Female Legislators and Forest Conservation in India *

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Abstract

Within a regression discontinuity framework, we use quasi-random variation in close mixed gender election races to examine the causal relationship between the gender of legislators and the expansion of forest cover in India. We find that there is a 6% increase in annual forest cover growth in assembly constituencies following the election of a female politician. However, this outcome is only applicable to constituencies reserved for politicians from historically marginalized groups. When we consider the growth rate of forest cover over the course of the electoral cycle, a female legislator is found to have a positive and significant impact on the extension of forest cover, not only for reserved constituencies but also for all constituencies. Finally, we discuss how differences in preferences and awareness of constraints faced while coping with environmental adversities by legislator identity can potentially explain our findings. Our results highlight the importance of legislator identity in affecting environmental conservation policies in India.

Keywords: forest conservation; female legislators; close elections; regression discontinuity; India

JEL Codes: D72; H70; J16; Q23; Q28; Q54

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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 the 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 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 behaviour (Masuda et al., 2020) and overall worker productivity (Masuda et al., 2021). Therefore, protection 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 states. 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

[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.

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 externality 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 favour 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

[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.

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 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 victory of a politician of a certain gender in "close" mixed gender race is potentially quasi-random. Hence, 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, 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 percentage of the female and male politicians who occupy the top two ranks in the race. Hence, constituencies in which a female politician wins belongs to the treatment group and here the margin of victory is non-negative. On the other hand, those in which a male politician wins forms our control group where the margin of victory is negative. Clearly, the margin of victory 0 defines the threshold/cut-off of our running variable that determines whether assembly constituencies would belong to the treatment or control groups. 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)).

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

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, Lunt, Matsuura, and Novosad, 2021). Our analysis shows that female politicians winning in close race 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] There are no significant effects for the sample of all constituencies or for constituencies that are unreserved. 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%. In this regard, our results are similar in spirit to Clots-Figueras (2011), who find that beneficial impacts of electing female politicians is largely driven by such politicians who also belong to lower 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 extremes 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 or no impact on subsequent year to year forest cover growth. Here, we find that while the impact of SC/ST female politicians on forest cover growth continues to be significant over their entire electoral term, there appears to be an overall positive and significant effect of electing female politicians on forest cover growth measured over an entire electoral term for all constituencies. Thus, it is possible that the environmental conservation efforts undertaken by all female politicians, in contrast to those of their counterparts in SC/ST reserved constituencies, accumulate over the course of their electoral terms rather than being reflected in the annual growth rate.[6]

[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 of 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)). 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 centred around human-forest/wildlife interactions in their constituencies during their term as MLAs such as Droupadi Murmu (accessed on February 2, 2024), Birbaha Hansda, (accessed on February 2, 2024), Chandana Bauri, (accessed on February 2, 2024) to name a few.

[6]There are additional anecdotal examples of non-SC/ST female politicians who have made efforts at

We assess the credibility of our RDD through a number of robustness and falsification tests, in addition to the McCrary and covariate continuity tests that have mainly been reported in the existing literature. We find no evidence of manipulation of the margin of victory (no failure of the McCrary density test) either in the whole sample or in the sample of SC/ST reserved constituencies. Additionally, covariate continuity continues to hold in our framework. Lastly, our results are also not unusually sensitive to observations close to the cut-off (the donut hole test), are robust to alternative bandwidth choices and there are no RD treatment effects observed when placebo cut-offs instead of true cut-off in our running variable are used. These additional tests help bolster our confidence in our RD estimates.

We, then, attempt to explore potential mechanisms that could help support our findings. Since we do not find any significant difference between female and male winners in close mixed gender races in SC/ST reserved constituencies in terms of observed characteristics such as age, education or asset ownership which could independently influence investments in environmental conservation (Saavedra Pineda et al. (2023); Harding et al. (2022)), it appears the difference in the environmental outcomes between constituencies with a female and male legislator is largely on account of their genders. Now, 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., 2023). 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 acknowledgment 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.

The positive impact of female legislators' gender on the growth of the forest cover is evident in the yearly growth rate during the election term in SC/ST reserved constituencies;

environmental conservation which are likely to yield benefits over their electoral term. These include Mamata Banerjee (accessed on February 2, 2024), Vasundhara Raje Scindia (accessed on February 2, 2024) and Sheila Dikshit (accessed on February 2, 2024).

but for all constituencies, it is only evident over the female MLAs' entire electoral term. Interestingly, the most stark difference between female and male MLAs for the sample of all constituencies is their age where female MLAs are found to be younger than their male counterparts. This is in contrast to our findings for MLAs from SC/ST reserved constituencies. We investigate whether the long term impact on forest cover growth over a female MLA's electoral cycle is driven by MLA's age. This is because younger politicians have been shown to invest in the environment that yield benefits in the future (Dahis et al., 2023). We find that for all constituencies, the beneficial impact on forest cover growth over the electoral term is largely driven by younger female MLAs.

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 describes the data used while Section 3 describes the empirical strategy; Section 4 presents the main findings; Section 5 provides alternative robustness and falsification tests to assess the credibility of the RDD framework; Section 6 discusses how legislator gender influences forest cover growth over an electoral cycle; Section 7 provides a discussion of the potential mechanisms while Section 8 concludes.

2 Data

The data used in our analysis comes from The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 2021). The SHRUG platform combines datasets on a number of socio-economic, demographic, environmental and political variables and makes it 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, Carroll, Sohlberg, Kim, Kelly, and Townshend, 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, Garg, and Novosad, 2020) who also provide a detailed description and potential advantages of the VCF over other existing forest cover data sources.[7] The outcome variable we use in our analysis is the annual growth of forest cover in a constituency. For this computation, we use the average percentage of an assembly constituency under forest cover in a given year. 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 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.[8]

Since we study 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 upto 2007 in our analysis. Once elected,

[7]For instance Asher, Garg, and Novosad (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, Garg, and Novosad, 2020).

[8]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, Garg, and Novosad, 2020).

legislators usually serve a five-year term.[9] Therefore, even though the last year of elections data used come from 2007 for some states, it is possible to use forest cover data for years beyond that (up to 2011 in our analysis).[10]

The elections data contain rich constituency level information such as electorate size, valid votes, turnout percentage, number of candidates contesting from the constituency as well as whether the constituency had a female legislator and whether the winner's party is aligned with the state's ruling party in previous elections, if winner is an incumbent and 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, Rockmore, and Uppal (2019). Given that 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 upto 2007, these candidate level information is only available for one election in each state (Prakash, Rockmore, and Uppal, 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).[11] 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.[12] 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

[9]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.

[10]See Prakash, Rockmore, and Uppal (2019) who follow a similar strategy.

[11]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.

[12]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 Deviation	Observations
Panel A:						
Forest Cover in t (%)	12.91	13.25	39,881	11.49	10.70	4,967
Growth of forest cover in t	0.03	0.37	35,929	0.02	0.37	4,564
Long Run Growth of Forest Cover	0.07	0.34	31,247	0.05	0.33	4,109
Log of Electorate Size in $t-1$	11.53	0.75	25,090	11.67	0.57	2,331
Log of Valid Votes in $t-1$	11.02	0.74	25,026	11.15	0.65	2,331
Number of Candidates in $t-1$	9.01	6.75	25,092	9.23	6.38	2,332
Turnout Percentage in $t-1$	61.58	13.99	25,090	61.27	13.18	2,331
Female Legislator in $t-1$	0.04	0.21	25,092	0.27	0.44	2,332
Winner's Party Aligned with State Ruling Party in $t-1$	0.58	0.49	25,092	0.62	0.48	2,332
Winner is Incumbent in t	0.16	0.36	25,092	0.14	0.35	2,332
Winner is from Congress in t	0.34	0.47	29,241	0.33	0.47	2,562
Winner is from BJP in t	0.13	0.34	29,241	0.15	0.36	2,562
SC Reserved Constituency	0.14	0.35	25,092	0.19	0.39	2,332
ST Reserved Constituency	0.11	0.31	25,092	0.10	0.30	2,332
Winner's Log Net Assets in t	15.05	1.59	1,475	14.97	1.45	172
Winner's Education (yrs.) in t	11.79	2.50	2,376	11.42	2.88	312
Winner's Age (yrs.) in t	48.64	10.15	3,452	47.42	10.50	442
Winner's Number of Crimes in t	3.14	8.66	2,518	2.04	7.54	325
Panel B: SC/ST Constituencies						
Forest Cover in t (%)	17.91	18.37	10,310	12.12	12.15	1,577
Growth of forest cover in t	0.02	0.33	9,248	0.02	0.35	1,446
Long Run Growth of Forest Cover	0.06	0.33	7,873	0.07	0.35	1,293
Log of Electorate Size in $t-1$	11.22	1.01	6,450	11.61	0.64	672
Log of Valid Votes in $t-1$	10.66	0.92	6,394	11.04	0.66	671
Number of Candidates in $t-1$	6.64	4.15	6,450	7.28	4.23	672
Turnout Percentage in $t-1$	58.65	17.76	6,450	58.49	14.22	672
Female Legislator in $t-1$	0.05	0.21	6,450	0.27	0.44	672
Winner's Party Aligned with State Ruling Party in $t-1$	0.63	0.48	6,450	0.64	0.47	672
Winner is Incumbent in t	0.18	0.38	6,450	0.12	0.33	672
Winner is from Congress in t	0.35	0.48	7,482	0.30	0.46	731
Winner is from BJP in t	0.13	0.34	7,482	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, Lunt, Matsuura, and Novosad, 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 2000-2011. Long run growth of forest cover represents the growth rate of forest cover the entire electoral term. Since data on forest cover is only available from 2000, we only take into account elections held in 2000 and later in order to determine the long run growth rate over the course of the five-year electoral term.

