Representation Alone?

Revisiting PESA's Role in Forest Conservation in India's Scheduled Areas

Utkarsh Choudhary* Sumit Mishra†

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Abstract

Gulzar et al. (2023) argue that Scheduled Tribe (ST) quotas under the Panchayat Extension to Scheduled Areas (PESA) Act increased forest cover and reduced deforestation. We identify and correct a major error in the construction of the treatment variable measuring the timing of the first PESA elections in each state, and find no evidence that holding PESA elections alone significantly affects forest outcomes. Moving beyond replication, we construct a novel index of PESA rule implementation (PESA-Intensity) and show that it does not improve forest conservation outcomes. Our extended analysis further demonstrates that the original results are highly sensitive to data restrictions and may instead reflect the influence of the Forest Rights Act (FRA) and the Panchayati Raj Institutions (PRI) Act. We also show substantial heterogeneity across states, suggesting that institutional and contextual factors mediate the relationship between representation and conservation. Overall, our findings indicate that the positive effects previously attributed to PESA are overstated and that institutional design beyond electoral quotas plays a more critical role in shaping forest outcomes.

Keywords: Affirmative action, Decentralization, Forest conservation, Scheduled area, Social justice

JEL codes: H77, J15, K32, P18, Q28, Q58

*Faculty Associate, T A Pai Management Institute Bengaluru, Manipal Academy of Higher Education, Manipal, India. Email: utkarsh.choudhary@manipal.edu.

†Assistant Professor, IFMR GSB, Krea University. Email: sumit.mishra@krea.edu.in.

1 Introduction

> *"Forest governance shouldn't be a constant battle between the government and Adivasi (Schedule Tribe) communities. We need a shared approach to manage, conserve, and make decisions about our forests together"*
>
> — Rinjo Sikaka, *Governing Forests* (Kodiveri, 2024)

India's forests have faced increasing pressure in recent decades, with a particularly sharp rise in deforestation between 2015 and 2020.[1,2] In fact, between 1990 and 2020, India suffered the most significant loss of forest cover worldwide, with a staggering 284,440 hectares of forest disappearing. This significant decline in forest area raises questions about the effectiveness of India's forest conservation efforts.

Against this backdrop, policymakers have implemented various measures to empower local communities and address forest degradation. One significant legislative initiative is the Panchayat Extension to Scheduled Areas (PESA) Act of 1996, which aims to devolve governance to local bodies, particularly in Scheduled Areas predominantly inhabited by the Scheduled Tribes (STs). Recently, Gulzar et al. (2023) (hereafter GLP) examined the impact of ST electoral quotas mandated by the PESA Act on forest conservation, concluding that PESA led to increased forest cover and reduced deforestation.

In this paper, we revisit the findings of GLP. We identify a significant coding error in their original analysis. The assignment of the first post-PESA election year for three out of nine PESA states (Himachal Pradesh, Maharashtra, and Chhattisgarh) is incorrect. More importantly, we argue that GLP narrowly describes the PESA Act by equating holding elections to implementation of PESA Act. The PESA Act consists of 16 distinct rules that collectively aim to empower ST communities across diverse domains such as forest governance, land alienation, local dispute resolution, and control over social sector programs. Electoral quotas represent only one of these provisions. We believe, by equating electoral quotas with PESA implementation, GLP conflate a specific provision under the PESA

[1] See https://www.utilitybidder.co.uk/compare-business-energy/deforestation-report/

[2] See https://www.thehindu.com/sci-tech/energy-and-environment/why-it-matters-india-has-lost-668400-ha-of-forest-cover-in-the-last-30-years/article66645294.ece

Act. This oversimplification neglects the multidimensional nature of the law and risks misinterpreting its true effects. We, therefore, contest their findings.

Forest-dwelling communities, particularly Scheduled Tribes (STs, hereafter), hold a vital stake in saving the forests in India. Representing roughly 8%[3] of Indian population, STs have traditionally resided in close proximity to forests, relying on them for their subsistence needs and livelihoods. Recognizing this fact, areas with large proportion of STs were given the status of Scheduled Areas under Part V of the Indian constitution. Historically, there has been a constant tussle between the state and the ST community. This tension plays out acutely in depleting forest cover and increasing conflict around the governance of forest resources in India.

Decentralization aims to empower local communities and improve public services. However, it is prone to elite capture in developing countries (Bardhan and Mookherjee, 2000; Bardhan, 2002). Policymakers have implemented affirmative action policies such as electoral quotas to overcome this. The aim is to provide marginalized groups and women with political representation at various levels of the government. Electoral reservations can positively influence social attitudes toward marginalized groups and increase their participation in local governance (Dunning, 2010; Chauchard, 2014). Representatives from these groups prioritize public goods and services benefiting their constituents (Besley et al., 2005; Bardhan et al., 2010; Chattopadhyay and Duflo, 2004). However, the long-term impact of political reservations on economic and environmental outcomes is uncertain. For instance, village council political quotas in India follow an interesting rule by which different marginalized groups get the position of council chairperson (*Pradhan*) on rotation. When the cycle ends, the specific group loses electoral quota and the marginal benefit of affirmative action dissipates (Girard, 2018). There is some evidence that reserving seats on the village council for marginalized groups has not significantly improved the distribution of local-level benefits (Dunning and Nilekani, 2013). This is likely due to several factors, including limited resources and a declining number of public jobs at the local government

[3]See https://tribal.nic.in/downloads/Statistics/STsStatisticalProfileAtaGlance_09072024.pdf

level in India compared to other countries like the US and China (Kapur, 2020). Additionally, India's skewed distribution of government jobs, primarily concentrated at the central and state levels, undermines the capacity of local governments to function effectively. For example, at the *Gram Panchayat* (GP, hereafter) level, the GP Secretary is the sole government official who is responsible for maintaining the records and implementing services under the village head's (*Sarpanch /Pradhan*) supervision. However, larger projects (building schools, Public Health Centers, roads, etc.) require the involvement of officials from the state government. Given that political power in India is often vested with the state government (Ministry of Tribal Affairs, 2014), the GP has limited power to deliver public goods effectively.

PESA is an unique Indian legislation that combines decentralization and affirmative action. Under the PESA Act, a village[4] in a Scheduled Area[5] must have a *Gram Sabha* (village council).[6] The PESA Act empowers *Gram Sabhas* by granting them significant powers over local and forest governance. The 16 model rules under the PESA Act enable *Gram Sabhas* to make decisions on resource management, development planning, and social welfare programs, including forest governance.[7] Key provisions related to forest governance include the ownership of minor forest produce and the requirement for *Gram Sabha* approval prior to granting mining licenses. These provisions empower *Gram Sabhas* to play a crucial role in safeguarding forests while also ensuring the well-being of forest-dependent communities.

India's forest governance is complex, with several conflicting laws. Table 1 provides an overview of laws related to forest conservation, specifying the level of authority empowered by each law and their respective areas of implementation.

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[4] A village shall ordinarily consist of a habitation or a group of habitations or a hamlet or a group of hamlets comprising a community and managing its affairs in accordance with traditions and customs.

[5] Scheduled Areas are specific geographical regions within certain Indian states that are designated by the President of India under the Fifth Schedule of the Indian Constitution. These areas are primarily inhabited by Scheduled Tribes (STs) and are subject to special provisions aimed at protecting their rights, customs, and traditions.

[6] Gram Sabha consists of persons whose names are included in the electoral rolls for the *Gram Panchayat* at the village level.

[7] See https://tribal.nic.in/actRules/PESA.pdf

Table 1: Forest conservation laws and authority

Law	Year	Authority	Area
Indian Forest Act	1927, 1947	State	All forest areas under the State Government
Coal Bearing Areas Act	1957	Center	Areas that contain or are likely to contain coal deposits
Widlife Protection Act	1972	Center, State	National Parks, Wildlife Sancturies, Conservation Reserves, Tiger Reserves, Reserve Forest and all the Protected Forests
Forest Conservation Act	1980	Center, State	All areas recorded as forest in government records
National Porest Policy	1988	Center, State	All India
Panchayati Raj Instituition (PRI) Act	1993	Local Governance Body	All India
Panchayati Raj Extension to Schedule Areas (PESA)	1996	Local Governance Body	Scheduled Areas
Forest Rights Act (FRA)	2006	Local Governance Body	All areas recorded as forest in government records

Note: The Indian Forest Act of 1927, a legacy of British colonial rule, was retained post-independence and subsequently amended in 1947.

While PESA recognizes community rights in the Schedule Areas, other laws such as Indian Forest Act 1927, Wildlife Protection Act 1972, Forest Conservation Act 1980, and National Forest Policy 1988 centralized state control. One potential reason for these conflicting laws is the overlap between Scheduled Areas and forested regions, with forty percent of Scheduled Areas covered by forests. This overlap often pits decentralization against state control and put the environmental citizenship of STs at stake (Kodiveri, 2022).

The PESA Act establishes a framework for empowering *Gram Sabhas*. However, its implementation remains uneven and filled with challenges. We illustrate this with an example. The Section 4(b) of PESA Act mandates the presence of a *Gram Sabha* to act as a basic unit of governance in every village not the *Gram Panchayat* within Scheduled Areas. The Act defines a village to be a hamlet, habitation or a group of habitations sharing same culture and customs. However, states have loosely interpreted the definition of "village" as envisaged by the Act (Planning Commision, 2008). For instance, Andhra Pradesh, despite adopting all PESA rules in 2011, continues to consider a village as a, which contains multiple villages. For example, Pullangi in Maredumilli Mandal, Andhra Pradesh, is a *Gram Panchayat* consisting of 11 habitations and a population size of approximately 1,050 (according to Census 2011). There is only one *Gram Sabha* for these habitations. Participatory democracy becomes challenging (Trivedi, 2020) when understaffed local governments are supposed to serve a larger population. Another example is the case of Himachal Pradesh. While the state has implemented all the PESA rules, it does not define "village" at all. In each of these cases, the model rules of PESA Act are neither adhered to nor achieved.

Furthermore, many states have delayed the process of drafting and implementing necessary rules. For instance, Jharkhand and Odisha have yet to finalize the PESA rules.[8,9] Even states with significant tribal populations, such as Madhya Pradesh (the state with ST population share of around 14 % of the total ST population in India) and Chhattisgarh (state with the largest ST population within the state, around 31 % of total state population), drafted PESA rules only in 2022, twenty-seven years after the Act's passage. The delay in implementation is one aspect; another one is the dilution of some of the rules by states while amending their respective Panchayati Raj Acts. For instance, in Odisha, Section 4(l) of the PESA Act grants *Gram Sabha* the authority to issue concessions for the exploitation of minor minerals. However, in Odisha, the *District Panchayat* actually holds this power, not the *Gram Sabha* (Dandekar and Satpathi, 2023). In Rajasthan, the Rajasthan Panchayat Act provisioned the *Gram Panchayat Sarpanch* (elected head) to lead *Gram Sabha* meetings which goes against the PESA regulations. These delays and inconsistencies in implementation undermine the Act's potential to empower tribal communities and protect their rights over forest resources (Ministry of Tribal Affairs, 2014). We define PESA to cover all the 16 rules outlined in the PESA Act. Unlike GLP, our analysis is based on whether different states have implemented each PESA rule over time. By constructing a variable that tracks the implementation dates of these rules, we believe that we provide a more precise measurement of PESA Act.

Our analysis yields several key findings that challenge the original conclusions. First, after correcting the identified coding error in GLP's assignment of the first post-PESA election dates, we find no statistically significant change in forest cover. However, we observe a reduction in deforestation of approximately 0.08 hectares. To assess the robustness of these results, we conduct additional analyses, including state-level heterogeneity, sensitivity tests based on ex-ante forest cover, and an

[8]For Jharkhand, see https://www.downtoearth.org.in/governance/implementing-pesa-act-in-jharkhand-is-not-an-easy-task-90666

[9]For Odisha, see https://www.thehindu.com/news/national/odisha/rules-under-pesa-act-to-be-presented-before-odisha-assembly-next-session-assures-minister/article68605669.ece

event study framework. These robustness checks consistently support our main findings.

Second, by constructing a new variable capturing the implementation of individual PESA rules, we similarly find no effect on forest outcomes. We use PESA-Intensity as the treatment variable to examine its impact on forest cover and deforestation and find no statistically significant effect on either outcome. To test the robustness of this result, we conduct three sensitivity analyses. First, we extend the GLP dataset to cover the full range of available data from 1990 to 2017, instead of the original 1995 to 2017 period. Second, we replace state-year fixed effects with district-year fixed effects to account for potential intra-state heterogeneity in PESA implementation. Third, we test whether the effect of PESA varies across different levels of initial forest cover by focusing on lower ex-ante forest cover deciles. The first sensitivity analysis reinforces our main conclusion: PESA has negligible impact on forest outcomes. The second analysis also reveals no effect, even after accounting for more granular district-level variation. The third analysis suggests that PESA's impact on forest cover becomes more pronounced only when higher deciles of ex-ante forest cover are included, indicating sensitivity to initial forest cover.

Third, we explore heterogeneous impacts across states through detailed analyses. First, we split the entire sample by the population share of STs, focusing on the following: a) above (and below) average ST share and b) ST share above (and below) 50% of the village population. We find that the deforestation is higher, on average, in villages with ST plurality. Second, we examine the state-wise heterogeneity in the effect of PESA on forest outcomes. Our analysis reveals heterogeneous effects on forest cover: a positive impact in Andhra Pradesh, Jharkhand, and Rajasthan and a negative impact in Gujarat, Himachal Pradesh, Madhya Pradesh, and Maharashtra. In case of deforestation, we find null effects across all states.

Fourth, our analysis shows that the original findings are sensitive to data choices, and some of the observed effects may be better explained by the Forest Rights Act (FRA) of 2006. We use the deforestation as an outcome variable and find no significant impact of FRA on deforestation in the four-state sample used by GLP.

We then include all the PESA states in the analysis and find a strikingly positive effect, with a reduction in deforestation by approximately 33 hectares compared to 6 hectares reported by GLP. This suggests that the FRA may drive some of the impact attributed to PESA by GLP.

Lastly, we test whether there is any effect of Panchayati Raj Institutions (PRIs, hereafter) on the forest cover index. GLP incorrectly codes the timing of PRI implementation for Madhya Pradesh. After correcting this error, we reassess the effects of PRI on the forest cover index. Contrary to GLP's findings of a small effect, we find a significant negative impact of PRIs on the forest cover index.

Put together, our analysis reveals that PESA has a limited impact on forest cover and deforestation. We find that the choice of fixed effects and the village-level ST population share changes the estimated impact of PESA. Additionally, the concurrent implementation of the Forest Rights Act (FRA) might confound the effects of PESA. Our state-level analysis shows heterogeneous effects of PESA on forest cover, with some states experiencing positive impacts while others negative. Overall, our findings suggest that the positive effects attributed to PESA by GLP may be overstated.

The remainder of the paper is structured as follows. Section 2 details the data and methods employed in the analysis. Subsequently, Section 3 presents the empirical results, and Section 4 concludes the paper by summarizing the key findings and their implications.

2 Data and Methods

2.1 Data

GLP uses two datasets for the analysis. First, they manually classify villages as Scheduled or Non-Scheduled based on Tribal Ministry, Government of India data, categorizing entire blocks as Scheduled if they contain at least one Scheduled village. They then use the year of the first *Gram Panchayat* election post-PESA enactment in each of the nine PESA states and use this to create a switching variable (treatment variable). Second, GLP leverages the MEaSURES VCF dataset (Song et al., 2018) and the GFC dataset (Hansen et al., 2013) to construct data on forest cover and deforestation at the village level. The MEaSURES VCF dataset provides annual indices of tree-canopy cover, non-tree vegetation, and bare ground at a 0.05-degree resolution from 1982 to 2016. The GFC dataset provides information on deforestation events between 2001 and 2017. The forest cover (from VCF dataset) and deforestation (in hectares) (from GFC dataset) serve as the primary outcome variables in the analysis.

