean forest cover growth rate observed over our study period for women-led SC/ST reserved constituencies.[24]

As a robustness to our choice of the MSE-optimal bandwidth, we use the CER-optimal bandwidth along with robust bias-corrected standard errors in Panel B. The CER-optimal bandwidth is typically smaller than the MSE-optimal bandwidth, which is what we find across all columns in Panel B. Nevertheless, we continue to find similar results in Panel B as we found in Panel A of Table 2.[25] We also check the sensitivity of our results to alternative bandwidths that are neither MSE nor CER optimal. The results are reported in Appendix Table A.3 along with associated discussion in Appendix B.1.

Fig. 1 graphically represents the findings of Panel A of Table 2 for the sample of all, SC/ST reserved, and unreserved constituencies, where each of the sub-figures is drawn using equally spaced bins along with local linear regression functions fitted separately for either side of the cut-off using the MSE-optimal bandwidth and the associated robust bias-corrected 95 % confidence interval. We find that while there is no discernible discontinuity between the fitted regression lines on either side of the cut-off for all constituencies (subfigure (a)) and unreserved constituencies (subfigure (c)), a discontinuous jump between the fitted regression lines can be observed as one moves from a negative margin of victory (representing a male winner) to a positive margin of victory (representing a female winner) at the cut-off of 0 only for the SC/ST reserved constituencies (subfigure (b)), and the confidence intervals on either side do not completely overlap. Our finding that conservation of forest cover is more likely to be found under female legislators who have won in close races against male politicians, but only in constituencies reserved for SC/ST groups, is similar in spirit to that of Clots-Figueras (2011).

It may also be important to understand the economic significance of our findings from Table 2 in terms of a rough estimate of carbon sequestration benefits from improved forest cover. The average assembly constituency is around 200 square kilometers in area, and given that the average forest cover in SC/ST mixed gender constituencies during our study period is around 12 % of the constituency area (from Table 1), this provides an average forest area of 24 square kilometers in such constituencies.[26] Mendelsohn

[22] Although the magnitude of the impact on subsequent annual forest cover growth, especially in the context of SC/ST reserved constituencies, may appear large, comparable magnitude of impact on annual deforestation on account of electing female mayors in Brazil have been found in Baragwanath and Zheng (2023).

[23] For example, Prakash et al. (2019) finds that the negative impact of criminal politicians on night light growth is approximately 22 percentage points, which is substantially larger than our RDD estimate. In their study, the RDD estimate corresponds to 80 % of the control group mean, which is a substantial effect, though smaller than the one identified in our analysis.

[24] We provide further analysis on the impact of female legislators on the growth rate of forest cover over the electoral term in Subsection 5.2.

[25] The size of the MSE optimal bandwidth across specifications in Table 2 is comparable to that of numerous recent studies (for example, please see Prakash et al., 2019, Jain et al., 2023). More importantly, as this is a data-driven optimal approach, it is not necessary for the MSE-optimal bandwidth to be extremely small as discussed in Section 4. For example, papers using RDD estimation where the optimal bandwidth is significantly large (and larger than ours) include Bhalotra et al. (2018), Meyersson (2014).

[26] A rough estimate of constituency area is used, as urban assembly constituencies are significantly smaller in area due to higher population density, and rural ones can even be more than 500 square kilometers due to smaller population densities. In particular, dividing the area administered by India by the number of assembly constituencies during the pre-delimitation period (which is roughly 4120 during the pre-delimitation period prior

Table 2
Results: Growth of Forest Cover.

Panel A:	All Constituencies	SC/ST Reserved Constituencies	Non-SC/ST Constituencies
Female Legislator Elected in Last Election	0.02 (0.02)	0.06** (0.03)	0.002 (0.02)
Optimal Bandwidth Type	MSE	MSE	MSE
Optimal Bandwidth	12.13	13.74	11.98
Control Mean	0.02	0.04	0.03
Number of Observations	3792	1205	2587
Effective Number of Observations	2309	796	1556
Kernel Type	Triangular	Triangular	Triangular
Panel B:	All Constituencies	SC/ST Reserved Constituencies	Non-SC/ST Constituencies
Female Legislator Elected in Last Election	0.02 (0.02)	0.06** (0.03)	0.004 (0.03)
Optimal Bandwidth Type	CER	CER	CER
Optimal Bandwidth	8.62	10.34	8.67
Control Mean	0.03	0.04	0.02
Number of Observations	3792	1205	2587
Effective Number of Observations	1744	638	1212
Kernel Type	Triangular	Triangular	Triangular

Note: The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). Robust and bias corrected standard errors clustered at the level of assembly constituencies are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % level of significance, respectively. RD estimates are from local linear regressions fitted with different slopes on either side of the cut-off. “Effective number of observations" refers to the number of observations within the MSE-optimal bandwidth in Panel A and the CER-optimal bandwidth in Panel B. The control means are the average annual forest cover growth rate for the constituencies within the optimal bandwidth and a male winner. The computation of RDD treatment effect coefficients, optimal bandwidths, and robust and bias corrected standard errors follow Cattaneo et al. (2019) and are implemented using “rdrobust" program in STATA.

et al. (2012) note that tropical forests can sequester up to 11 tonnes of carbon dioxide per hectare per year in the form of trees, foliage, and deadwood litter.[27] Since most of India’s forests are tropical forests, a 6 percentage point increase in yearly forest cover at the level of the constituency is likely to result in an increase in sequestration of approximately 1584 tonnes of carbon dioxide annually. While these are very rough estimates and actual figures would vary given the exact area of a constituency and consequently under forest cover, exact consumption based carbon emissions per person at the constituency level, the age as well as type of forest, and so on, this computation provides an important perspective. During our study period, the average annual carbon dioxide emission per person is approximately 1.2 tonnes.[28] This indicates that reforestation estimated in our paper offsets the carbon dioxide emissions of around 1300 individuals. As India’s population is approximately 1.4 billion and there are roughly 4120 constituencies, this yields a population size of approximately 340,000 per constituency. Therefore, reforestation mitigates roughly 0.4 % of the annual carbon dioxide emissions of a constituency.[29]

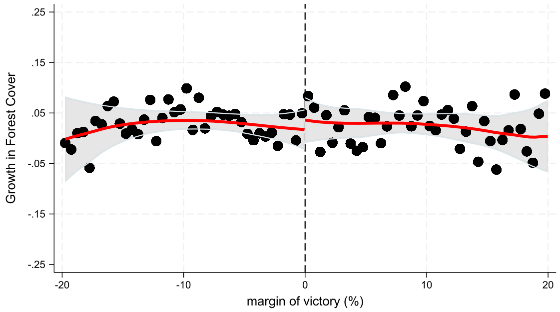
It would also be interesting to examine whether there is any heterogeneity in our findings obtained in Table 2 in terms of the initial extent of forest cover in the assembly constituencies. For this purpose we classify constituencies, both overall as well as according to reservation status, by the extent of forest cover at the start of our study period, 2000. In particular, we divide constituencies by whether the fraction of area under forest cover in the year 2000 was below or at least as large as the 75th percentile of the initial distribution of the proportion of the constituency’s area under forests. We can then consider the latter set of constituencies as being particularly densely forested and the former set of constituencies as relatively sparsely forested at the start of the study period. We employ the MSE optimal bandwidth as in Panel A of Table 2 and report our findings in Table 3 here. Panel A shows that for all constituencies, as well as SC/ST reserved constituencies, the election of a female legislator to the state assembly results in the significant growth of forest cover only for those constituencies that were relatively sparsely forested at the start of our study period, and we continue to find a positive but insignificant effect of electing a female legislator on subsequent annual forest cover growth for relatively sparsely

to 2008 and the period of our study) yields an average constituency size of roughly 780 square kilometers. Therefore, the measure of 200 square kilometers is sufficiently modest.

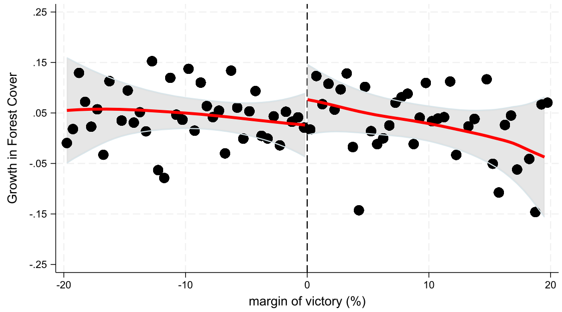
[27] 1 $km^2 = 100$ hectares.

[28] This figure represents the average for the period from 2000 to 2014. The data source is https://www.worldometers.info/co2-emissions/india-co2-emissions/

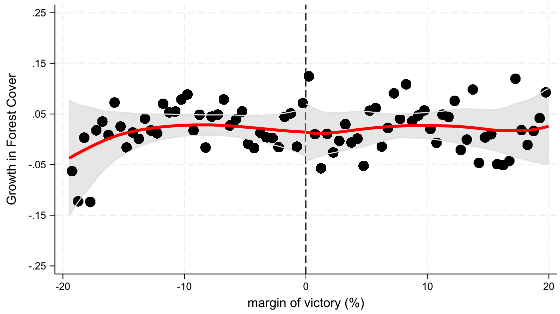
[29] See Time series of per capita consumption based carbon emissions for India. (accessed on June 23, 2024).



(a) All Constituencies



(b) SC/ST Reserved Constituencies



(c) Non-SC/ST (Unreserved) Constituencies

Fig. 1. Annual growth in forest cover at the constituency level is the dependent variable. The running variable is the margin of victory of female politicians and is computed as the difference in vote shares of female and male politicians in mixed gender electoral races. Positive values indicate a female winner and negative a male winner, with 0 being the cut-off. The scatter plots are binned outcome means over each successive interval of 0.5 % of the margin of victory. Local linear regression lines using MSE-optimal bandwidth and triangular kernel have been plotted separately for either side of the cut-off along with the 95 % confidence interval. The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021).

forested unreserved constituencies (although the point estimate is larger than that reported in Table 2). Our findings indicate that the positive and statistically significant influence of female legislators in constituencies with initially low forest coverage is entirely attributable to SC/ST reserved constituencies. On the other hand, for constituencies that were densely forested in 2000, we find that election of a female politician has a negative impact on the growth of forest cover (Panel B). This is specifically found for the sample of all and non-SC/ST constituencies and is less prominent for the sample of SC/ST reserved constituencies (just significant at the 10 % level with a p-value of 0.10). Upon comparing the coefficients and significance levels, it can be concluded that the negative impact of female legislators on forest cover expansion in densely forested constituencies is largely on account of the unreserved constituencies. Our data also indicates that the ratio of male to female winners is nearly equal (approximately 50 % for each) in closely contested elections for constituencies that were initially relatively sparsely forested, irrespective of reservation status. However, the proportion of female winners in constituencies that were initially densely forested is only 40 %-42 %. The disproportionate number of female winners, significantly lower than that of male winners, may distort the RDD estimations in constituencies where the initial forest cover is at least as large as the 75th percentile of its distribution in 2000.[30]

Lastly, since we find overall statistically significant findings in Table 2 only for the sub-sample of SC/ST reserved constituencies, we conduct a number of additional tests with regard to sample restrictions, exclusion of outliers in terms of forest cover, and inclusion of state and year fixed effects to assess the impact of these exercises on our results for the sample of reserved constituencies. Table 4 presents these results. At first we limit the sample to include only the major states in India.[31] In subsequent columns, we restrict the

[30] Upon conducting the McCrary density test, we find evidence of discontinuity for constituencies above the 75th percentile of the initial forest cover distribution. In contrast, no such discontinuity is observed for constituencies below this threshold. Therefore, the findings for constituencies with forest cover above the 75th percentile should be interpreted with caution.

[31] Major states are large states in India that also account for a large proportion of the population. These include Andhra Pradesh, Assam, Bihar, Chhattisgarh, Gujarat, Haryana, Himachal Pradesh, Jammu & Kashmir, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, Uttarakhand, and West Bengal. This exercise is also motivated to assess whether our results are robust to the exclusion of states in North-East India, following Asher et al. (2021).

Table 3
Results: Growth of Forest Cover by Heterogeneity of Initial Forest Cover.

	All Constituencies	SC/ST Reserved Constituencies	Non-SC/ST Constituencies
Panel A: < 75th percentile			
Female Legislator Elected in Last Election	0.05*	0.09**	0.02
	(0.02)	(0.03)	(0.03)
Optimal Bandwidth Type	MSE	MSE	MSE
Optimal Bandwidth	10.54	11.71	11.95
Control Means	0.04	0.06	0.03
Number of Observations	2977	927	2050
Effective Number of Observations	1559	553	1200
Kernel Type	Triangular	Triangular	Triangular
Panel B: ≥ 75th percentile			
Female Legislator Elected in Last Election	-0.06***	-0.04*	-0.07**
	(0.02)	(0.02)	(0.03)
Optimal Bandwidth Type	MSE	MSE	MSE
Optimal Bandwidth	10.75	8.36	9.18
Control Means	0.02	0.003	0.02
Number of Observations	815	278	537
Effective Number of Observations	485	137	270
Kernel Type	Triangular	Triangular	Triangular

Note: The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). The sample divisions of < and ≥ 75th percentile refer to whether the initial forest cover in the constituency given by the sample starting period, 2000, was lower than or at least as large as the 75th percentile of the distribution of the proportion of forest cover in the constituency in 2000. Robust and bias corrected standard errors clustered at the level of assembly constituencies are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % level of significance, respectively. RD estimates are from local linear regressions fitted with different slopes on either side of the cut-off. “Effective number of observations" refers to the number of observations within the MSE-optimal bandwidth. The control means are the average annual forest cover growth rate for the constituencies within the optimal bandwidth and a male winner. The computation of RDD treatment effect coefficients, optimal bandwidths, and robust and bias corrected standard errors follow Cattaneo et al. (2019) and is implemented using the “rdrobust" program in STATA.

sample of analysis by excluding outliers in the measure of forest cover. For instance, the “Above 5 %" and “Above 10 %" columns in Table 4 represent samples comprising constituencies whose forest cover in the year 2000 is at least as large as 5 % and 10 % of the average forest cover over all constituencies in 2000, respectively. Additionally, the “Within 3 SD" sample in Table 4 includes only constituencies whose forest cover in 2000 is within 3 standard deviations of the mean of the forest cover over all constituencies in 2000. Lastly, the “Within 5th & 95th Percentile" sample in Table 4 includes constituencies whose forest cover in 2000 is at least as large as the 5th percentile but no larger than the 95th percentile of the distribution of forest cover over all constituencies in 2000, while the “Within 1st & 99th Percentile" sample includes constituencies whose forest cover in 2000 is at least as large as the 1st percentile but no larger than the 99th percentile of the distribution of forest cover over all constituencies in 2000. As Table 4 shows, our findings in Table 2 with respect to SC/ST reserved constituencies are robust to these sample restrictions. The coefficient estimate and statistical significance continue to be similar to what we found in Table 2 before. Finally, we revert back to the original sample as in Table 2 but include state and year fixed effects. In general, inclusion of controls is not necessary in an RDD setup.[32] In our framework, as stated, we include state and year fixed effects as additional controls to assess the robustness of our results. We find that the RDD coefficient estimate is lower but positive and statistically significant, albeit at the 10 % level of significance. A potential explanation of this could be that the inclusion of state and year fixed effects imposes severe restrictions on the estimation framework, wherein close mixed-gender elections in SC/ST reserved constituencies within states and years are to be compared.

We examine the credibility of our RDD using a number of tests suggested in the literature. We assess the findings from the McCrary density test (McCrary, 2008), the test for continuity of covariates at the threshold, the donut hole test, and the usage of placebo thresholds for the running variable as suggested by Cattaneo et al. (2019); Cunningham (2021). These correspond to Appendix Figs. A.1–A.8 along with associated discussion in Appendix B.2–B.5. We also examine whether the collaborative structure of state legislatures enables policy decisions to produce positive externalities that extend beyond specific constituencies that are led by female

[32] Additionally, one must be cautious regarding the inclusion of controls as controls that are not balanced between the treatment and control groups do not help in correcting such imbalances, as in standard linear regression models. Inclusion of controls, however, can improve the precision of the estimation of standard errors of the coefficients as in estimation frameworks such as randomized control trials (Cattaneo et al., 2019).

Table 4
Robustness Results: Growth of Forest Cover in SC/ST Constituencies.

