Growing with greener pastures: Examining the role of graduate politicians on forest cover in India

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Abstract

Forests are vital for environmental and health benefits, making forest management a top priority for policymakers. Using datasets that combine remote sensing forest data and temporal state assembly election information, we investigate the role of graduate politicians in promoting growth of forest cover in India. We employ regression discontinuity design using close elections between graduate and non-graduate politicians to tease out the causal effects. Our findings reveal a significant increase in forest cover growth in constituencies led by graduate politicians. On exploring the reasons, we find that higher aggregate demand for forest products across the country can be one of the drivers of the increase in forest growth. This increase in forest growth also explains why constituencies led by educated politicians may tend to show higher growth in economic activity and exhibit increased employment opportunities in forest-related industries. Nevertheless, we also provide suggestive evidence highlighting the possibility of environmental awareness among educated leaders driving their forestation efforts.

Keywords: Forest cover; educated politicians; close elections; India; demand for forest products; economic growth

JEL Codes: Q23; Q28; Q54; I26

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1. Introduction

Forests are carbon sinks and are critical for reducing greenhouse gases, pollution, and the pace of climate change. Prolonged deforestation has been found to reduce rainfall, increase temperature, and affect biodiversity (IPCC, 2022). Between 1990 and 2020, forest cover fell by over 420 million hectares, and around 90% of this loss was concentrated in tropical areas (IPCC, 2022). Deforestation, owing to changes in land use patterns, is the second leading source of carbon emissions after the burning of fossil fuels (IPCC, 2014). Therefore, reducing the rate of deforestation and improving forest management is often proposed as a cost-effective climate change mitigation strategy (Gibbs et al., 2010; Griscom et al., 2017). In addition to environmental benefits, studies have documented significant health benefits of forests through decreased incidence of malaria (Vittor et al., 2006; Myers et al., 2013; Garg, 2019), diarrhea among children, and respiratory illness (Pienkowski et al., 2017).

Policymakers have recognized the role of forest management in sustainable development, given these environmental benefits and positive externalities. Existing literature has studied the role of political business cycles in logging and deforestation (Burgess *et al.* 2012, Pailler, 2018). Other studies have found that democracies with competitive elections can reduce forest cover. (Klopp, 2012; Sanford, 2023). However, the impact of politician's personal characteristics, in particular educational attainment on pro-environmental interventions like improving forest cover remains an understudied area. In this paper, we fill this gap by exploring the influence of educated political leaders in the context of India.

Theoretically, educated politicians can improve forest cover in at least two ways. First, education may be considered as a proxy for the quality of politicians. Education may influence politician's outlook and preferences, thereby motivating the leaders occupying public offices to serve the public. Educated politicians are found to be good for achieving higher economic growth and investments at the national level (Besley *et al.*, 2011; Brown, 2020; François *et al.,* 2020; Jain *et al.*, 2023). Electing educated leaders has also been found to improve public good provisioning and reduce corruption (Besley, 2005; Martinez-Bravo, 2017). If education captures the quality and performance of the politician, one may expect that having an educated politician will benefit environmental outcomes like an increase in forest cover growth. Here it is important to note that studies in different contexts have also documented contradicting evidence of a limited role played by politician's education on welfare outcomes (Carnes and

Lupu 2016; Lahoti and Sahoo 2020). In such cases, overall increase in the level of educational attainment among politicians may not necessarily improve forest cover growth.

Second, education can improve the environmental awareness of politicians. Formal education can impart skills and knowledge, enabling politicians to understand the value of the environment and the negative consequences of environmental degradation. There is an emerging body of literature documenting a positive association between education and environmental concerns and behavior (Torgler and Valiñas, 2007; Meyer, 2015; Chankrajang and Muttarak, 2017). However, a set of studies contradicts these inferences and does not find any relationship between education and environmental concerns (Wessells et al. 1999; Ek and Söderholm, 2008). Hence, ex-ante, the effect of educated politicians is ambiguous, and this paper studies this aspect in the context of India.

India is an interesting case study to link forest cover growth and the education of the governing politician for two specific reasons. First, India has pledged to reduce its GDP emission intensity by almost 45% by 2030[1]. According to the third Biennial Update Report (MoEFCC, 2021), India has already reduced its GDP emissions by 24% between 2005 and 2016. As a part of its effort to reduce emissions, the government has focused on improving forest cover. The India State of Forest Reports[2] published by the Forest Survey of India indicates that the forest cover in the country has been increasing during the last two decades. In fact, between 2001 and 2021, the forest cover increased from 20.55% to 21.4% of total geographical area (ISFR, 2001; 2021). Therefore, it is essential to understand the factors that are causally associated with forest growth to ensure that India is on track towards achieving its target of reducing emissions.

Second, the debate on whether there should be a minimum education level for contesting elections in India has been a longstanding debate in public discourse[3]. In fact, in 2015, Haryana, one of the states in northern India, mandated that candidates contesting local elections should have at least 10 years of formal education.[4] Proponents believe that certain years of formal education are crucial for effectively discharging political responsibilities, whereas others argue that setting minimum education requirements for contesting an election

[1] https://pib.gov.in/PressReleaseIframePage.aspx?PRID=1847812 (Accessed on July 16, 2024)
[2] https://fsi.nic.in/forest-report-2019 (Accessed on June 14, 2024)
[3] https://indianexpress.com/article/opinion/columns/unacademy-sacking-formal-education-does-not-guarantee-a-politician-is-good-8921113/ (Accessed on October 11,, 2023).
[4] https://www.thehindu.com/news/national/other-states/Minimum-qualification-set-as-Haryana-passes-Panchayati-Raj-Bill/article60210639.ece (Accessed on October 11, 2023)

is exclusionary and that education may not be a definitive factor that captures the ability of the politician. Rajasthan, another northwestern state of India, also passed a similar bill in 2015, which was later scrapped in 2018[5]. Such state-specific instances indicate the presence of stakeholders for and against regulations on the educational requirements of politicians in the country. As mentioned earlier, studies in the Indian context have documented the positive implications of having educated leaders on economic growth, and education (Lahoti and Sahoo, 2020; Jain et al. 2023), providing a rationale for policies like mandating minimum education for politicians. In this regard, our study adds to the existing evidence by exploring the causal effect of education level of politicians on forest cover growth.

The paper uses remotely sensed forest cover temporal data to measure our outcome variable from 2012 to 2019. To construct the primary political variable of interest, we use the information on state elections in India. In particular, we gather data on the educational attainment of the candidates contesting these elections. To overcome the potential bias due to the non-random selection of educated political leaders, which can be driven by unobserved voter and constituency characteristics, we employ a Regression Discontinuity Design (RDD) using close elections between politicians based on their level of education. Here, we gauge the causal effect of educated politicians by comparing closely fought electoral constituencies governed by graduate and non-graduate leaders. The underlying identification assumption is that an educated leader winning in closely fought elections is random.

The findings indicate a statistically significant increase in forest cover growth in constituencies won by a graduate leader. We observe that the growth in forest cover is higher by 2.4 percentage points on average in areas led by a graduate politician during the period of our study. These findings are qualitatively robust and stable to different specifications and bandwidths and also to an alternate threshold of education, that is higher secondary level of education.

Why do we observe higher forest growth in constituencies governed by educated politicians? We argue that India's phenomenal economic growth in the last decade led to a considerable rise in the demand for forest-related goods. In our period of study, we find domestic industries like the manufacturing of paper, and wood products, which are major consumers of wood, have grown considerably in terms of various indicators like total output,

[5]https://www.ndtv.com/india-news/bill-passed-to-scrap-minimum-education-qualification-for-civic-polls-in-rajasthan-1991920 (Accessed on October 11, 2023)

gross value added, number of factories, and number of employees. The rise in higher domestic demand could have led educated political leaders to invest more in forestation. Importantly, this complements the argument presented in an important paper by Foster and Rosenzweig (2003) that explains India's higher forest cover growth on account of rising domestic demand for forest products. We support this argument by showing that the forest growth has been significantly higher in constituencies led by educated politicians from relatively developed states as well as more urbanized ones, which are likely to have higher demand for forest products. This lends credence to our argument about forestation efforts from educated politicians being driven by higher demand for forest-related goods.

However, one question still remains unanswered - if there is increased demand for forest products across India, why is it the case that educated politicians respond more by increasing their forestation efforts? To answer this, we use the citizen-candidate model that predicts the divergence in policies based on the politician's preferences (Osborne and Slivinski, 1996; Besley and Coate, 1997). Educated politicians may have unique policy preferences like economic growth which may lead them to increase forest growth. We provide two evidence to support our argument. First using RDD design, we examine the effect of educated political leaders on the economic growth in their own constituency by using temporal changes in the intensity of night-lights. We do not find any evidence of fall in economic growth and in fact, we document suggestive evidence of higher economic growth in constituencies led by educated politicians. Second, we use two rounds of the Periodic Labour Force Survey (PLFS) conducted in 2017-18 and 2018-19 by the Ministry of Statistics and Programme Implementation in India and observe an increase in employment in forest-related industries in districts with a higher share of educated politicians. Overall, our analysis suggests that concerns about local economic growth may drive educated politicians to invest in forestation efforts by tapping into the higher demand for forest products.

To further investigate why forest growth is higher in constituencies led by educated leaders, we test for the possibility of greater concerns about sustainability and environmental awareness among them leading to an increase in forest growth. While data on environmental awareness among politicians is unavailable, we provide a few pieces of evidence that do not allow us to eliminate this channel. Firstly, the impact of educated politicians on forest cover growth is found to be absent in constituencies dominated by the tribal population. Since, the tribal population is highly dependent on forests for their livelihood and habitation, even less-educated politicians whose primary objective is electoral success will be compelled to focus on forest growth, leading to policy convergence across both graduate and non-graduate politicians. However, among constituencies not dominated by tribal groups, we find higher gains in those led by educated politicians, possibly driven by higher awareness and environmental concerns. Further, the positive impact of educated politicians on forest cover growth is only observed in constituencies led by non-criminal politicians, while the impact is absent in those governed by educated leaders accused of criminal charges. For criminally accused politicians engaging in rent-seeking to divert resources for personal gains, the importance attached to environmental concerns might possibly be negligible though for the non-accused ones, this may not be the case. The observed effects in constituencies governed by educated leaders with no criminal charges underscore the possibility of environmental awareness being one of the drivers of forestation efforts in their constituencies. Moreover, we also find weak evidence that the incidence of forest related crimes is lower in districts with a higher share of graduate politicians. If environmental awareness facilitates the prevention of such crimes, it is possible that such concerns may potentially lead to forestation efforts.

In terms of policy implications, our study assumes significance in two broad dimensions. First, we complement Foster and Rosenzweig (2003) argument about strengthening domestic demand for forest produce to help expand forest cover and succeed in forestation efforts. Second, we provide additional evidence in favor of mandating minimum educational qualifications for candidates contesting elections. It is important to note here that such policy mandates can have adverse effects on equity and may lead to lower representation of marginalized communities with lower educational levels in general. Nevertheless, our paper provides a basis for policy discussion and debate that can ensure equality along with tapping the benefits of education among policy makers.

The study makes several contributions. First, it relates to the large literature on environment and climate change. Within this domain, several studies have focused on the determinants of forest cover and deforestation. Evidence indicates that changes in land use patterns like mining activities, expansion of agricultural activities to meet food demands of the growing population and road construction, have direct as well as indirect effects on forest cover (Chomitz and Gray, 1996; Pfaff, 1999; Pendrill *et al.*, 2019; Giljum *et al.*, 2022; Shapiro *et al.*, 2023). At the same time, studies have also highlighted the critical role of government and elections in affecting forest cover (Burgess *et al.,* 2012; Klopp, 2012; Pailler, 2018; Sanford, 2023). Our study contributes to this subfield by providing evidence that politicians' educational attainment is an important factor in determining forest cover.

Second, this study contributes to the empirical political economy literature by examining the importance of the identity of the politician in affecting outcomes. In an influential paper, Besley (2005) shows that politicians' demographic characteristics are key to their commitment and economic outcomes. Following this, studies have documented the effect of various demographic markers of the politician on development outcomes. For example, literature shows that the gender of the elected candidate matters (Chattopadhyay and Duflo, 2004; Clot-Figueras, 2012; Bhalotra and Clot-Figueras, 2014), and so does education, caste (Pande, 2003), crime records (Prakash *et al.*, 2019), among others. In the same vein, our study complements this literature by providing evidence that education, indeed, is one of the elected leader's characteristics that affect pro-environmental outcomes like growth in forest cover.

Third, our study adds to the understanding of education as a determinant of the quality of the leaders. We provide evidence that educated politicians improve forest cover, suggesting education can be considered a proxy for the quality of politicians in India. This finding complements the other studies that document the positive effect of a college degree on politician's performance (Besley, 2005; Besley *et al.*, 2011; Martinez-Bravo, 2017).

Finally, our study also contributes to the vast literature on returns to education. There is overwhelming evidence documenting the positive effect of education on employment and wages and other outcomes (Mwabu and Schultz, 1996; Harmon et al., 2003). We add to this literature by providing evidence of social returns to higher education. We show that the college degree of politicians has a positive impact on local environmental quality, as given by the higher growth of forests.

