Effect of Environmental Policies on Forest Cover: Evidence from India's National Forest Policy*

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Abstract

Environmental policies provide a promising avenue for mitigating and adapting to climate change, but the complex relationships between climate, resources, and policies necessitate empirical evidence to guide effective policymaking. This study investigates the effects of the federal adoption of India's 1988 National Forest Policy on forest cover using district-level data from the Village Dynamics in South Asia dataset. The policy, notable for its emphasis on community participation, was adopted by states in a staggered manner. We leverage this variation through a staggered difference-in-differences model using a semi-parametric estimation method. Additionally, heterogeneous effects on forest cover across districts with open, less dense, and dense forest categories reveal the policy's nuanced effect. Whereas less dense forests experience a positive forest cover trend in the medium run, open forests experience a decline in forest cover. We conjecture that the policy aligns conservation effort with collective action by sharing the use rights of non-timber forest products, thus improving forest density and reforestation, but is insufficient to counteract the benefits from extractive socioeconomic development in a developing country.

Keywords: Forest; Climate; Public Policy; India

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1 Introduction

The cascading effects of climate change on socioeconomic indicators intimately link ecological and economic processes (Dell, Jones, & Olken, 2014). Whereas economic development has historically externalized ecological processes from economic decision-making, climate change effects manifest in extreme weather events, biodiversity loss, altered climatic/rainfall patterns, rising ocean levels and global temperatures. These, in turn, have significant socioeconomic costs. For instance, the loss from extreme weather events stands at \$2 trillion for the last decade, and is estimated to cost the global economy \$39 trillion per year by 2049 (Kotz, Levermann, & Wenz, 2024). Mitigation and adaptation strategies primarily act on either renewable energy sources, improved technological efficiencies, or afforestation[1] (Sarkodie, Adams, & Leirvik, 2020). However, the costs of switching to renewable technology and improving energy efficiency are significant[2] (Sheldon & Dua, 2024). Alternatively, afforestation is evidenced to mitigate the climate change crisis, and the abatement cost associated with afforestation is much lower than switching to renewable energy (Busch et al., 2024).

Environmental policies, particularly for rejuvenation and regeneration of forests, present a beacon of hope in mitigating and adapting to climate change. National and sub-national environmental policies could afford greater context-specification for responding to climate change by alignment of local socioeconomic and ecological welfare to global objectives (Corbera, Martin, Springate-Baginski, & Villaseñor, 2020; Nijnik & Halder, 2013; Howes et al., 2017). For instance, Indonesia's oil palm regulations reduced deforestation, and Mexico's ecosystem services program could improve a watershed ecosystem (Carlson et al., 2018; Sims et al., 2014). Among others, participatory management measures accrue better results, especially in developing countries (Reed, 2008; Fujitani, McFall, Randler, & Arlinghaus, 2017; Duchelle et al., 2014). In India, National Forest Policies have had a rich history, emphasizing resource-use regulation, co-management, conservation and ecological accounting among

[1] Over the last decade, global temperatures have increased by a 0.27°C average owing to deforestation (Prevedello, Winck, Weber, Nichols, & Sinervo, 2019).

[2] Each additional electric vehicle sold costs an incentive between \$14,857 and \$62,443 (Sheldon & Dua, 2024)

others (Guha, 1990). The 1988 Forest Policy, in particular, highlighted participatory forest management to align environmental and socioeconomic welfare (Chakrabarti & Datta, 2009). The subsequent adoption of Joint Forest Management (JFM) legislation by various states over the years evidences the catalyzing effect of this national policy. However, with complex interlinkages between climate change, natural resources, and policy effects, there is a need for empirical exploration to bridge the gap between ecological mechanisms and policy design (Blackman, Li, & Liu, 2018; de Wit & Mourato, 2022; Duflo, Greenstone, & Hanna, 2008)

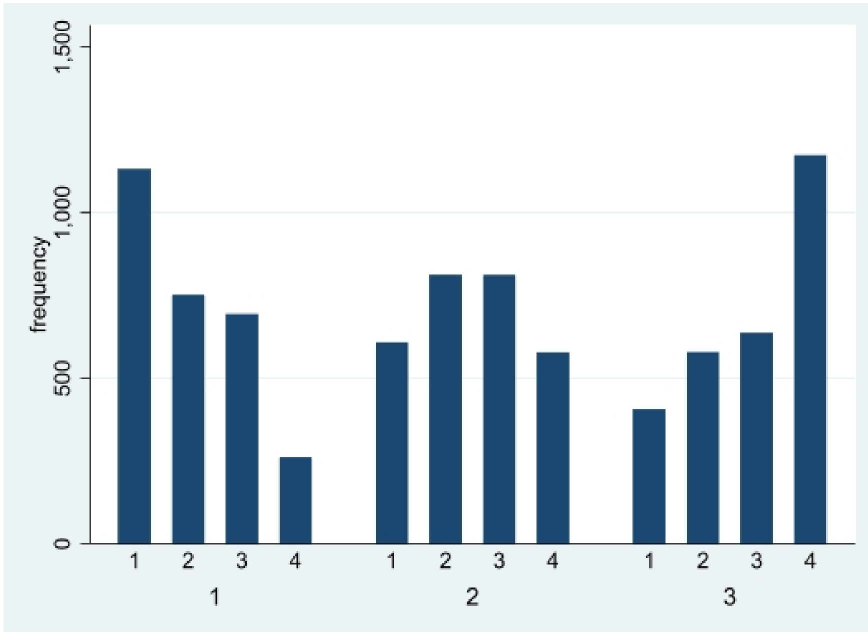
In this paper, we empirically study the effect of the federal adoption of the 1988 National Forest Policy using panel data from the district-level Village Dynamics in South Asia (VDSA) dataset maintained by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). The policy's emphasis on community participation in managing forest resources distinguishes it from other national forest policies. Though the 1952 National Forest Policy set the basis for participatory forest management, it was the 1988 policy that catalyzed the Joint Forest Management movement across states (Chakrabarti & Datta, 2009). The 1988 policy reiterated afforestation targets and sought to align socioeconomic welfare with environmental improvement in conservation practice.

For a comprehensive timeline of the policy effect, we explore the dynamic effects of the policy post adoption, which is further studied across short-, medium-, and long-run. The effects on forest cover are expected to vary with the time of intervention and type of forest density. Therefore, we explore the heterogeneous policy effects across states, forest types, and rainfall intensity categories. We recognize the limitations of the two-way fixed-effects estimation model in a staggered adoption design, and use a semi-parametric estimation setup for inference (Goodman-Bacon, 2021). Accounting for the time varying federal adoption of the policy, we use the staggered difference-in-differences estimation for a multiple period setup, as proposed by Callaway and Sant'Anna (Callaway & Sant'Anna, 2021). Our results indicate an aggregated negative effect, and further nuanced effects of the JFM adoption on the forest cover of the country.

The 1988 forest policy emphasized forest protection and community forestry. The two tenets align to: 1) improve collective conservation behaviour by increasing opportunity cost of over-extraction, and 2) lowered cost of conservation through access to non-timber forest products (NTFPs) (Palátová et al., 2023; Naidu, 2011). Thus, we expect an increase in afforestation, reforestation, and forest conservation. Whereas the forest-community fringe lines are more likely to intersect in open and less dense forests, illegal logging and forest fires for shifting cultivation are leading causes of degradation in dense forests (Gao, Skutsch, Paneque-Gálvez, & Ghilardi, 2020). By providing substitutes like NTFP access to such extraction, the policy is expected to have a tempering effect on extractive activity and improve conservation behaviour (Mulungu & Kilimani, 2023). However, the countervailing effects of agricultural expansion, and development preclude certainty.

The interactions between climate change, policy effects, and natural resources are complex and endogenous. Natural ecosystems can absorb and store greenhouse gas emissions, with denser forests acting as more effective carbon sinks. This capability helps mitigate climate change by reducing global warming (Pavani & Chandrasekar, 2021). However, climate change can also affect these ecosystems (Halder, Chowdhury, Fuentes, Possell, & Merchant, 2021; Sharma et al., 2017), as rainfall pattern variation affects forest distribution (refer to Figure 1) . We find that the state-level effect of adopting JFM legislation is pronounced in areas with lower rainfall intensity. An additional year of JFM legislation adoption has a negative effect on forest cover in districts with lower rainfall intensity.

Figure 1: ***Frequency distribution of district rainfall intensity across forest cover categories***



Note: This frequency distribution graph shows districts classified into forest categories, denoted by 1, 2, and 3 to represent open, less dense, and dense forests respectively, on the x-axis. Within each forest category, four rainfall intensity categories, denoted by least (1), low-moderate (2), moderate-high (3), and highest (4), are mapped. The y-axis denotes the districts lying in the respective categories in 1971.

To further strengthen our claims, we do exhaustive checks with an altered dataset, and a falsification test. Thus, our paper addresses the empirical gap in understanding the intricate and endogenous relationships between natural resources, climate change, and policy by studying the effects of forest policy, both directly and differentiated by rainfall intensity and forest density across national and state-level policy adoptions.

