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Female Legislators and Forest Conservation in India *

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Abstract

We study the causal impact of legislator gender on forest cover growth in India. Exploiting quasi-random variation in close mixed gender electoral races in a regression discontinuity framework, we find that assembly constituencies where a female politician won witnessed an increase in subsequent annual forest cover growth by 6%. However, this result is limited to constituencies that are reserved for historically marginalized communities. Our findings underscore the role of legislator identity in influencing environmental conservation and thereby achieving sustainable development in India.

Keywords: forest; 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 as a major carbon sink 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 widely 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. Now 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. It is to be noted that politicians elected to state assembly constituencies could exert important influence on environmental and in particular forest conservation policies as 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]

There are three main reasons that motivate us to pursue this research question. Firstly, adverse impacts of climate change such as extreme temperature, erratic rainfall and extreme weather events have been shown to adversely affect child survival, maternal health and violence against women (Banerjee and Maharaj (2020); Kim et al. (2021); Kumar et al. (2016); Currie and Rossin-Slater (2013); Sekhri and Storeygard (2014); Sekhri and Hossain (2023)). Given that there is now a large body of literature in economics that has established that women politicians are responsive to issues that are more likely to affect women and chil-

[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. This shows the preeminent role that members of the state legislature continue to play in forest governance and conservation.

dren 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 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 plausibly conceptually distinct and therefore the impact of female politicians in mitigating air pollution need not apply to their role in 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. However, whether these preferences of women are indeed translated to women in positions of power is largely understudied. Now, a recent cross-country study suggests 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 absent. 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 has often been viewed as being at loggerheads with each other. Therefore, ex ante, it is not clear whether women politicians would necessarily promote forest cover growth. However with increased acknowledgement of the need of sustainable growth, examining whether female legislators indeed can help promote a sustainable growth path is an interesting question.

Now identifying the impact of female politicians on forest cover growth is challenging because 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 race. 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 "barely" 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).[2] 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 number of variety of outcomes (Clots-Figueras (2011); Clots-Figueras (2012); Bhalotra and Clots-Figueras (2014); Broockman (2014)Brollo and Troiano (2016); Bhalotra et al. (2018); Baskaran et al. (2023)).

For our analysis, we combine forest cover data for the period 2000-2014 and corresponding state assembly elections data from The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, 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 disadvantaged communities, the Scheduled Castes (SCs) and Scheduled Tribes (STs). 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%.

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

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. 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).

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), the choice of the number of observations close to the cut-off that is used for estimating the RD treatment effect (sensitivity to bandwidth choice) 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.

Since we do not find any significant difference between female and male winners in "close" mixed gender race 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. Gender differences in behavioral traits such as patience or risk aversion (Bauer and Chytilová (2013); Croson and Gneezy (2009)), greater awareness of the adverse impacts of climate change (Jagnani and Mahadevan, 2023) in addition to acknowledgment of greater vulnerability of disadvantaged communities to climate change could be potential mechanisms influencing our results. Our findings are also similar in spirit to Leone (2019) who demonstrate that gender composition of decision makers in collective action bodies aimed at forest conservation matter. Our results underscore large potential role of female legislators, especially those from historically marginalized communities, in combating climate change.

Our paper is organized as follows: Section 2 describes the data used while Section 3 describes the empirical strategy used; Section 4 presents the main findings as well as a number of alternative robustness and falsification tests to assess the credibility of the RDD framework; Section 5 includes a short discussion of the potential mechanisms governing our results and Section 6 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.[3] The outcome variable we use in our analysis is the 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. 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.[4]

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,

[3] 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).

[4] 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.[5] 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).[6]

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
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
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
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'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.

[5] 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 from the sample is unlikely to result in significant distortion to the representativeness of the sample.

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

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 any given electoral cycle. We use past values of these covariates for our covariate continuity test as predetermined values of these variables should not be influenced with victory margins of future elections. 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).[7] 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.[8] Panel A also shows that among all constituencies where mixed gender elections have taken place 19% and 10% are found to be reserved for SC and ST candidates respectively.

Before providing a detailed description of the summary statistics, it may be important to take note of the occurrence of mixed gender elections during our study period. Appendix Table A.1 reports the occurrence of mixed gender elections during the period for which 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

[7] 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.

[8] 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.

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.[9]

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 for all constituencies as well as for all SC/ST reserved constituencies, irrespective of whether mixed gender elections have taken place during the period for which elections data is available in the SHRUG platform. 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. Both the average number of candidates running for office in state assembly elections and turnout percentage for all constituencies and SC/ST reserved constituencies, irrespective of the occurrence of mixed gender elections are close in magnitude to those found

[9] Appendix Table A.2 reports the annual growth rate of forest cover computed by excluding the year of forest cover when state assembly elections were also held. This is to avoid using measures of growth in forest cover that could be influenced by the legislator elected during the last election. We find that on, average, measures of growth in forest cover in Appendix Table A.2 are largely similar to the ones reported in Table 1 here across different categories of constituencies.

for constituencies where mixed gender elections have occurred. 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. The figures for all constituencies and all SC/ST reserved constituencies are similar to the corresponding figures for constituencies in each of these categories where mixed gender elections have taken place.[10]

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.

3 Empirical Strategy

We intend 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 causal impact of legislator gender on our outcome; the empirical strategy that we adopt is the sharp regression discontinuity design (RDD).

The 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 $t-1$. $T_{i,s,t-1}$ is the treatment variable that assumes the value 1 if the winner in constituency i in state s in the preceding election held in $t-1$ 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

[10] 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.

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 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. Our treatment variable here is, therefore, a deterministic function of our running variable. In other words, $T_{i,s,t-1}$ assumes the value 1 if $margin_{i,s,t-1} \geq 0$ and 0 if $margin_{i,s,t-1} < 0$. 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. [11] $\varepsilon_{i,s,t}$ is the regression disturbance term, which is clustered at the assembly constituency level. [12]

β is the coefficient of interest. It attempt 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 or "narrow" margin of victory. 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, that is growth in the forest cover, 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

[11] 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 local quadratic polynomial functions for estimation and inference.