The structure of the paper is as follows. Section 2 provides the context of our study by presenting a background on forest cover and elections in India. Section 3 elaborates the empirical strategy and Section 4 discusses the data. Section 5 presents the main results of the study along with the validity of the regression design and various robustness checks. It also discusses the potential reasons why forest growth is found to be higher in constituencies led by graduate politicians. Section 6 concludes the study with broad policy implications.

2 Context

2.1 Forest cover in India

According to the Global Forest Assessment Report (2020) by the Food and Agricultural Organization (FAO), India ranks tenth in terms of total forest area. The India State of Forest Report (ISFR) published by the Forest Survey of India every two years since 1987, give the official estimates of forest cover at the national, state and district levels. The forest cover is estimated to be 21.4% of the geographical area as of 2021 and these estimates are based on a spatial resolution of 23.5m and a scale of 1:50,000 obtained from the LISS-III sensor of the IRS Resroucesat satellite series of Indian Space Research Organisation (ISRO). As per the official definition, forest cover refers to tree patches with more than 10% canopy density with a minimum mapping unit of at least one hectare, regardless of its land use, legal status and ownership (ISFR, 2021[6]). The forest cover is further divided into very dense (tree density of at least 70%), moderately dense (tree density of at least 40% but less than 70%) and open forest (tree density between 10% and 40%). There is a large variation in forest cover across the states of India. For example, the state of Madhya Pradesh located in the central part of the country has the highest forest area, whereas the north-eastern states have forest cover ranging over 70% of their geographical area, on the other hand, there are states like Haryana and Rajasthan and with as low as 3%-4% of their geographical area under forest cover.

It is important to note that forest cover is not the same as forest area. Technically, Recorded Forest Area (RFA), refers to geographical areas that have been recorded as forests under the Indian Forest Act (1927). As per ISFR, 2021, 23.58% of the country's area comes under RFA. The RFA is categorized into protected forests, reserved forests, and unclassed forests. In reserved forests, all activities are prohibited, whereas in protected forests, all activities are allowed unless prohibited. Unclassed forests comprise forest areas that do not fall into either reserve or protected forests and can be owned by the government or private entities. The subsequent discussion in the section is based on forest cover and not RFA.

The forest land in India has been showing an uptrend during the last two decades. In fact, between 2001 and 2021, the forest cover increased from 20.55% to 21.4%, a 0.85 percentage point or a 4.4% increase in forest cover (ISFR, 2001[7]; ISFR, 2021)[8]. This increasing trend can be attributed to conservation measures like Joint Forest Management (JFM), and various other

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[6] https://fsi.nic.in/forest-report-2021-details (Accessed on July 4, 2024)
[7] https://fsi.nic.in/documents/sfr_2001_hindi.pdf (Accessed on July 4, 2024)
[8] During the same period, RFA increased from 23.28% to 23.58%, a 1.29% increase.

policies like the Forest Rights Act, 2006 (FRA). National Forest Policy enacted in 1988 mentioned the role of JFM in addition to increasing forest cover. JFM paved the way for the involvement of local communities in the protection, conservation, and management of forests. Literature suggests that JFM implementation is positively associated with forest cover increase in India (Raghavan and Shrimali, 2015) while deriving higher returns when women are present in local forest management groups (Agarwal, 2009)

FRA on the other hand distributed forest rights to individuals as well as communities so that they can access and utilize forest resources as they deem fit, along with protecting, managing, and conserving them. While it has been touted as a landmark act that recognizes the rights of tribal people and other communities who largely depend upon forest resources for dwelling, livelihoods, and others[9], several issues like high rejection rates, variation in distribution of titles across states have been observed (Lee and Wolf, 2018).

2.2 Elections in India

India is the world's largest democracy with over 960 million registered voters[10]. The Constitution of India laid down the electoral system in India in 1950 and the Election Commission of India is responsible for conducting elections in the country. National elections are conducted every five years to elect Members of Parliament (MP) to the lower house (Lok Sabha). Similarly, state elections elect Members of the Legislative Assembly (MLAs) to the State Assemblies. The political representatives at the national as well as state elections are elected based on the first-past-the-post voting method wherein each constituent can cast only one vote in their particular constituency, and the candidate with a maximum number of votes is declared as the winner of the election. The constituencies are typically smaller than a district and the boundaries of constituencies for the national as well as state elections are determined by the Delimitation Commission. The commission adjusts the boundaries to account for population growth in the area. The constituency boundaries were drawn under the Delimitation Act 1972 based on the Population Census of 1971. Subsequently, on the basis of the population census of 2001, these boundaries were redrawn by the fourth Delimitation Commission under the Delimitation Act 2002. The recommendations of the commission were accepted and implemented by states in the year of 2008. Due to differences in the boundaries of the

[9] https://tribal.nic.in/fra.aspx (Accessed on July 3, 2024).
[10] https://pib.gov.in/PressReleasePage.aspx?PRID=2005189 accessed on July 4, 2024.

constituencies, the characteristics of the constituencies are not comparable pre- and post-2008. Evidence suggests that this delimitation process is largely apolitical and is done in a neutral manner (Iyer and Reddy, 2013).

With the multiparty system in place, political competition in state elections is high and has been increasing (Dash and Mukherjee, 2015), and the chances of incumbents emerging as winners in these elections are rather less (Uppal, 2009; Ravishankar, 2009). The state legislators, that is MLAs, represent their constituents at the state assembly and also formulate policies. MLAs have access to local area development funds, which they utilize for implementing various policies and the development of the constituency. The MLAs care about their constituencies either to ensure electoral success in successive elections, or have certain policy preferences, or both. There is ample evidence that MLAs have an impact on constituency-level outcomes in India. For instance, female MLAs improve economic growth (Baskaran et al. 2023), whereas criminal ones have been found to deter growth (Prakash *et al.,* 2019).

3 Empirical Strategy

The main objective of the paper is to examine the effect of electing an educated political (graduate or above) leader on the growth of forest cover in their constituency. If the winning of a graduate candidate is random, constituencies with a non-graduate candidate winner will serve as a valid counterfactual to the constituencies where a graduate candidate wins the election. However, the election of a graduate leader in a constituency is likely to be endogenous. For example, other things being equal, a more progressive, educated, and environmentally concerned electorate might choose a more educated leader over a lesser educated one. Therefore, an average estimate of the impact of a graduate leader over non-graduated leader on forest growth is likely to be confounded with correlated unobservable factors, leading to a biased estimate.

To address this identification challenge, we consider closely fought elections between graduate and non-graduate politicians. A close election is defined as one where the margin of victory between the top two candidates is arbitrarily small. We exploit the discontinuity in election outcomes and apply the RDD, which enables us to estimate the causal impact of a treatment by exploiting the discontinuity in the treatment. In particular, we use the discontinuity in election outcomes of close elections in first-past-the-post electoral systems between top two candidates where one is graduate and the other is non-graduate. The identification strategy is contingent upon the assumption that the identity of the politician winning such close elections is quasi-random (Lee, 2008; Imbens and Lemieux, 2008). Notably, a number of papers have exploited the quasi-randomness of close election outcomes to assess the impact of politician characteristics on outcomes (Prakash *et al.* 2019, Baskaran *et al.* 2023). The RDD specification for the estimated model is as follows:

$$GF_{ist} = \alpha + \beta * Graduate_{ist} + f(Margin_{ist}) + \mu_{ist} \tag{1}$$

$$\forall\, Margin_{idst} \in (c\text{-}h,\ c+h)$$

where GF_{ist} is the growth of forest cover in constituency 'i', in state 's', and in year 't' defined as the difference in logarithmic value of forest cover at year, $t+1$ and that in year, t multiplied by 100. The $Graduate_{ist}$ is the treatment variable which takes value '1' if the winner in a constituency has completed graduation (treatment group) and '0' if a non-graduate wins the election (control group). The $Margin_{ist}$ is margin of victory that serves as a forcing variable to assign the treatment that a candidate is graduate. More specifically, $Margin_{ist}$ is defined as the difference between the vote shares of the graduate and the non-graduate candidate in the restricted sample of constituency elections where the top two positions are taken by graduate and non-graduate leaders. By construction, a positive margin of victory in a close election setup indicates that a graduate candidate is elected against a non-graduate candidate. Similarly, if a non-graduate wins against a graduate, the margin of victory is negative. A discontinuous change in the education of the leader is observed around the zero margin of victory. Hence, $Graduate_{ist}$ is our binary interest variable that is defined as follows:

$$Graduate = \begin{cases} 1, & if\ Margin_{ist} > 0 \\ 0, & if\ Margin_{ist} \leq 0 \end{cases} \tag{2}$$

In RDD framework, we consider a close neighbourhood 'h' around the zero-cut off (c) such that as h tends to zero, there is no difference in constituencies that elected a graduate leader and those where a non-graduate leader emerged winner. Therefore, constituencies that barely elected a non-graduate leader serve as a valid counterfactual for constituencies that barely elected a graduate leader and allows us to estimate the causal impact of education on forest cover growth:

$$\underset{h\to c}{\mathrm{Lt}}\, E(GF_{ist} | c < Margin_{ist} \leq h) - \underset{h\to c}{\mathrm{Lt}}\, E(GF_{ist} | -h \leq Margin_{ist} < c) = \beta \tag{3}$$

The coefficient of interest is β that captures the difference in average outcomes of constituencies where a graduate leader won in a close election to that of constituencies where non-graduate leader was a winner in a close contest. In other words, it measures local average treatment effect (LATE) of electing a graduate leader on the growth of forest cover. The last term in equation (1) is the error term. The standard errors are clustered at the constituency level to account for correlation among constituency level errors.

We consider a linear specification for the forcing variable (Gelman and Imbens, 2019). The neighbourhood '*h*', also called the bandwidth around the zero cut-off (c) is selected based on data-driven optimal bandwidth that minimizes mean-square error (MSE) with a triangular kernel (Imbens and Kalyanaraman, 2012; Cattaneo *et al*., 2019). However, we also provide estimates based on alternate bandwidths to check the sensitivity of our results.

4. Data

We combine multiple datasets to examine the effect of educated politicians on forest cover changes and change in night-lights.

4.1 Forest Cover

We obtain data on our main dependant variable - forest cover from the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) for the period 2012 to 2019[11]. The total forest cover data is remotely sensed, which is captured by Moderate Resolution Imaging Spectroradiometer (MODIS) and called Vegetation Continuous Field (VCF). It is a high-resolution data recorded at the resolution of 250 meters. VCF characterizes land cover into three types: tree cover, non-tree vegetation, and non-vegetated surface plus surface water (DiMiceli *et al.*, 2015 and 2021). Based on a machine learning model, the VCF-based measure of total forest cover is derived as a prediction of the proportion of a pixel covered by the tree cover. (Asher *et al.,* 2020). VCF uses thermal signature which allows it to identify forest cover and differentiate it from non-forest plantations based on temperature difference. The VCF data is considered to be superior to other satellite data providing information on forest cover (see Asher *et al.*, 2020 for details). The total forest in an area is defined as the total log pixel value of tree cover plus one (Asher *et al.*, 2020). The land cover

[11] The data computation is explained in detail in Asher *et al.* (2021 & 2022), Townsend et al. (2013) and DiMiceli et al. (2015, 2021).

characteristics are defined as a continuous field and not in discrete units. Therefore, the magnitude of loss or gain in forest cover can be computed based on the VCF data. This dataset has been employed by studies analysing the forest growth and deforestation in India (Asher *et al.,* 2020; Aggarwal *et al.*, 2023).

Moreover, we also assess the relationship between forest cover data obtained from SHRUG with official forest cover data (see Section 2.1 for details). Specifically, we collect the official forest cover statistics at the state level from the biennial ISFRs of various years - 2013, 2015, 2017 and 2019[12]. The ISFR of a particular year presents the area under forest cover two years preceding the reporting year. For example, the ISFR of 2013 provides information pertaining to forest cover at the state level in 2011 and similarly for other years. The plot of the logarithm of forest cover obtained from the two sources at the state-year level exhibits a positive and statistically significant association between the two (Appendix Figure F1).

4.2 Electoral Data

The electoral data is sourced from the Trivedi Centre for Political Data (TCPD). It provides detailed information on the State Legislative Assembly elections which are compiled from the Election Commission of India's web portal. The state elections generally take place after every five years; however, the year of the election may vary across states. There are 4,121 constituencies in the country[13], and an MLA is elected in each constituency. TCPD provides detailed candidate level data, including name, gender, education, age, caste, party affiliation, total votes received, size of the electorate. Our main variable of interest is the educational attainment of the winner and the runner-up candidate.[14] The missing values of the education indicator are filled using political data from the *myneta.info* web portal which is an open data repository platform of Association for Democratic Reforms (ADR). It provides detailed election related information in the public domain.

We consider all states of India and exclude the Union Territories for our analysis. Table 1 provides the summary statistics of the variables for the entire sample and also separately for mixed elections between graduate and non-graduate candidates. It is worth noting that around

[12] The reports were obtained from https://fsi.nic.in/index.php (Accessed on June 17, 2024)
[13] Information compiled from Assembly Constituencies in India | State Wise Assembly Constituencies (elections.in)
[14] The winning candidate is the MLA.