Section 2 sets the literature and historical context of this study, while section 3 describes the data used in empirical analysis. The identification strategy is outlined in Section 4. The estimation results follow in Section 5. We report the policy effect, the effect differenced by rainfall intensity, and the heterogeneous analysis in this section. To strengthen these results, a series of robustness checks follow in Section 6. In Section 7, we discuss the results. Section 8 concludes with policy suggestions and lists the limitations of this work.

2 Background

The sixth report by the Intergovernmental Panel on Climate Change (IPCC AR6) states that human activity is responsible for global greenhouse gas (GHG) emissions and warming (Calvin et al., 2023). This leads to eroding ecosystems and subsequent damage to human livelihoods, necessitating policy solutions. Among various adaptation and mitigation methods, carbon dioxide removal emphasizes carbon sequestration, relying on increasing and managing forest cover to mitigate climate change. International missions to prevent deforestation, such as the Reduction of Emissions through Deforestation and Forest Degradation (REDD+), highlight the importance of forest ecosystems in sequestering carbon. Perhaps testament to the improving adaptation and mitigation actions, global net forest loss has decreased over the decades: from 10.2 million hectares per year in 1970-1980 to 7.8 million hectares per year in 1980-1990, 5.1 million hectares per year in 1990-2000, and 4.7 million hectares per year in 2010-2020 (FAO, 2020). Despite this progress, the positive net forest loss and rising GHG emissions threaten irreversible ecosystem damage before we achieve net zero emissions (Ritchie, Rosado, & Roser, 2023).

2.1 Forest Cover and National Climate Action

The critical first step to realize international coordination, however, is to study the characteristics of and manage diverse natural resources. Forest cover helps improve carbon sequestration and offsetting, thus reducing the carbon footprint and mitigating the greenhouse effect. Carbon sequestration through forests affords a greater degree of control than other resources (Guo & Costello, 2013). Forest density, capturing the nuances of forest types (open, less dense, dense), informs a nation's climate change mitigation efforts across carbon, energy, and water flux channels (Wang, Yan, & Wang, 2014). In turn, the cascading effects of climate change on rainfall patterns affect forests in complex ways like fires, droughts, and water flux (Malmsheimer et al., 2011a). Thus, effective natural resource management (NRM) policies can enhance both local and global sustainability efforts. Increasing forest cover increases a nation's climate action capability, owing to the carbon storage potential of forests. Coordinated national action is essential for mitigating and adapting to climate change. Large international programs like REDD+ set a global agenda but cannot be credited entirely for results. Context-specific policies are crucial to translate global goals into on-ground targets (Pandit, Neupane, & Wagle, 2017). National and federal policies must align with international sustainability goals (United Nations, 2015).

2.2 Natural Resource Management and Development

For developing countries, NRM policy is crucial to balance environmental and socioeconomic welfare. While developed economies can afford environmental investments, developing nations face an acute trade-off between environmental and socioeconomic well-being (Barbier, 2010). Further, climate change vulnerability disproportionately affects communities with the least carbon footprint (Calvin et al., 2023). Forest produce accounts for 22 percent of rural household income in developing economies (Vedeld, Angelsen, Bojö, Sjaastad, & Kobugabe Berg, 2007). In the context of high poverty, environmental welfare is often subordinate to socioeconomic welfare in these regions (Barbier, 2010). Environment policies in developing countries vary across command-and-control regulations in China, bottom-up management in Latin America, central government schemes in India, and corporate tie-ups in Southeast Asia. Given their weak institutions, developing economies must design policies adeptly to balance environmental and socioeconomic welfare and avoid perverse outcomes (Howlader & Ando, 2020; Dasgupta, 1998; Nieto-Romero, Parra, & Bock, 2021). Indeed, positive socioeconomic outcomes of environmental policy substantiate its role in developing economies, especially through governance innovations (Tyagi & Das, 2020; Kumar & Managi, 2009). This paper studies the effects of an inclusive forest policy in India, exploring shifting forest cover patterns and the role of climate change on outcomes.

Environmental policy mechanisms range from Pigouvian taxation to Coasean negotiation. Command-and-control schemes regulate natural resource access, use, and upkeep. China's 1998 natural forest protection program, a top-down approach, imposes strict logging bans

(Qiao, Yuan, & Ke, 2021). Alternatively, China's 1999 sloping land conversion program is an incentive-based top-down program rewarding households for converting steep agricultural land to forests (Bennett, 2008). Grassroots NRM and collective action emerged as solutions to the tragedy of the commons (Ostrom, 1990). Communities dependent on natural resources voluntarily manage them sustainably. India implemented this approach in its 1988 national forest policy (Chakrabarti & Datta, 2009).

2.3 Indian Forest Policy Landscape

The national forest policy in India, introduced in 1988, encouraged Joint Forest Management with active community participation to improve environmental and socioeconomic welfare (Shyamsundar & Ghate, 2014). India's forest policies date back to 1855 with timber trade regulation and mitigation forest abuse (Rangarajan, 1994). Post-independence, the 1952 Forest Conservation Act aimed to address the marginalization of tribal and forest-dependent communities by introducing community participation in reserved forest management and setting forest cover targets of 33 percent in plains and 60 percent in hilly states (Guha, 1990; Joshi, Pant, Kumar, Giriraj, & Joshi, 2011). The National Forest Policy of 1988 (NFP1988 hereon) proved instrumental in promoting collective natural resource management in India. It emphasized JFM to align environmental and socioeconomic welfare, recognizing forest-dwellers' rights and encouraging partnerships between communities and the state to manage forested areas. State governments adopted JFM legislation to promote local stewardship of forests, and ensure sociocultural, economic, and environmental sustainability (Bhattacharya, Pradhan, & Yadav, 2010; Chakrabarti & Datta, 2009). JFM and community-based forestry, including agro-forestry initiatives, have shaped the Indian forest resource landscape. NFP1988 also reiterated forest cover targets for states: 33 percent for plains and 66 percent for hilly/mountainous states (Joshi et al., 2011).

2.4 Expected Policy Channels

We expect the two tenets of this policy – targeted state forest cover and JFM – to show heterogeneous effects across different forest categories. To meet their forest cover target, states can undertake large-scale afforestation in non-forest wastelands or degraded forests, which is likely to increase open and less dense forest cover (Joshi et al., 2011). JFM aims to divert human activity from degrading to restoring forest cover through the use of non-timber forest products, thereby reducing threats to dense forests from illegal logging (Afreen, Sharma, Chaturvedi, Gopalakrishnan, & Ravindranath, 2011). Besides, in developing countries, JFM performs better for carbon sequestration when designed to meet local forest product demand. (Kadekodi & Ravindranath, 1997). By 2003, most states had passed JFM legislation, which covered approximately 15 million hectares, or around 15 percent of India's forest area (Sahays, 2003). This includes degraded forestland and wasteland transitioning to open forest. Positive effects of JFM would show as 1) increased open and less dense forest cover and 2) increased dense forest cover.

3 Data

We use annual district-level data from the Village Dynamics in South Asia[3] database maintained by ICRISAT. The data comprises micro and meso variables capturing social and economic factors at a granular level. Although the village-level micro-indicators' dataset spans 1966-67 to 2013-14, the district-level data with our variables of interest has records till 2011. The meso data we use is reported at the district level and includes demographic, economic, institutional, and agro-ecological metrics. It sources data from the Directorate of Economics and Statistics, various state Directorates of Agriculture, the India Meteorological Department, the Centre for Monitoring Indian Economy - States of India database, and the Census of India.

The VDSA meso data covers 19 of the 28 Indian states. In 2000, a major restructuring

[3] See here: https://vdsa.icrisat.org/vdsa-database.aspx

of states in India resulted in the creation of Chhattisgarh from Madhya Pradesh, Jharkhand from Bihar, and Uttarakhand from Uttar Pradesh. Consequently, in the VDSA database, districts belonging to these new states are removed from their parent states post-2000.[4] To evaluate the effect of the 1988 Forest Policy, we merge the newly created states with their respective parent states to maintain temporal comparability. Next, we view the adoption of JFM legislation as the intervention at the state-level to implement community-based NRM. We extract the adoption year from State Forest Department websites. The movement originated from a 1972 experiment in West Bengal, followed by Haryana's legislation in 1976 (Ashish Aggarwal et al., 2004). The last adopter was Punjab in 2003.

This study utilizes land use, rainfall, state gross domestic product (GDP), and population census data. The land use data reports the total geographical area, forest area, barren land, cultivable land, pastureland, and more in thousands of hectares. Forest cover, defined as the geographical region with more than 10 percent forest area, is the outcome variable. Controls include the monthly seasonal rainfall data by districts (in millimeters), the decadal population census (in thousands), and the state-level GDP at factor cost (at 2004-05 constant prices).

Detailed summary statistics for forest cover and the control variables used in the study are reported in Table 1.

