Journal of Environmental Economics and Management 128 (2024) 103070

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

Labor market impacts of eco-development initiatives in protected areas

Anca Balietti [a,1,*], Sreeja Jaiswal [b,1], Daniel Schäffer [c]

[a] Alfred Weber Institute for Economics, Heidelberg University, Heidelberg, Germany
[b] Mercator Research Institute on Global Commons and Climate Change, Berlin, Germany
[c] Technical University Berlin, Germany

ARTICLE INFO

JEL classification:
D04
D10
O10
Q20
Q56

Keywords:
Environmental protection
Eco-development
Labor market impacts
Land use changes

ABSTRACT

Eco-development seeks to balance economic development with biodiversity conservation, enhancing the effectiveness of protected area management. This paper examines the labor market impacts of eco-development initiatives implemented in the protected areas of the Western Ghats, India, a significant biodiversity hotspot facing intense socio-economic pressures. Our findings show that eco-development has substantially altered labor market outcomes in villages within and surrounding protected areas, resulting in a higher share of non-farm employment. This shift is marked by a reduction in year-round work and an increase in seasonal employment. These effects appear to stem from the specific types of jobs created by eco-development and the changes in land use patterns it promotes, such as a higher proportion of forested land and increased reliance on rainfed agriculture over irrigated farming. Descriptive evidence also suggests that, despite improvements in literacy, the affected villages experience lower consumption levels and higher poverty rates.

Protected areas are among the most widely used tools in the global effort to halt biodiversity loss (Waldron et al., 2017; Jones et al., 2018). To maximize conservation benefits, these areas are typically established in regions of high biodiversity, many of which are concentrated in tropical zones (Myers et al., 2000). However, these regions – predominantly located in developing countries – face intense economic development pressures (Cincotta et al., 2000).

Since protected areas often restrict or prohibit land use and resource exploitation, tensions frequently emerge between conservation objectives and the development needs of local communities (Ma et al., 2019; Estifanos et al., 2020). As a result, the impact of protected areas on poverty, human well-being, and other socio-economic outcomes remains a subject of ongoing debate within conservation policy (Ferraro and Hanauer, 2014).

In response to these challenges, eco-development initiatives in protected areas aim to provide alternative income-generating activities for local populations. These initiatives are designed to reduce dependence on protected area resources and mitigate the environmental impact of human activities (Ministry of Environment and Forest, Government of India, 2002).

In this paper, we assess the long-term impact of implementing 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 high population density, the region ranks as one of the world's most critically threatened biodiversity hotspots at high risk from human pressure (Cincotta et al., 2000).

* Corresponding author.
E-mail addresses: anca.balietti@awi.uni-heidelberg.de (A. Balietti), jaiswal@mcc-berlin.net (S. Jaiswal), daniel.schaeffer@mailbox.org (D. Schäffer).

[1] Anca Balietti and Sreeja Jaiswal contributed equally to this study. Authors are listed in alphabetical order.

https://doi.org/10.1016/j.jeem.2024.103070
Received 26 December 2023

Available online 16 October 2024

We examine differences in labor force participation and sectoral composition between villages near protected areas where eco-development initiatives have been implemented and those further away. The analysis leverages village-level data from three rounds of the Indian Population Census: 1991 (baseline), 2001 (intermediate), and 2011 (endpoint). Evaluating these changes over two decades is essential due to the slow and gradual implementation of eco-development initiatives. Moreover, this extended time horizon aligns with the context of developing countries, where labor and capital mobility tend to be greater in the long run than over shorter periods (Asher et al., 2021; Blakeslee et al., 2023).

Our empirical strategy employs a weighted difference-in-differences approach, using the Covariate Balancing Propensity Score (CBPS) method (Imai and Ratkovic, 2014) to compute weights that account for treatment assignment while ensuring covariate balance. We demonstrate the robustness of our results by testing alternative definitions of treatment and control groups, as well as using the estimator proposed by Callaway and Sant'Anna (2021).