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

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).[13] 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

4.1 Main Findings

We present our main results in Table 2 here. Using the MSE optimal bandwidth, 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 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. Figure 1 graphically represents the findings of Table 2, where each of the sub-figures are drawn using equally spaced mimicking variance method along with local linear regression functions fitted separately for either sides of the cut-off using MSE-optimal bandwidth and the associated 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 and those that are unreserved (sub-figures a) and b)); 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

[13] We also provide results that assess the sensitivity of bandwidth choice.

(sub-figure c)) 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).

Table 2: Results: Growth of Forest Cover

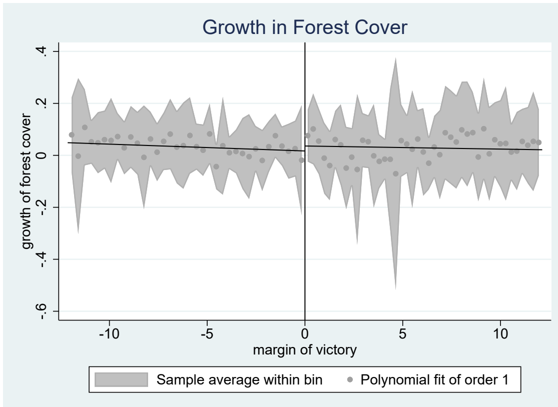
	All Constituencies	Non-SC/ST Constituencies	SC/ST Constituencies
Female Legislator Elected in Last Election	0.02	0.002	0.06**
	(0.02)	(0.02)	(0.03)
Optimal Bandwidth Type	MSE	MSE	MSE
Optimal Bandwidth	12.13	11.98	13.74
Number of Observations	3792	2587	1205
Effective Number of Observations	2309	1556	796
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). Standard errors are clustered at the level of assembly constituencies and 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.

Since we find statistically significant findings 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 3 presents these results. At first we limit the sample to include only the major states in India.[14] 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 3 represent samples comprising of 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. Additionally the "Within 3 SD" sample in Table 3 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. Lastly, the "Within 5th & 95th Percentile" sample in Table 3 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 3 shows, our findings in Table 2 with respect to SC/ST reserved constituencies are robust to these sample

[14] 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).



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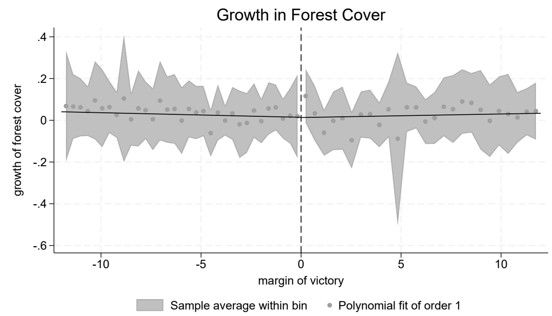

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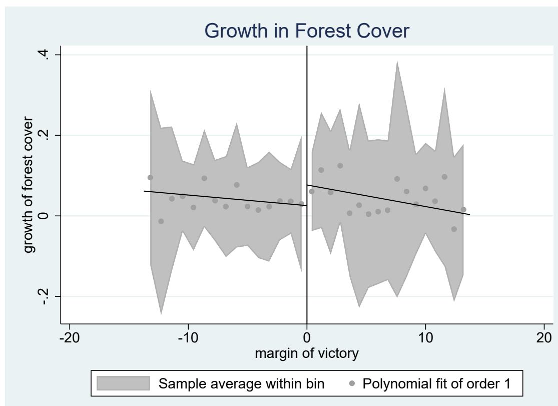


(c)

Figure 1: Growth in Forest Cover in: (a) All Constituencies (b) Only Non-SC/ST (Unreserved) Constituencies (c) Only SC/ST Reserved Constituencies. Binned outcome means using evenly spaced bins and mimicking variance method have been plotted. Local linear regression lines using MSE-optimal bandwidth and triangular kernel have been plotted along with the 95% confidence interval on either sides of the cut-off. Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 2021).

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%. 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. [15] 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

[15] 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 in randomized control trials(Cattaneo et al., 2019).

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.

Table 3: 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). Standard errors are clustered at the level of assembly constituencies. ***, **, * 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. "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.

4.2 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, sensitivity to the choice of bandwidth, 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 to bandwidth choice and especially the donut hole and placebo cut-off tests are relatively rare.

4.2.1 Non-Manipulation of the Victory Margin

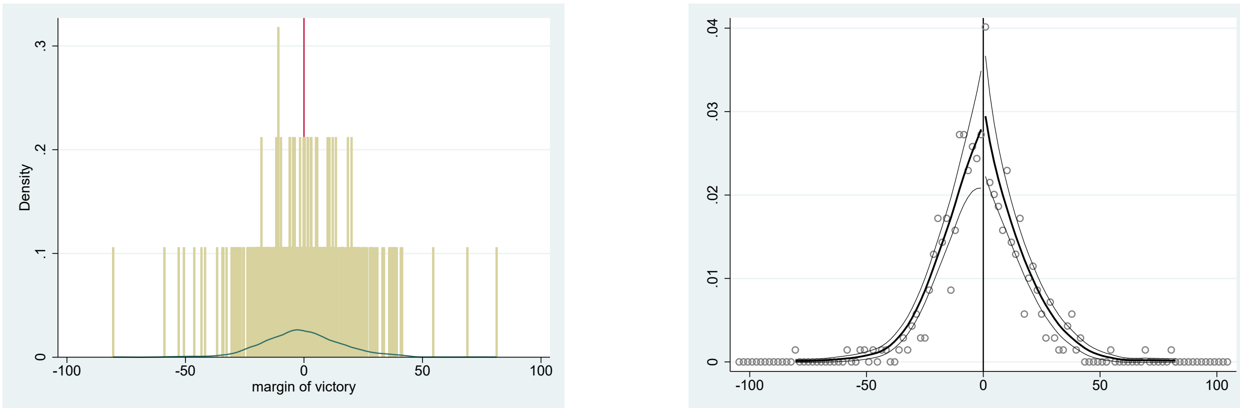


Figure 2: (a) Histogram depicting the distribution of the margin of victory in mixed gender elections for SC/ST constituencies for election years 1996 and beyond. (b) Corresponding McCrary density test where estimated log difference in height: 0.078, standard error: 0.193.