[4] See here: https://vdsa.icrisat.org/vdsa-mesodoc.aspx

Table 1: *Summary Statistics*

Variables	Observations	Mean
Outcomes:		
log($ForestCover$)	13,912	4.141
(log of cover in thousands of hectare)		(1.747)
Controls:		
Annual Rainfall	13,383	1100.828
(yearly rainfall in mm in a district)		(684.735)
Total Population	11,248	2474.826
(in thousands in a district)		(1709.218)
Gross State Domestic Product	9,344	13.840
(log of state GDP at factor cost, 2004-05)		(0.755)
Moisture Availability Index	13,912	0.665
(Annual index assigned to each district)		(0.432)

Note: This table shows the summary statistics for the VDSA data from 1966 to 2011. Summary statistics for both outcome and control variables used in this study are reported. Column 1 reports the number of observations and Column 2 reports the variable's mean value. Standard deviations are reported in parentheses.

4 Identification Strategy

In this section, we introduce our strategy to capture the effect of the federal adoption of JFM legislation on the shifting patterns of forest cover. Our empirical design has multiple time-periods of adoption. As such, we use a semi-parametric estimation strategy for a $2 \times T$ multi-period framework, which accounts for the temporal variation in adopting the JFM legislation (Callaway & Sant'Anna, 2021).

4.1 Event Time Framework

In contrast to the classic difference-in-differences (DID) model, which leverages the 2×2 framework for causal inference, the staggered adoption design incorporates multiple time periods. This is particularly suited in cases where the time of intervention varies across the different entities or cohorts studied ('staggered' adoption of intervention). Whereas the DID model has two periods and two groups to compare, the staggered adoption model has multiple time periods, and dynamic comparison groups for every cohort. Since the control groups are dynamic and cohorts vary in the time of JFM legislation adoption (g), the chronological scale of reference as used in the DID setup fails in the staggered adoption setup. As such, the event time framework uses the relative time to and from the event (intervention) for estimation. Pre-treatment and post-treatment lead and lag indicators are therefore referred to in relative time to and from the event respectively. The event time framework further serves to analyze the temporal variations of the policy's effect at a period-by-period granularity for the staggered adoption setup.

We interpret JFM as a significant mechanism for increasing forest cover and states adopt this legislation in a staggered manner. As so, the event study framework in terms of event time takes the year of JFM legislation adoption as the event, and maps the pre-treatment and post-treatment indicators. We leverage the staggered adoption across states to identify effects on forest cover trends. Each cohort comprises states that adopt JFM legislation in a common year, g. We use the following event study model for a district d in the time t, when JFM legislature is adopted by the cohort at g.

$$log(FOREST_{dt}) = \alpha_i + \lambda_t + \sum_{k \neq -1} \beta_k \cdot 1\{t - g_i = k\} + \epsilon_{dt} \tag{1}$$

In Equation 1, $FOREST_{dt}$ is the forest cover in district d in time t in thousands of hectares. The year before the event, $g - 1$, is designated as the reference period for each cohort. The treatment lead and lag coefficients are the ATE (average treatment effect) estimates, captured by β_k in equation 1. Cohorts adopt in various years ranging from 1971 to 2003. The two-way fixed-effects (TWFE) estimation used in DID models fails in the context of staggered intervention design (Sun & Abraham, 2021). This is a serious flaw in identification for estimation purposes. We use a semi-parametric estimation that relies on dynamic not-yet-treated comparison groups for every treatment group or cohort (Callaway & Sant'Anna, 2021).

4.2 Identification and Assumptions

Causal literature implementing the DID methodology relies on robust two-way fixed effects models. However, in the case of staggered DID, estimates from a TWFE have limited causal interpretation (Goodman-Bacon, 2021). The TWFE model cannot distinguish between the treatment effects of previously treated cohorts and the pre-treatment trends when estimating the ATE for later-treated cohorts. As such, the identification is flawed in the case of multiple policy adoption periods, and estimates fail to capture the ATE of policy adoption. Additionally, it assigns homogeneous treatment effects in the post-period, thereby precluding dynamic treatment effects. For a valid, robust, and identified estimation in the $2 \times T$ framework, the comparison group and choice of parallel trends assumptions guide the selection of a difference-in-differences estimator (Marcus & Sant'Anna, 2021). Crucially, the choice depends on the availability of 'never-treated' comparison groups and the choice of parallel trends assumption.

The JFM legislation in India was adopted by every state eventually. As such, no never-treated cohort is available in our dataset. Though Punjab, the last adopting state, could be used as a comparison group, this is infeasible. The number of observations in the treated cohorts would far outweigh the singular state in the control cohort (Sun & Abraham, 2021). Sun and Abraham (2021) suggest a parallel trends assumption, which utilizes a group of the later adopting cohorts as controls for the early adopters. However, there is no clear demarcation between 'early' and 'late' cohorts in our dataset, and therefore, identification conditions are unmet for their parallel trends assumption. On the other hand, the weak parallel trends assumption proposed by Callaway and Sant'anna (2021) imposes parallel trends restrictions only for groups treated after the first treatment event, enabling a "not-yet-treated" comparison group (Callaway & Sant'Anna, 2021). This assumption is recommended in cases where the macroeconomic conditions significantly differ between pre- and post-treatment periods, or where groups are likely to have divergent pre-treatment trends (Marcus & Sant'Anna, 2021). For our dataset, economic conditions between 1966-1988 were significantly different from the post-1988 period. Indeed, the country underwent economic liberalization in 1991. Further, states likely had non-parallel forest cover trends owing to different growth and demand patterns on forest cover, for example, mining sector demands in Andhra Pradesh and Haryana. Further, multiple years of observations (1966-1971) leading up to the first event (1971) strengthen the case for this parallel trends assumption. Additionally, under this weak parallel trends assumption, nonzero pre-treatment coefficients in the event study function as a placebo test exercise (Marcus & Sant'Anna, 2021).

Having ascertained the parallel trends assumption informing our identification strategy, we follow Callaway and Sant'Anna (2021) to report a *cohort* × *time* average treatment on the treated estimator that generates doubly robust estimates for staggered DID (Callaway & Sant'Anna, 2021). Equation 2 outlines the average treatment on the treated (ATT) estimate for period t comparing the outcome of cohorts treated in time t (for observations with $g \leq t$) with that of not-yet-treated cohorts (observations with $g > t$ or $g = .$) by time t.

$$ATT(g,t) = \mathbb{E}[FOREST_t(g) - FOREST_t(0) \mid G_g = 1], \tag{2}$$

where $FOREST_t()$ denotes the outcome variable, and G is the set of adoption years for all states. We use the *csdid* module in stata for estimation (refer to Equation 1). Thus, for states in the cohort adopting JFM in g, the post-treatment $ATT(g,t)$ compares the forest cover (in percentage terms) in time t with cohorts that are not treated by t, with reference to the base year, $g-1$. For the pre-treatment period, estimates compare treatment and control cohorts in t with $t-1$. Standard errors are clustered at the state-level, owing to the staggered adoption variation across states. Results use the delta or sandwich estimation method, which is shown to over-reject the treatment effects (Callaway & Sant'Anna, 2021).

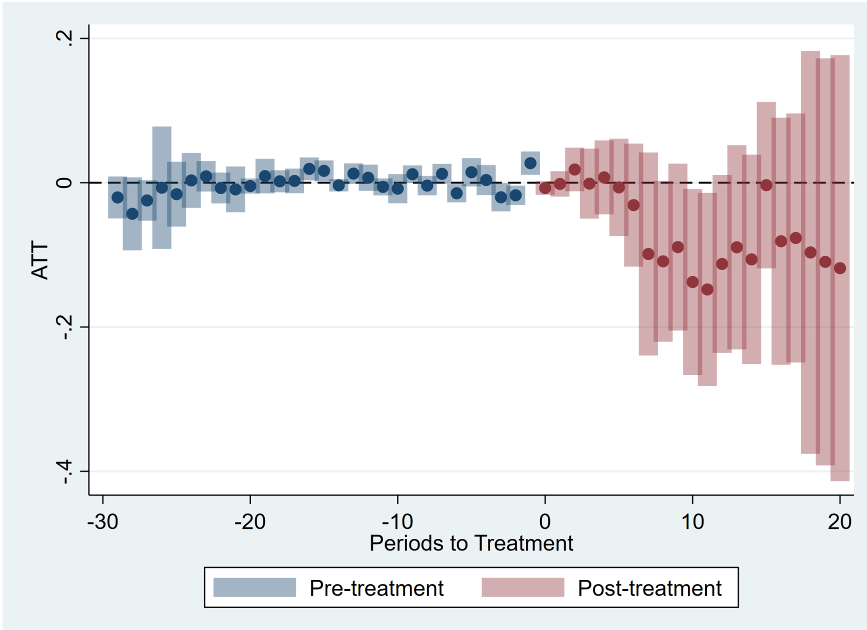
We first report the heterogeneous effects of the policy across states to explore differences, if any, across early and late adopters. This aggregates results by groups, viz., group of states that have adopted the JFM policy in a given year - $g1971$, $g1976$, $g2003$ and so on. Second, the dynamic effects of the policy at an aggregated $cohort \times time$ level elicit immediate, short-run, medium-run, and long-run effects of policy adoption. Lastly, we study the effect heterogeneity across open, less dense, and dense forest categories as a district-level characteristic. We report dynamic policy effects for each of these categories as well. A robustness analysis links rainfall intensity to forest cover density, and studies the effect heterogeneity across districts categorized as receiving (1) least, (2) low-moderate, (3) moderate-high , and (4) highest rainfall intensity.

