Labor Market Impacts of Protected Area Policies

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Abstract

Balancing economic development with biodiversity conservation poses a significant challenge in protected area management. This paper investigates the long-term labor market impacts of eco-development initiatives in the protected areas of the Western Ghats in India, recognized as one of the world's biodiversity hotspots and experiencing the highest human pressure globally. Our findings reveal a notable shift towards non-farm employment, accompanied by a substantial decline in year-round employment and a corresponding increase in employment for less than six months a year. We attribute this shift primarily to distinct changes in land use patterns, particularly a transition from irrigated to rainfed agricultural land, which facilitates seasonal employment. Furthermore, we observe increases in literacy rates. However, villages closer to protected areas continue to grapple with lower consumption levels and higher poverty rates.

JEL Classification: D04, D10, O10, Q20, Q56.

Keywords: Environmental protection; Labor market impacts; Land use changes.

Protected areas serve as one of the foremost tools in the global effort to combat extensive biodiversity loss (Waldron et al., 2017; Jones et al., 2018). To maximize conservation benefits, protected areas are ideally located in the most biodiverse regions, many of which are found in the tropical regions of the Earth (Myers et al., 2000). However, these regions, predominantly belonging to developing countries, are also under immense economic development pressure (Cincotta, Wisnewski and Engelman, 2000).

As protected areas impose restrictions or prohibitions on land use exploitation, tensions frequently arise between conservation goals and the development needs of the local population (Ma et al., 2019; Estifanos et al., 2020). Consequently, the impact of protected areas on poverty, human well-being, and other socio-economic outcomes remains a topic of substantial and ongoing debate within the sphere of conservation policy (Ferraro and Hanauer, 2014). To address these tensions, eco-development initiatives in protected areas aim to generate activities that provide local populations with alternative income sources. This is intended to reduce dependency on protected area resources and minimize the environmental impacts of human activity (Ministry of Environment and Forest, Government of India, 2002).

In this paper, we assess the long-term impact of eco-development initiatives in protected areas on the labor force participation and composition of village communities. Our geographic focus is the Western Ghats in India, recognized as a global biodiversity hotspot (Myers et al., 2000) and a UNESCO World Heritage site. Additionally, due to its highest population density, the region ranks globally as the biodiversity hotspot most at risk of human pressure (Cincotta, Wisnewski and Engelman, 2000).

We estimate differences in labor force participation and sectoral composition between villages in close proximity to protected areas and villages further away, two decades after the commencement of eco-development initiatives. Our empirical strategy relies on a synthetic difference-in-differences approach with village fixed effects. We employ the Covariate Balancing Propensity Score (CBPS) method developed by Imai and Ratkovic (2014) to compute weights that reflect the probability of treatment. Relying on covariates that are likely to impact labor market outcomes, this approach ensures balance and aims to establish parallel trends between treated villages and the constructed counterfactual. Moreover, it is known for yielding robust and efficient estimators (Arkhangelsky et al., 2021) and has been increasingly employed in recent literature across various contexts to address endogeneity concerns (Waldron et al., 2017; Goodair and Reeves, 2022; Caloffi et al., 2022).

We evaluate labor market outcomes utilizing high-resolution data from three successive rounds of the Indian Population Census. Specifically, we rely on village-level data from the year 1991 as the baseline prior to the initiation of eco-development endeavors, 2001 as an intermediate assessment point, and 2011 as the comprehensive long-term endpoint. Assessing changes over two decades is key for analyzing the long-term outcome in the labor market in the context of developing countries, where labor and capital mobility are higher in the long run than over short horizons (Asher et al., 2021; Blakeslee et al., 2023).

The analysis unveils that from 1991 to 2011, amid a stable labor force participation, eco-development initiatives in protected areas resulted in a significant decline in year-round employment, accompanied by a concurrent rise in employment for less than half a year. Moreover, we find evidence of a shift in labor composition away from agriculture towards non-farm employment. Furthermore, recognizing that specific initiatives within the eco-development framework were tailored towards women, while others were geared more towards men, we investigate heterogeneity in labor market responses by gender. Overall, the estimated changes are present among both women and men, although they appear to have stronger magnitudes among the former. By the end of our study period in 2011, we find that the affected population still lags behind in terms of poverty and consumption compared to nearby areas.

We analyze several potential mechanisms that could elucidate how eco-development influences local employment dynamics. Firstly, we find no evidence that eco-development affected the local migration patterns, as measured by both the female-to-male ratio and the population counts of females and males. Secondly, we note higher literacy rates in treatment villages compared to control villages, an effect evident across genders. This improvement in educational outcomes is consistent with the presence of a greater number of industrial schools. Thirdly, we observe changes in land use patterns, with treatment villages showing significantly lower shares of cultivated land compared to control villages. This effect is primarily driven by substantially lower shares of irrigated land, partially offset by higher shares of rainfed land. Additionally, the share of forested land is higher in treatment villages. These effects align with the core objectives of eco-development, which are centered around the safeguarding of forests, soil, and water resources.

To further investigate whether restrictions in irrigation for water conservation purposes have influenced labor market outcomes, we employ a CBPS-weighted triple difference model, leveraging the exogenous discontinuity in the irrigation potential of villages. Following Asher et al. (2021), the discontinuity we explore is given by the relative altitude of villages to irrigation canals. The analysis acknowledges that canal irrigation is a significant water source in India, with most canals constructed centuries ago. Specifically, we restrict the sample to treatment and control villages in close proximity to an irrigation canal, defining villages with direct irrigation potential as those whose relative altitude is lower than that of the canal. In contrast, villages near irrigation canals but at higher altitudes are considered to have no direct access to irrigation, given the gravity-driven distribution of canal water. We demonstrate that villages with higher irrigation potential, where actual irrigation is more probable, experience a more significant restriction in the share of irrigated land following the initiation of eco-development activities in protected areas. In contrast, land use practices in villages with lower canal irrigation potential, and thus less reliant on irrigation practices, remain unaffected by eco-development.

The transition away from irrigated land to rainfed agriculture appears a valid candidate to explain the notable increase in the share of the population employed for less than six months a year. As rainfed agriculture is subject to the inherent variability of rainfall, it increases the demand for seasonal work. The shift away from year-round employment plausibly indicates an increase in the share of the population with irregular incomes.

This paper adds to a growing literature assessing the impacts of different types of environmental protection on labor market outcomes (Berman and Bui, 2001; Walker, 2013; Ferris, Shadbegian and Wolverton, 2014; Curtis, 2018; Hafstead and Williams III, 2018; Ferris and Frank, 2021; Cheng, Sims and Yi, 2023). We contribute by offering strong evidence of significant labor market effects in a developing country context. This is especially relevant given the pronounced tensions between the development needs of the local population and the imperative to preserve the rich biodiversity habitats. Unlike other large developing countries such as Brazil and China, which possess expansive protected areas in sparsely populated regions, India grapples with accommodating millions of inhabitants living in close proximity to protected areas (Cincotta, Wisnewski and Engelman, 2000; Jones et al., 2018; Pimm, Jenkins and Li, 2018; Ghosh-Harihar et al., 2019). This scenario presents significant challenges in harmonizing conservation efforts with development objectives.

A large share of the existing literature aims to identify the impact of conservation initiatives on poverty rates and consumption using individual or household-level survey data. The existing body of evidence yields a diverse range of findings, indicating positive, negative, or no effects on poverty and income levels for households and communities residing in or around protected areas (*e.g.,* Andam et al., 2010; Sims, 2010; Ferraro et al., 2013; Robalino and Villalobos, 2015; Ma et al., 2019; Estifanos et al., 2020). Studies from India have so far been limited to either qualitative assessments or case studies covering a limited number of households in protected areas (Gubbi, Linkie and Leader-Williams, 2008; Karanth and Nepal, 2012; Karanth et al., 2012; Chaudhuri, 2013; Ramachandra, Bharath and Gupta, 2018; Ghosh-Harihar et al., 2019). In a work closely related to ours, Cheng, Sims and Yi (2023) investigate the economic development and environmental impacts of China's Nature Reserves using county-level panel data between 1980 and 2010. Beyond a different geographical focus, we enhance granularity by conducting a detailed analysis at the village level employing census data. This approach offers a more comprehensive and representative understanding of the effects stemming from changes in protected area policies.

More broadly, our paper is part of a growing literature that studies determinants of labor force participation in developing countries (*e.g.*, Bryan, Chowdhury and Mobarak, 2014; Kaur, 2019; Asher and Novosad, 2020; Breza, Kaur and Shamdasani, 2021). The results presented in this study highlight that protected area management can significantly impact the workforce composition of the affected population. With these findings, we add to the existing body of evidence that, in developing countries, labor markets are rather flexible in the long term and adjust significantly to external shocks (Imbert and Papp, 2015; Akram, Chowdhury and Mobarak, 2017; Breza and Kinnan, 2021).

Furthermore, by uncovering changes in land use patterns, our study contributes to the literature examining the link between shocks in agricultural productivity and structural changes (Foster and Rosenzweig, 1996, 2007; Hornbeck and Keskin, 2015; Asher et al., 2021). Unlike previous studies, which concentrate on positive shocks to agricultural productivity, our paper provides evidence on the labor market impacts of a negative shock in the form of restrictions on irrigation and the promotion of rainfed agriculture.

The findings of our paper hold important policy implications. The employment opportunities generated by eco-development lead to a significant shift away from year-round employment to less than six-months in a year employment. This shift can result in less consistent income patterns throughout the year, potentially causing increased variability in consumption. Irregular incomes may exacerbate liquidity constraints, affect eligibility for financial credits, and heighten financial uncertainty among affected households (Beck, Levine and Loayza, 2000; Bauer, Chytilová and Morduch, 2012; Fafchamps, 2013; Hertzberg, Liberman and Paravisini, 2018). In regions with high poverty rates, such income patterns can be particularly concerning, raising questions about their impact on the overall well-being of the affected population (Fink, Jack and Masiye, 2020). Therefore, further research is essential to comprehensively understand the short- and long-term consequences of experiencing irregular incomes. From a policy perspective, it may be necessary to explore more stable employment creation through eco-development and integrate it with financial schemes[1] designed to help individuals manage irregular income flows.

I. Setting

A. The Western Ghats and Its Protected Areas

Amidst significant global biodiversity decline (Barnosky et al., 2011), protected areas stand as the cornerstone in the global battle against this loss (Jones et al., 2018). To maximize conservation benefits, protected areas should ideally be located in biodiversity hotspots, regions distinguished by elevated levels of species endemism (Cincotta, Wisnewski and Engelman, 2000). Worldwide, 25 biodiversity hotspots have been identified as high-priority regions for conservation (Myers et al., 2000). Remarkably abundant in biodiversity, the Western Ghats stands as the sole biogeographic region in India included in this top rank.

Designated as a UNESCO World Heritage Site, the Western Ghats is a mountain range that spans six states and runs for 1600 kilometres parallel to the western coastline of India. Despite covering less than six percent of India's total land area, the Western Ghats harbors over thirty percent of the country's total plant, fish, amphibian, reptile, bird, and mammal species. This region is the habitat for thirty percent of Asia's elephant population. It hosts 18 percent of the wild tigers, both distributed across an extensive network of national parks, wildlife sanctuaries, and tiger reserves (Bawa et al., 2007).

India follows a biogeographic zone classification system for planning and managing a representative network of protected areas. These zones encompass expansive, distinct land units categorized according to shared ecological attributes, representation of biomes, and the presence of similar communities and species. Among India's ten biogeographic zones, the Western Ghats has the highest percentage of terrestrial area under protection, amounting to ten percent. Approximately one-third of the Western Ghats, spanning over 160,000 square kilometers, comprises natural habitats. Within this region, there were 50 designated protected areas, including national parks and wildlife sanctuaries, in 1991. Collectively, these areas covered a combined area of 12,716 square kilometers, which represents approximately 8 percent of the region's total natural habitat area. Figure 1 illustrates the study area, emphasizing the Western Ghats biogeographic zone, along with the protected areas under analysis and the remaining non-protected regions.

[1]There are notable examples of financial schemes that aim to reduce the impacts of income variability, specifically tailored to a developing country context, aiming at improving financial inclusion (see, *e.g.* Barboni and Agarwal, 2023, and references therein).

In India, as well as globally, ecoregions endure significant human pressure, both within and outside protected areas (Jones et al., 2018; Maan and Chaudhry, 2019). The Western Ghats, known for its exceptionally high population density, faces the most intense human pressure among all global biodiversity hotspots (Cincotta, Wisnewski and Engelman, 2000). Indeed, Ramachandra, Bharath and Gupta (2018) demonstrate that from 1973 to 2016, forest cover in protected areas within the Western Ghats significantly diminished due to activities such as mining, agricultural plantations, and human habitation.

Governed by the Wildlife Protection Act (1972), India's protected areas are established with the primary goal of achieving biodiversity conservation, which involves imposing restrictions on wildlife hunting, poaching, and forest exploitation (Wildlife Protection Act, 1972). In the Western Ghats, the restrictions imposed in protected areas often diverge from strict adherence to biodiversity conservation as categorized by the International Union for Conservation of Nature (IUCN) under categories I and II. Instead, these areas permit certain human activities and resource extraction, categorized under III and IV. As observed by Anand et al. (2010), "many protected areas resemble doughnuts, with human land use within (e.g., hydro-electric projects, tea and coffee plantations) and around them." Main human activities in protected areas encompass the grazing of cattle, agricultural cultivation, mining, and tourism (Maan and Chaudhry, 2019).

The non-protected portion of the Western Ghats landscape features a blend of natural habitats and diverse land uses, encompassing human settlements, artificial reservoirs, and various agricultural activities. Moreover, broadly distributed forestry plantations play a significant role, constituting a substantial portion of human-utilized land throughout the Western Ghats landscape (Kale et al., 2016). Bhagwat et al. (2005) conducted a comparative analysis of protected and surrounding areas in the Kodagu district of the Western Ghats, revealing notable similarities in the distribution of biodiversity across both protected and non-protected surrounding areas.

Protected areas are established by either the central or state governments based on the biodiversity characteristics of the target areas, and it is not within the discretion of villages whether they will be included or not (Wildlife Protection Act, 1972).

B. Eco-development

Traditional approaches to biodiversity conservation historically established protected areas with stringent boundaries and minimal involvement of local communities. Critics argued that these methods often led to conflicts with local populations and failed to address the underlying drivers of resource exploitation, being ineffective in ensuring conservation (see Karanth and Nepal, 2012, and references therein). In response to these critiques, the concept of Integrated Conservation and Development Programs (ICDPs) emerged during the late 1970s and early 1980s, advocating for more participatory approaches. In India, a similar shift in the conservation paradigm occurred, recognizing the opportunity costs borne by local communities in the pursuit of biodiversity preservation (Gubbi and MacMillan, 2008; Chaudhuri, 2013).

The implementation of the ICDP approach in India was facilitated through a novel centrally sponsored scheme named the "Eco-development Scheme in and around National Parks and Sanctuaries including Tiger Reserves," initiated in 1991. This scheme provided financial support from the Central government to state governments to enable the implementation of eco-development initiatives in protected areas.

While the primary objective of protected areas remains biodiversity conservation of flora and fauna, with a special emphasis on forest preservation and wildlife conservation, eco-development initiatives within these areas aim to promote the economic development of the local population in a manner that is congruent with these goals. Eco-development facilitates a variety of activities, including: (1) lessening the reliance of local communities on resources from protected areas through the creation of alternative avenues for income and employment; (2) enhancing the ecological productivity of buffer zones; (3) introducing alternative energy sources; (4) implementing initiatives for soil and water conservation; (5) developing essential infrastructure for transport, education, and healthcare (*e.g.*, Ministry of Environment and Forest, Government of India, 1992, 2002). These goals clearly indicate that the concept of eco-development is inherently broad, encompassing a complex set of objectives and guidelines for sustainable economic development.

Table A-2 illustrates the timeline of eco-development activity implementation in India from 1991 to 2011. It is evident from the timeline that eco-development initiatives were funded through several rounds, covering multiple areas with overlaps in time, space, and scope. This setup aligns with eco-development's broad set of objectives. Moreover, the extended timeline and wide scope of the initiatives suggest that the impacts of eco-development activities unfold over the long term, rather than over a short time span.

II. Empirical Strategy

A. Data

We combine socio-economic and geospatial data to estimate the long-term impact of eco-development initiatives on labor market outcomes in protected areas. Our final dataset is structured as a georeferenced panel dataset at the village level in the Western Ghats region, covering three time points: 1991, 2001, and 2011. Table A-3 presents a comprehensive list of all variables utilized in our analysis, along with their definitions, temporal availability, and data sources.

Our analysis of intermittently available state-wise eco-development funding data, individual protected area management plans, and reports assessing the management of protected areas indicates that, out of the 50 Protected Areas in the Western Ghats in 1990, all but 2 National Parks and 4 Wildlife Sanctuaries were involved in various eco-development activities by 2000.

Hence, our analysis focuses solely on the 44 Protected Areas that initiated eco-development activities by 2000.