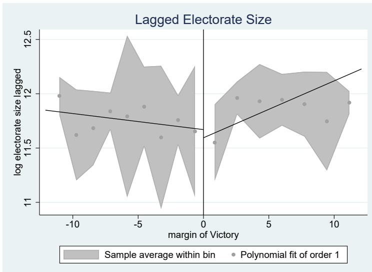
One of the concerns that can arise in the RDD setup is that if units can manipulate the threshold that determines treatment status, then treatment status is no longer exogenously determined and estimating causal effect of the treatment would then be challenging. In our setup, this concern translates 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 that determines treatment status. 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 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 for all constituencies (both reserved and unreserved). This, therefore, provides some evidence in support of the credibility of our RDD strategy.

4.2.2 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, if the constituency had a female legislator and 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 cycles. 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. These include 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).

At first we visually assess the continuity of these constituency and candidate characteristics at the threshold of the margin of victory. 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



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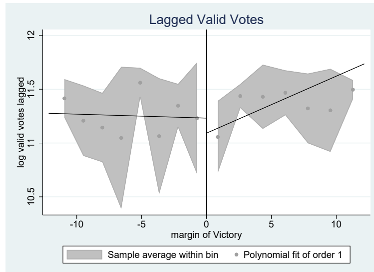

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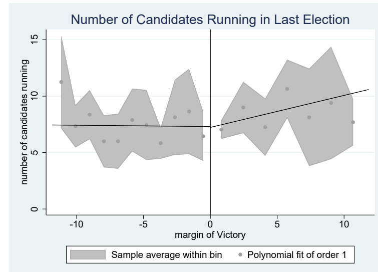

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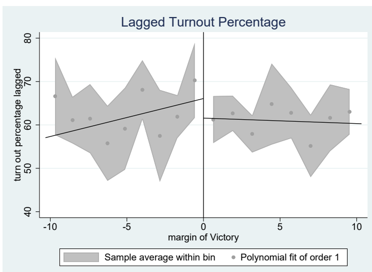

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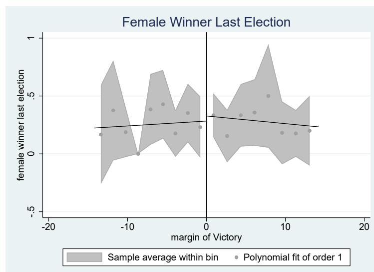

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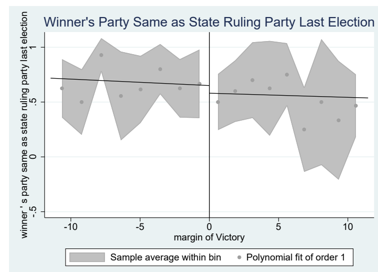

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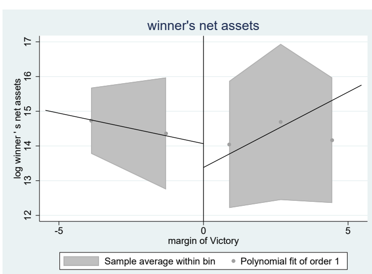

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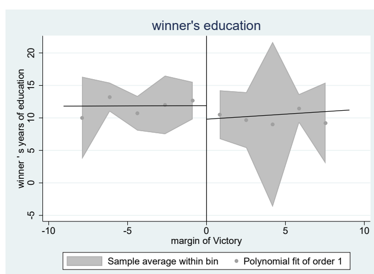

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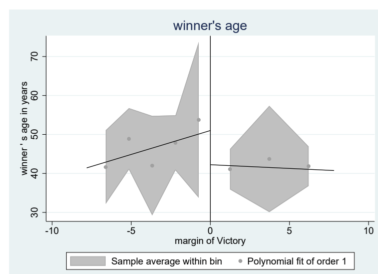

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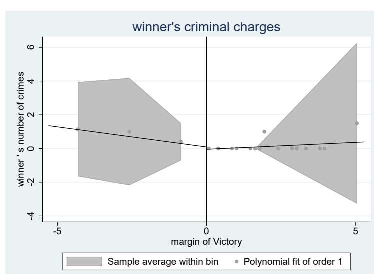

(j)

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's Log Net Assets in t (h) Winner's Years of Education in t (i) Winner's Age in t (j) Winner's Number of Crimes in t. Binned outcome means using evenly spaced bins and mimicking variance method have been plotted. Local linear regression lines using MSE-optimal bandwidth and triangular kernel have been plotted along with the 95% confidence interval on either sides of the cut-off. 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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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 cut-off of the margin of victory. In addition to electoral characteristics of the constituencies, we also assess whether there is any discontinuity at the threshold of the running variable in terms of past socio-economic and demographic characteristics of the constituencies. These include 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.[16] 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).[17] 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.

Table 4 provides a more formal analysis of assessing covariate continuity using the MSE optimal bandwidth, similar to our analysis for our main results in Table 2. Our findings in Table 4 show that there are no discontinuities in any of the predetermined constituency level characteristics and winning candidate characteristics are also not found to be discontinuous at the threshold of the margin of victory as none of the coefficient estimates are found to be statistically significant. While it is reassuring that predetermined covariates show no discontinuities at the cut-off (which is what one might expect); the finding that winner's characteristic such as age, education, net assets and number of crimes is unlikely to be discontinuous at the cut-off indicate that these characteristics are unlikely to be associated with the winner's gender. [18] This is likely to suggest that it is the gender identity of the legislator which is potentially driving our main result.