5 Results

This section reports the event study and staggered DID estimation results of the semi-parametric $ATT(g,t)$ estimations for studying the effects of adopting JFM legislation on forest cover.

The policy effect aggregated at the $cohort \times time$ level comprises the main results. Results from the semi-parametric estimation (Eq. 1) are aggregated for available observations across groups that cater to each relative event time. Each ATT compares treated cohorts in t with cohorts not-yet-treated in $g+t$ (for post-treatment periods) or $g-t$ (for pre-treatment periods) (Callaway & Sant'Anna, 2021). Figure 2 illustrates the plot of the aggregated treatment effects generated from Equation 1 relative to the base year $(g-1)$.

Figure 2: ***Policy effect on Forest Cover***



Note: This graph plots the $ATT(g,t)$ aggregated at $cohort \times time$ level from 29 pre-treatment years to 20 post-treatment years, with reference to one year prior to the adoption of JFM legislation for post-treatment estimates. The bars represent 95% confidence intervals

Figure 2 reports the effect on forest cover with years of policy adoption aggregated across groups. Although treatment effects are estimated from -31 to 31 relative years, the scant observations informing the extremes of this range call for a truncated, and therefore, more generalizable event window (Refer to Figure 6). Observations informing the estimates within the (-2920) relative years window comprise an acceptable majority. We observe that the pre-treatment effects are close to zero and insignificant, which visually reinstates the parallel trends assumption (Marcus & Sant'Anna, 2021). Table 2 reports the aggregated results. The pre-treatment average effects are calculated using short and long gaps between comparable years. For the cohort treated in 1988, for instance, short pre-treatment gaps compare each pre-treatment year (1985, for instance) with its immediate neighbour (1986). Long pre-treatment gaps, on the other hand, compare each pre-treatment year with the year preceding event year. Results show that pre-treatment trends remain nonsignificant in the model using short gaps, whereas that using long gaps shows significant pre-treatment effects.

However, once we use the truncated event window, we see the pre-treatment average effect loses significance. This ascertains that the parallel trends assumption holds in our pre- and post-treatment periods. Contrary to expectations, these outcomes reveal a negative effect on forest cover after the adoption of JFM legislature, with the 95 percent confidence intervals turning significant in the longer runs. The event study thus elicits a more detailed picture of the event time chronology of the broad effects on forest cover. It demonstrates how the effect evolved and sustained over time. Moreover, it evidences the need to further explore the shifting patterns of forest cover with JFM legislation adoption by different states.

Table 2: *Aggregate ATTs, Pre- and Post-Treatment*

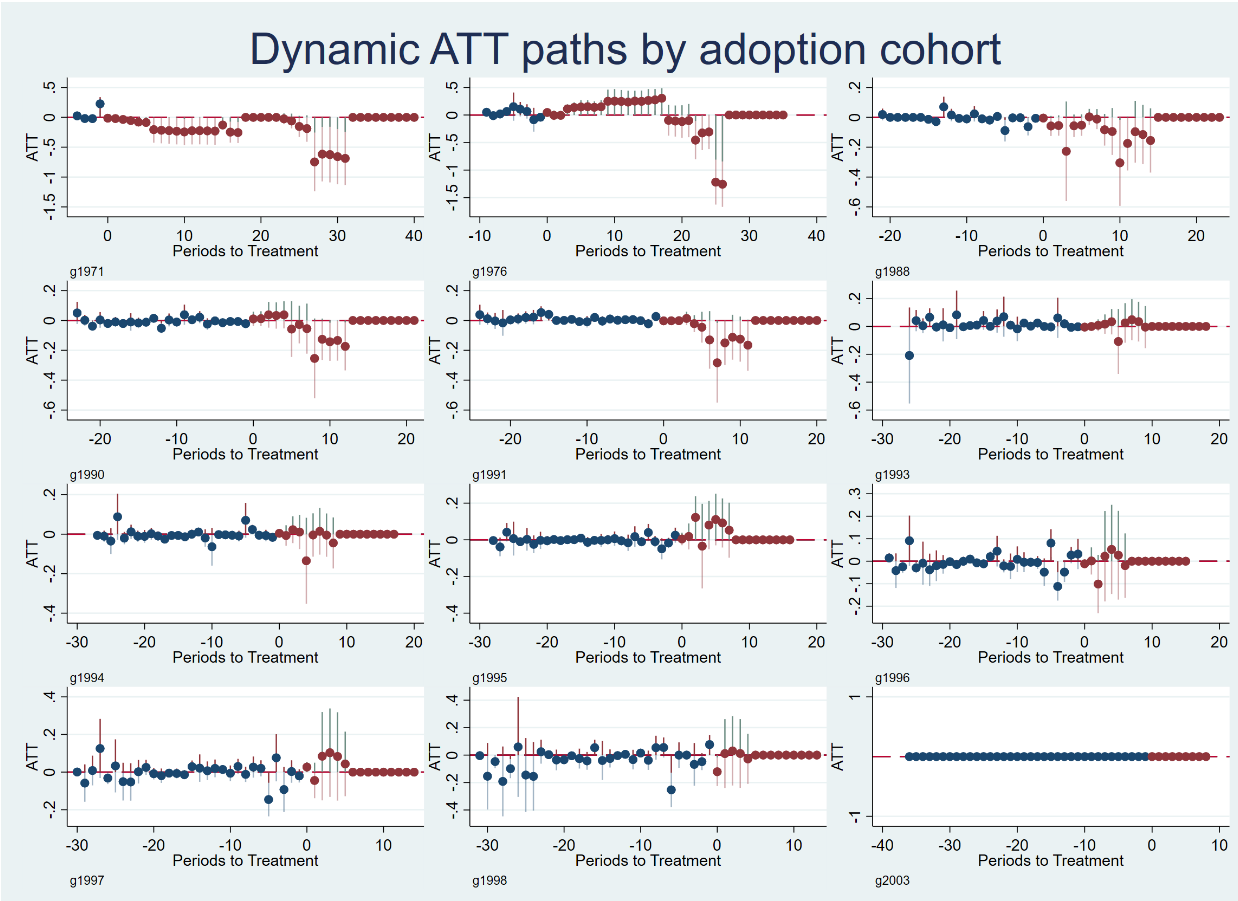
Average effects on forest cover across event windows:			
	(-31 31)	(-29 20)	(-12 9)
	(1)	(2)	(3)
Pre_avg	-0.005	0.002++	-0.003
	(0.004)	(0.002)	(0.003)
Pre_avg(long gaps)	-0.073**	-0.028	-0.039**
	(0.036)	(0.026)	(0.016)
Post_avg	-0.205***	-0.067++	-0.209**
	(0.057)	(0.042)	(0.090)
N	11198		4169
Controls	No	No	Yes

Note: Rows report the aggregated average treatment effects on the treated ($ATT(g,t)$). The first row reports pre-treatment average estimates using short gaps, while the second row reports estimates using long gaps. Row three reports post-treatment average estimate, followed by number of observations and the inclusion of controls in the model. Main results are reported in column (1). Extreme ends of the range of relative years (-31 to 30, for instance) exhibit a low frequency of observations that inform the aggregated estimates; estimates with too few (<100) observations are excluded to report the aggregated pre- and post-treatment effects for the "narrowed" event window reported in column (2). Column (s) reports the model with controls, which lies within the generalizable event window. Doubly-robust standard errors are reported in parentheses. + $p < 0.20$; ++ $p < 0.15$;* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

5.1 Adoption Heterogeneity: Cohort-wise policy effects

States in India underwent separate growth trajectories. Recognizing the variation in states' priorities and trade-offs in meeting development and other demands, we study the cohort-wise effect of the JFM legislation. States that adopted the JFM legislation in the same year comprise a cohort. A cohort-level analysis reveals any differences in the policy effect across early and late-adopting groups. This may offer further insight into state or regional characteristics that could moderate the forest cover trends.

Figure 3: ***State-wise Policy effect on Forest Cover***



Note: For each cohort adopting JFM legislation in year g, the graphs plot treatment lead and lag indicators. Lag indicators are relative to one year prior to adoption ($g-1$). The bars represent 95 percent confidence intervals

As Figure 3 shows, starting from the first cohort in 1971 ($g1971$), cohorts exhibit a negative effect on forest cover. However, in cohorts adopting beyond 1995, there is a positive bend in the post-treatment periods, though the 95 percent confidence interval bars remain nonsignificant. This suggests that late-adopters could be better-off in terms of forest cover compared to the states that adopted JFM earlier. However, the control groups in our empirical design are dynamic across cohorts. The later adopters have increasingly fewer not-yet-treated districts in the post-treatment period for comparative estimation. For instance, the last adopter, $g2003$ (comprising the state of Punjab), has no not-yet-treated comparison groups, and therefore no $ATT(g, t)$ observations can be estimated, whereas $g1998$ has only one comparison group. Therefore, cohorts adopting in the earlier periods reflect the most reliable results. Even so, most reliable estimates with sizable control groups are negative and marginally insignificant. Thus, the policy's negative effect on forest cover is evidenced across most cohorts. Though the early and late adopters of the JFM legislation show different trends, these could likely be attributable to the changing number of comparison groups. These results warrant a further look into how the effects of this legislation vary across forest characteristics and over time.