61% of the elected politicians are graduate politicians in state elections. On specifically considering mixed elections, around half of the time graduate politicians won. The variable definitions are provided in Appendix Table T1.

A look at the Appendix Figure F2, which shows the distribution of the share of graduate MLAs at the district level in India in 2012 and 2018 indicates considerable spatial variation across the country and substantial change as well. We also present the map depicting the share of graduate MLAs defeating non-graduate MLAs at the district level in 2012 and then in 2018 (Appendix figure F3). Further, we present similar maps showing this share only for elections where the margin of victory is 5% and 10% (Appendix figure F4 and F5 respectively). All these maps indicate not only a sizeable spatial variation but also considerable changes from 2012 to 2018.

4.3 Night time lights data

We consider night-time light (NTL) data as a proxy of economic growth and development due to paucity of GDP data at the constituency level[15]. NTL dataset is remotely sensed obtained from VIIRS satellites, which are considered to be spatially and temporary more accurate than the DMSP-OLS based measures of NTL. The data from VIIRS is available at monthly frequency from 2012 and is obtained from SHRUG. It is noteworthy that a number of studies have used NTL data to measure the level of economic activity and documented it to be a reliable indicator (Doll *et al*. 2006; Chen and Nordhas, 2011; Henderson *et al.* 2012). More importantly, several studies have utilized the NTL data at the constituency level analysis as a proxy for economic growth (Prakash *et al.* 2019; Jain *et al.* 2023; and Baskaran *et al.* 2023).

For our study, we consider data for the period 2012-19 and our regression analysis spans 2012 to 2018 (we use 2019 data to compute forest cover growth of 2019 over 2018). We exclude data post-2019 specifically owing to the COVID-19 shock of 2020. This is important because studies have documented that in several phases of the lockdowns and the subsequent effects of the pandemic, the economy experienced significant growth cuts.[16] Any changes in our estimates post 2019 may be confounded by COVID time effects.

[15] GDP estimates are only available at the aggregate national or state level

[16] Please refer https://www.economicsobservatory.com/how-has-covid-19-affected-indias-economy (accessed on June 15, 2024)

Table 1: Summary Statistics

	Whole Sample			Mixed elections		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Annual growth rate of forest cover	28,669	3.10	32.69	11,568	3.210	33.207
Annual growth of Night Lights	28,669	10.43	25.83	11,568	10.751	25.428
Graduate winners	27,563	0.616	0.486	11,571	0.499	0.500
Graduate runner ups	27,569	0.614	0.487	11,571	0.501	0.500
Number of candidates	28,677	10.941	5.363	11,571	11.229	5.480
Electors (log)	28,637	11.99	0.784	11,557	12.039	0.736
Turnout Percentage	28,637	72.251	12.159	11,557	72.198	11.567
SC Constituencies	28,677	0.149	0.356	11,571	0.152	0.359
ST Constituencies	28,677	0.134	0.341	11,571	0.131	0.337
Female candidates	28,677	0.846	1.045	11,571	0.861	1.059
Female winners	28,677	0.085	0.279	11,571	0.087	0.281
Age of the winner	27,778	51.145	10.472	11,209	51.204	10.556
Aligned with central government	28,677	0.276	0.447	11,571	0.272	0.445
Aligned with state government	28,677	0.534	0.499	11,571	0.523	0.499
Crime of the winner	28,410	1.091	3.009	11,471	1.161	2.919
Assets of the winner (log)	28,221	16.574	1.652	11,390	16.573	1.652
Liabilities of the winner (log)	19,441	14.309	1.971	7,886	14.285	1.997

The unit of observation is Assembly constituency. Therefore constituency-election year observation constitutes each data point. Whole Sample is the sample of the all constituencies during the period 2012-2019. Mixed elections are those where top two candidates (winner or runner-up) were a graduate and a non-graduate.

5. Results

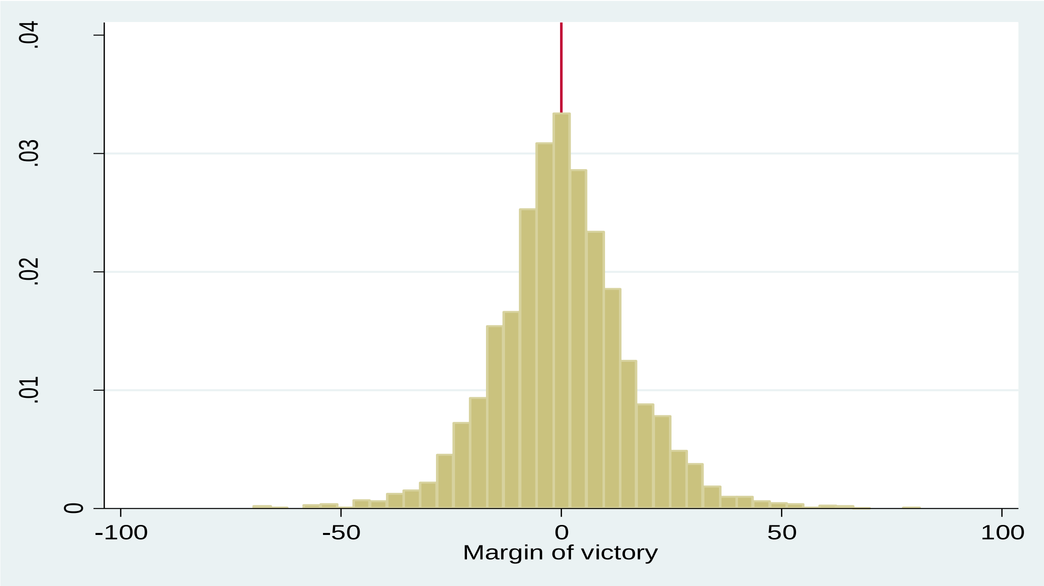
5.1 Validity of Regression Discontinuity Design

The validity of RDD design relies on the crucial assumption of the randomness of close election outcomes. Following Imbens and Lemieux (2008), we conduct two tests to establish the validity of the RDD. First, is the McCrary (2008) density test that tests the presence of any sorting around the victory margin of zero. The intuition is that if educated candidates manipulate elections in their favor, then they may find it easier to manipulate closely fought elections. As a result, the density of graduate winners will be higher in the neighborhood of the zero cut-off. In other words, it tests whether the density of graduate politicians changes abruptly on either side of the zero cut-off. If indeed there is manipulation of elections by graduate winners, then the close election RDD design for estimating the causal impact of educated politicians on forest growth becomes invalid. Hence, the absence of a discernable difference in the distribution of graduate winners around the zero cut-off is a necessary condition for eliminating any concerns about election manipulation rendering validity to RDD estimates. Figure 1 presents the density of graduate winners and shows no difference in the frequency of graduate winners to the left and right of the zero margin of victory. Importantly, the McCrary test statistic is insignificant suggesting that graduate and non-graduate candidates are equally likely to win around the zero threshold (point estimate of -0.0196 with a standard error of 0.037).

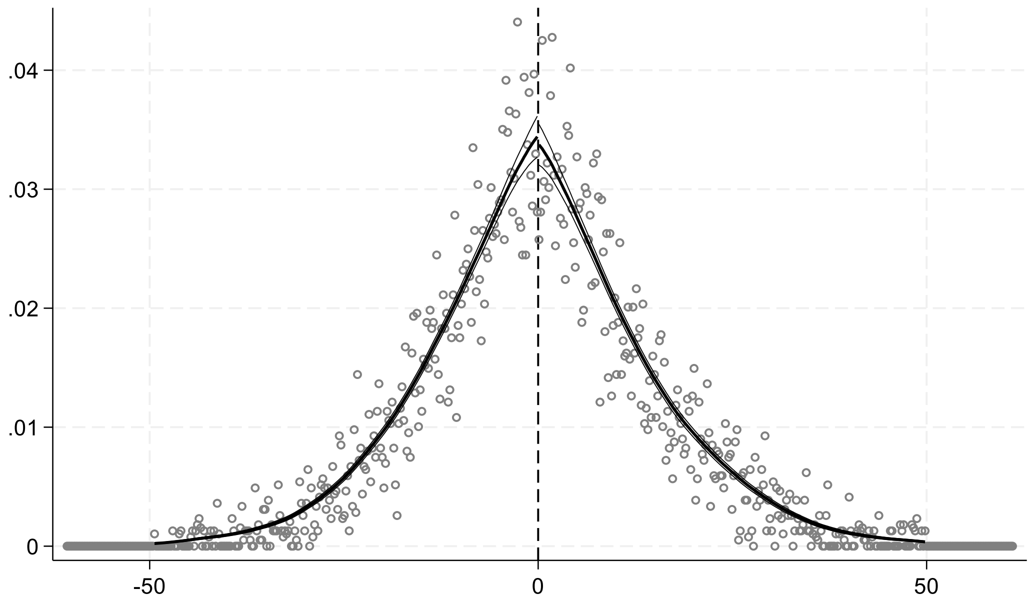
Second, the validity of RDD is contingent upon the continuity of other constituency-level characteristics around the zero cut-off. In other words, it is necessary to demonstrate that other factors do not change abruptly as we move from mixed-election constituencies where graduate candidates barely lose to constituencies where graduate candidates just win against a non-graduate candidate. For this, we consider a set of variables including growth of night light in the previous period, voter turnout, size of electorate, number of female candidates, number of valid votes, age of the winner, number of candidates, assets and liabilities of the winner and criminal cases of the winner. Figure 2 presents these plots. We observe no discrete jump at around the zero-victory margin for most of these variables, suggesting that the constituency as well as candidate characteristics in either side of the zero margin of victory are similar.

Figure 1: McCrary density test

Panel A: Density of Margin of Victory



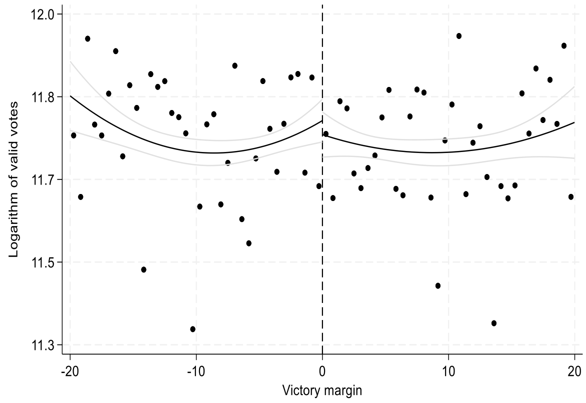
Panel B: McCrary density test



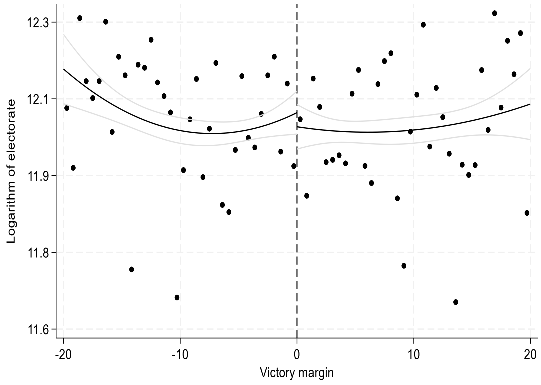
Note: The figure plots the density of the margin of victory, which is the difference between vote shares of the graduate and non-graduate candidates in those elections in which top two candidates are a graduate and a non-graduate. By construction, margin of victory is positive when the winner is graduate and negative for non-graduate winners. The magnitude of the discontinuity (log difference in height) is -0.0196 (with a standard error of 0.037).