The analysis identifies two key labor market impacts of eco-development initiatives in protected areas. First, by 2011, labor force participation remained similar between treatment and control villages; however, year-round employment was significantly lower in treatment villages, with a corresponding increase in the share of seasonal employment. Second, there was a notable shift in labor composition from agriculture to non-farm employment, with evidence indicating a relative increase in jobs in the forestry and education sectors.

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, descriptive evidence indicates that the affected population experienced higher levels of poverty and lower consumption compared to nearby areas.

We investigate several mechanisms through which eco-development may influence local employment dynamics. First, we find no evidence that eco-development impacted migration patterns. Second, eco-development is associated with higher literacy rates, with gains observed across both genders. This aligns with the increased presence of industrial schools and higher employment in the education sector by the end of our study period. Third, we observe notable land use changes, with treatment villages showing a higher proportion of forested land. This aligns with the rise in employment within the forestry sector and likely explains the growth in seasonal employment, as eco-development programs often create temporary jobs in forest protection, reforestation, fire management, anti-poaching, and habitat restoration.

Additionally, we find that the share of cultivated land is lower in treatment villages, primarily due to a reduced share of irrigated land, which is only partially offset by a relatively higher share of rainfed land compared to control villages. Consistent with these findings, the 2006–2014 Management Effectiveness Evaluation Report of protected areas underscores the delicate balance between expanding irrigation for agriculture and achieving water conservation goals (Wildlife Institute of India, 2016). Limiting irrigation and regulating water use are presented as essential for protecting biodiversity, as excessive water diversion for agriculture can degrade habitats and reduce water availability for wildlife and future agricultural needs.

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 differing dynamics of land use between irrigated and rainfed agriculture in treatment versus control villages offer another plausible explanation for the notably higher share of seasonal employment in the former, following the implementation of eco-development initiatives. Since rainfed agriculture is more vulnerable to the variability of rainfall, it tends to drive a greater demand for seasonal labor.

Beyond the effects on farm-related employment, water management practices introduced by eco-development initiatives may have also influenced seasonal employment in other sectors. Notably, the 2006–2014 Management Effectiveness Evaluation Report and the available protected areas management plans highlight activities related to water use regulation, prioritizing the creation and maintenance of water holes and check dams for conservation and agricultural purposes, while limiting excessive use from rivers and stationary sources (Wildlife Institute of India, 2016, see also Appendix E). Implementing such initiatives is often associated with temporary labor demands.

This paper makes several contributions to the existing literature. A substantial body of research evaluates conservation policies, with a particular emphasis on the establishment of protected areas (for recent reviews, see Börner et al., 2020; Reynaert et al., 2024). Traditionally, biodiversity conservation – often measured by forest cover – has been the primary outcome of interest. However, recent studies increasingly emphasize the role of local context, highlighting how human pressures and the development needs of surrounding communities drive variations in policy outcomes (Ferraro et al., 2011; Pfaff et al., 2015; Rico-Straffon et al., 2023). In addition, a growing body of work extends the analysis beyond environmental outcomes to examine socio-economic impacts, such as poverty alleviation, while exploring the trade-offs and complementarities between conservation and development objectives (Sims, 2010; Ferraro and Hanauer, 2011; Alix-Garcia et al., 2015; Miranda et al., 2016; Sims and Alix-Garcia, 2017; Alix-Garcia et al., 2018; Cheng et al., 2023). In parallel, complementary literature focuses more exclusively on socio-economic outcomes, offering mixed findings on the effects of protected areas on poverty and income levels for nearby households and communities (*e.g.,* Andam et al., 2010; Robalino and Villalobos, 2015; Ma et al., 2019; Estifanos et al., 2020).

Our paper builds on these studies by investigating the effects of eco-development policies implemented within already established protected areas, focusing specifically on key socio-economic outcomes, such as labor market participation, sectoral shifts, and land use changes in adjacent villages. To our knowledge, no other study has directly examined the impact of eco-development on labor market outcomes in protected areas, either in India or globally. Most prior research in India has been limited to qualitative assessments or small-scale case studies, exploring outcomes like conservation awareness (Gubbi et al., 2008; Karanth and Nepal, 2012; Chaudhuri, 2013), perceived benefits and costs (Karanth and Nepal, 2012), and human-wildlife conflicts (Karanth et al., 2012). Moreover, these studies often rely on cross-sectional data, limiting their ability to isolate the effects of eco-development from those of broader conservation efforts.