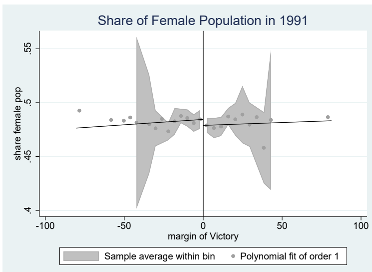
Appendix Figure A.2 and A.3 and Table A.3 provide analogous exposition for the entire sample of constituencies (that is, both reserved and unreserved). Almost all of the covariates show no discontinuity at the threshold.[19] Lastly, the reservation status of a constituency in

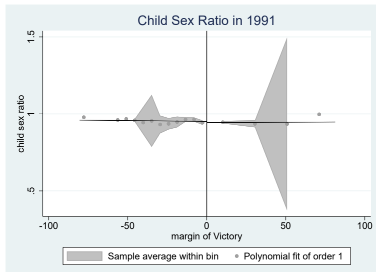
[16]The Census of India defines main workers as those who have worked for at least 6 months in a 12 month period; while marginal workers are those who have worked for less than 6 months during the same period.

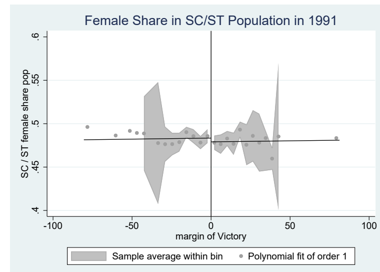
[17]Since the earliest year of election in our study is 1996, we use census figures from the population census preceding it (which is the 1991 Population Census) for assessing covariate continuity of these pre-determined variables.

[18]It is desirable to exercise some caution while assessing the lack of discontinuity of these candidate level characteristics due to limited number of observations within the optimal bandwidth. This is largely on account of data availability regarding these variables as we have discussed earlier. However, given the data, there is no evidence of discontinuity in these covariates at the cut-off of the running variable.

[19]Exception to this finding is the number of candidates running from the constituency in the last election,







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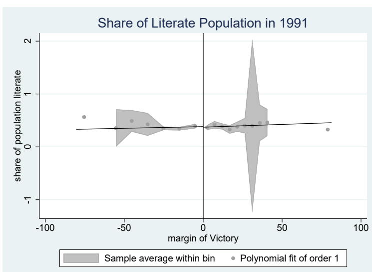

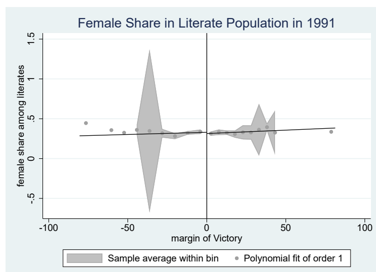

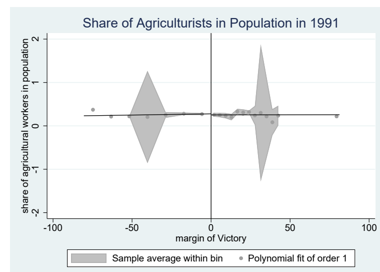

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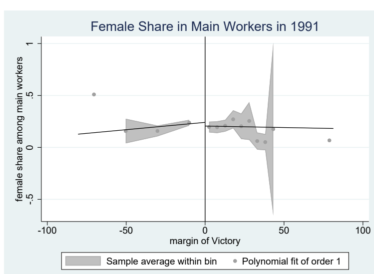

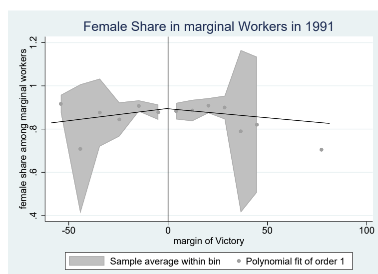

(g) (h)

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. Binned outcome means using evenly spaced bins and mimicking variance method have been plotted. Local linear regression lines using MSE-optimal bandwidth and triangular kernel have been plotted along with the 95% confidence interval on either sides of the cut-off. 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.

Table 4: Formal Analysis of Covariate Continuity in SC/ST Constituencies

Variable	MSE-Optimal Bandwidth	RD Estimate	Effective Number of Observations
Log of Electorate Size in $t-1$	12.09	-0.12 (0.26)	213
Log of Valid Votes in $t-1$	12.16	-0.19 (0.25)	216
Number of Candidates in $t-1$	11.83	-0.37 (1.13)	210
Turnout Percentage in $t-1$	10.31	-5.66 (3.63)	183
Female Legislator in $t-1$	14.24	0.06 (0.14)	235
Winner's Party Aligned with State Ruling Party in $t-1$	11.46	-0.03 (0.16)	207
Winner's Log Net Assets in t	5.47	-0.94 (1.82)	26
Winner's Education (yrs.) in t	9.06	-2.24 (2.40)	52
Winner's Age (yrs.) in t	7.82	-9.78 (6.78)	65
Winner's Number of Crimes in t	5.30	-0.28 (0.56)	35
Share of Females in Population (1991 Census)	9.51	0.002 (0.01)	105
Female to Male in 0-6 years Population (1991 Census)	8.16	0.03 (0.02)	89
Share of Females in SC/ST Population (1991 Census)	8.61	0.01 (0.01)	96
Share of Literates in Population (1991 Census)	11.73	-0.10 (0.08)	129
Share of Females in Literate Population (1991 Census)	15.46	-0.03 (0.03)	155
Share of Agriculturists in Population (1991 Census)	10.60	0.01 (0.06)	120
Share of Females among Main Workers (1991 Census)	9.56	-0.002 (0.09)	105
Share of Females among Marginal Workers (1991 Census)	9.82	0.04 (0.04)	105