Figure 2: RDD Continuity plots

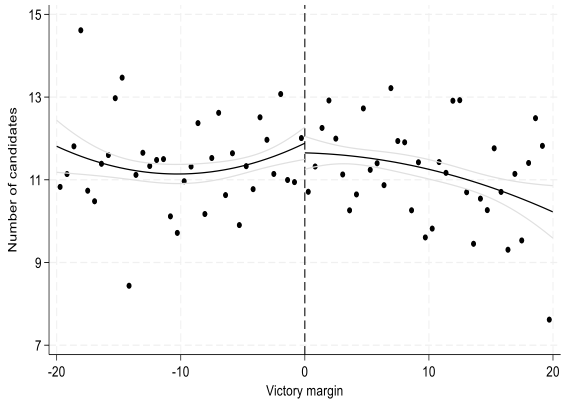
a. Number of valid votes in t-1 (log)



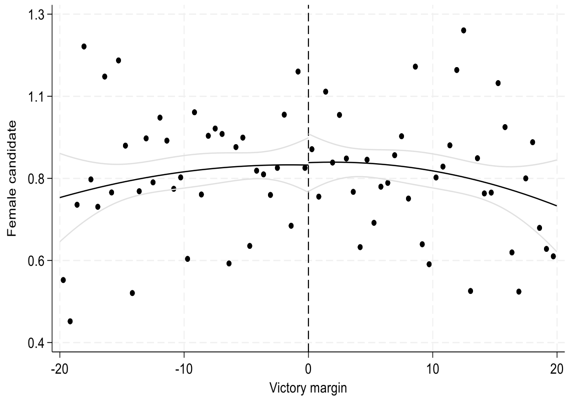
b. Size of electorate in t-1 (log)



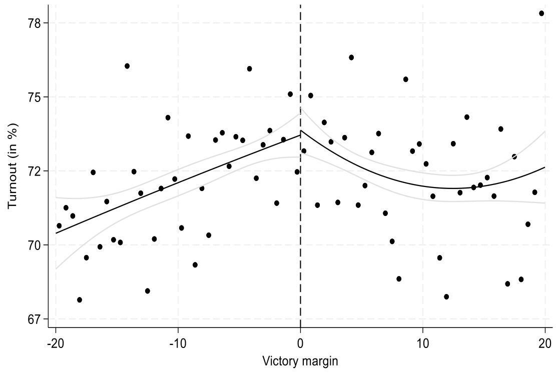
c. Number of candidates in t-1



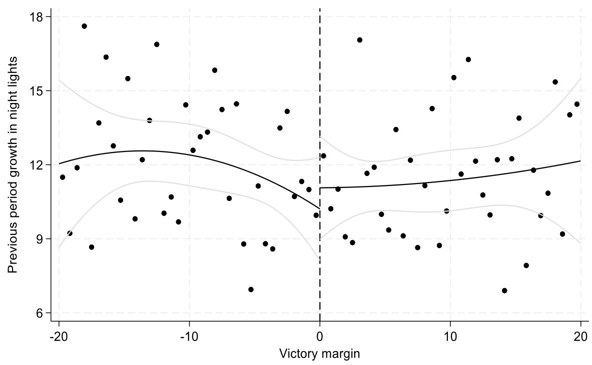
d. Number of female candidates in t-1



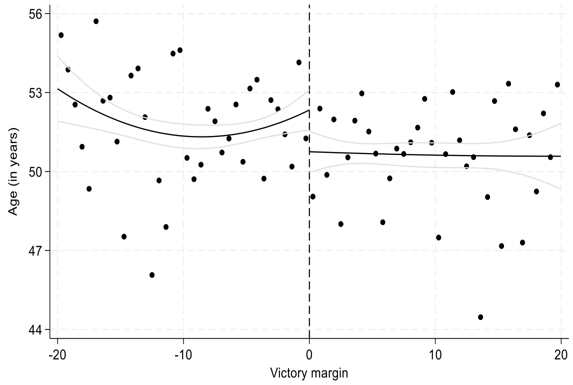
e. Turnout (%) in t-1



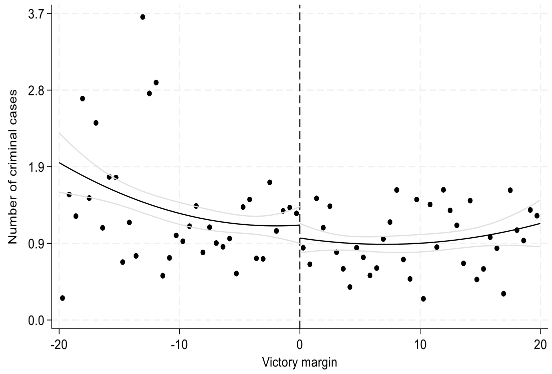
f. Growth in night lights in t-1



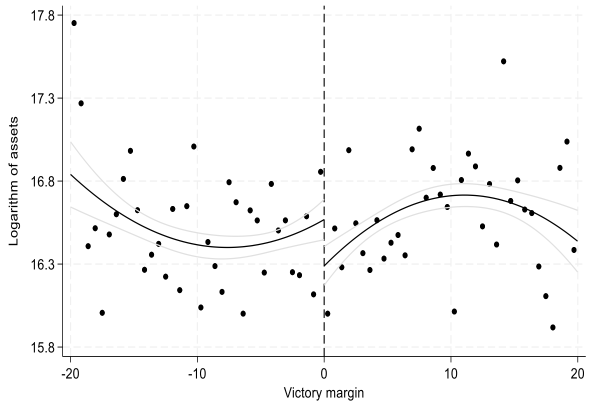
g. Age of the winner (years) in t-1



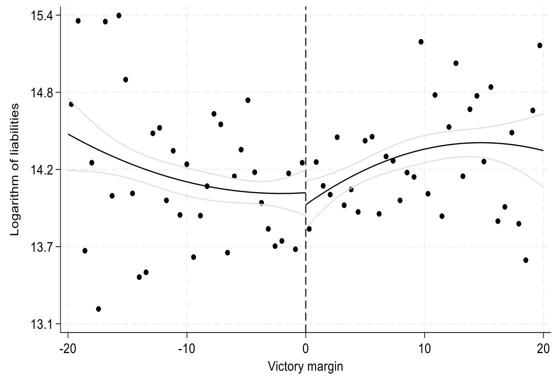
h. Number of criminal cases of the winner in t-1



i. Assets of the winner (log) in t-1



j. Liabilities of the winner (log) in t-1



Note: The margin of victory is difference between vote shares of the graduate and non-graduate candidate in those elections in which top two candidates are a graduate and a non-graduate. By construction, margin of victory is positive when the winner is graduate and negative for non-graduate winner. The solid lines are estimated using a local regression of variables on margin of victory separately on either side of the cutoff of zero.

Further, the RDD results of graduate versus non-graduate close elections where the above discussed candidate and constituency level factors are considered as outcomes are presented in Appendix Table T2. As expected, the RDD estimate turns out to be insignificant in all the regressions. In line with our graphical exposition, we find no evidence of statistical difference in other characteristics above and below the threshold of zero providing credence and validity to our RDD estimates.

5.2 Main results

In this section, we present the causal impact of electing a graduate leader as opposed to a non-graduate leader on forest cover growth. As specified earlier, our main findings are derived from the RDD framework using a sample of close elections between graduate and non-graduate politicians as elucidated through equation (1). The point estimates from the RDD regressions are reported in Table 2. We employ the data driven optimal bandwidth criterion based on minimization of MSE as proposed by Imbens and Kalyanaraman (2012). Estimating a local linear regression, we find an average increase of 2.4 percentage points in forest growth in constituencies where a graduate politician is elected over a non-graduate politician in close elections and the relationship is found to be statistically significant at a 5% level (column 1).

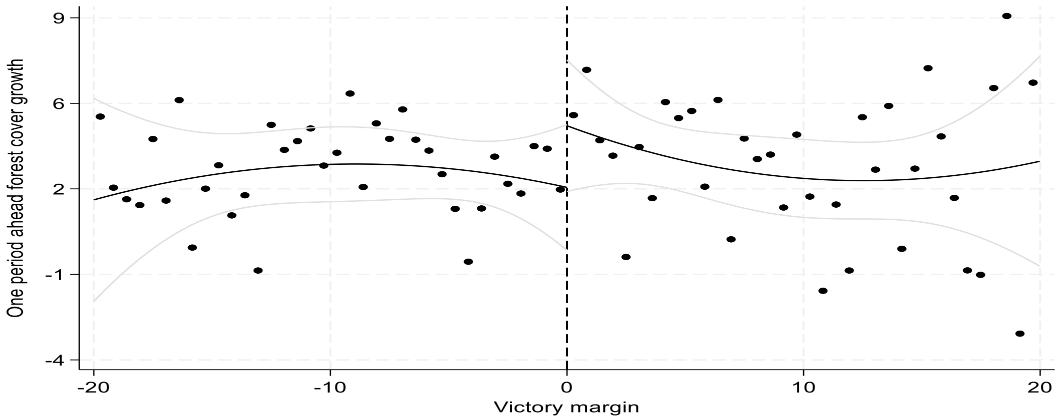
Table 2: Effect of graduate politicians on growth of forest cover

	(1) Optimal bandwidth	(2) h/2	(3) 2h
Graduate politician	2.406**	4.711**	2.403**
	(1.198)	(2.276)	(1.115)
Bandwidth	11.16	5.58	22.32
Observations	11,568	11,568	11,568
Effective observations	6,912	4,147	10,044

Notes: (i) The dependant variable is the annual growth in forest cover, defined as $(\text{Log}(\text{Forest}_{t+1})$ - $\text{Log}(\text{Forest}_t))*100$ (ii) All the models are estimated on the basis of Regression Discontinuity Design. (iii) The main explanatory variable - graduate politician is a dummy which takes value 1 if a graduate candidate wins against a non-graduate candidate, and '0' if a non-graduate wins against a graduate candidate. (iv) Models 1-3 differ on the basis of different bandwidth. (v) Robust standard errors are clustered at the constituency level and given in the parentheses. (vi) All the models are estimated by a local linear regression using a triangular kernel. (vii) The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure 3 graphically demonstrate the effect of educated politician on growth of forest cover. Here we plot the average growth rate of forest cover across successive intervals with bins of width of 0.5 percentage points. The range of margin of victory is restricted between [-20%, 20%]. The figure exhibits a discontinuous jump as we move from constituencies where a graduate loses in a close election to constituencies where a graduate candidate wins in a close election against a non-graduate candidate. The RDD estimate reported in Table 2 above confirm that this difference is statistically significant. Moreover, as we move beyond the optimal bandwidth, the difference in forest growth between graduate and non-graduate led constituencies vanishes.

Figure 3: Effect of graduate politicians on forest growth



Note: The dependent variable is the annual growth in forest cover at the constituency level defined as ($Log(Forest_{t+1})$ - $Log(Forest_t)$)*100. The margin of victory is difference between vote shares of the graduate and non-graduate candidates in those elections in which top two candidates are a graduate and a non-graduate. By construction, margin of victory is positive when the winner is graduate and negative for non-graduate winners. The solid lines are estimated using a local regression of forest growth on margin of victory separately on either side of the cutoff of zero.

5.3 Robustness checks

In this section we discuss a number of checks performed to ensure that the results are qualitatively robust.

Sensitivity to bandwidths: First, we use bandwidths that are half and twice the size of the optimal bandwidth calculated through minimizing MSE. The estimates are presented in columns 2-3 of Table 2. While the estimated coefficient increases when we use lower one, the impact of graduate leaders on forest growth remains positive and significant.

Sensitivity to addition of covariates: In section 4.1, we show that the covariates are balanced at the zero margin of victory. If the covariates are continuous around the threshold, adding covariates should not affect the bandwidth or the effect size considerably. However, another way to account for covariate imbalance, if any is to control for the covariates in the RDD framework. Moreover, even if there is no covariate imbalance, the additional covariates stand to improve the precision of the estimator (Imbens and Kalyanaraman, 2012). Hence, we include various covariates and check the sensitivity of our RDD estimates, the results of which are reported in Table 3. In column 1, we include constituency fixed effects; thereafter, in Columns 2 and 3, we additionally include year effects and other covariates, respectively. Our RDD result remains robust to the inclusion of additional controls. Next, in column 4, we include district fixed effects instead of constituency effects, along with year effects and other covariates and again, we obtain the positive effect of graduate politicians on forest cover growth. Furthermore, we also use the alternate optimal bandwidth that minimizes the Coverage Error Rate (CER) (Calonico *et al.*, 2020). Column 5 indicates that the RDD estimate of the impact of educated politician on forest growth remains intact using the CER optimal bandwidth along with the covariates, district and year fixed effects.

Alternate definition of educated politician: In the paper, we consider graduate politicians as a proxy for educated politicians. However, if we consider higher secondary and above as education cut-off and re-estimate the model, the results remain qualitatively similar (Column 6 of Table 3). However, we also consider at least 10 years of schooling as an indicator of an educated politician and run the same regressions. While the impact of educated politicians (those who completed at least 10 years of formal education) on forest growth remains positive, it is statistically insignificant indicating no discernible difference in forest rejuvenation between leaders with at least 10 years of education and those below this level (Column 7 of Table 3).

Table 3: Robustness checks

	AC FE	AC and Year FE	AC and Year FE and covariates	District and Year FE with covariates	Covariates with District and Year FE-CER	12^{th} pass	10^{th} pass	Excluding obs beyond 3SD	Excluding J&K	Till 2020
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Graduate politician	4.666***	5.045***	5.141***	2.434**	1.773**	2.367*	2.800	2.418**	2.432**	1.983*
	(0.755)	(0.648)	(0.618)	(1.028)	(0.901)	(1.378)	(1.856)	(1.207)	(1.233)	(1.116)
Bandwidth	11.16	11.16	11.16	11.16	4.952	11.376	15.674	11.296	10.962	13.265
Observations	11,568	11,568	11,206	11,206	11,206	8,533	3,850	11,333	11,355	13,192
Effective observations	6,912	6,912	6,683	6,683	4,929	5,229	2,860	6,839	6.725	8,838

Note: (i) The dependant variable is the annual growth in forest cover, defined as $(\text{Log}(\text{Forest}_{t+1})$ - $\text{Log}(\text{Forest}_t))*100$. (ii) All the models are estimated on the basis of Regression Discontinuity Design. (iii) Models differ on the basis of different fixed effects, control variables and alternative sample. (iv) Models in Column (1) & (2) include AC (assembly constituency) FEs; AC and year FEs respectively. Model in column (3) adds the covariates: dummy for female winner, election year, alignment with state government; alignment with central government, ST reserved constituency; number of female candidates; Turnout percentage; and Age of the winner. Model in column (4) includes district FEs, year FEs and covariates. This model is re-estimated using alternate optimal bandwidth-CER and reported in column (5). (v) The models in columns (5 & 6) are estimated based on alternative education threshold i.e. at least 12^{th} pass and at least 10^{th} pass respectively. (vi) Models in columns (8, 9 & 10) are estimated based on alternative samples. In column (8), we exclude observations beyond 3SD. Column (9) is estimated excluding the state of J&K and column (10) is estimated till 2020 period. (vii) All the models are estimated by a local linear regression using a triangular kernel. (viii) Robust standard errors are clustered at the constituency level and given in the parentheses. (ix) The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Measurement issues: To ensure that our RDD estimate is not driven by outliers in forest cover growth, we exclude the observations that are beyond the 3 standard deviations from the mean forest cover to calculate forest cover growth. Results tabulated in Column 8 of Table 3 indicate that our RDD estimate is not influenced by the presence of outliers in the forest cover data, and the effect size turns out to be close to the main result (Column 1 of Table 2).