5.2 Forest Cover Heterogeneity

Leveraging the district-level data in VDSA, we categorize each district as having open, less dense, or dense forest cover at the time of the first adoption event, i.e., 1971. The policy is expected to affect different forest categories via different channels, and as such, this subsample analysis highlights the trajectories of forest cover in open, less dense, and dense forest districts.

Table 3 reports results from the same semi-parametric estimation for staggered adoption design for sub-samples of the three forest cover categories. The significant negative effect on forest cover seems to be driven by open and less dense forests. In the model without controls, open forest districts show an 18.7 percent decrease in forest cover. On introducing controls, the results turn nonsignificant. Less dense forests, on the other hand, show a marked increase of 12.7 percent forest cover without controls, but on the inclusion of controls in the model, the effect turns significantly negative to a 10.3 percent decrease in forest cover post-legislation adoption.

Though the results contrast and seem to change sign, we recognize that on the inclusion of controls, observations are severely reduced in the sub-sample analysis. Results reported here are the aggregated estimates from the $Event \times Time$ cohort effects. These were in turn

Table 3: *Heterogeneous Policy Effect: Forest Cover*

Average effects on forest cover by type				
	(1)		(2)	
	Post_avg	**N**	**Post_avg**	**N**
Open forests				
$FOREST_{d,t}$	-0.187***	2908	1.296	1192
	(0.064)		(1.834)	
Less dense forests				
$FOREST_{d,t}$	0.127***	3041	-0.103***	1408
	(0.015)		(0.025)	
Dense forests				
$FOREST_{d,t}$	-0.010	2495	-0.021	1370
	(0.015)		(0.021)	
Controls	No		Yes	

Note: The table reports estimates at *event* × *time* aggregated across cohorts for the districts categorized as having open, less-dense, and dense forests (ref 1971). Column (1) excludes controls; column (2) includes them. Doubly-robust standard errors are reported in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

estimated using the available estimate furnished by each cohort. If during the sub-sampling, there are too few suitable cohorts to inform the estimation of the cohort-wise $ATT(g, t)$, the outcome could be unreliable. As such, the outcome for less dense forest districts with controls relies on six post-treatment periods, whereas that for the outcome without controls has all 31 post-treatment periods. Interestingly, on aggregating the post-treatment outcomes for only the first six periods in the model without controls, we find the aggregated effect to be positive and significant for the less dense forest districts. In noting this, we recognize that the policy, for the first six years, had a positive effect, whereas over thirty-one years, it had a negative effect on forest cover in this sub-sample. This is ample evidence to motivate an inquiry into how the policy effect has evolved over time for the full sample, as well as each of the forest-category based sub-samples.

5.2.1 Dynamic Policy Effect

A clear picture of how the policy adoption affected forest cover dynamically over time is crucial for this analysis. Further, results of environmental policy interventions are likely to bear fruit in the long run. Table 4 reports the policy effect over various time bins to demonstrate the evolution of its effect on forest cover. We classify the first decade (1 to 10 years after adoption) as the short run for forest cover effects. The second decade (11 to 20 years) is the medium run, and the third decade (beyond 21 years) is classified as the long run. Thus, for all observed districts, we see a 6.7 percent decrease in forest cover in the short-run period after adopting the JFM legislation, then a 26.2 percent and 64.3 percent decrease in the long run. This effect seems to be driven by the large negative effects on open forest districts in the long run. For the less dense forests, however, the legislation adopting cohorts lose forest cover in the short run (12.5 percent aggregate decrease), then gain in the medium run (around 44 and 49 percent increase in the forest cover).

Table 4: ***Average effects of JFM legislation adoption on forest cover by relative time and forest type***

	Average effects on forest cover across years:						
	1 to 31	1 to 5	6 to 10	11 to 15	16 to 20	21 to 25	26 to 30
Full sample							
$FOREST_{d,t}$	**-0.212*****	0.003	**-0.093***	-0.092++	-0.096	**-0.262*****	**-0.643*****
	(0.059)	(0.020)	(0.056)	(0.057)	(0.099)	(0.093)	(0.204)
Open forests							
$FOREST_{d,t}$	**-0.194*****	0.031	-0.018	-0.010	-0.152+	**-0.589*****	**-1.349*****
	(0.066)	(0.053)	(0.068)	(0.070)	(0.115)	(0.133)	(0.228)
Less-dense forests							
$FOREST_{d,t}$	**0.131*****	0.012	**-0.125*****	**0.442*****	**0.487*****	-0.002	
	(0.015)	(0.012)	(0.031)	(0.046)	(0.021)	(0.007)	
Dense forests							
$FOREST_{d,t}$	-0.011	-0.009	-0.017				
	(0.016)	(0.011)	(0.036)				

Note: The table reports the dynamic policy effect on forest cover trends across panels for the full sample, and districts categorized as having open, less-dense, and dense forests (ref 1971). Estimates for the model without controls are aggregated at *event* × *time*, reporting the aggregated post-treatment average effect in the first column for each panel. Dynamic post-treatment effects follow in 5-year spans, ranging from 1 to 30 years after the adoption of JFM legislation. Doubly-robust standard errors are reported in parentheses $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Since open forests are most susceptible to development and the expanding urban sprawl, the results indicate a likely failure of the relevant policy tenets to counteract these socioeconomic preferences. Conversely, the effect is positive and significant in the medium run for less dense forests, which indicates the ability to counter illegal logging with JFM-activity substitutes and an NTFP usufruct eventually. As a caution, we note that our aggregate results cluster the doubly-robust standard errors at the state level due to adoption variation, and the $event \times time$ estimates use the default csdid SE estimation, which could over-reject estimates in the staggered adoption design. (Callaway & Sant'Anna, 2021). As such, we test our inference with a robustness analysis, which leverages the correlation between rainfall intensity of a district and its forest cover.

6 Robustness

6.1 Rainfall Intensity Heterogeneity with Forest Cover

Forest cover is influenced by long-run rainfall intensity patterns, with forest cover closely following rainfall intensity categories (refer to Figure 1). As such, repeating the analysis across districts categorized by their rainfall intensity is expected to yield results akin to those reported in Table 4. Thus, we utilise district-level differences in rainfall intensity to examine changes in forest cover. The variable $ANNRF_d$ captures the long-run averages of rainfall in millimetres across 50 years, 1900-1950. The distribution of these long-run rainfall averages suggests four categories of districts: least, low-moderate, moderate-high, and highest rainfall intensity districts. The heterogeneous policy effect across these rainfall intensity classifications is reported in Table 5.

Results show that the aggregate treatment effect on the forest cover for districts that receive the least rainfall is negative on the whole, with a short run increase of 6 percent in the short run, and a significant long run decrease of 50 to 124 percent in the long run. However, the figures reported in the long run for subsample analysis must be viewed with caution due to the depletion of the control group. Districts receiving low-moderate rainfall see is an increase of around 37 to 48 percent forest cover in the medium run, followed by a 22 to 84 percent decrease in the same in the long run. For moderate-heavy rainfall districts, there is an aggregated 78 percent decrease in forest cover overall. The immediate run, or the first five years following JFM legislation adoption, there is a 6.5 percent increase in

Table 5: *Average effects of JFM legislation adoption on forest cover by relative time and rainfall intensity category*

	Average effects on forest cover across years:						
	1 to 31	1 to 5	6 to 10	11 to 15	16 to 20	21 to 25	26 to 30
Full sample							
$FOREST_{d,t}$	**-0.212*****	0.003	**-0.093***	-0.092++	-0.096	**-0.262*****	**-0.643*****
	(0.059)	(0.020)	(0.056)	(0.057)	(0.099)	(0.093)	(0.204)
Least rainfall							
$FOREST_{d,t}$	**-0.118***	**0.060****	0.052	0.072	-0.058	**-0.492*****	**-1.244*****
	(0.063)	(0.026)	(0.061)	(0.078)	(0.111)	(0.132)	(0.225)
Low–moderate rainfall							
$FOREST_{d,t}$	0.060	-0.036	-0.114	**0.477*****	**0.374*****	**-0.222*****	**-0.845*****
	(0.052)	(0.060)	(0.093)	(0.092)	(0.048)	(0.063)	(0.063)
Moderate–heavy rainfall							
$FOREST_{d,t}$	**-0.767*****	**0.065****	**-0.050****	**-0.119*****	**-0.155****	-0.489++	**-2.950*****
	(0.047)	(0.028)	(0.024)	(0.036)	(0.064)	(0.312)	(0.014)
Most rainfall							
$FOREST_{d,t}$	**-0.360*****	**-0.212*****	**-0.391*****	**-0.433*****	-0.148	0.067	**-0.649*****
	(0.037)	(0.028)	(0.048)	(0.084)	(0.121)	(0.061)	(0.034)