Panel A:	Only Major States	Above 5 % Sample	Above 10 % Sample	Within 3 SD Sample
Female Legislator Elected in Last Election	0.07**	0.06**	0.06**	0.05**
	(0.03)	(0.03)	(0.03)	(0.02)
Optimal Bandwidth Type	MSE	MSE	MSE	MSE
Optimal Bandwidth	13.46	13.74	13.74	14.03
Control Means	0.04	0.04	0.04	0.04
Number of Observations	1099	1205	1205	1175
Effective Number of Observations	732	796	796	782
Kernel Type	Triangular	Triangular	Triangular	Triangular

Panel B:	Within 5th & 95th Percentile Sample	Within 1st & 99th Percentile Sample	State & Year Fixed Effects
Female Legislator Elected in Last Election	0.06**	0.05**	0.06**
	(0.03)	(0.02)	(0.03)
Optimal Bandwidth Type	MSE	MSE	MSE
Optimal Bandwidth	12.71	14.02	13.75
Control Means	0.04	0.04	0.04
Number of Observations	1121	1186	1205
Effective Number of Observations	721	793	796
Kernel Type	Triangular	Triangular	Triangular

Note: The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021).Robust and bias corrected standard errors clustered at the level of assembly constituencies are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % level of significance, respectively. RD estimates are from local linear regressions fitted with different slopes on either sides of the cut-off. “Effective number of observations" refers to the number of observations within the MSE-optimal bandwidth. “Major states" include the large states in India-Andhra Pradesh, Assam, Bihar, Chhattisgarh, Gujarat, Haryana, Himachal Pradesh, Jammu & Kashmir, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, Uttarakhand, and West Bengal. “Above 5 %" and “Above 10 %" samples include constituencies whose forest cover in 2000 is at least as large as 5 % and 10 % of the average forest cover over all constituencies in 2000, respectively. “Within 3 SD" sample includes only constituencies whose forest cover in 2000 is within 3 standard deviations of the mean of the forest cover over all constituencies in 2000. "Within 5th & 95th Percentile" sample includes constituencies whose forest cover in 2000 is at least as large as the 5th percentile but no larger than the 95th percentile of the distribution of forest cover over all constituencies in 2000. "Within 1st & 99th Percentile" sample includes constituencies whose forest cover in 2000 is at least as large as the 1st percentile but no larger than the 99th percentile of the distribution of forest cover over all constituencies in 2000. The control means are the average annual forest cover growth rate for the constituencies within the optimal bandwidth and a male winner. The computation of RDD treatment effect coefficients, optimal bandwidths, and robust and bias corrected standard errors follow Cattaneo et al. (2019) and are implemented using “rdrobust" program in STATA.

politicians, indicating potential spillover effects beyond the constituency boundaries of female legislators. These results are presented in Appendix Tables A.6–A.9 along with associated discussion in Appendix B.6. Finally, we investigate the impact of female electoral victories in closely contested races on forest loss outcomes, utilizing the Global Forest Change dataset (Hansen et al., 2013). The results of this analysis are presented in Appendix Tables A.10 and A.11 along with suitable explanations in Appendix B.7.

5.2. Growth of forest cover over the electoral term

So far we have studied the impact of electing a female politician on subsequent annual forest cover growth. We now study whether the effects on forest cover growth build up over time during the course of one’s electoral cycle. In other words, we try to investigate whether the election of a female politician impacts the growth of forest cover over an entire electoral term. For this purpose, the dependent variable is computed as the logarithm of the forest cover in the last year of one’s electoral term net of the logarithm of the forest cover in the year immediately after one’s election to office.[33] The results of this analysis are reported in Table 5 here.

Panel A of Table 5 shows that constituencies where female politicians won against their male counterparts appear to have increased forest cover growth over their electoral term (although the effect is weakly significant at the 10 % level of significance) using the MSE optimal bandwidth. Interestingly, effects are seen across all constituencies but are driven by SC/ST reserved ones, as estimates for non-SC/ST constituencies remain insignificant. Notably, the point estimates of the treatment effect are found to be larger than their corresponding counterparts reported in Table 2 for yearly growth in forest cover (the weaker statistical significance here is likely because the number of observations are aggregated by electoral term for each constituency, resulting in a decline in sample

[33] We continue to exclude the year of election from the computation of the growth in forest cover on account of the reason outlined before in the “Empirical Strategy" section of the paper.

Table 5
Results: Growth of Forest Cover Over an Electoral Term.

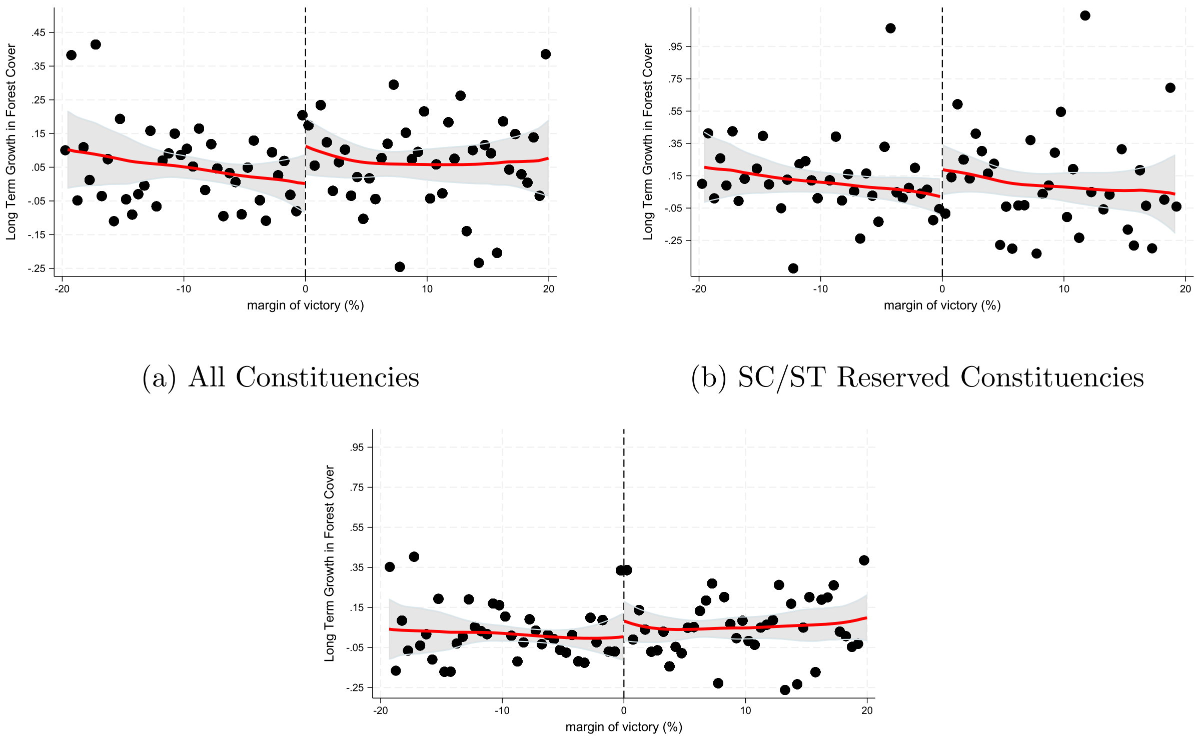
Panel A:	All Constituencies	SC/ST Reserved Constituencies	Non-SC/ST Constituencies
Female Legislator Elected in Last Election	0.12*	0.19*	0.09
	(0.07)	(0.12)	(0.09)
Optimal Bandwidth Type	MSE	MSE	MSE
Optimal Bandwidth	13.42	12.71	12.26
Control Means	0.03	0.07	0.01
Number of Observations	834	262	572
Effective Number of Observations	550	167	356
Kernel Type	Triangular	Triangular	Triangular
Panel B:	All Constituencies	SC/ST Reserved Constituencies	Non-SC/ST Constituencies
Female Legislator Elected in Last Election	0.13*	0.21*	0.09
	(0.08)	(0.12)	(0.10)
Optimal Bandwidth Type	CER	CER	CER
Optimal Bandwidth	9.64	9.67	8.97
Control Means	0.02	0.08	-0.01
Number of Observations	834	262	572
Effective Number of Observations	426	134	277
Kernel Type	Triangular	Triangular	Triangular

Note: The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). Robust and bias corrected standard errors clustered at the level of assembly constituencies are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % level of significance, respectively. RD estimates are from local linear regressions fitted with different slopes on either side of the cut-off. “Effective number of observations" refers to the number of observations within the MSE-optimal bandwidth and CER-optimal bandwidth, wherever applicable. The control means are the average forest cover growth rate over the electoral term for the constituencies within the optimal bandwidth with a male winner. The computation of RDD treatment effect coefficients, optimal bandwidths, and robust and bias corrected standard errors follow Cattaneo et al. (2019) and is implemented using “rdrobust" program in STATA.

size). The long-term effect on the forest cover growth rate is the aggregate result of annual growth rates. Specifically, the overall growth rate during the entire electoral term for the constituencies can be roughly approximated by adding up the year-to-year growth rates (although it is not exactly equal to the sum of the yearly growth rates reflecting plausible non-linearities in how growth may accumulate over time). Since the annual growth rate for SC/ST constituencies is higher than that for all constituencies, the cumulative impact over the full electoral term is driven by the SC/ST reserved constituencies and is therefore bigger for them (19 percentage points) than for all constituencies with mixed-gender close elections (12 percentage points). Additionally, even though reserved constituencies do not dominate the sample of all constituencies, the positive impact of a female legislator on forest cover growth over the electoral term in SC/ST reserved constituencies is plausibly large enough to drive the positive impacts found for all constituencies. Similar findings are also obtained when the CER-optimal bandwidth is used, as Panel B shows. Results using alternative bandwidths that are neither MSE nor CER optimal are reported for all constituencies, and specifically SC/ST reserved constituencies in Appendix Tables A.4 and A.5, respectively, with associated discussion in Appendix B.1. Fig. 2 provides a graphical representation of the findings of Panel A of Table 5 that use the MSE-optimal bandwidth for the sample of all constituencies in subfigure (a), SC/ST reserved constituencies in subfigure (b), and non-SC/ST constituencies in subfigure (c).

Table 6 repeats an exercise that is analogous to Table 3. Using the MSE-optimal bandwidth, we find that the positive effects of female legislators on forest cover growth are driven by constituencies that were sparsely forested at the start of the study period (Panel A). This finding is similar in spirit to what we have found in Table 3 on yearly growth outcome earlier. We also find that the magnitude of the treatment effect is high for the SC/ST reserved constituencies that were relatively sparsely forested in 2000, indicating that these constituencies are potentially contributing to the results obtained overall for all constituencies that are below the 75th percentile of the initial constituency level distribution of forest cover. However, unlike Table 3, the point estimate for SC/ST reserved constituencies in Panel A is not statistically significant (computed p-value of 0.11, indicating that it narrowly misses being statistically significant at conventional levels). This is likely contributed by the further reduction in the sample size when we conduct this heterogeneity analysis by initial density of forest cover.

Lastly, concerns regarding multiple testing often emerge when a dataset is partitioned into several subgroups or subsamples, followed by the execution of statistical tests on each segment. This can elevate the likelihood of incurring a Type-I error. However, in our paper, the division of the sample into SC/ST reserved and non-SC/ST categories is inherently logical. This is because it intuitively arises from the institutional context pertaining to the caste system and the mandated constitutional provision of reservation



(a) All Constituencies

(b) SC/ST Reserved Constituencies

(c) Non-SC/ST (Unreserved) Constituencies

Fig. 2. Growth in forest cover over an electoral term at the constituency level is the dependent variable. The running variable is the margin of victory of female politicians and is computed as the difference in vote shares of female and male politicians in mixed gender electoral races. Positive values indicate a female winner and negative a male winner, with 0 being the cut-off. The scatter plots are binned outcome means over each successive interval of 0.5 % of the margin of victory. Local linear regression lines using MSE-optimal bandwidth and triangular kernel have been plotted separately for either side of the cut-off along with the 95 % confidence interval. The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021).

for historically marginalized castes in India (as has been discussed in Section 2 before).[34] Moreover, the result that SC/ST female politicians are the primary drivers of our findings remains robust across alternative definitions of forest cover growth, a range of model specifications, and multiple sub-sample analyses. Therefore, concerns related to multiple testing arising from the division of the sample into SC/ST-reserved and non-SC/ST constituencies are unlikely to materially affect the validity of our analysis.

6. Discussion of potential mechanisms and limitations

6.1. Potential mechanisms

This paper finds that the gender of the legislator matters for environmental outcomes in India. In particular, electing a female legislator in close mixed-gender races positively affects the subsequent annual forest cover growth rate. However, this finding is found to be statistically significant for constituencies that have been reserved for the historically disadvantaged communities, the SCs and STs. In this regard, our results are similar in spirit to those of Clots-Figueras (2011). When we consider the growth of forest cover over a legislator's electoral term (or long-term growth), we find that electing a female legislator positively impacts this outcome overall for all constituencies, and additionally, this effect is found to be largely driven by the SC/ST reserved constituencies, indicating a consistency in the findings obtained for the yearly and long-term forest cover growth related outcomes. Further, as the long-term growth rates largely reflect the accumulation of yearly growth rates, the same underlying mechanism likely explains the evolution of both these outcomes in female-led constituencies.

We explore whether male and female politicians overall and especially in SC/ST reserved constituencies are different in terms of observed characteristics such as age, education, asset ownership, and criminality, as these characteristics could potentially influence

[34] In this context, see Munshi (2019) for a detailed literature survey on the influence of caste on Indian society and economic life. An important study that has specifically studied the implications of electing female politicians by their caste identities is Clots-Figueras (2011).

Table 6
Results: Long Run/Dynamic Growth of Forest Cover by Heterogeneity of Initial Forest Cover.

	All Constituencies	SC/ST Reserved Constituencies	Non-SC/ST Constituencies
Panel A: < 75th percentile			
Female Legislator Elected in Last Election	0.16*	0.23	0.10
	(0.09)	(0.14)	(0.11)
Optimal Bandwidth Type	MSE	MSE	MSE
Optimal Bandwidth	12.86	11.99	12.93
Control Means	0.04	0.12	0.002
Number of Observations	652	204	448
Effective Number of Observations	406	123	279
Kernel Type	Triangular	Triangular	Triangular
Panel B: ≥ 75th percentile			
Female Legislator Elected in Last Election	0.01	0.04	0.15
	(0.10)	(0.18)	(0.14)
Optimal Bandwidth Type	MSE	MSE	MSE
Optimal Bandwidth	12.86	9.69	7.56
Control Means	0.02	-0.0004	0.03
Number of Observations	182	58	124
Effective Number of Observations	131	34	57
Kernel Type	Triangular	Triangular	Triangular

Note: The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). The sample divisions of < and ≥ 75th percentile refer to whether the initial forest cover in the constituency given by the sample starting period, 2000 was lower than or at least as large as the 75th percentile of the distribution of the proportion of forest cover in the constituency in 2000. Robust and bias corrected standard errors clustered at the level of assembly constituencies are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % level of significance, respectively. RD estimates are from local linear regressions fitted with different slopes on either side of the cut-off. “Effective number of observations" refers to the number of observations within the MSE-optimal bandwidth. The control means are the average forest cover growth rate over the electoral term for the constituencies within the optimal bandwidth and a male winner. The computation of RDD treatment effect coefficients, optimal bandwidths, and robust and bias corrected standard errors follow Cattaneo et al. (2019) and is implemented using “rdrobust" program in STATA.

the decision to invest in activities such as environmental conservation.[35] However, especially for SC/ST reserved constituencies, we do not find systematic differences in these observable characteristics between female and male politicians (see Appendix Fig. A.3). Further, age is the only covariate showing a significant gender difference, with female politicians being younger than their male counterparts when we consider the sample of all constituencies. It is likely that, in our context, it is not the difference in these observable characteristics between the elected politicians that is influencing our findings (with the possible exception of age for the overall sample of constituencies).

This brings us to the question about why we might expect women legislators to be more likely to invest in the preservation and growth of forest resources in their constituencies. Unfortunately, our data is unable to provide additional resources to explicitly test for potential mechanisms for our results. Instead, we discuss what could be the potential explanations of our findings by relying on the existing literature.