GLP reports the aggregate trend of tree canopy from the VCF dataset and the annual deforested area from the GFC dataset. GLP shows that the average tree canopy increases over the entire span of the VCF dataset, and deforestation increase over the entire span of the GFC dataset. Since the focal point of the paper is the differences in forest outcomes between Scheduled and non-Scheduled Areas, it is important to examine the evolution of the main outcome variables. Figure 2 shows the annual aggregated trend of tree canopy cover for Scheduled and non-Scheduled areas, revealing no significant change in the entire study time frame. Figure 3 shows the state-wise trend of aggregated tree canopy cover before and after GLP's PESA implementation dates. We find no significant differences, except in Rajasthan and Gujarat, where forest cover decreases in Scheduled Areas compared to non-Scheduled Areas after the introduction of ST reservation rules. Figure 4 shows deforested area (in hectares) for both Scheduled and non-Scheduled Areas. We observe that deforestation increases in the Scheduled Areas, while in the non-Scheduled Areas, it initially increases and then decreases, eventually converging with the deforested area of the Scheduled Areas. Lastly, we examine state-wise variations in deforested areas. Except for Madhya Pradesh and Maharashtra, where deforested areas in non-Scheduled Areas reduce compared to Scheduled Areas, no significant changes occur in other states, as shown in 5. Overall, our preliminary observation suggests that there has been no change in forest cover or deforestation between Scheduled and non-Scheduled Areas. In the next section, we examine the problems associated with GLP's treatment variable.

2.2 Problems with the GLP Treatment Variable

As noted in Section 2, GLP utilizes the timing of the first post-PESA *Gram Panchayat* election to construct the treatment variable. However, their treatment variable is incorrectly constructed. Firstly, the GLP study does not cite the original source for the timing of the first post-PESA *Gram Panchayat* election. Secondly, GLP's claim regarding the timing of the first *Gram Panchayat* elections is incorrect. We find errors in the timing of first PESA elections for three states, namely Himachal Pradesh, Maharashtra and Chhattisgarh. We discuss each of these three cases.

In the case of Himachal Pradesh, the 2000 *Gram Panchayat* election was conducted under the *Himachal Pradesh Panchayati Raj Act* of 1994, which excluded *Gram Panchayats* in Scheduled Areas from the election process.[10] Moreover, if we specifically look at the ST reservation rule, it is unlikely that the *Gram Panchayat* election of 2000[11] followed the ST reservation rule because Himachal Pradesh amended its *Panchayati Raj Act* in 2004 to mandate 50% reservation for STs in Scheduled Areas. Therefore, GLP's identification of the first *Gram Panchayat* election with the ST reservation rule conducted in the year 2000 for Himachal Pradesh (see Panel A of Table 10) is erroneous.

In Maharashtra, the Panchayati Raj Act was amended in 1997 to provide reservations for STs in Scheduled Areas.[12] Subsequently, on February 16, 1998, the State Election Commission issued a circular clarifying that *Gram Panchayat* elections under the new ST reservation rules would be implemented only after the completion of each panchayat's five-year term. As a result, although the amendment was enacted in 1997, the first elections held under the ST reservation provisions took place only in 2002, following the conclusion of the 1998–2002 term.[13]

[10] The Himachal Pradesh Annual Administrative Report (2016-17) states, "Second general elections of Panchayati Raj bodies of this State, except in Development Block Lahaul and Development Block Pangi, were held during December, 2000 and the Panchayats started functioning w.e.f. 23rd January, 2001 and the 5 years term expired on 22nd January, 2006. In Development Block Lahaul and Development Block Pangi the second general elections were held during May, 2006 ." (p-4). The quoted text is from page 4 of annual administrative report, 2016-17 of Himachal Pradesh. To access see https://hppanchayat.nic.in/PDF/AARE2016-17.pdf

[11] The year of first-post PESA election complying with all PESA rules according to GLP.

[12] For the text of the Act, see Section 10(2)(b) of the Maharashtra Panchayati Raj Act amendment of 1997.

[13] For the circular, see https://archive.org/details/29-16021998.

Therefore, GLP's identification of 2007 as the starting point for ST reservation in *Gram Panchayat* elections in Maharashtra is wrong, since the actual implementation began in 2002.

Lastly, in the case of Chhattisgarh, *Gram Panchayat* elections were held during 1999–2000 in undivided Madhya Pradesh.[14] These elections followed the ST reservation rule under Rule 4(g) of the PESA Act. In 2000, Chhattisgarh separated from Madhya Pradesh and inherited the Scheduled Area designations and administrative frameworks, including those under PESA. Since the *Gram Panchayat* elections predate the bifurcation, Madhya Pradesh and Chhattisgarh must share the same coding for their first PESA election. However, in GLP paper, it is incorrectly coded (year 2000 for Madhya Pradesh and 2005 for Chhattisgarh).

Thirdly, and perhaps most importantly, GLP's conceptualization of "PESA implementation" is problematic, as it implies adherence to all PESA rules by the virtue of holding elections. We believe, that PESA is deemed to be implemented if and only if all the rules under the law have been enforced. Figure 1 shows this discrepancy, highlighting the temporal gap between the GLP-designated PESA implementation year and the actual year of PESA implementation by the states. According to GLP, Madhya Pradesh and Rajasthan have been PESA-compliant since 2000. However, according to official notifications (see Table A1), Madhya Pradesh implemented all PESA rules only in 2022. Before 2022, Madhya Pradesh failed to implement the rules such as prior consultation with *Gram Sabhas* for prospecting licenses and mining leases[15], exploitation of minor minerals[16], and control over social sector institutions[17]. Rajasthan fully complied with PESA rules as early as 1998. Orissa and Jharkhand, which are listed as PESA-compliant in 2002 and 2010, respectively, by GLP, have yet to fully implement all PESA rules[18,19].

[14]The Madhya Pradesh Election Commission document on elections states that the number of Scheduled Tribe candidates reduces from 12,315 to 7,739 in the *Gram Panchayat* elections of 2000 and 2005, reflecting the bifurcation of candidates due to the formation of the new state of Chhattisgarh. To access see https://archive.org/details/new-doc-02-06-2025-20.29-1

[15]Rule 8 in Table A1

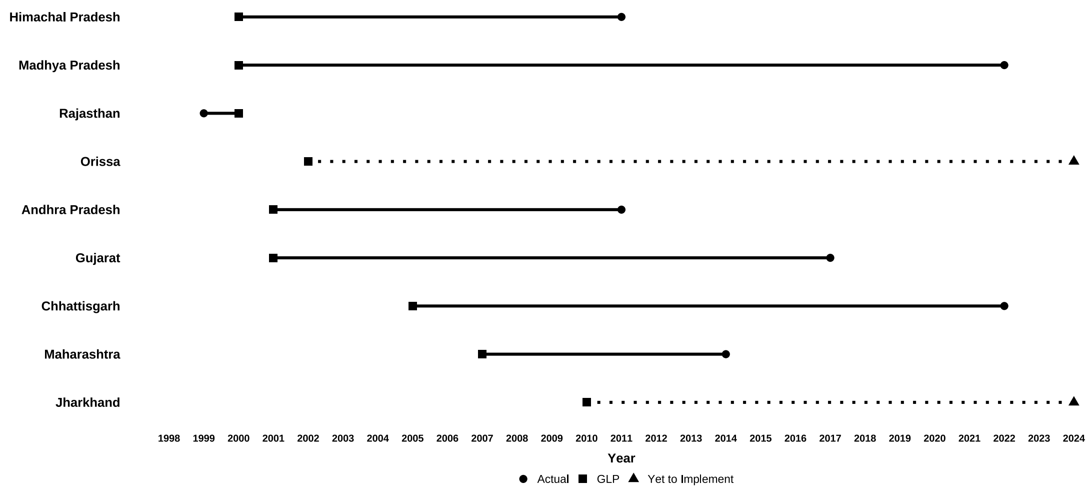
[16]Rule 9 in Table A1

[17]Rule in Table A1

[18]Orissa is yet to implement Rule 5, 6, 7, 9 and 15 in Table A1

[19]Jharkhand is yet to implement Rule 12 and 14 in Table A1

Figure 1: Differences between GLP and Actual PESA implementation year



Note: The figure shows the year of PESA compliance for each state, as indicated by GLP and the Actual year of implementation. States with dotted lines have not yet fully implemented the PESA Act rules.

We have carefully pored through state gazettes and various documents available on the Ministry of Panchayati Raj to construct, what we believe, is the correct measure of PESA implementation.

2.3 Other issues

GLP analyzes the effect of PRI on forest cover by utilizing the implementation dates of PRIs in PESA states to generate the treatment variable for staggered rollout. We identify a discrepancy in the PRI implementation dates for Madhya Pradesh and Chhattisgarh. GLP codes the implementation year of PRI in Madhya Pradesh as 1994 and in Chhattisgarh as 1995, which is not possible, as Chhattisgarh was part of Madhya Pradesh until 2000. Therefore, Chhattisgarh should have the same year of PRI implementation as Madhya Pradesh. Based on discussions with administrators in both Madhya Pradesh and Chhattisgarh, we have verified that the PRI elections in Madhya Pradesh indeed took place in 1994.

2.4 PESA-Intensity

The PESA Act mandates implementing 16 primary rules within a state with Scheduled Areas. These rules encompass a broad spectrum of domains critical to tribal self-rule, such as forest governance (ownership of minor forest produce and Gram

Sabha approval for mining licenses), development planning (water management, village markets, control over finances), cultural preservation (customary practices), and ST reservation. However, compliance with these rules varies across states.

We use official notifications issued by nine states and the Indian government's Tribal and Panchayati Raj Ministry website to create the treatment variable. We employ a two-step process: first, for each state, we create a dummy variable for each of the 16 PESA rules, assigning a value of 1 to years after the rule's implementation and 0 otherwise.

$$P_{ist} = \begin{cases} 1 & \text{if rule } i \text{ is implemented in state } s \text{ since year } t \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Second, we combine these dummies into an intensity variable, which we call PESA-Intensity, representing the degree of PESA compliance by a particular state. PESA-Intensity ranges from 0 to 16, with a score of 0 representing no compliance and 16 indicating full PESA compliance.

$$(\text{PESA-Intensity})_{st} = \sum_{i=0}^{16} P_{ist} \tag{2}$$

To illustrate the construction of PESA-Intensity, consider the example of Gujarat. In 1998, Gujarat amended its Panchayati Raj Act[20] and implemented 9 PESA rules[21], thus we code these 9 rules as 1 from 1998 onwards, resulting in an intensity value of 9. In 2001 Gujarat conducted its first post-PESA elections, hence implementing ST reservation rule, taking tally of implemented PESA rules to 10. Subsequently, in 2010, Gujarat amended its Mines and Minerals (Development and Regulation) Act, 1957, to align mining leasing rules with PESA rule 4(K) and 4(L)[22]. As a result, we code the dummy variables for these rules as 1 from 2010 onwards, raising the intensity value to 12. Finally, in 2017, Gujarat implemented all remaining PESA rules, bringing the intensity value to 16.

[20] To access the Act, see Gujarat act 005 of 1998 : Gujarat Panchayats (Amendment) Act, 1998

[21] The implemented PESA rules include: Rule 4(d), Rule 4(e), Rule 4(f), Rule 4(h), Rule 4(m)(i), Rule 4(m)(ii), Rule 4(m)(v), and Rule 4(m)(vi). List of 15 PESA rules is provided in Table A2.

[22] To access the Act, see Gujarat Minor Mineral Concession Rules, 2010

A detailed list of referenced gazettes and the 16 PESA rules is provided in Tables A1 and A2, respectively. Panel C of Figure 10 shows the PESA-Intensity.

2.5 Empirical Strategy

GLP uses a difference-in-differences (DD) approach to assess the impact of PESA on forest cover and deforestation. Following the GLP's empirical strategy, we first estimate a two-way fixed effect model using the VCF and GFC panel data with corrected coding based on first *Gram Panchayat* election with ST reservation rule as our treatment variable. Equation 3 shows the two-way fixed effect (TWFE) model.

$$Y_{ist} = \tau \text{Scheduled Area}_{is} \times \text{PESA Election Year}_{ist} + \delta_i + \gamma_t + \epsilon_{ist} \tag{3}$$

where i indexes pixels/villages, s indexes state, and t indexes years. Y_{ist} is the forest index for pixel i located in state s in year t or total area (in hectares) deforested in village i located in state s in year t (in GFC). (Scheduled Area $\times$ PESA Election Year$_{it}$) is a dummy variable that takes a value and 1 for pixels/villages in Scheduled Areas where first election with PESA rules is conducted, and 0 otherwise. δ_i is a pixel/village fixed effect, and γ_t is a year fixed effect. τ corresponds to the average treatment effect of the introduction of an additional PESA rule on forest cover /deforestation in Scheduled Areas.

As difference-in-differences (DD) design hinges on the parallel trends assumption, GLP incorporates pixel/village-level linear time trends to account for time-varying confounders that could be correlated with both treatment assignment and outcomes. Additionally, GLP introduces state $\times$ year fixed effects to address time-varying state-level policies, such as the Forest Rights Act (FRA), that might confound the treatment effect. We use the same model with PESA-Intensity as our treatment variable. Equation 4 shows the DD model.

$$Y_{ist} = \tau \text{Scheduled Area}_{is} \times \text{PESA Election Year}_{ist} + \delta_i + \zeta_{st} + \delta_i t + \epsilon_{ist} \tag{4}$$

where we add village-specific linear time trend $\delta_i t$ and state-year fixed effect ζ_{st}

to Equation 3.

Next, we estimate 3 and 4 with PESA-Intensity as our treatment variable. Equation 5 shows the two-way fixed effect (TWFE) model and Equation 6 shows the DD model with village specific linear time-trends.

$$Y_{ist} = \tau \text{Election}_{ist} \times \text{PESA-Intensity}_{ist} \times \text{Scheduled Area}_{is} + \delta_i + \gamma_t + \epsilon_{ist} \quad (5)$$

where i indexes pixels/villages, s indexes state, and t indexes years. Y_{ist} is the forest index for pixel i located in state s in year t or total area (in hectares) deforested in village i located in state s in year t (in GFC). (Scheduled Area $\times$ PESA-Intensity$_{it}$) is a continuous variable that takes a value between 0 and 15 for pixels/villages in Scheduled Areas, reflecting the intensity of PESA implementation. Election$_{ist}$ is the dummy variable that takes value 1 for all years following the first village council elections held under PESA rules in village/pixel i and state s. δ_i is a pixel/village fixed effect, and γ_t is a year fixed effect. τ corresponds to the average treatment effect of the introduction of an additional PESA rule after the first village council elections held under PESA rules on forest cover /deforestation in Scheduled Areas.

$$Y_{ist} = \tau \text{Election}_{ist} \times \text{PESA-Intensity}_{ist} \times \text{Scheduled Area}_{is} + \delta_i + \zeta_{st} + \delta_i t + \epsilon_{ist} \quad (6)$$

where we add village-specific linear time trend $\delta_i t$ and state-year fixed effect ζ_{st} to Equation 5.