As the first step in the data generation process, we obtain the shapefile for the Western Ghats biogeographic zone from the India Biodiversity portal. We overlay it with the shapefiles of the protected areas, sourced from the Wildlife Institute of India.[2] Following this procedure, we identify a total of 44 protected areas in the Western Ghats region that were established before 1991 and had initiated eco-development initiatives before 2000. Table A-1 presents a comprehensive list of the protected areas included in our analysis, offering details regarding their type, state, notification year, and area coverage.[3] Subsequently, we identify villages of interest by overlaying these preceding geographic layers with the shapefiles of villages situated in the Western Ghats zone. The village shapefiles were acquired from the Socioeconomic Data and Applications Center (SEDAC), which operates under the purview of the U.S. National Aeronautics and Space Administration (NASA) (Meiyappan et al., 2018). This step of the data generation process is crucial for identifying treatment and control villages, as elaborated further in Section B. Figure 1 illustrates the study area.

Second, we merge the set of identified villages of interest with village-level socio-economic characteristics sourced from the open-access repository titled the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG). We utilize the most recent version of SHRUG available (SHRUG v.2.0) to extract socio-economic variables from the three most recent rounds of the Census of India: 1991, 2001, and 2011 (Asher et al., 2021).[4,5] This procedure provides us with access to the primary labor force outcomes for our analysis.

Third, we take several steps to enrich the village-level panel with a comprehensive set of fixed and time-varying characteristics. Specifically, from SHRUG v.2.0, we extract corresponding time-varying village-level data on population counts, literacy rates, number of schools, and land use.[6] Additionally, we acquire time-invariant geographical controls, including village-level

[2]Access to the protected areas shapefiles was generously granted by Malaika Mathew Chawla of Nature Conservation Foundation, India (Srivathsa et al., 2020).

[3]Out of the 50 protected areas established before 1991 in the Western Ghats, we excluded 6 areas from the analysis due to the absence of eco-development activities. Therefore, our analysis focuses on a total of 44 retained protected areas.

[4]As of the time of writing, the latest available Indian Population Census data is for the year 2011. A new wave was initially scheduled for 2021 but has been postponed due to the COVID-2019 pandemic. It is now anticipated to take place after the Indian national elections in October 2024.

[5]Merging the different waves of the Indian Population Censuses directly presents significant challenges. These challenges encompass variations in location identifiers, alterations in district boundaries, as well as the amalgamation and division of villages and towns. Additionally, the transition of villages to towns between Censuses further complicates the process. The SHRUG overcomes these limitations by providing a consistent set of location keys called the shrid. In the words of (Asher et al., 2021), "A shrid describes a geographical unit that can be mapped consistently across all rounds of the Indian Population and Economic Censuses from 1990 to 2013. In the majority of cases, a shrid describes a single village or town. When villages or towns have merged or separated in the sample period, [they have been aggregated] in the periods where they appear separately, such that the aggregation is represented by a single consistent shrid in all of the data." SHRUG v.2.0 was released in 2023.

[6]All variables are accessible upon merging the Village Directory of the Indian Census with the Primary Census Abstract.

mean elevation, terrain ruggedness (measured by the TRI index), distances from each village centroid to the nearest river and to the command area of the closest irrigation canal, as well as distances to the nearest town and the nearest town with a population of 100,000 and above.[7] Supplementary variables related to the relative altitude of irrigation canals compared to villages are sourced from Asher et al. (2021).

Fourth, we merge poverty and consumption estimates, exclusively available for the year 2011, utilizing the Socio-Economic Caste Census data sourced from the SHRUG v.2.0 database (Asher et al., 2021; Ministry of Rural Development, 2011).

Finally, we acquire annual village-level climatic variables (rainfall, maximum and minimum temperature) for each year between 1991 and 2011, utilizing data from the Indian Meteorological Department (IMD) (Srivastava, Rajeevan and Kshirsagar, 2009). Additionally, we calculate the distance from each village centroid to the nearest water body using water bodies shapefiles provided by the Shuttle Radar Topography Mission (STRM).

B. Identification

To assess the impact of the shift in the conservation paradigm towards eco-development in 1991 on labor force outcomes, we compare villages within or in immediate proximity to protected areas, which were subject to eco-development activities, with villages situated farther away, which are neither encompassed within protected areas nor exposed to eco-development activities. We restrict the analysis to protected areas in the Western Ghats that were established before or in the year 1990 and had commenced eco-development activities by at least year 2000.

The endogeneity challenge in our study stems from the potential selection of villages into treated and control groups. While villages cannot self-select into or out of protected areas, the determination of protected area boundaries is the responsibility of state and central governments, guided by biodiversity considerations (Wildlife Protection Act, 1972). While not explicitly documented, this inclusion might plausibly depend on characteristics at the village level. As a result, villages with specific attributes may be more likely to be located within protected areas. In fact, compared to the national average, protected areas are often found in remote locations, away from cities, or lands less suitable for agriculture due to higher elevation and steeper slopes (Ferraro, Hanauer and Sims, 2011). A simple comparison between treated and control villages may therefore not solely capture the effects of eco-development initiatives but also pre-existing differences at the village level that influenced subsequent labor market outcomes, potentially biasing estimates of the causal effect of eco-development initiatives.

We undertake four steps to address the non-random assignment of village locations. First, we restrict the control group villages to the Western Ghats biogeographic zone to ensure they

[7] The latter three variables are obtained from the SHRUG v.1.5 database, as they are not available in SHRUG v.2.0 at the time of writing. In this process, we lose 0.17 percent of the observations in our panel data out, overwhelmingly affecting control villages.

share similar attributes such as altitude, climate, topography, and vegetation with the treatment villages. Second, we rely on a synthetic difference-in-difference approach, where we weight observations according to the covariate balancing propensity score (CBPS) method developed by Imai and Ratkovic (2014). This adjustment addresses potential endogeneity by computing propensity scores that quantify the conditional probability of treatment assignment while ensuring covariate balance. Third, we incorporate village fixed effects to control for unobservable factors specific to each village and enhance the precision of our estimates (Arkhangelsky et al., 2021). Fourth, we introduce interaction terms between the post-period dummy and baseline village characteristics to further alleviate concerns about potential non-parallel trends. Overall, the key identifying assumption in this CBPS weighted difference-in-difference regression is that the remaining variation in treatment – conditional on the complete set of fixed effects and included controls – is unrelated to potential labor market outcomes. The results may be interpreted as causal impacts to the extent that this assumption is fulfilled.

Treatment definition. We assess the impact of protected areas implementing eco-development initiatives on the labor force participation of the local population. Figure 1 illustrates the map of the study area, encompassing the Western Ghats in India. Furthermore, it illustrates the geographic demarcation between the treatment and control villages. We designate villages from 0 to 1 kilometers from the protected area boundary as treatment villages. On the other hand, control villages are defined as those situated within a distance of 20 to 50 kilometers from the boundary of the protected area.[8] To mitigate the potential impact of spillover effects between treatment and control villages, we implement a buffer zone, excluding all villages within 1 to 20 kilometers from the protected area. Section III.A shows the robustness of our main results when subjected to varying definitions of treatment and control zones.

Covariate Balancing Propensity Score weighted Difference-in-differences. We rely on a synthetic difference-in-differences (SDID) framework, where the main model estimated is given by:

$$Y_{it} = \beta_1 \text{Post}_t + \beta_2 \text{Post}_t \times \text{Treatment}_i + X_{it}^{c\,\prime}\,\Gamma + \sum_k \delta_k X_{ik}^{g} \times \text{Post}_t + \gamma_i + \epsilon_{it} \tag{1}$$

where Y_{it} is one of the labor force outcomes, measured in village i in the year t. The primary outcome variables encompass the workforce participation rate and the proportion of main workers, defined as individuals employed for more than six months a year among the total workforce. Furthermore, we estimate shifts within the distribution of main workers across sectors, examining impacts on the proportion of cultivators and the proportion of workers engaged in

[8] We set the threshold for control villages at 50 kilometers, considering our focus on confining control villages to the Western Ghats region. The villages within the Western Ghats are situated at a maximum distance of 76 kilometers from the protected area, with approximately 96 percent of them located within a 50-kilometer of the protected area.

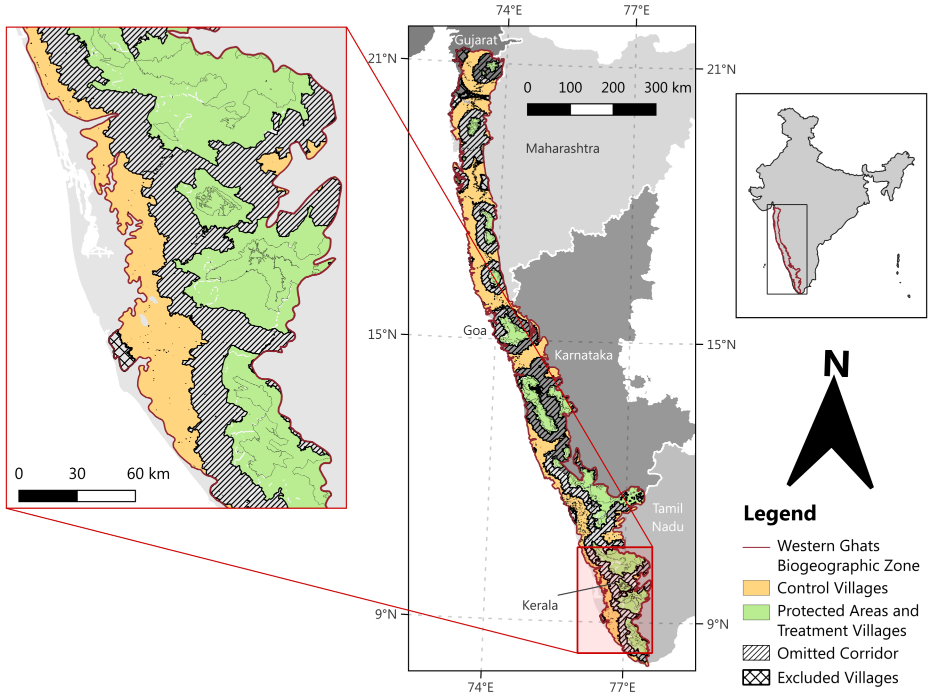

Figure 1 – Study Area Map with Treatment and Control Village Identification.

Notes: This map illustrates the location and boundaries of the Western Ghats bio-geographic region in India, highlighting its protected areas, including National Parks and Wildlife Sanctuaries. Additionally, it indicates the location of treatment and control villages, as defined for the purpose of this study. The boundary of the Western Ghats region is depicted in red. The protected areas and treatment villages are shown in green, with the boundaries of the protected areas represented by green lines. Treatment villages are identified as those whose boundaries are located within 0-1 km of the protected area boundary. Control villages (depicted in yellow) lie between 20-50 km away from the protected area boundary. Villages within 1-20 km of the protected area boundary are omitted, depicted as the gray shaded area. Source: Figure generated by the authors.

agricultural labor, household industry, and other occupations.

In our primary specification, we assess changes over a two-decade period following the initiation of eco-development activities, with 1991 serving as the baseline year and 2011 as the endpoint. Under this definition, Post_t is a binary indicator equal to 1 for the year 2011 and equal to 0 for 1991. Treatment_i represents the treatment dummy variable, which assumes a value of 1 for villages located within 1 kilometer of the protected area boundary and 0 for control villages, as defined above. Furthermore, the model incorporates a set of time-varying climatic controls X^c_{it} for annual rainfall, minimum annual temperature, and maximum annual temperature. Additionally, we introduce interaction terms between the Post_t dummy and a set of time-invariant geographic controls X^g_i, such as elevation, slope, terrain ruggedness, distance from the nearest town, and distance from the nearest large town. Furthermore, γ_i are village fixed effects and ϵ_{it} is the error term clustered at the village level. Finally, the model applies the SDID approach, where each observation is weighted by a vector of weights computed using the CBPS approach.

In an alternative specification, we estimate the CBPS-weighted difference-in-differences model including a time-invariant treatment indicator, while replacing the village fixed effects with district fixed effects:

$$Y_{it} = \beta_1 \text{Treatment}_i + \beta_2 \text{Post}_t + \beta_3 \text{Post}_t \times \text{Treatment}_i + X_{it}^{c\,\prime}\Gamma + \sum_k \delta_k X_{ik}^g \times \text{Post}_t + \theta_d + \epsilon_{it} \quad (2)$$

where all variables are defined as in Equation (1), and θ_d represents district fixed effects. The model allows us to recover an estimate for the average difference in outcome variables between treatment and control villages, both in the baseline and endline years. The same set of CBPS weights are applied as in Equation 1.

The CBPS Approach. We employ a synthetic DID method, where we rely on the Covariate Balancing Propensity Score (CBPS) method developed by Imai and Ratkovic (2014) to compute the vector of weights applied. The CBPS-weighted DID method estimates average treatment effects assuming unconfoundedness. Specifically, given observed confounding factors, the treatment assignment is considered random (Athey and Imbens, 2017). Alternative identification strategies operating under the unconfoundedness assumption consist of matching methods, reweighting, or propensity scores (see Heckman and Vytlacil, 2007; Imbens and Rubin, 2015, for reviews).

We integrate CBPS-weighting into the DID framework, akin to the synthetic control approach originally developed by Abadie and Gardeazabal (2003) and Abadie, Diamond and Hainmueller (2010), where the average treatment effect is estimated relying on a weighted average of several control units. While Abadie and Gardeazabal (2003) employ a minimum distance approach over selected covariates to calculate the weights, Doudchenko and Imbens (2016) propose alternative methods for computing weights, particularly when dealing with a large number of control units.

However, these weighting methods have faced criticism for not adequately prioritizing covariates that reduce bias. Specifically, they may not effectively emphasize covariates correlated with both outcomes and the treatment indicator. More effective methods involve estimating the relationships between potential outcomes and covariates, as well as between the treatment indicator and covariates (Athey and Imbens, 2017). To address these concerns, the recent literature proposes computing weights that directly balance covariates between treatment and control groups (Hainmueller, 2012; Graham, de Xavier Pinto and Egel, 2012; Graham, Pinto and Egel, 2016; Imai and Ratkovic, 2014; Athey, Imbens and Wager, 2018; Arkhangelsky et al., 2021). This reweighting process aims to more closely emulate randomized treatment assignment.

We adopt the approach proposed by Imai and Ratkovic (2014), which aligns with recent advancements in synthetic difference-in-differences and offers a robust estimator with favorable asymptotic properties (Arkhangelsky et al., 2021). CBPS weighting represents an advancement over traditional propensity score methods, which typically focus on either modeling treatment assignment or optimizing covariate balance. In contrast, CBPS performs both tasks simultaneously by computing propensity scores for treatment assignment and ensuring that the resulting weights achieve covariate balance, utilizing flexible models (Imai and Ratkovic, 2014).

The CBPS procedure utilizes a set of moment conditions that are implied by the covariate balancing property, ensuring mean independence between treatment and covariates after inverse propensity score weighting. Furthermore, the standard estimation procedure, such as the score condition for maximum likelihood, is incorporated whenever appropriate (Imai and Ratkovic, 2014).

Employing CBPS weighting instead of matching enables us to retain the entire sample, thereby reducing selection bias. This approach stands in contrast to previous studies on protected area policies, where matching techniques may result in the loss of a significant portion of the sample (for example, Cheng, Sims and Yi, 2023).

The CBPS method is increasingly employed across diverse research domains to address selection bias. For instance, Waldron et al. (2017) utilize CBPS weighting to evaluate the effectiveness of conservation investments in curbing biodiversity loss across 109 countries. Similarly, Alkon (2018) employ CBPS estimation to address pre-treatment disparities in economic development levels among sub-districts in India, with the aim of assessing the spillover effects of special economic zones. Bensch, Kluve and Stöterau (2021) use CBPS weighting to account for variations in individual entrepreneur attributes in a study on the dissemination of improved cookstoves and small solar products in Kenya. Gomez et al. (2021) employ CBPS-weighting to assess the impact of banks' income gap on the transmission of monetary policy to bank lending. Fukumoto, McClean and Nakagawa (2021) utilize CBPS-weighting to assess the impact of school closures on the spread of COVID-19 cases. Goodair and Reeves (2022) investigate the impact of outsourcing medical care services to the private sector on treatable mortality rates in England. Lastly, Caloffi et al. (2022) rely on CBPS-weighting to evaluate the impact of innovation policy mixes on small and medium enterprises' propensity to innovate and engage in R&D.

Constructing CBPS Weights. To compute CBPS weights, the first crucial step involves selecting village-level characteristics likely to influence treatment assignment while remaining unaffected by the treatment itself. Moreover, covariate selection is based on their capacity to impact the outcomes of interest, ensuring that in the absence of treatment, outcomes should be comparable between treatment and control villages. This is essential for minimizing concerns related to the existence of non-parallel trends.[9]

Existing research has shown that protected areas are frequently situated in more remote regions, often characterized by steeper slopes and higher elevations (Andam et al., 2010; Ferraro, Hanauer and Sims, 2011). To mitigate potential disparities in these geographic features, we incorporate average slope, elevation, and terrain ruggedness as covariates when computing the

[9]To derive the CBPS weights, we use the Stata command 'psweight' with the *ate* option to estimate the average treatment effect in the population (Kranker, 2019).