Note: Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 2021). Each row reports the RD treatment effect estimate from distinct RD specifications with a different outcome variable. RD estimates are from local linear regressions fitted with different slopes on either sides of the cut-off. Standard errors are clustered at the level of assembly constituencies and are reported in parentheses beside the RD coefficient estimate. ***, **, * indicate statistical significance at the 1%, 5% and 10% level of significance respectively. MSE-optimal bandwidth using a triangular kernel has been used for the RD estimation. "Effective number of observations" indicate the number of observations that lie in the optimal bandwidth.

the number of crimes that the winner has been charged with, female share in overall population and in SC/ST population from the 1991 Population Census. However, these are weakly significant at the 10% level of significance and the coefficient estimates on the RD treatment effect are rather small for the demographic variables. The only robust discontinuity is in the candidate's age. It appears that female candidates who win are significantly younger than male winners during the current election. Hence, it is advisable to exercise 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 marginal of victory in mixed gender elections.

4.2.3 Sensitivity to Bandwidth Choice

We study how the selection of bandwidth can potentially influence our results. Our RD treatment effect estimations rely on the MSE optimal bandwidth. Cattaneo et al. (2019) suggest that alternative reasonable bandwidth choices that can be used to assess the sensitivity of the RDD result to bandwidth choice are twice of the MSE optimal bandwidth, CER (that is, bandwidth choice which minimizes the approximation to the coverage error of the confidence interval of the RD treatment effect) and twice of the CER optimal bandwidth. In our context, we use these alternative bandwidths to check for the robustness of our findings for the sample of SC/ST reserved constituencies.

Table 5: Sensitivity to Bandwidth Choice: Growth of Forest Cover in SC/ST Constituencies

	(1)	(2)	(3)	(4)
Female Legislator Elected in Last Election	0.06**	0.06**	0.06**	0.05*
	(0.03)	(0.02)	(0.03)	(0.03)
Optimal Bandwidth Type	MSE	2MSE	CER	2CER
Optimal Bandwidth	13.74	27.49	10.34	20.68
Number of Observations	1205	1205	1205	1205
Effective Number of Observations	796	1116	638	1015
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). Standard errors are clustered at the level of assembly constituencies and 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.

We report our findings in Table 5 here. For ease of exposition, we report our main finding of the impact of female legislator on current forest cover growth in SC/ST reserved constituencies from Table 2 in column (1) of Table 5 here. MSE-optimal bandwidth was used to estimate the RD treatment effect of electing a female politician in a close mixed gender race against a male politician. In column (2), (3) and (4) of Table 5 we report similar RD treatment effects by using twice MSE optimal, CER and twice of CER optimal bandwidths respectively. We find that across all the columns, our coefficient estimate and standard errors remain stable. We continue to find that a female legislator elected in a close mixed gender race causes improvement in future forest cover growth by 5-6% and this effect is statistically

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.

significant.[20] Hence, our main results of Table 2 for SC/ST reserved constituencies do not appear to be driven by our choice of bandwidth.

4.2.4 Donut Hole Test

Table 6: Robustness Results using Donut Hole Approach: Growth of Forest Cover in SC/ST Constituencies

Panel A: $|margin_{i,s,t-1}| \geq$	0.10	0.15	0.20	0.25	0.30
Female Legislator Elected in Last Election	0.06**	0.06**	0.06**	0.07**	0.08***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Optimal Bandwidth Type	MSE	MSE	MSE	MSE	MSE
Optimal Bandwidth	13.69	13.69	13.82	12.95	12.32
Number of Observations	1199	1199	1192	1184	1177
Effective Number of Observations	790	790	783	751	723
Kernel Type	Triangular	Triangular	Triangular	Triangular	Triangular
Panel B: $|margin_{i,s,t-1}| \geq$	0.35	0.40	0.45	0.50	0.60
Female Legislator Elected in Last Election	0.08***	0.08***	0.08***	0.08***	0.07**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Optimal Bandwidth Type	MSE	MSE	MSE	MSE	MSE
Optimal Bandwidth	11.83	11.83	11.83	11.77	12.34
Number of Observations	1168	1168	1168	1164	1152
Effective Number of Observations	691	691	691	687	702
Kernel Type	Triangular	Triangular	Triangular	Triangular	Triangular
Panel C: $|margin_{i,s,t-1}| \geq$	0.70	0.75	0.80	0.90	1.00
Female Legislator Elected in Last Election	0.07**	0.07**	0.07**	0.06**	0.07*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Optimal Bandwidth Type	MSE	MSE	MSE	MSE	MSE
Optimal Bandwidth	11.86	12.35	12.19	12.04	12.23
Number of Observations	1143	1139	1135	1127	1123
Effective Number of Observations	670	689	677	660	665
Kernel Type	Triangular	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). Standard errors are clustered at the level of assembly constituencies and 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.

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)).[21] If observations closest to the cut-off are unlikely to be disproportionately influential in the

[20] Using twice of the CER optimal bandwidth reduces the magnitude of the point estimate slightly, making it statistically significant at the 10% level.

[21] This robustness check method is, therefore, known as the "donut hole" approach.

estimation of the 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 report our findings in Table 6 here. As Table 6 shows that at first we exclude constituencies whose margins of victory lie in the interval $[-0.1, 0.1]$. 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 continue to rely on the MSE-optimal bandwidth as in Table 2 for this exercise. As expected, the length of the MSE-optimal bandwidth changes as the estimation sample changes. However across all columns in Table 6, we find that the estimated RD coefficient is largely the same or is very close in magnitude to the point estimate obtained in Table 2 for SC/ST reserved constituencies. Hence, in our framework, it is unlikely that observations very close to the cut-off of the margin of victory had been driving our baseline results in Table 2.