Next, we estimate Equation 5 and 6, substituting state fixed effects with district fixed effects. The resulting equations are 7 and 8, respectively.

$$Y_{idt} = \tau \text{Election}_{ist} \times \text{PESA-Intensity}_{ist} \times \text{Scheduled Area}_{is} + \delta_i + \gamma_t + \epsilon_{idt} \quad (7)$$

where i indexes pixels/villages, d indexes district, and t indexes years. Y_{idt} is the forest index for pixel i of district d in year t or total area (in hectares) deforested in village i of district d in year t (in GFC). All other notations are the same as

Equation 5.

$$Y_{idt} = \tau \text{Election}_{ist} \times \text{PESA-Intensity}_{ist} \times \text{Scheduled Area}_{is} + \delta_i + \zeta_{dt} + \delta_i t + \epsilon_{idt} \quad (8)$$

where ζ_{dt} is district-year fixed effect.

Further, we perform heterogeneity tests by substituting the Scheduled Area variable with the ST population share of the village. For this exercise, we use the GFC dataset[23]. We match the GFC dataset with the SHRUG database[24] using the unique village-level identifier called `shrid` to get additional data on ST population and other village-level variables. Using this merged dataset, we estimate the impact of areas with significant ST populations and PESA-Intensity on deforestation. We use two measures of ST population which are explained below.

$$\text{ST Dummy}_{is1} = \begin{cases} 1 & \text{if ST population of the village is above mean ST population} \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

$$\text{ST Dummy}_{is2} = \begin{cases} 1 & \text{if ST population is above 50\% of village population} \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

The resulting TWFE and DD model specifications using equations 9 and 10 are given by Equation 11 and Equation 12, respectively.

$$Y_{ist} = \tau \text{Election}_{ist} \times \text{ST Dummy}_{isj} \times \text{PESA-Intensity}_{ist} + \delta_i + \gamma_t + \epsilon_{ist} \quad (11)$$

$$Y_{ist} = \tau \text{Election}_{ist} \times \text{ST Dummy}_{isj} \times \text{PESA-Intensity}_{ist} + \delta_i + \zeta_{st} + \delta_i t + \epsilon_{ist} \quad (12)$$

[23]We are unable to merge ST population information with VCF data due to the mismatch in spatial resolution. VCF data, measured at the pixel level, is generally coarser than village-level data, preventing accurate identification of villages within pixels.

[24]Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) is a linkable dataset covering a wide range of socioeconomic variables in India such as Population Census, Economic Census, Elections, Forest Cover, Population and Night Lights. It has SHRUG ID which felicitates merging the mentioned dataset at village, blocks, sub-district and district level.

where ST Dummy$_{isj}$ are dummy variables as defined by Equation 9 and 10, respectively, and $j = 1, 2$. All other notations follow Equation 5 and 6.

Lastly, we examine the impact of FRA on the deforestation using Equation 13 and the impact of PRI on the forest cover index using Equation 14.

$$Y_{ist} = \tau \text{FRA}_t \times \text{Scheduled}_i + \delta_i + \zeta_{st} + \delta_i t + \epsilon_{ist} \tag{13}$$

where FRA$_t$ is a dummy variable that takes value 1 for all years after 2008 and 0 otherwise. Scheduled is a dummy that takes value 1 if the village i is a scheduled village and 0 otherwise. All other notations follow Equation 5 and 6.

$$Y_{ist} = \tau \text{PRI}_{st} \times \text{Non-Scheduled}_i + \delta_i + \zeta_{st} + \delta_i t + \epsilon_{ist} \tag{14}$$

where PRI$_{st}$ is a dummy variable that takes the value of 1 for all years after the introduction of PRI in the state and 0 otherwise. Non-Scheduled is a dummy that takes value 1 if the village i is a non-Scheduled village, and 0 otherwise. All other notations follow Equation 5 and 6.

3 Results

We present the results in two sections. In Section 3.1, we examine the impact of ST reservation on forest conservation using the corrected timing of the first post-PESA election in states. In Section 3.2, we report our main findings on the impact of PESA-Intensity on forest conservation. We also analyze the roles of the Forest Rights Act (FRA) and the Panchayati Raj Institutions (PRI) Act in shaping forest conservation, and present these results in Sections 3.3 and 3.4, respectively.

3.1 Impact of ST reservation on forest conservation

Table 2 reports regression results on the impact of ST reservation in Gram Panchayat elections on forest conservation. Columns 1–3 use VCF data with forest cover as the dependent variable; Columns 4–6 use GFC data with the deforestation (in hectares) as the dependent variable. Across all specifications, treatment variable is the interaction between First Election Post ST Reservation and the Schedule Area dummy. Columns 1 and 4 present τ estimates from Equation 3; Columns 2 and 5 add state × year fixed effects; Columns 3 and 6 include pixel/village linear time trends, our preferred specification (Equation 4).

Our results show that ST reservation in *Gram Panchayat* elections has no impact on forest cover. Using the TWFE model (Column 1), we find that forest cover increases by approximately 14% over 22 years. Under our preferred specification, the estimated magnitude of τ is about 11%; however, the estimates are too noisy and statistically insignificant, in contrast to the significant 36% effect reported in GLP. When we use deforestation as the outcome variable, we find a reduction of roughly 0.08 hectares over 17 years, significant only at the 10% level.

To examine whether states with incorrect coding of the first election after ST reservation timing influence GLP's results, we re-run our analysis separately for states with erroneous coding and those with correct coding, using our preferred specification for the VCF data. Table 3 presents the findings of this analysis. Panels A and B shows outcomes based on erroneous and correct coding, respectively. Column 1 shows estimates for states with erroneous coding, Column 2 for those with correct coding, and Column 3 combines all states. The results suggest a substantial decline in forest cover in states with erroneous coding, about 54% over 22 years, or roughly 4.5% per year.

We further examine the influence of incorrectly coded states on the results. Table 4 shows that Maharashtra experiences the largest loss in forest cover and drives the overall effect, while Chhattisgarh and Himachal Pradesh have statistically insignificant negative coefficients. Overall, these findings indicate that errors in coding the first election after ST reservation timing substantially affect the results, suggesting that GLP overstates the impact of ST reservation on forest cover.

3.1.1 Sensitivity Analysis

GLP omits villages with low forest cover in 1990 (ex-ante forest cover), specifically, those below the 50th percentile for the forest cover analysis and below the 75th percentile for the deforestation analysis. While excluding villages with zero forest cover may be reasonable for the deforestation analysis, it is less justified for the forest cover analysis, as ST reservation could still plausibly influence forest growth in these areas. To test robustness to this restriction, we examine whether the estimated impact of the first election after ST reservation on forest cover and deforestation varies across levels of ex-ante forest cover. Figure 6 shows estimates by deciles of ex-ante forest cover using our preferred specification.The impact on forest cover is statistically insignificant up to the 80th percentile of initial forest cover, whereas the impact on deforestation is statistically significant across all deciles, using VCF and GFC data, respectively. These results suggest that GLP's findings are sensitive to sample restrictions based on ex-ante forest cover: the forest cover effect appears concentrated in areas with high initial forest cover, whereas the deforestation effect extends to areas with lower initial forest cover as well.

3.1.2 Robustness: Event study

To test the robustness of our findings, we conduct an event study to examine the dynamic effects of the first election after ST reservation on forest cover. We estimate impacts in the years before (leads) and after (lags) the first election, using the year immediately preceding the election as the reference period. Figure 7 shows that, unlike in GLP paper, which reports no pre-existing trend, we find a clear upward trend in forest cover in the years leading up to the first election with ST reservation. This pattern holds across sub-samples defined by quintiles of ex-ante forest cover. The presence of such a pre-treatment trend raises concerns about the parallel trends assumption, suggesting that observed post-election increases in forest cover may partly reflect a continuation of existing trends rather than the causal effect of ST reservation.

3.2 Main Results

This section presents our main results. We extend the analysis by using PESA-Intensity as the treatment variable to examine its impact on forest cover and deforestation.

3.2.1 Impact of PESA-Intensity on Forest Conservation

Table 6 presents regression results PESA-Intensity on forest conservation. Columns 1–3 use VCF data with forest cover as the dependent variable, and Columns 4–6 use GFC data with deforestation as the dependent variable. All specifications use the interaction term (Election $\times$ PESA-Intensity $\times$ Scheduled Area) as treatment. Columns 1 and 4 report the τ estimates from Equation 5. Columns 2 and 5 add state $\times$ year fixed effects, and Columns 3 and 6 further include pixel- or village-level linear time trends, which represent our preferred specification as outlined in Equation 6. To maintain comparability with the main results in GLP, we use the same time frame: 1995–2017 for VCF and 2001–2017 for GFC.

Our results show that the implementation of PESA has no statistically significant impact on forest cover or deforestation. Using both the standard two-way fixed effects (TWFE) model and our preferred specification, we consistently find null effects. These findings suggest that the substantial impacts reported by GLP may be driven by factors other than the implementation of PESA.

3.2.2 Sensitivity Analyses

In this section, we conduct several sensitivity tests. First, we examine whether the impact of PESA-Intensity on forest cover and deforestation varies across different levels of ex-ante forest cover (forest cover in 1990). Figure 9 presents the estimates across quantiles of ex-ante forest cover, using our preferred specification. As shown in Figure 9, the impact of PESA on forest cover remains statistically insignificant up to the 80th percentile of initial forest cover. For the GFC data, we observe no significant effect across all levels of initial forest cover. These findings suggest that the impact of PESA on forest outcomes becomes more pronounced in areas with relatively higher pre-existing forest cover.

Second, we estimate equations 5 and 6 using an expanded VCF dataset. While GLP restricts the analysis to the 1995 to 2017 period, the full dataset covers the years 1990 to 2017. Over this 27-year span, we observe only a minimal increase in forest cover—approximately 3%. Column 3 of Table 7 reports the results for PESA-Intensity using our preferred specification. The findings indicate that the estimated impact of PESA-Intensity remains negligible.

Third, we estimate equations 5 and 6 using district-year fixed effects instead of state-year fixed effects. This choice addresses potential heterogeneity in the implementation of PESA regulations across districts. We conduct the analysis on two samples: the first includes the four states analyzed by GLP for comparability, and the second comprises all nine states covered under PESA. We estimate these models using equations 7 and 8. Tables 8 and 9 present the results for the four-state and nine-state samples, respectively. Columns 1–3 in each table report the estimates using PESA-Intensity as the treatment variable. In both samples, we find no significant impact of PESA-Intensity on deforestation, neither in GLP's four-state sample nor in the full nine-state sample.

3.2.3 Heterogeneity Analyses

We conduct two heterogeneity analyses to assess the differential impact of PESA. First, we examine the potential relationship between the Scheduled Tribe (ST) population share and forest conservation by estimating Equations 11 and 12 using the GFC dataset for both GLP's four-state sample and the full nine-state sample. Tables 10, 11, 12, and 13 present the results. Tables 10 and 12 use the village-level ST share definition from Equation 9, while Tables 11 and 13 rely on the definition from Equation 10. In each table, Columns 1–3 report estimates using PESA-Intensity as the treatment variable. Across all specifications, we find that in areas with an ST population share above the mean or exceeding 50%, deforestation increase following PESA implementation. This suggests that in regions with a dominant ST population, forest use may have intensified. One possible explanation is that PESA grants greater autonomy to local tribal communities, which may prioritize forest use for livelihood and subsistence needs over conservation. Second, we examine the heterogeneous impact of PESA across the nine PESA states using PESA-Intensity. Figure 8 presents our analysis revealing heterogeneous impacts on forest cover: positive impacts in Andhra Pradesh, Jharkhand, and Rajasthan and negative impacts in Gujarat, Madhya Pradesh, Himachal Pradesh and Maharashtra. We find no significant impact in Chhattisgarh and Odisha and a null effect on deforestation across all states.

3.3 Role of the Forest Rights Act (FRA)

The FRA and the PESA were enacted to empower the ST communities. PESA was implemented in 1996, while FRA was enacted in 2006 and implemented in 2008. Since both laws operate in Scheduled Areas, we investigate FRA's potential impact on forest conservation. We examine the impact of the FRA on deforestation, using Equation 11. While GLP finds no significant impact of the FRA on forest cover, we focus on deforestation. We present the results in Table 14. Column 1 shows the results for the four-state sample, and Column 2 shows the estimates for the entire sample, which is our preferred specification. We find no significant impact of the FRA on deforestation in Column 1. However, in Column 2, we observe a significant 33-hectare reduction in deforestation, suggesting that the effects of the FRA might drive some of the impact attributed to PESA by GLP.

3.4 Role of the Panchayati Raj Institutions (PRI) Act

The PRI Act of 1993 introduced local governance in non-Scheduled Areas under the 73^{rd} Amendment of the Indian Constitution. This Act established five-year rotating quotas for STs, SCs, and Other Backward Classes (OBCs) instead of fixed quotas. We utilize VCF data from 1990 to 1999, when the ST ST reservation rule was not yet implemented in any states under the PESA Act, to measure the impact of PRI on forest cover using Equation 12. Initially, we excluded Maharashtra and Jharkhand from our sample. The rationale for this exclusion is that for the 1990-1999 period, their status remains unchanged; Maharashtra implemented PRI in 1958 and Jharkhand in 2010. Subsequently, we include these states to assess any resulting changes in the estimates. Figure 12 illustrates the impact of PRI using different samples. Panel A of Figure 12 shows the impact of PRI on forest cover, excluding the states of Maharashtra and Jharkhand. Panel B shows the impact after including Maharashtra, and Panel C shows the impact after including all PESA states. We find a significant negative impact of PRI on forest cover, which is higher compared to the estimates obtained by GLP. The negative impact remains consistent regardless of the inclusion of Maharashtra and Jharkhand in the analysis. One reason for this large significant impact may be the incorrect coding of the year of PRI implementation in Madhya Pradesh and Chhattisgarh.

4 Conclusion

This paper shows that GLP study erroneously defines PESA, leading to inaccurate conclusions regarding its impact on forest cover and deforestation. Using the corrected PESA definition (PESA-Intensity), we do not detect any significant impact of PESA on forest-related outcomes. Furthermore, contrary to GLP, the Forest Rights Act (FRA) might also explain some of the effects previously attributed to PESA. We also document state-wise heterogeneity in the estimates. For some states, we find a positive association between PESA and forest outcomes, while for others, we report an adverse effect of PESA. In short, we find weak support for the central claim of GLP when we correct data issues with the paper.

PESA Act aims to empower ST communities through increased self-governance. However, its effectiveness hinges on the willingness of states to devolve power to local authorities (Bardhan, 2002). The extant literature on PESA suggests that the power granted to village councils through PESA is neither adequate nor effective (Dandekar and Satpathi, 2023; Dandekar and Choudhury, 2010; Ministry of Tribal Affairs, 2014; Ray, 2009; Gupta and Roy-Chowdhury, 2017). Our finding that there is no effect of representation of STs or PESA in its entirety can be explained using two routes. First, although PESA provides a framework for community control, in practice, many of the granted rights are subject to approval from higher authorities, limiting their effective implementation. Gupta and Roy-Chowdhury (2017) and Dandekar and Choudhury (2010) show the inefficiency of PESA in curbing illegal mining activities and land transfer in PESA states. Agarwal et al. (2023) show that after the first PESA election with ST reservation, the increase in forest cover is lower in Scheduled Areas compared to non-scheduled areas in Chhattisgarh. However, there is a rise in forest cover at a higher administrative level (Assembly Constituency level). This suggests that the ST community faces limitations in using constitutional provisions due to unequal power distribution among different levels of government.

Second, there is a lack of political will to strengthen the PESA laws. The presence of conflicting forest governance laws exacerbates struggle between STs and the Indian state. While ST representation at the village council level is a crucial and important first step, it may not be sufficient to overcome the state's ability to exercise its authority through other legislative means. For example, the landmark Samatha[25] case used the PESA Act to prohibit illegal cutting of trees, land transfers to non-tribals, and granting mineral extraction leases in Scheduled Areas across India. However, the judgment was bypassed using a series of notifications and orders issued by various ministries to divert the forest lands.[26,27] There is a growing literature that supports this argument (Burgess et al., 2019; Mangonnet et al., 2022; Garay, 2024).