CBPS weights.

Moreover, we incorporate covariates that may influence the composition of the labor force by affecting agricultural productivity. Specifically, we account for decadal averages of climatic variables, including rainfall, minimum temperature, and maximum temperature. We include the mean annual rainfall for the periods 1991-2001 and 2002-2011, along with the mean values of both minimum and maximum temperatures over the same periods.

In addition to climate variables affecting the temporal availability of water for agriculture, we incorporate two key variables describing a village's consistent access to water. Firstly, we use the distance from the village centroid to the nearest water body as a measure of irrigation accessibility. Secondly, we include a binary variable indicating whether the village lies within 10 kilometers of a canal's command area, serving as a more refined indicator of irrigation access (Asher et al., 2021; Blakeslee et al., 2023). Section III.B.2 presents supplementary analyses that delve deeper into a village's irrigation potential.

To address potential disparities in access to labor markets outside the village, we incorporate the distance from a village's centroid to the nearest town, as well as to the nearest large town with a population exceeding 100,000. Including both variables allows for a more comprehensive assessment of the village's connectivity to external labor markets. The distance to the nearest town offers insight into the proximity of basic amenities and services, potentially attracting labor from the village. Conversely, the distance to the nearest large town signifies access to a broader array of job opportunities, amenities, and infrastructure, which could notably impact labor market dynamics within the village.

Incorporating this set of ten covariates, we compute CBPS weights that ensure balance between treatment and control villages. After excluding villages with missing covariate or outcome variable data, our analysis includes a total of 6,705 villages, with 1,265 villages in the treatment group and 5,440 villages in the control group.

Figure 2 depicts the distribution of the computed CBPS weights and their relative magnitudes. Panel A displays CBPS weight values in the control group across various percentiles, ranging from 0.79 at the 1st percentile to 2.13 at the 99th percentile. The narrow distribution of weights is further illustrated in Panel B, where we order control villages in ascending order based on the magnitude of their weight and compute cumulative weights. The gray diagonal line at a 45-degree angle illustrates a hypothetical scenario in which all control villages would have been allocated equal weights of 1. The black solid line represents the cumulative sum of ordered CBPS weights in our sample. The consistent positioning of the black line below the gray diagonal line indicates that the distribution of CBPS weights in our sample is non-uniform. Some villages are assigned weights below 1, while others receive weights above 1. However, the proximity of the black line to the gray one suggests a narrow distribution of weights, ensuring that no control village is massively underrepresented or overrepresented.

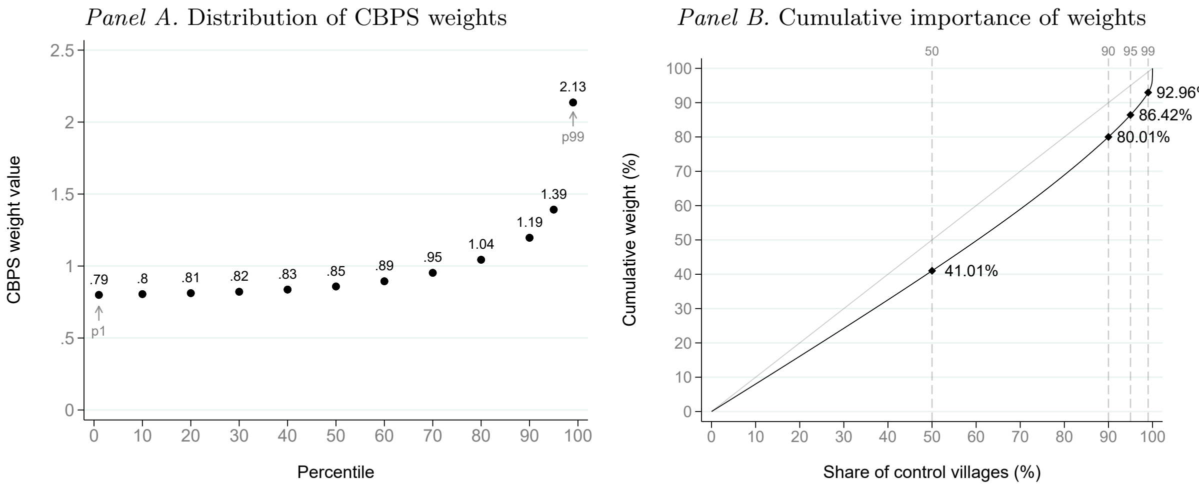

Figure 2 – CBPS weights distribution and relative importance.

Notes: This figure presents the distribution and relative importance of CBPS weights applied to villages in the control group (N = 5,440). The weights correspond to those analyzed in Table 1. Panel A illustrates the distribution of CBPS weights values at different percentiles of the weight distribution, ranging from percentile 1 to percentile 99. Panel B displays the cumulative importance of weights, with control villages arranged in ascending order of their CBPS weight values. The arrangement progresses from lowest on the left-hand side to highest on the right-hand side. The Y-axis represents the cumulative weight, calculated as the sum of the ordered CBPS weights. The gray diagonal line, angled at 45 degrees, illustrates the scenario where all control villages would have been assigned an equal weight of 1. The black solid line represents the cumulative sum of the ordered CBPS weights in our sample. The vertical dashed gray lines mark four points in the cumulative weight distribution, representing the moments where the share of control villages reaches 50%, 90%, 95%, and 99%, respectively.

Covariate Balance. Table 1 provides an overview of village-level characteristics for both treatment and control villages. Furthermore, it compares mean differences across the two groups, both without and with the constructed CBPS weights.

In the absence of CBPS weights, significant differences between treatment and control villages emerge at the baseline, as evidenced by p-values < 0.001 in the pairwise t-tests assessing the difference in means, along with the F-test of joint significance. While statistically significant, differences in magnitude across all variables are relatively low, except for elevation and rainfall. Treatment villages consistently show a higher mean elevation but lower rainfall.

Applying the CBPS weights ensures statistical balance across covariates, as evidenced by pairwise t-tests with p-values > 0.1 for each mean difference, as well as the F-test for joint significance, yielding p-values above 0.90 in each year. Notably, both the mean absolute standardized difference and the maximum absolute standardized difference exhibit minimal values.[10]

[10]The mean absolute standardised difference is a measure of the average standardized difference in covariate means between the treated and control groups after applying weights. A lower value indicates better balance and suggests that the treatment and control groups have similar distributions of covariates. The maximum absolute standardized difference is the largest absolute standardized difference among all covariates after applying propensity score weights. It identifies the covariate that contributes the most to the imbalance between the treatment and control groups. A smaller maximum absolute standardized difference indicates better balance and suggests no individual covariate strongly drives the imbalance.

Table 1 – Sample characteristics and balance tests for treatment and control villages.

	Village-level characteristics		Difference in means			
	Treatment	Control	Unweighted	CBPS-weighted		
	1991 (1)	1991 (2)	1991 (3)	1991 (4)	2001 (5)	2011 (6)
Mean Elevation (m)	550.83	257.89	292.94***	0.95	0.95	0.95
	(8.45)	(3.65)				
Mean Slope (degrees)	10.25	8.43	1.82***	0.01	0.01	0.01
	(0.13)	(0.06)				
Annual Rainfall (mm)	2089.82	2728.36	-638.55***	-10.28	-8.11	-1.41
	(30.67)	(17.53)				
Annual Average Max temperature (° C)	30.52	31.38	-0.86***	-0.04	-0.03	-0.01
	(0.04)	(0.01)				
Annual Average Min temperature (° C)	19.92	20.43	-0.51***	-0.01	-0.01	-0.02
	(0.03)	(0.01)				
Distance from water body (km)	5.91	6.61	-0.71***	-0.02	-0.02	-0.02
	(0.18)	(0.09)				
Canal within 10 km	0.35	0.48	-0.13***	-0.00	-0.00	-0.00
	(0.01)	(0.01)				
Terrain ruggedness	13.29	10.78	2.51***	0.01	0.01	0.01
	(0.21)	(0.08)				
Distance from closest town (km)	26.26	24.40	1.86***	0.10	0.10	0.10
	(0.46)	(0.26)				
Distance from large town (km)	76.40	66.91	9.49***	-0.31	-0.31	-0.31
	(0.86)	(0.45)				
F-test of joint significance (P-value)			<0.001	0.918	0.969	0.988
Mean absolute standardized diff.				0.01	0.01	0.01
Max absolute standardized diff.				0.03	0.02	0.02
Observations	1,265	5,440	6,705	6,705	6,705	6,705

Notes: This table presents summary statistics of pre-treatment village-level characteristics and balance tests between control and treatment villages. Standard deviations are reported in parentheses. Columns (3) to (6) capture the difference in means between treatment and control characteristics. Column (3) presents the unweighted differences in means for the year 1991. Columns (4) - (6) present the difference in means for the years 1991, 2001, and 2011, respectively, where the CBPS-weights have been applied. See Table A-3 for variable definitions. Significant t-test estimates are denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Achieving covariate balance across time is crucial in panel data analysis. While we construct a fixed set of CBPS weights across different years, these weights are specifically computed to ensure balance in each of the years 1991, 2001, and 2011. This approach ensures that variations in rainfall and temperature over time do not disrupt balance.[11]

[11] Note that the only time-varying village level variables are rainfall, annual maximumum temperature, and annual minimum temperature. All other village covariates are fixed.

III. Results

A. Labor force participation

A.1 Full sample estimates

The primary outcomes of interest center around the participation of the population in the labor force. Our main focus is on the workforce participation rate and the proportion of main workers. Main workers are defined as individuals working for 6 months or more every year. We estimate the CBPS-weighted difference-in-differences models of Equations (1) and (2) with village fixed-effects and district fixed-effects, respectively.

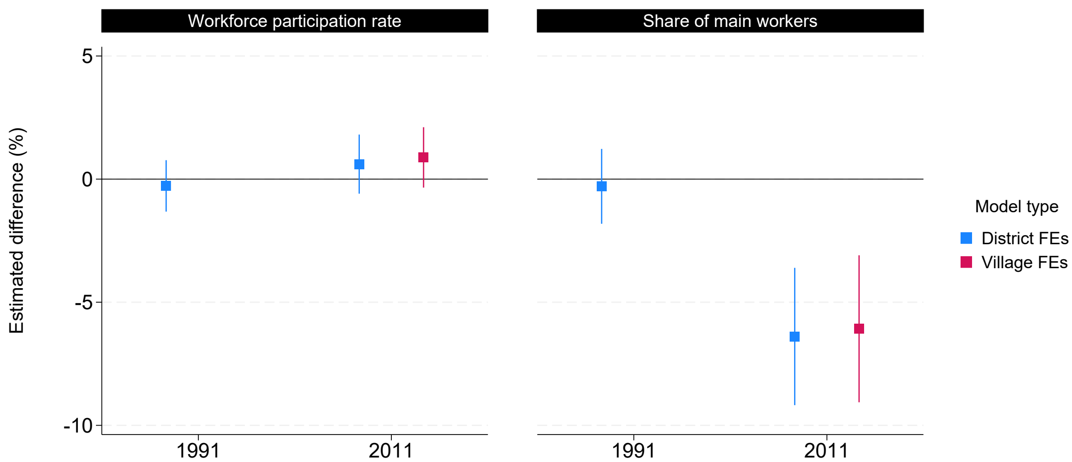

Figure 3 – Estimated Differences in Workforce Participation Rate and Share of Main Workers Between Treatment and Control Villages in 1991 and 2011

Notes: This figure presents estimates of Equations (1) and (2) from the main text. The CBPS weights applied correspond to those analyzed in Table 1. The dependent variables are the annual workforce participation rate (left panel) and the share of main workers (right panel). Both panels present the estimated marginal treatment effect in 1991 and 2011. The coefficients depicted in blue are estimated with SDID models with district fixed effects, while controlling for time-varying village characteristics (rainfall, and minimum and maximum temperature), as well as time-invariant ones (elevation, slope, terrain ruggedness, distance to the closest water body, vicinity to the command areas of a canal within 10 km, distance to closest town, and distance to closest large town). The coefficients depicted in red are estimated with SDID models with village fixed effects, controlling for the same set of time-varying village characteristics. Additionally, these models include interaction terms between the *2011* dummy with the set of time-invariant village-level controls. By including the village fixed effects, it is not possible to estimate the marginal treatment effect for 1991. In all models, standard errors are clustered at the village level. See Table A-3 for variable definitions. The confidence intervals correspond to the 95 level.

Figure 3 provides a visual representation of our key findings. In a nutshell, the workforce participation of treated villages appears to be at a similar level to that of control villages, both in 1991 and 2011, indicating no differential development over time. Moreover, the share of main workers starts at similar levels in 1991 in control and treatment villages. However, by 2011, treatment villages exhibit a workforce participation rate 6 percentage points lower than control villages. This suggests that the eco-development initiatives affecting villages in and around protected areas may have shifted the participation of the village population from year-round employment to employment for less than 6 months a year. Results appear robust across the two model specifications.

To further investigate these results, we analyze different sectors of employment. Table 2 presents the CBPS-weighted DID coefficients estimated using village fixed-effects models of Equation (1), capturing differential changes in labor force participation between treatment and control villages by 2011. Panel A presents the estimation results for the full sample.[12] The 6 percentage point difference in the share of main workers between treatment and control villages in 2011, as observed in Figure 3, can be attributed to reduced year-round employment in the agricultural and household industry sectors. Specifically, these sectors account for an estimated difference of approximately 3.08 percentage points (p-value $= 0.053$) and 0.97 percentage points (p-value < 0.001), respectively.

In summary, our analysis reveals that over the two decades since the initiation of eco-development initiatives in protected areas, the overall workforce participation rate of the population has exhibited similar trends in villages located in and around protected areas compared to those further away. However, we find evidence of differential changes in employment patterns, with treated villages experiencing lower rates of year-round employment, particularly in the agricultural and household industry sectors. As the overall workforce participation remains unaffected, the reduced year-round employment is substituted with employment for less than six months a year.[13]

The observed decrease in agricultural employment aligns with research findings from other developing countries. Cheng, Sims and Yi (2023) document a negative impact on county-level employment in China, along with changes in the composition of employment. These changes include a shift away from resource-intensive primary and secondary industries towards service-based tertiary industries. This shift suggests additional employment opportunities related to tourism and other service sectors. Moreover, Clements and Milner-Gulland (2015) bring evidence from Cambodia indicating that households residing near protected areas have diversified their livelihoods post-conservation initiatives, engaging in non-agricultural activities like retail operations or service provision.

A.2 Heterogeneous Effects by Gender

Eco-development initiatives may have differential impacts on women's labor force participation compared to men. This hypothesis gains support from the fact that certain eco-development initiatives, such as the establishment of self-help groups and provision of micro-credit loans, specifically target women, potentially diverting their employment away from the agricultural sector. Conversely, other types of initiatives may be more geared towards men. For instance, the Management Effectiveness Evaluation Reports highlight vocational training initiatives, including

[12] Appendix Table A-4 presents the results of estimating Equation (1) without the CBPS weights. These results are largely aligned in sign and significance with those in Table 2 (Panel A).

[13] Due to lack of data availability for 1991, we cannot present the results of the differences-in-differences estimation for the sectoral composition of employment for less than six months a year.

Table 2 – Changes in labour force participation, 1991 - 2011.

	Workforce participation rate	Share main workers	Share of main workers by sector: Cultivators	Agricultural labor	Household industry	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All						
Post × Treatment	0.882	-6.079***	-0.152	-3.079*	-0.967***	-0.049
	(0.626)	(1.523)	(1.187)	(1.593)	(0.197)	(1.423)
Observations	13,410	13,410	13,394	13,394	13,394	13,394
adj. R^2	0.438	0.203	0.674	0.367	0.211	0.535
Panel B: Male						
Post × Treatment	-0.310	-4.367***	-0.682	-2.138	-0.284*	3.104**
	(0.470)	(1.313)	(1.175)	(1.503)	(0.172)	(1.451)
Observations	13,410	13,410	13,390	13,390	13,390	13,390
adj. R^2	0.520	0.258	0.675	0.345	0.179	0.681
Panel C: Female						
Post × Treatment	1.915*	-7.608***	1.365	-5.224***	-2.247***	6.105***
	(0.985)	(2.189)	(1.519)	(1.809)	(0.392)	(1.768)
Observations	13,408	13,306	13,146	13,146	13,146	13,146
adj. R^2	0.438	0.165	0.584	0.381	0.201	0.564

Notes: This table presents CBPS-weighted difference-in-differences estimates of Equation (1) from the main text to measure the impact of eco-development on village-level labour market outcomes. The CBPS weights applied correspond to those analyzed in Table 1. Treatment villages are defined as those that lie between 0-1km of the protected area. Control villages are villages located 20-50km away. The baseline year is 1991. *Post* is a dummy indicator equal to 1 for observations in year 2011 and 0 for observations from 1991. *Post* × *Treatment* is the DID estimate of interest, capturing the difference in outcomes between treatment and control villages in 2011 relative to 1991. All regressions include village fixed effects and time-varying controls for rainfall, and minimum and maximum temperature. Additionally, we interact the *Post* dummy with time-invariant village-level controls, including elevation, slope, distance to the nearest water body, being within 10-km distance from the command area of an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. Standard errors are clustered at the village level. See Table A-3 for variable definitions. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

carpentry, masonry, electrical work, plumbing, and roles such as drivers and tour guides, organized by protected area management (Wildlife Institute of India, 2016). Furthermore, changes in the workforce participation of one gender could have spillover effects on the employment patterns of the other. For example, previous research on gender-based labor division suggests that a shift of male workers away from agriculture could lead to an increase in farming-related tasks undertaken by women (see Jayachandran, 2015, and references theirein).