There are two ways we can conceptualize the potential mechanisms influencing our findings. One way is understanding differences in preferences between female and male legislators with regard to environmental protection, and another avenue is to understand the extent to which constraints affect policy choices made by female and male legislators. For example, if women are likely to be

[35] See, for example, Dahis et al. (2023) for the impact of young politicians on environmental conservation and Johannesson and Ågren (2022) for the impact of criminal politicians on deforestation. Baragwanath and Zheng (2023) find a positive impact of electing women mayors on deforestation in Brazil and demonstrate that lower corruption and a lower likelihood of having connections/receiving campaign donations from agriculture or industrial sectors (that encourage deforestation) for female mayors as the potential explanations of their results. Unfortunately, such detailed information on politician's connections and campaign finance sources are unavailable for India. But Vaishnav (2011) has also demonstrated that SC/ST reserved constituencies are less likely to have criminal candidates running for office. Additionally, if we assume that criminality is positively correlated with being corrupt, then differences in corruption levels between female and male politicians in SC/ST reserved constituencies cannot explain our findings. Hence, a politician's nexus with vested interest groups and subsequent corruption is unlikely to explain why female candidates in SC/ST reserved constituencies are effective in promoting forest cover growth unlike their male counterparts.

disproportionately impacted by climate change related adverse events, then female politicians are more likely to invest in climate protection in the spirit of Chattopadhyay and Duflo (2004). Additionally, there could be an intersection of these two issues.

Plausible behavioral/preference differences between men and women have been explored in numerous studies. The existing literature has demonstrated that women are more likely to be patient and risk averse in some contexts (Bauer and Chytilová (2013); Croson and Gneezy (2009)). Since environmental conservation mediated through growth in forest cover is likely to yield benefits only in the future and forest conservation can play a crucial role in combating the risks associated with climate change, potential differences between women and men in terms of these preferences and behaviors could be a plausible channel explaining our main result. Additionally, there is some evidence that women are likely to be more altruistic than men, especially if giving is relatively costly (Andreoni and Vesterlund, 2001). We can imagine that conserving the environment to protect against climate related disasters in the future represents an intergenerational transfer, which is likely to be governed by altruistic behavior. It is possible that if investing in forest conservation is perceived as relatively costly, then our results can also be explained by differences in altruism between male and female legislators.[36] Empirically, there is also some support that women are more inclined to protect the environment relative to men. For example, Funk and Gathmann (2015) show that women, in general, favor greater public spending for environmental protection. Specifically in the context of India, a recent wave of the World Values Survey (WVS, 2022) asked respondents whether they agree that environmental protection should be prioritized even if it may result in lower economic growth. Around 61 % of women in the sample agreed with the statement, while 55 % of men did (where the sample comprised 958 men and 734 women). Although these responses pertain to citizens, such preferences are likely to be translated to the preferences of politicians themselves in the framework of the citizen-candidate model of Besley and Coate (1997).

If these channels are indeed important in explaining our main result, it is important to note that these potential behavioral differences are not homogeneous across all women. They appear to be more salient for women from historically disadvantaged communities such as the SC/STs. A potential reason behind this could be the different constraints that SC/STs, and particularly women among SC/ST groups, might face on account of coping with climate change related adversities. There is some evidence from the social science literature outside economics documenting greater vulnerability of these communities to climate change on account of limited adaptation strategies available to them (Venus et al., 2022; George and Sharma, 2023; Bishwakarma and Roongtawanreongsri, 2024). This might explain why women politicians from historically disadvantaged communities such as the SC/ST are more likely to invest in forest conservation in their constituencies relative to their male counterparts. Additionally, it is found that risk aversion is negatively associated with wealth; however, it declines more slowly for women than for men with the same increase in wealth levels (Jianakoplos and Bernasek, 1998). Since individuals belonging to SC/ST communities often possess limited resources or endowments, female legislators from these communities may perceive risks associated with climate change as reasonably large, thereby providing a potential explanation of our finding.[37]

Previous studies have shown that political representation of historically disadvantaged communities such as the SC/ST combined with special legal provisions such as the PESA and FRA have been instrumental in improving forest cover (Gulzar et al., 2024). However, a recent study by Agarwal et al. (2023) investigates the efficacy of forest conservation on account of reservation of historically marginalized communities by levels of government and finds that relative to reservation at the local *Gram Panchayat*/village council level, reservation at the assembly constituency levels yields the greatest positive impact on environmental conservation. This provides some suggestive evidence that political representation of marginalized communities such as the SC/ST, especially at the assembly constituency level, is likely to result in significant positive impact on forest cover growth.[38] But, unlike our paper, these studies do not analyze whether the overall effectiveness of forest conservation is largely driven by female politicians in these constituencies. Political representation of marginalized communities through reservations and extension of control of local forests to these communities, along with a potentially greater preference of women in conserving the environment, are plausible mechanisms explaining our findings on why we observe increases in forest cover following the election of a female legislator, especially in reserved constituencies.

Finally, we attempt to investigate whether differences in legislator age could also play some role in explaining our findings on the impacts of legislator gender on forest cover growth over the legislator's electoral term for all constituencies. This is in the spirit of Dahis et al. (2023) who find that younger politicians elected in mayoral races in Brazil reduce deforestation rates. Although the minimum age for being elected to state legislatures in India is 25 years, most MLAs are significantly older.[39] For our purpose, we use the age cutoff of 60 years and, alternatively, 63 years to demarcate between old and young MLAs.[40] We report the results in the Appendix Table A.12. We find that our results on the long-term impacts of female legislators in all constituencies on forest cover growth over the electoral term are driven by “relatively" younger female MLAs using these alternative age thresholds.

[36] This is additionally supported by Lades et al. (2021) who find that altruism, in general, influences pro-environment behavior and Cason et al. (2022) also show that women are more likely to make choices/decisions that are “kinder" to external parties.

[37] This plausible explanation differs from Baragwanath and Zheng (2023) who reject preference differences between female and male politicians as an explanation of why female politicians are more likely to reduce deforestation.

[38] Additionally, Kodiveri (2021) discusses how much of the discourse surrounding environmental legislation takes into account largely the STs, despite the SCs facing similar disadvantages in accessing and preserving natural resources.

[39] See, for example, the following media reports on different state legislatures from the recent past: Telengana state legislature profile (accessed on February 7, 2024); Rajasthan, Chhattisgarh, Telengana, Madhya Pradesh state legislature profiles (accessed on February 7, 2024); Age profile of politicians across all levels of government (accessed on February 7, 2024)

[40] These choices of these age cutoffs largely ensure that similar numbers of observations are available on either side of these age cutoffs while also being largely representative of the age profile of the MLAs.

6.2. Limitations

In the Appendix, we conduct several robustness checks to validate our RDD estimates. These include the McCrary density test, the test for covariate continuity around the cut-off, the donut hole test, and tests using placebo cut-offs (see Appendix Figs. A.1–A.8 and the associated explanations in Appendix B.2–B.5). However, a recent study by Marshall (2024) highlights additional caveats associated with the estimation of RDDs using politician characteristics. Marshall (2024) illustrates that when assessing the influence of a specific politician trait, we end up frequently evaluating the effect of a combination of characteristics.

Specifically in the context of this paper, we estimate the effect of female politicians on the growth rate of constituency level forest cover by exploiting closely contested elections. Identifying gender as a distinct treatment poses conceptual challenges because it often encompasses a bundle of correlated attributes. Women who narrowly win elections may differ from their male counterparts in unobserved ways, such as personality, qualifications, or policy preferences, which may not be separable from gender itself. To estimate the causal effect of electing women, researchers must clearly define which attributes constitute the treatment (here, gender) and which are potential confounders. This requires disentangling gender from other correlated characteristics that may independently influence outcomes. However, identifying potential confounders and isolating their effects from those of gender is particularly challenging, as many of these confounders are unobserved, precluding the use of standard continuity assessment methods. Following Marshall (2024), we can assume “competence" as a potential confounder. The question is whether it is reasonable to assume that men and women who narrowly win elections are equally competent. If voters exhibit a preference for men due to stereotypes, media dynamics, or elite support, then male candidates benefit from an electoral advantage unrelated to competence. As a result, men in close races must, on average, be less competent than the women they compete against. This implies that among narrowly elected candidates, competence is not equal across genders, undermining the assumption of parity at the margin. So competency may be correlated with gender and also likely determines the outcomes of close elections. This can then bias the estimated treatment effect. Therefore, the validity of the RDD estimates identifying the causal effect of gender depends strongly on the specific context and the composition of observations near the threshold. While our estimation strategy provides internally consistent estimates of the causal effect of women politicians on forest conservation, these results may not generalize to other contexts where the pool or composition of women candidates or elected politicians differs. Consequently, increasing the number of female politicians in other settings may not necessarily produce the same findings as those obtained in this study. In line with the argument by Marshall (2024), we therefore advise and practice caution when extrapolating our findings to different contexts.

7. Conclusion

We study the impact of electing female legislators in state assembly elections in India on subsequent growth of forest cover in their constituencies. It is well understood that simply comparing constituencies that elected a male to those that elected a female politician would not capture the causal effect of legislator gender on our outcome of interest on account of potential unobserved differences between these constituencies. As a close election between a male and female politician is likely to be quasi-random, we exploit this variation and compare constituencies where a female politician won to those where a male politician won in a close mixed gender race in the framework of a sharp RDD. We find that the victory of a female politician in a close race against a male politician causes an increase in constituency-level subsequent annual forest cover growth by around 6 percentage points. However, this finding is limited only to the constituencies that are reserved for candidates from the historically disadvantaged communities, the SC/STs. Our results appear to survive a number of different robustness exercises used to assess the credibility of the RDD, which likely further bolsters our confidence in our findings. We also investigate whether impacts on forest cover growth build up over a legislator’s term in office, even if there are no immediate subsequent impacts on environmental conservation. Here we find that forest cover growth increases by around 12 percentage points in all constituencies with a female legislator over their term in office. We find that over the entire electoral term, the impact observed for all constituencies is mainly driven by SC/ST-reserved constituencies. Over the course of the electoral term, the impact roughly reflects the accumulated annual gains observed in constituencies with female legislators.

We explain our findings through behavioral/preference differences (such as those of patience, risk aversion, and altruism) between men and women, as well as possibly greater awareness about constraints such as the vulnerability of the SC/STs to the adverse impacts of climate change. These are the potential channels that could explain why female SC/ST legislators are more likely to invest in forest cover growth after being elected to office. Finally, we also find that the impact on forest cover growth over an electoral term is also influenced by the younger female politicians. This is consistent with our observation that age is the only covariate exhibiting a significant difference between female and male politicians overall for all constituencies, with female politicians being younger on average.

Our results show that the gender of politicians impacts environmental conservation, but the role of caste identity is also salient. As climate change is one of the most important challenges facing humankind and conservation of forest resources is widely understood as one of the strategies to combat it, the role of legislator identity in influencing environmental conservation policies cannot be ignored.

Data availability

Data will be made available on request.

Declaration of competing interest

This study received funding from Ashoka University's Centre for Climate Change and Sustainability (3CS) and Indian Institute of Management, Indore. There are no known conflicts of interest with any individual or organization. IRB approval is not applicable as the study uses publicly available secondary data.

Appendices

Appendix A. Tables & Figures

Table A.1
Occurrence of Mixed Gender Elections.

Mixed Gender Constituencies	All Constituencies	SC/ST Reserved Constituencies
Panel A: All Years		
Percentage	8.78 %	9.84 %
Total No. of Observations	29,172	7427
Panel B: From 1996 Onwards		
Percentage	11.98 %	15.04 %
Total No. of Observations	9893	2506

Note: The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021).Total no. of observations refer to the total number of assembly constituency-election year combinations in the dataset. Mixed gender constituencies refer to those where the winner and the runner-up are of opposite genders.

Table A.2
Descriptive Statistics: Additional Sample Restrictions.

All Constituencies				Mixed Gender Constituencies		
Variable	Mean	Standard Deviation	Observations	Mean	Standard	Observations Deviation
Panel A:						
Log of Electorate Size in $t-1$	11.71	0.77	9789	11.83	0.56	1173
Log of Valid Votes in $t-1$	11.27	0.73	9739	11.36	0.65	1173
Number of Candidates in $t-1$	10.35	7.42	9790	10.03	7.07	1174
Turnout Percentage in $t-1$	64.95	12.88	9789	64.36	11.41	1173
Female Legislator in $t-1$	0.05	0.23	9790	0.26	0.44	1174
Winner's Party Aligned with State Ruling Party in $t-1$	0.54	0.50	9790	0.59	0.49	1174
Winner is Incumbent in t	0.19	0.39	9790	0.17	0.38	1174
Winner is from Congress in t	0.28	0.45	9942	0.28	0.45	1185
Winner is from BJP in t	0.20	0.40	9942	0.19	0.39	1185
SC Reserved Constituency	0.14	0.35	9790	0.21	0.41	1174
ST Reserved Constituency	0.11	0.32	9790	0.11	0.31	1174
Panel B: SC/ST Constituencies						
Log of Electorate Size in $t-1$	11.38	1.06	2530	11.74	0.66	373
Log of Valid Votes in $t-1$	10.96	0.94	2483	11.26	0.65	372
Number of Candidates in $t-1$	7.35	4.62	2530	7.74	4.32	373
Turnout Percentage in $t-1$	64.14	16.31	2530	62.47	11.68	373
Female Legislator in $t-1$	0.06	0.25	2530	0.26	0.44	373
Winner's Party Aligned with State Ruling Party in $t-1$	0.58	0.49	2530	0.63	0.48	373
Winner is Incumbent in t	0.20	0.40	2530	0.14	0.34	373
Winner is from Congress in t	0.29	0.45	2551	0.23	0.42	377
Winner is from BJP in t	0.20	0.40	2551	0.21	0.41	377

Note: Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). Mixed gender constituencies refer to those where the winner and the runner up are of opposite genders. Data corresponds to election years available from 1996 - 2007, that correspond to the relevant period of elections in our analysis.

Table A.3
Annual Growth - SC/ST Constituencies: Alternative Bandwidths by Reducing Bandwidth Size and Bias.

Panel A:	(1)	(2)	(3)	(4)	(5)
Female Legislator Elected in Last Election	0.06**	0.06**	0.06**	0.06**	0.06*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Bandwidth Type	MSE-Optimal	Manual	Manual	Manual	Manual
Bandwidth Size	13.74	12.00	11.00	10.00	9.00
Bandwidth Bias	23.11	21.47	19.68	17.89	16.10
Bandwidth Size to Bias Ratio	0.559	0.559	0.559	0.559	0.559
Number of Observations	1205	1205	1205	1205	1205
Effective Number of Observations	796	735	702	611	559
Kernel Type	Triangular	Triangular	Triangular	Triangular	Triangular
Panel B:	(6)	(7)	(8)	(9)	
Female Legislator Elected in Last Election	0.06*	0.05	0.04	0.03	
	(0.03)	(0.04)	(0.04)	(0.04)	
Bandwidth Type	Manual	Manual	Manual	Manual	
Bandwidth Size	8.00	7.00	6.00	5.00	
Bandwidth Bias	14.31	12.52	10.73	8.94	
Bandwidth Size to Bias Ratio	0.559	0.559	0.559	0.559	
Number of Observations	1205	1205	1205	1205	
Effective Number of Observations	509	459	412	335	
Kernel Type	Triangular	Triangular	Triangular	Triangular	

Note: The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). Robust and bias corrected standard errors clustered at the level of assembly constituencies are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels of significance, respectively. RD estimates are from local linear regressions fitted with different slopes on either side of the cut-off. “Effective number of observations" refers to the number of observations within the MSE-optimal bandwidth or other manually chosen bandwidths. The computation of RDD treatment effect coefficients, optimal bandwidths, and robust and bias corrected standard errors follow Cattaneo et al. (2019) and are implemented using “rdrobust" program in STATA. Column (1) represents the estimated effect using the MSE optimal bandwidth and is the same as Column (2) in Panel A of Table 2. Bandwidths chosen manually are such that they preserve the ratio of bandwidth size to bias from the MSE-optimal bandwidth algorithm.

Table A.4
Dynamic Effects- All Constituencies: Alternative Bandwidths by Reducing Bandwidth Size and Bias.