Forest conservation remains a critical global challenge. We find limited impact of mandated representation of marginalized communities on forest conservation. Future research can examine channels such as the role of market forces in deforestation (Berman et al., 2023), local institution's capacity to carry out forest conservation (Agarwal et al., 2017; Ballabh et al., 2002; Ostwald and Baral, 2000), and the economic interests of the state (Barr and Sayer, 2012). Additionally, research is needed to estimate the economic value of forests beyond timber and mineral extraction, assess the social costs of deforestation, and inform policies that incentivize conservation. Crucially, research should examine the distribution of benefits and costs associated with forest conservation, focusing on how these initiatives impact indigenous communities, who often bear the brunt of conservation efforts. Addressing these critical questions is essential for developing effective and equitable policies that promote forest conservation and indigenous communities' well-being.

[25] Samatha vs State Of Andhra Pradesh And Ors on 11 July, 1997.

[26] https://forestrightsact.com/corporate-projects/timeline-of-attempts-to-sabotage-forest-rights-for-large-projects/

[27] https://eparlib.nic.in/bitstream/123456789/647018/1/146301.pdf

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5 Tables

5.1 Main Results

Table 2: Deforestation and Forest cover index regression estimates (ex-ante median cutoff) using corrected GLP treatment

	Forest Cover Index			Annual Deforestation in Hectares		
	(1)	(2)	(3)	(4)	(5)	(6)
First Election Post ST Reservation × Scheduled	0.1378*	0.0496	0.1110	-0.0682***	-0.0200	-0.0812*
	(0.0683)	(0.0658)	(0.1065)	(0.0202)	(0.0216)	(0.0352)
Summary Statistics						
Mean Y (Non-Sch)	9.571	9.571	9.571	0.0500	0.0800	0.0800
Mean Y (Sch)	12.01	12.01	12.01	0.1000	0.1000	0.1000
Dataset	VCF	VCF	VCF	GFC	GFC	GFC
Timespan	1995-2017	1995-2017	1995-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Pixel	✓	✓	✓			
Year	✓			✓		
State × Year		✓	✓		✓	✓
Village				✓	✓	✓
Time Trends						
t (Pixel)			✓			
t (Village)						✓
Fit statistics						
# Pixel	30,843	30,843	30,843	–	–	–
# Year	22	–	–	17	–	–
# State × Year	–	198	198	–	68	68
# Village	–	–	–	52,776	31,601	31,601
Number of Observations	678,546	678,546	678,546	897,192	537,217	537,217
R^2	0.90259	0.90870	0.91564	0.35930	0.26600	0.42138

*Note: Standard errors are clustered at the block level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 3: Forest cover index regression estimates (ex-ante median cutoff)

	Forest Cover Index		
	(1)	(2)	(3)
Panel A: With Erroneous Treatment			
First Election Post ST Reservation × Scheduled	0.2797	0.3910**	0.3624**
	(0.2454)	(0.1271)	(0.1136)
Panel B: With Corrected Treatment			
First Election Post ST Reservation × Scheduled	-0.5444**	0.3910**	0.1110
	(0.1943)	(0.1271)	(0.1065)
Summary Statistics			
Dataset	VCF	VCF	VCF
Timespan	1995-2017	1995-2017	1995-2017
Fixed-effects			
Pixel	✓	✓	✓
State × Year	✓	✓	✓
Time Trends			
t (Pixel)	✓	✓	✓
Fit statistics			
# Pixel	10,475	20,368	30,843
# State × Year	66	132	198
# Observations	230,450	448,096	678,546
R^2	0.91949	0.91027	0.91565

*Note: Standard errors are clustered at the block level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Model 1 includes samples from three states (Chhattisgarh, Maharashtra and Himachal Pradesh) where the first election post-ST reservation rule implementation was incorrectly coded. Model 2 includes samples from six states (Andhra Pradesh, Rajasthan, Madhya Pradesh, Odisha, Jharkhand, and Gujarat) with correctly coded data. Model 3 shows the estimates with overall GLP treatment.*

Table 4: State-wise forest cover index regression estimates (ex-ante median cutoff)

	Forest Cover Index								
	Chhattisgarh	Maharashtra	Himachal Pradesh	Odisha	Jharkhand	Madhya Pradesh	Andhra Pradesh	Gujarat	Rajasthan
Panel A: With Erroneous Treatment									
First Election Post ST Reservation × Scheduled	**0.4296**	**0.1630**	**-0.2775**	0.5311$^{\cdot}$	-0.0930	-0.7424***	2.108***	-0.0097	0.6070***
	(0.3840)	(0.2595)	(0.8941)	(0.3099)	(0.2088)	(0.2071)	(0.3320)	(0.1963)	(0.1786)
Panel B: With Corrected Treatment									
First Election Post ST Reservation × Scheduled	**-0.3412**	**-0.7012****	**-1.907**$^{\cdot}$	0.5311$^{\cdot}$	-0.0930	-0.7424***	2.108***	-0.0097	0.6070***
	(0.2820)	(0.2290)	(1.037)	(0.3099)	(0.2088)	(0.2071)	(0.3320)	(0.1963)	(0.1786)
Summary Statistics									
Dataset	VCF	VCF	VCF	VCF	VCF	VCF	VCF	VCF	VCF
Timespan	1995-2017	1995-2017	1995-2017	1995-2017	1995-2017	1995-2017	1995-2017	1995-2017	1995-2017
Fixed-effects									
Pixel	✓	✓	✓	✓	✓	✓	✓	✓	✓
State × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time Trends									
t (Pixel)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics									
# Pixel	3,916	5,377	1,182	4,354	1,876	5,998	5,690	1,543	907
# State × Year	22	22	22	22	22	22	22	22	22
# Observations	86,152	118,294	26,004	95,788	41,272	131,956	125,180	33,946	19,954
R^2	0.92160	0.89111	0.84817	0.90322	0.88328	0.88783	0.90353	0.64579	0.69487

*Note: Standard errors are clustered at the block level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 5: State-wise deforestation regression estimates (ex-ante median cutoff)

	Annual Deforestation in Hectares			
	Chhattisgarh	Jharkhand	Maharashtra	Odisha
	(1)	(2)	(3)	(4)
Panel A: With Erroneous Treatment				
First Election Post ST Reservation (GLP) × Scheduled	0.0219	-0.0816***	-0.0882	-0.0944
	(0.0660)	(0.0217)	(0.1124)	(0.0580)
Panel B: With Corrected Treatment				
First Election Post ST Reservation × Scheduled		-0.0816***	**-0.0204**	-0.0944
		(0.0217)	(0.0688)	(0.0580)
Summary Statistics				
Dataset	GFC	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017	2001-2017
Fixed-effects				
Village	✓	✓	✓	✓
State × Year	✓	✓	✓	✓
Time Trends				
t (Village)	✓	✓	✓	✓
Fit statistics				
# Village	4,440	5,015	7,783	14,363
# State × Year	17	17	17	17
# Observations	75,480	85,255	132,311	244,171
R^2	0.31737	0.29522	0.33784	0.46983

*Note: Standard errors are clustered at the block level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 6: Deforestation and Forest cover index regression estimates (ex-ante median cutoff) using PESA Intensity

	Forest Cover Index			Annual Deforestation in Hectares		
	(1)	(2)	(3)	(4)	(5)	(6)
Election × PESA Intensity × Scheduled	0.0109$^{\cdot}$	0.0059	0.0166	-0.0035	0.0004	-0.0039
	(0.0060)	(0.0058)	(0.0108)	(0.0024)	(0.0027)	(0.0027)
Summary Statistics						
Dataset	VCF	VCF	VCF	GFC	GFC	GFC
Timespan	1995-2017	1995-2017	1995-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Pixel	✓	✓	✓			
Year	✓			✓		
State × Year		✓	✓		✓	✓
Village				✓	✓	✓
Time Trends						
t (Pixel)			✓			
t (Village)						✓
Fit statistics						
# Pixel	30,843	30,843	30,843	–	–	–
# Year	22	–	–	17	–	–
# State × Year	–	198	198	–	68	68
# Village	–	–	–	52,776	31,601	31,601
# Observations	678,546	678,546	678,546	897,192	537,217	537,217
R^2	0.90259	0.90870	0.91564	0.35929	0.26599	0.42136

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Intensity ranges from 1 to 15. *** p<0.01, ** p<0.05, * p<0.1.*

Table 7: Forest cover index regression estimates (full sample from 1990 - 2017) using PESA Intensity

	Forest Cover Index		
	(1)	(2)	(3)
Election × PESA Intensity × Scheduled	0.0140*	0.0119*	0.0336**
	(0.0062)	(0.0056)	(0.0104)
Summary Statistics			
Dataset	VCF	VCF	VCF
Timespan	1990-2017	1990-2017	1990-2017
Fixed-effects			
Pixel	✓	✓	✓
Year	✓		
State × Year		✓	✓
Time Trends			
t (Pixel)			✓
Fit statistics			
# Pixel	30,843	30,843	30,843
# Year	27	–	–
# State × Year	–	243	243
# Observations	832,761	832,761	832,761
R^2	0.88070	0.88749	0.90104

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Index ranges from 1 to 15. *** p<0.01, ** p<0.05, * p<0.1.*

Table 8: Deforestation index regression estimates (ex-ante median cutoff) with district fixed effects

	Annual Deforestation in Hectares		
	(1)	(2)	(3)
Election × PESA Intensity × Scheduled	-0.0035	0.0037	-0.0046
	(0.0024)	(0.0045)	(0.0043)
Summary Statistics			
Dataset	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017
Fixed-effects			
Village	✓	✓	✓
Year	✓		
District × Year		✓	✓
Time Trends			
t (Village)			✓
Fit statistics			
# Village	52,774	31,601	31,601
# Year	17	–	–
# District × Year	–	1,540	1,540
# Observations	897,158	537,217	537,217
R^2	0.35929	0.28260	0.43430

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Index ranges from 1 to 15. *** p<0.01, ** p<0.05, * p<0.1.*

Table 9: Deforestation index regression estimates (ex-ante median cutoff) with district fixed effects and all state sample

	Annual Deforestation in Hectares		
	(1)	(2)	(3)
Election × PESA Intensity × Scheduled	-0.0035	0.0061	-0.0026
	(0.0024)	(0.0042)	(0.0042)
Summary Statistics			
Dataset	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017
Fixed-effects			
Village	✓	✓	✓
Year	✓		
District × Year		✓	✓
Time Trends			
t (Village)			✓
Fit statistics			
# Village	52,774	52,774	52,774
# Year	17	–	–
# District × Year	–	3,016	3,016
# Observations	897,158	897,158	897,158
R^2	0.35929	0.40819	0.45793

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Index ranges from 1 to 15. *** p<0.01, ** p<0.05, * p<0.1.*

Table 10: Deforestation index regression estimates using share of ST population (above and below mean)

	Annual Deforestation in Hectares		
	(1)	(2)	(3)
Election × PESA Intensity × ST Share > Mean	-0.0015	0.0011	0.0037*
	(0.0014)	(0.0016)	(0.0017)
Summary Statistics			
Dataset	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017
Fixed-effects			
Village	✓	✓	✓
Year	✓		
State × Year		✓	✓
Time Trends			
t (Village)			✓
Fit statistics			
# Village	50,926	30,255	30,255
# Year	17	–	–
# State × Year	–	68	68
# Observations	865,742	514,335	514,335
R^2	0.36078	0.26477	0.42422

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Intensity ranges from 1 to 15. Village ST Share > Mean takes value 1 if the share of village ST population is above mean and 0 otherwise. Coloumn 2 and 3 uses sub-sample which comprises four states (Chhatisgarh, Jharkhand, Odisha, and Maharashtra) that have variation in PESA implementation in the sample given by GLP, which is why the number of observations falls from approximately 51,000 villages in column 1 to approximately 30,000 villages in columns 2 and 3. *** p<0.01, ** p<0.05, * p<0.1.*

Table 11: Deforestation index regression estimates using share of village ST population (above and below 50 percent ST population)

	Annual Deforestation in Hectares		
	(1)	(2)	(3)
Election rule × PESA Intensity × Village ST Share > 50%	-0.0010	0.0019	0.0021
	(0.0015)	(0.0016)	(0.0015)
Summary Statistics			
Dataset	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017
Fixed-effects			
Village	✓	✓	✓
Year	✓		
State × Year		✓	✓
Time Trends			
t (Village)			✓
Fit statistics			
# Village	50,926	30,255	30,255
# Year	17	–	–
# State × Year	–	68	68
# Observations	865,742	514,335	514,335
R^2	0.36078	0.26477	0.42421

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Index ranges from 1 to 15. Variable Village ST Share takes value 1 if Village ST Share > 50 percent of the village population and 0 otherwise. Coloumn 2 and 3 uses sub-sample which comprises four states (Chhatisgarh, Jharkhand, Odisha, and Maharashtra) that have variation in PESA implementation in the sample given by GLP, which is why the number of observations falls from approximately 51,000 villages in column 1 to approximately 30,000 villages in columns 2 and 3. *** p<0.01, ** p<0.05, * p<0.1.*

Table 12: Deforestation index regression estimates (above and below mean) using all state sample

	Annual Deforestation in Hectares		
	(1)	(2)	(3)
Election rule × PESA Intensity × ST Share > Mean	-0.0015	0.0006	0.0043*
	(0.0014)	(0.0016)	(0.0017)
Summary Statistics			
Dataset	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017
Fixed-effects			
Village	✓	✓	✓
Year	✓		
State × Year		✓	✓
Time Trends			
t (Village)			✓
Fit statistics			
# Village	50,926	50,926	50,926
# Year	17	–	–
# State × Year	–	153	153
# Observations	865,742	865,742	865,742
R^2	0.36078	0.36924	0.41938

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Index ranges from 1 to 15. Village ST Share > Mean takes value 1 if the share of village ST population is above mean and 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.*

Table 13: Deforestation index regression estimates (above and below 50 percent ST population) using all state sample

	Annual Deforestation in Hectares		
	(1)	(2)	(3)
Election rule × PESA Intensity × Village ST Share > 50%	-0.0010	0.0013	0.0031*
	(0.0015)	(0.0016)	(0.0016)
Summary Statistics			
Dataset	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017
Fixed-effects			
Village	✓	✓	✓
Year	✓		
State × Year		✓	✓
Time Trends			
t (Village)			✓
Fit statistics			
# Village	50,926	50,926	50,926
# Year	17	–	–
# State × Year	–	153	153
# Observations	865,742	865,742	865,742
R^2	0.36078	0.36924	0.41938

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Index ranges from 1 to 15. Variable Village ST Share takes value 1 if Village ST Share > 50 percent of the village population and 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.*

Table 14: FRA impact on Deforestation (in Hectares) (ex-ante median cutoff)

	Annual Deforestation in Hectares	
	(1)	(2)
FRA × Scheduled	-0.0670	-0.3324***
	(0.0455)	(0.0997)
Summary Statistics		
Mean Y (Non-Sch)	0.2200	0.2200
Mean Y (Sch)	0.1600	0.1600
Dataset	GFC	GFC
Timespan	2001-2017	2001-2017
Fixed-effects		
Village	✓	✓
State × Year	✓	✓
Time Trends		
Village + Village[t]	✓	✓
Fit statistics		
# Village	31,601	52,776
# State × Year	68	153
# Observations	537,217	897,192
R^2	0.42139	0.41901

*Note: Standard errors are clustered at the block level and reported in parentheses. FRA is a dummy variable which takes value 1 if year >=2008 and 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.*

6 Graphs

Figure 2: Aggregate Trends of Scheduled and Non-Scheduled Areas in Forest Cover Index in VCF Data