4.2.5 Using Placebo Cut-off

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

Table 7: Robustness Results using Placebo Cutoff Approach: Growth of Forest Cover in SC/ST Constituencies

Panel A: c =	1	1.5	2	2.5	3	4
RD Treatment Effect	-0.10	0.01	-0.02	0.05	0.02	0.08
	(0.09)	(0.07)	(0.13)	(0.13)	(0.06)	(0.25)
Optimal Bandwidth Type	MSE	MSE	MSE	MSE	MSE	MSE
Optimal Bandwidth	3.18	3.52	2.81	3.04	2.92	1.79
Number of Observations	565	565	565	565	565	565
Effective Number of Observations	152	165	165	188	191	98
Kernel Type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
Panel B: c =	-1	-1.5	-2	-2.5	-3	-4
RD Treatment Effect	0.04	-0.10	0.05	-0.05	0.07	-0.06
	(0.11)	(0.09)	(0.03)	(0.04)	(0.05)	(0.07)
Optimal Bandwidth Type	MSE	MSE	MSE	MSE	MSE	MSE
Optimal Bandwidth	2.72	2.85	2.47	2.48	2.24	2.83
Number of Observations	640	640	640	640	640	640
Effective Number of Observations	129	154	154	170	165	188
Kernel Type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
Panel C: c =	5	6	7	8	9	10
RD Treatment Effect	-0.06	0.01	0.06	-0.07	0.04	-0.04
	(0.12)	(0.10)	(0.04)	(0.09)	(0.05)	(0.04)
Optimal Bandwidth Type	MSE	MSE	MSE	MSE	MSE	MSE
Optimal Bandwidth	1.93	2.53	2.89	2.89	2.64	2.86
Number of Observations	565	565	565	565	565	565
Effective Number of Observations	113	124	121	143	119	124
Kernel Type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
Panel D: c =	-5	-6	-7	-8	-9	-10
RD Treatment Effect	0.10	-0.01	-0.06	-0.04	0.10*	0.03
	(0.09)	(0.07)	(0.04)	(0.06)	(0.06)	(0.05)
Optimal Bandwidth Type	MSE	MSE	MSE	MSE	MSE	MSE
Optimal Bandwidth	2.13	3.01	2.30	3.74	2.60	4.18
Number of Observations	640	640	640	640	640	640
Effective Number of Observations	133	193	156	243	176	225
Kernel Type	Triangular	Triangular	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). Standard errors are clustered at the level of assembly constituencies and 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. In Panels A and C, the sample is restricted to constituencies with a female winner; while in Panels B and D, the sample is restricted to constituencies with a male winner.

where only male politicians have won for placebo cut-offs that are positive and negative respectively. We use 24 placebo cut-offs on either sides of our true cut-off, 0 and report the findings in Table 7 here.

The first entry at the top in Table 7 is the estimated RD treatment effect using the sample of constituencies where only female politicians won using the MSE-optimal bandwidth, but 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.[22] Our findings from Table 7 lend some support to the credibility of our main RD treatment effect estimate for SC/ST reserved constituencies found in Table 2.

5 Discussion of Potential Mechanism

This paper finds that gender of the legislator matters for environmental outcomes in India. 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). Now, we found that male and female politicians 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. Since the literature has demonstrated that these characteristics often influence the decision to invest in activities such as environmental conservation which only yield returns in the future; it is likely that it is not the difference in these characteristics between the elected politicians but the differences in their gender itself 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 their constituencies. Unfortunately, our dataset is unable to provide additional resources to 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.

One potential explanation could be possible behavioral differences between men and women. 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 difference in women and men in terms of these preferences and behaviours could be one plausible channel explaining our main result. Additionally, there is some evidence that women are likely to be more altruistic than men,

[22] An exception to this finding is the RD treatment effect corresponding to the placebo cut-off of -9; however the coefficient is weakly significant only at the 10% level of significance.

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 altrusitic 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.

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 SCs/STs. 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 likely to invest in forest conservation in their constituencies. There is also some evidence 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. Another potential explanation could be greater awareness among women politicians about the adverse effects of climate change on child and maternal health. For example, extreme heat exposure during pregnancy has been demonstrated to adversely affect child survival and maternal health and droughts have been found to be negatively impacting child nutrition (Banerjee and Maharaj (2020); Kim et al. (2021); Kumar et al. (2016)). As periods of extreme temperature and erratic rainfall is more likely to become frequent on account of climate change, greater awareness among women politicians about the detrimental health impacts of climate change may imply why women politicians and especially those from SC/ST communities might pay great importance to forest conservation. Jagnani and Mahadevan (2023) find that women local leaders display greater awareness of the adverse health impacts of air pollution. Therefore, it is possible that overall greater awareness about the health impacts of environmental outcomes among women and especially those from historically marginalized communities such as the SC/ST may be another potential explanation of our result.

6 Conclusion

We study the impact of electing female legislators in state assembly elections in India on subsequent growth of forest cover in the constituencies. Simply comparing constituencies that elected a male to those that elected a female politician would not capture the causal effect of the gender of the legislator on our outcome on account of potential unobserved differences between these constituencies. As close election between a male and a female politician is likely to be quasi-random, we exploit this variation and compare constituencies where a female politician "barely" won to those where a male politician won in close mixed gender race in the framework of a sharp regression discontinuity design (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 SCs/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. Behavioral differences such as those of patience and risk aversion between men and women, possibly greater awareness among women politicians about adverse health impacts of climate change and greater vulnerability of disadvantaged communities such as the SCs/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. 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:						
Growth of forest cover in t	0.03	0.36	30,137	0.03	0.36	3,792
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
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						
Growth of forest cover in t	0.03	0.33	7,793	0.04	0.35	1,205
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

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. Growth of forest cover is computed by excluding forest cover years that are also state assembly election years.