Alternate sample: In our estimation sample, we include Jammu and Kashmir (J&K). However, there was political instability in the northern state of J&K during the period of our study. For example, it was under President's rule in 2018 and thereafter in 2019, as per the J&K Reorganization Act, the state of J&K was reorganized into the UT of Ladakh and the UT of J&K[17]. In light of this, similar to Baskaran et al. (2023), we exclude J&K from our sample. The result reported in Column 9 of Table 3 reinforces that the positive impact of graduate politician on forest cover growth is robust to the exclusion of the disputed J&K state from our sample. Moreover, even though the forest cover data is available till 2020 in SHRUG, in our main analysis we consider data till 2019 to ensure that our estimates are not confounded by the COVID shock of 2020. As robustness, we include the 2020 data in our sample and re-estimate the impact of educated politicians. The RDD estimate turns out to be positive and significant using data till 2020 (Column 10). Hence, our RDD estimates are robust to the choice of sample and period of study.

Placebo thresholds: To further ensure internal validity, we perform RDD using placebo thresholds. If our RDD is indeed capturing the impact of graduate politicians on forest growth, then using placebo thresholds of non-zero cut-offs should yield insignificant results. We consider a total of 20 placebo thresholds - 10 positive and 10 negative thresholds at increments of 0.5 each. For positive cut-offs we consider sample of only graduate winners (treated units), whereas for negative cut-offs we rely on a sample of only non-graduate winners (control units). Table 4 presents the results of using placebo thresholds in the RDD framework. Unsurprisingly, in all the specifications of the RDD except one, the estimate turns out to be statistically insignificant, providing credibility to our findings of a positive impact realized through educated politicians.

[17] https://igr.jk.gov.in/files/J&K%20Reorganisation%20Act,%202019.pdf (Accessed on June 21, 2024)

Table 4: Placebo cut-offs

	(1) +0.5	(2) +1	(3) +1.5	(4) +2	(5) +2.5	(6) +3	(7) +3.5	(8) +4	(9) +4.5	(10) +5
Graduate politician	-4.991	-3.194	0.605	-0.612	4.099	0.327	-0.079	0.475	-0.862	-2.023
	(5.385)	(5.032)	(3.511)	(2.744)	(2.899)	(2.992)	(2.889)	(2.985)	(3.379)	(3.165)
Bandwidth	2.718	2.783	2.838	2.638	2.293	2.541	2.166	2.164	1.917	1.756
Observations	5,776	5,776	5,776	5,776	5,776	5,776	5,776	5,776	5,776	5,776
Effective observations	1,197	1,383	1,611	1,705	1,694	1,859	1,557	1,432	1,246	1,110

	(1) -0.5	(2) -1	(3) -1.5	(4) -2	(5) -2.5	(6) -3	(7) -3.5	(8) -4	(9) -4.5	(10) -5
Graduate politician	-1.349	5.677*	0.715	-1.893	4.350	-0.097	2.571	0.129	-0.958	-0.272
	(3.940)	(3.363)	(3.162)	(2.838)	(2.692)	(2.846)	(2.775)	(3.137)	(2.838)	(3.137)
Bandwidth	2.493	2.355	2.453	2.336	2.005	1.931	2.433	1.833	1.835	1.724
Observations	5,792	5,792	5,792	5,792	5,792	5,792	5,792	5,792	5,792	5,792
Effective observations	1,135	1,260	1,511	1,661	1,520	1,480	1,758	1,318	1,333	1,165

Note: (i) The dependant variable is the annual growth in forest cover, defined as $(\text{Log}(\text{Forest}_{t+1}) - \text{Log}(\text{Forest}_t))*100$. (ii) All the models are estimated on the basis of Regression Discontinuity Design. (iii) The main explanatory variable - graduate politician is a dummy which takes value 1 if a graduate candidate wins against a non-graduate candidate, and '0' if a non-graduate wins against a graduate candidate. (iv) All the models are estimated by a local linear regression using a triangular kernel. (v) Robust standard errors are clustered at the constituency level and given in the parentheses. (vi) The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

5.4 What explains this increase in forest growth?

5.4.1 Higher demand for forest and forest related products

In this section, we assess the reasons why educated politicians may care for forest growth. One factor driving forest growth can be the rising demand for forest related products like firewood, paper and furniture because of higher economic activity in India over the last 25 years. This potential relationship stems from an influential study by Foster and Rosenzweig (2003), which highlights the possibility of observing higher growth in forest cover led by increased demand for forest products. In particular, the authors argue that countries like India have seen an economic growth that is associated with increased demand for forest related products. Given that these products are less tradeable and are essentially produced domestically with low share of imports, the increased demand leads to an increase in forest cover.

To gauge the state of domestic industries that primarily depend upon wood, we source data from the reports of the Annual Survey of Industries (ASI). ASI is a national and state-representative survey that collects data on the registered manufacturing sector (factories) in

India since 1959[18]. We consider the indicators like total output, gross value added, number of factories, and number of employees at the All-India level for the factories surveyed in 2014 to 2019 classified under 3-digit National Industrial Classification (NIC) codes[19] 162, 170 and 310. NIC-162 consists of factories engaged in the manufacturing of products of wood, cork, straw, and plaiting materials, NIC-170 includes factories involved in the manufacturing of paper and paper products and NIC-310 comprises entities engaged in manufacture of furniture. We consider these NIC codes given their reliance on wood as a primary raw material. Appendix Figure F6 shows that across indicators, these three industries have shown an upward trend between 2014 and 2019. In fact, gross value added has increased by over 12%, whereas the number of employees in both these industries has also increased in the range of 5% to 8%. Furthermore, recent findings indicate that paper and pulp, furniture and construction industries in India, the major consumers of wood, have exhibited high growth rates of 10% or more between 2012 to 2018 (Kant and Nautiyal, 2020).[20] Importantly, the trade statistics data obtained from World Integrated Trade Solution (WITS) database indicates that during the same period, the value of import of wood and related products in India remained fairly stable with a year-on-year growth of approximately 2%.[21] Given the rise in imports has not been proportionate to the growth in forest products industries, higher domestic demand for raw materials could have induced the educated political leaders to invest more in forestation.[22]

While the paucity of relevant data prevents us from directly testing this line of argument, we provide some indicative evidence to provide credence to this conjecture. Here, we argue if graduate politicians increase forest growth to cater to the increase in demand for forest products, one can expect this effect to be higher in more developed states relative to less developed ones where the aggregate demand, including demand for forest products is likely to be higher. In order to test this, we consider three indicators to classify states into more and less developed states. First, we classify the states into more and less developed based on the National State Domestic Product (NSDP) in 2011, which is one year prior to our period of analysis. We consider a state as developed one if the income is more than median level and is classified as less developed state if otherwise (less than or equal to the median level). Using

[18] Available at https://www.mospi.gov.in/download-reports (Accessed on June 15, 2024)
[19]The National Industrial Classification 2008 is used in the survey (https://www.ncs.gov.in/Documents/NIC_Sector.pdf)..
[20] Growth rates are based on data provided in Tables 2.6.1, 2.6.3 and 2.6.5 of the study.
[21] Data obtained from https://wits.worldbank.org/CountryProfile/en/Country/IND/StartYear/2005/EndYear/2020/TradeFlow/Import/Indicator/MPRT-TRD-VL/Partner/WLD/Product/44-49_Wood# (Accessed on June 13, 2024).
[22] Kant and Nautiyal (2020) show that production of wood increased in India during the last decade.

this classification, we observe that the RDD coefficient is positive and significant in developed states while the effect is insignificant in less developed ones (Columns 1-2 of Table 5). Second, we use the median per capita NSDP instead of NSDP levels and classify the states into more and less developed ones in a similar manner. Columns 3-4 indicate that in more developed states graduate politicians increase forest growth by 2.96 percentage points, whereas there is no effect in the less developed states. Next, we consider the BIMAROU (Bihar, Jharkhand, Madhya Pradesh, Chhattisgarh, Rajasthan, Odisha, Uttar Pradesh, and Uttarakhand) and non-BIMAROU status of states that classify them into less developed and relatively developed states, respectively. The BIMAROU states are those that have fallen short in terms of economic development as well as other development indicators compared to the national average. The RDD results suggest that there are no gains in forest growth in BIMAROU states, whereas educated politicians are likely to significantly increase forest growth by 2.56 percentage points in non-BIMAROU states (Columns 5-6). Importantly, we use another indicator to classify states with high demand for forest products: the urbanization rate based on the share of urban population as per Census 2011. The more urbanized states witness higher construction activity, and the construction sector is a major consumer of wood and related products. Using this categorization as well, we find that the graduate politician increases forest growth only in more urbanized states (columns 7-8). Overall, we find evidence in favor of our argument that higher demand for forest related products could be one of the reasons why graduate politicians increase growth of forest cover.

Table 5: Effect of educated politicians based on level of development and urbanization

	(1) High NSDP States	(2) Low NSDP States	(3) High PCI States	(4) Low PCI States	(5) BIMAROU States	(6) Non-BIMAROU States	(7) More urbanised states	(8) Less urbanised states
Graduate politician	2.584*	2.536	2.955**	1.424	2.800	2.259*	2.649*	2.541
	(1.479)	(1.774)	(1.478)	(1.802)	(2.262)	(1.186)	(1.380)	(1.950)
Bandwidth	12.498	12.379	11.920	11.837	13.243	12.849	12.250	12.441
Observations	5,828	5,740	5,578	5,990	4,361	7,207	5,957	5,611
Effective observations	3,822	3,582	3,380	3,788	3,014	4,631	3,779	3,591

Note: (i) The dependant variable is the annual growth in forest cover, defined as $(\text{Log}(\text{Forest}_{t+1}) - \text{Log}(\text{Forest}_t))*100$. (ii) All the models are estimated on the basis of Regression Discontinuity Design. (iii) The main explanatory variable - graduate politician is a dummy which takes value 1 if a graduate candidate wins against a non-graduate candidate, and '0' if a non-graduate wins against a graduate candidate. (iv) States are divided on the basis of level of NSDP, Per-capita Income (PCI), BIMAROU and Non-BIMAROU; and urbanisation level. (v) All the models are estimated by a local linear regression using a triangular kernel. (vi) Robust standard errors are clustered at the constituency level and given in the parentheses. (vii) The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Therefore, it can be argued that the higher demand for forest and forest related products can potentially motivate educated leaders to invest in forest growth. Nevertheless, if benefits from increasing forest growth can be accrued by both graduate and non-graduate leaders, why would not the latter respond by improving the forest growth? To answer this, we invoke the citizen-candidate model that explains the divergence in policies based on the politician's policy preferences (Osborne and Slivinski, 1996; and Besley and Coate, 1997). Here, education can be a proxy for politician's quality, thereby educated politicians may have unique policy preferences. If educated politicians are concerned about economic growth in their constituency, which is among their policy preference, they may invest disproportionately more in forestation efforts to cater to growing demand for forest products.

To study this aspect, we examine the influence of graduate political leaders on the economic growth in her own constituency by employing a similar RDD regression framework as outlined in equation 1.