Panel A:	(1)	(2)	(3)	(4)	(5)
Female Legislator Elected in Last Election	0.12*	0.13*	0.13*	0.14*	0.14*
	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)
Bandwidth Type	MSE-Optimal	Manual	Manual	Manual	Manual
Bandwidth Size	13.42	12.00	11.00	10.00	9.00
Bandwidth Bias	22.94	20.51	18.80	17.09	15.38
Bandwidth Size to Bias Ratio	0.585	0.585	0.585	0.585	0.585
Number of Observations	834	834	834	834	834
Effective Number of Observations	550	512	481	435	403
Kernel Type	Triangular	Triangular	Triangular	Triangular	Triangular
Panel B:	(6)	(7)	(8)	(9)	
Female Legislator Elected in Last Election	0.13	0.15	0.16	0.17	
	(0.09)	(0.10)	(0.11)	(0.12)	
Bandwidth Type	Manual	Manual	Manual	Manual	
Bandwidth Size	8.00	7.00	6.00	5.00	
Bandwidth Bias	13.68	11.96	10.26	8.55	
Bandwidth Size to Bias Ratio	0.585	0.585	0.585	0.585	
Number of Observations	834	834	834	834	
Effective Number of Observations	372	342	302	252	
Kernel Type	Triangular	Triangular	Triangular	Triangular	

Note: The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). Robust and bias corrected standard errors clustered at the level of assembly constituencies are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % level of significance, respectively. RD estimates are from local linear regressions fitted with different slopes on either sides of the cut-off. “Effective number of observations" refers to number of observations within the MSE-optimal bandwidth or other manually chosen bandwidths. The computation of RDD treatment effect coefficients, optimal bandwidths, robust and bias corrected standard errors follow Cattaneo et al. (2019) and are implemented using “rdrobust" program in STATA. Column (1) represents the estimated effect using the MSE optimal bandwidth and is the same as Column (1) in Panel A of Table 5. Bandwidths chosen manually are such that they preserve the ratio of bandwidth size to bias from the MSE-optimal bandwidth algorithm.

Table A.5
Dynamic Effects- SC/ST Constituencies: Alternative Bandwidths by Reducing Bandwidth Size and Bias.

Panel A:	(1)	(2)	(3)	(4)	(5)
Female Legislator Elected in Last Election	0.19*	0.19*	0.20*	0.22*	0.23*
	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)
Bandwidth Type	MSE-Optimal	Manual	Manual	Manual	Manual
Bandwidth Size	12.71	12.00	11.00	10.00	9.00
Bandwidth Bias	21.57	20.37	18.68	16.98	15.28
Bandwidth Size to Bias Ratio	0.589	0.589	0.589	0.589	0.589
Number of Observations	262	262	262	262	262
Effective Number of Observations	167	162	155	136	126
Kernel Type	Triangular	Triangular	Triangular	Triangular	Triangular
Panel B:	(6)	(7)	(8)	(9)	
Female Legislator Elected in Last Election	0.22	0.21	0.18	0.15	
	(0.14)	(0.15)	(0.16)	(0.17)	
Bandwidth Type	Manual	Manual	Manual	Manual	
Bandwidth Size	8.00	7.00	6.00	5.00	
Bandwidth Bias	13.58	11.88	10.19	8.49	
Bandwidth Size to Bias Ratio	0.589	0.589	0.589	0.589	
Number of Observations	262	262	262	262	
Effective Number of Observations	115	103	92	74	
Kernel Type	Triangular	Triangular	Triangular	Triangular	

Note: The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). Robust and bias corrected standard errors clustered at the level of assembly constituencies are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % level of significance, respectively. RD estimates are from local linear regressions fitted with different slopes on either sides of the cut-off. “Effective number of observations" refers to number of observations within the MSE-optimal bandwidth or other manually chosen bandwidths. The computation of RDD treatment effect coefficients, optimal bandwidths, robust and bias corrected standard errors follow Cattaneo et al. (2019) and are implemented using “rdrobust" program in STATA. Column (1) represents the estimated effect using the MSE optimal bandwidth and is the same as Column (2) in Panel A of Table 5. Bandwidths chosen manually are such that they preserve the ratio of bandwidth size to bias from the MSE-optimal bandwidth algorithm.

Table A.6
Spillover Effects - Yearly Forest Cover Growth Rate (Fuzzy RDD Estimation).

First Stage Estimates:	All Constituencies	SC/ST Reserved Constituencies	Non-SC/ST Constituencies
Female Legislator Elected in Last Election	0.009*	0.048**	0.012**
	(0.005)	(0.022)	(0.006)
Optimal Bandwidth Type	MSE	MSE	MSE
Optimal Bandwidth	11.55	11.43	13.39
Number of Observations	3792	1205	2587
Effective Number of Observations	2234	720	1679
Kernel Type	Triangular	Triangular	Triangular
Treatment Effect Estimates:			
Proportion of Female Winner in a State	0.03	0.01	0.002
	(0.03)	(0.008)	(0.023)

Note: The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). The computation of fuzzy RDD treatment effect coefficients, optimal bandwidths, robust and bias corrected standard errors follow Cattaneo et al. (2024) and are implemented using "rdrobust" program in STATA. The estimation is done in two stages. The outcome variable in the first stage is the proportion of female winners in a state and the running variable is the margin of victory at the constituency level. The first stage estimate examines whether the constituencies with female winning candidates in close elections have a significantly higher proportion of female winners in the states to which they belong. In the second stage, the treatment effect is estimated using the state-level proportion of female winners, instrumented by the proportion of female winners in closely contested elections within the state. The outcome variable in the second stage is the yearly growth rate of forest cover. The robust and bias corrected standard errors clustered at the level of assembly constituencies are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % level of significance, respectively. The "rdrobust" program computes a single MSE optimal bandwidth for both the first and second stages of the estimation.

Table A.7
Spillover Effects - Growth Rate of Forest Cover Over the Electoral Term (Fuzzy RDD Estimation).

First Stage Estimates:	All Constituencies	SC/ST Reserved Constituencies	Non-SC/ST Constituencies
Female Legislator Elected in Last Election	0.008	0.06***	0.01*
	(0.005)	(0.02)	(0.006)
Optimal Bandwidth Type	MSE	MSE	MSE
Optimal Bandwidth	13.451	11.735	15.141
Number of Observations	834	262	572
Effective Number of Observations	551	161	409
Kernel Type	Triangular	Triangular	Triangular
Treatment Effect Estimates:			
Proportion of Female Winner in a State	0.15	0.03*	0.07
	(0.12)	(0.02)	(0.11)

Note: The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). The computation of fuzzy RDD treatment effect coefficients, optimal bandwidths, and robust and bias corrected standard errors follow Cattaneo et al. (2024) and are implemented using "rdrobust" program in STATA. The estimation is done in two stages. The outcome variable in the first stage is the proportion of female winners in a state, and the running variable is the margin of victory at the constituency level. The first stage estimate examines whether the constituencies with female winning candidates in close elections have a significantly higher proportion of female winners in the states to which they belong. In the second stage, the treatment effect is estimated using the state-level proportion of female winners, instrumented by the proportion of female winners in closely contested elections within the state. The outcome variable in the second stage is the growth rate of forest cover over the electoral term. The robust and bias corrected standard errors clustered at the level of assembly constituencies are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels of significance, respectively. The "rdrobust" program computes a single MSE optimal bandwidth for both the first and second stages of the estimation.

Table A.8
Spillover Effects - State Average of Yearly Forest Cover Growth Rate (Fuzzy RDD Estimation).

First Stage Estimates:	All Constituencies	SC/ST Reserved Constituencies	Non-SC/ST Constituencies
Female Legislator Elected in Last Election	0.008 (0.005)	0.048** (0.022)	0.01* (0.006)
Optimal Bandwidth Type	MSE	MSE	MSE
Optimal Bandwidth	11.491	12.401	12.745
Number of Observations	3792	1205	2587
Effective Number of Observations	2230	759	1626
Kernel Type	Triangular	Triangular	Triangular
Treatment Effect Estimates:			
Proportion of Female Winner in a State	0.003 (0.013)	0.003 (0.004)	-0.001 (0.001)

Note: The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). The computation of fuzzy RDD treatment effect coefficients, optimal bandwidths, robust and bias corrected standard errors follow Cattaneo et al. (2024) and are implemented using “rdrobust" program in STATA. The estimation is done in two stages. The outcome variable in the first stage is the proportion of female winners in a state and the running variable is the margin of victory at the constituency level. The first stage estimate examines whether the constituencies with female winning candidates in close elections have a significantly higher proportion of female winners in the states to which they belong. In the second stage, the treatment effect is estimated using the state-level proportion of female winners, instrumented by the proportion of female winners in closely contested elections within the state. The outcome variable in the second stage is the average of the yearly growth rate of forest cover in a state. The robust and bias corrected standard errors clustered at the level of assembly constituencies are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % level of significance, respectively. The “rdrobust" program computes a single MSE optimal bandwidth for both the first and second stages of the estimation.

Table A.9
Spillover Effects - State Average Growth Rate of Forest Cover Over the Electoral Term (Fuzzy RDD Estimation).

First Stage Estimates:	All Constituencies	SC/ST Reserved Constituencies	Non-SC/ST Constituencies
Female Legislator Elected in Last Election	0.008 (0.005)	0.06*** (0.02)	0.01* (0.006)
Optimal Bandwidth Type	MSE	MSE	MSE
Optimal Bandwidth	13.112	12.875	14.652
Number of Observations	834	262	572
Effective Number of Observations	543	170	396
Kernel Type	Triangular	Triangular	Triangular
Treatment Effect Estimates:			
Proportion of Female Winner in a State	0.08 (0.08)	0.02 (0.01)	0.03 (0.07)

Note: Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). The computation of fuzzy RDD treatment effect coefficients, optimal bandwidths, and robust and bias corrected standard errors follow Cattaneo et al. (2024) and are implemented using “rdrobust" program in STATA. The estimation is done in two stages. The outcome variable in the first stage is the proportion of female winners in a state, and the running variable is the margin of victory at the constituency level. The first stage estimate examines whether the constituencies with female winning candidates in close elections have a significantly higher proportion of female winners in the states to which they belong. In the second stage, the treatment effect is estimated using the state-level proportion of female winners, instrumented by the proportion of female winners in closely contested elections within the state. The outcome variable in the second stage is the state-level average growth rate of forest cover over the electoral term. The robust and bias corrected standard errors clustered at the level of assembly constituencies are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % levels of significance, respectively. The “rdrobust" program computes a single MSE optimal bandwidth for both the first and second stages of the estimation.

Table A.10
Results: Loss of Forest Cover Over The Electoral Term.

	All Constituencies	SC/ST Reserved Constituencies	Non-SC/ST Constituencies
Female Legislator Elected in Last Election	-0.32 (0.3)	-0.82 (0.92)	-0.22 (0.16)
Optimal Bandwidth Type	MSE	MSE	MSE
Optimal Bandwidth	11.856	11.310	12.883
Control Means	0.39	0.87	0.18
Number of Observations	1176	374	802
Effective Number of Observations	679	207	502
Kernel Type	Triangular	Triangular	Triangular

Note: The data sources are the Global Forest Change(GFC) Dataset (Hansen et al., 2013) and The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). The outcome variable is the gross forest loss over the electoral term measured in square kilometers. Robust and bias-corrected standard errors clustered at the level of assembly constituencies are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % level of significance respectively. RD estimates are from local linear regressions fitted with different slopes on either sides of the cut-off. “Effective number of observations" refers to number of observations within the MSE-optimal bandwidth. The control means are the average loss of forest cover over the electoral term for the constituencies within the optimal bandwidth and a male winner. The computation of RDD treatment effect coefficients, optimal bandwidths, robust and bias corrected standard errors follow Cattaneo et al. (2019) and are implemented using“rdrobust" program in STATA.

Table A.11
Results: Loss of Forest Cover Over The Entire Study Period.

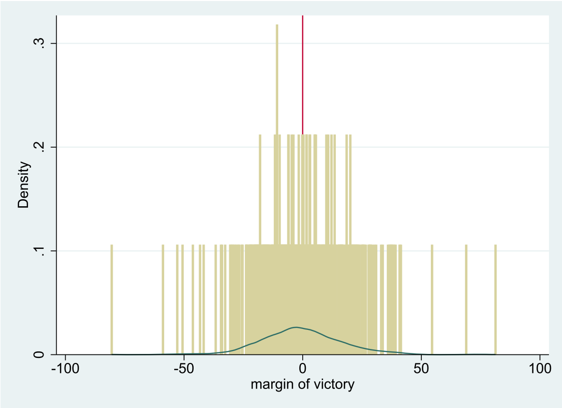
	All Constituencies	SC/ST Reserved Constituencies	Non-SC/ST Constituencies
Female Legislator Elected in Last Election	-0.88 (0.98)	-4.003 (3.64)	-0.16 (0.31)
Optimal Bandwidth Type	MSE	MSE	MSE
Optimal Bandwidth	14.897	11.694	15.883
Control Means	1.61	4.01	0.73
Number of Observations	2253	730	1823
Effective Number of Observations	1544	371	1136
Kernel Type	Triangular	Triangular	Triangular

Note: Data sources are the Global Forest Change(GFC) Dataset (Hansen et al., 2013) and The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). The outcome variable is the gross forest loss measured in square kilometers over the entire study period i.e., 2000–2013. Robust and bias corrected standard errors clustered at the level of assembly constituencies are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 % and 10 % level of significance, respectively. RD estimates are from local linear regressions fitted with different slopes on either sides of the cut-off. “Effective number of observations" refers to the number of observations within the MSE-optimal bandwidth. The control means are the average loss of forest cover over the entire study period for the constituencies within the optimal bandwidth and a male winner. The computation of RDD treatment effect coefficients, optimal bandwidths, robust and bias corrected standard errors follow Cattaneo et al. (2019) and are implemented using“rdrobust" program in STATA.

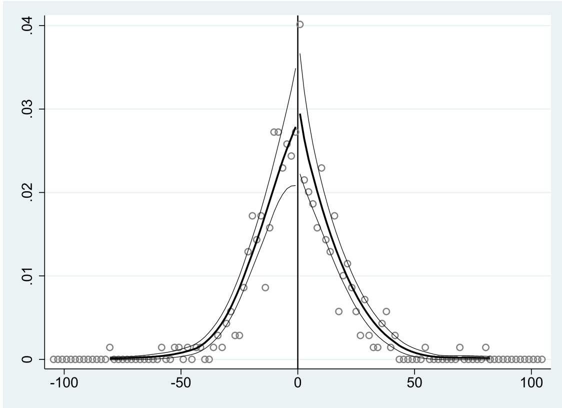
Table A.12
Growth of Forest Cover Over an Electoral Term by Legislator Age for All Constituencies.

Panel A:	< 60 years	≥ 60 years	< 63 years	≥ 63 years
Female Legislator Elected in Last Election	0.28**	0.04	0.28**	0.002
	(0.12)	(0.08)	(0.12)	(0.09)
Optimal Bandwidth Type	MSE	MSE	MSE	MSE
Optimal Bandwidth	10.03	12.69	9.65	11.12
Control Means	-0.02	0.07	-0.01	0.07
Number of Observations	383	454	410	427
Effective Number of Observations	220	272	230	231
Kernel Type	Triangular	Triangular	Triangular	Triangular
Panel B:	< 60 years	≥ 60 years	< 63 years	≥ 63 years
Female Legislator Elected in Last Election	0.31**	0.02	0.30**	-0.02
	(0.13)	(0.09)	(0.13)	(0.09)
Optimal Bandwidth Type	CER	CER	CER	CER
Optimal Bandwidth	7.45	9.36	7.14	8.22
Control Means	-0.04	0.07	-0.04	0.06
Number of Observations	383	454	410	427
Effective Number of Observations	185	208	191	175
Kernel Type	Triangular	Triangular	Triangular	Triangular

Note: The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). Robust and bias corrected standard errors clustered at the level of assembly constituencies are reported in parentheses. ***, **, * indicate statistical significance at the 1 %, 5 % and 10 % level of significance respectively. RD estimates are from local linear regressions fitted with different slopes on either sides of the cut-off. “Effective number of observations" refers to number of observations within the MSE-optimal bandwidth in Panel A and CER-optimal bandwidth in Panel B. The control means are the average forest cover growth rate over the electoral term for the constituencies within the optimal bandwidth with a male winner. The computation of RDD treatment effect coefficients, optimal bandwidths, robust and bias corrected standard errors follow Cattaneo et al. (2019) and are implemented using “rdrobust" program in STATA.