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 elections 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.

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 a 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 outcome variable of interest. We find that the average annual growth rate of forest 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. We also find that the average growth rate of forest cover over an electoral term, referred to as the long run growth of the forest cover, ranges between 5-7% across the different types of constituencies considered in Table 1.

Table 1 further reports summary statistics of other constituency level and candidate characteristics. For constituency level characteristics, the lagged values of these variables 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 one year 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 is 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.[13] 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 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 is 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.

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.

[13] 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.

3 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 year 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 $t-1$. In an alternative specification, we also use growth of forest cover over an entire electoral term as the dependent variable (details are provided in section 6). $T_{i,s,t-1}$ is the treatment variable that assumes the value 1 if the winner in 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 sides of the cut-off.[14] $\varepsilon_{i,s,t}$ is the regression disturbance term, which is clustered at the assembly constituency level.[15]

[14] 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.

[15] 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

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 neighbourhood 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 neighbourhood 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 adhoc bandwidths (even though they may be intuitively appealing), Cattaneo et al. (2019) advise against using adhoc 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

cover in the year preceding the year of the election and the latter measure would correspond to the previously elected politician.

inference.[16] 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 adhoc approach is to employ these conventional confidence intervals with a smaller or "under-smoothed" 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 utilised 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 re-adjusted). [17] 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.[18]

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

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

[18]The coverage error is the discrepancy between the nominal level of the confidence interval and its empir-

Now for the RDD to yield credible causal estimate of the impact of female politician 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 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 in the following sections that potentially support the validity of our RDD strategy.

4 Results

Table 2: Results: Growth of Forest Cover

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

Note: Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 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 computation of RDD treatment effect coefficients, optimal bandwidths, robust and bias corrected standard errors follow Cattaneo et al. (2019) and are implemented using "rdrobust" programme in STATA.

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 creating a robust bias-corrected confidence interval. We find that overall female politicians who won in a close race against a male politician have no significant impact on the annual growth in forest cover in their constituencies. However, significant heterogeneity appear to be present in terms of the impact of female politicians on forest cover change

ical 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.

when we examine constituencies that have been reserved for the historically marginalized communities, the SC/ST and those that are unreserved. While no significant effect of electing female politicians on forest cover growth can be found in unreserved constituencies; electing a female politician in a close race against a male politician increases annual forest cover growth by 6% in reserved constituencies.[19]

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. It must be noted that 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.[20] Additionally, 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 adhoc 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 adhoc 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. 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 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

[19] Although the magnitude of the impact on subsequent annual forest cover growth may appear large, even larger or similar magnitude of impact on annual deforestation on account of electing female mayors in Brazil have been found in Baragwanath and Zheng (2023).

[20] 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 3. For example, papers using RDD estimation where the optimal bandwidth is significantly large (and larger than ours) include Bhalotra et al. (2018), Meyersson (2014).

reduction in the number of observations available for estimation.

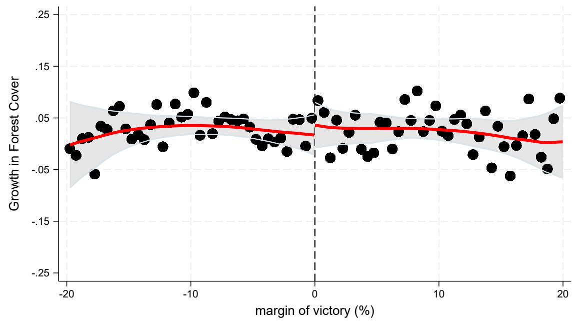
Figure 1 graphically represents the findings in Panel A of Table 2 for the sample of all and SC/ST reserved constituencies, where each of the sub-figures are drawn using equally spaced bins along with local linear regression functions fitted separately for either sides of the cut-off using MSE-optimal 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 sides of the cut-off for all constituencies (sub-figures a)); a discontinuous jump between the fitted regression lines can be observed as one moves from a negative margin of victory (representing 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 (sub-figure b)) and the confidence intervals on either sides 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.[21] Now, Mendelsohn et al. (2012) note that tropical forests can sequester upto 11 tonnes of carbon dioxide per hectare per year in the form of trees, foliage, deadwood litter.[22] Since most of India's forests are tropical forests, a 6% increase in yearly forest cover at the level of the constituency is likely to result in an increase in sequestration of approximately 1,584 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. For example, this number is significantly higher than the average per person consumption based annual carbon emissions of 1.1 tonnes during our study period.[23]

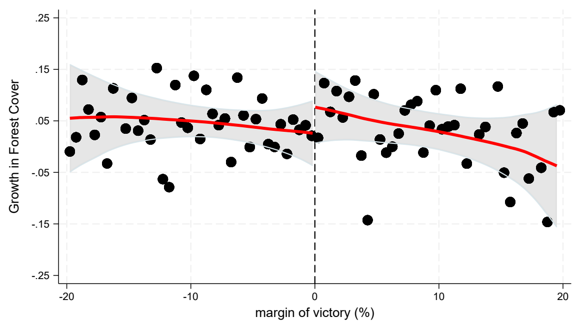
[21] A rough estimate of constituency area is used as urban assembly constituencies are significantly smaller in area due to higher population density and rural ones can even be more than 500 square kilometers due to smaller population densities. In particular, dividing the area administered by India by the number of assembly constituencies during the pre-delimitation period (which is roughly 4,120 during the pre-delimitation period prior 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.

[22] 1 square kilometre=100 hectares.

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



(a)



(b)

Figure 1: Growth in Forest Cover in: (a) All Constituencies (b) Only SC/ST Reserved 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, Lunt, Matsuura, and Novosad, 2021).

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 those reserved for SC/ST politicians, 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 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. We find that for all constituencies as well as SC/ST reserved constituencies, the election of a female legislator to the state assembly results in the growth of forest cover only for those constituencies that were relatively sparsely

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

	$< 75th$ percentile All Constituencies	$\geq 75th$ percentile All Constituencies	$< 75th$ percentile SC/ST Constituencies	$\geq 75th$ percentile SC/ST Constituencies
Female Legislator Elected in Last Election	0.05*	-0.07***	0.09***	-0.04*
	(0.02)	(0.02)	(0.04)	(0.03)
Optimal Bandwidth Type	MSE	MSE	MSE	MSE
Optimal Bandwidth	10.75	9.33	11.67	8.09
Number of Observations	2902	815	915	274
Effective Number of Observations	1540	425	540	133
Kernel Type	Triangular	Triangular	Triangular	Triangular

Note: Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 2021). The sample divisions of $<$ and $\geq$ 75th percentile refer to whether the initial forest cover in the constituency given by the sample starting period, 2000 was lower than or atleast 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. ***, **, * 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 computation of RDD treatment effect coefficients, optimal bandwidths, robust and bias corrected standard errors follow Cattaneo et al. (2019) and are implemented using "rdrobust" programme in STATA.

forested at the start of our study period. In particular 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. This is specifically found for the sample of all constituencies and is less prominent for the sample of SC/ST reserved constituencies. On the other hand, the positive impacts of electing a female politician on subsequent forest cover growth is particularly large for constituencies that are both reserved for SC/ST politicians and those which were relatively sparsely forested at the start of our study period. This analysis shows that our findings in Table 2 are likely to be largely driven by the constituencies that had relatively lower forest cover in 2000.

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.[24] In subsequent columns, we restrict the 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 of constituencies whose forest cover in the year 2000 is at least as large as 5% and 10% of the average forest cover

[24] 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 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
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**	0.03*
	(0.03)	(0.02)	(0.02)
Optimal Bandwidth Type	MSE	MSE	MSE
Optimal Bandwidth	12.71	14.02	15.70
Number of Observations	1121	1186	1205
Effective Number of Observations	721	793	855
Kernel Type	Triangular	Triangular	Triangular

Note: Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 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. "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 deviation 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 computation of RDD treatment effect coefficients, optimal bandwidths, robust and bias corrected standard errors follow Cattaneo et al. (2019) and are implemented using "rdrobust" programme in STATA.

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. In other words, electing a female politician in SC/ST reserved constituencies is potentially likely to promote growth in forest cover by a magnitude of 5-7% depending on our sample restrictions.