Table 6: Effect of educated politicians on growth of night-time lights

	Without covariates	With AC and year FE	With AC FE, year FE and covariates	With District and year FE with covariates	h/2	2h	District and year FE with covariates-CER	AC FE, year FE with covariates-CER
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Graduate politician	-1.744 (1.492)	1.234*** (0.343)	1.519*** (0.314)	0.374 (0.771)	0.237 (2.878)	-1.678 (1.384)	0.852 (0.835)	0.814*** (0.303)
Bandwidth	9.835	9.835	9.835	9.835	4.91	19.67	6.578	6.578
Observations	11,568	11,568	11,206	11,206	11,568	11,568	11,206	11,206
Effective observations	6,366	6,366	6,152	6,152	3,652	9,524	4,451	4,451

Notes: (i) The dependant variable is the annual growth in Night-time Lights (NTL), defined as (Log(NTL_{t+1} +1) - Log(NTL_t +1))*100 (ii) All the models are estimated on the basis of Regression Discontinuity Design. (iii) Models differ on the basis of different fixed effects, control variables and alternative sample. (iv) Models in Column (2) include AC and year FEs. Model in column (3) adds the covariates: dummy for female winner, election year, alignment with state government; alignment with central government, ST reserved constituency; number of female candidates; Turnout percentage; and Age of the winner. Model in column (4) includes district FEs, year FEs and covariates. This model is re-estimated half and double of optimal thresholds and reported in column (5 & 6). (v) The models in column (7 & 8) are re-estimated based on alternative optimal threshold-CER. (vi) All the models are estimated by a local linear regression using a triangular kernel. (vii) Robust standard errors are clustered at the constituency level and given in the parentheses. (viii) The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

In the absence of economic output at the assembly constituency level, as discussed earlier, we use the NTL as a proxy for economic activity widely used in the literature (Baskaran *et al.,* 2023; Prakash *et al.*, 2019; and Jain *et al.* 2023). We run the RDD regressions using specifications that are used to estimate the impact on forest cover growth. While in some of these specifications, we do not observe any gains in night lights, in other specifications (3 out of 8), we find significant growth (Table 6). Notably, our findings that educated political leaders care for economic growth also corroborate the findings of Jain *et al.* (2023). Their study finds that electing graduate leaders in India led to an increase in economic activity using data for the period 2009 to 2013 which is prior to our period of analysis.

If concerns related to economic growth among graduate politicians can motivate them to invest in forest growth and cater to the higher demand for forests and forest related products, employment opportunities in industries related to forests and forest products should also increase in such districts. The Periodic Labour Force Survey (PLFS) conducted in 2017-18 and 2018-19 by the Ministry of Statistics and Programme Implementation in India allows us to explore this aspect. The first round covered 102,113 households, and a total of 101,579 households were surveyed in the second round. We pool the two repeated cross-sectional datasets and explore the employment details of the household members and the industry they are engaged in. This allows us to look at the temporal changes in employment in forest related industries in districts with a higher share of graduate politicians. We consider the industry classifications that pertain to works related to forest and forest products that include the following: (i) Forestry and logging; (ii) Manufacture of paper and paper products; (iii) Manufacture of wood and products of wood and cork, except furniture, manufacture of articles of straw and plaiting materials; and (iv) Manufacture of furniture[23]. For individuals in the working age population (25 to 60 years) coming from districts with higher share of graduate leaders, we find an overall increase in the likelihood of being engaged in industries catering forest and forest related products (Appendix Table T3).

To sum up, India' economic growth led to a substantial rise in the demand for forest related goods. This is one potential reason why educated politicians invest in forestation efforts to ensure higher supply of raw materials in forest related industries. This also ensures higher economic growth being achieved locally by educated leaders while providing higher

[23] The National Industrial Classification 2008 is used in the survey (https://www.ncs.gov.in/Documents/NIC_Sector.pdf). The divisions for these industry classifications are 2, 16, 17 and 31 respectively.

employment opportunities among working age population in industries catering to forests and forest related products.

5.4.2 Do environmental awareness also play a role?

In the introduction section, we argued about the possibility of educated politicians increasing forest growth because of their higher environmental awareness or concerns about sustainability. In absence of direct data on awareness or concerns of the politicians, we are unable to test for this channel. Nevertheless, using the existing datasets, we make some indirect inferences on whether environmental awareness among educated politicians can potentially play a role in forest expansion efforts.

First, we look at the effects of having educated politicians separately in constituencies dominated by the Scheduled Tribes (ST) vis-à-vis those with lesser share of STs. The tribal population (the STs) in India disproportionately depends upon the forests for their habitation as well as their livelihood (Kashwan, 2017) Notably, the National Forest Policy (1988) led to the decentralization of forest management as well as the formation of JFM Committees at the village level involving local communities, especially local tribal communities, in forest management and protection. As mentioned in Section 2.1, the FRA, also recognizes the forest rights of tribal population. Evidence suggests that decentralization efforts led to a fall in deforestation in scheduled areas with a large ST population base (Gulzar *et al.*, 2024). In constituencies where a large fraction of the population has similar preferences like that for STs, one may expect convergence in policies across candidates. This is in line with the prominent median voter theory which postulates that politician characteristics do not matter (Downs, 1957). According to this view, one would expect convergence of policies since politicians cater to the preferences of the median voter in order to be re-elected. In our context, the ST population is highly dependent on forests, therefore, non-graduate politicians might also be compelled to involve themselves in forest growth in those areas like the educated ones to maximize votes. However, in areas not dominated by STs, the observed gains in forest growth by graduate leaders might be a direct result of higher environmental awareness or issues pertaining to sustainability.

We re-estimate the results for the sub-sample of constituencies reserved for STs but observe no discernable impact of graduate politicians on forest growth in such constituencies (Column 1 of Table 7). For the unreserved constituencies, however, the effect is significantly positive (Column 2). This provides some suggestive evidence as to why we consider political awareness among educated leaders as a potential channel that can explain higher forestation.

Next, we explore the implications of criminally accused but graduate politicians on the forest cover growth. Evidence suggests that criminal politicians often engage in rent-seeking activities (Chemin, 2012; Prakash *et al.*, 2019). If the environmental concern of educated politicians is a reason why they invest more in forestation efforts, it should be the case that the graduate politicians engaging in rent-seeking would not be overly concerned with the environment per se. In fact, the impact of educated politicians on forest cover growth should primarily be concentrated in constituencies with graduate leaders with no criminal record.

Table 7: Role of environmental awareness

	(1) ST reserved	(2) Unreserved	(3) No criminal charges	(4) Criminal politician
Graduate politician	1.177	2.670*	3.541**	0.244
	(2.129)	(1.387)	(1.432)	(2.462)
Bandwidth	15.746	10.886	12.64	9.90
Effective observations	2430	4909	4,862	1,225
Observations	3,239	8,329	7,458	2,299

Note: (i) The dependant variable is the annual growth in forest cover, defined as $(\text{Log}(\text{Forest}_{t+1}) - \text{Log}(\text{Forest}_t))*100$. (ii) All the models are estimated on the basis of Regression Discontinuity Design. (iii) The main explanatory variable - graduate politician is a dummy which takes value 1 if a graduate candidate wins against a non-graduate candidate, and '0' if a non-graduate wins against a graduate candidate. (iv) Column (1&2) bifurcates the sample for Scheduled Tribe (ST) reserved and unreserved constituencies. Columns (3 & 4) bifurcate the base sample based on the criminality of the winner. In column 3, sample includes those constituencies where the winner has no criminal charge and at least one criminal charge in column (4). (v) All the models are estimated by a local linear regression using a triangular kernel. (v) Robust standard errors are clustered at the constituency level and given in the parentheses. (vi) The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

To test for the aforementioned, we gather data on the criminal charges of the election winner using the *myneta.info* web portal, which assembles background reports on criminal activities of which the candidates are accused. Next, we segregate the winners accused of at least one criminal charge and run the RDD regressions to estimate the heterogenous effects of educated political leaders who have criminal charges against them. In constituencies led by non-accused educated leaders, we find a significant increase in forest growth (Column 3). However, the findings presented in Column 4 indicate no positive gains from educated but criminally accused politicians. These results are indicative of suggestive evidence that environmental awareness that comes through education may play a role in their forestation efforts. These findings are further complemented when we look at the incidence of forest related crimes obtained from the National Crime Records Bureau (NCRB). The forest crimes come under Special and Local Crimes (SLL). The data on the number of forest related crimes is available at the district level from 2014 onwards. It is reasonable to think that politicians who are more sensitive and aware of issues pertaining to the environment and sustainability are likely to take actions that could reduce forest-related crime. These include implementation and enforcement of policies aimed at protecting forests and curbing illegal activities. The regression of the number of forest related crimes at the district level on the share of graduate politicians for the period 2014 to 2019 yields a weak negative relation (Appendix Table T4). These observations together prevent us from discarding environmental awareness/ concerns among educated leaders as a possible channel that explains their efforts in improving forest growth.

6. Conclusion

Environmental and health benefits derived from forests have been well documented, therefore exploring ways to improve forest management and sustainable development remains critical from policymakers' viewpoint. While studies have specifically assessed the role of political regimes in determining deforestation, the effect of having an educated political leader on forestation efforts remain unexplored. Using datasets from multiple sources that involve remotely sensed forest data and temporal election data, we examine the role of educated leaders in improving forest cover growth in India and the possible reasons that explain the observations.

The findings indicate a significant rise in forest growth in constituencies led by a graduate politician. In terms of the effect size, we find an increase in forest growth of about 2.4 percentage points. On exploring the reasons that explain this growth, the rise in the demand for forest related products potentially incentivized educated politicians to invest in forestation. This may allow them to achieve higher economic growth in their own area and also provide employment opportunities in forest and forest related industries. Nevertheless, we also find some suggestive evidence that higher awareness of environmental issues among educated leaders could also have led to higher forest cover growth.

The findings from the paper shed light on the crucial role of educational attainment in shaping the environmental policies and outcomes. The observed significant rise in forest cover growth in constituencies led by graduate politicians underscores the importance of education in policymaking. This finding has important implications for political parties and voters alike.

Parties may consider fielding candidates with a higher level of education in constituencies where environmental concerns and forestation are critical issues. Additionally, voters can make more informed choices by considering the educational background of candidates when casting their ballots, with the potential for a positive impact on local environmental outcomes. It further contributes to the broader debate on whether a certain minimum level of education is a desirable attribute of politicians. In this regard, it is worth noting that our paper does not specifically test the threshold level of education post which the environmental benefits of educated politicians are observable, even though our analysis in section 4.2 does indicate a positive gradient for education. This remains an area for future research.

This research provides valuable insights into how policy tools can be used strategically to simultaneously enhance environmental sustainability through improving growth of forest cover and economic well-being in local areas. It underlines the need for additional resources and complementary policies focusing on regions with non-graduate politicians to reduce the regional/ spatial gap in the growth of forests. By adopting a holistic approach that aligns conservation goals with employment and economic development, governments can work towards a greener and more resilient future for their constituencies.

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Appendix

Table T1: Variable definition

Variable	Description	Data Source
Outcome variables		
Growth in Forest Cover	Annual growth of forest cover defined as $Log(Forest_{t+1})$-$Log(Forest_t)$)*100	SHRUG
Growth of NTL	Annual growth of night-time lights defined as ($Log(NTL_{t+1}$ +1) - $Log(NTL_t$ +1))*100	SHRUG
Forest-related employment	=1 if individual in the age-group of 25 to 60 years is engaged in jobs in (i) Forestry and logging; (ii) Manufacture of paper and paper products; (iii) Manufacture of wood and products of wood and cork, except furniture, manufacture of articles of straw and plaiting materials; and (iv) Manufacture of furniture; 0 otherwise	PLFS
SLL Crimes	Number of SLL crimes at the district level defined as Log(1+No. of SLL Crimes)	NCRB
Forest crime	Number of forest crimes at the district level defined as Log(1+No. of forest crime recorded during the year)	NCRB
Explanatory variable		
Graduate	=1 if Margin>0; 0 otherwise; where Margin=vote share of graduate-vote share of non-graduate	TCPD
Share of graduate winners	The number of winners with at least a graduate degree in the district divided by the number of state assembly seats in the district	TCPD
Other political variables		
Education	Education level of the candidates	TCPD
Female candidate	Number of female candidates in the constituency	TCPD
Female winner	= 1 if the winner is a female, otherwise 0	TCPD
Election Year	=1 for election years and 0 otherwise	TCPD
Age	Age of the winner (in years)	TCPD
Turnout	Voter turnout during at the election (in percentage)	TCPD
State aligned	=1 if the winner belongs to the same party as the party in power at the state, 0 otherwise	TCPD
Centre aligned	=1 if the winner belongs to the same party as the party in power at the centre, 0 otherwise	TCPD

Non-political variables at the constituency level

Total Population, and ST Population

In order to obtain the constituency level population and ST population, we utilize Population Census 2011 (PC 2011); village level shape files corresponding to PC 2011; and the shapefiles of state assembly constituencies post-delimitation (post-2008). The data was obtained in the following steps:

- Step 1: The spatial maps of villages and constituencies were interacted to find the respective constituency of each village.

- Step 2: The population of villages falling in a constituency was added to obtain the population of that constituency. The individual villages/towns largely belonged to one particular constituency. In a scenario, where a village/town fell in more than one constituency, i.e. their spatial boundaries did not overlap perfectly, the population of that village/town was divided in more than one constituency depending upon the area of the village shared between those constituencies. Similarly for ST population was obtained for each constituency.