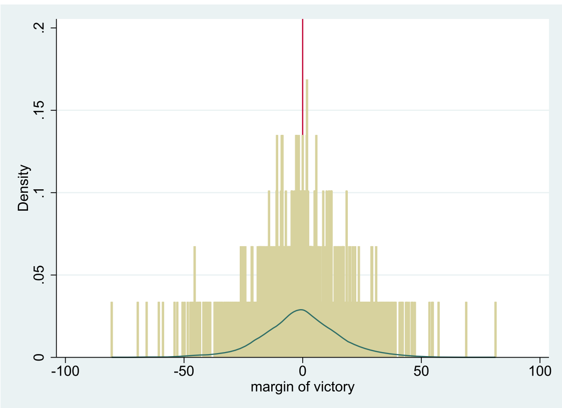


(a) Histogram

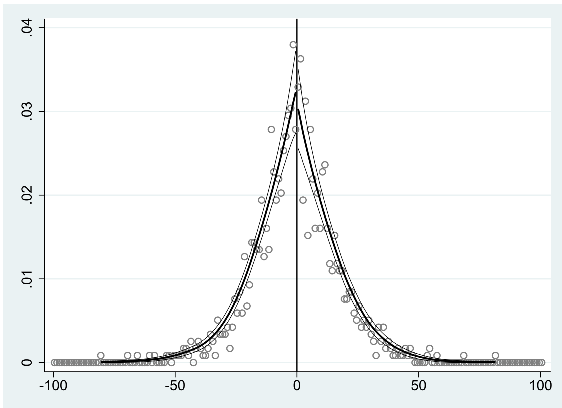


(b) Corresponding McCrary density test

Fig. A.1. McCrary density test for SC/ST reserved constituencies for election years 1996 and beyond. Subfigure (a) depicts the histogram of the distribution of the margin of victory in mixed gender elections. For Subfigure (b), estimated log difference in height: 0.078, standard error: 0.193.

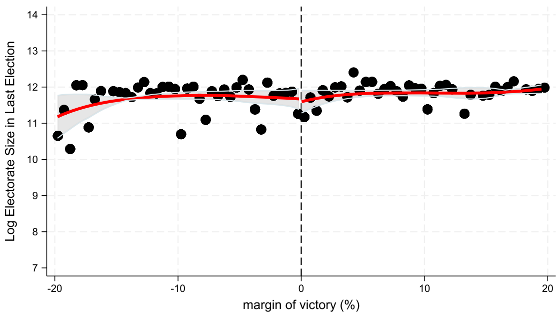


(a) Histogram

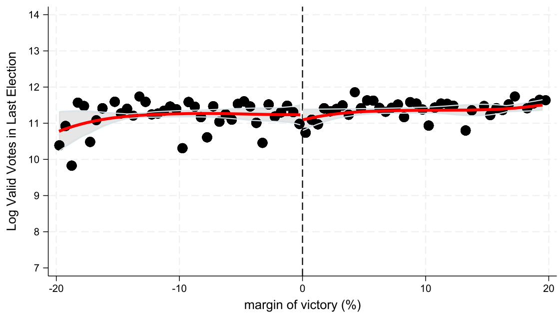


(b) Corresponding McCrary density test

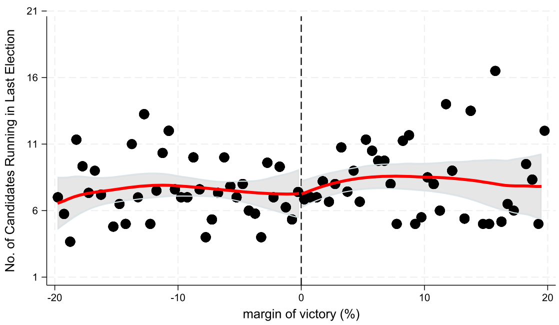
Fig. A.2. McCrary density test for all constituencies for election years 1996 and beyond. Subfigure (a) depicts the histogram of the distribution of the margin of victory in mixed gender elections. For Subfigure (b), estimated log difference in height: −0.062, standard error: 0.117.



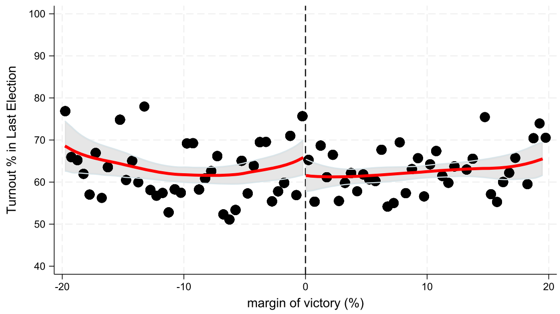
(a) Log Electorate Size in $t-1$



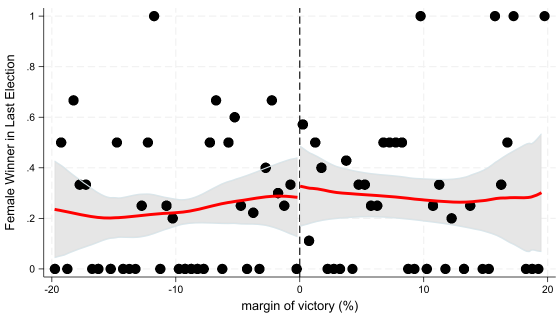
(b) Log Valid Votes in $t-1$



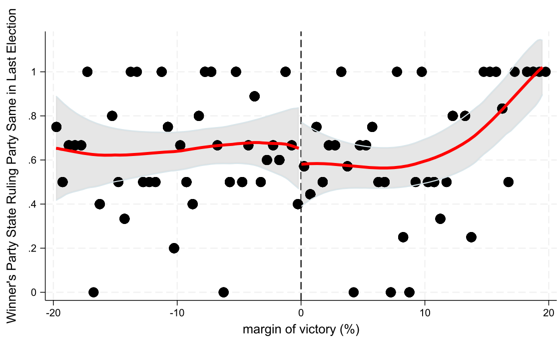
(c) Number of Candidates in $t-1$



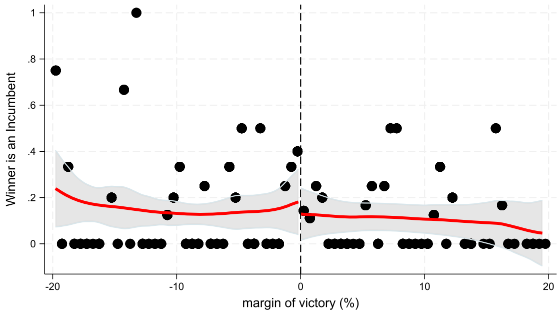
(d) Turnout Percentage in $t-1$



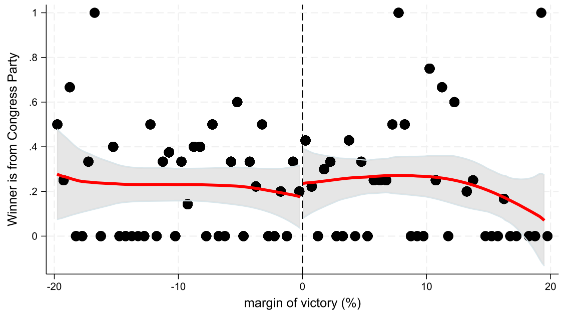
(e) Female Legislator in $t-1$



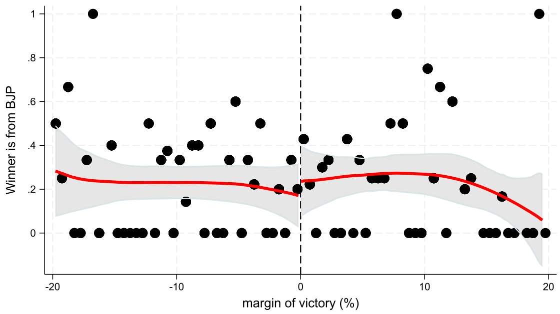
(f) Winner's party aligned with State Ruling Party in $t-1$



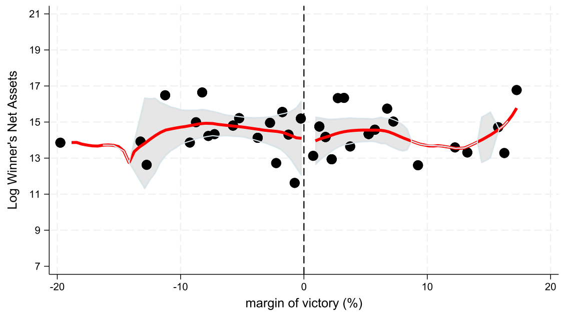
(g) Winner is the incumbent in t



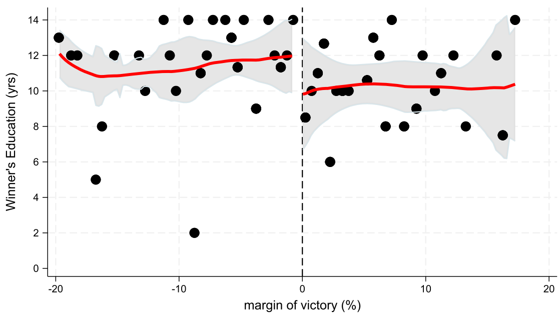
(h) Winner is from Congress Party in t



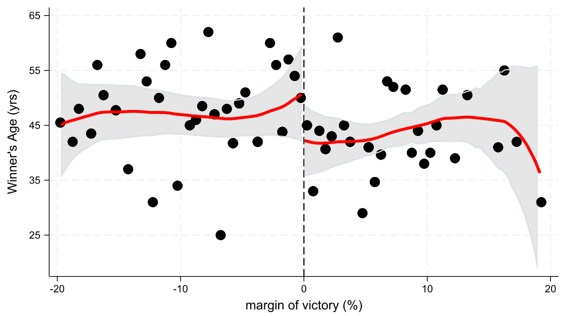
(i) Winner is from BJP in t



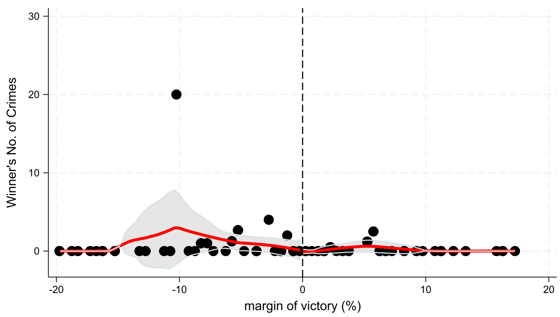
(j) Winner's Log Net Assets in t



(k) Winner's Years of Education in t

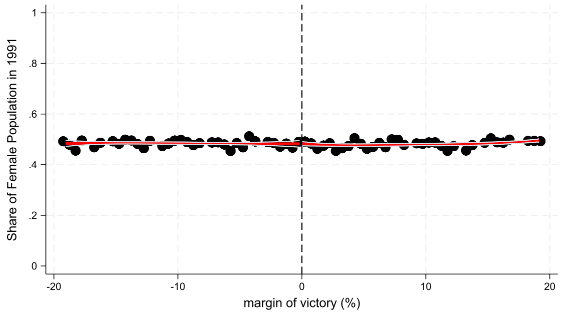


(l) Winner's Age in t

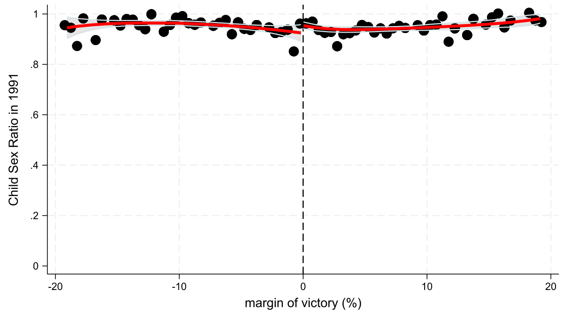


(m) Winner's Number of Crimes in t

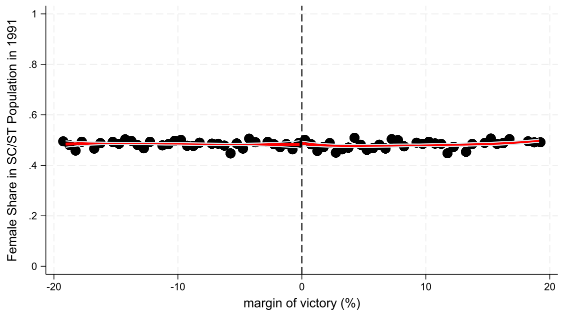
Fig. A.3. Continuity of Past Constituency & Current Candidate Characteristics in SC/ST Reserved Constituencies: Dependent variable in each subfigure is described in the corresponding caption. For all other details, see Figs. 1 and 2. Years of election start from 1996 onwards.



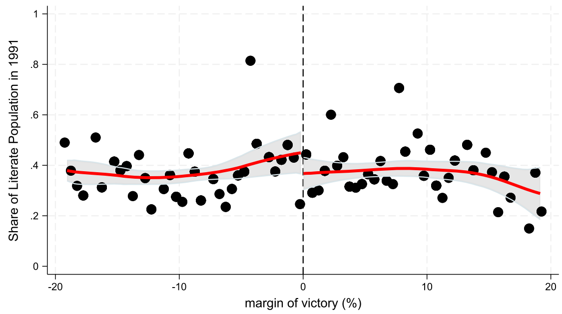
(a) Share of Females in Population



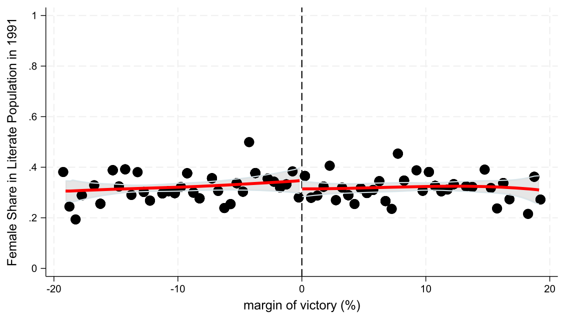
(b) Female to Male Child Sex Ratio



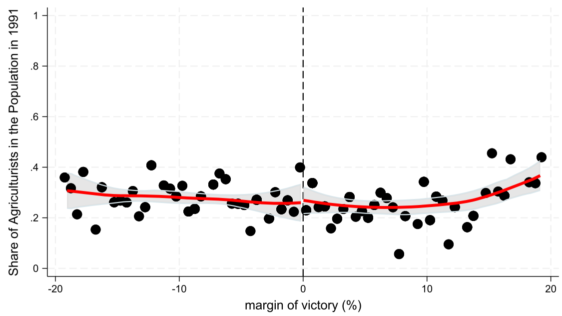
(c) Share of Females in the SC/ST population



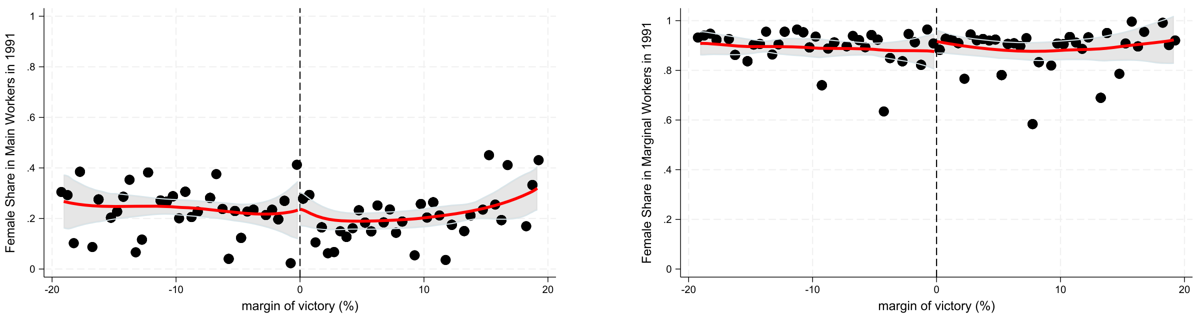
(d) Share of Literates in the Population



(e) Share of Females in the Literate Population

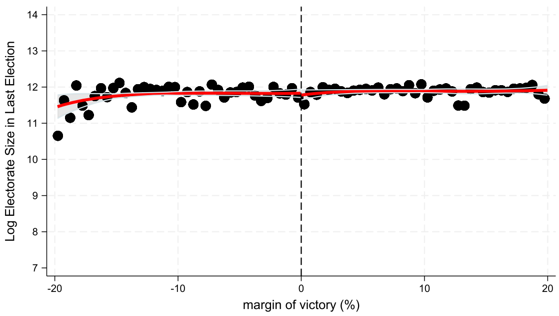


(f) Share of Agriculturists in the Population

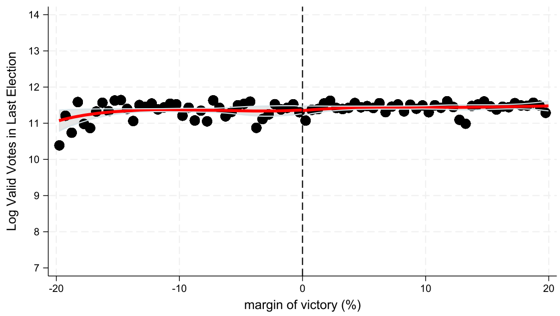


(g) Share of Females among Main Workers (h) Share of Females among Marginal Workers

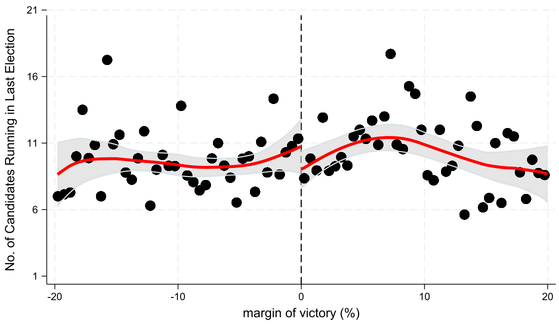
Fig. A.4. Continuity of Past Demographic Characteristics in SC/ST Reserved Constituencies: Dependent variable in each subfigure is described in the corresponding caption. For all other details, see Figs. 1 and 2. Years of election start from 1996 onwards.