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.[25] 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 inclusion of state and year fixed effects impose severe restriction on the estimation framework, wherein close mixed gender elections in SC/ST reserved constituencies within states and years are to be compared.

5 Validity of the RDD

Here, 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 usage of placebo thresholds for the running variable as suggested by Cattaneo et al. (2019); Cunningham (2021). We discuss each of these tests in the following subsections. While the McCrary density and covariate continuity tests have been extensively used in the existing literature; to the best of our knowledge, studies assessing the sensitivity of findings especially in the context of the donut hole and placebo cut-off tests are relatively rare.

5.1 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 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, 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. Figure 2 here depicts the distribution of the margin of victory between female and male politician winners in SC/ST reserved constituencies. There appears to be no observed discontinuous jumps in the density

[25] 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).

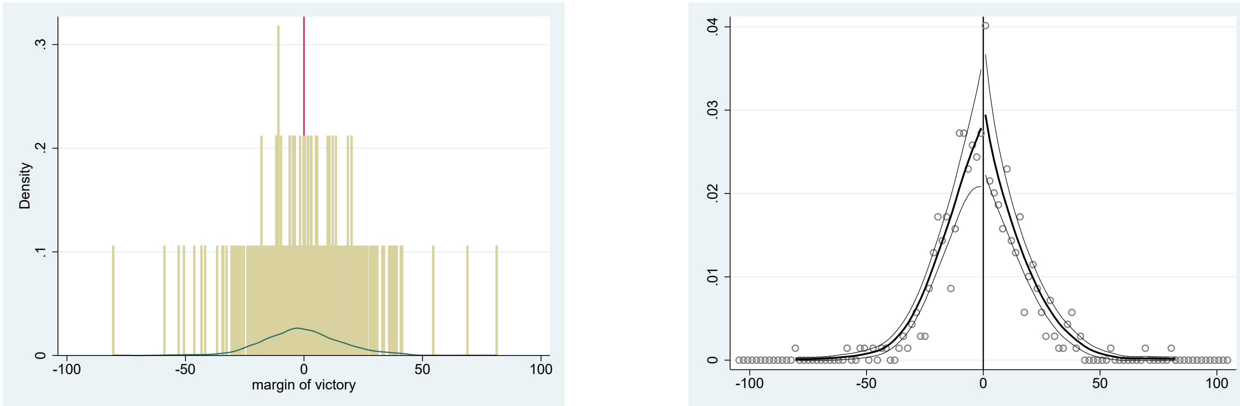


Figure 2: (a) Histogram depicting the distribution of the margin of victory in mixed gender elections for SC/ST constituencies for election years 1996 and beyond. (b) Corresponding McCrary density test where estimated log difference in height: 0.078, standard error: 0.193.

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 Figure 2 a). However, a formal test of discontinuity in the density of the running variable has been proposed by McCrary (2008) which we show in Figure 2 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 sides of the threshold is not found to be statistically significant.

Our findings from the McCrary density test show that manipulation of victory margin around the threshold of victory in mixed gender elections is unlikely in SC/ST reserved constituencies. Additionally, Appendix Figure A.1 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.

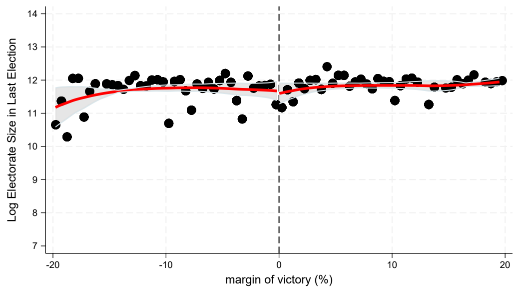
5.2 Continuity of Covariates

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 are 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).[26] 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).

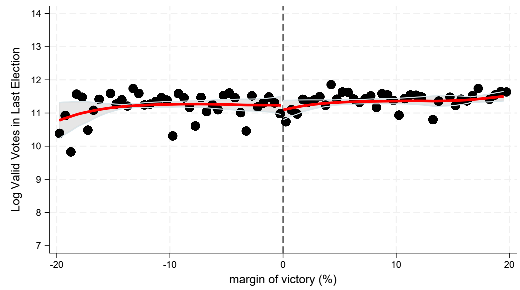
Additional candidate level characteristics that could matter in our context are the winner's net assets (in logarithm), years of education, age and number of crimes. These candidate level attributes are for the winners in the current electoral term. This is because of two reasons. Firstly, as has been discussed in earlier sections, 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 (Saavedra Pineda 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., 2022). 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).

Figure 3 depicts these covariate continuity graphs. We find that in SC/ST 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 sides of the threshold either appear to have no visible discontinuity or have large, overlapping confidence intervals; indicating no statistically significant discontinuity on either sides of the

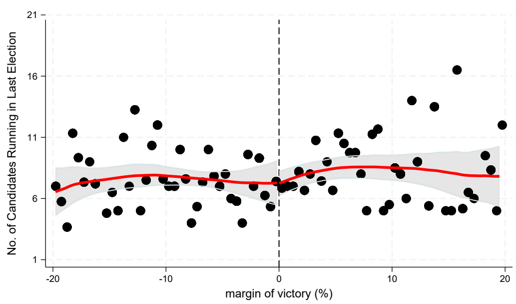
[26] India is a multi-party democracy and hence belonging to Congress and BJP are not mutually exclusive outcomes as there are other major political parties. However, these are the largest political parties in terms of presence of Members of Parliament (MPs) in the lower house of the Indian Parliament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


Log Electorate Size in Last Election
margin of victory (%)

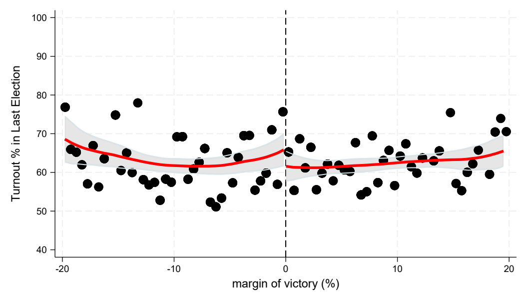
(a)


Log Valid Votes in Last Election
margin of victory (%)

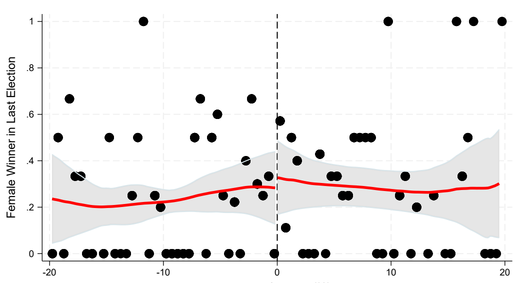
(b)


No. of Candidates Running in Last Election
margin of victory (%)

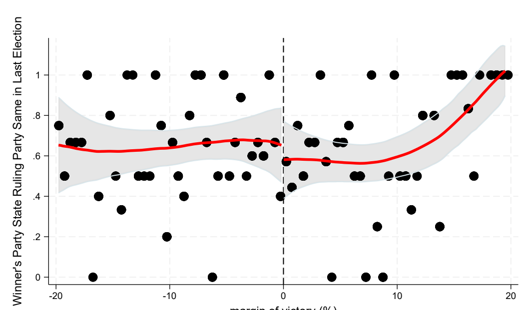
(c)


Turnout % in Last Election
margin of victory (%)

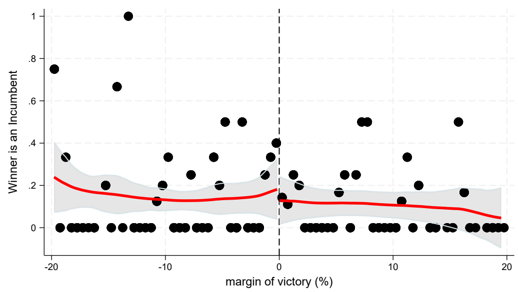
(d)


Female Winner in Last Election
margin of victory (%)

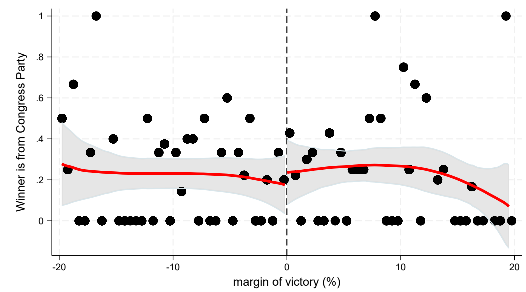
(e)


Winner's Party State Ruling Party Same in Last Election
margin of victory (%)

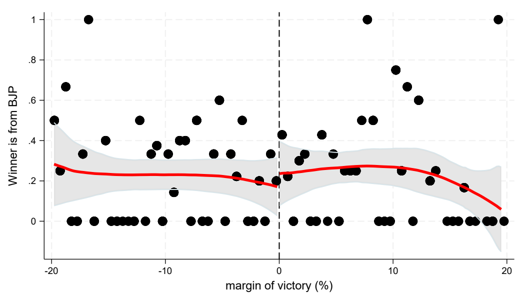
(f)