Table T2: Effect of graduate politicians on covariates

	(1) Logarithm of valid votes	(2) Logarithm of electorates	(3) Number of candidates	(4) Female candidate	(5) Turnout %	(6) 1-period lagged NL growth	(7) Age	(8) Number of criminal cases	(9) Logarithm of assets	(10) Logarithm of liabilities
Graduate politician	-0.065	-0.070	-0.178	0.018	0.084	0.360	-1.643	-0.308	-0.219	0.046
	(0.083)	(0.090)	(0.634)	(0.121)	(1.243)	(1.541)	(1.236)	(0.329)	(0.194)	(0.269)
Bandwidth	10.609	10.459	12.249	14.157	12.540	11.655	10.975	9.527	9.519	10.948
Observations	11,571	11,557	11,571	11,571	11,557	9,875	11,209	11,471	11,390	7,886
Effective observations	6,684	6,605	7,330	8,099	7,442	6,021	6,625	6,172	6,113	4,615

Robust standard errors clustered at the constituency level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table T3: Employment in forest related product industries

	(1)	(2)	(3)	(4)	(5)	(6)
60% graduate* Round 2018-19	0.001					
	(0.001)					
70% graduate* Round 2018-19		0.002**				
		(0.001)				
75% graduate* Round 2018-19			0.002			
			(0.001)			
80% graduate* Round 2018-19				0.003**		
				(0.001)		
85% graduate* Round 2018-19					0.004**	
					(0.002)	
90% graduate* Round 2018-19						0.002
						(0.002)
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	211,473	211,473	211,473	211,473	211,473	211,473

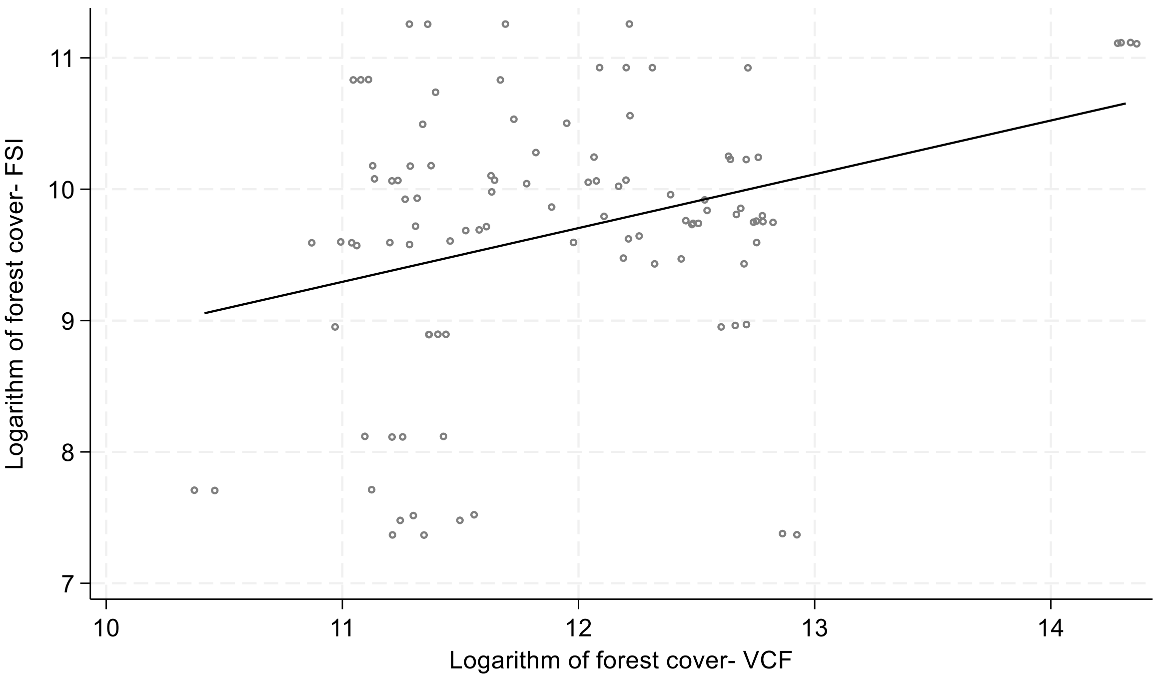
Estimations from Ordinary Least Squares (OLS) are presented along with robust standard errors. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table T4: Share of graduate politician and incidence of forest crime

	Dependent variable:	
	Log(1+SLL Crimes)	Log(1+Number of forest related crimes)
	(1)	(2)
Share of graduate politicians	-0.113**	-0.087
	(0.066)	(0.065)
Year effects	No	Yes
Observations	4,585	4,585

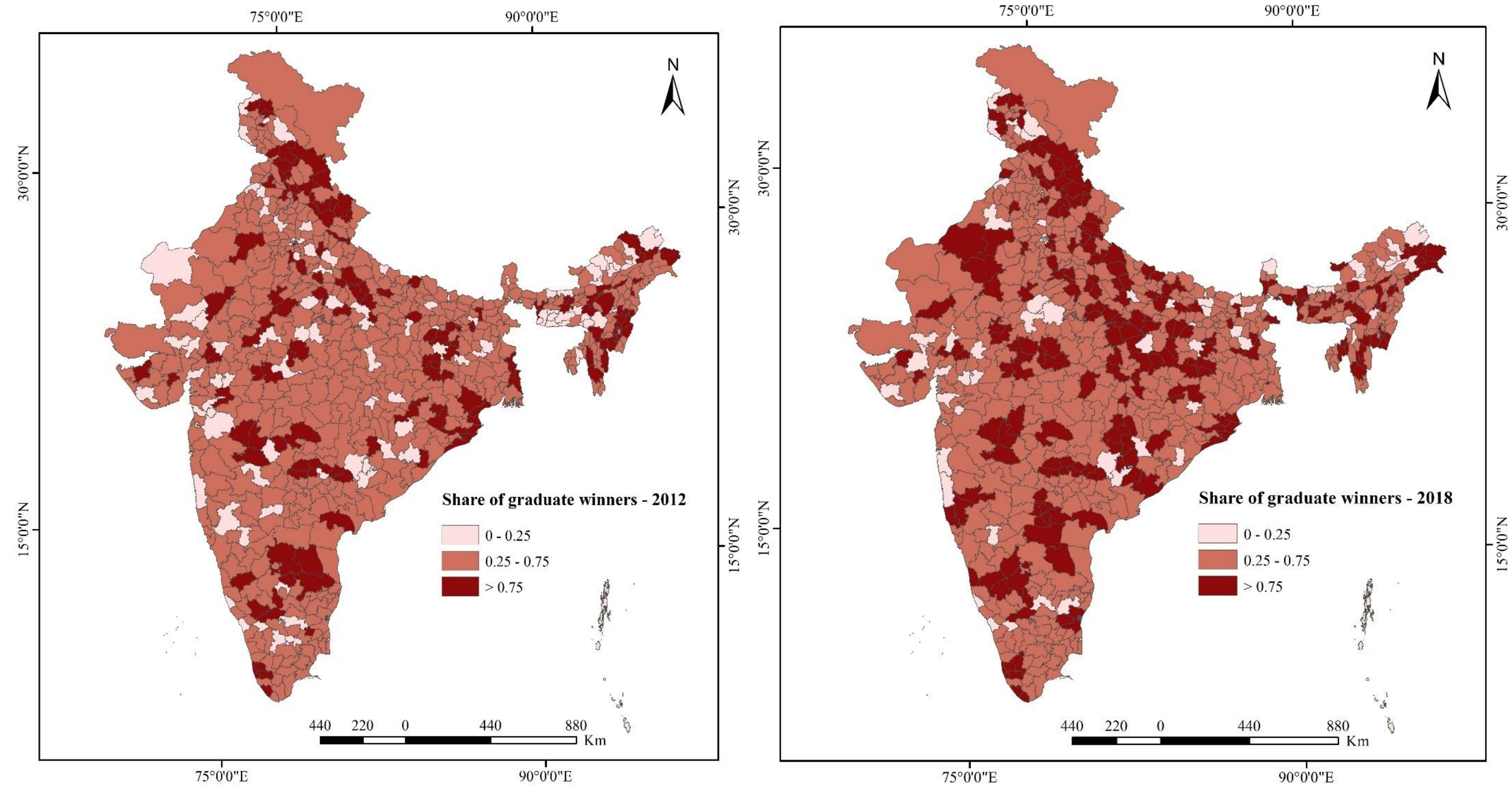
Estimations from Ordinary Least Squares (OLS) are presented along with robust standard errors. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure F1: Scatter plot



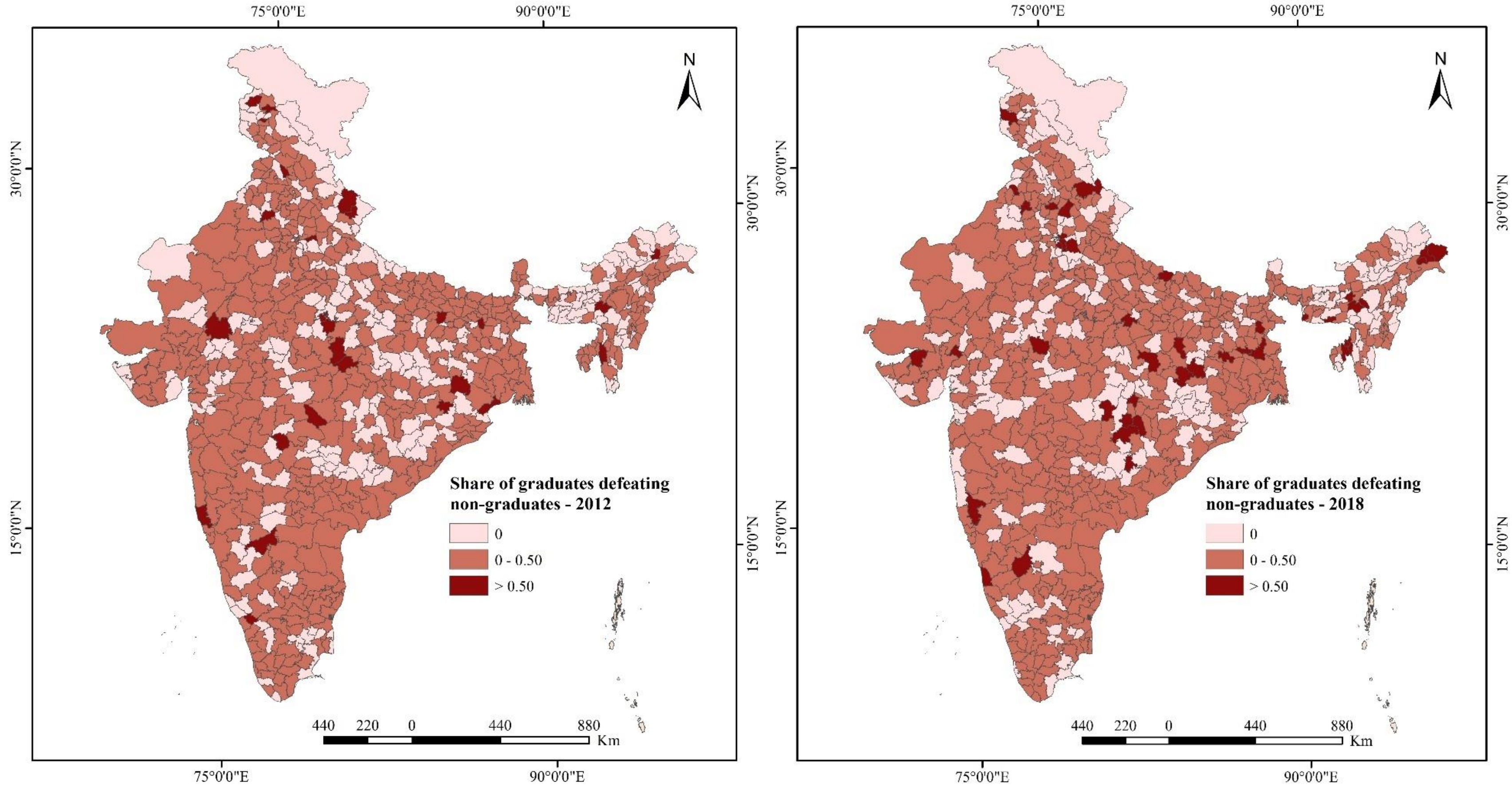
Note: Figure gives the scatter plot of the log of (official) forest cover obtained from Indian State of Forest Reports on the log of forest cover generated by VCF (SHRUG)). The straight line depicts the fitted values.