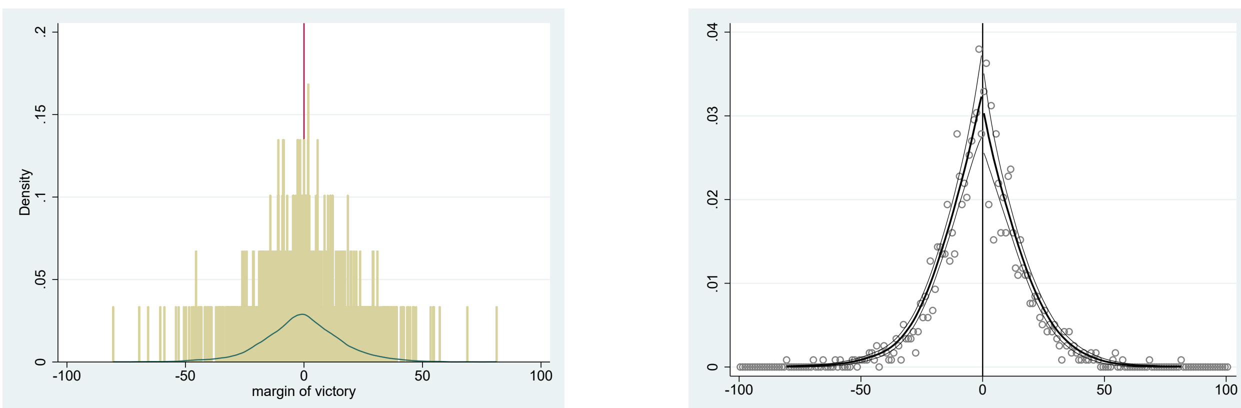
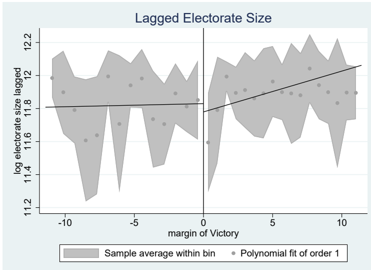
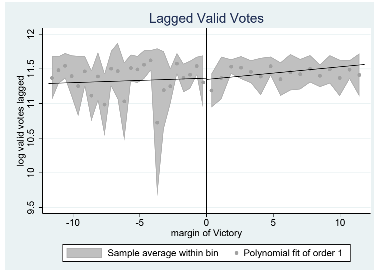


Figure A.1: a) Histogram depicting the distribution of margin of victory in mixed gender elections for all constituencies for election years 1996 and beyond. b) Corresponding McCrary density test where estimated log difference in height: -0.062, standard error: 0.117.



(a)



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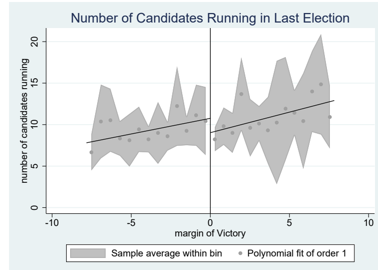

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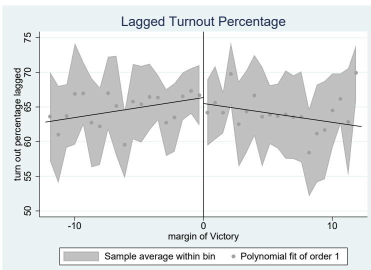

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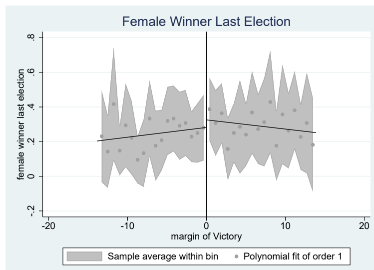

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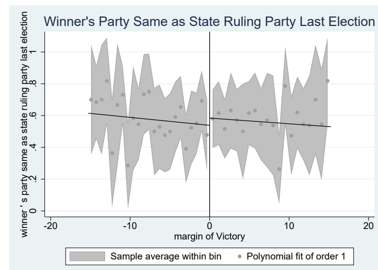

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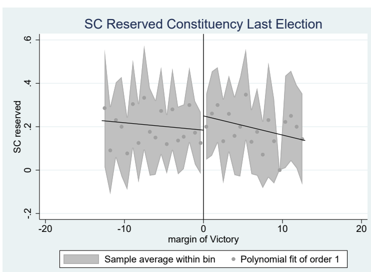

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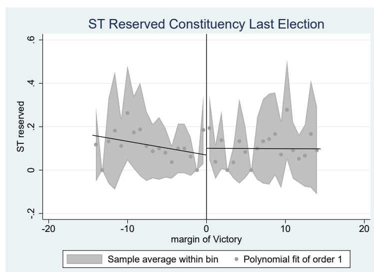

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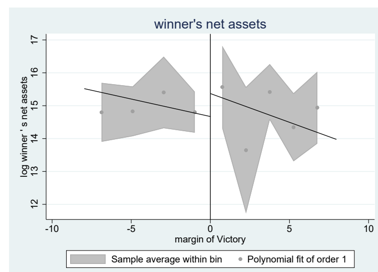

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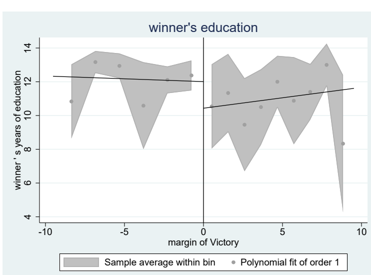

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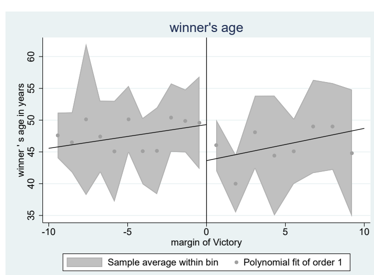

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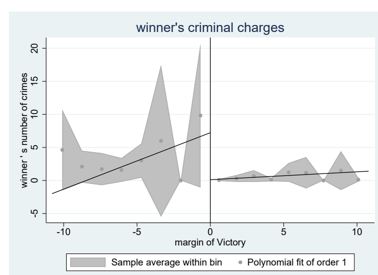
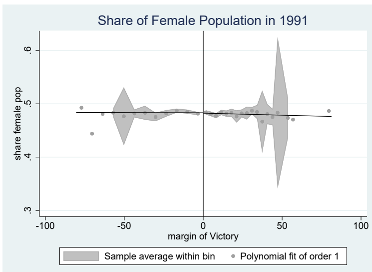