To address such considerations, we provide estimates of the labor market impacts of eco-development for each gender (see Panels B and C in Table 2). First, as noted previously, we observe no disparities in the workforce participation rate between treatment and control villages in 2011 among the overall population. However, the gender-specific analysis reveals that, while male workforce participation remains unaffected, the workforce participation of females is approximately 1.9 percentage points (p-value = 0.052) higher in 2011 in treatment villages compared to control villages.

Second, the decline in year-round employment in 2011 in treatment villages compared to control villages is evident across genders, although the extent varies. Specifically, while the share of main workers among males is lower by 4.37 percentage points (p-value = 0.001), among females, the difference widens to 7.61 percentage points (p-value = 0.001).

Third, when examining shifts in year-round employment across sectors, we find that the decrease in participation in the agricultural and household industry sectors is consistently more pronounced among women than among men. In 2011, the share of female main workers employed in agriculture drops by 5.22 percentage points (p-value = 0.004) in treatment villages compared to control villages, while male employment in agriculture remains unaffected on average (with an effect size of -2.14 percentage points, p-value = 0.155). Similarly, household industry employment decreases by 2.25 percentage points (p-value $<$ 0.001) for women, but only by 0.28 percentage points (p-value = 0.099) for men.

Furthermore, both female and male year-round workforce participation in *other* industries experiences a significant increase in 2011 in treatment villages compared to control villages. However, the effect is more pronounced among women, with an increase of 6.11 percentage points (p-value = 0.001), compared to men, who experience an increase of 3.10 percentage points (p-value $<$ 0.001).

Overall, our findings provide consistent evidence that over the first two decades, eco-development initiatives in protected areas have led to structural shifts in the labor force of affected villages. The observed changes in the sectoral composition of year-round employment, moving away from agriculture and into other sectors, align with the scope and structure of eco-development initiatives. Specifically, eco-development programs typically generate person-days of non-farm employment, encompassing various activities such as habitat improvement and development projects, afforestation programs, fire management, revitalization of indigenous saplings, excavation of trenches for elephant protection, construction and maintenance of solar fences, and the establishment and upkeep of additional infrastructure such as roads. Additionally, community-based ecotourism within protected areas provides local residents with employment opportunities as tourist guides, trekking guides, safari vehicle drivers, canteen operators, and involvement in branding and selling local products and non-timber forest products through eco-shops, authorized by protected area authorities (Wildlife Institute of India, 2016).

A.3 Impacts between 1991-2001

Our main analysis concerns changes in labor force participation over two decades. Given that eco-development programs commenced as early as 1991, it prompts the inquiry into how fast the labor market responded to these initiatives. With this scope, we conduct our primary model estimation incorporating three distinct time points: 1991 as the baseline year, 2001 as the midline reference, and 2011 as the concluding endline assessment. This approach enables us to gauge dynamic treatment effects for 2001 and 2011, respectively. Our findings reveal that the discernible divergence in labor force participation between treatment and control villages surfaces only over the extended time horizon (refer to Appendix Table A-9). This suggests that the influence of eco-development on the labor force primarily materialized over the longer duration rather than in the short term.

The outcomes observed for the period 1991-2001 come as no surprise, given the slow and gradual implementation of the eco-development approach; for specific details, refer to Appendix Table A-2. A considerable amount of time and resources were devoted to preparatory measures, encompassing the establishment of village eco-development committees, the facilitation of alternative employment opportunities through training, the initiation of microenterprises, and the cultivation of trust and rapport between protected area managers and local communities (Wildlife Institute of India, 2016).

Our results underscore thus the imperative of evaluating cumulative impacts over extended timeframes, as shifts in livelihood strategies prompted by conservation initiatives can unfold gradually over the course of several years (Reynaert, Souza-Rodrigues and van Benthem, 2023; Beauchamp, Clements and Milner-Gulland, 2018; Ferraro and Pressey, 2015).

A.4 National Parks and Wildlife Sanctuaries

The 44 protected areas in our sample consist of 11 National Parks and 33 Wildlife Sanctuaries. National Parks and Wildlife Sanctuaries differ in their levels of protection and the extent of constraints imposed on human activities. National Parks, distinguished by their elevated protection status, prohibit grazing of livestock and private landholding within their bounds. In contrast, within a wildlife sanctuary, grazing of livestock is generally allowed, though it may be regulated, controlled, or even prohibited under certain circumstances. Additionally, while the extraction or utilization of forest resources in a Wildlife Sanctuary necessitates approval from the state authorities, such activities within a National Park mandate endorsement from the national authorities (Wildlife Protection Act, 1972).

To address these underlying differences in protection, we estimate a triple difference model. In this model, we interact the type of protected area with the treatment indicator and the dummy variable representing the year 2011. Thus, we estimate the following CBPS-weighted triple difference model:

$$\begin{aligned} Y_{it} =& \beta_1 \text{Post}_t + \beta_2 \text{Post}_t \times \text{Treatment}_i + \beta_3 \text{Post}_t \times \text{PA type}_i + \\ & \beta_4 \text{Post}_t \times \text{Treatment}_i \times \text{PA type}_i + X_{it}^{c\prime}\Gamma + \sum_k \delta_k X_{ik}^g \times \text{Post}_t + \gamma_i + \epsilon_{it} \end{aligned} \tag{3}$$

where all variables are defined as in the main model described in Equation (1), and PA type_i is a binary indicator equal to 1 if village i is closest to a protected area classified as a National Park, and equal to 0 if it is closest to a Wildlife Sanctuary. The distinction applies to both control and treatment villages. Given the 44 protected areas in our sample, we have a total of

1,820 villages (consisting of 343 treatment and 1,477 control) in close proximity to a National Park, and 4,885 villages (comprising 992 treatment and 3,963 control) in close proximity to a Wildlife Sanctuary. Consequently, statistical power is higher for estimating treatment effects in the case of Wildlife Sanctuaries compared to National Parks.

Figure A-1 in the Appendix presents the results of the estimation. We find that the aggregate results presented in Table 2 are driven by villages close to Wildlife Sanctuaries. In 2011, among villages close to Wildlife Sanctuaries, we estimate that the workforce participation rate is 1.55 percentage points (p-value = 0.022) larger in treatment villages than in control villages. Moreover, the proportion of the workforce employed year-round is 7 percentage points lower in treatment villages than in control villages (p-value < 0.001). In contrast, no significant differences between treatment and control villages close to National Parks arise in 2011, neither in terms of the workforce participation rate nor the share of year-round employment.

The results are consistent with the heightened protection and stricter regulations on human activities enforced within National Parks. Given the more limited scope for human activities within National Parks, we observe diminished impacts of eco-development initiatives on both the workforce participation and composition.

A.5 Robustness

Treatment definition. Our primary specification defines treatment villages as those situated within 1 km of the protected area boundary. This choice aligns with the 2022 decision of the Supreme Court of India, which mandates a minimum eco-sensitive zone of 1 kilometer around each protected area. To test for robustness, we initially narrow down the treatment definition to include only villages situated within the boundary of the protected area. Second, to account for previous extended delineations of eco-sensitive zones and potential spillover effects on the labor force in neighboring villages, we expand the treatment group to encompass all villages within a maximum radius of either 5 or 10 kilometers from the boundary of the protected area.[14]

We compute new CBPS weights for each treatment definition to ensure balance with the control villages in each respective case. Across all treatment definitions, the estimated SDID coefficients consistently show similar signs and levels of significance compared to those observed in the main specification. Specifically, the workforce participation rate remains similar in treatment and control villages across all specifications.

Furthermore, regardless of the treatment definition, the share of main workers in treatment villages is significantly lower than that in control villages in 2011. However, this difference

[14] Prior to the 2022 ruling, the Wildlife Board of India adopted the 2002 Wildlife Conservation Strategy, which proposed designating land within a 10-kilometer radius of the boundaries of national parks and wildlife sanctuaries as Eco-Fragile Zones under the Environmental Protection Act. This initiative aimed to restrict development activities around protected areas. However, opposition from many states, driven by human population and development pressures, led to a revised decision in 2005. This decision suggested that the delineation of eco-sensitive zones should be tailored to each site. For example, the Kalakad Mundanthurai National Park, utilized a 5-kilometer radius as the zone of influence.

diminishes as the treatment definition expands to include villages located farther away from the protected areas (see Appendix Figure A-2). To elaborate, in the main specification using the 0-1 km definition, the proportion of main workers in treatment villages is 6.09 percentage points lower than in the control group. When restricting the treatment to only villages located within the boundary of the protected areas, this difference increases to 6.36 percentage points. Additionally, the estimates indicate a difference of 4.84 and 4.23 percentage points for treatment definitions of 0-5 km and 0-10 km, respectively (all estimated coefficients have a p-value < 0.001).

Overall, the evidence suggests that the effects of eco-development on labor force participation diminish as the distance to the protected areas increases. Nevertheless, these effects remain significant and extend beyond the immediate boundaries of the protected areas, albeit to a lesser degree, impacting neighboring villages.

Control definition. We alter the constraint regarding the minimum distance of control villages from the protected area boundary. While the main specification included only villages situated within a 20 to 50-kilometer range from the protected area boundary in the control group, we now explore two additional scenarios: one encompassing villages within the 15 to 50-kilometer range and the other within the 25 to 50-kilometer range. Both scenarios confirm the robustness of our main results (see Appendix Figure A-3).

Covariates and error clustering. We provide evidence that our main results are robust to estimating Equation (1) without time-varying covariates and without time-invariant controls interacted with the *Post* (see Appendix Table A-5). This is expected, given that the SDID approach applied relies on CBPS weights that are specifically computed to ensure covariate balance between treatment and control villages, while estimating the probability of treatment assignment. Moreover, our results are robust to estimating Equation (1) with state-by-year fixed effects (see Appendix Table A-6). Finally, results are robust to clustering the standard errors at higher administrative units, such as sub-district or district levels (see Appendix Table A-7 and Table A-8).

B. Mechanisms

In this section, we explore potential mechanisms by which eco-development initiatives have led to shifts in the labor force participation of the impacted population. We pursue two avenues of inquiry: firstly, an examination of changes in the socio-demographic characteristics of the population, and secondly, an exploration of shifts in land use patterns.

B.1 Socio-Demographic Changes

Migration. When considering socio-demographic attributes, one of the key factors that can shape the labor supply is the migration patterns of the population (*e.g.*, Bryan, Chowdhury and

Mobarak, 2014; Kleemans and Magruder, 2018). For instance, the eco-development approach may stimulate local economic activities and attract in-migration. Alternatively, the various restrictions imposed on agriculture and collection of natural resources around protected areas, may draw people away from agriculture, and without an alternative employment generation, it may push people to out-migrate in search of economic opportunities. Such migration trends could manifest directly in alterations to the population's workforce participation and composition.

To evaluate shifts in male-dominated migration patterns, the female-to-male sex ratio – *i.e.*, the number of women per thousand men – serves as a commonly used proxy (Angrist, 2002). Male-dominated out-migration for work can result in an inflated regional female-to-male sex ratio surpassing 1000 females per 1000 males. We estimate the CBPS-weighted difference-in-differences model from Equation (1) using the female-to-male sex ratio as an outcome variable to assess differential migration patterns in treatment and control villages. Moreover, we assess changes in the population count of males and females separately to allow for the possibility of in- and out-migration of both sexes.[15]

Table 3 displays the outcomes of our estimation. In the model where the female-to-male sex ratio serves as the dependent variable, the coefficient of interest $Post \times Treatment$ in the SDID framework is found to be not statistically different from zero, indicating that eco-development initiatives in protected areas have not influenced the pace of out-migration, either by slowing it down or accelerating it. Moreover, these findings are further supported by analyzing the population counts of both males and females, where the SDID coefficient is also not statistically different than zero, showing that the adult population size exhibited similar trends in treatment and control villages over 1991-2011. Overall, the results consistently suggest that migration did not contribute significantly to the divergent development of the labor market in villages affected by eco-development initiatives compared to control villages.

A limitation of relying on the sex ratio and population counts to measure migration is that we can only estimate net changes in population size, without accounting for changes in population composition. It is possible that incoming and outgoing migration flows balanced each other, resulting in stable population counts, yet the quality and work availability of the population may have changed. While village-level data is unavailable to directly test this hypothesis, the evidence provided by other migration proxies suggests otherwise. For this hypothesis to hold true, the number of individuals moving in would need to equal those moving out across both genders and between treatment and control villages. Although this scenario is possible, the likelihood of meeting these multiple conditions is low.

Education. A second mechanism we investigate is that of changes in the education level of the workforce. To this aim, we first assess shifts in the literacy rate of the village population. In 2011, we observe higher literacy rates for both genders in treatment villages compared to control ones.

[15] To capture a more accurate portrayal of population dynamics influencing the available workforce, we exclude individuals aged 6 years or younger from this analysis.

Table 3 – Changes in Population Count and Literacy, 1991 - 2011.

	Sex Ratio	Population count		Literacy Rate	
		Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)
Post x Treatment	8.179	3.159	10.439	1.960***	2.296***
	(32.708)	(11.496)	(28.107)	(0.690)	(0.686)
Observations	13,410	13,410	13,410	13,410	13,408
adj. R^2	0.965	0.646	0.969	0.781	0.858

Notes: This table presents CBPS-weighted difference-in-differences estimates of Equation (1), where the dependent variable is either the female-to-male sex ratio, the population count, or the literacy rate of population aged 6 and above. See Table A-3 for variable definitions. Treatment villages are defined as those that lie between 0-1km of the protected area. Control villages are villages located 20-50km away. The baseline year is 1991. *Post* is a dummy indicator equal to 1 for observations in year 2011 and 0 for observations from 1991. $Post \times Treatment$ is the DID estimate of interest, capturing the estimate difference in outcomes between treatment and control villages in 2011. All regressions include village fixed effects and time-vaying controls for rainfall, and minimum and maximum temperature. Additionally, we interact the *Post* dummy with time-invariant village-level controls, including elevation, slope, distance to the nearest water body, being within 10-km distance from the command arrea of an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. Standard errors are clustered at the village level. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Specifically, the effect sizes are +1.96 (p-value = 0.005) for males and +2.3 (p-value = 0.001) for females; see Table 3.

To further probe this channel, we investigate changes in the number and type of schools. Table 4 illustrates the SDID estimates, revealing no divergent changes in the number of schools across most levels, with the exception of industrial schools. Specifically, we observe that the number of industrial schools is marginally higher (effect size +0.006, p-value = 0.007) in treatment villages in 2011 compared to control villages. The results align with the objectives of eco-development initiatives, which often prioritize enhancing the skill sets of the labor force for diverse non-farm employment opportunities. This observation echoes the discussion presented in Section III.A.1.

Summarizing our analysis, we find no significant alterations in migration patterns attributable to eco-development initiatives in protected areas. Hence, we conclude that migration is not a primary mechanism influencing labor force participation in this context throughout the study period. Instead, the significant rise in literacy rates and the increased presence of industrial schools emerge as probable channels that have facilitated the observed shift toward non-farm employment. This trend aligns with qualitative findings from Cambodia, where households with higher levels of education living near protected areas showed a tendency to diversify into non-agricultural activities (Clements et al., 2014).

Table 4 – Changes in the Number of Schools, 1991 - 2011.