More broadly, our paper contributes to the growing literature on the impact of environmental protection on labor market outcomes (Berman and Bui, 2001; Walker, 2013; Ferris et al., 2014; Curtis, 2018; Hafstead and Williams III, 2018; Ferris and Frank, 2021; Cheng et al., 2023). We add to this body of work by providing robust evidence of significant labor market effects in a developing country context, where the tension between local development needs and biodiversity conservation is particularly acute.

Finally, our study connects to the literature on labor force participation in developing countries (*e.g.*, Bryan et al., 2014; Kaur, 2019; Asher and Novosad, 2020; Breza et al., 2021). We show that eco-development can substantially reshape workforce composition in affected communities. These findings align with existing evidence that labor markets in developing countries tend to adapt flexibly to external shocks over time (Imbert and Papp, 2015; Akram et al., 2017; Breza and Kinnan, 2021).

The findings of our paper carry important policy implications. Eco-development has led to a significant shift from year-round to seasonal employment, which may result in irregular income patterns throughout the year, potentially increasing consumption variability. Such fluctuations in income can exacerbate liquidity constraints, affect access to financial credit, and heighten financial uncertainty for affected households (Beck et al., 2000; Bauer et al., 2012; Fafchamps, 2013; Hertzberg et al., 2018). In regions with high poverty rates, these income patterns are particularly concerning, raising questions about their impact on overall well-being (Fink et al., 2020). From a policy perspective, it is crucial to explore strategies for creating more stable employment opportunities through eco-development and to integrate these efforts with financial schemes[2] designed to help individuals manage irregular income flows.

The observed land use changes carry significant environmental and socio-economic implications. On the one hand, the increase in forested land likely contributed to biodiversity conservation. On the other hand, limiting the expansion of irrigation-based agriculture presents a complex set of implications, as it has likely affected water use and agricultural productivity, though we lack sufficient data to measure the overall impacts. Rigorous testing is needed to evaluate the broader environmental and socio-economic impacts on the affected populations.

These land use changes also carry important implications for climate change adaptation. Eco-development has increased forested land, which may have enhanced ecosystem resilience and improved the capacity to cope with climate-related stresses, such as shifting weather patterns (Mansourian et al., 2009; Pramova et al., 2012). However, we lack sufficient data to assess the presence or magnitude of these potential effects. Additionally, eco-development initiatives seem to have restricted the expansion of irrigation while promoting rainfed agriculture, which may heighten vulnerability to climate variability by impacting productivity and thereby threatening food security. Further research is needed to assess the overall impact of eco-development on climate resilience and adaptive capacity.

1. Setting

1.1. The Western Ghats and its protected areas

Designated as a UNESCO World Heritage Site, the Western Ghats is a 1600-kilometer mountain range running parallel to India's western coast, covering an area of 140,000 square kilometers across six states. It is recognized as one of the world's eight "hottest hotspots" of biological diversity due to its remarkably high levels of biodiversity and endemism. Within India, 10 percent of the Western Ghats is designated for conservation, giving it the highest proportion of protected land among all the country's biogeographic regions.[3]

In India, protected areas are governed by the Wildlife Protection Act of 1972, which initially established National Parks and Wildlife Sanctuaries as two categories of protected areas.[4] These areas permit controlled resource use based on the protection level. National Parks are the most restrictive, generally prohibiting human activities like hunting, grazing, and resource extraction. Wildlife Sanctuaries, however, may allow sustainable use by local communities, such as grazing and collecting minor forest produce, depending on specific regulations. As Anand et al. (2010) observed, "many protected areas [in the Western Ghats] resemble

[2] Examples of financial schemes aimed at reducing the effects of income variability, particularly in developing country contexts, include flexible financial inclusion programs (see, *e.g.* Barboni and Agarwal, 2023, and references therein).

[3] India uses a biogeographic zone classification system to plan and manage its network of protected areas. There are 10 bio-geographic zones representing distinct ecological units based on shared biomes and species.