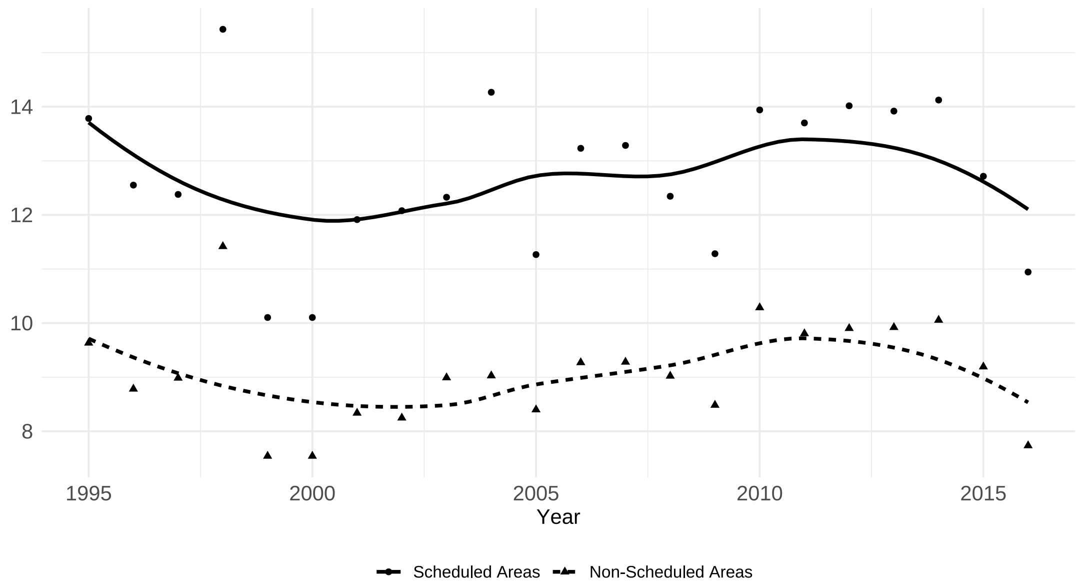


Figure 3: State wise aggregate Trends of Scheduled and Non-Scheduled Areas in Forest Cover Index in VCF Data

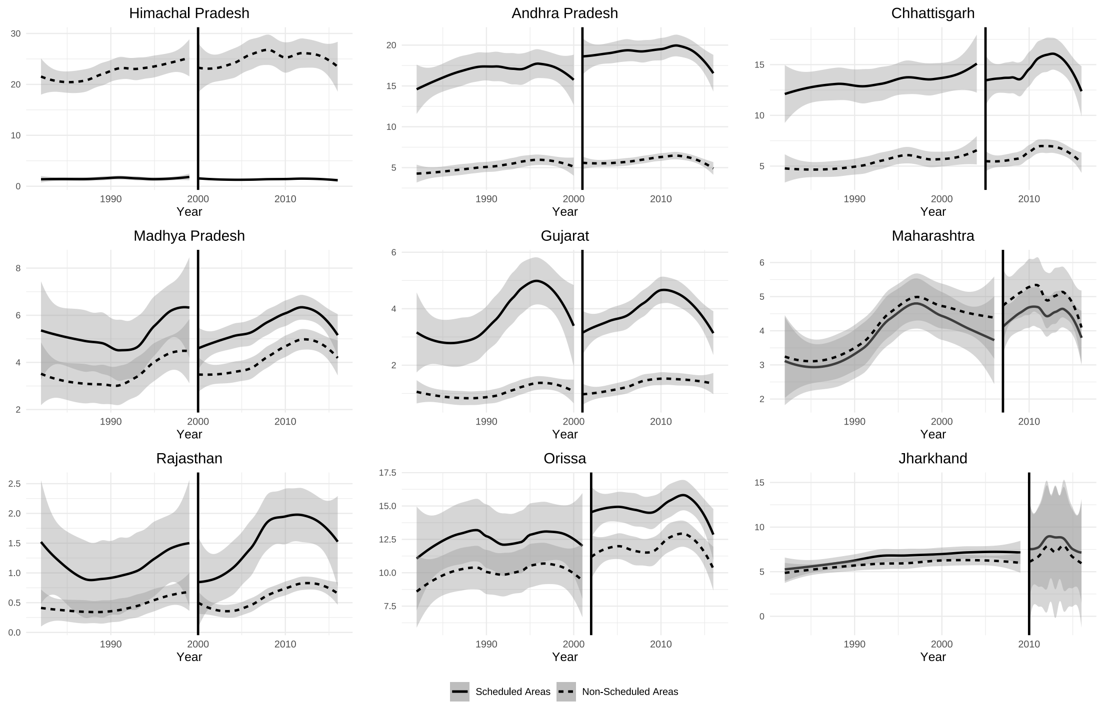


Figure 4: Aggregate Trends of Scheduled and Non-Scheduled Areas in Total Deforested Area in GFC

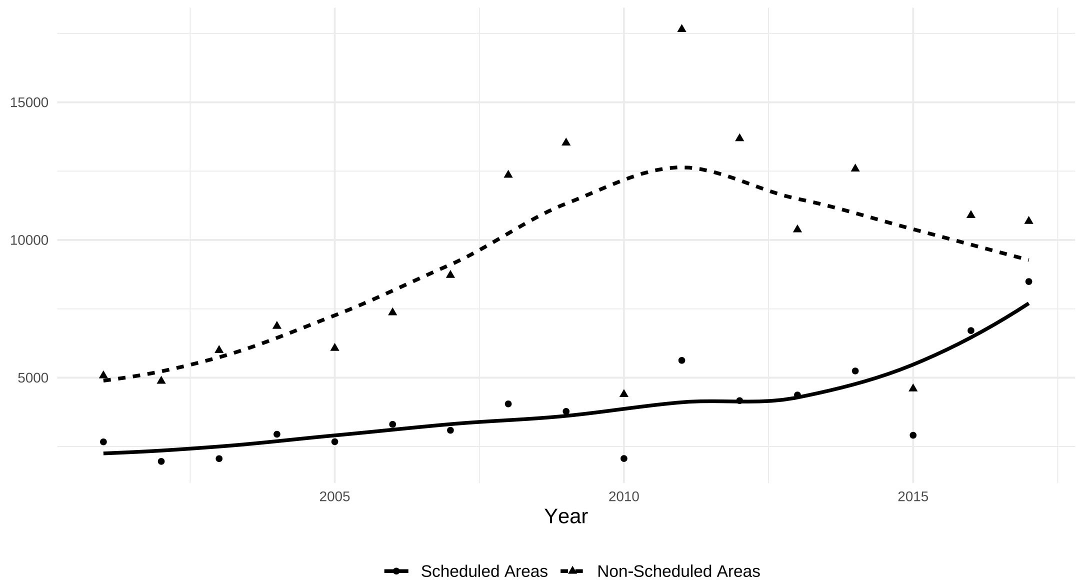


Figure 5: State wise aggregate Trends of Scheduled and Non-Scheduled Areas in Total Deforested Area in GFC

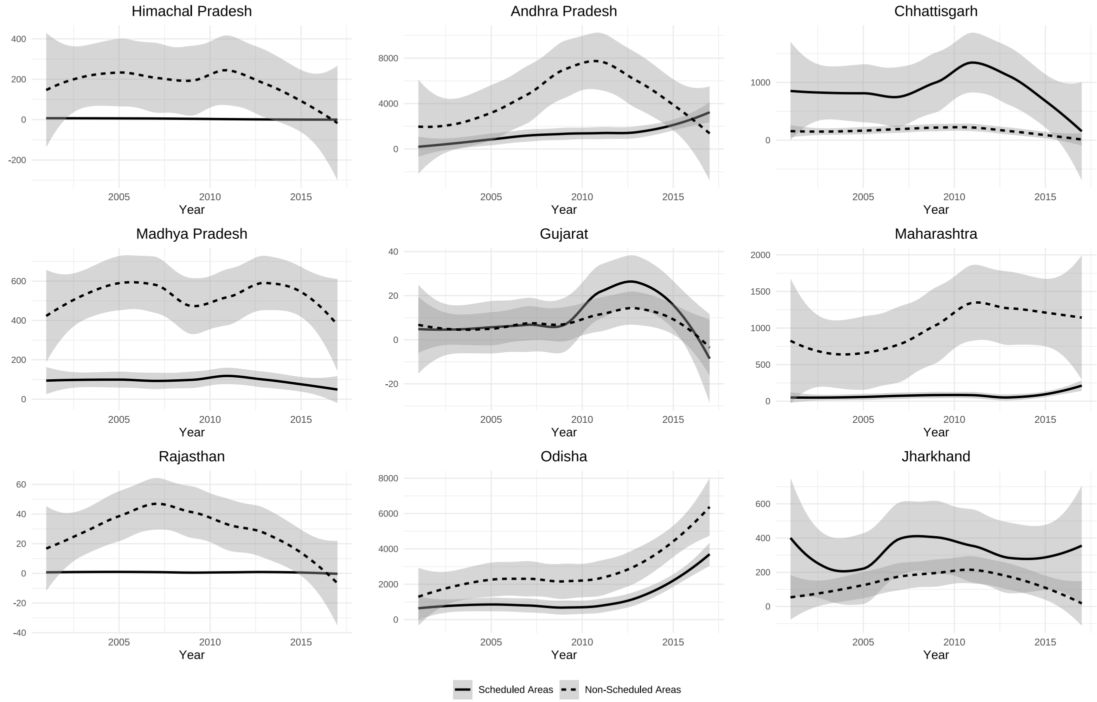


Figure 6: Deforestation and forest cover index regression estimates (ex-ante decile cutoff) using corrected coding

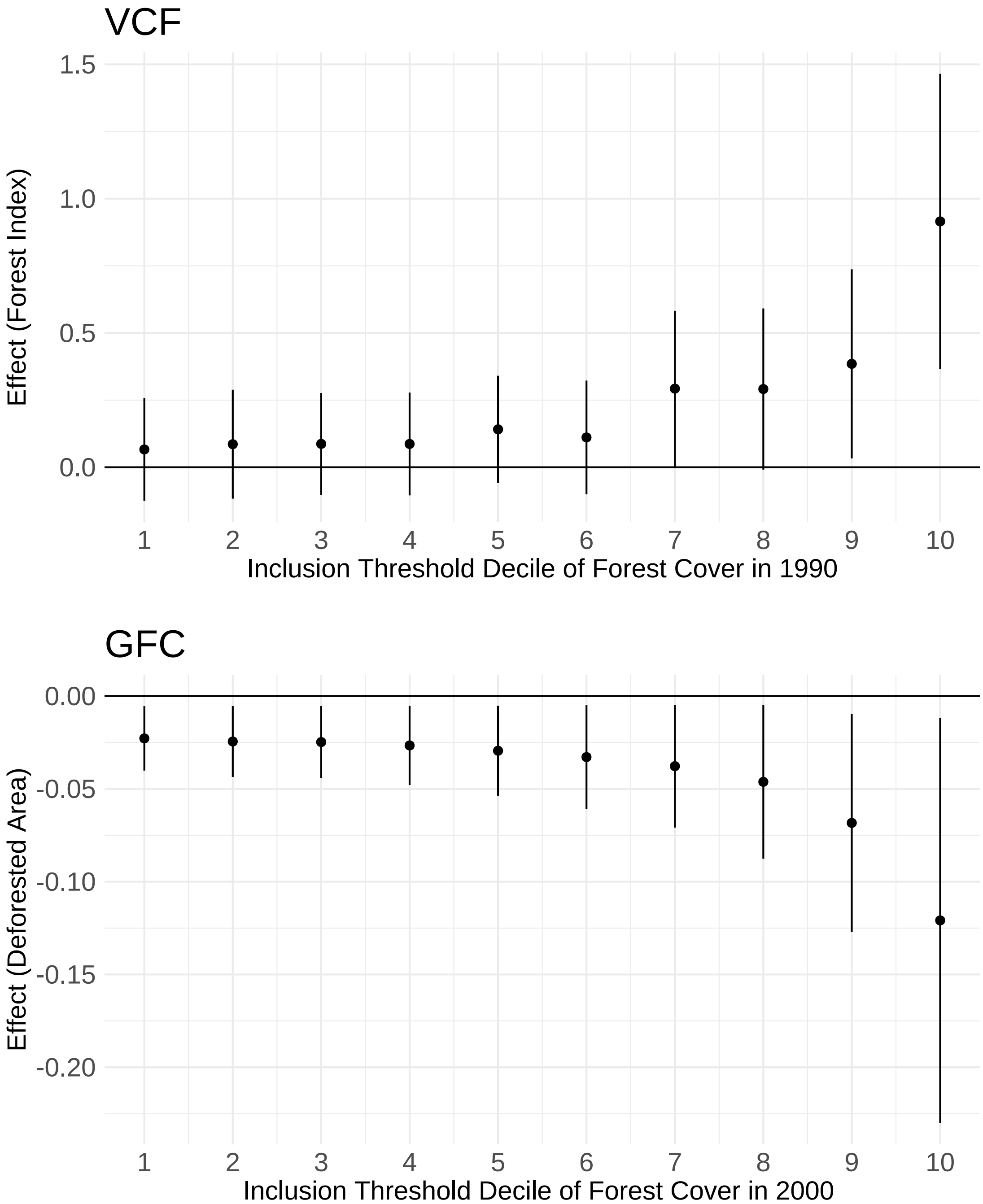


Figure 7: Dynamic Treatment Effects of PESA Adoption on Forest Index using corrected coding