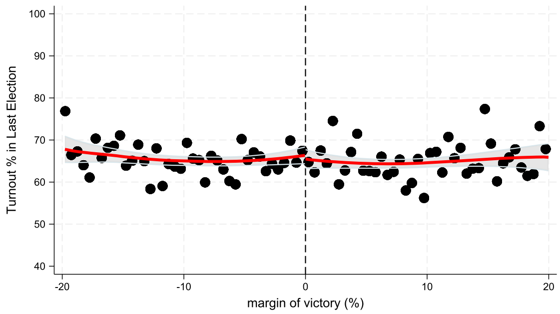
(a) Log Electorate Size in $t-1$



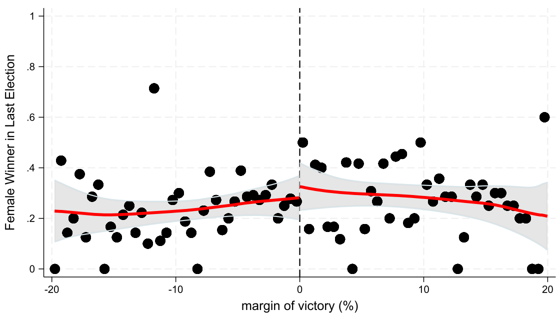
(b) Log Valid Votes in $t-1$



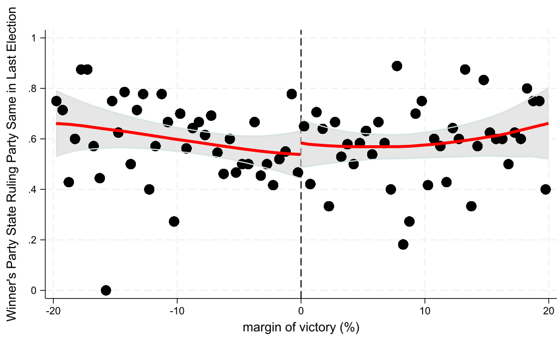
(c) Number of Candidates in $t-1$



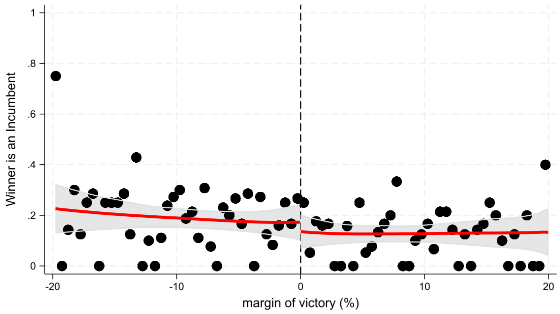
(d) Turnout Percentage in $t-1$



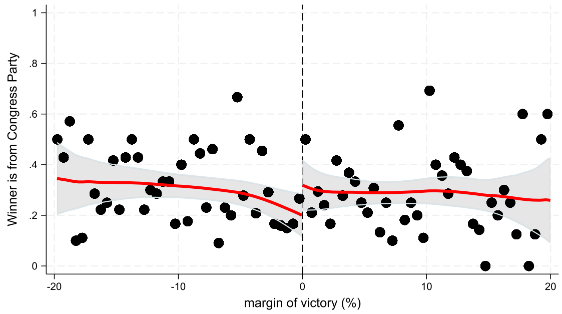
(e) Female Legislator in $t-1$



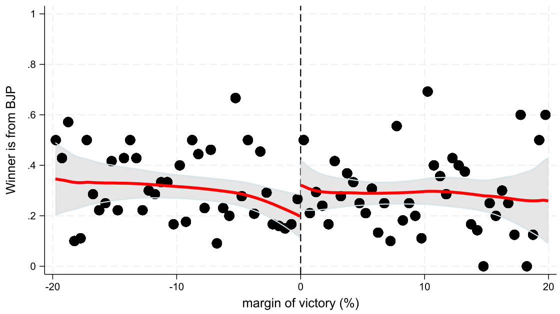
(f) Winner's party aligned with State Ruling Party in $t-1$



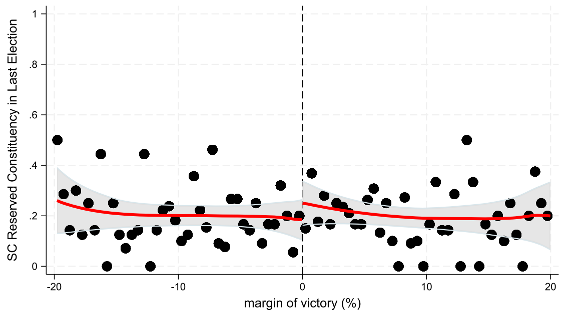
(g) Winner is the incumbent in t



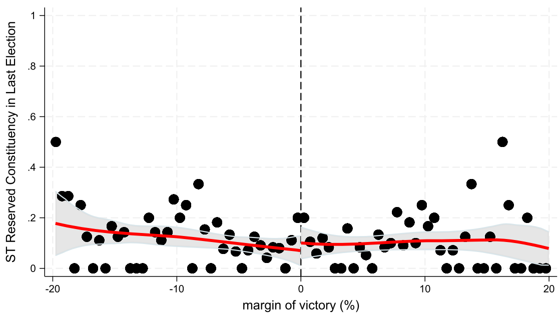
(h) Winner is from Congress Party in t



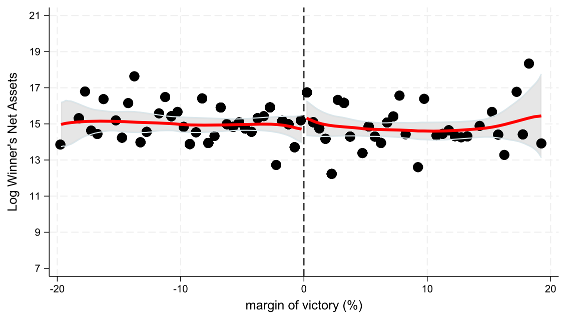
(i) Winner is from BJP in t



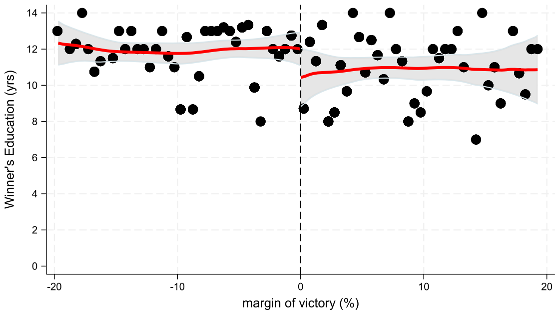
(j) SC Reserved in $t-1$



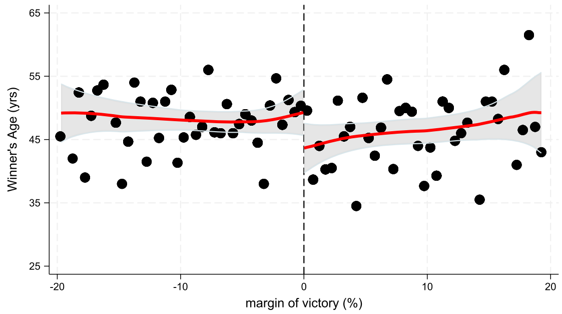
(k) ST Reserved in $t-1$



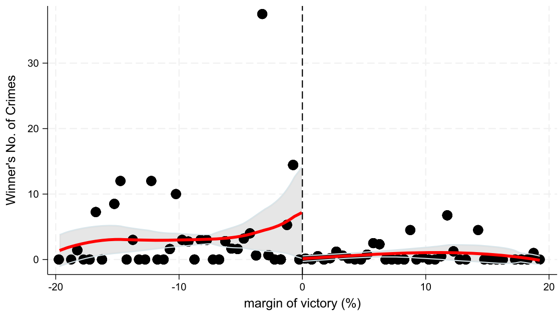
(l) Winner's Log Net Assets in t



(m) Winner's Years of Education in t

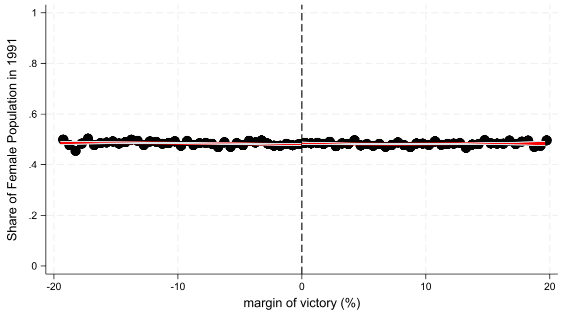


(n) Winner's Age in t

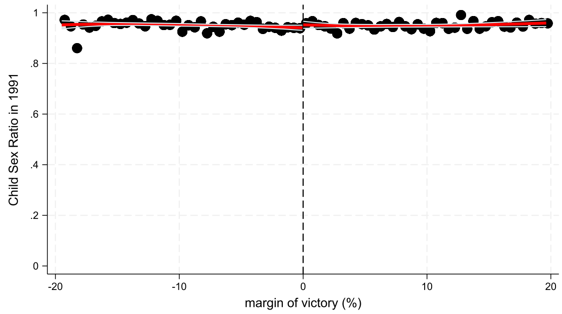


(o) Winner's Number of Crimes in t

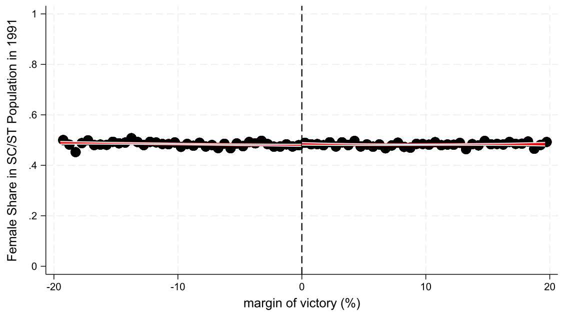
Fig. A.5. Continuity of Past Constituency & Current Candidate Characteristics in All Constituencies: Dependent variable in each subfigure is described in the corresponding caption. For all other details, see Figs. 1 and 2. Years of election start from 1996 onwards.



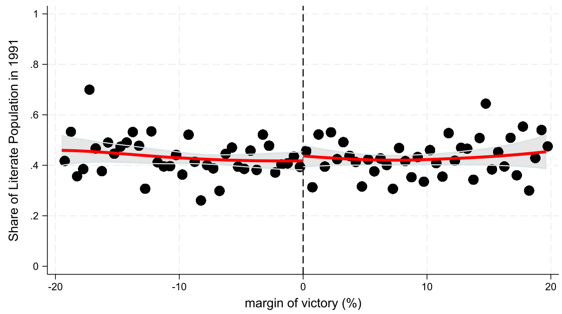
(a) Share of Females in Population



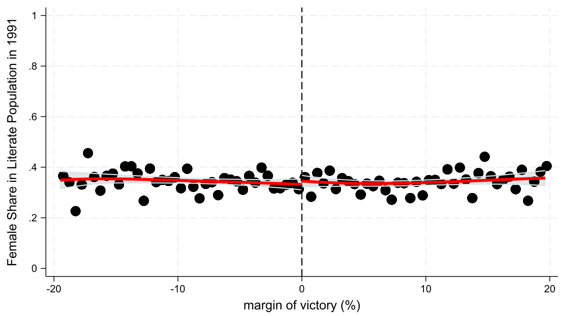
(b) Female to Male Child Sex Ratio



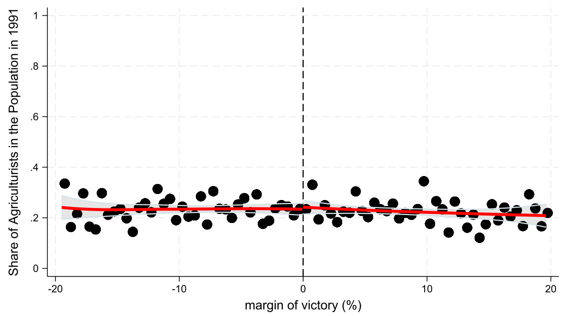
(c) Share of Females in the SC/ST population



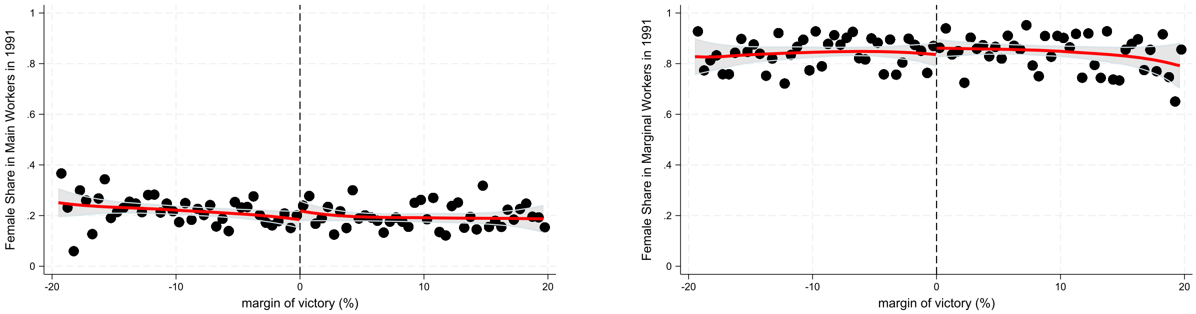
(d) Share of Literates in the Population



(e) Share of Females in the Literate Population



(f) Share of Agriculturists in the Population



(g) Share of Females among Main Workers (h) Share of Females among Marginal Workers

Fig. A.6. Continuity of Past Demographic Characteristics in All Constituencies: Dependent variable in each subfigure is described in the corresponding caption. For all other details, see Figs. 1 and 2. Years of election start from 1996 onwards.