[4] A 2002 amendment introduced Conservation Reserves and Community Reserves as additional categories.

doughnuts, with human land use within (e.g., hydro-electric projects, tea and coffee plantations) and around them''. Other economic activities in these regions include agriculture, mining, and tourism (Maan and Chaudhry, 2019).

Outside the protected areas, the Western Ghats landscape features a mix of natural habitats, human settlements, artificial reservoirs, and agricultural lands. Large-scale forestry and agricultural plantations, such as tea, coffee, and rubber, dominate much of the land use (Kale et al., 2016). In a comparative study of protected and non-protected areas in the Kodagu district of the Western Ghats, Bhagwat et al. (2005) found similar biodiversity distributions across both zones, suggesting that non-protected areas also play an important role in biodiversity conservation.

1.2. Eco-development

Traditional approaches to biodiversity conservation historically established protected areas with strict 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, ultimately proving ineffective in achieving long-term conservation goals (see Karanth and Nepal, 2012, and references therein). In response to this criticism, 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 the conservation of biodiversity, with a particular focus on wildlife conservation and forest preservation, eco-development initiatives within these areas aim to promote the economic development of the local population in a manner that is consistent 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 implementation in India from 1991 to 2011, along with the allocated funding, where such data is available. 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.

2. Empirical strategy

2.1. 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 a georeferenced panel at the village level in the Western Ghats, covering three time points: 1991, 2001, and 2011. Table A-3 provides a comprehensive list of all variables used in the analysis, along with definitions, temporal availability, and data sources.

Our review of state-level eco-development funding data, protected area management plans, and management effectiveness reports 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 eco-development activities by 2000; see Appendix E for the list of plans and reports.[5] Thus, we focus on the 44 Protected Areas that had initiated eco-development by 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.

To construct the dataset, the shapefile for the Western Ghats biogeographic zone was first obtained from the India Biodiversity Portal and overlaid with shapefiles of the protected areas from the Wildlife Institute of India.[6] Villages were then identified by overlaying these protected area boundaries with village shapefiles obtained from the Socioeconomic Data and Applications Center (SEDAC) at NASA (Meiyappan et al., 2018). This step was crucial for determining treatment and control villages, as outlined in Section 2.2. Fig. 1 illustrates the study area.

Subsequently, the villages were merged with socio-economic data from the Socioeconomic High-resolution Rural–Urban Geographic Platform for India (SHRUG) v.2.0, which includes village-level data from the 1991, 2001, and 2011 Indian Population

[5] The reasons for not implementing eco-development in the six protected areas varied. In some cases, such as Mollem National Park, Bondla, and Bhagwan Mahavir Wildlife Sanctuary in Goa, and Karnala Wildlife Sanctuary in Maharashtra, it was due to the lack of dependence of fringe villages on forest resources. In Cotigaon Wildlife Sanctuary in Goa, the absence of a concrete management plan for public participation in eco-development was the limiting factor.

[6] Access to protected area shapefiles was kindly provided by Malaika Mathew Chawla of Nature Conservation Foundation, India (Srivathsa et al., 2020).