Note: The table reports the dynamic policy effect on forest cover trends across panels for the full sample, and districts categorized as having least, low-moderate, moderate-high, and highest rainfall intensity (ref 1971). Estimates for the model without controls are aggregated at $event \times time$, reporting the post-treatment average effect in the first column for each panel. Dynamic post-treatment effects follow in 5-year spans, ranging from 1 to 30 years after the adoption of JFM legislation. Doubly-robust standard errors are reported in parentheses.$^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table 6: ***Average effects of JFM legislation adoption on forest cover: Pre- and Post-treatment aggregates by forest type***

	(1)				(2)			
	(-31 31)				(-12 9)			
Pre-treatment gaps:	**Pre_avg Short**	**Pre_avg Long**	**Post_avg**	**N**	**Pre_avg Short**	**Pre_avg Long**	**Post_avg**	**N**
Full sample								
$FOREST_{d,t}$	-0.005	-0.073**	-0.205***	11198	-0.003	-0.039**	-0.209**	4169
	(0.004)	(0.036)	(0.057)		(0.003)	(0.016)	(0.090)	
Open forests								
$FOREST_{d,t}$	-0.004	-0.070	-0.187***	2908	0.046***	0.074	1.296	1192
	(0.016)	(0.055)	(0.064)		(0.018)	(0.066)	(1.834)	
Less dense forests								
$FOREST_{d,t}$	0.031***	-0.067***	0.127***	3041	-0.009***	-0.063***	-0.103***	1408
	(0.008)	(0.016)	(0.015)		(0.003)	(0.021)	(0.025)	
Dense forests								
$FOREST_{d,t}$	0.002***	0.022**	-0.010	2495	-0.010*	0.025	-0.021	1370
	(0.001)	(0.011)	(0.015)		(0.005)	(0.031)	(0.021)	
Least rainfall intensity								
$FOREST_{d,t}$	0.008*	0.047	-0.113*	2886	-0.005	-0.02	0.537+	912
	(0.005)	(0.039)	(0.061)		(0.006)	(0.033)	(0.407)	
Low-moderate rainfall intensity								
$FOREST_{d,t}$	-0.010++	-0.124***	0.057	2883	-0.0005	-0.076***	-0.007	1180
	(0.006)	(0.048)	(0.051)		(0.010)	(0.028)	(0.067)	
Moderate-high rainfall intensity								
$FOREST_{d,t}$	-0.018**	-0.255***	-0.738***	2841	0.004	-0.059+	-0.056**	1093
	(0.007)	(0.081)	(0.045)		(0.006)	(0.042)	(0.027)	
Highest rainfall intensity								
$FOREST_{d,t}$	-0.003*	-0.117***	-0.352***	2588	-0.005	-0.077++	-0.187***	944
	(0.002)	(0.021)	(0.036)		(0.007)	(0.052)	(555)	(0.024)
Controls		**No**				**Yes**		

Note: The table reports the policy effect on forest cover trends for the full sample, and districts categorized as having open, less-dense, and dense forests. Estimates are aggregated at *event* × *time*. Pre-treatment averages are estimated using short and long gaps. The third column reports aggregated post-treatment average effect for each model. Doubly-robust standard errors are reported in parentheses $*\,p < 0.10$, $**\,p < 0.05$, $***\,p < 0.01$.

forest cover, but this quickly turns negative in the short run, increasingly decreasing over time. For districts that received the most rainfall, however, the effect remains consistently negative for each period to induce an aggregated 36 percent loss of forest cover. Results exhibit a reassuring similarity across the heterogeneous effects of the policy by forest cover and rainfall intensity. Open forests show a decrease in forest cover in the long run. The driest districts align with this. Interestingly, these districts further show an increase in their forest cover in the short run. For the less dense forests, cover declined in the short-run and increased in the medium-run. Low- to moderate-rainfall intensity districts also show a rise in forest cover in the medium term. Moderate-high rainfall intensity districts, on the other hand, show an immediate positive effect, which quickly turns negative and remains consistent till the long run. This indicates a premature yet significant similarity to the dynamic of the less-dense forest category. Results from the forest-type heterogeneity do not lend themselves to inferences on the dense forest categories. However, for the most rainfall-receiving districts, forest cover has steadily decreased through the years, perhaps indicating a previously unobserved effect. This similarity instils further confidence in the observed trend of forest cover following the federal adoption of JFM legislation.

6.2 Falsification

The staggered federal adoption of legislation for joint forest management offers a unique opportunity to identify and report on its effects across forest cover categories. To reinstate the validity and robustness of the reported results, we conduct additional placebo falsification tests. To this end, two falsification specifications are used. The years of JFM legislation adoption for each state are falsified. In the first specification, these placebo years are assigned to random states within the same range of treatment years. The original adoption years range from 1971 to 2003, and we generate random years within this range to assign to each state. In the second specification, the placebo years are deliberately chosen to lie in the relative pre-treatment period for each state. For Uttar Pradesh, for instance, the actual adoption year was 1995. The falsified year, 1988, is randomly selected from 1971 to 1995.

6.2.1 Randomize JFM Adoption Years

The years of adoption of JFM legislation in this falsification exercise range from 1975 to 2002 (refer to Table 7). The placebo adoption years alter the range of years for which estimates are generated from the original (-31 31) to (-34 26) for models without controls, and from (-12 9) to (-8 9) for models with controls. Table 7 reports the results with pre-treatment and post-treatment average estimates, grouped by event. Although this falsification specification shows a significant decrease in forest cover for the full sample with no controls, the significant corresponding pre-treatment average invalidates the identifying condition. Accounting for the loss of generalizable estimates at the extreme ends of the relative years, we find 95 percent of the observations lie within the range of relative years reported in Table 7. As such the identification cannot be improved by estimating within a more precise event window. Further, the models with controls show no significant effect on forest. Thus, this placebo specification strengthens the validity of the reported results.

6.2.2 Relative Pre-treatment Assignment of JFM Adoption Years

The random assignment of JFM legislation year does not ensure that the falsified years of adoption lie in the respective pre-treatment regions for treated cohorts. This may conflate some significant outcomes of the adoption with placebo timing. As such, we ensure each cohort is assigned a random falsified year of legislation adoption that lies within its actual pre-treatment period. Years of JFM legislation adoption range from 1970 to 1994 in this specification 8. Models with no control variables generate estimates within the range of (-23 22), whereas those with control variables generate estimates within (-6 5). The reported ranges span 86% and 26% of the data respectively. Results are reported in Table 8. All models, with or without control variables, show no significant aggregate post-treatment effect. No improvement of the identification is possible since the range of years for which estimates are generated is limited. Thus we see no significant effect in this falsification specification that could confound the primary results.

Table 7: ***Average effects of JFM legislation adoption on forest cover by forest type***

	(1)				(2)			
	(-34 26)				(-8 9)			
Pre-treatment gaps:	**Pre_avg Short**	**Pre_avg Long**	**Post_avg**	N	**Pre_avg Short**	**Pre_avg Long**	**Post_avg**	N
Full sample								
$FOREST_{d,t}$	0.00713***	0.132***	-0.0803**	10788	0	0	0.00449	2389
	(0.00253)	(0.0275)	(0.0321)		(.)	(.)	(0.0250)	
Open forests								
$FOREST_{d,t}$	0.0294***	0.209***	-0.0324	3025	0.0710***	0.0810++	-0.0601	623
	(0.00529)	(0.068)	(0.0672)		(0.0239)	(0.0499)	(0.0579)	
Less dense forests								
$FOREST_{d,t}$	0.00659**	0.0974***	-0.0357	3019	0.000377	0.00552	0.0683*	662
	(0.00277)	(0.0358)	(0.037)		(0.00725)	(0.0283)	(0.0411)	
Dense forests								
$FOREST_{d,t}$	0.000608	0.0411**	-0.00034	2879	-0.0199*	-0.0627++	0.0257	871
	(0.00316)	(0.0174)	(0.0177)		(0.0120)	(0.0414)	(0.0423)	
Least rainfall intensity								
$FOREST_{d,t}$	0.0143***	0.145+	-0.240***	2808	-0.0291++	-0.0456	-0.0328	348
	(0.00363)	(0.102)	(0.0764)		(0.0179)	(0.0362)	(0.158)	
Low-moderate rainfall intensity								
$FOREST_{d,t}$	0.0156***	0.114***	0.00625	2805	0	0	0.0748	795
	(0.00425)	(0.044)	(0.0537)		(.)	(.)	(0.0616)	
Moderate-high rainfall intensity								
$FOREST_{d,t}$	0.00215	0.187***	-0.0449	2763	0.0173++	0.0271	-0.0899***	849
	(0.00508)	(0.0416)	(0.0402)		(0.0111)	(0.0384)	(0.0223)	
Highest rainfall intensity								
$FOREST_{d,t}$	-0.00612*	-0.0372++	0.0183	2412	0	0	0	378
	(0.0032)	(0.0236)	(0.0272)		(.)	(.)	(.)	
Controls	No				Yes			