	All schools	Primary	Middle	Secondary	Industrial	Training
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Treatment	-0.054	-0.029	-0.040	-0.004	0.006***	0.014
	(0.121)	(0.095)	(0.042)	(0.036)	(0.002)	(0.020)
Observations	13,410	13,410	13,410	13,410	13,410	13,410
adj. R^2	0.835	0.763	0.751	0.679	0.011	0.053

Notes: This table presents CBPS-weighted difference-in-differences estimates of Equation (1), where the dependent variable is number of schools in a village, by type. See Table A-3 for variable definitions. Treatment villages are defined as those that lie between 0-1km of the protected area. Control villages are villages located 20-50km away. The baseline year is 1991. *Post* is a dummy indicator equal to 1 for observations in year 2011 and 0 for observations from 1991. $Post \times Treatment$ is the DID estimate of interest, capturing the estimate difference in outcomes between treatment and control villages in 2011. All regressions include village fixed effects and time-vaying controls for rainfall, and minimum and maximum temperature. Additionally, we interact the *Post* dummy with time-invariant village-level controls, including elevation, slope, distance to the nearest water body, being within 10-km distance from the command area of an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. Standard errors are clustered at the village level. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

B.2 Changes in Land Use Patterns

The primary objective of protected areas is to safeguard the natural habitat (Jones et al., 2018). Eco-development initiatives within these areas are designed to engage the local population in diverse activities, aimed at creating alternative sources of employment to reduce dependency on protected area resources and promoting soil and water conservation (see Section I.B). For instance, eco-development objectives may encompass afforestation efforts that extend beyond forest preservation (Ministry of Environment and Forest, Government of India, 2002). Furthermore, the established guidelines for management may impose restrictions on specific land use practices to minimize adverse effects on soil and water resources, potentially triggering shifts in the dynamics of the labor supply as a consequence.

We investigate this mechanism by analyzing changes in the distribution of land use across various categories. The estimation results, presented in Table 5, focus on three specific land use types: forest land, cultivated land (divided into irrigated and rainfed), and non-cultivated land (divided into non-agricultural and culturable wasteland).

Firstly, in comparison to control villages, the proportion of forest land is approximately 2.5 percentage points (p-value $= 0.003$) higher in treatment villages in 2011.

Secondly, we observe that the proportion of cultivated land is 4.3 percentage points lower (p-value < 0.001) in treatment villages compared to control ones in 2011. Furthermore, when distinguishing between irrigated and rainfed cultivated land, our analysis indicates that the diminished share of cultivated land in treatment villages compared to control villages is primarily driven by a significantly lower proportion of irrigated land. Specifically, the proportion of irrigated land is approximately 8.4 percentage points lower (p-value < 0.001) in treatment villages. In contrast, treatment villages exhibit a 3.8 percentage points higher share of rainfed land (p-value $= 0.006$) compared to control villages.

Thirdly, we note no significant differences in the overall proportion of non-cultivated land. However, the share of non-agricultural land is notably higher in treatment villages compared to control villages in 2011 (effect size of $+1.6$ percentage points, p-value $= 0.043$).

Collectively, our findings provide evidence that eco-development initiatives in protected areas have influenced the distribution of land used for various economic activities. These effects manifest in two main ways. Firstly, treatment villages exhibit higher rates of forested land, reflecting the overarching objectives of biodiversity conservation in these areas. Secondly, we observe a significant reduction in the proportion of cultivated land in treatment villages, driven by a sizable drop in irrigated agricultural land, and partly offset by an increase in the share of rainfed land.

These results are consistent with the decline in year-round employment in the agricultural sector and the simultaneous increase in year-round non-farm employment as documented in Table 2. Moreover, they can offer an explanation to the significant rise in employment for less than six months a year. Irrigation, being less reliant on precipitation patterns, enables crop produc-

Table 5 – Changes in Land Use, 1991 - 2011.

	Share of land use, by type.						
	Forest	Cultivated			Non-cultivated		
		All	Irrigated	Rainfed	All	Non-agriculture	Culturable wasteland
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post x Treatment	2.491***	-4.310***	-8.436***	3.818***	1.819	1.610**	0.209
	(0.825)	(1.231)	(1.196)	(1.397)	(1.226)	(0.794)	(0.890)
Observations	13,410	13,410	13,410	13,410	13,410	13,410	13,410
adj. R^2	0.892	0.602	0.527	0.547	0.470	0.342	0.330

Notes: This table presents CBPS-weighted difference-in-differences estimates of Equation (1), where the dependent variable is either the population count, the sex ratio, or the literacy rate of population aged 6 and above. See Table A-3 for variable definitions. Treatment villages are defined as those that lie between 0-1km of the protected area. Control villages are villages located 20-50km away. The baseline year is 1991. *Post* is a dummy indicator equal to 1 for observations in year 2011 and 0 for observations from 1991. $Post \times Treatment$ is the DID estimate of interest, capturing the estimate difference in outcomes between treatment and control villages in 2011. All regressions include village fixed effects and time-vaying controls for rainfall, and minimum and maximum temperature. Additionally, we interact the *Post* dummy with time-invariant village-level controls, including elevation, slope, distance to the nearest water body, being within 10-km distance from an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. Standard errors are clustered at the village level. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

tion expansion throughout the seasons (Blakeslee et al., 2023), thereby generating employment opportunities throughout the year. In contrast, the timing and quantity of rainfall closely govern the planting and harvesting seasons in rainfed agriculture, leading to concentrated periods of activity during the rainy season and thereby creating seasonal employment opportunities.

Irrigation potential

Our analysis identifies changes in land use patterns, particularly the limitation in irrigated agricultural land, as a key mechanism by which eco-development initiatives in protected areas influence the composition of the labor force among nearby populations. However, the validity of this mechanism hinges on crucial assumptions within our empirical identification strategy. Specifically, it requires strong balance between the samples of control and treatment villages in terms of their irrigation potential, as well as the presence of parallel trends in actual irrigation patterns before the initiation of eco-development activities.

Throughout our analysis, we ensured balance between treatment and control by applying CBPS-weights computed from key determinants of irrigation potential, including time-varying climate factors (rainfall and temperature), as well as fixed geographical characteristics (elevation, slope, terrain ruggedness, distance from the nearest water body, and an indicator for proximity to the command area of an irrigation canal within a 10-kilometer radius). Additionally, to further mitigate concerns regarding non-parallel trends, the CBPS-weighted DID models were estimated with controls for both the time-varying climate factors and an interaction between the time-invariant geographical characteristics and the *Post* dummy.

We now present two additional tests to further probe the impacts of eco-development on land use patterns, in particular the share of irrigated land. To this aim, we leverage additional variation in the irrigation potential of villages. The main hypothesis underlying this analysis is that changes in irrigation patterns are more likely to occur in areas with higher irrigation potential. This hypothesis is grounded in the expectation that villages equipped with established irrigation systems are prime candidates for modifications or restrictions imposed by eco-development initiatives. Conversely, villages with lower initial irrigation potential may have less infrastructure subject to regulation or modification, leading to comparatively smaller impacts on the proportion of irrigated land.

As a first step in testing this hypothesis, we categorize both treatment and control villages using a naive measure of their irrigation potential. We use the distance between a village's centroid and the nearest river or the command area of the closest irrigation canal as a proxy for irrigation potential. By applying a threshold of 10 kilometers, we differentiate between villages with higher irrigation potential (distances less than 10 kilometers) and villages with lower irrigation potential (distances greater than 10 kilometers). The choice of cutoff reflects the severe restrictions on irrigation for villages located more than 10 kilometers away from the water source (Asher et al., 2021; Blakeslee et al., 2023).

The pre-dating of rivers and irrigation canals to that of protected areas is crucial for our identification. Specifically, rivers came into existence in prehistoric times, while the network of irrigation canals, India's second source or irrigation after groundwater, has mostly been built in the 19th and early 20th centuries. Furthermore, due to the substantial costs associated with their construction, canal routes are challenging to modify once they are established (see Asher et al., 2021, and references therein).

We incorporate this binarization of a village's irrigation potential into a triple difference model, expressed as:

$$\begin{aligned} SI_{it} =& \beta_1 \text{Post}_t + \beta_2 \text{Post}_t \times \text{Treatment}_i + \beta_3 \text{Post}_t \times \text{Close}_i + \\ & \beta_4 \text{Post}_t \times \text{Treatment}_i \times \text{Close}_i + X_{it}^{c\prime}\Gamma + \sum_k \delta_k X_{ik}^g \times \text{Post}_t + \gamma_i + \epsilon_{it} \end{aligned} \tag{4}$$

where SI_{it} is share of irrigated land in village i in the year t. Post_t is a dummy indicator equal to 1 for the year 2011 and equal to 0 in 1991. Treatment_i is the treatment dummy, which takes the value 1 for villages within 1 kilometer of the protected area boundary and 0 for control villages, as defined above. Close_i is the indicator for a village located within 10 kilometers of a river or the command area of an irrigation canal. The model incorporates a set of time-varying climatic controls X_{it}^c for annual rainfall, minimum annual temperature, and maximum annual temperature. Additionally, we introduce interaction terms between the Post_t dummy and a set of time-invariant geographic controls X_i^g, such as elevation, slope, terrain ruggedness, distance from the nearest town, and distance from the nearest large town. Finally, γ_i are village fixed effects and ϵ_{it} is the error term clustered at the village level.

The results of the triple difference estimation with CBPS-weighting are displayed in *Panel A* of Figure 4. We find consistent evidence that the treatment has a greater impact on the share of irrigated land in villages with higher irrigation potential compared to those with more limited irrigation potential. Specifically, treated villages located within 10 kilometers of the nearest river exhibit a share of irrigated land that is 12.7 percentage points lower (p-value < 0.001) than that of control villages with similar irrigation potential and other geographic characteristics. In turn, the difference shrinks to 6.7 percentage points (p-value < 0.001) when comparing treatment and control villages with lower irrigation potential (located more than 10 kilometers away from a river). When the irrigation potential is proxied by distance to the closest irrigation canal, the differences between treatment and control villages are estimated as -9.6 percentage points (p-value < 0.001) and -7.6 (p-value < 0.001) for villages with higher and lower irrigation potential, respectively. Overall, the findings support the hypothesis that the effects of eco-development initiatives on the share of irrigated land in villages near protected areas are more pronounced when the irrigation potential is higher.

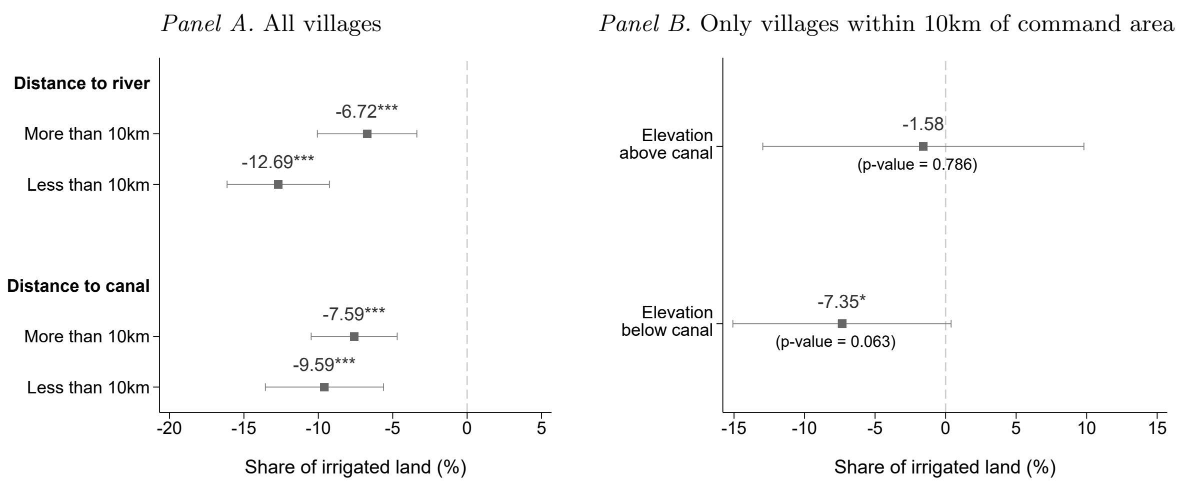

Figure 4 – Changes in the share of irrigated area in treatment villages compared to control villages in 2011, by access to irrigation source.

Notes: This figure presents estimates of Equation (4) from the main text. The dependent variable is the share of irrigated land of a village. *Panel A* employs the entire sample for estimation and utilizes the CBPS weights described in Table 1. *Panel B* restricts the sample to villages located within 10 kilometers of distance and within 50 meters of elevation from the command area of a canal, excluding villages within 2.5 meters in elevation of the canal, following the procedure in Asher et al. (2021). For the analysis in Panel B, new CBPS weights have been constructed to ensure balance between treatment and control villages in the reduced sample. All depicted coefficients correspond to the estimated SDID coefficient *Treatment* $\times$ *Post*, distinguishing between villages with higher irrigation and lower irrigation potential. All regressions include village fixed effects and time-varying controls for annual rainfall, annual minimum temperature, and annual maximum temperature. Additionally, we interact the *Post* dummy with time-invariant village-level controls, including elevation, slope, distance to the nearest water body, being within 10-km distance from an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. In Panel B, we additionally control for an interaction term between the relative elevation of a village to the canal and the *Post* dummy. Standard errors are clustered at the village level. See Table A-3 for variable definitions. The confidence intervals correspond to the 95 level. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

While proximity to a river or irrigation canal can offer an indication of irrigation potential, it may also introduce noise into the measurement. Among others, variations in altitude could impede the efficient utilization of the water source. Canal water distribution primarily relies on gravity, with water flowing downhill from canals, rendering it accessible only to villages situated at lower altitudes than the canal itself. Conversely, villages located near canals but at higher altitudes do not reap the benefits of irrigation (Asher et al., 2021). Taking these factors into account, Asher et al. (2021) utilize the relative elevation of villages to canals as the running variable in a regression discontinuity design to estimate the impacts of irrigation on long-term agricultural productivity in India.

As a second test for our hypothesis, we now utilize the relative elevation of villages to irrigation canals as a more accurate proxy for irrigation potential. Importantly, the discontinuity at zero in relative elevation constitutes an exogenous source of variation in irrigation potential, facilitating a causal interpretation of results. To ensure comparability across the geographic characteristics of villages in all aspects except for irrigation potential, we restrict our sample according to three criteria, following the methodology established by Asher et al. (2021). Firstly, we include only villages located within a 10-kilometer radius of the command area of an irrigation canal, beyond which access to canal irrigation is severely restricted, even for villages situated at lower altitudes than the canal. Secondly, to enhance comparability, we retain only villages within a vertical elevation range of +-50 meters from the canal. Thirdly, to account for villages with parts both above and below the canal, we exclude villages within 2.5 meters in elevation of the nearest canal in either direction.

Following this restriction process, we retain a sample of 1,872 villages, comprising 265 villages located within 1 kilometer of a protected area boundary and 1,607 control villages.[16] The sample restriction, though reducing statistical power, ensures high comparability between villages with and without direct access to irrigation. For this sample, we calculate new CBPS-weights and estimate a triple difference model using Equation (4), where the Close_i indicator is replaced with a binary variable equal to 1 if the elevation of the village is below that of the canal (indicating direct access to irrigation) or above (indicating no access to irrigation). In addition to the covariates outlined in Equation (4), we include an interaction term between the relative elevation of a village to that of a canal and the Post_t dummy.

Panel B in Figure 4 presents the estimated difference between treatment and control villages in 2011, distinguishing between villages with direct access to irrigation and those without. We find evidence aligned with that of *Panel A*. Namely, in 2011, two decades after the commencement of eco-development activities, treatment villages with direct access to irrigation exhibit a share of irrigated land that is 7.35 percentage points lower (p-value = 0.063) than that of control villages with direct access to irrigation. In contrast, the difference is not statistically significant between treatment and control villages without direct access to irrigation (effect size

[16] Among the 265 treatment villages, 138 villages are situated at an altitude below the canal, while 127 villages are above the canal. Among the control villages, 1,066 villages are located above the canal, with 541 villages below the canal.

-1.58, p-value = 0.786).

In summary, this section offers robust evidence that since the initiation of eco-development initiatives, villages situated near protected areas have diminished their share of irrigated land, partially offsetting this reduction with an increase in the proportion of rainfed land for agriculture. Such shifts in land use appear to align with the observed decline in the proportion of year-round employment in the agricultural sector and the concurrent rise in non-farm employment. Additionally, as rainfed agriculture tends to generate seasonal employment, it emerges as a plausible mechanism driving the observed increase in the proportion of employment for less than six months a year.

C. Poverty and Consumption Estimates

The changes induced by eco-development in the regional labor market prompt inquiries concerning the broader well-being of the affected population. In this section, we investigate existing differences in the economic standards between the villages in and near the protected areas and the control villages. Historically, the population residing around protected areas has typically been poorer and less economically developed compared to other regions (Ferraro, Hanauer and Sims, 2011). Here, our investigation focuses on determining whether substantial disparities continue to exist between the treatment and control villages at the end of the study horizon.

Drawing on village-level poverty and consumption data – available solely for 2011 – we conduct a weighted linear regression, employing the same set of CBPS weights as in our primary analysis to maintain balance between the baseline characteristics of treatment and control villages. We estimate the following model:

$$I_i = \beta \, \text{Treatment}_i + X_i^{c\prime}\Gamma + X_i^{g\prime}\Delta + \epsilon_i \tag{5}$$

where I_{it} is the outcome variable for village i in the year 2011. We consider two sets of outcome variables. The first set comprises aggregated poverty measures, while the second set examines ownership of various assets specific to agricultural labor. We include climatic controls X_i^c for annual rainfall, minimum annual temperature, and maximum annual temperature. Additionally, we include a set of geographic controls X_i^g, such as elevation, slope, terrain ruggedness, distance from the nearest town, and distance from the nearest large town.