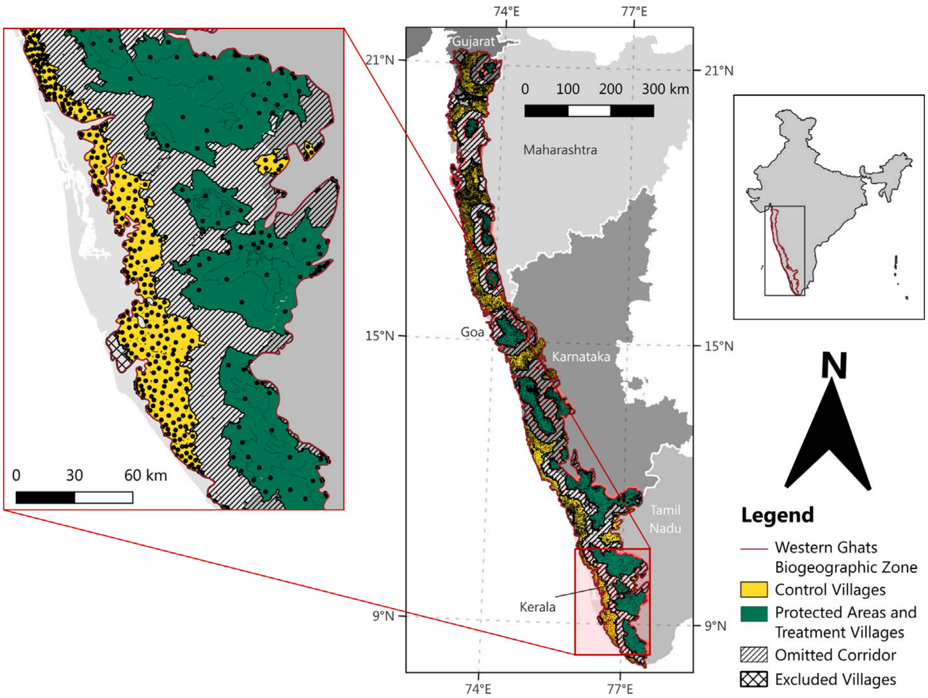

Fig. 1. Study area map with treatment and control village identification.
Notes: This map illustrates the location and boundaries of the Western Ghats bio-geographic region in India, highlighting its protected areas, including National Parks and Wildlife Sanctuaries. Additionally, it indicates the location 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 dark 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. Village centroids are represented by dots. Villages within 1–20 km of the protected area boundary are omitted, depicted as the gray shaded area. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Figure generated by the authors.

Census rounds (Asher et al., 2021).[7,8] Through this process, access to labor force data for the analysis was obtained. To further examine sectoral employment, four rounds of the Indian Economic Census (1990, 1998, 2005, and 2013) were used, with data from 90 sectors aggregated into 17 main categories (see Appendix A-3).

Next, the village-level panel was enriched with a comprehensive set of fixed and time-varying characteristics. Specifically, time-varying village-level data on population counts, literacy rates, number of schools, and land use were extracted from SHRUG v.2.0.[9] Additionally, time-invariant geographical controls were obtained, including village-level mean elevation, terrain ruggedness (measured by the TRI index), distances from each village centroid to the nearest river and 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 or more.[10] Supplementary variables related to the relative altitude of irrigation canals compared to villages are sourced from Asher et al. (2021).

Poverty and consumption estimates for 2011 were integrated using data from the Socio-Economic Caste Census available in SHRUG v.2.0 (Asher et al., 2021; Ministry of Rural Development, Government of India, 2011). Climate data (rainfall and temperature from 1991 to 2011) were sourced from the Indian Meteorological Department (IMD) (Srivastava et al., 2009). Village distances to the nearest water bodies were also calculated using Shuttle Radar Topography Mission (SRTM) data. Lastly, forest cover was tracked using remotely sensed data from Vancutsem et al. (2021).

---

[7] The most recent Population Census data available is from 2011. The 2021 Census was delayed due to the COVID-19 pandemic and is now expected to take place after the 2024 general elections.

[8] The SHRUG dataset provides consistent location keys (shrid) across Census rounds, overcoming challenges like location identifier changes and village boundary adjustments (Asher et al., 2021).

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

[10] 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.

2.2. Identification

To evaluate the impact of eco-development initiatives on labor force outcomes, we focus our analysis on protected areas within the Western Ghats that were established on or before 1990. Eco-development activities were introduced in villages located within or in close proximity to these protected areas starting after 1991. These villages constitute our treatment group. In contrast, the control group comprises villages situated outside these protected areas where eco-development initiatives have not been implemented.[11]

The endogeneity challenge in our study stems from the potential selection of villages into treatment and control groups. 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 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 et al., 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 share similar attributes such as altitude, climate, topography, and vegetation with the treatment villages. Second, we employ a weighted difference-in-differences approach, utilizing the covariate balancing propensity score (CBPS) method as developed by Imai and Ratkovic (2014) to weight observations. 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 control for potential differences between treatment and control villages. 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. Fig. 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 km 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 km from the boundary of the protected area.[12] 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 km from the protected area. Section 3.1 shows the robustness of our main results when subjected to varying definitions of treatment and control zones.