Note: The table reports the results using the first placebo falsification specification. Estimates are aggregated at *event* × *time*, reporting the aggregated post-treatment average effect in the first column for each panel. Dynamic post-treatment effects follow in in 5-year spans, ranging from 1 to 30 years after the adoption of JFM legislation. Doubly-robust standard errors are reported in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: ***Average effects of JFM legislation adoption on forest cover by forest type***

	(1)				(2)			
		(-23 22)				(-6 5)		
	Pre_avg Short	**Pre_avg** Long	**Post_avg**	N	**Pre_avg** Short	**Pre_avg** Long	**Post_avg**	N
Full sample								
$FOREST_{d,t}$	-0.0195***	-0.140***	-0.0125	8395	-0.0143+	0.0167	-0.0173	1523
	(0.00721)	(0.0468)	(0.0652)		(0.0102)	(0.0357)	(0.101)	
Open forests								
$FOREST_{d,t}$	-0.0179+	-0.0576	0.220++	1953	0.00575	-0.0316	0	597
	(0.0135)	(0.0463)	(0.141)		(0.135)	(0.804)	(.)	
Less dense forests								
$FOREST_{d,t}$	0.00677***	-0.0591***	0.0506	2149	-0.0169	-0.0335	-0.0185	372
	(0.00181)	(0.0106)	(0.0536)		(0.0348)	(0.124)	(0.0454)	
Dense forests								
$FOREST_{d,t}$	-0.000471	-0.0492***	-0.0521***	1749	-0.000674	0	0.0226**	182
	(0.00291)	(0.0189)	(0.0151)		(0.00450)	(.)	(0.0104)	
Least rainfall intensity								
$FOREST_{d,t}$	-0.00262	-0.00586	0.0524	2184	0.0279	0.0200	-0.0477	202
	(0.00814)	(0.0527)	(0.0837)		(0.0492)	(0.0543)	(0.0810)	
Low-moderate rainfall intensity								
$FOREST_{d,t}$	-0.0243**	-0.0619*	0.0528	2182	0	0	-0.0604	342
	(0.0122)	(0.0372)	(0.0781)		(.)	(.)	(0.164)	
Moderate-high rainfall intensity								
$FOREST_{d,t}$	-0.0515***	-0.516***	-0.453***	2144	-0.0326***	-0.0412***	-0.191***	329
	(0.0141)	(0.112)	(0.0588)		(0.0100)	(0.0121)	(0.0697)	
Highest rainfall intensity								
$FOREST_{d,t}$	-0.000281	-0.0191	0.00739	1885	0.0119	0.0423*	0.402+	267
	(0.00439)	(0.0399)	(0.0460)		(0.0128)		(0.292)	
Controls		No				Yes		

Note: The table reports the policy effect on forest cover trends across panels for the full sample, and districts categorized as having open, less-dense, and dense forests (ref 1971). Estimates are aggregated at $event \times time$, reporting the aggregated post-treatment average effect in the first column for each panel. Dynamic post-treatment effects follow in in 5-year spans, ranging from 1 to 30 years after the adoption of JFM legislation. Doubly-robust standard errors are reported in parentheses $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6.2.3 Swapping Control and Treated Cohorts

With varying adoption times of JFM legislation, the staggered difference-in-differences approach implemented in this paper allots not-yet-treated cohorts as the control group for estimation. Early adopters have many more control cohorts than those who adopt later. To reaffirm the validity of our analysis using this bifurcation, we invert the cohorts. That is, the last cohort to adopt the legislation is assigned the first year of adoption, whereas the first adopter is assigned the last year of adoption. Essentially, this exchanges the control and treatment cohorts. As in the original analysis, JFM legislation adoption years span 1971 to 2003. Estimates in this specification are generated for (-31, 31) for the model without controls and (-14, 9) for the model with controls. This comprises 26 percent of the sample. Table 9 indicates a significant pre-treatment average in both short- and long-gap estimations for the model without controls. However, once the controls are added, the pre-treatment estimates lose significance, and the post-treatment average shows a significant negative effect. Although this could be a consequence of the lower number of observations informing the model with controls, it does suggest the need for improved controls and additional inquiry. In contrast, the sub-samples in the model with controls in Table 9 report nonsignificant post-treatment estimates with the exception of districts with low-moderate rainfall intensity. However, the effect is positive and significant in this case, which does not lend to the negative aggregate post-treatment effect on the full sample. Further, no improvement in the window of estimation is feasible for the model with controls.

7 Discussion

The adoption of community-based forestry at the state level was expected to improve the forest cover through improved participation and state forest cover targets. Our analysis, however, reveals a decrease in the forest cover at the aggregate level; on average, after adopting JFM legislation, forest cover declined across states. Our estimation draws on the staggered federal adoption of JFM legislation to demonstrate its effect on forest cover. The

Table 9: ***Average effects of JFM legislation adoption on forest cover by forest type***

	(1)				(2)			
	(-31 31)				(-14 9)			
	Pre_avg Short	**Pre_avg** Long	**Post_avg**	N	**Pre_avg** Short	**Pre_avg** Long	**Post_avg**	N
Full sample								
$FOREST_{d,t}$	-0.003*	-0.038**	0.212*	10058	-0.003	-0.027	-0.341***	3872
	(0.002)	(0.018)	(0.118)		(0.004)	(0.042)	(0.112)	
Open forests								
$FOREST_{d,t}$	0.012***	0.036	0.099*	2469	0	-0.012	-0.246	1128
	(0.004)	(0.037)	(0.056)		(.)	(0.07)	(0.834)	
Less dense forests								
$FOREST_{d,t}$	-0.006*	-0.011	-0.034	2717	-0.008++	0	0	1232
	(0.003)	(0.018)	(0.086)		(0.006)	(.)	(.)	
Dense forests								
$FOREST_{d,t}$	-0.002*	-0.04	0.014	2480	0	-0.056	-0.015	1071
	(0.001)	(0.033)	(0.043)		(.)	(0.048)	(0.018)	
Least rainfall intensity								
$FOREST_{d,t}$	-0.01***	-0.084**	0.061	2496	0.012*	0.014	0.348	767
	(0.003)	(0.037)	(0.09)		(0.007)	(0.034)	(0.465)	
Low-moderate rainfall intensity								
$FOREST_{d,t}$	0.004	-0.044++	0.157*	2493	0.008+	0.048**	0.077***	1010
	(0.003)	(0.03)	(0.089)		(0.006)	(0.021)	(0.027)	
Moderate-high rainfall intensity								
$FOREST_{d,t}$	-0.007*	-0.017	2.136***	2546	0.005	-0.018	-0.134+	1077
	(0.003)	(0.043)	(0.03)		(0.005)	(0.06)	(0.101)	
Highest rainfall intensity								
$FOREST_{d,t}$	-0.001	-0.035*	0.102***	2438	-0.018	0.063	0	909
	(0.004)	(0.019)	(0.03)		(0.019)	(0.065)	(.)	
Controls		No				Yes		

Note: The table reports the policy effect on forest cover trends across panels for the full sample, and districts categorized as having open, less-dense, and dense forests (ref 1971). Estimates are aggregated at $event \times time$, reporting the aggregated post-treatment average effect in the first column for each panel. Dynamic post-treatment effects follow in in 5-year spans, ranging from 1 to 30 years after the adoption of JFM legislation. Doubly-robust standard errors are reported in parentheses $*\,p < 0.10$, $**\,p < 0.05$, $***\,p < 0.01$.

lack of data on the implementation of the JFM program precludes any causal testing for the channels through which the outcomes could have taken place. We discuss plausible albeit untested channels that could explain these dynamics.

JFM can improve afforestation in two ways. First, through plantation in non-forested wasteland, which is most likely to show up as a positive effect in open forest districts. Our analysis shows that forest cover declined in the open forest districts, with some indication of a short run increase, which eventually turns negative. As such, the JFM adoption could be insufficient to result in net afforestation. Second, JFM can improve afforestation through reforestation in degraded forest land, which is likely to show up as an increase in open and less dense forest districts (Sundar, 2017). We see a qualified forest cover increase in the medium run in less dense districts, which is reinforced by the robustness analysis. This could be indicative of an increase in collective JFM activity that restored degraded forest land, or prevented deforestation and checked damage to forested areas. The major threat to open and less dense forests emerges from the pressures of developmental and agricultural expansion. Further analysis is needed to evidence how growth interacts with collective action towards conservation and natural resource management in the case of JFM in India.