Winner is an Incumbent
0
.2
.4
.6
.8
1
-20
-10
0
10
20
margin of victory (%)

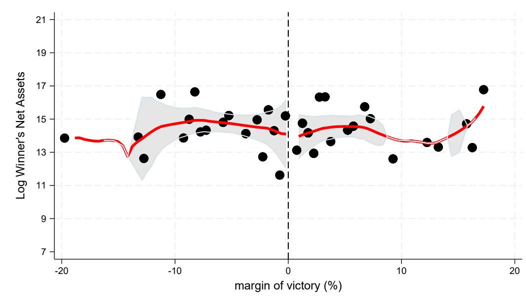
(g)


Winner is from Congress Party
0
.2
.4
.6
.8
1
-20
-10
0
10
20
margin of victory (%)

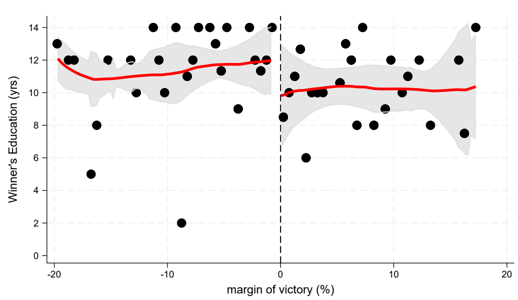
(h)


Winner is from BJP
0
.2
.4
.6
.8
1
-20
-10
0
10
20
margin of victory (%)

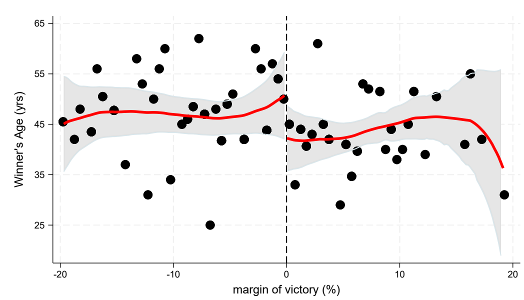
(i)


Log Winner's Net Assets
7
9
11
13
15
17
19
21
-20
-10
0
10
20
margin of victory (%)

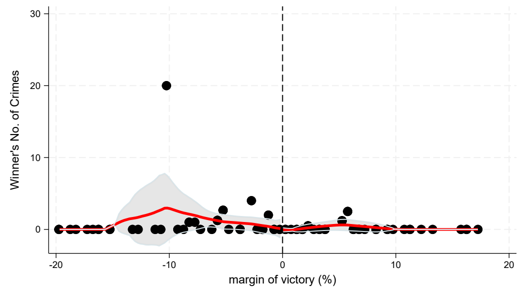
(j)


Winner's Education (yrs)
0
2
4
6
8
10
12
14
-20
-10
0
10
20
margin of victory (%)

(k)


Winner's Age (yrs)
25
35
45
55
65
-20
-10
0
10
20
margin of victory (%)

(l)



(m)

Figure 3: Continuity of Past Constituency & Current Candidate Characteristics in SC/ST Constituencies: (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. 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, Lunt, Matsuura, and Novosad, 2021). Years of election start from 1996 onwards.

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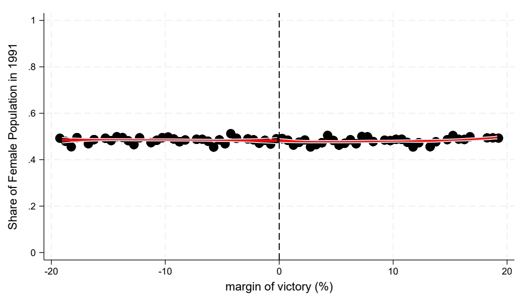
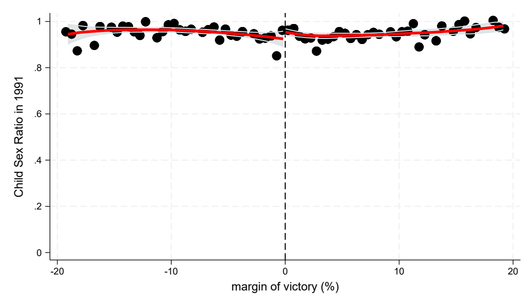
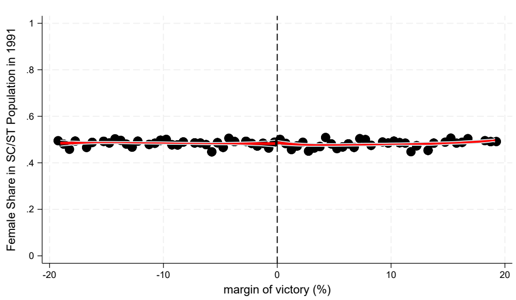
cut-off of the margin of victory.



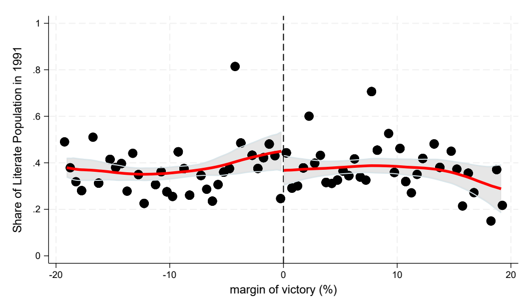
(a)



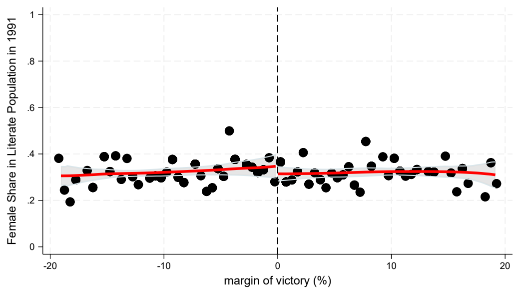
(b)



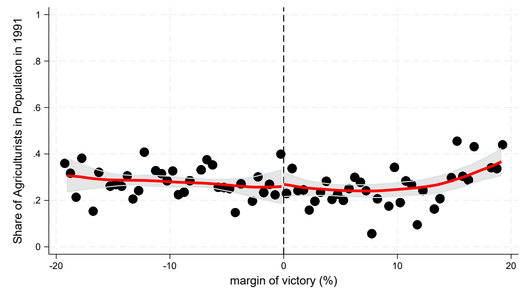
(c)



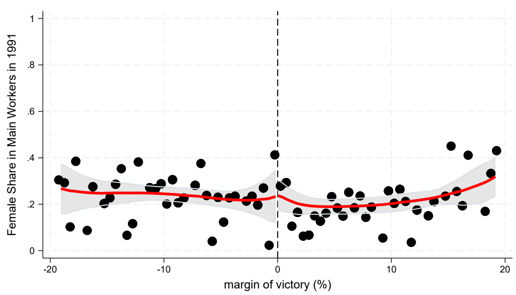
(d)



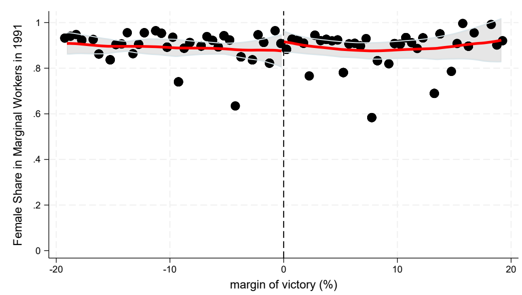
(e)



(f)



(g)



(h)

Figure 4: Continuity of Past Constituency Demographic Characteristics in SC/ST Constituencies: (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. 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 1991 Population Census figures at the constituency level obtained from The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 2021). Years of election start from 1996 onwards.

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 share of females in the population, child sex ratio (that is female to male ratio in the 0-6 years population), share of females in the SC/ST population, population share of literates as well as share of females in the literate population, population share of agriculturists and share of females among main and marginal workers.[27] The information on these variables are obtained from the Population Census of 1991 and have been made available at the assembly constituency level by the SHRUG platform (Asher, Lunt, Matsuura, and Novosad, 2021).[28] Figure 4 plots these covariate continuity graphs. 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 Figures A.2 and A.3 provide analogous exposition for the entire sample of constituencies (that is, both reserved and unreserved). Almost all of the covariates show no discontinuity at the threshold.[29] 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.

5.3 Donut Hole Test

Recent recommendations for conducting robustness exercises for RDD include assessing how sensitive are the results 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

[27] 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.

[28] 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.

[29] The only robust discontinuity is in the candidate's age and years of education. It appears that female candidates who win are significantly younger and have lower educational attainment than male winners during the current election. Hence, it is advisable to exercise some caution while assessing the credibility of the RD design for the sample of all constituencies despite most covariates displaying no discontinuity at the threshold of the margin of victory in the current election.