The Covariate Balancing Propensity Score (CBPS) Approach. To address potential endogeneity in treatment assignment, we rely on the covariate balancing propensity score (CBPS) methodology developed by Imai and Ratkovic (2014). 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 (Imai and Ratkovic, 2014). Moreover, the method offers a robust estimator with favorable asymptotic properties (Arkhangelsky et al., 2021).

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).[13]

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 et al., 2023).

[11] To assess the impact of eco-development initiatives, we exclude the six protected areas in the Western Ghats that had not initiated these initiatives by 2000. As a result, villages associated with these areas are excluded from both the treatment and control groups. This approach ensures a clear comparison between treated and never-treated villages.

[12] We set the threshold for control villages at 50 km, 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 km from the protected area, with approximately 96 percent of them located within a 50-kilometer of the protected area.

[13] The CBPS method is increasingly used across diverse research fields to address selection bias. For example, Waldron et al. (2017) apply CBPS weighting to evaluate the effectiveness of conservation investments in reducing biodiversity loss across 109 countries. Similarly, Alkon (2018) use CBPS to correct for pre-treatment disparities in economic development levels among sub-districts in India when assessing the spillover effects of special economic zones. In a study on the dissemination of improved cookstoves and small solar products in Kenya, Bensch et al. (2021) employ CBPS to account for variations in entrepreneur attributes. Gomez et al. (2021) use CBPS to examine the impact of banks' income gaps on the transmission of monetary policy to lending practices. Fukumoto et al. (2021) apply CBPS to analyze the effect of school closures on the spread of COVID-19. Goodair and Reeves (2022) investigate the impact of outsourcing medical care services to the private sector on treatable mortality rates in England, while Caloffi et al. (2022) rely on CBPS to evaluate the impact of innovation policy mixes on small and medium enterprises' likelihood to innovate and engage in R&D.

While the CBPS-approach has been initially developed for cross-sectional studies, Imai and Ratkovic (2015) generalized the method for the longitudinal setting. In our study, we apply the CBPS approach in the difference-in-differences framework. 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).[14]

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.

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 et al., 2011). To mitigate potential disparities in these geographic features, we incorporate average slope, elevation, and terrain ruggedness as covariates when computing the 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 incorporate the mean annual rainfall and the mean minimum and maximum temperatures for the periods 1991–2001 and 2002–2011. This approach accounts for temporal variations in rainfall and temperature, ensuring balance in each of the years 1991, 2001, and 2011.

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 km of a canal's command area, serving as a more refined indicator of irrigation access (Asher et al., 2021; Blakeslee et al., 2023). Section 3.2.2 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.[15] While a single set of weights is used, they are specifically tailored to achieve balance in each of the years 1991, 2001, and 2011. After excluding villages with missing covariate or outcome variable data, our analysis includes a total of 6705 villages, with 1265 villages in the treatment group and 5440 villages in the control group. Section D in the Appendix provides details on the distribution of the computed CBPS weights.

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.[16]

CBPS-weighted Difference-in-differences. We rely on a CBPS-weighted difference-in-differences 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} represents one of the labor force outcomes observed in village i during year t. In our primary specification, we rely on panel data from the years 1991 and 2011 and 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

[14] 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).

[15] 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).

[16] The mean absolute standardized 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	1991	1991	1991	2001	2011
	(1)	(2)	(3)	(4)	(5)	(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	1265	5440	6705	6705	6705	6705

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.

1 for villages located within 1 km 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_{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. Furthermore, γ_i are village fixed effects and ϵ_{it} is the error term clustered at the village level. Finally, when performing the estimation, each observation is weighted by a vector of weights computed using the CBPS approach.

The primary outcome variables include the workforce participation rate and the proportion of year-round employment, defined as the share of individuals employed for more than six months a year within the total workforce. Furthermore, we estimate shifts within the distribution of year-round employment across sectors, examining impacts on the proportion of cultivators and the proportion of workers engaged in agricultural labor, household industry, and other occupations.

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

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

where all variables are defined as in Eq. (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 Eq. (1).