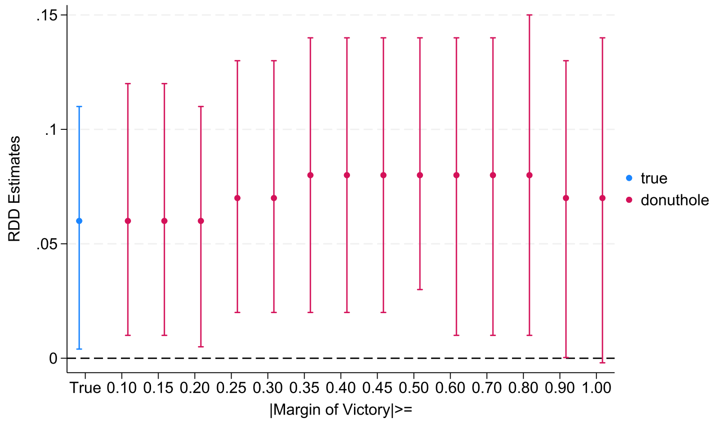


Fig. A.7. Donut Hole Regressions: RDD point estimates and robust and bias-corrected 95 % confidence intervals from local linear regressions with different slopes on either side of the cut-off using MSE-optimal bandwidth and triangular kernel function have been plotted for SC/ST reserved constituencies. The true point estimate and confidence interval (from column (2) of Panel A of Table 2) is plotted in blue, while donut hole RDD estimates are in red. Each of the donut hole regressions are obtained by removing observations that lie within a specified interval of the margin of victory on either sides of the cut-off, 0. For eg: the point estimate and 95 % confidence interval corresponding to |Margin of Victory|≥ 0.1 are obtained by excluding observations that correspond to margins of victory in the interval [−0.1, 0.1]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

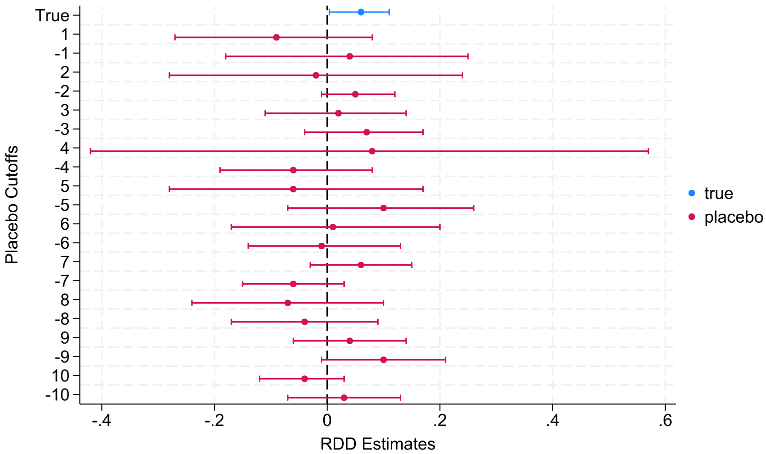


Fig. A.8. Placebo Cut-off Regressions: RDD point estimates and robust and bias-corrected 95 % confidence intervals from local linear regressions with different slopes on either sides of the cut-off using MSE-optimal bandwidth and triangular kernel function have been plotted for SC/ST reserved constituencies. The true point estimate and confidence interval (from column (2) of Panel A of Table 2) is plotted in blue, while placebo cut-off RDD estimates are in red. Each of the placebo cut-off regressions are obtained by using different false cut-offs. For eg: the point estimate and 95 % confidence interval corresponding to placebo cut-off 1 is obtained by assuming 1 as the cut-off instead of the true cut-off, 0. The sample is restricted to include only female winner constituencies for positive false cut-offs and only male winner constituencies for negative false cut-offs to prevent contamination from true treatment effects. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

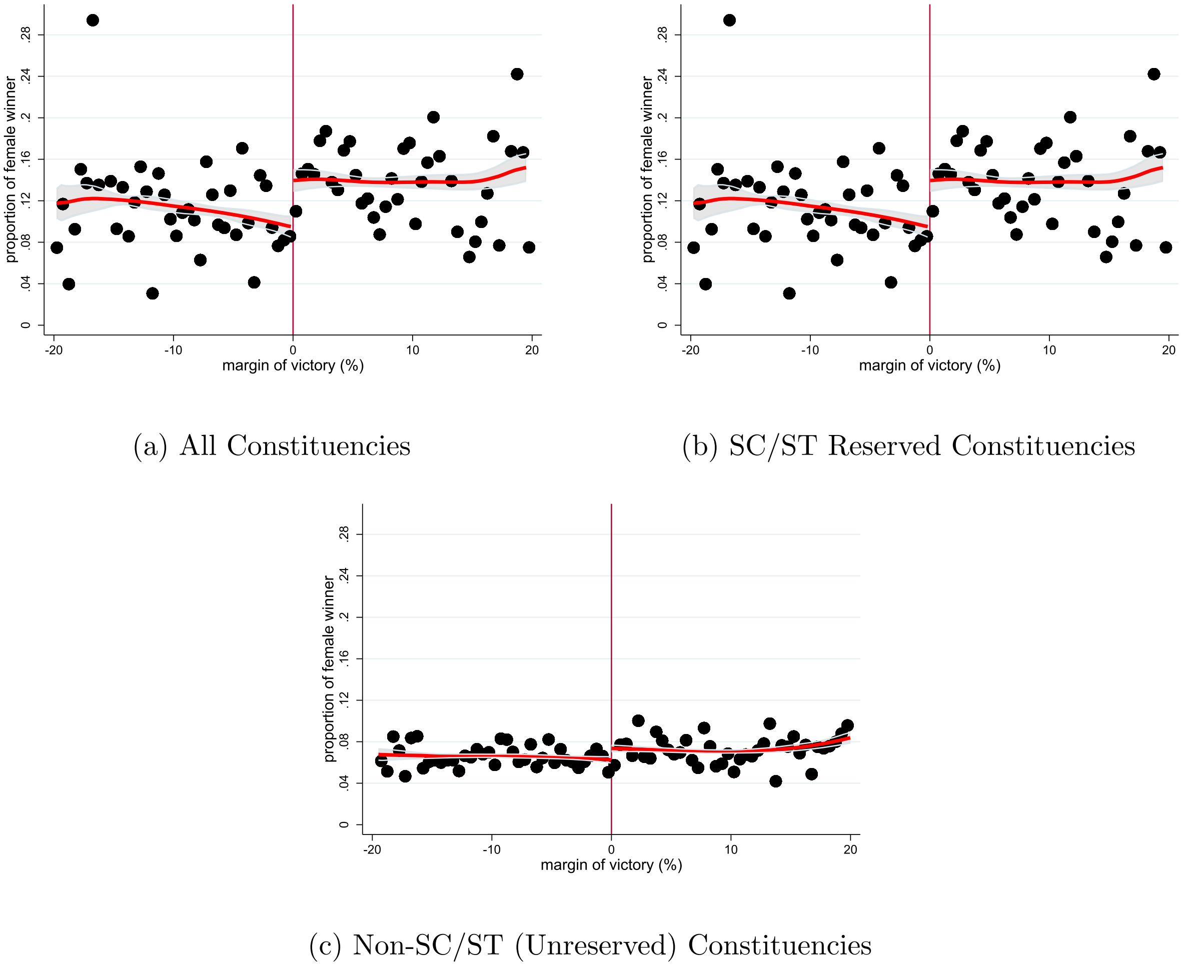
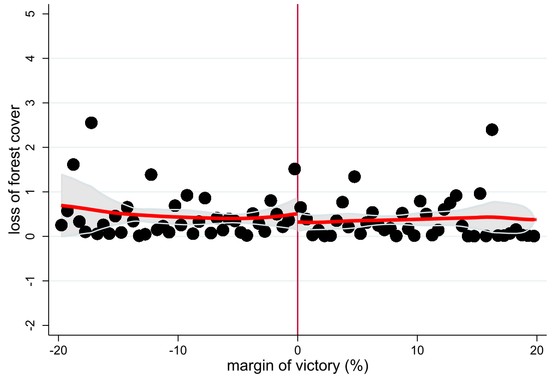
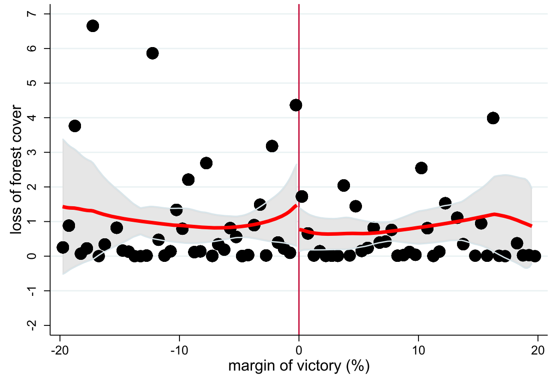


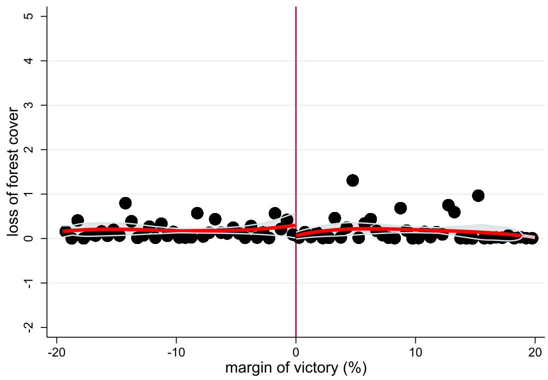
Fig. A.9. Proportion of female winner at the state level in various types of constituencies. The graphs above represent the first stage results of the fuzzy RDD estimation. The proportion of female winners denotes the fraction of assembly seats in a state during a certain year secured by female politicians. The running variable is the margin of victory of female politicians and is computed as the difference in vote shares of female and male politicians in mixed gender electoral races. Positive values indicate a female winner and negative a male winner with 0 being the cut-off. The scatter plots are binned outcome means over each successive interval of 0.5 % of the margin of victory. Local linear regression lines using MSE-optimal bandwidth and triangular kernel have been plotted separately for either sides of the cut-off along with the 95 % confidence interval. The data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021).



(a) All Constituencies



(b) SC/ST Reserved Constituencies



(c) Non-SC/ST (Unreserved) Constituencies

Fig. A.10. Cumulative loss of forest cover over the entire electoral term in various types of constituencies. The running variable is the margin of victory of female politicians and is computed as the difference in vote shares of female and male politicians in mixed gender electoral races. Positive values indicate a female winner and negative a male winner with 0 being the cut-off. The scatter plots are binned outcome means over each successive interval of 0.5 % of the margin of victory. Local linear regression lines using MSE-optimal bandwidth and triangular kernel have been plotted separately for either sides of the cut-off along with the 95 % confidence interval. Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021) and the Global Forest Change (GFC) data of (Hansen et al., 2013).

Appendix B. Appendix Notes

B.1. Alternative bandwidth

We attempt to assess whether our findings in Table 2 are robust to other alternative bandwidth choices that are not MSE or CER-optimal. The challenge of doing so would be that we would need to choose ad hoc bandwidths whose bias-variance characteristics would be unknown as well as conducting statistical inference with such bandwidths. Standard bias correction for inference purpose requires the bandwidth size to bias ratio to be as small as possible and in particular rules out bandwidth size to bias ratio of 1, which is associated with ad hoc bandwidth choices performed manually. In the absence of clear econometric guidelines or recommendation of how to reduce the bandwidth below the MSE or CER optimal bandwidths and yet appropriately conduct estimation and inference, we adopt the following approach. We manually choose the bandwidth, while also reducing the bandwidth bias such that the ratio of the bandwidth size to bias is the same as that obtained for the MSE-optimal bandwidth. Appendix Table A.3 reports these findings for the sample of SC/ST reserved constituencies for which we have statistically significant results in Table 2, where the yearly growth rate of forest cover is the outcome variable. We continue to find significant results for bandwidth sizes lower than the MSE-optimal bandwidth. For example, lowering the bandwidth size from the MSE-optimal bandwidth to up to 8 % does not alter the size or statistical significance of the RDD estimate. However, smaller bandwidths increase variability and result in higher standard errors due to the limited number of observations. This is what we observe for bandwidths that are even lower than 8 %. Although the coefficient estimate remains stable, the standard errors increase resulting in the loss of statistical significance. Hence, the lack of statistically significant coefficient for sufficiently smaller bandwidths here is on account of reduction in the number of observations available for estimation.

Appendix Tables A.4 and A.5 present results where the outcome variable is forest cover growth over the electoral term and where bandwidth sizes other than the MSE-optimal bandwidth are chosen for the sample of all constituencies and specifically SC/ST reserved constituencies respectively, along with adjustment of the bandwidth bias to assess additional robustness of our results to bandwidth size. This exercise is similar in spirit to that reported in Appendix Table A.3 for year to year growth. We find that we continue to obtain similar results as Panel A of Table 5 for bandwidths that are neither MSE or CER optimal but are lower than the MSE optimal bandwidth with analogous adjustment of bandwidth bias. However, for successively smaller bandwidth sizes (that is, 8 % or lower), the RDD point estimates lose statistical significance due to lack of power.

B.2. Non-manipulation of the victory margin

One of the concerns that can arise in the RDD setup is that if units can manipulate the threshold that determines treatment status, then treatment status is no longer exogenously determined, and estimating the causal effect of the treatment would then be challenging. In our setup, this concern translates into the ability of agents to manipulate the margin of victory to enable selection into the treatment group, that is, to end up with a female legislator. Additionally, this concern is more likely to arise for constituencies that are close to the threshold of the margin of victory. This would normally show up as a discontinuous increase in the proportion of constituencies where a female politician won in a close race against a male politician around the threshold of the margin of victory. Appendix Fig. A.1 depicts the distribution of the margin of victory between female and male politician winners in SC/ST reserved constituencies. There appear to be no observed discontinuous jumps in the density of the margin of victory between constituencies in which female and male politicians won around the threshold of victory, as is seen from the histogram in Appendix Fig. A.1(a). However, a formal test of discontinuity in the density of the running variable has been proposed by McCrary (2008) which we show in Appendix Fig. A.1(b). The McCrary density test echoes the finding from the histogram. In particular, the estimated log difference in the heights of the densities of the margin of victory on either side of the threshold is not found to be statistically significant. Therefore, manipulation of the victory margin around the threshold of victory in mixed gender elections is unlikely in SC/ST reserved constituencies. Additionally, Appendix Fig. A.2 shows that such concern is unlikely even in the sample of all constituencies (both reserved and unreserved). This, therefore, provides some evidence in support of the credibility of our RDD strategy.

B.3. Continuity of covariates

Another standard test to assess the credibility of the RDD is testing for the continuity of covariates that are unlikely to be influenced by treatment at the cut-off of the running variable. In this regard we examine whether pre-determined constituency characteristics such as the logarithm of electorate size and valid votes, turnout percentage, the number of candidates contesting from the constituency, if the constituency had a female legislator, and whether the winner's party was aligned with the state ruling party in the last election are indeed continuous at the threshold of the margin of victory in the current election cycle. It is reasonable to assume that since each of these covariates is determined prior to the current election, they should be continuous at the cut-off of the margin of victory corresponding to the current election. Additionally, we also study whether certain characteristics of the winning candidate are substantially different at the cut-off of the margin of victory. Some relevant characteristics in this regard are whether the winning candidate is an incumbent and belongs to certain political parties. In particular, we consider whether the winner belongs to one of the two major national political parties, the Congress and the Bharatiya Janata Party (BJP).[41] These characteristics are relevant in our set up as incumbency can have important implications on the efficacy of implementing environmental conservation measures. Further, political party affiliation can also influence a politician's inclination to protect the environment, as has been shown by Nishijima and Pal (2023).

Additional candidate level characteristics that could matter in our context are the winner's net assets (in logarithm), years of education, age, and number of crimes. These candidate level attributes are for the winners in the current electoral term. This is because of two reasons. Firstly, as has been discussed earlier, the information on candidate characteristics is available for elections held from 2004 onwards. Given our forest cover data and taking into account constituency delimitation measures, we effectively have data on these characteristics for only one election cycle for each state. Secondly, testing for continuity in these covariates could also shed light on whether there is any other mechanism besides legislator gender (but which could also be correlated with the legislator's gender) that could explain our findings. For example, younger relative to older politicians are often found to invest in environmental conservation and education as these are likely to yield benefits in the future (Dahis et al., 2023). Further, candidates whose campaigns are self-funded are more likely to invest in environmental conservation relative to those who received donor funding (Harding et al., 2024). If a candidate's net worth is indicative of whether they are likely to self-finance or receive donor funding, then continuity of this covariate at the threshold of the margin of victory would also need to be assessed. Lastly, if male and female politicians are significantly different from each other in terms of observed characteristics, then attributing our main results to legislator gender would be difficult (Rocha et al., 2018).

Appendix Fig. A.3 depicts the covariate continuity graphs of the electoral and candidate level characteristics for SC/ST reserved constituencies. We find that in reserved constituencies, there is no robust evidence of discontinuity of these characteristics at the threshold of the running variable. The fitted local linear regression lines on either side of the threshold either appear to have no visible discontinuity or have large, overlapping confidence intervals, indicating no statistically significant discontinuity on either side of the cut-off of the margin of victory.

In addition to electoral characteristics of the constituencies, we also assess whether there is any discontinuity at the threshold of the running variable in terms of past socio-economic and demographic characteristics of the constituencies. These include the share of females in the population, the child sex ratio (that is the female to male ratio in the 0–6 years population), the share of females in the SC/ST population, the population share of literates as well as the share of females in the literate population, the population share of agriculturists and the share of females among main and marginal workers.[42] The information on these variables are obtained from the Population Census of 1991 and has been made available at the assembly constituency level by the SHRUG platform (Asher et al., 2021).[43] Appendix Fig. A.4 plots these covariate continuity graphs for SC/ST reserved constituencies. Once again, there does not appear to be any robust evidence of discontinuity in these pre-determined constituency level socio-economic and demographic characteristics at the threshold of the margin of victory in current election cycles.