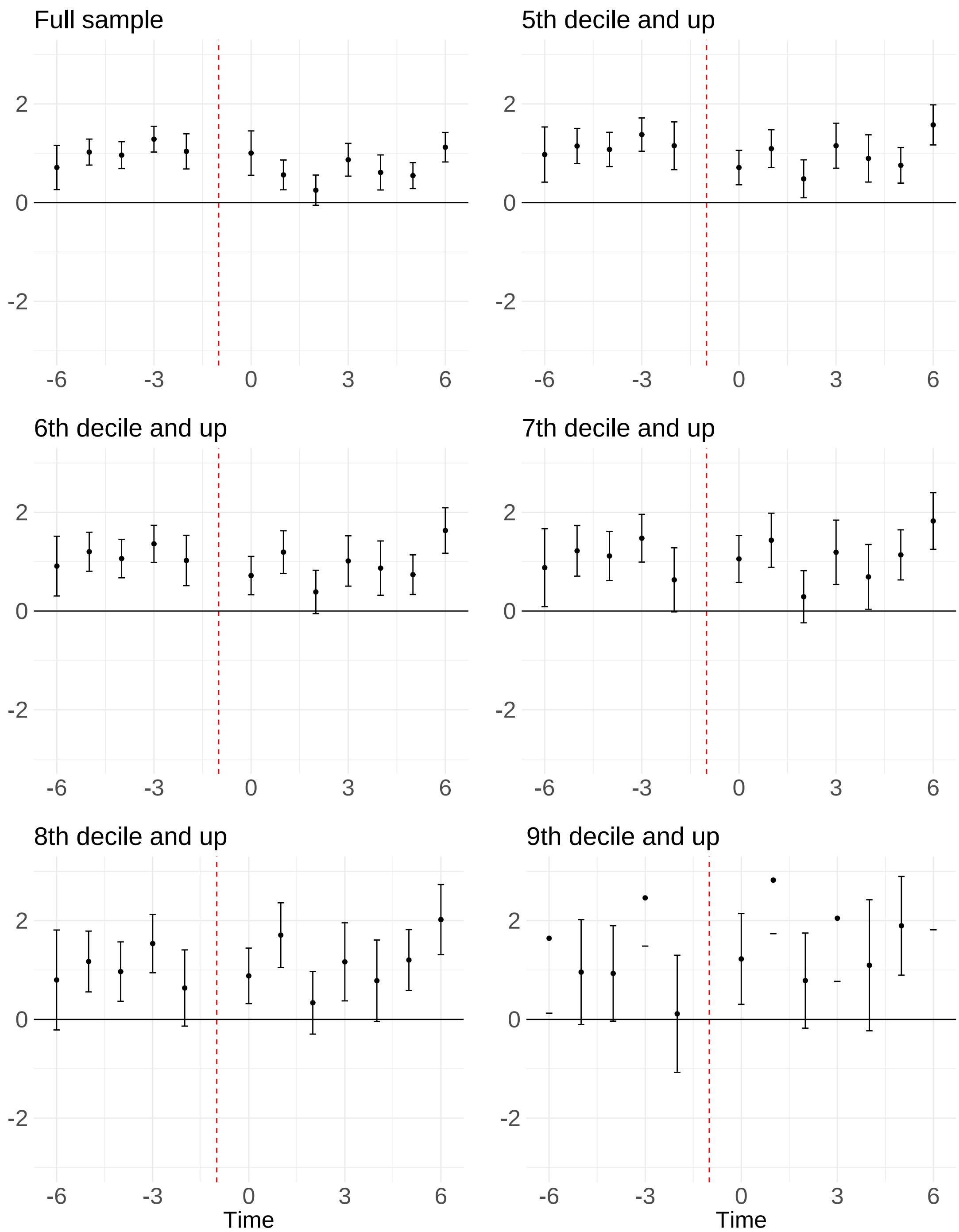
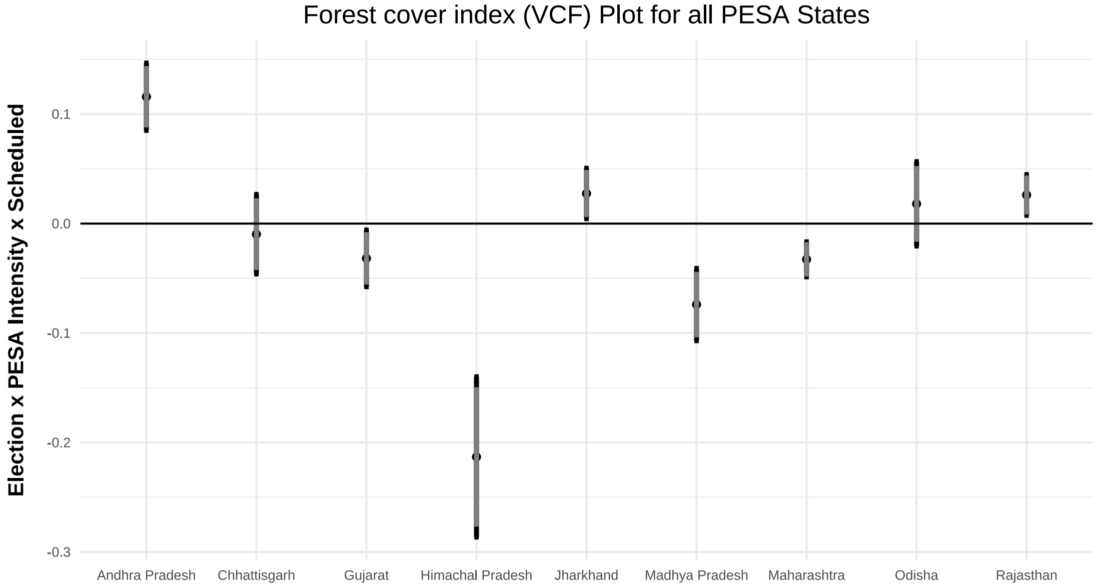


Figure 8: State-wise comparison using PESA Intensity



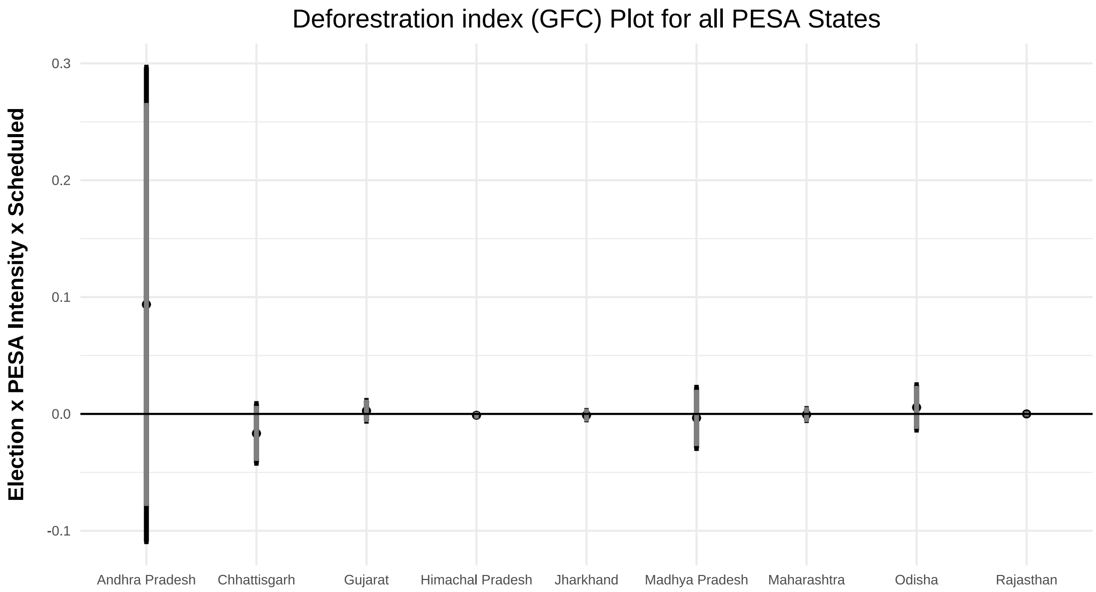


Figure 9: Estimates using varying ex-ante forest cover quantiles using PESA Intensity

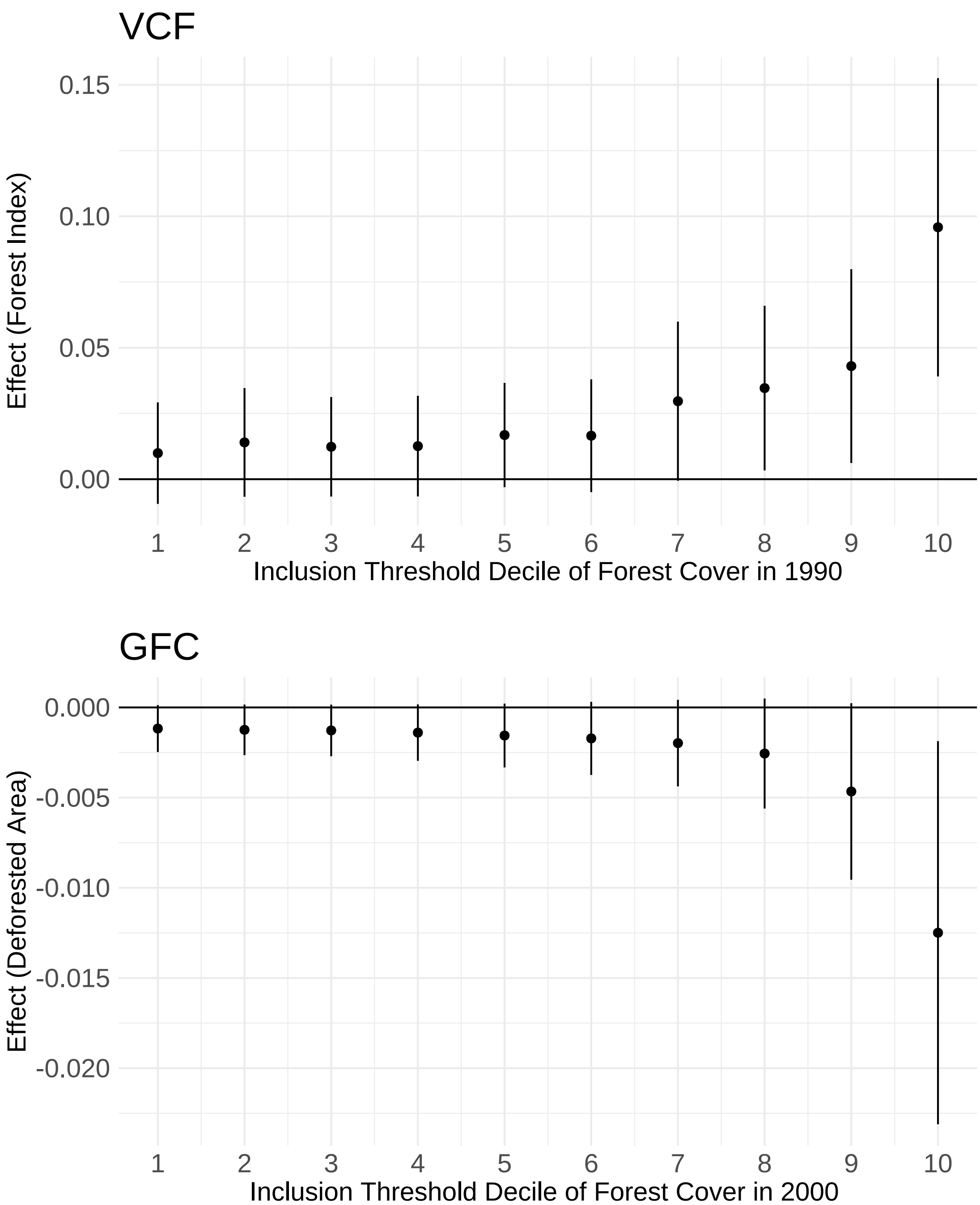


Figure 10: PESA Act implementation Timing (GLP vs Ours)