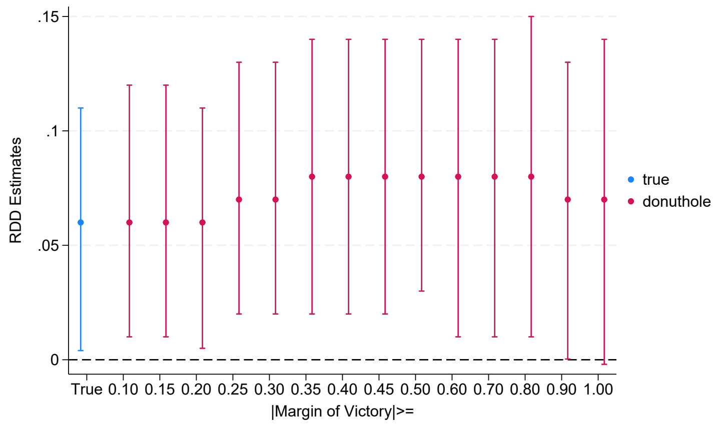


Figure 5: Donut Hole Regressions: RDD point estimates and robust and bias-corrected 95% confidence intervals from local linear regressions with different slopes on either sides of the cut-off using MSE-optimal bandwidth and triangular kernel function have been plotted. The true point estimate and confidence 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|$\geq$ 0.1 are obtained by excluding observations that correspond to margins of victory in the interval [-0.1, 0.1].

RD treatment effect, then removing a few observations from either sides 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 by removing several observations from either sides of the threshold of the margin of victory repeatedly and represent our findings graphically in Figure 5. We continue to rely on the MSE-optimal bandwidth as in Panel A of Table 2 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 represent 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 $[-0.1, 0.1]$.[30] 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

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

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.

5.4 Using Placebo Cut-off

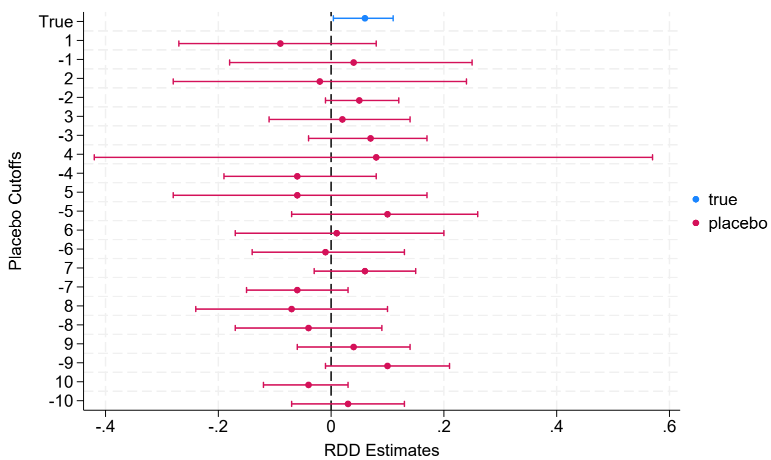


Figure 6: Placebo Cut-off Regressions: RDD point estimates and robust and bias-corrected 95% confidence intervals from local linear regressions with different slopes on either sides of the cut-off using MSE-optimal bandwidth and triangular kernel function have been plotted. The true point estimate and 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 false negative cut-offs to prevent contamination from true treatment effects.

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 sides of our true cut-off, 0 and report the findings in Figure 6 here.

The blue line in Figure 6 represents the RDD point estimate and 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 estimate 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 RD 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 Figure 6, therefore, lend some support to the credibility of our main RD treatment effect estimate for SC/ST reserved constituencies found in Table 2.

6 Dynamic Effects: Forest Cover Growth Over Electoral Term

So far we have studied the impact of electing a female politician on subsequent annual forest cover growth. As discussed, we found no significant impact for the sample of all constituencies, but positive significant effects for the sample of SC/ST reserved constituencies. 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.[31] 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

[31] Recall that our sample does not include bye-elections that take place typically if an MLA dies or resigns from office without completing their full term.

one's election to office.[32] The results of this analysis are reported in Table 5 here.

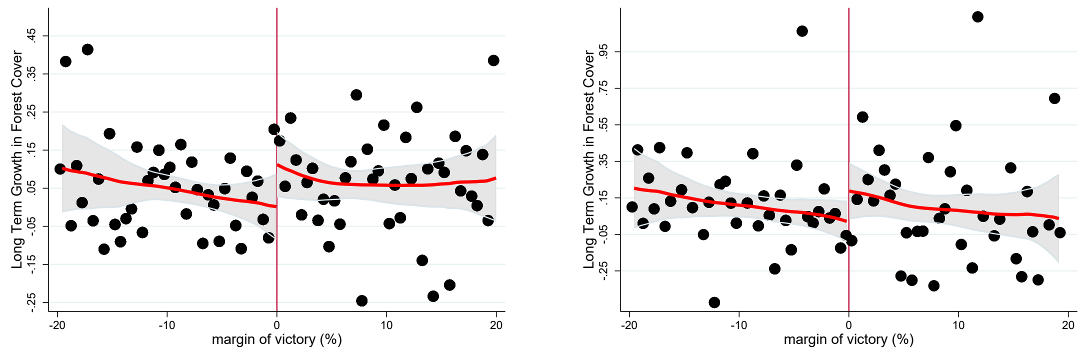
Table 5: Results: Growth of Forest Cover Over an Electoral Term

Panel A:	All Constituencies	All Constituencies	SC/ST Constituencies	SC/ST Constituencies
Female Legislator Elected in Last Election	0.12*	0.13*	0.19*	0.21*
	(0.07)	(0.08)	(0.12)	(0.12)
Optimal Bandwidth Type	MSE	CER	MSE	CER
Optimal Bandwidth	13.42	9.64	12.71	9.67
Number of Observations	834	834	262	262
Effective Number of Observations	550	426	167	134
Kernel Type	Triangular	Triangular	Triangular	Triangular
Panel B:	< 75th percentile	≥ 75th percentile	< 75th percentile	≥ 75th percentile
	All Constituencies	All Constituencies	SC/ST Constituencies	SC/ST Constituencies
Female Legislator Elected in Last Election	0.16*	0.03	0.26*	0.002
	(0.09)	(0.11)	(0.15)	(0.17)
Optimal Bandwidth Type	MSE	MSE	MSE	MSE
Optimal Bandwidth	12.63	11.35	11.66	10.50
Number of Observations	634	181	201	35
Effective Number of Observations	387	116	119	57
Kernel Type	Triangular	Triangular	Triangular	Triangular

Note: Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 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 and CER-optimal bandwidth, wherever applicable. 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 atleast as large as the 75th percentile of the distribution of the proportion of forest cover at the constituency level in 2000. 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" programme in STATA.

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 in the odd numbered columns. Interestingly, now we find that effects are observed not only for the SC/ST reserved constituencies, but also overall for all constituencies. The magnitude of the impact is higher for the SC/ST reserved constituencies (19%) than that for all the constituencies that had mixed gender close elections (12%). A possible reason why the point estimate of the effect is higher for the SC/ST constituencies relative to the all constituencies is that the short term (that is, year to year) increments in forest cover growth is also significant for these constituencies unlike for all constituencies as has been shown in Table 2. Therefore, dynamic impacts as defined by forest cover growth over an entire electoral term is likely to be higher for the SC/ST constituencies than for all constituencies that had mixed gender elections. In fact, the overall growth rate during the

[32] 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" and "Results" sections of the paper.



(a) (b)

Figure 7: Growth in Forest Cover over an Electoral Term in: (a) All Constituencies (b) Only SC/ST Reserved 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, Lunt, Matsuura, and Novosad, 2021).

entire electoral term for the SC/ST 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). This principle applies to every other electoral constituency as well, as the influence of electing a female politician on environmental conservation seems to accumulate gradually over time. Thus, the effect on all constituencies becomes evident when we focus on the entirety of a female politician's electoral term, rather than analyzing yearly fluctuations. Figure 7 here represents the findings of the odd numbered columns in Panel A of Table 5 that use the MSE-optimal bandwidth graphically for the sample of all constituencies in subfigure (a) and specifically SC/ST reserved constituencies in subfigure (b). We also find that using the relatively smaller CER optimal bandwidth does not qualitatively alter our findings as can be seen from the even numbered columns in Panel A of Table 5. Appendix Tables A.4 and A.5 present results where bandwidth sizes lower 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 whose details have been explained previously in the "Results" section of the paper. 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.

Panel B of Table 5 repeats an exercise that is analogous to Table 3. Using the MSE-optimal bandwidth we find that the results obtained in Panel B are largely driven by constituencies whose fraction of area under forest cover at the start of the study period, 2000 was below the 75th percentile of the distribution of the area under forest cover at the constituency level in 2000. These findings are, therefore, similar in spirit to those obtained for yearly growths in Table 3 reported before.

7 Discussion of Potential Mechanisms

7.1 Annual Growth Rates: Female Politicians in SC/ST Constituencies

This paper finds that gender of the legislator matters for environmental outcomes in India. In particular, electing a female legislator in close mixed gender races positively affects subsequent annual forest cover growth rate. However, this finding is limited to constituencies which 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).