Table 6 presents the estimation results for 6 proxies of poverty, indicating that in 2011, two decades after the commencement of eco-development activities, villages near protected areas exhibit higher poverty rates compared to those farther away. This is evidenced by higher shares of the village population with incomes below the poverty line, measured at 4.98 percentage points (p-value < 0.001) according to the World Bank definition and at 4.26 percentage points (p-value < 0.001) according to the Tenduklar definition. Furthermore, this is reflected in lower levels of per capita consumption, with an average annual disparity of 1,281 INR (p-value <

0.001), approximately 7.2% lower than that of control villages. We find further robustness of these results when analyzing the nightlights index – a measure of luminosity captured by satellites during nighttime, serving as a proxy for economic activity and development levels in a given area. Specifically, treatment villages exhibit a nightlight index approximately 6.7 points (p-value = 0.009) or 7% lower than that of control villages. Finally, we investigate two measures reflecting overall household economic well-being, which are not influenced by seasonal fluctuations: the proportion of households with solid roofs and the proportion with solid walls. We find that treatment households are 9.1 percentage points less likely to reside in a house with solid roofs (p-value < 0.001), while the share of households with solid walls does not significantly differ from that of households in control villages. Table A-10 and Table A-11 show qualitative robustness of these results when standard errors are clustered at the sub-district and district levels, accordingly.

Table 6 – Poverty and Consumption Estimates, 2011.

	World Bank poverty rate	Tenduklar poverty rate	Per capita consumption (annual INR)	Nightlights index	Share of households with solid roof	Share of households with solid walls
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	4.980***	4.262***	-1281.233***	-6.685***	-9.104***	-0.614
	(0.603)	(0.568)	(160.928)	(2.544)	(0.669)	(0.861)
Observations	6,161	6,161	6,161	6,161	6,161	6,161
adj. R^2	0.400	0.411	0.272	0.226	0.164	0.259

Notes: This table presents CBPS-weighted estimates of Equation (5) to quantify the difference in poverty rates and consumption levels between villages in close proximity to protected areas and those located further away, as measured in the year 2011. Each column corresponds to a different dependent variable. See Table A-3 for variable definitions. Treatment villages are defined as those that lie between 0-1km of the protected area. Control villages are villages located 20-50km away. All regressions include controls for rainfall, minimum and maximum temperature, elevation, slope, distance to the nearest water body, being within 10-km distance from the command area of an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Next, to inform our results on changes in labor force participation and sectoral composition, we examine the prevalence of ownership shares of labor-related assets. Table 7 presents the estimation results of CBPS-weighted linear regressions over 6 outcome variables. We find that in treatment villages, the share of households that own agricultural equipment is 0.64 percentage points (p-value = 0.082) below that of control villages. Additionally, a disparity of -0.79 percentage points (p-value = 0.024) emerges in terms of ownership of irrigation equipment. Furthermore, the share of households in treatment villages owning a vehicle is lower by 1.17 percentage points (p-value = 0.005) for vehicles with 2-3 wheels, and by 0.04 percentage points (p-value = 0.089) for vehicles with 4 wheels. Finally, we observe no statistical differences in the share of households owning an enterprise or mechanized agricultural equipment between treatment and control villages.

In summary, we find evidence of higher poverty rates and lower consumption levels among

Table 7 – Ownership shares, 2011.

	Enterprise	Agricultural equipment	Mechanized agricultural equipment	Irrigation equipment	Vehicle with 2 or 3 wheels	Vehicle with 4 wheels
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.105	-0.644*	0.040	-0.786**	-1.174***	-0.042*
	(0.307)	(0.370)	(0.170)	(0.347)	(0.421)	(0.025)
Observations	6,161	6,161	6,161	6,161	6,161	6,161
adj. R^2	0.029	0.137	0.076	0.129	0.203	0.118

Notes: This table presents CBPS-weighted estimates of the difference in poverty rates and consumption levels between villages in close proximity to protected areas and those located further away, as measured in the year 2011. The CBPS weights applied correspond to those analyzed in Table 1. Each column corresponds to a different dependent variable. Treatment villages are defined as those that lie between 0-1km of the protected area. Control villages are villages located 20-50km away. All regressions include controls for rainfall, minimum and maximum temperature, elevation, slope, distance to the nearest water body, being within 10-km distance from the command area of an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. See Table A-3 for variable definitions. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

the population residing close to protected areas two decades following the commencement of eco-development initiatives. While previous literature notes that these areas were generally less economically developed at the outset, our results suggest that, even with potential advancements, a considerable disparity persists in 2011 compared to the surrounding regions. Additionally, we observe a reduced share of ownership in assets typically associated with agricultural employment, such as vehicles and agricultural and irrigation equipment. This aligns with our main results, indicating that exposure to eco-development initiatives has shifted the labor force away from the agricultural sector and led to a decrease in the proportion of irrigated land.

IV. Discussion and Conclusions

Protected areas are widely regarded as effective policy measures for safeguarding biodiversity (Waldron et al., 2017), yet their success is often constrained by the significant pressure exerted by the economic development needs of surrounding populations (Cincotta, Wisnewski and Engelman, 2000; Jones et al., 2018). Eco-development initiatives in protected areas aim to alleviate these tensions by offering alternative employment opportunities, thereby reducing dependence on protected area resources and mitigating the adverse environmental impacts of economic activities.

In this paper, we investigate the labor market impacts of eco-development initiatives undertaken in 44 protected areas of the Western Ghats, one of the world's most important biodiversity hotspots (Myers et al., 2000). Additionally, due to its highest population density, the region experiences unparalleled human pressure globally (Cincotta, Wisnewski and Engelman, 2000).

We find robust evidence that eco-development initiatives have influenced the labor market during the period from 1991 to 2011. By the end of the study period, while workforce participation rates remain comparable, villages within or near protected areas exhibit a diminished share of year-round employment, coupled with a higher proportion of employment lasting less than 6 months annually compared to more distant villages. Analysis of the sectoral composition of year-round employment reveals a shift away from agricultural and household industry employment towards other occupations. The primary mechanism identified is a reduction in irrigated agricultural land, partially counterbalanced by an increase in rainfed agriculture, conducive to seasonal employment. In 2011, the end of our study period, we find that the affected population still lags behind in terms of poverty and consumption relative to nearby areas.

Shifting employment towards the non-farm sector is likely to play a significant role in the long-term success of India's conservation initiatives. However, if not accompanied by stable income and employment generation, such a shift can potentially enhance the vulnerability of the local population. In this context, it is crucial that future research further investigates the short- and long-term effects of a shift toward seasonal or irregular employment in protected areas. A valuable insight for eco-development policy would then be to integrate tailored financial strategies to assist individuals in managing income variability and its consequences and explore avenues for generating employment that provides stable incomes.

One positive outcome evident in our analysis is the increase in literacy rates across genders and the establishment of a higher number of industrial schools. Although we note that by 2011, affected villages still exhibit higher poverty levels compared to surrounding areas, this disparity may narrow over time, facilitated by improved education. However, due to data availability constraints, our analysis cannot assess more recent trends. Nonetheless, such an opportunity will arise with the completion of the next round of the Indian Population Census, expected in 2025.

While our study provides valuable insights into the labor market impacts of eco-development initiatives in protected areas, it is essential to acknowledge certain limitations inherent in our analysis. Firstly, the data availability spans three decades, but lacks data for periods preceding 1991 or succeeding 2011. While the CBPS-weighted DID approach is designed to ensure comparability in trends between treatment and control areas, data limitations constrain our ability to empirically demonstrate the presence of parallel trends for the period preceding the commencement of eco-development activities. Additionally, we are not able to explore recent developments in labor market outcomes. Furthermore, in absence of higher frequency data, we are not able to estimate more granular dynamic effects of eco-development. Secondly, the paper's analysis is constrained by the overlapping timing of different eco-development activities across protected areas. This overlap limits our measurement to aggregate average effects and prevents us from delineating the impacts of specific initiatives. Thirdly, as common to many empirical analyses, the findings of our paper pertain to a specific region. We concentrate on the Western Ghats in India, a critical area for biodiversity conservation. Consequently, the findings presented here hold particular relevance. However, given the focused nature of our analysis, we have limited insight into whether these findings can be generalized to other regions in India or beyond. Fourthly, we have explored various mechanisms through which eco-development initiatives could impact labor market outcomes. However, there could be additional mechanisms that we have not investigated. For example, the promotion of seasonal employment for wildlife tourism or fire management, both of which fall under the scope of eco-development, could significantly influence local employment patterns and economic activities. Unfortunately, we lack the necessary data to test such mechanisms. Finally, while our empirical approach relies on a fixed effects differences-in-differences model with CBPS weights, acknowledged for its ability to address endogeneity concerns, it does not enjoy the benefits of evaluating policy effects with field experiments. While a randomized controlled trial would offer more transparency with respect to mechanisms, its implementation might not be feasible in this context due to practical constraints such as the long-term nature of eco-development initiatives and ethical considerations regarding the random allocation of interventions in protected areas.

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Appendix

A. Protected Areas in the Western Ghats

Table A-1 – Protected Areas in the Western Ghats: Status as of 1990.

No.	Name	Type	State	Notification Year	Area (km^2)
1	Bansda	National Park	Gujarat	1979	23.99
2	Purna	Wildlife Sanctuary	Gujarat	1990	160.84
3	Shettihally	Wildlife Sanctuary	Karnataka	1974	395.6
4	Bandipur	National Park	Karnataka	1974	874.2
5	Brahmagiri	Wildlife Sanctuary	Karnataka	1974	181.29
6	Someshwara	Wildlife Sanctuary	Karnataka	1974	88.4
7	Sharavathi Valley	Wildlife Sanctuary	Karnataka	1974	431.23
8	Mookambika	Wildlife Sanctuary	Karnataka	1974	247
9	Bhadra	Wildlife Sanctuary	Karnataka	1974	492.46
10	Nugu	Wildlife Sanctuary	Karnataka	1974	30.32
11	Dandeli	Wildlife Sanctuary	Karnataka	1975	475.02
12	Biligiri Rangaswamy Temple	Wildlife Sanctuary	Karnataka	1987	539.52
13	Pushpagiri	Wildlife Sanctuary	Karnataka	1987	102.92
14	Talakaveri	Wildlife Sanctuary	Karnataka	1987	105.01
15	Anshi	National Park	Karnataka	1987	250
16	Kudremukh	National Park	Karnataka	1987	600.32
17	Nagarahole (Rajiv Gandhi)	National Park	Karnataka	1988	643.39
18	Gudavi	Wildlife Sanctuary	Karnataka	1989	0.74
19	Peechi-Vazhani	Wildlife Sanctuary	Kerala	1958	125
20	Neyyar	Wildlife Sanctuary	Kerala	1958	128
21	Wayanad	Wildlife Sanctuary	Kerala	1973	344.44
22	Parambikulam	Wildlife Sanctuary	Kerala	1973	285
23	Idukki	Wildlife Sanctuary	Kerala	1976	70
24	Eravikulam	National Park	Kerala	1978	97
25	Periyar	National Park	Kerala	1982	350
26	Peppara	Wildlife Sanctuary	Kerala	1983	53
27	Thattekadu	Wildlife Sanctuary	Kerala	1983	25.16
28	Chinnar	Wildlife Sanctuary	Kerala	1984	90.44
29	Chimmony	Wildlife Sanctuary	Kerala	1984	90
30	Aralam	Wildlife Sanctuary	Kerala	1984	55
31	Silent Valley	National Park	Kerala	1984	89.52
32	Shendurney	Wildlife Sanctuary	Kerala	1984	100.32
33	Radhanagari	Wildlife Sanctuary	Maharashtra	1958	351.16
34	Tansa	Wildlife Sanctuary	Maharashtra	1970	304.81
35	Chandoli	National Park	Maharashtra	1985	308.97
36	Koyana	Wildlife Sanctuary	Maharashtra	1985	423.55
37	Bhimashankar	Wildlife Sanctuary	Maharashtra	1985	130.78
38	Phansad	Wildlife Sanctuary	Maharashtra	1986	69.79
39	Kalakad	Wildlife Sanctuary	Tamil Nadu	1976	223.58
40	Mundanthurai	Wildlife Sanctuary	Tamil Nadu	1977	567.38
41	Srivilliputhur (Grzd.Sqrl)	Wildlife Sanctuary	Tamil Nadu	1988	485.2
42	Indira Gandhi (Annamalai)	National Park	Tamil Nadu	1989	117.1
43	Indira Gandhi (Annamalai)	Wildlife Sanctuary	Tamil Nadu	1989	117.1
44	Mudumalai	National Park	Tamil Nadu	1990	103.23

Notes: This table presents a comprehensive list of all protected areas included in our analysis, arranged by state. It exclusively features protected areas established prior to 1991. Protected areas situated in the Western Ghats that were established after 1991 are excluded from our analysis.

B. Eco-development Implementation Timeline

Table A-2 – Eco-development Implementation Timeline 1991-2011.

Year	Implementation
1991 - 1992	In the initial phase, the Centrally Sponsored Scheme (CSS) "Eco-development in and around National Parks and Sanctuaries including Tiger Reserves" (henceforth Eco-development Scheme) was launched with an initial budget allocation of INR 111 lakhs. Implementation commenced in 18 national parks and wildlife sanctuaries across 10 states. Eco-development plans for 11 out of the initial 18 Tiger Reserves were formulated and processed.
1992 - 1993	Eco-development plans for 12 out of 19 Tiger Reserves were processed. The National Afforestation and Eco-Development Board (NAEB) was established to promote afforestation, tree planting, ecological restoration, and eco-development activities nationwide. Emphasis is placed on rejuvenating degraded forest areas and lands adjacent to forested areas, as well as ecologically fragile regions, including the Western Ghats.
1993 - 1994	Participatory eco-development programs were initiated in all 21 Tiger Reserves. The Management Action Plan for Nilgiri Biosphere Reserve, prepared by State Governments, was sanctioned to facilitate various activities, including eco-development.
1994 - 1995	Launch workshops were organized for initiating eco-development activities under the assistance of IDA Forestry Research, Education, and Extension Project (FREEP) in two protected areas, namely Kalakad (Tamil Nadu) and the Great Himalayan National Park (Himachal Pradesh). Multiple grassroots-level workshops were organized to initiate and encourage community participation in eco-development activities across various Tiger Reserves.
1996 - 1997	Financial support was provided to 12 out of 83 National Parks and 24 out of 447 Wildlife Sanctuaries across India as part of the Eco-development scheme. The India Eco-development Project was initiated in seven Protected Areas across seven different States as the externally aided component of the CSS Eco-development scheme. It encompasses two National Parks and five Tiger Reserves, including two reserves in the Western Ghats.
1997 - 1999	Financial assistance was extended to 6 National Parks and 37 Wildlife Sanctuaries in 1997-98, and to 12 National Parks and 40 Wildlife Sanctuaries in 1998-99 under the eco-development scheme. Additionally, five Protected Areas were earmarked for intensive eco-development efforts.
1999 - 2002	The initial National Wildlife Action Plan (NWAP) from 1983 underwent revision, resulting in the adoption of the new Wildlife Action Plan (2002-2016). This updated plan delineates strategies, action points, and priority projects aimed at conserving wild fauna and flora in the country, with a particular emphasis on fostering people's participation and garnering their support for wildlife conservation efforts. In 1999-2000, INR 217.19 lakh was disbursed to various states under the Eco-development scheme, followed by INR 8.98 crores in 2000-2001, and INR 15.15 crores in 2001-2002.
2002 - 2003	During the tenth Five Year Plan (2002-2007), the Eco-development scheme underwent integration with "Project Tiger" for tiger reserve areas and with the "Development of National Parks and Sanctuaries" scheme for wildlife sanctuaries and national parks. This expanded scheme aims to establish infrastructural amenities for enhanced protection and management of Protected Areas. It also provides financial aid for eco-development, training, capacity building, research studies, relocation of villages within Protected Areas to outside areas, and settlement of rights.
2003 - 2007	In the fiscal year 2003-04, financial assistance totaling INR 43.19 crores was disbursed under the Development of National Parks and Sanctuaries scheme, benefiting 269 National Parks and Sanctuaries across 28 states. Subsequent to this, in 2004-2005, financial aid was extended to 278 National Parks and Sanctuaries in 26 states. The following years saw a progressive increase in the number of Protected Areas receiving assistance: 316 in 2005-2006 and 340 in 2006-2007.

Continued on next page

Table A-2 – continued from previous page

Year	Implementation
2008 - 2009	In December 2008, the "Development of National Parks and Sanctuaries" scheme underwent modifications, expanding its scope and incorporating additional components and activities. Renamed as the "Integrated Development of Wildlife Habitats," the revamped scheme boasts a total outlay of INR 800 crores for the Eleventh Year Plan period. In addition to its ongoing support for Protected Areas, which includes habitat improvement practices, infrastructure development, eco-development activities, and anti-poaching measures, the modified scheme encompasses new components. These include initiatives for the protection of wildlife outside designated protected areas and recovery programs tailored for critically endangered species.