Appendix Figs. A.5 and A.6 provide analogous exposition for the entire sample of constituencies, irrespective of reservation status. Almost all of the covariates show no discontinuity at the threshold.[44] Lastly, the reservation status of a constituency in the last election does not appear to be discontinuous at the cut-off of the margin of victory in the current election, indicating that the probability that a constituency is reserved for historically disadvantaged communities such as the SC/ST is orthogonal to the margin of victory in current mixed gender elections.

B.4. Donut hole test

Recent recommendations for conducting robustness exercises for RDD include assessing how sensitive the results are to observations near the cut-off. Since RDD relies on estimating local linear regression using observations close to the cut-off of the running variable, it is advisable to test whether removing observations closest to the cut-off results in significant changes in the RD treatment effect estimate (Cattaneo et al., 2019; Cunningham, 2021). This robustness check method is, therefore, known as the "donut hole" approach. If observations closest to the cut-off are unlikely to be disproportionately influential in the estimation of the RD treatment effect, then removing a few observations from either side of the cut-off should not result in large changes in the RD coefficient estimate. To the best of our knowledge, econometric theory does not direct the number of observations to be excluded from the sample for this estimation, but the recommendation is to reiterate this exercise several times by taking care that exclusion of observations around the cut-off does not result in moving "too" far-away from the cut-off.

We perform the donut hole test for the sample of SC/ST reserved constituencies (as these constituencies appear to be overall driving our findings) by removing several observations from either side of the threshold of the margin of victory repeatedly and represent our findings graphically in Appendix Fig. A.7. We continue to rely on the MSE-optimal bandwidth as in Panel A of Table 2

[41] India is a multi-party democracy, and hence belonging to Congress and BJP are not mutually exclusive outcomes, as there are other major political parties. However, these are the largest political parties in terms of presence of Members of Parliament (MPs) in the lower house of the Indian Parliament in recent years and naturally have a prominent presence throughout multiple states in the country.

[42] The Census of India defines main workers as those who have worked for at least 6 months in a 12 month period; while marginal workers are those who have worked for less than 6 months during the same period.

[43] Since the earliest year of election in our study is 1996, we use census figures from the population census preceding it (which is the 1991 Population Census) for assessing covariate continuity of these pre-determined variables.

[44] The only robust discontinuity is in the candidate's age and it appears that female candidates who win are significantly younger than male winners during the current election.

for this exercise. The blue line represents our RDD coefficient estimate from Column (2) of Panel A of Table 2 and the associated robust and bias corrected 95 % confidence interval. Each of the red lines represents RDD coefficient estimates and the associated 95 % robust and bias corrected confidence intervals from distinct donut hole regressions. For example, the red line corresponding to $|MarginofVictory| \geq 0.10$ involves obtaining the RDD estimate by excluding SC/ST reserved constituencies whose margins of victories in mixed gender races lie in the interval $[-0.1, 0.1]$.[45] Therefore, the estimation sample includes observations where the absolute value of the margin of victory is at least as large as 0.10. We repeat this exercise by excluding observations within different intervals of margins of victory on either sides of the cut-off up until the estimation sample includes constituencies whose margins of victory lie outside the interval $[-1, 1]$. We find that almost all the coefficient estimates from the donut hole regressions are statistically significantly different from 0 and they are close in magnitude to the true coefficient estimate. This provides confidence that our estimation result obtained in Table 2 for SC/ST reserved constituencies is unlikely to be disproportionately influenced by observations closest to the cut-off.

B.5. *Using placebo cut-off*

Another recommendation for testing the credibility of the RDD framework is to assess whether the estimated local linear regression functions are continuous at points that are not the true cut-off that determines treatment status. The intuition behind such a test is that we should not expect any discontinuity/ treatment effect at cut-offs that are not the true cut-off. The estimation under this falsification exercise is conducted in the usual manner using the MSE-optimal bandwidth, but by using artificial/placebo cut-offs instead of the true one. However, to prevent real treatment effects from “contaminating" the findings from this falsification exercise, Cattaneo et al. (2019) recommend using only treatment observations for placebo cut-offs above the true cut-off and only control observations for placebo cut-offs below the true cut-off. We follow this recommendation here and explore the presence of treatment effects at a variety of placebo cut-offs both above and below the true cut-off of 0 in our running variable, the margin of victory for SC/ST reserved constituencies. We restrict our estimation sample to constituencies where only female candidates have won and those where only male politicians have won for placebo cut-offs that are positive and negative, respectively. We use 20 placebo cut-offs on either side of our true cut-off, 0, and report the findings in Fig. A.8 here.

The blue line in Fig. A.8 represents the RDD point estimate and the robust and bias corrected 95 % confidence interval using the true cut-off of 0. This is therefore, a graphical representation of the RDD coefficient estimate from Column (2) of Panel A of Table 2. All red lines represent RDD point estimates and the associated robust and bias corrected 95 % confidence interval using various placebo cut-offs. For instance, the graphical representation corresponding to the placebo cut-off of 1 corresponds to using the threshold of the margin of victory at 1 %. In other words, this RD treatment effect attempts to compare constituencies in terms of forest cover growth where female politicians have won with a margin of victory of at least 1 % with those where a female politician won with a margin of victory below 1 %. In general, there should be no reason why we should observe any statistically significant treatment effect here. Indeed, that is what we find here, where the RDD treatment effect is statistically insignificant. Repeating this exercise using different placebo cut-offs, we find that the estimated RD coefficient estimates are largely all statistically insignificant, as the robust and bias corrected 95 % confidence intervals are often large and contain 0, and most point estimates are close to zero or lower in magnitude than the true RDD point estimate using the correct cut-off. Our findings from Fig. A.8, therefore, lend some support to the credibility of our main RD treatment effect estimate for SC/ST reserved constituencies found in Table 2.

B.6. *The spillover effect*

State legislatures may operate collaboratively. Hence, there may be beneficial spillover effects of electing female politicians in any constituency to other constituencies within a state, indicating that the impact of female legislators could be underestimated. To investigate this relationship, we compute the proportion of female electoral winners in each state and assess whether constituencies located in states with a higher proportion of female winning candidates exhibit higher growth in forest cover. Alternatively, we also aggregate the constituency level growth of forest cover up to the state level and explore whether states with a higher proportion of women in their legislatures are likely to have higher state level growth rates in forest cover.

For this analysis as well, the constituency level closely contested elections can be utilized to conduct the RD analysis. Given that the proportion of female legislators at the state level is being used as the explanatory variable of interest, we essentially aggregate the constituency specific discontinuities in treatment assignment within states, in accordance with the principles of a fuzzy RDD.

We perform the fuzzy RDD estimation following Cattaneo et al. (2024). In a fuzzy RDD estimation framework, the treatment variable, namely the proportion of female winners in a state, is instrumented by the proportion of female winners in closely contested elections within that state. Specifically, the estimation is conducted in two stages. In the first stage, we assess the relationship between the treatment and the instrument. Here, we investigate whether the constituencies with female winning candidates in close elections have a substantially higher proportion of female winners in the state legislatures to which they belong. In the second stage, using the MSE-optimal bandwidth, the impact of the state-specific proportion of female winners (instrumented by the state-specific proportion of female winners in closely contested elections) on constituency level and, alternatively, state-level forest cover growth is estimated.

The first stage results are found to be statistically significant, as is evident from the jumps observed around the threshold of the margin of victory in the Appendix Fig. A.9 for all types of constituencies. Specifically, when constituency-level annual forest

[45] These numbers, like 0.1 and -0.1 represent the difference between the percentage of vote obtained by female and male candidates.

cover growth is used as the outcome variable of interest, the upper panel of Appendix Table A.6 also demonstrates these first stage relationships for all types of constituencies. This potentially serves as evidence that constituencies with female winners in closely contested mixed gender races are more likely to belong to states with a higher proportion of women in the state legislatures. Appendix Table A.6 also reports the second-stage estimation results. The influence of a higher proportion of female electoral winners in a state on the constituency level yearly forest cover growth is found to range between 0.2 percentage points and 3 percentage points; however, this effect is not found to be statistically significant. This evidence indicates that a higher share of female electoral victories at the state level does not, in itself, translate into markedly faster forest growth within local constituencies. In accordance with Cattaneo et al. (2024), the estimation procedures for both the first and the second stages are implemented using a common optimal bandwidth and an identical set of observations.

Appendix Table A.7 reports the estimated spillover effects on long-term growth rates. The first-stage estimates are very similar, which is expected (the only difference is the smaller sample size because duplicate observations at the constituency-year level are removed to create the RDD estimation dataset used to assess the impact on long-term growth rates). The second-stage treatment effects are larger in magnitude, as the long-term growth rate is an accumulation of yearly growth rates. However, they are not statistically significant, except for SC/ST reserved constituencies, where a higher proportion of state-specific female winners has a weakly statistically significant positive effect on long-term forest cover growth.

As an alternative approach to capturing the spillover effect, we also use state-level averages of both the annual and electoral term forest cover growth rates instead of constituency level yearly and long-term growth rates. The results are presented in Appendix Tables A.8 and A.9, respectively. These fuzzy RDD estimates follow the same specification as Appendix Tables A.6 and A.7 but use state-level average outcomes instead of constituency level data. The treatment effects are statistically insignificant and even weaker in magnitude, likely a result of the limited variability in the outcome when aggregated at the state level. Finally, although the outcome variables presented in Appendix Tables A.8 and A.9 are aggregated at the state level, the reported number of observations reflects the constituency level sample sizes consistent with those in Appendix Tables A.6 and A.7, respectively. This similarity stems from the use of a fuzzy RDD procedure, following Cattaneo et al. (2024), which jointly estimates the first and second stages using a common sample, with the instrument defined at the constituency level in the first stage. Using a fuzzy RDD estimation technique with an instrument defined at a more disaggregated level than the outcome variable is consistent with other studies (Priyanka, 2020; Bhalotra et al., 2014).

To examine potential spillover effects in another way, we implement a sharp RDD, employing the margin of victory as the running variable and the average forest cover growth across constituencies within a state as the outcome variable. Consistent with our earlier findings, this alternative specification reveals no statistically significant impact of the narrow electoral victories of female candidates on state-level forest cover growth, indicating the absence of potential spillover effects. While these results are not reported, they are available upon request.

B.7. Female politicians and forest loss

The Global Forest Change (GFC) dataset is a high-resolution, continuously updated global resource that provides detailed information on forest cover dynamics from the year 2000 to the present. Developed by researchers at the University of Maryland and led by Dr. Matthew Hansen (Hansen et al., 2013), the dataset leverages imagery from the Landsat satellite program to monitor changes in tree cover at a spatial resolution of 30 m. The GFC dataset includes several key variables. In our analysis, we focus on the year of gross forest cover loss, recorded as 'lossyear' in the dataset, as it helps us in constructing our outcome variable of interest, forest loss. In particular, we attempt to explore whether the election of female politicians in closely contested races influences deforestation patterns using forest loss as an alternative outcome variable.

Although the GFC data spans up to the year 2020, we choose the period 2000–2013 to ensure comparability with our main RDD estimation dataset. Forest loss during the period 2000–2013 is defined as a stand-replacing disturbance, representing a complete removal of tree canopy or a transition from forest to non-forest land cover. Loss is recorded on a per-pixel basis and encoded as an integer value. A value of 0 indicates no forest loss during the observation period, while values ranging from 1 to 13 denote the year in which forest loss was detected, corresponding to the years 2001 through 2013, respectively. A pixel represents a single grid cell in the satellite imagery used to monitor forest cover change. Therefore, from the extracted geospatial data, it is possible to determine whether forest loss occurred at a given pixel in a specific year. By spatially aggregating this information within the boundaries of a particular assembly constituency, one can compute the total number of pixels and consequently an approximated area measured in square kilometers that experienced forest loss in a constituency in a specific year (note that 0.000900 square kilometers is the area of each pixel, which is based on the pixel size grid from the data source, 30-meter resolution, or 1 arc second). This serves as a yearly measure of the extent of forest loss within the constituency, allowing for temporal and spatial analysis of deforestation patterns at a subnational administrative level. This forest loss variable generated using the GFC dataset is then merged with the combined election and candidates dataset that we have extracted from the SHRUG database. For each assembly constituency, we then compute cumulative forest loss over the five-year electoral term of a legislator by aggregating the yearly forest loss variable. Hence, we use this cumulative forest loss as the outcome variable and examine how the gender of the elected legislator influences subsequent forest cover loss within the constituency. As both the treatment and outcome variables are measured at the constituency level, we exploit potential quasi-random assignment of legislator gender in closely contested mixed gender elections to identify the causal effect of legislator gender on our outcome of interest in a sharp RDD framework and using an estimation specification analogous to Eq. (1).

The findings are presented in the Appendix Table A.10, where the RDD point estimation is conducted using the MSE-optimal bandwidth and inference is obtained by relying on the robust bias-corrected confidence interval, as before. We find that across all types of constituencies, both reserved and unreserved, the cumulative forest loss over the electoral term is lower in constituencies where a female politician narrowly defeated a male opponent by nearly 0.32 square kilometers. Specifically, the point estimate measuring the impact of a female legislator on subsequent forest cover loss is the highest in absolute value for SC/ST reserved constituencies (0.82 square kilometers). However, these findings are not found to be statistically significant. Appendix Fig. A.10 provides the graphical illustration of the results reported in Appendix Table A.10 for all constituencies, as well as by constituency reservation status. In contrast to yearly forest loss, which we have used to construct forest loss over a legislator's electoral term, the GFC does not include a variable that captures yearly forest gain. Therefore, we are unable to conduct a similar exercise with forest gain as the outcome variable.

The findings of Appendix Table A.10 remain unaffected when the CER-optimal bandwidth is used instead of the MSE-optimal bandwidth in the RDD estimation. Alternatively, we consider the cumulative forest loss over a legislator's electoral term relative to the forest loss in their first year in office as an alternative unit-free outcome variable to serve as a proxy for the dynamics of the evolution of forest loss over the electoral term. We find that the election of a female legislator is negatively associated with this outcome variable, indicating that forest loss during the electoral term decreases after the election of a female legislator relative to their first year in office. However, this finding was not found to be statistically significant. These results are not reported here, for ease of exposition, but are available upon request.

So far, we have focused on the five-year terms of female leaders to clearly measure their impact on forest loss during their time in office. But we also attempt to explore whether their efforts in protecting forests can last beyond their time in office. This is because laws or policies that legislators put in place may have long-term effects, implying that our results obtained so far may be partially capturing the true impact of female leaders on protecting forests. To capture long-term forest change, we utilize the variable "loss" from the GFC dataset as the outcome measure. This binary variable equals 1 if any forest loss occurred within a pixel at any year between 2000 and 2013, the full duration of our analysis, and 0 otherwise. The approximate area of forest loss within each constituency can then be estimated by multiplying the total area of the constituency (in square kilometers) by the proportion of pixels within it that experienced forest loss. A limitation of this area-based measure is that it aggregates forest cover loss over the entire 2000–2013 period, rather than isolating forest loss that occurred only after the election of female politicians. Therefore, the total area of forest loss over the entire period can at best serve as an approximation of the long-run impact (that is, more than five years in office) of female politicians on forest cover. Using this forest loss measure as the outcome variable, we find that constituencies where female politicians won by narrowly defeating male opponents have lower forest loss between 2000 and 2013. However, these estimates continue to be statistically insignificant. Appendix Table A.11 presents these results, which appear to be qualitatively similar to those of Appendix Table A.10 but with larger RDD point estimates in absolute value, likely reflecting effects accumulated over a longer period of time.

Even though the point estimates obtained from the GFC data are not statistically significant, the analysis conducted using this dataset that shows that electing female politicians has a negative (albeit insignificant) effect on forest loss is similar in spirit to our findings from the SHRUG dataset that shows that the growth rate of forest cover improves following the election of female politicians. The lack of statistical significance for the results from the GFC dataset may be attributable to the limited sample size, as the outcome variable, aggregate forest loss, is measured over the entire electoral term or over the entire duration of our study period. Additionally, the measure of forest loss in the GFC dataset ignores any net changes in forest cover. Therefore, as the GFC and SHRUG databases are fundamentally different in scope and methodology, making direct comparisons of their findings is likely inappropriate. Nevertheless, as has been pointed out, the analysis conducted using GFC data yields no evidence that contradicts the conclusions previously drawn from the SHRUG dataset.

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