Figure F2: Share of graduate MLAs at the district level (2012 and 2018)



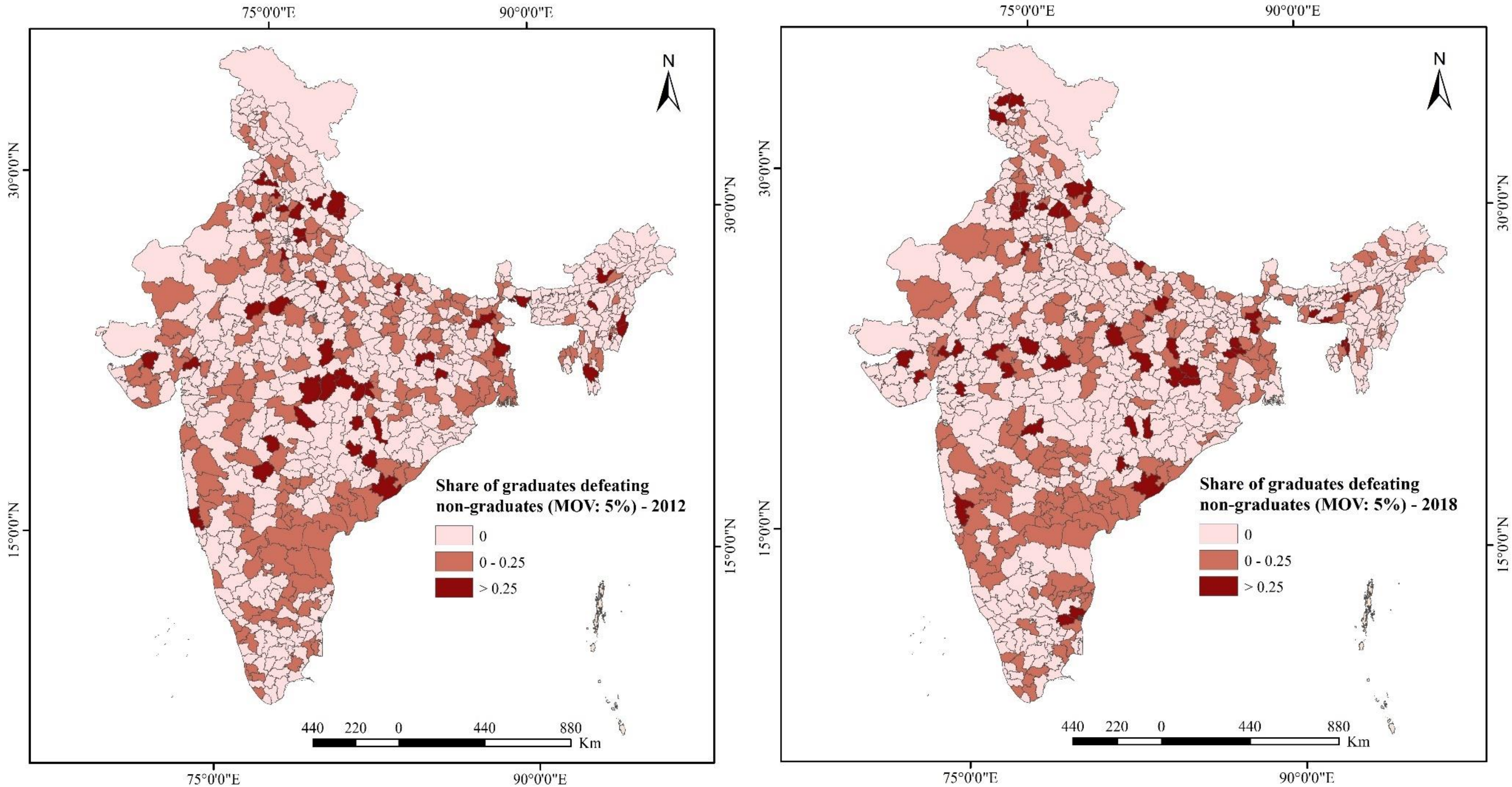
The figures show the share of constituencies within a district which a graduate candidate won an assembly constituency seat in state elections in 2012 and 2018.

Figure F3: Share of graduate MLAs defeating non-graduate MLAs at the district level (2012 and 2018)



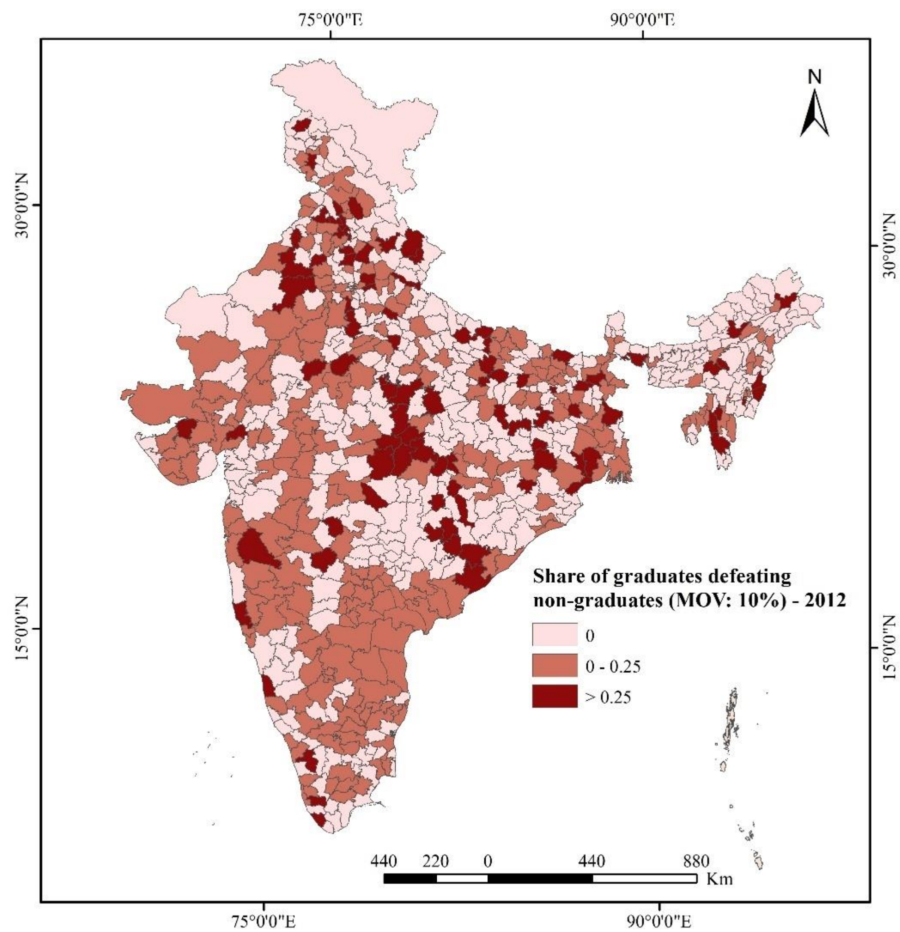
The figures show the share of constituencies within a district which a graduate candidate won an assembly constituency seat defeating a non-graduate candidate in state elections in 2012 and 2018.

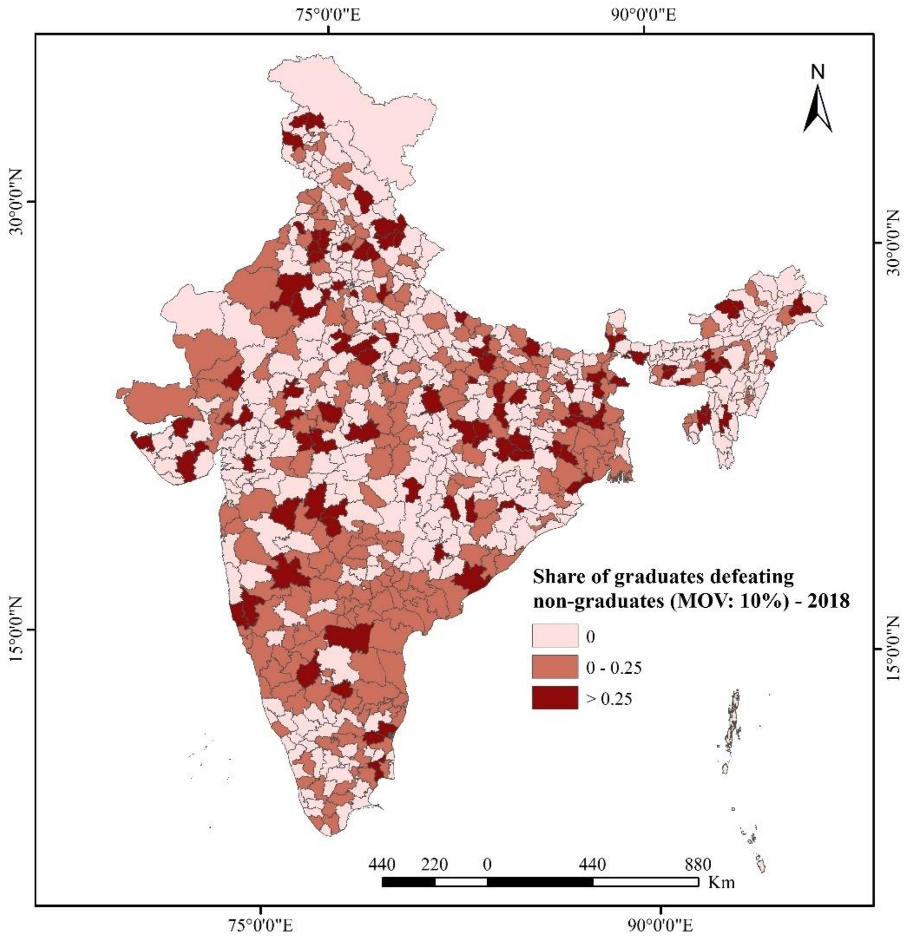
Figure F4: Share of graduate MLAs defeating non-graduate MLAs at the district level with margin of victory: 5% (2012 and 2018)



The figures show the share of constituencies within a district which a graduate candidate won an assembly constituency seat defeating a non-graduate candidate with a margin of victory of 5% or below in state elections in 2012 and 2018.

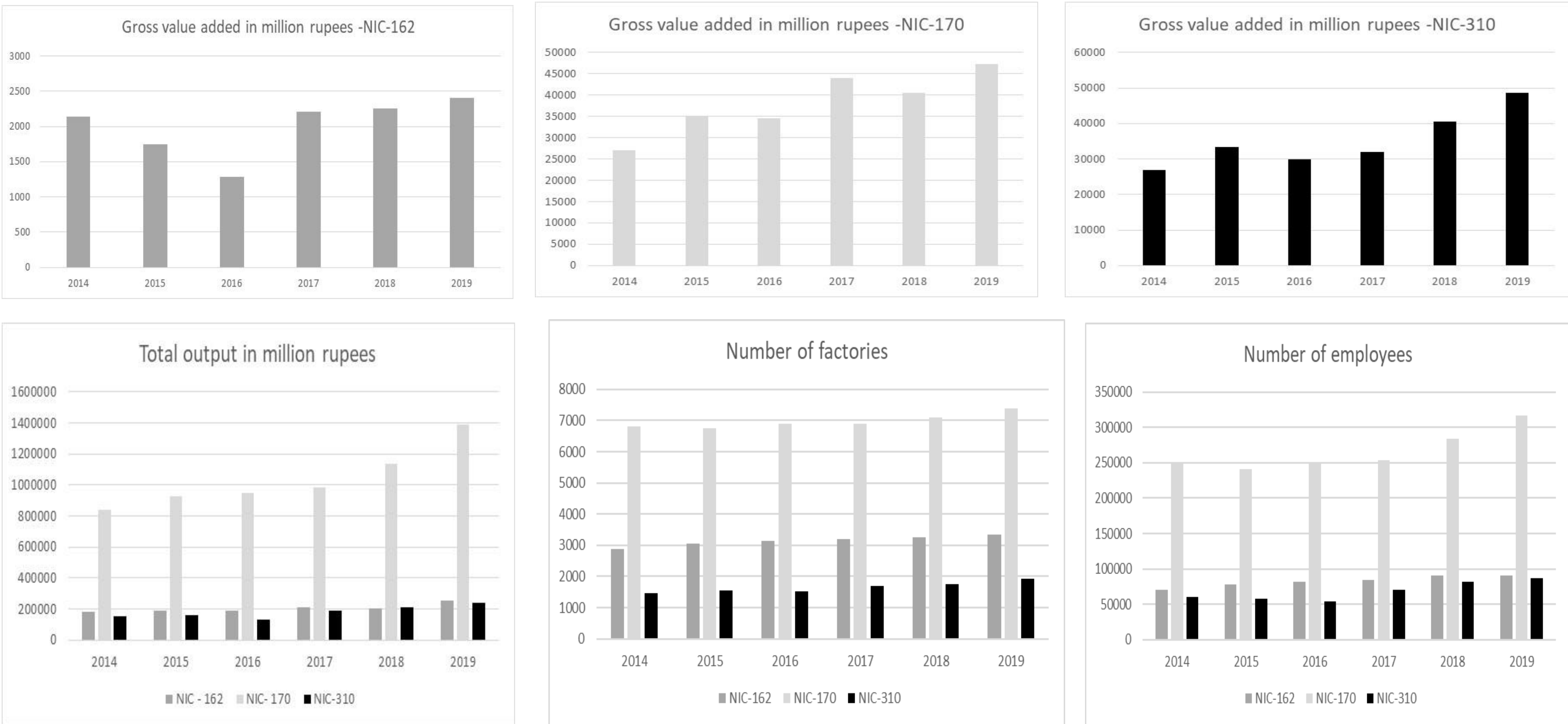
Figure F5: Share of graduate MLAs defeating non-graduate MLAs at the district level with margin of victory: 10% (2012 and 2018)





The figures show the share of constituencies within a district which a graduate candidate won an assembly constituency seat defeating a non-graduate candidate with a margin of victory of 10% or below in state elections in 2012 and 2018.

Figure F6: Industry indicators for sectors relying on wood



Note: Figure shows the trend in gross value added, total output, number of factories and number employees for the wood dependent industries based on data obtained from the annual reports of Annual Survey of Industries for the time period 2014 to 2019.

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