Notes: This table presents the timeline of eco-development activities in India.
The information was compiled by the authors using the MoEFCC Annual Reports.

C. Definitions of Key Variables for Analysis

Table A-3 – Variable definitions.

Variable	Definition	Year
	Panel A: Labor Force	
Workforce participation rate	The crude workforce participation rate in each village, calculated as the percentage of total workers to the total population. Data source: SHRUG v.2.0 compiled based on three waves of the Census of India.	1991 2001 2011
Share of main workers	Percentage of main workers among total workers in each village. Main workers, as defined by the Census, are individuals who have worked for the majority of the reference period, typically 6 months or more. Data source: SHRUG v.2.0.	1991 2001 2011
Share of cultivators	Percentage of main cultivators among total main workers in each village. According to the Census, a person is classified as a cultivator if they are engaged in cultivating land owned or held from government or private individuals or institutions for payment in money, kind, or share. Cultivation encompasses effective supervision or direction. A person who leases out their land for cultivation or does not oversee cultivation is not considered a cultivator. Similarly, individuals working on others' land for wages in cash, kind, or both (agricultural laborers) are not classified as cultivators. Data source: SHRUG v.2.0.	1991 2001 2011
Share of agricultural labor	Percentage of main agricultural laborers among total main workers for a village. An agricultural laborer is defined as a person who works on another person's land for wages in money, kind, or share. They bear no risk in cultivation and solely provide labor on another person's land for wages. Agricultural laborers do not possess any rights of lease or contract on the land they work on. Data source: SHRUG v.2.0.	1991 2001 2011
Share of household industry workers	Percentage of main household industry workers among total main workers for each village. Household industry is defined as an industry conducted by one or more members of the household at home or within the village in rural areas. The majority of workers in household industries are typically members of the household itself. These industries operate on a smaller scale compared to registered factories and are not required to be registered under the Indian Factories Act. Typical household industries include the production of food, beverages, tobacco products, wool or silk manufacture, manufacture of wood and wood products, and paper and paper products. Data source: SHRUG v.2.0.	1991 2001 2011
Share of other workers	Percentage of main other workers among total main workers for each village. Other workers are individuals engaged in some form of economic activity during the last year but are not classified as cultivators, agricultural laborers, or household industry workers. This category includes government servants, municipal employees, teachers, factory workers, plantation workers, individuals engaged in trade, commerce, business, transport, banking, mining, construction, political or social work, priests, entertainment artists, etc. Data source: SHRUG v.2.0.	1991 2001 2011
	Panel B: Socio-Demographics	
Male and Female population count	Total population count of males or females in each village. Data source: SHRUG v.2.0.	1991 2001 2011
Female to male sex ratio	The number of females per 1000 males. Data source: SHRUG v.2.0.	1991 2001 2011

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Table A-3 – Variable definitions (continued)

Variable	Definition	Year
Literacy rate	Percentage of the literate population among individuals above 6 years of age in the village. Data source: SHRUG v.2.0.	1991 2001 2011
Number of schools	The count of schools in a village, categorized into primary (grades 1-4), middle (grades 5-8), secondary (grades 9-12), industrial, and training centers. Data source: SHRUG v.2.0.	1991 2001 2011
	Panel C: Land Use	
Share of forest land	Percentage of forest land among total land area in the village. This encompasses all land categorized as forest under any legal enactment or administered as forest, irrespective of ownership (state-owned or private) or whether wooded or maintained as potential forest land. The area of crops cultivated in forests and grazing lands, as well as areas open for grazing within forests, are included within the "forest area." Data source: SHRUG v.2.0.	1991 2001 2011
Share of irrigated land	Percentage of irrigated land among total land area in the village. This includes land assumed to be irrigated for cultivation through various sources such as canals (government and private), tanks, tube wells, other wells, and other sources. Data source: SHRUG v.2.0.	1991 2001 2011
Share of rainfed land	Percentage of rainfed land among total land area in the village. This includes land that relies on rainfall for cultivation and does not utilize irrigation from sources such as canals, tanks, tube wells, or other wells. Data source: SHRUG v.2.0.	1991 2001 2011
Share of cultivated land	The sum of the share of irrigated land and the share of rainfed land.	1991 2001 2011
Share of culturable wasteland	Percentage of culturable wasteland among total land area in the village. This category includes land available for cultivation but has not been utilized for cultivation for five years or more, including the current year, for various reasons. Such land may be fallow or covered with shrubs and jungles, remaining unused. It can be accessible or inaccessible and may be located in isolated blocks or within cultivated holdings. Data source: SHRUG v.2.0.	1991 2001 2011
Share of non-agricultural land	Percentage of non-agricultural land among total land area in the village. This comprises all land occupied by buildings, roads, railways, water bodies such as rivers and canals, and other land utilized for purposes other than agriculture. Data source: SHRUG v.2.0.	1991 2001 2011
Share of non-cultivated land	The sum of the shares of culturable wasteland and non-agricultural land in the village.	1991 2001 2011
	Panel D: Poverty and Consumption	
World Bank poverty rate	Percentage of households living below the World Bank poverty threshold of less than $2 per capita per day. Data source: SHRUG v.2.0.	2011
Tenduklar poverty rate	Percentage of households living below the Tendulkar poverty threshold. In 2011-2012, the national poverty line according to the Tendulkar methodology was set at 815 Indian Rupees per capita per month for villages. Data source: SHRUG v.2.0.	2011
Per capita consumption	Annual per capita consumption in rural areas, measured in Indian Rupees (Rs.). Data source: SHRUG v.2.0.	2011

Continued on the next page

TABLE A-3 – Variable definitions (continued)

Variable	Definition	Year
Nightlights index	A measure derived from satellite imagery that quantifies the intensity of artificial night-time lighting in a given area, often used as a proxy for economic activity, urbanization, and development. Data source: SHRUG v.2.0.	2011
Share of households with solid roof	Percentage of households within the village that have roofs constructed from durable materials such as concrete, tiles, or metal sheets, as opposed to temporary or less durable materials like thatch or mud. Data source: SHRUG v.2.0.	2011
Share of households with solid walls	Percentage of households within the village that have walls made of sturdy materials such as bricks, concrete, or stone, as opposed to less durable materials like mud or wood. Data source: SHRUG v.2.0.	2011
	Panel E: Climate and Geography	
Annual rainfall	The mean annual rainfall of a village in millimeters, using yearly climate data provided by the India Meteorological Department (IMD) (Pai et al., 2014). The data has a spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$. We downloaded the data for 1991-2011 using `imdlib` (Nandi, Patel and Swain, 2022) and calculated the sum of daily rainfall for the years. The data is then converted using EPSG code 7755. Annual rainfall values per village are constructed using QGIS's (QGIS Development Team, 2009) zonal statistics plugin.	1991-2011
Average max. temperature	The annual average maximum temperature of a village in Celsius, using yearly climate data provided by IMD Srivastava, Rajeevan and Kshirsagar (2009). The data has a spatial resolution of $1^{\circ} \times 1^{\circ}$. We downloaded the data for 1991-2011 using `imdlib` (Nandi, Patel and Swain, 2022) and calculated the mean of daily maximum temperature for the year. The data is then converted using EPSG code 7755. Annual average maximum temperature values per village are constructed using QGIS's (QGIS Development Team, 2009) zonal statistics plugin.	1991-2011
Average min. temperature	The annual average minimum temperature of a village in Celsius, using yearly climate data provided by IMD (Srivastava, Rajeevan and Kshirsagar, 2009). The data has a spatial resolution of $1^{\circ} \times 1^{\circ}$. We downloaded the data for 1991-2011 using `imdlib` (Nandi, Patel and Swain, 2022) and calculated the mean of daily minimum temperature for each year. The data is then converted using EPSG code 7755. Minimum temperature values per village per year are constructed using QGIS's (QGIS Development Team, 2009) zonal statistics plugin.	1991-2011
Distance to nearest water body	The distance to the closest water body (oceans, lakes and rivers) in meters, using water body shapefiles provided by SRTM (U.S. Geological Survey, 2018). The data comes in several tiles, which we first merge to a single file and then convert using EPSG code 7755. The closest distance values for each village are constructed using QGIS' (QGIS Development Team, 2009) NNJoin plugin, which calculates closest distances on a nearest neighbor relationship.	1991
Mean slope	The mean slope for each village in degrees. It is constructed using the QGIS Ver. 3.28.0 zonal statistics plugin. Slopes are generated from ASTER DEM data using the GDAL Ver. 3.6.0 `gdaldem slope` algorithm with computed edges (NASA).	1991
Mean elevation	The average elevation of a village, measured in meters. Data source: SHRUG v.2.0.	1991
Distance to nearest town	The distance from the village centroid to the nearest statutory town, measured in kilometers. A statutory town is defined as one with a municipality, corporation, cantonment board, or notified town area committee. Data source: SHRUG v.2.0.	1991
Distance to nearest large town	The distance from the village centroid to the nearest town with a population of at least 100,000, measured in kilometers. Data source: SHRUG v.1.5.	1991

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Table A-3 – Variable definitions (continued)

Variable	Definition	Year
Distance to nearest river	The distance from the village centroid to the nearest river, measured in kilometers. Data source: SHRUG v.1.5.	1991
Distance to canal command area	The distance from the village centroid to the command area of the nearest irrigation canal, measured in kilometers. Data source: SHRUG v.1.5.	1991
Relative elevation	The difference in elevation between the mean elevation of a village and the elevation of the nearest canal area, measured in meters. Data source: Asher et al. (2021).	1991
Terrain ruggedness	The variability in elevation within a village, providing an indicator of the roughness or unevenness of the terrain, as measured by the TRI (terrain ruggedness index). Data source: SHRUG v.1.5.	1991

D. Additional Analysis and Robustness Tests

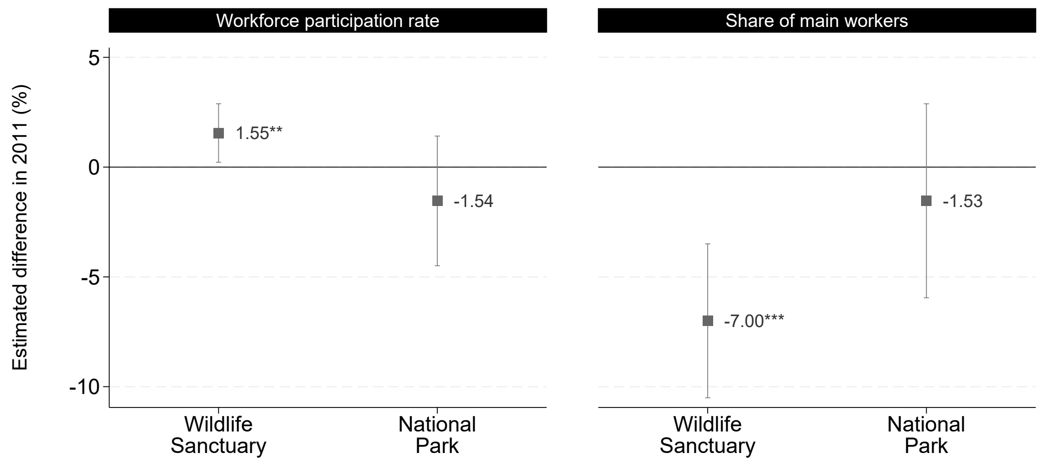

Figure A-1 – Estimated Differences in Workforce Participation Rate and Share of Main Workers Between Treatment and Control Villages in 2011, for National Parks and Wildlife Sanctuaries

Notes: This figure presents estimates of marginal treatment effects in 2011 based on Equation (3) in the main text. The CBPS weights applied correspond to those analyzed in Table 1. The dependent variables are the annual workforce participation rate (left panel) and the share of main workers (right panel). Treatment villages are defined as those that lie between 0-1km of the protected area. Control villages are villages located 20-50km away. The baseline year is 1991. All regressions include village fixed effects and time-vaying controls for rainfall, and minimum and maximum temperature. Additionally, we interact the *Post* dummy with time-invariant village-level controls, including elevation, slope, distance to the nearest water body, being within 10-km distance from the command area of an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. Standard errors are clustered at the village level. See Table A-3 for variable definitions. The confidence intervals correspond to the 95 level.

Table A-4 – Changes in labour force participation, 1991 - 2011. No CBPS-weighting.

	Workforce participation rate (1)	Share main workers (2)	Share of main workers by sector: Cultivators (3)	Agricultural labor (4)	Household industry (5)	Other (6)
Panel A: All						
Post × Treatment	0.720	-3.785***	-0.862	-2.725***	0.001	0.359
	(0.450)	(0.925)	(0.896)	(0.984)	(0.183)	(0.967)
Observations	13,410	13,410	13,394	13,394	13,394	13,394
Baseline mean	0.392	0.182	0.640	0.401	0.186	0.504
Panel B: Male						
Post × Treatment	-0.651**	-1.977***	-1.618*	-2.165**	-0.106	3.889***
	(0.313)	(0.721)	(0.885)	(0.911)	(0.129)	(0.888)
Observations	13,410	13,410	13,390	13,390	13,390	13,390
adj. R^2	0.523	0.238	0.639	0.380	0.170	0.665
Panel C: Female						
Post × Treatment	1.767**	-4.778***	2.065*	-4.692***	0.024	2.603**
	(0.745)	(1.418)	(1.165)	(1.294)	(0.392)	(1.122)
Observations	13,408	13,306	13,146	13,146	13,146	13,146
adj. R^2	0.395	0.148	0.560	0.403	0.175	0.530

Notes: This table presents unweighted difference-in-differences estimates of Equation (1) from the main text to measure the impact of eco-development on village-level labour market outcomes. Treatment villages are defined as those that lie between 0-1km of the protected area. Control villages are villages located 20-50km away. The baseline year is 1991. *Post* is a dummy indicator equal to 1 for observations in year 2011 and 0 for observations from 1991. $Post \times Treatment$ is the DID estimate of interest, capturing the difference in outcomes between treatment and control villages in 2011 relative to 1991. All regressions include village fixed effects and time-vaying controls for rainfall, and minimum and maximum temperature. Additionally, we interact the *Post* dummy with time-invariant village-level controls, including elevation, slope, distance to the nearest water body, being within 10-km distance from the command area of an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. Standard errors are clustered at the village level. See Table A-3 for variable definitions. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Table A-5 – Changes in labour force participation, 1991 - 2011. Models without time-varying controls and without time-invariant controls interacted with the Post dummy.

	Workforce participation rate	Share main workers	Share of main workers by sector: Cultivators	Agricultural labor	Household industry	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All						
Post × Treatment	0.858	-6.073***	-0.345	-3.436**	-0.791***	-0.220
	(0.636)	(1.560)	(1.263)	(1.687)	(0.189)	(1.887)
Observations	13,410	13,410	13,394	13,394	13,394	13,394
adj. R^2	0.404	0.187	0.654	0.323	0.120	0.417
Panel B: Male						
Post × Treatment	-0.302	-4.365***	-0.896	-2.516	-0.261	3.672**
	(0.465)	(1.373)	(1.271)	(1.595)	(0.172)	(1.599)
Observations	13,410	13,410	13,390	13,390	13,390	13,390
adj. R^2	0.498	0.216	0.660	0.303	0.169	0.648
Panel C: Female						
Post × Treatment	1.851*	-7.557***	1.059	-5.412***	-1.822***	6.174***
	(1.021)	(2.228)	(1.547)	(1.937)	(0.368)	(1.940)
Observations	13,408	13,306	13,146	13,146	13,146	13,146
adj. R^2	0.399	0.157	0.560	0.334	0.073	0.529

Notes: This table presents CBPS-weighted difference-in-differences estimates of Equation (1) from the main text to measure the impact of eco-development on village-level labour market outcomes. The CBPS weights applied correspond to those analysed in Table 1. Treatment villages are defined as those that lie between 0-1km of the protected area. Control villages are villages located 20-50km away. The baseline year is 1991. *Post* is a dummy indicator equal to 1 for observations in year 2011 and 0 for observations from 1991. $Post \times Treatment$ is the DID estimate of interest, capturing the difference in outcomes between treatment and control villages in 2011 relative to 1991. All models include village fixed effects. See Table A-3 for variable definitions. Standard errors are clustered at the village-level. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Table A-6 – Changes in labour force participation, 1991 - 2011. State-by-year fixed effects.