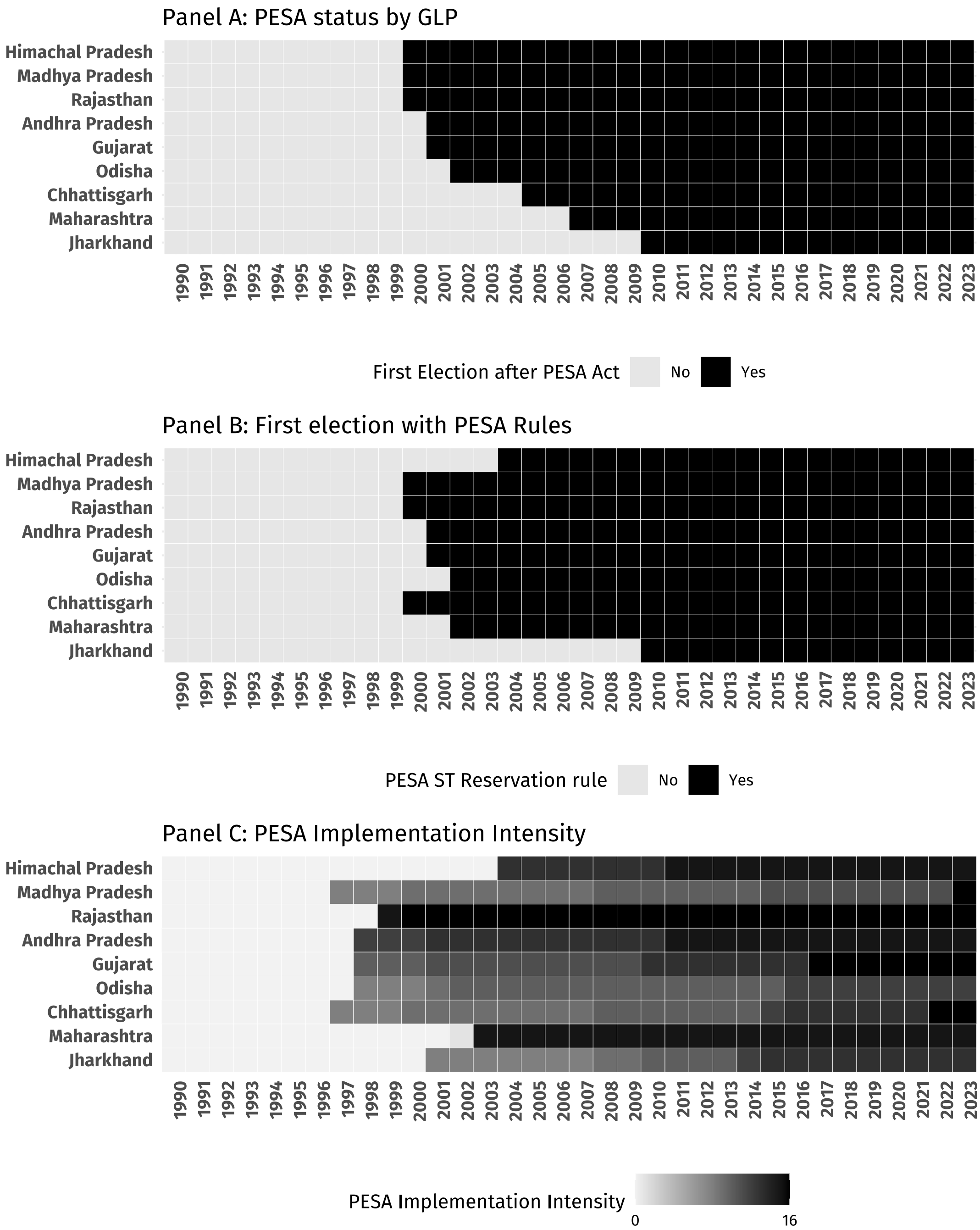


Figure 11: The Effect of Forest Rights Act on Deforestation

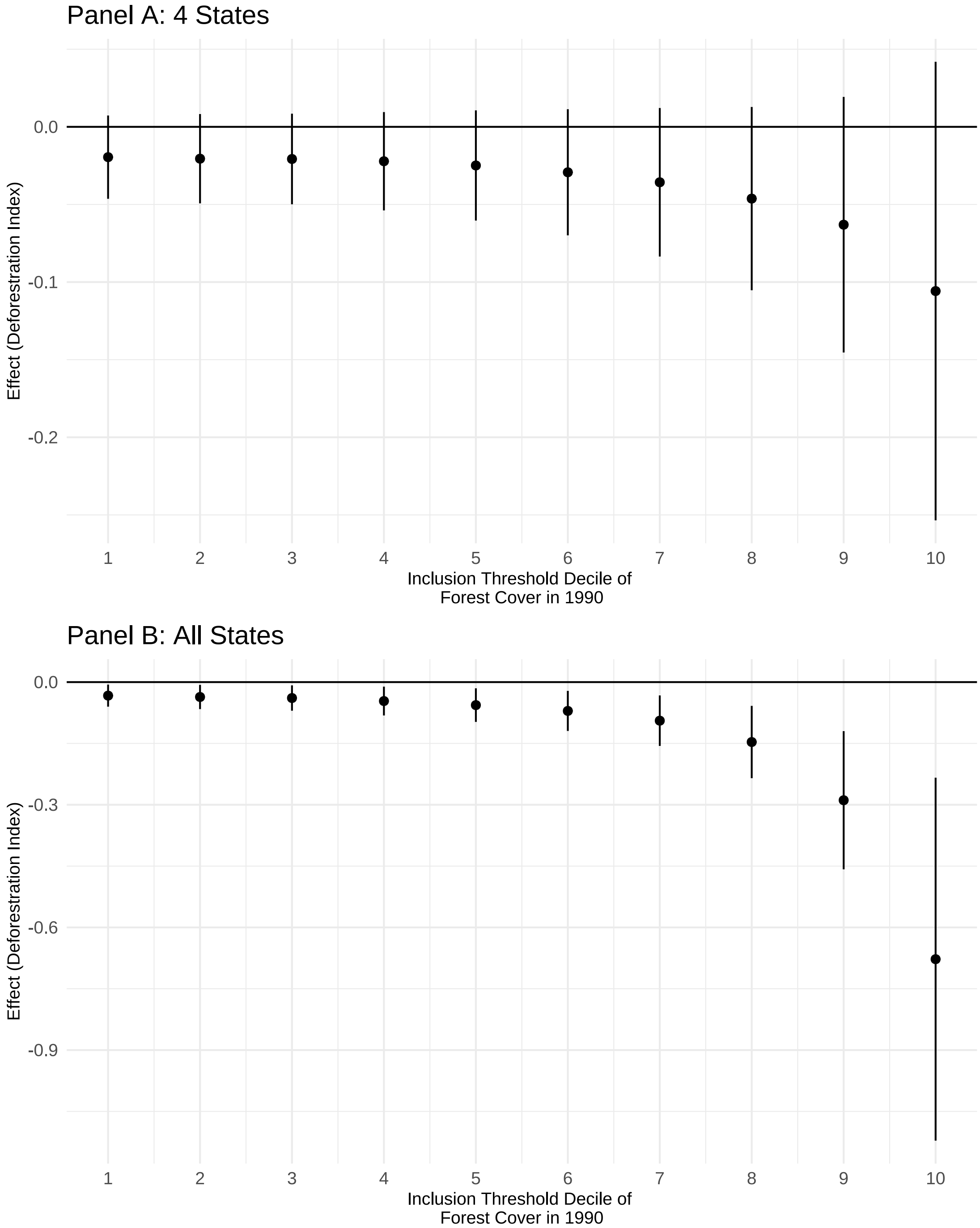
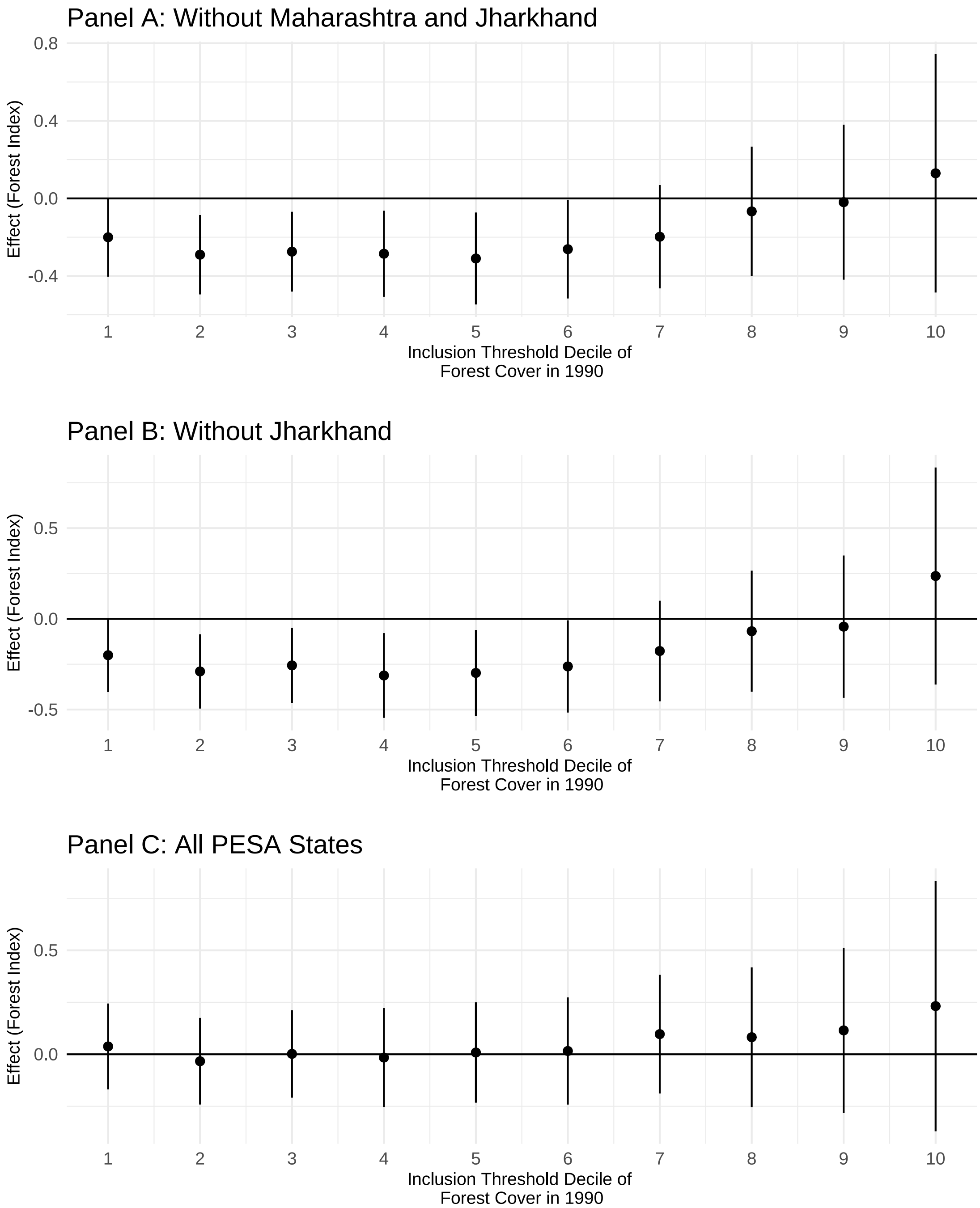


Figure 12: The Effect of PRI on Forest Cover



A Appendix Tables

A.1 All PESA rules implementation timing

The Panchayat Extension to Scheduled Areas (PESA) Act was enacted in 1996. However, its adoption by Indian states was not uniform. The subsequent table delineates the specific timelines for full PESA Act implementation across states. It is important to note that Orissa and Jharkhand have yet to fully incorporate all PESA provisions and consequently, maintain a partial compliance status.

Table A1: Implementation year of all PESA rules

SNo	**State Name**	**PESA Implementation Date**	**Official Gazette link**
1	Andhra Pradesh	24.03.2011	Official Gazette
2	Telangana	02.06.2014	Official Gazette
3	Gujarat	08.02.2017	Official Gazette
4	Madhya Pradesh	15.11.2022	Official Gazette
5	Maharashtra	04.03.2014	Official Gazette
6	Orissa	Yet to Adopt all Rules	
7	Jharkhand	Yet to Adopt all Rules	
8	Rajasthan	26.06.1999 / 01.11.2011	Official Gazette ; Official Gazette
9	Himachal Pradesh	05.03.2011	Official Gazette
10	Chhattisgarh	08.08.2022	Official Gazette

A.2 PESA rules indicated in PESA ACT by Ministry of Tribal Affairs, Government of India

Table A2: Rules names and their description

S. No.	Rule	Rule Description
1	rule 4(d)	Customary mode of conflict resolution by the Gram Sabha
2	rule 4(e)	Selection of programme beneficiaries by Gram Sabha
3	rule 4(f)	Gram Panchayat to obtain Utilisation Certificate from Gram Sabha
4	rule 4(g)	The reservation of seats in the Scheduled Areas at every Panchayat shall be in proportion to the population of the communities in that Panchayat for whom reservation is sought to be given under Part IX of the constitution; Provided that the reservation for the Scheduled Tribes shall not be less than one-half of the total number of seats.
5	rule 4(h)	Nomination by State Government of persons of ST not represented in intermediate & district PRI
6	rule 4(i)	Consultation with Gram Sabha or PRI before land acquisition & resettlement & rehabilitation
7	rule 4(j)	Planning & management of water bodies by Gram Sabha or PRI
8	rule 4(k)	Recommendation by Gram Sabha or PRI before grant of prospecting license or mining lease
9	rule 4(l)	Recommendation by GS or PRI before exploitation of minor minerals
10	rule 4(m)(i)	Power to restrict sale of intoxicant to PRI and Gram Sabha
11	rule 4(m)(ii)	Ownership of Minor Forest Produce to PRI and Gram Sabha
12	rule 4(m)(iii)	Power to prevent land alienation to PRI and Gram Sabha
13	rule 4(m)(iv)	Power to manage village markets to PRI and Gram Sabha
14	rule 4(m)(v)	Control money lending to PRI and Gram Sabha
15	rule 4(m)(vi)	Control of social sector institutions & functionaries to PRI and Gram Sabha
16	rule 4(m)(vii)	The power to control over local plans and resources for such plans including tribal sub-plans

Source: Government of India, Tribal Ministry. Link: PESA Rules

A.3 Additional Results using PESA Index

The PESA Index captures the degree of compliance with the PESA rules. We create the PESA Index using official notifications issued by nine states and the Indian government's Tribal and Panchayati Raj Ministry website. We employ a two-step process: first, for each state, we create a dummy variable for each of the 15 PESA rules, as provided in A2, assigning a value of 1 to the years following the rule's implementation and 0 otherwise. We then use Principal Component Analysis (PCA) to create an index based on the 15 primary rules. We transform the index such that it ranges from 0 to 1, with a PESA index value of 1 signifying full compliance. We employ a two-step process to transform the PESA index: first, we add the minimum value of the index to the index.
Let PI tbe original PESA index, PI_{min} be the minimum value of the index.

$$PI^{'} = PI_{min} + PI \tag{15}$$

This step adjusts the index so that the minimum value is now zero.
Second, we divide the index with the maximum value obtained from Equation 15.
Let $PI^{'}_{max}$ be the maximum value of the $PI^{'}$.

$$PI^{''} = PI^{'}/PI^{'}_{max} \tag{16}$$

This step scales the index to range from 0 to 1, with the maximum value now being 1. $PI^{''}$ is the transformed PESA index that ranges from 0 to 1. The tables below show the results using the PESA Index.

Table A3: Deforestation and Forest cover index regression estimates (ex-ante median cutoff) using PESA Index

	Forest Cover Index			Annual Deforestation in Hectares		
	(1)	(2)	(3)	(4)	(5)	(6)
PESA Index × Scheduled	-0.1701*	-0.1615·	-0.3253*	-0.0402	0.0649	0.0564
	(0.0850)	(0.0831)	(0.1483)	(0.0711)	(0.0786)	(0.0903)
Summary Statistics						
Dataset	VCF	VCF	VCF	GFC	GFC	GFC
Timespan	1995-2017	1995-2017	1995-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Pixel	✓	✓	✓			
Year	✓			✓		
State × Year		✓	✓		✓	✓
Village				✓	✓	✓
Time Trends						
t (Pixel)			✓			
t (Village)						✓
Fit statistics						
# Pixel	30,843	30,843	30,843	–	–	–
# Year	22	–	–	17	–	–
# State × Year	–	198	198	–	68	68
# Village	–	–	–	52,776	31,601	31,601
# Observations	678,546	678,546	678,546	897,192	537,217	537,217
R^2	0.90259	0.90870	0.91564	0.35928	0.26600	0.42135

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Index ranges from 0 to 1. *** p<0.01, ** p<0.05, * p<0.1.*

Table A4: Forest cover index regression estimates (full sample from 1990 - 2017) using PESA Index

	Forest Cover Index		
	(1)	(2)	(3)
PESA Index × Scheduled	0.1426*	-0.0764	0.1099
	(0.0713)	(0.0699)	(0.1358)
Summary Statistics			
Dataset	VCF	VCF	VCF
Timespan	1990-2017	1990-2017	1990-2017
Fixed-effects			
Pixel	✓	✓	✓
Year	✓		
State × Year		✓	✓
Time Trends			
t (Pixel)			✓
Fit statistics			
# Pixel	64,828	64,828	64,828
# Year	27	–	–
# State × Year	–	243	243
# Observations	1,750,356	1,750,356	1,750,356
R^2	0.90405	0.90945	0.92008

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Index ranges from 0 to 1. *** p<0.01, ** p<0.05, * p<0.1.*

Table A5: Deforestation index regression estimates (ex-ante median cutoff) with district fixed effects

	Annual Deforestation in Hectares					
	(1)	(2)	(3)	(4)	(5)	(6)
PESA $\times$ Scheduled	-0.0882***	-0.0134	-0.1211*			
	(0.0202)	(0.0331)	(0.0560)			
PESA Index $\times$ Scheduled				-0.0404	0.0931	-0.0179
				(0.0711)	(0.0729)	(0.0897)
Summary Statistics						
Dataset	GFC	GFC	GFC	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Village	✓	✓	✓	✓	✓	✓
Year	✓			✓		
District $\times$ Year		✓	✓		✓	✓
Time Trends						
t (Village)			✓			✓
Fit statistics						
# Village	52,774	31,601	31,601	52,774	31,601	31,601
# Year	17	–	–	17	–	–
# District $\times$ Year	–	1,540	1,540	–	1,540	1,540
# Observations	897,158	537,217	537,217	897,158	537,217	537,217
R^2	0.35932	0.28260	0.43433	0.35928	0.28260	0.43430

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Index ranges from 0 to 1. *** p<0.01, ** p<0.05, * p<0.1.*

Table A6: Deforestation index regression estimates (ex-ante median cutoff) with district fixed effects and all state sample

	Annual Deforestation in Hectares					
	(1)	(2)	(3)	(4)	(5)	(6)
PESA $\times$ Scheduled	-0.0882***	-0.0134	-0.1211*			
	(0.0202)	(0.0331)	(0.0560)			
PESA Index $\times$ Scheduled				-0.0404	0.1292$^{\cdot}$	0.0169
				(0.0711)	(0.0673)	(0.0796)
Summary Statistics						
Dataset	GFC	GFC	GFC	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Village	✓	✓	✓	✓	✓	✓
Year	✓			✓		
District $\times$ Year		✓	✓		✓	✓
Time Trends						
t (Village)			✓			✓
Fit statistics						
# Village	52,774	52,774	52,774	52,774	52,774	52,774
# Year	17	–	–	17	–	–
# District $\times$ Year	–	3,016	3,016	–	3,016	3,016
# Observations	897,158	897,158	897,158	897,158	897,158	897,158
R^2	0.35932	0.40819	0.45794	0.35928	0.40819	0.45793

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Index ranges from 0 to 1. *** p<0.01, ** p<0.05, * p<0.1.*

Table A7: Deforestation index regression estimates using share of ST population (above and below mean)

	Annual Deforestation in Hectares					
	(1)	(2)	(3)	(4)	(5)	(6)
PESA × Village ST Share > Mean	-0.0765***	-0.0151	0.0536·			
	(0.0175)	(0.0194)	(0.0301)			
PESA Index × ST Share > Mean				-0.0418	-0.0039	0.1162**
				(0.0341)	(0.0384)	(0.0357)
Summary Statistics						
Dataset	GFC	GFC	GFC	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Village	✓	✓	✓	✓	✓	✓
Year	✓			✓		
State × Year		✓	✓		✓	✓
Time Trends						
t (Village)			✓			✓
Fit statistics						
# Village	50,926	30,255	30,255	50,926	30,255	30,255
# Year	17	–	–	17	–	–
# State × Year	–	68	68	–	68	68
# Observations	865,742	514,335	514,335	865,742	514,335	514,335
R^2	0.36082	0.26477	0.42423	0.36078	0.26477	0.42424

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Index ranges from 0 to 1. Village ST Share > Mean takes value 1 if the share of village ST population is above mean and 0 otherwise. Coloumn 2,3,5, and 6 uses sub-sample which comprises four states (Chhatisgarh, Jharkhand, Odisha, and Maharashtra) that have variation in PESA implementation in the sample given by GLP, which is why the number of observations falls from approximately 53,000 villages in column 4 to approximately 32,000 villages in columns 5 and 6. *** p<0.01, ** p<0.05, * p<0.1.*

Table A8: Deforestation index regression estimates using share of village ST population (above and below 50 percent ST population)