(l)

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) SC Reserved Constituency in $t-1$ (h) ST Reserved Constituency in $t-1$ (i) Winner's Log Net Assets in t (j) Winner's Years of Education in t (k) Winner's Age in t (l) Winner's Number of Crimes in t. Binned outcome means using evenly spaced bins and mimicking variance method have been plotted. Local linear regression lines using MSE-optimal bandwidth and triangular kernel have been plotted along with the 95% confidence interval on either sides of the cut-off. 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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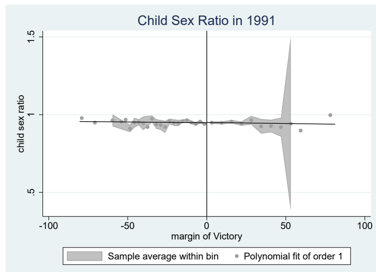

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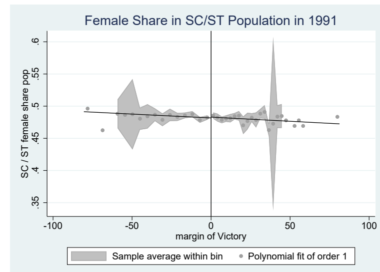

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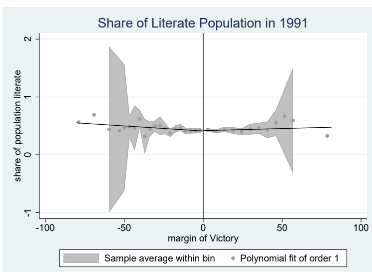

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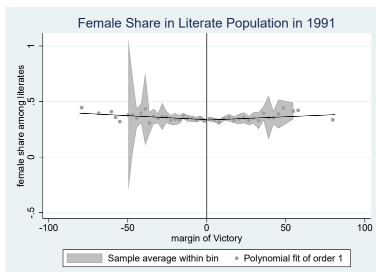

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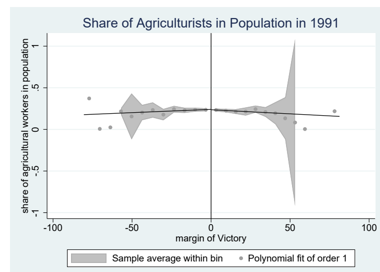

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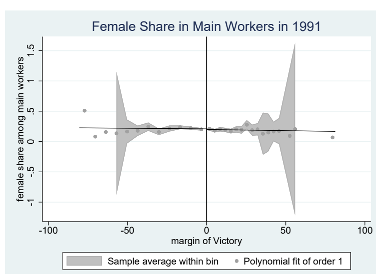

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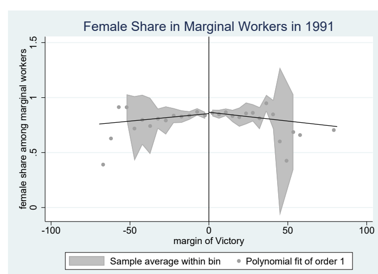

(h)

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. Binned outcome means using evenly spaced bins and mimicking variance method have been plotted. Local linear regression lines using MSE-optimal bandwidth and triangular kernel have been plotted along with the 95% confidence interval on either sides of the cut-off. 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.

Table A.3: Formal Analysis of Covariate Continuity in All Constituencies

Variable	MSE-Optimal Bandwidth	RD Estimate	Effective Number of Observations
Log of Electorate Size in $t-1$	11.42	-0.08 (0.11)	665
Log of Valid Votes in $t-1$	11.84	-0.04 (0.11)	678
Number of Candidates in $t-1$	7.83	-2.31* (1.36)	492
Turnout Percentage in $t-1$	12.27	-1.02 (1.77)	702
Female Legislator in $t-1$	13.89	0.05 (0.08)	753
Winner's Party Aligned with State Ruling Party in $t-1$	15.25	0.05 (0.08)	802
SC Reserved Constituency in $t-1$	12.87	0.08 (0.07)	726
ST Reserved Constituency in $t-1$	14.46	0.04 (0.05)	776
Winner's Log Net Assets in t	7.97	0.94 (0.79)	97
Winner's Education (yrs.) in t	9.52	-1.56 (0.99)	176
Winner's Age (yrs.) in t	10.00	-6.30** (2.84)	251
Winner's Number of Crimes in t	10.79	-8.20* (4.61)	201
Share of Females in Population (1991 Census)	12.38	0.01* (0.004)	441
Female to Male in 0-6 years Population (1991 Census)	12.46	0.01 (0.01)	444
Share of Females in SC/ST Population (1991 Census)	14.10	0.01* (0.004)	475
Share of Literates in Population (1991 Census)	13.95	0.02 (0.04)	471
Share of Females in Literate Population (1991 Census)	12.84	0.02 (0.02)	451
Share of Agriculturists in Population (1991 Census)	14.94	0.01 (0.02)	492
Share of Females among Main Workers (1991 Census)	11.53	0.04 (0.03)	420
Share of Females among Marginal Workers (1991 Census)	14.27	0.03 (0.04)	475

Note: Data source is The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher, Lunt, Matsuura, and Novosad, 2021). Each row reports the RD treatment effect estimate from distinct RD specifications with a different outcome variable. RD estimates are from local linear regressions fitted with different slopes on either sides of the cut-off. Standard errors are clustered at the level of assembly constituencies and are reported in parentheses beside the RD coefficient estimate. ***, **, * indicate statistical significance at the 1%, 5% and 10% level of significance respectively. MSE-optimal bandwidth using a triangular kernel has been used for the RD estimation.