	Workforce participation rate	Share main workers	Share of main workers by sector: Cultivators	Agricultural labor	Household industry	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All						
Post × Treatment	0.973*	-5.715***	-2.420*	3.696***	-0.841***	-0.495
	(0.575)	(1.381)	(1.254)	(1.371)	(0.219)	(1.452)
Observations	13,410	13,410	13,402	13,402	13,402	13,402
adj. R^2	0.235	0.148	0.378	0.185	0.163	0.549
Panel B: Male						
Post × Treatment	0.688**	-4.163***	-1.402	3.586***	-0.238*	-1.947
	(0.334)	(1.293)	(1.282)	(1.323)	(0.144)	(1.493)
Observations	13,410	13,410	13,400	13,400	13,400	13,400
adj. R^2	0.318	0.245	0.349	0.166	0.034	0.377
Panel C: Female						
Post × Treatment	1.278	-7.370***	-3.791***	3.527**	-1.807***	2.072
	(0.939)	(1.729)	(1.367)	(1.512)	(0.406)	(1.619)
Observations	13,409	13,356	13,265	13,265	13,265	13,265
adj. R^2	0.254	0.090	0.405	0.214	0.217	0.403

Notes: This table presents CBPS-weighted difference-in-differences estimates of Equation (1) from the main text to measure the impact of eco-development on village-level labour market outcomes. The CBPS weights applied correspond to those analysed in Table 1. Treatment villages are defined as those that lie between 0-1km of the protected area. Control villages are villages located 20-50km away. The baseline year is 1991. *Post* is a dummy indicator equal to 1 for observations in year 2011 and 0 for observations from 1991. $Post \times Treatment$ is the DID estimate of interest, capturing the difference in outcomes between treatment and control villages in 2011 relative to 1991. All regressions include *state-by-year* fixed effects and time-vaying controls for rainfall, and minimum and maximum temperature. Additionally, we interact the *Post* dummy with time-invariant village-level controls, including elevation, slope, distance to the nearest water body, being within 10-km distance from an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. Standard errors are clustered at the *village* level. See Table A-3 for variable definitions. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Table A-7 – Changes in labour force participation, 1991 - 2011. Standard errors clustered at the sub-district level.

	Workforce participation rate	Share main workers	Share of main workers by sector: Cultivators	Agricultural labor	Household industry	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All						
Post × Treatment	0.882	-6.079***	-0.152	-3.079	-0.967*	-0.049
	(0.856)	(2.257)	(1.524)	(2.033)	(0.523)	(3.120)
Observations	13,410	13,410	13,394	13,394	13,394	13,394
adj. R^2	0.438	0.203	0.674	0.367	0.211	0.535
Panel B: Male						
Post × Treatment	-0.310	-4.367**	-0.682	-2.138	-0.284*	3.104*
	(0.651)	(2.014)	(1.435)	(1.809)	(0.171)	(1.751)
Observations	13,410	13,410	13,390	13,390	13,390	13,390
adj. R^2	0.520	0.258	0.675	0.345	0.179	0.681
Panel C: Female						
Post × Treatment	1.915	-7.608***	1.365	-5.224*	-2.247*	6.105**
	(1.354)	(2.717)	(2.421)	(3.148)	(1.243)	(2.430)
Observations	13,408	13,306	13,146	13,146	13,146	13,146
adj. R^2	0.438	0.165	0.584	0.381	0.201	0.564

Notes: This table presents CBPS-weighted difference-in-differences estimates of Equation (1) from the main text to measure the impact of eco-development on village-level labour market outcomes. The CBPS weights applied correspond to those analysed in Table 1. Treatment villages are defined as those that lie between 0-1km of the protected area. Control villages are villages located 20-50km away. The baseline year is 1991. *Post* is a dummy indicator equal to 1 for observations in year 2011 and 0 for observations from 1991. $Post \times Treatment$ is the DID estimate of interest, capturing the difference in outcomes between treatment and control villages in 2011 relative to 1991. All regressions include village fixed effects and time-vaying controls for rainfall, and minimum and maximum temperature. Additionally, we interact the *Post* dummy with time-invariant village-level controls, including elevation, slope, distance to the nearest water body, being within 10-km distance from the command area of an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. Standard errors are clustered at the *sub-district* level (N = 219 clusters). See Table A-3 for variable definitions. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Table A-8 – Changes in labour force participation, 1991 - 2011. Standard errors clustered at the district level.

	Workforce participation rate	Share main workers	Share of main workers by sector			
			Cultivators	Agricultural labor	Household industry	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All						
Post × Treatment	0.882	-6.079***	-0.152	-3.079**	-0.967*	-0.049
	(0.910)	(1.925)	(1.364)	(1.521)	(0.545)	(2.420)
Observations	13,410	13,410	13,394	13,394	13,394	13,394
adj. R^2	0.438	0.203	0.674	0.367	0.211	0.535
Panel B: Male						
Post × Treatment	-0.310	-4.367***	-0.682	-2.138	-0.284	3.104*
	(0.580)	(1.520)	(1.550)	(1.439)	(0.181)	(1.785)
Observations	13,410	13,410	13,390	13,390	13,390	13,390
adj. R^2	0.520	0.258	0.675	0.345	0.179	0.681
Panel C: Female						
Post × Treatment	1.915	-7.608***	1.365	-5.224*	-2.247*	6.105**
	(1.456)	(2.565)	(1.973)	(2.658)	(1.192)	(2.418)
Observations	13,408	13,306	13,146	13,146	13,146	13,146
adj. R^2	0.438	0.165	0.584	0.381	0.201	0.564

Notes: This table presents CBPS-weighted difference-in-differences estimates of Equation (1) from the main text to measure the impact of eco-development on village-level labour market outcomes. The CBPS weights applied correspond to those analysed in Table 1. Treatment villages are defined as those that lie between 0-1km of the protected area. Control villages are villages located 20-50km away. The baseline year is 1991. *Post* is a dummy indicator equal to 1 for observations in year 2011 and 0 for observations from 1991. $Post \times Treatment$ is the DID estimate of interest, capturing the difference in outcomes between treatment and control villages in 2011 relative to 1991. All regressions include village fixed effects and time-vaying controls for rainfall, and minimum and maximum temperature. Additionally, we interact the *Post* dummy with time-invariant village-level controls, including elevation, slope, distance to the nearest water body, being within 10-km distance from the command area of an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. Standard errors are clustered at the *district* level (N = 49 clusters). See Table A-3 for variable definitions. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Table A-9 – Changes in labour force participation, 1991 - 2001 - 2011.

	Workforce participation rate	Share main workers	Share of main workers by sector: Cultivators	Agricultural labor	Household industry	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All						
2001 × Treatment	-0.133	-2.094	1.036	-1.888	-0.298	-3.342**
	(0.551)	(1.473)	(1.033)	(1.304)	(0.221)	(1.448)
2011 × Treatment	0.987	-6.101***	-0.282	-3.379**	-0.809***	0.242
	(0.617)	(1.518)	(1.193)	(1.638)	(0.197)	(1.464)
Observations	20,115	20,115	20,103	20,103	20,103	20,103
adj. R^2	0.444	0.225	0.693	0.433	0.353	0.625
Panel B: Male						
2001 × Treatment	-0.084	-0.920	0.722	-1.717	-0.206	1.202
	(0.418)	(1.044)	(1.043)	(1.206)	(0.180)	(1.170)
2011 × Treatment	-0.180	-4.355***	-0.806	-2.454	-0.255	3.516**
	(0.462)	(1.315)	(1.185)	(1.555)	(0.172)	(1.499)
Observations	20,115	20,115	20,099	20,099	20,099	20,099
adj. R^2	0.558	0.255	0.696	0.411	0.225	0.721
Panel C: Female						
2001 × Treatment	-0.174	-2.906	2.784**	-2.868*	-0.611	0.695
	(0.823)	(2.225)	(1.374)	(1.560)	(0.458)	(1.276)
2011 × Treatment	2.004**	-7.558***	1.172	-5.494***	-1.876***	6.197***
	(0.979)	(2.185)	(1.510)	(1.840)	(0.385)	(1.805)
Observations	20,114	20,044	19,863	19,863	19,863	19,863
adj. R^2	0.486	0.195	0.606	0.435	0.379	0.601

Notes: This table presents CBPS-weighted difference-in-differences estimates of Equation (1) from the main text to measure the impact of eco-development on village-level labour market outcomes. The CBPS weights applied correspond to those analysed in Table 1. Treatment villages are defined as those that lie between 0-1km of the protected area. Control villages are villages located 20-50km away. The baseline year is 1991. 2001 is a dummy indicator equal to 1 for observations in year 2001 and 0 otherwise. 2011 is a dummy indicator equal to 1 for observations in year 2011 and 0 otherwise. $2001 \times Treatment$ is a DID estimate capturing the difference in outcomes between treatment and control villages in 2001 relative to 1991. $2011 \times Treatment$ is a DID estimate capturing the difference in outcomes between treatment and control villages in 2011 relative to 1991. All regressions include village fixed effects and time-vaying controls for rainfall, and minimum and maximum temperature. Additionally, we interact each of the 2001 and 2011 dummies with time-invariant village-level controls, including elevation, slope, distance to the nearest water body, being within 10-km distance from the command area of an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. Standard errors are clustered at the village level. See Table A-3 for variable definitions. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

E. Robustness Tests for Treatment Group Definition

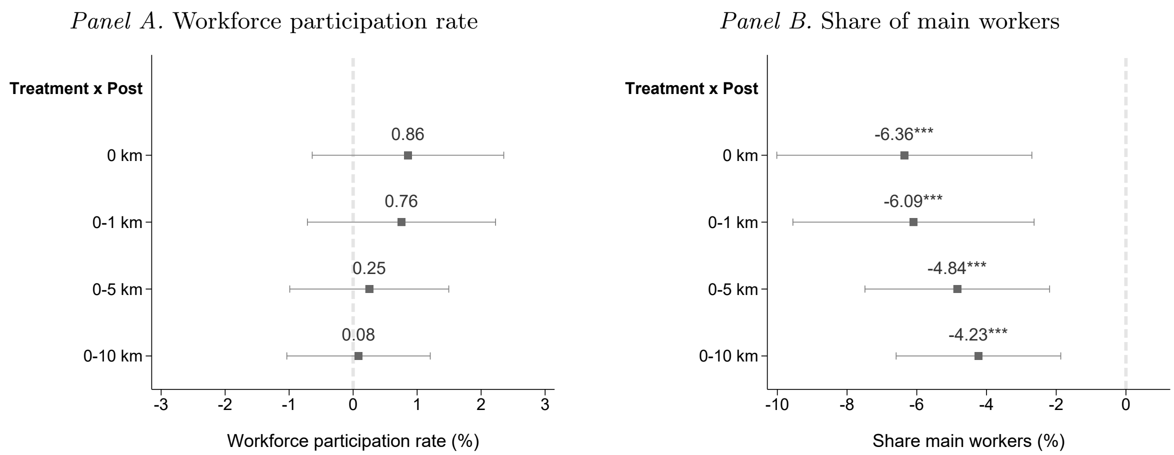

Figure A-2 – Changes in the workforce participation rate in treated villages compared to control villages in 2011, by different cutoffs for the definition of the treatment villages.

Notes: This figure presents the estimates of the SDID coefficient *Treatment* × *Post* from Equation (1) in the main text, where the dependent variable is the workforce participation rate (Panel A) and the share of main workers (Panel B). In all models, control villages are located 20-50km away from the protected area boundary. Each plotted coefficient comes from a different estimation. The models are estimated separately for different cutoffs used in the definition of the treatment villages, whereby the village centroid is located either (i) within the protected area boundary (0km), (ii) 0-1km away from the protected area boundary, (iii) 0-5km away from the protected area boundary, or (iv) 0-10km away from the protected area boundary. For each treatment definition, a new set of CBPS weights is computed using the same set of covariates as in Table 1 to ensure balance between the characteristics of treated and control villages in 1991, 2001, and 2011. All regressions include village fixed effects and time-vaying controls for rainfall, and minimum and maximum temperature. Additionally, we interact the *Post* dummy with time-invariant village-level controls, including elevation, slope, distance to the nearest water body, being within 10-km distance from the command area of an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. Standard errors are clustered at the village level. See Table A-3 for variable definitions. The confidence intervals presented as whiskers in the figure correspond to the 95 level. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

F. Robustness Tests for Control Group Definition

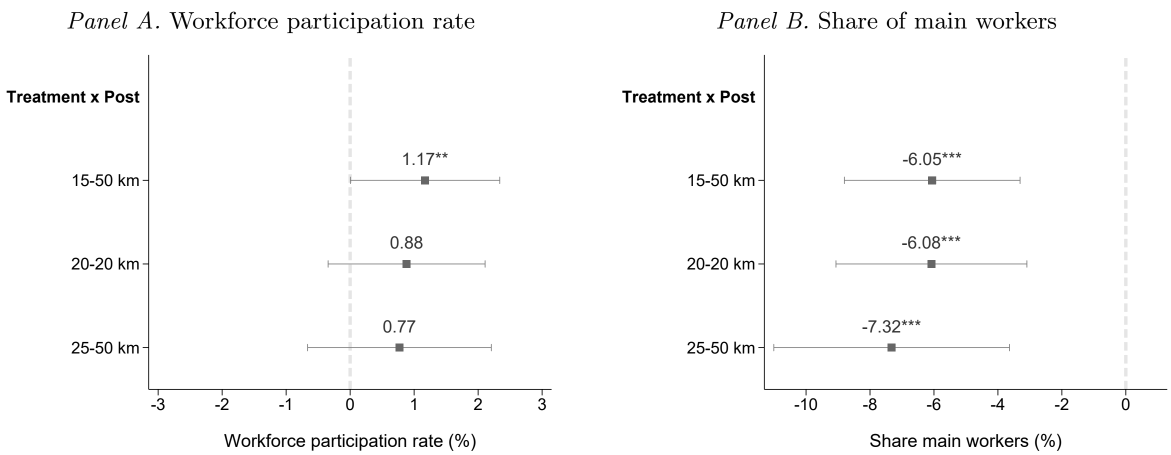

Figure A-3 – Changes in the workforce participation rate in treated villages compared to control villages in 2011, by different cutoffs for the definition of the control villages.

Notes: This figure presents the estimates of the SDID coefficient *Treatment* × *Post* from Equation (1) in the main text, where the dependent variable is the workforce participation rate (Panel A) and the share of main workers (Panel B). In all models, treatment villages are located 0-1km away from the protected area boundary. Each plotted coefficient comes from a different estimation. The models are estimated separately for different cutoffs used in the definition of the control villages, whereby the village centroid is located either (i) 15-50km away from the protected area boundary, (ii) 20-50km away from the protected area boundary, or (iii) 25-50km away from the protected area boundary. For each control definition, a new set of CBPS weights is computed using the same set of covariates as in Table 1 to ensure balance between the characteristics of treated and control villages in 1991, 2001, and 2011. All regressions include village fixed effects and time-varying controls for rainfall, and minimum and maximum temperature. Additionally, we interact the *Post* dummy with time-invariant village-level controls, including elevation, slope, distance to the nearest water body, being within 10-km distance from the command area of an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. Standard errors are clustered at the village level. See Table A-3 for variable definitions. The confidence intervals presented as whiskers in the figure correspond to the 95 level. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

A-1. Additional Tests on Poverty and Consumption Estimates

Table A-10 – Poverty and Consumption Estimates, 2011. Standard errors clustered at the sub-district level.

	World Bank poverty rate	Tenduklar poverty rate	Per capita consumption (annual INR)	Nightlights index	Share of households with solid roof	Share of households with solid walls
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	4.980*	4.262*	-1281.233*	-6.685	-9.104***	-0.614
	(2.624)	(2.494)	(675.388)	(9.827)	(2.637)	(2.561)
Observations	6,161	6,161	6,161	6,161	6,161	6,161
adj. R^2	0.400	0.411	0.272	0.226	0.164	0.259

Notes: This table presents CBPS-weighted estimates of the difference in poverty rates and consumption levels between villages in close proximity to protected areas and those located further away, as measured in the year 2011. Each column corresponds to a different dependent variable. See Table A-3 for variable definitions. Treatment villages are defined as those that lie between 0-1km of the protected area. Control villages are villages located 20-50km away. All regressions include controls for rainfall, minimum and maximum temperature, elevation, slope, distance to the nearest water body, being within 10-km distance from the command area of an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. Standard errors are clustered at the sub-district level. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Table A-11 – Poverty and Consumption Estimates, 2011. Standard errors clustered at the district level.

	World Bank poverty rate	Tenduklar poverty rate	Per capita consumption (annual INR)	Nightlights index	Share of households with solid roof	Share of households with solid walls
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	4.980*	4.262	-1281.233	-6.685	-9.104**	-0.614
	(2.885)	(2.816)	(808.487)	(10.207)	(3.847)	(3.116)
Observations	6,161	6,161	6,161	6,161	6,161	6,161
adj. R^2	0.400	0.411	0.272	0.226	0.164	0.259

Notes: This table presents CBPS-weighted estimates of the difference in poverty rates and consumption levels between villages in close proximity to protected areas and those located further away, as measured in the year 2011. Each column corresponds to a different dependent variable. See Table A-3 for variable definitions. Treatment villages are defined as those that lie between 0-1km of the protected area. Control villages are villages located 20-50km away. All regressions include controls for rainfall, minimum and maximum temperature, elevation, slope, distance to the nearest water body, being within 10-km distance from the command area of an irrigation canal, terrain ruggedness (TRI), distance to the closest town, as well as distance to the closest large town. Standard errors are clustered at the district level. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.