	Annual Deforestation in Hectares					
	(1)	(2)	(3)	(4)	(5)	(6)
PESA × Village ST Share > 50%	-0.0744***	-0.0110	0.0154			
	(0.0174)	(0.0160)	(0.0264)			
PESA Index × Village ST Share > 50%				-0.0338	0.0050	0.0993**
				(0.0364)	(0.0394)	(0.0362)
Summary Statistics						
Dataset	GFC	GFC	GFC	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Village	✓	✓	✓	✓	✓	✓
Year	✓			✓		
State × Year		✓	✓		✓	✓
Time Trends						
t (Village)			✓			✓
Fit statistics						
# Village	50,926	30,255	30,255	50,926	30,255	30,255
# Year	17	–	–	17	–	–
# State × Year	–	68	68	–	68	68
# Observations	865,742	514,335	514,335	865,742	514,335	514,335
R^2	0.36082	0.26477	0.42421	0.36078	0.26477	0.42423

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Index ranges from 0 to 1. Variable Village ST Share takes value 1 if Village ST Share > 50 percent of the village population and 0 otherwise. Coloumn 2,3,5, and 6 uses sub-sample which comprises four states (Chhatisgarh, Jharkhand, Odisha, and Maharashtra) that have variation in PESA implementation in the sample given by GLP, which is why the number of observations falls from approximately 53,000 villages in column 4 to approximately 32,000 villages in columns 5 and 6. *** p<0.01, ** p<0.05, * p<0.1.*

Table A9: Deforestation index regression estimates (above and below mean) using all state sample

	Annual Deforestation in Hectares					
	(1)	(2)	(3)	(4)	(5)	(6)
PESA × Village ST Share > Mean	-0.0765***	-0.0151	0.0536$^{\cdot}$			
	(0.0175)	(0.0194)	(0.0301)			
PESA Index × ST Share > Mean				-0.0418	-0.0116	0.1089**
				(0.0341)	(0.0333)	(0.0338)
Summary Statistics						
Dataset	GFC	GFC	GFC	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Village	✓	✓	✓	✓	✓	✓
Year	✓			✓		
State × Year		✓	✓		✓	✓
Time Trends						
t (Village)			✓			✓
Fit statistics						
# Village	50,926	50,926	50,926	50,926	50,926	50,926
# Year	17	–	–	17	–	–
# State × Year	–	153	153	–	153	153
# Observations	865,742	865,742	865,742	865,742	865,742	865,742
R^2	0.36082	0.36924	0.41938	0.36078	0.36924	0.41938

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Index ranges from 0 to 1. Village ST Share > Mean takes value 1 if the share of village ST population is above mean and 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.*

Table A10: Deforestation index regression estimates (above and below 50 percent ST population) using all state sample

	Annual Deforestation in Hectares					
	(1)	(2)	(3)	(4)	(5)	(6)
PESA × Village ST Share > 50%	-0.0744***	-0.0110	0.0154			
	(0.0174)	(0.0160)	(0.0264)			
PESA Index × Village ST Share > 50%				-0.0338	-0.0065	0.1032**
				(0.0364)	(0.0356)	(0.0350)
Summary Statistics						
Dataset	GFC	GFC	GFC	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Village	✓	✓	✓	✓	✓	✓
Year	✓			✓		
State × Year		✓	✓		✓	✓
Time Trends						
t (Village)			✓			✓
Fit statistics						
# Village	50,926	50,926	50,926	50,926	50,926	50,926
# Year	17	–	–	17	–	–
# State × Year	–	153	153	–	153	153
# Observations	865,742	865,742	865,742	865,742	865,742	865,742
R^2	0.36082	0.36924	0.41938	0.36078	0.36924	0.41938

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Index ranges from 0 to 1. Variable Village ST Share takes value 1 if Village ST Share > 50 percent of the village population and 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.*

Table A11: Deforestation and Forest cover index regression estimates (ex-ante median cutoff) using PESA Intensity

	Forest Cover Index			Annual Deforestation in Hectares		
	(1)	(2)	(3)	(4)	(5)	(6)
PESA Intensity × Scheduled	-0.0106·	-0.0101·	-0.0211*	-0.0009	0.0044	0.0041
	(0.0055)	(0.0054)	(0.0097)	(0.0047)	(0.0052)	(0.0058)
Summary Statistics						
Dataset	VCF	VCF	VCF	GFC	GFC	GFC
Timespan	1995-2017	1995-2017	1995-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Pixel	✓	✓	✓			
Year	✓			✓		
State × Year		✓	✓		✓	✓
Village				✓	✓	✓
Time Trends						
t (Pixel)			✓			
t (Village)						✓
Fit statistics						
# Pixel	30,843	30,843	30,843	–	–	–
# Year	22	–	–	17	–	–
# State × Year	–	198	198	–	68	68
# Village	–	–	–	52,776	31,601	31,601
# Observations	678,546	678,546	678,546	897,192	537,217	537,217
R^2	0.90259	0.90870	0.91564	0.35928	0.26600	0.42136

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Intensity ranges from 0 to 16. *** p<0.01, ** p<0.05, * p<0.1.*

Table A12: Forest cover index regression estimates (full sample from 1990 - 2017) using PESA Intensity

	Forest Cover Index		
	(1)	(2)	(3)
PESA Intensity × Scheduled	0.0083$^{\cdot}$	-0.0054	0.0064
	(0.0046)	(0.0045)	(0.0088)
Summary Statistics			
Dataset	VCF	VCF	VCF
Timespan	1990-2017	1990-2017	1990-2017
Fixed-effects			
Pixel	✓	✓	✓
Year	✓		
State × Year		✓	✓
Time Trends			
t (Pixel)			✓
Fit statistics			
# Pixel	64,828	64,828	64,828
# Year	27	–	–
# State × Year	–	243	243
# Observations	1,750,356	1,750,356	1,750,356
R^2	0.90405	0.90945	0.92008

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Intensity ranges from 0 to 16. *** p<0.01, ** p<0.05, * p<0.1.*

Table A13: Deforestation index regression estimates (ex-ante median cutoff) with district fixed effects

	Annual Deforestation in Hectares					
	(1)	(2)	(3)	(4)	(5)	(6)
PESA × Scheduled	-0.0882***	-0.0134	-0.1211*			
	(0.0202)	(0.0331)	(0.0560)			
PESA Intensity × Scheduled				-0.0009	0.0061	-0.0007
				(0.0047)	(0.0048)	(0.0058)
Summary Statistics						
Dataset	GFC	GFC	GFC	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Village	✓	✓	✓	✓	✓	✓
Year	✓			✓		
District × Year		✓	✓		✓	✓
Time Trends						
t (Village)			✓			✓
Fit statistics						
# Village	52,774	31,601	31,601	52,774	31,601	31,601
# Year	17	–	–	17	–	–
# District × Year	–	1,540	1,540	–	1,540	1,540
# Observations	897,158	537,217	537,217	897,158	537,217	537,217
R^2	0.35932	0.28260	0.43433	0.35928	0.28260	0.43430

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Intensity ranges from 0 to 16. *** p<0.01, ** p<0.05, * p<0.1.*

Table A14: Deforestation index regression estimates (ex-ante median cutoff) using district FE with all state sample

	Annual Deforestation in Hectares					
	(1)	(2)	(3)	(4)	(5)	(6)
PESA × Scheduled	-0.0882***	-0.0134	-0.1211*			
	(0.0202)	(0.0331)	(0.0560)			
PESA Intensity × Scheduled				-0.0009	0.0088$^{\cdot}$	0.0015
				(0.0047)	(0.0046)	(0.0052)
Summary Statistics						
Dataset	GFC	GFC	GFC	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Village	✓	✓	✓	✓	✓	✓
Year	✓			✓		
District × Year		✓	✓		✓	✓
Time Trends						
t (Village)			✓			✓
Fit statistics						
# Village	52,774	52,774	52,774	52,774	52,774	52,774
# Year	17	–	–	17	–	–
# District × Year	–	3,016	3,016	–	3,016	3,016
# Observations	897,158	897,158	897,158	897,158	897,158	897,158
R^2	0.35932	0.40819	0.45794	0.35928	0.40819	0.45793

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Intensity ranges from 0 to 16. *** p<0.01, ** p<0.05, * p<0.1.*

Table A15: Deforestation index regression estimates using PESA Intensity and share of ST population (above and below mean)

	Annual Deforestation in Hectares					
	(1)	(2)	(3)	(4)	(5)	(6)
PESA × Village ST Share > Mean	-0.0765***	-0.0151	0.0536·			
	(0.0175)	(0.0194)	(0.0301)			
PESA Intensity × ST Share > Mean				-0.0013	8.07×10^{-5}	0.0076***
				(0.0024)	(0.0024)	(0.0023)
Summary Statistics						
Dataset	GFC	GFC	GFC	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Village	✓	✓	✓	✓	✓	✓
Year	✓			✓		
State × Year		✓	✓		✓	✓
Time Trends						
t (Village)			✓			✓
Fit statistics						
# Village	50,926	30,255	30,255	50,926	30,255	30,255
# Year	17	–	–	17	–	–
# State × Year	–	68	68	–	68	68
# Observations	865,742	514,335	514,335	865,742	514,335	514,335
R^2	0.36082	0.26477	0.42423	0.36078	0.26477	0.42425

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Intensity ranges from 0 to 16. Village ST Share > Mean takes value 1 if the share of village ST population is above mean and 0 otherwise. Coloumn 2,3,5, and 6 uses sub-sample which comprises four states (Chhatisgarh, Jharkhand, Odisha, and Maharashtra) that have variation in PESA implementation in the sample given by GLP, which is why the number of observations falls from approximately 53,000 villages in column 4 to approximately 32,000 villages in columns 5 and 6. *** p<0.01, ** p<0.05, * p<0.1.*

Table A16: Deforestation index regression estimates using PESA Intensity and share of village ST population (above and below 50 percent ST population)

	Annual Deforestation in Hectares					
	(1)	(2)	(3)	(4)	(5)	(6)
PESA × Village ST Share > 50%	-0.0744***	-0.0110	0.0154			
	(0.0174)	(0.0160)	(0.0264)			
PESA Intensity × Village ST Share > 50%				-0.0007	0.0008	0.0067**
				(0.0025)	(0.0025)	(0.0023)
Summary Statistics						
Dataset	GFC	GFC	GFC	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Village	✓	✓	✓	✓	✓	✓
Year	✓			✓		
State × Year		✓	✓		✓	✓
Time Trends						
t (Village)			✓			✓
Fit statistics						
# Village	50,926	30,255	30,255	50,926	30,255	30,255
# Year	17	–	–	17	–	–
# State × Year	–	68	68	–	68	68
# Observations	865,742	514,335	514,335	865,742	514,335	514,335
R^2	0.36082	0.26477	0.42421	0.36078	0.26477	0.42424

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Index ranges from 0 to 16. Variable Village ST Share takes value 1 if Village ST Share > 50 percent of the village population and 0 otherwise. Coloumn 2,3,5, and 6 uses sub-sample which comprises four states (Chhatisgarh, Jharkhand, Odisha, and Maharashtra) that have variation in PESA implementation in the sample given by GLP, which is why the number of observations falls from approximately 53,000 villages in column 4 to approximately 32,000 villages in columns 5 and 6. *** p<0.01, ** p<0.05, * p<0.1.*

Table A17: Deforestation index regression estimates (above and below mean) using PESA Intensity and ST share above mean for all state sample

	Annual Deforestation in Hectares					
	(1)	(2)	(3)	(4)	(5)	(6)
PESA $\times$ Village ST Share > Mean	-0.0765***	-0.0151	0.0536$^{\cdot}$			
	(0.0175)	(0.0194)	(0.0301)			
PESA Intensity $\times$ ST Share > Mean				-0.0013	-0.0005	0.0074***
				(0.0024)	(0.0022)	(0.0022)
Summary Statistics						
Dataset	GFC	GFC	GFC	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Village	✓	✓	✓	✓	✓	✓
Year	✓			✓		
State $\times$ Year		✓	✓		✓	✓
Time Trends						
t (Village)			✓			✓
Fit statistics						
# Village	50,926	50,926	50,926	50,926	50,926	50,926
# Year	17	–	–	17	–	–
# State $\times$ Year	–	153	153	–	153	153
# Observations	865,742	865,742	865,742	865,742	865,742	865,742
R^2	0.36082	0.36924	0.41938	0.36078	0.36924	0.41938

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Intensity ranges from 0 to 16. Village ST Share > Mean takes value 1 if the share of village ST population is above mean and 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.*

Table A18: Deforestation index regression estimates (above and below 50 percent ST population) using PESA Intensity for all state sample

	Annual Deforestation in Hectares					
	(1)	(2)	(3)	(4)	(5)	(6)
PESA $\times$ Village ST Share > 50%	-0.0744***	-0.0110	0.0154			
	(0.0174)	(0.0160)	(0.0264)			
PESA Intensity $\times$ Village ST Share > 50%				-0.0007	-5.99×10^{-5}	0.0072**
				(0.0025)	(0.0024)	(0.0023)
Summary Statistics						
Dataset	GFC	GFC	GFC	GFC	GFC	GFC
Timespan	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017	2001-2017
Fixed-effects						
Village	✓	✓	✓	✓	✓	✓
Year	✓			✓		
State $\times$ Year		✓	✓		✓	✓
Time Trends						
t (Village)			✓			✓
Fit statistics						
# Village	50,926	50,926	50,926	50,926	50,926	50,926
# Year	17	–	–	17	–	–
# State $\times$ Year	–	153	153	–	153	153
# Observations	865,742	865,742	865,742	865,742	865,742	865,742
R^2	0.36082	0.36924	0.41938	0.36078	0.36924	0.41938

*Note: Standard errors are clustered at the block level and reported in parentheses. PESA Intensity ranges from 0 to 16. Variable Village ST Share takes value 1 if Village ST Share > 50 percent of the village population and 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.*

Table A19: SHRUG VCF results

	Mean Forest Cover Index			
	(1)	(2)	(3)	(4)
PESA × Scheduled	-0.2149·	-0.3457·	-0.0562	-0.2761
	(0.1221)	(0.1790)	(0.1896)	(0.2198)
Summary Statistics				
Dataset	VCF	VCF	VCF	VCF
Timespan	2001-2020	2001-2020	2001-2020	2001-2020
Fixed-effects				
Village	✓	✓	✓	✓
State × Year	✓		✓	
District × Year		✓		✓
Time Trends				
t (Village)	✓	✓	✓	✓
Fit statistics				
# Village	286,327	286,327	242,188	242,188
# State × Year	180	–	180	–
# District × Year	–	4,940	–	4,763
# Observations	5,726,540	5,726,540	3,292,172	3,292,172
R^2	0.91609	0.93507	0.89411	0.91632

*Note: Standard errors are clustered at the block level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns 1 and 2 provide the results for the complete dataset, while Columns 3 and 4 offer a comparative analysis based on an ex-ante median division, with the median calculated from the 2001 data.*

Table A20: State-Wise SHRUG VCF results

	Mean Forest Cover Index		
	Odisha	Jharkhand	Maharashtra
PESA × Scheduled	0.9908**	-1.105***	-0.7326*
	(0.3268)	(0.2616)	(0.3373)
Summary Statistics			
Dataset	VCF	VCF	VCF
Timespan	2001-2020	2001-2020	2001-2020
Fixed-effects			
Village	✓	✓	✓
State × Year	✓	✓	✓
Time Trends			
t (Village)	✓	✓	✓
Fit statistics			
# Village	44,969	20,799	40,387
# State × Year	20	20	20
# Observations	613,986	229,920	684,440
R^2	0.86628	0.82975	0.74805

*Note: Standard errors are clustered at the block level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*