We found that male and female politicians from SC/ST reserved constituencies do not appear to be systematically different along observed characteristics such as age, education, asset ownership or the number of crimes that one has been charged with (from the covariate continuity analysis in Figure 3). In general, the literature has demonstrated that these characteristics often influence the decision to invest in activities such as environmental conservation.[33] It is likely that, in our context, it is not the difference in these characteristics between the elected politicians in these constituencies that is influencing our findings. 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 these constituencies. Unfor-

[33] See for example, Dahis et al. (2023) for the impact of young politicians on environmental conservation; Johannesson and Ågren (2022) for the impact of criminal politicians on deforestation. Baragwanath and Zheng (2023) find positive impact of electing women mayors on deforestation in Brazil and demonstrate that lower corruption and 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, politician nexus with vested interest groups and subsequently corruption is unlikely to explain why female candidates in SC/ST reserved constituencies are effective in promoting forest cover growth unlike their male counterparts.

tunately, 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 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 intersection of these two issues.

Plausible behavioral/preference differences between men and women has 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 behaviours 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 behaviour. 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.[34] 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, favour 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% women in the sample agreed with the statement while 55% men did (where the sample comprised of 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

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

Besley and Coate (1997).

If these channels are indeed important in explaining our main result; it is important to note that these potential behavioural 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 (George and Sharma, 2023). 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, interaction between preferences and constraints is possible. For example, 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.[35]

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., 2023). 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.[36] 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, extension of control of local forests to these communities

[35]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.

[36]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.

along with potentially greater preference of women in conserving the environment are plausible mechanisms explaining our findings on why we observe annual increases in forest cover following the election of a female legislator in reserved constituencies.

7.2 Dynamic Effects: Female Politicians in all & SC/ST Constituencies

Our analysis found that positive effects on environmental conservation in all constituencies with a female legislator often build up over a legislator's term in office. Here, we attempt to understand a possible mechanism that could explain this finding. Appendix Figure A.2 shows that for the sample of all constituencies, a strong difference between constituencies electing a female and a male politician in mixed gender races is in terms of legislator's age.[37] In particular, female legislators are found to be around 6 years younger than their male counterparts. We, therefore, attempt to investigate whether difference in legislator age could explain our findings on the impacts of legislator gender on forest cover growth over a relatively longer span of time, that is, their electoral term. 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 of being elected to state legislatures in India is 25 years, most MLAs are significantly older.[38] For our purpose, we use the age cutoff of 60 years and alternatively 63 years to demarcate between old and young MLAs.[39] We report the results in Table 6 here.

We find that our results on dynamic impacts of female legislators in all constituencies on forest cover growth is driven by "relatively" younger female MLAs. Panel A of Table 6 shows that in the sample of MLAs who are younger than 60 years old at the time of the election, the impact of electing a female legislator in a mixed gender race on forest cover growth over the electoral term is large (27%) and statistically significant, using the MSE-optimal bandwidth. However, for MLAs who are aged 60 years or older, no significant difference is observed

[37] Notably female winning candidates appear to have fewer number of years of education than their male counterparts. Although this is not surprising, what is important to note is that higher educational attainment of politicians leading to better environmental conservation (either through education influencing the leader's better awareness or greater ability to implement conservation policies) cannot be an explanation of why female politicians are likely to promote forest cover growth during their electoral term relative to their male counterparts.

[38] 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)

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

Table 6: 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	0.27**	0.04	0.27**	0.002
	(0.12)	(0.08)	(0.12)	(0.09)
Optimal Bandwidth Type	MSE	MSE	MSE	MSE
Optimal Bandwidth	10.14	12.69	9.76	11.12
Number of Observations	380	454	407	427
Effective Number of Observations	221	272	231	231
Kernel Type	Triangular	Triangular	Triangular	Triangular
Panel B:	< 60 years	≥ 60 years	< 63 years	≥ 63 years
Female Legislator Elected in Last Election	0.30**	0.02	0.30**	-0.02
	(0.13)	(0.09)	(0.13)	(0.09)
Optimal Bandwidth Type	CER	CER	CER	CER
Optimal Bandwidth	7.53	9.36	7.23	8.22
Number of Observations	380	454	407	427
Effective Number of Observations	185	208	192	175
Kernel Type	Triangular	Triangular	Triangular	Triangular

Note: Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 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 computation of RDD treatment effect coefficients, optimal bandwidths, robust and bias corrected standard errors follow Cattaneo et al. (2019) and are implemented using "rdrobust" programme in STATA.

between female and male MLAs in terms of evolution of forest cover over one's term in office. Similar findings are obtained if we considered 63 years as the age cutoff instead. This age cutoff further ensures more equitable distribution of observations on either sides of the age cutoff. Our results are, therefore, similar to Dahis et al. (2023) indicating that relatively younger politicians have incentive to invest in policies that are often likely to yield benefits over the long term, such as environmental conservation. Relatively younger politicians are also likely to survive an electoral term and hence may invest in environmental conservation over time during their time in office. Using the CER-optimal bandwidth in Panel B yields similar results as Panel A.

Although the above explanation is likely to be applicable for all constituencies, it may not be a plausible explanation if we consider only the sample of SC/ST reserved constituencies. This is because Figure 3 shows that there appears to be no significant difference in ages between female and male legislators in mixed gender races in these constituencies. Further, the dynamic impact on forest cover growth over a female legislator's electoral term (from Table 5) appears to be largely similar to an aggregation of the annual forest cover growth rates in these constituencies (from Table 2). As the impact of female MLAs from the SC/ST reserved constituencies on the annual growth rate of forest cover is evident, the year-to-year cumulative effects largely determine the dynamic consequences on the growth of forest cover in these constituencies. Therefore, the plausible reasons that influence yearly forest cover growth after the election of a female politician in SC/ST reserved constituencies is likely to hold in the context of the dynamic impacts on forest cover growth in these constituencies.

8 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 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 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%. However, this finding is limited only to the constituencies which 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 impact on environmental conservation. Here we find that forest cover growth increases by around 12% in all constituencies with a female legislator over their term in office; while the impact for SC/ST reserved constituencies roughly reflect an aggregation of the positive annual growth rate found for these constituencies with a female legislator.

We do not find significant differences in observable characteristics (such as education, age, asset ownership, criminality, incumbency) which often influence environmental conservation between female and male politicians in SC/ST reserved constituencies. Therefore, it is likely that 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 vulnerability of the SC/STs to adverse impacts of climate change 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. Further the impact on forest cover growth for all constituencies over a legislator's electoral term are largely found to be driven by younger female politicians as, unlike in only SC/ST constituencies, the most striking difference between male and female politicians in all constituencies are their ages.

Our results show that gender of politicians impact 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.

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Appendix

Table A.1: Occurrence of Mixed Gender Elections

Mixed Gender Constituencies	All Constituencies	Only SC/ST Constituencies
Panel A: All Years		
Percentage	8.78%	9.84%
Total No. of Observations	29,172	731
Panel B: From 1996 Onwards		
Percentage	11.98%	15.04%
Total No. of Observations	9,893	377

Note: Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 2021). Total no. of observations refer to 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 Deviation	Observations
Panel A:						
Log of Electorate Size in $t-1$	11.71	0.77	9,789	11.83	0.56	1,173
Log of Valid Votes in $t-1$	11.27	0.73	9,739	11.36	0.65	1,173
Number of Candidates in $t-1$	10.35	7.42	9,790	10.03	7.07	1,174
Turnout Percentage in $t-1$	64.95	12.88	9,789	64.36	11.41	1,173
Female Legislator in $t-1$	0.05	0.23	9,790	0.26	0.44	1,174
Winner's Party Aligned with State Ruling Party in $t-1$	0.54	0.50	9,790	0.59	0.49	1,174
Winner is Incumbent in t	0.19	0.39	9,790	0.17	0.38	1,174
Winner is from Congress in t	0.28	0.45	9,942	0.28	0.45	1,185
Winner is from BJP in t	0.20	0.40	9,942	0.19	0.39	1,185
SC Reserved Constituency	0.14	0.35	9,790	0.21	0.41	1,174
ST Reserved Constituency	0.11	0.32	9,790	0.11	0.31	1,174
Panel B: SC/ST Constituencies						
Log of Electorate Size in $t-1$	11.38	1.06	2,530	11.74	0.66	373
Log of Valid Votes in $t-1$	10.96	0.94	2,483	11.26	0.65	372
Number of Candidates in $t-1$	7.35	4.62	2,530	7.74	4.32	373
Turnout Percentage in $t-1$	64.14	16.31	2,530	62.47	11.68	373
Female Legislator in $t-1$	0.06	0.25	2,530	0.26	0.44	373
Winner's Party Aligned with State Ruling Party in $t-1$	0.58	0.49	2,530	0.63	0.48	373
Winner is Incumbent in t	0.20	0.40	2,530	0.14	0.34	373
Winner is from Congress in t	0.29	0.45	2,551	0.23	0.42	377
Winner is from BJP in t	0.20	0.40	2,551	0.21	0.41	377