Further, state-level forest cover targets emphasize conservation and stewardship with usufruct of non-timber forest products (Afreen et al., 2011). These can influence forest cover in various ways. Legal sanctions raise the opportunity cost of extraction and are thereby expected to reduce illegal logging in dense and less dense forest districts. Though we see a medium-run growth in less dense forest cover, results do not lend to a direct reading on dense forests. Inference from the analysis using rainfall intensity suggests highest rainfall intensity districts show a consistent decline in forest cover. Second, offering usufruct of non-timber forest products can help substitute away from extractive economic activity in open and less dense forest districts, which are more likely to feature forest-dependent communities. This potential substitution effect raises the opportunity cost of extraction, leading to better conservation and management (Cacho, Marshall, & Milne, 2005). Further, joint forest management marries communities and the state mechanism, thereby improving the gains from collective action. Together, forest protection measures and sanctions are expected to deter illegal logging, while shared forest management duties and rights to non-timber forest products lower the cost of conservation (Sarker & Das, 2006; Kadekodi & Ravindranath, 1997). The positive effect on less dense forests likely reflects this dual effect of JFM conservation activities and forest stewardship (Murty, 1994; Bošković, Chakravorty, Pelli, & Risch, 2023). On the other hand, the negative effects on open forests indicate that neither the JFM interventions nor the substitution of non-timber forest products can sufficiently counteract the economic forces acting upon open forests: development and agriculture.

Policies towards forest management, therefore, necessarily need to internalize the economic costs of development and create efficient and sufficient substitutes away from extractive human activity. In the case of emerging economies, socioeconomic trade-offs are significantly higher. Although we capture positive effects on forest cover in the districts with less dense forests, the outcome seems limited and cannot match the scale of the socioeconomic demand for development, since cover in the open forest districts unequivocally declined. Thus, though the federal adoption of JFM legislation could likely improve the collective action for forest management and encourage forest stewardship in the less dense forest regions, it is not enough to counteract the socioeconomic necessity for development and extraction at the frontiers of human – nature interactions in open forest regions. The JFM initiative seeks to bundle conservation, management, and restoration. Despite failing to meet the economic costs of conservation, the initiative could plausibly be seen as a positive step towards instituting collective action for natural resource management in a low and middle income country.

8 Conclusion

In response to the climate crisis, there is a need for an academic exploration of the interlinkages of climate change, natural resources, and environmental policy. Empirical evidence on these linkages is essential to inform and progress this agenda. To this end, in this paper, we carry out an empirical investigation on the effects of the federal adopting of India's 1988 forest policy on forest cover trends. We analyze the policy's effect on forest cover using cohort-level heterogeneity, and its dynamic effect using temporal heterogeneity.

The staggered adoption design is pressed into action to estimate the federal adoption of JFM legislation. The $cohort \times time$ based analysis using relative time for creating control groups is preferred to the TWFE analysis used in difference-in-differences models, which is viable in case of a single adoption period. Heterogeneity analysis presents a granular view of the nuanced effects by state cohorts and forest types. These are verified and restated through a robustness check using the long run rainfall intensity patterns of districts. Further, the dynamic temporal analysis of the post-treatment effect offers a period-by-period inference of the policy's effect across short, medium, and long runs.

Given the emphasis of the National Forest Policy of 1988, we expected Joint Forest Management to increase forest cover through three interlinked mechanisms. First, by increasing forest cover through afforestation, reforestation, and gap plantation activities at the fringes of the forest. Second, by reducing illegal logging in dense forests. And third, by increasing collective action and stewardship for forest management and offering usufruct of non-timber forest products. Results indicate an increase in the forest cover of less dense forest districts following the federal adoption of JFM legislation. However, open forests show a marked decline and dense forests are conjectured to have a decline as well, though the results are inconclusive. As such, though collective action and shared NTFP usufruct shows a positive outcome, these benefits cannot overcome the economic benefits of extraction and is countervailed by the needs of developmental expansion.

The reported interaction and heterogeneous effects of the policy can add to the research agenda on interlinking climate change adaptation and mitigation with policy in low and middle income countries. In analyzing the heterogeneous effects of the policy, we use doubly robust estimates for standard errors clustered at the state level, owing to adoption variation. This clustering, however, does not remove the bias arising from small number of clusters (19 instead of the recommended $>= 40$). Future studies could address the same by explicitly mapping the standard error variation, using alternative weighted or pair-wise bootstrapped SE estimators. Secondly, our results are based on secondary panel data. There is a pressing need create a rich database on JFM implementation, which could help triangulate our proposed results. Despite these limitations, our findings on the dynamic effect of environmental policy are significant in informing policymakers at all governance levels for sustainability.

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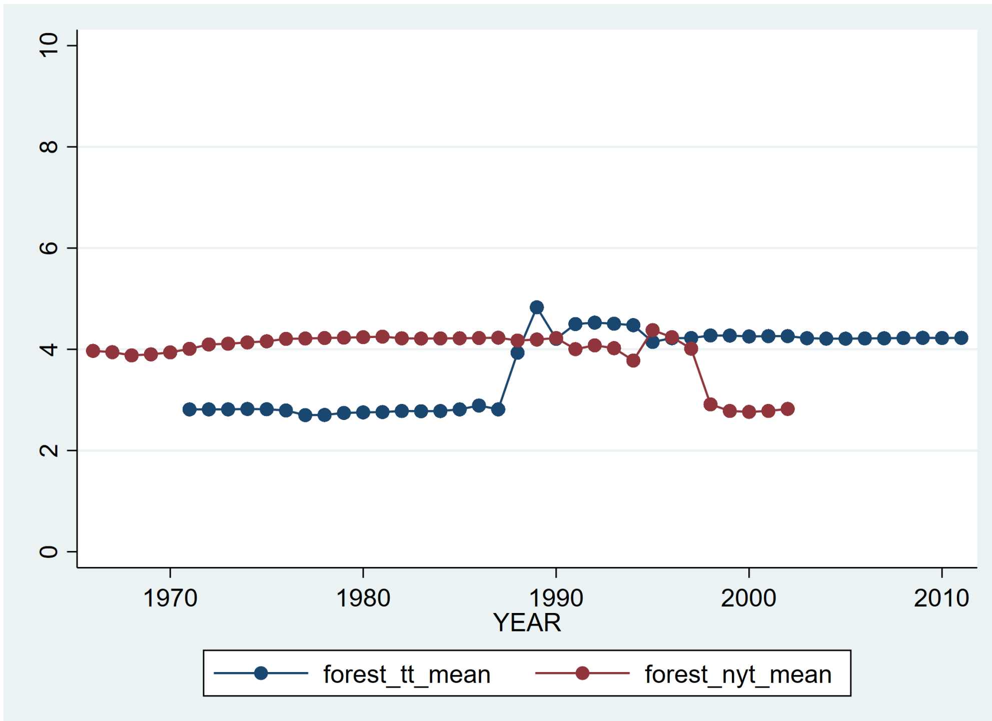
APPENDIX

8.1 Parallel Trends Assumption

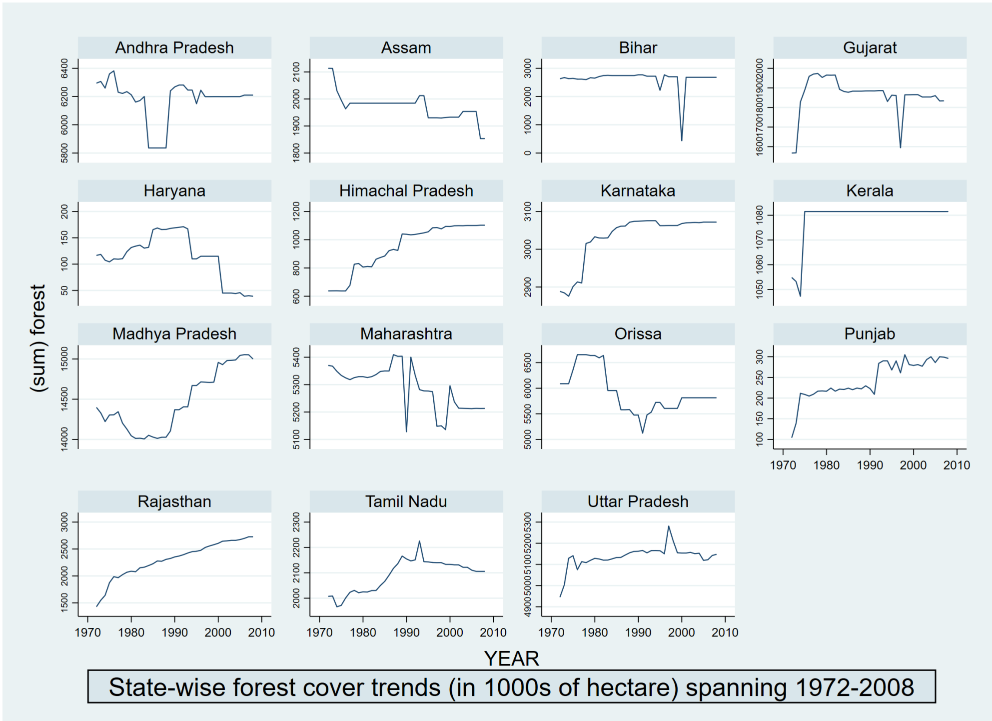
Figure 4: ***Weak parallel trends assumption with not yet treated units as comparison***



Note: This graph plots the mean outcome variable of the treatment versus control groups across time

8.2 Raw forest cover trends: State-wise variation

Figure 5: ***Raw trends of Forest Cover: State-wise***



8.3 Frequency of Observations across Relative Years

Figure 6: ***Histogram of relative years for 1966-2011***