Note: Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 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	20.18	18.49	16.81	15.13
Bandwidth Size to Bias Ratio	0.60	0.60	0.60	0.60	0.60
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	13.45	11.77	10.09	8.41	
Bandwidth Size to Bias Ratio	0.60	0.60	0.60	0.60	
Number of Observations	1205	1205	1205	1205	
Effective Number of Observations	509	459	412	335	
Kernel Type	Triangular	Triangular	Triangular	Triangular	

Note: Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 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 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" programme 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	0.58	0.58	0.58	0.58	0.58
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	13.67	11.96	10.25	8.54	
Bandwidth Size to Bias Ratio	0.58	0.58	0.58	0.58	
Number of Observations	834	834	834	834	
Effective Number of Observations	372	342	302	252	
Kernel Type	Triangular	Triangular	Triangular	Triangular	

Note: Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 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 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" programme in STATA. Column (1) represents the estimated effect using the MSE optimal bandwidth and is the same as Column (1) 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	20.36	18.66	16.97	15.27
Bandwidth Size to Bias Ratio	0.59	0.59	0.59	0.59	0.59
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	13.57	11.88	10.18	8.48	
Bandwidth Size to Bias Ratio	0.59	0.59	0.59	0.59	
Number of Observations	262	262	262	262	
Effective Number of Observations	115	103	92	74	
Kernel Type	Triangular	Triangular	Triangular	Triangular	

Note: Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 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 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" programme in STATA. Column (1) represents the estimated effect using the MSE optimal bandwidth and is the same as Column (3) of Table 5. Bandwidths chosen manually are such that they preserve the ratio of bandwidth size to bias from the MSE-optimal bandwidth algorithm.

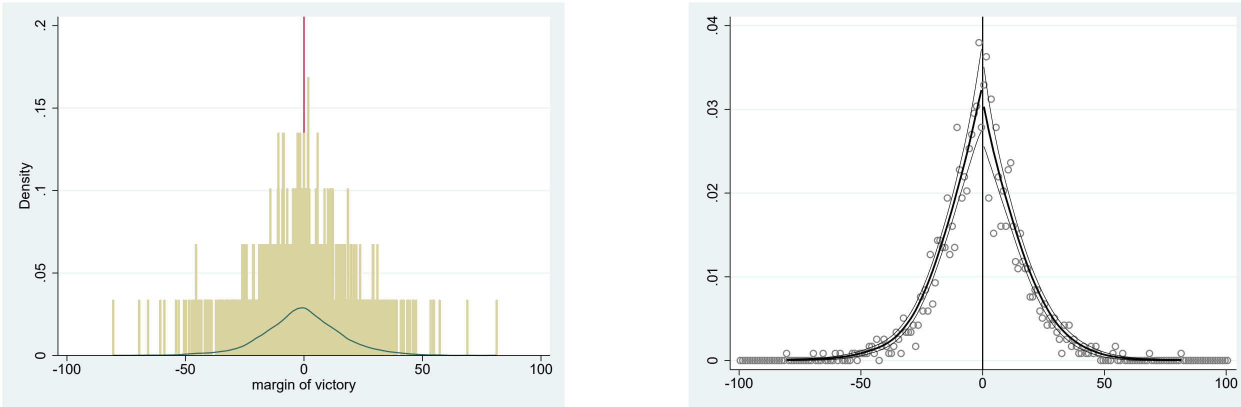
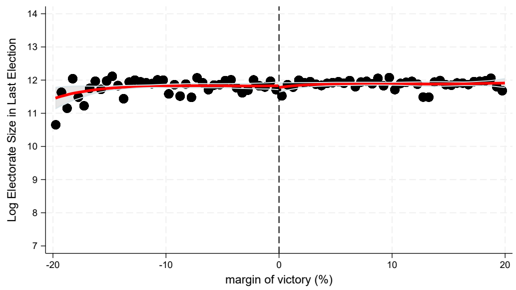
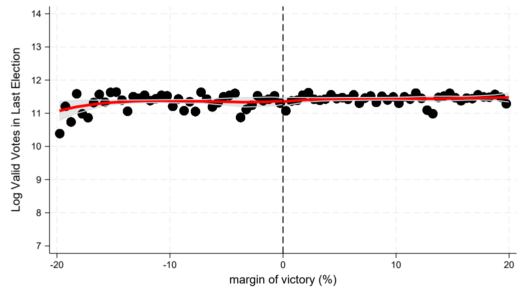


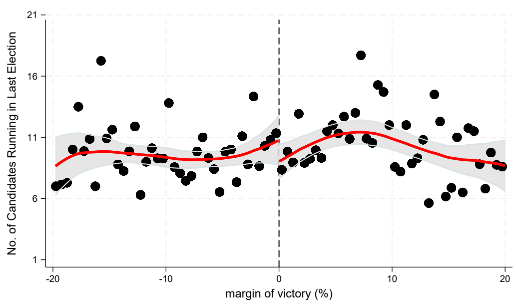
Figure A.1: a) Histogram depicting the distribution of margin of victory in mixed gender elections for all constituencies for election years 1996 and beyond. b) Corresponding McCrary density test where estimated log difference in height: -0.062, standard error: 0.117.


Log Electorate Size in Last Election
14
13
12
11
10
9
8
7
-20
-10
0
10
20
margin of victory (%)

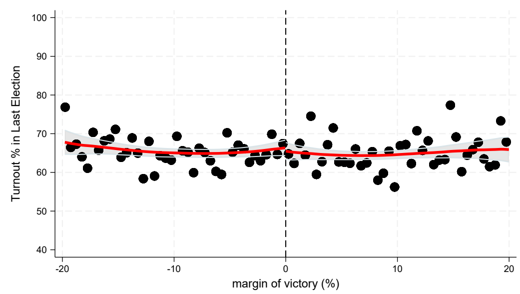
(a)


Log Valid Votes in Last Election
14
13
12
11
10
9
8
7
-20
-10
0
10
20
margin of victory (%)

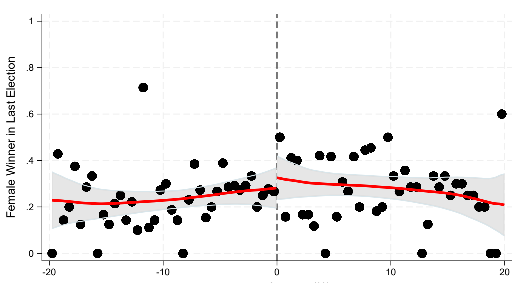
(b)


No. of Candidates Running in Last Election
21
16
11
6
1
-20
-10
0
10
20
margin of victory (%)

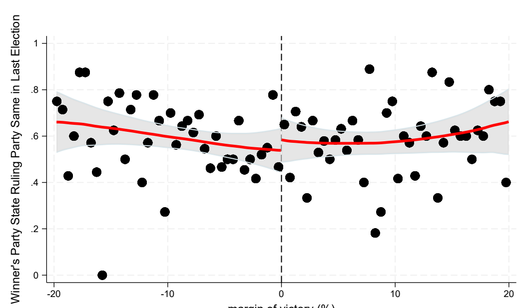
(c)


Turnout % in Last Election
100
90
80
70
60
50
40
-20
-10
0
10
20
margin of victory (%)

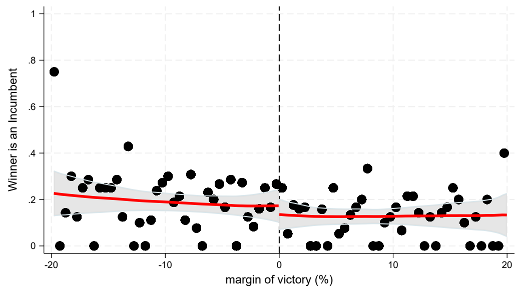
(d)


Female Winner in Last Election
1
.8
.6
.4
.2
0
-20
-10
0
10
20
margin of victory (%)

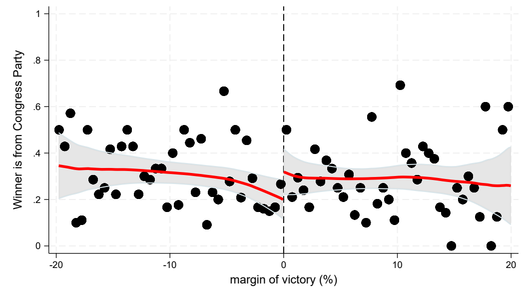
(e)


Winner's Party State Ruling Party Same in Last Election
1
.8
.6
.4
.2
0
-20
-10
0
10
20
margin of victory (%)

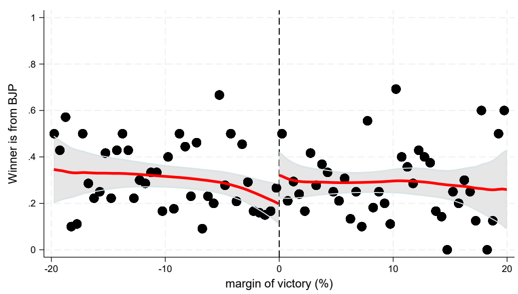
(f)


Winner is an Incumbent
margin of victory (%)

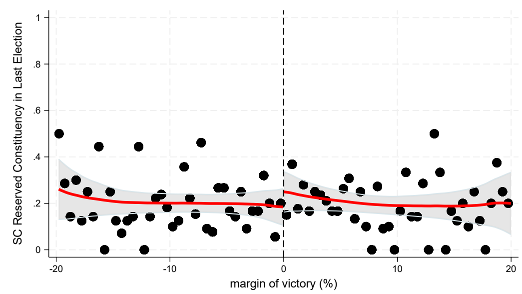
(g)


Winner is from Congress Party
margin of victory (%)

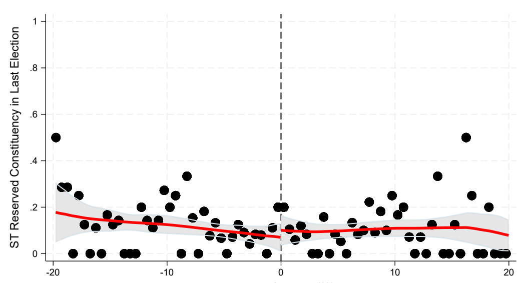
(h)


Winner is from BJP
margin of victory (%)

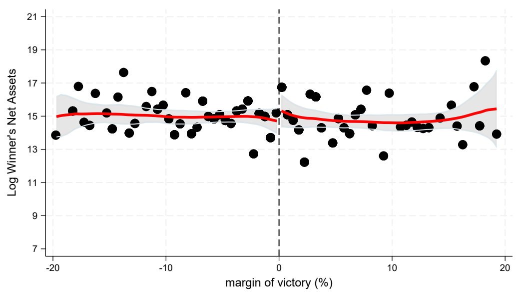
(i)


SC Reserved Constituency in Last Election
margin of victory (%)

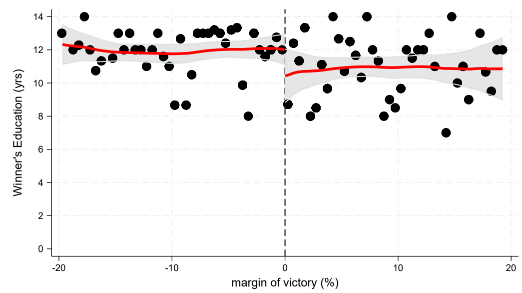
(j)


ST Reserved Constituency in Last Election
margin of victory (%)

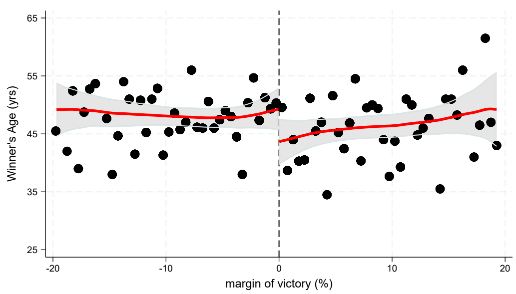
(k)



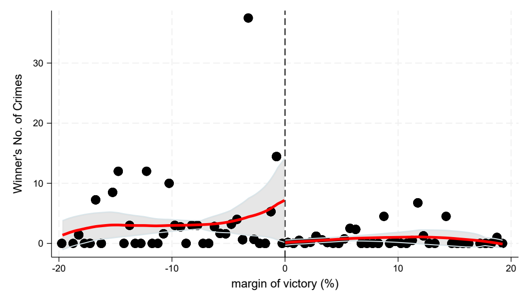
(l)



(m)

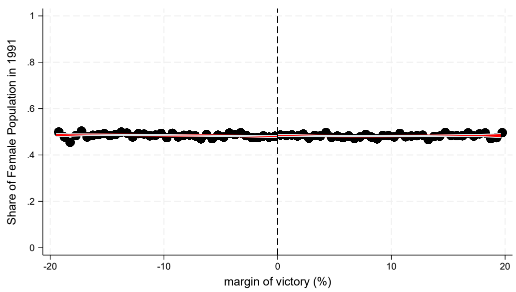


(n)

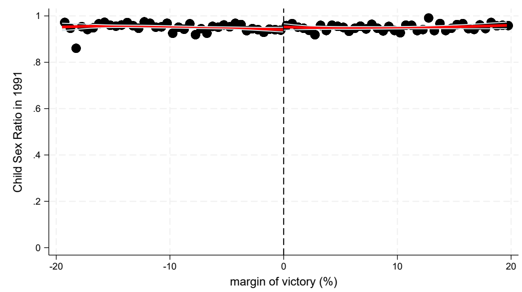


(o)

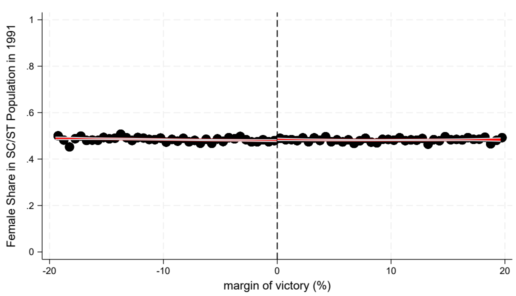
Figure A.2: Continuity of Past Constituency & Current Candidate Characteristics in All Constituencies: (a) Log Electorate Size in $t-1$ (b) Log Valid Votes in $t-1$ (c) Number of Candidates in $t-1$ (d) Turnout Percentage in $t-1$ (e) Female Legislator in $t-1$ (f) Winner's party aligned with State Ruling 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 Constituency in $t-1$ (k) ST Reserved Constituency 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. 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, Lunt, Matsuura, and Novosad, 2021). Years of election start from 1996 onwards.


Share of Female Population in 1991
0
.2
.4
.6
.8
1
-20
-10
0
10
20
margin of victory (%)

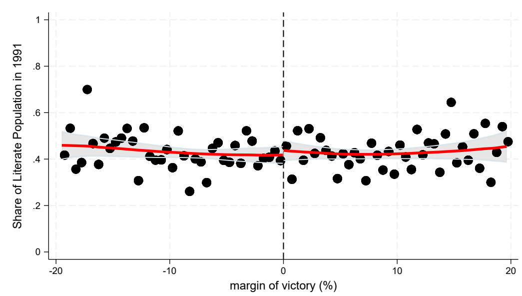
(a)


Child Sex Ratio in 1991
0
.2
.4
.6
.8
1
-20
-10
0
10
20
margin of victory (%)

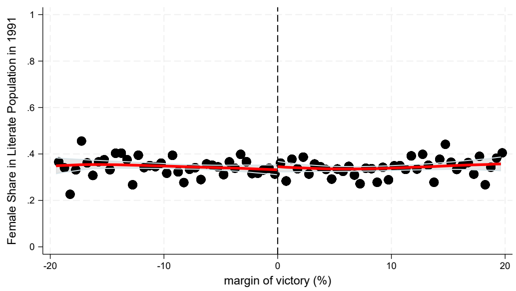
(b)


Female Share in SC/ST Population in 1991
0
.2
.4
.6
.8
1
-20
-10
0
10
20
margin of victory (%)

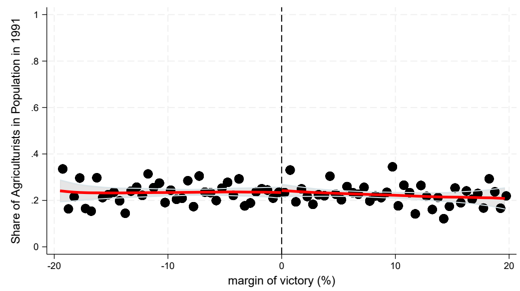
(c)


Share of Literate Population in 1991
0
.2
.4
.6
.8
1
-20
-10
0
10
20
margin of victory (%)

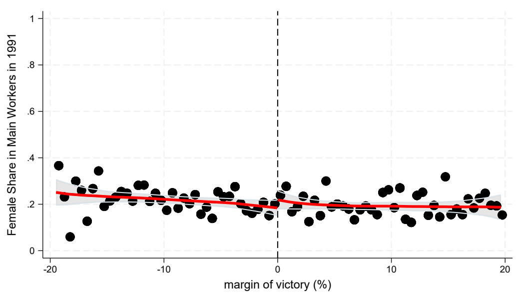
(d)



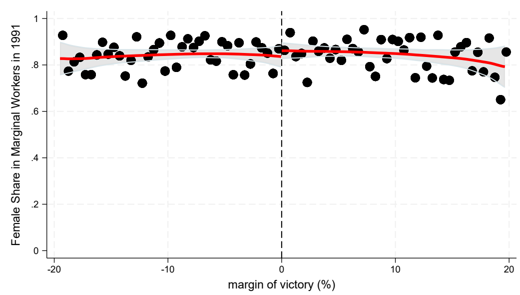
(e)



(f)



(g)



(h)

Figure A.3: Continuity of Past Constituency Demographic Characteristics in All Constituencies: (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. 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 1991 Population Census figures at the constituency level obtained from The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 2021). Years of election start from 1996 onwards.