3. Results

3.1. Labor force participation and composition

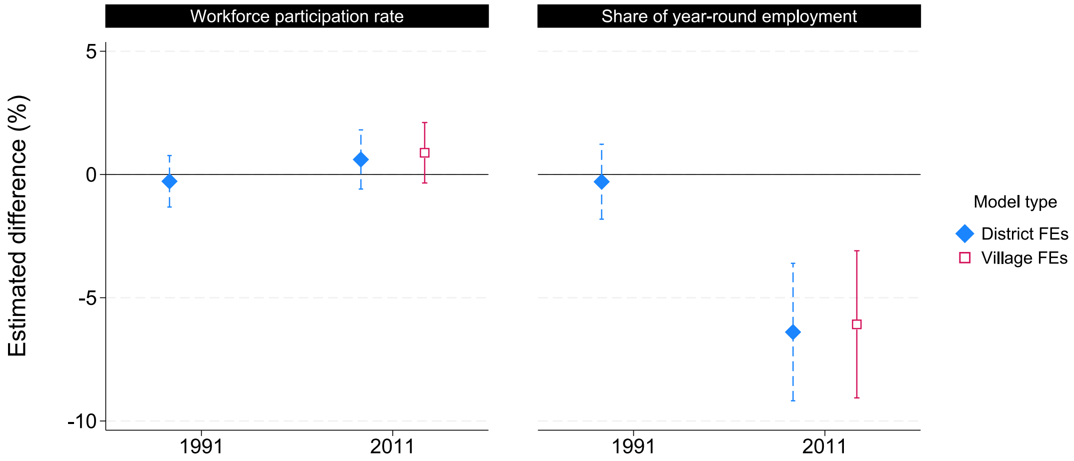

Fig. 2. Estimated differences in workforce participation rate and share of year-round employment between treatment and control villages in 1991 and 2011. *Notes:* This figure presents estimates of Eqs. (1) and (2) from the main text. The CBPS weights applied correspond to those analyzed in Table 1. The dependent variables are the annual workforce participation rate (left panel) and the share of year-round employment (right panel). Both panels present the estimated difference between treatment and control villages in 1991 and 2011. The coefficients depicted in blue (diamond symbol) are estimated according to the model in Eq. (2) 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 (square symbol) are estimated according to the model in Eq. (1) 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 coefficient for 1991. In all models, standard errors are clustered at the village level. Table A-4 in the appendix provides the estimation results corresponding to this figure. See Table A-3 for variable definitions. The confidence intervals correspond to the 95 level. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.1.1. Full sample estimates

Our primary focus is on labor force participation and composition as key outcomes of interest. Specifically, we examine the workforce participation rate and the proportion of year-round employment, defining year-round workers as individuals employed for six months or more within a given year. We estimate the CBPS-weighted difference-in-differences models of Eqs. (1) and (2) with village fixed-effects and district fixed-effects, respectively.

Fig. 2 provides a visual representation of our key findings. The coefficients depicted in blue (diamond symbol) are estimated using the DID model in Eq. (2), with CBPS weights from Table 1. The model uses data from 1991 and 2011 and includes a treatment indicator, a post dummy (equal to one for 2011 observations), and an interaction term between the treatment and post indicators. Additionally, the model includes district fixed effects, time-varying village characteristics (rainfall, and minimum and maximum temperature), and time-invariant factors (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).[17]

In a nutshell, we find that in 1991, prior to the implementation of eco-development initiatives, both the workforce participation rate and the share of year-round employment were similar in treatment and control villages, as indicated by the 1991 coefficients, which are not statistically different from zero. However, after the implementation of eco-development initiatives, while the workforce participation rate remained comparable between the two groups, by 2011, treatment villages experienced a 6 percentage point lower share of year-round employment. This suggests that eco-development initiatives may have contributed to a shift from year-round to seasonal employment. Results appear robust across the two model specifications.[18]

To further investigate these findings, we analyze employment across different sectors as categorized by the Indian Population Census. The Census classifies year-round employment into four sectors: (1) *cultivators*, defined as individuals who cultivate land that they either own or lease; (2) *agricultural laborers*, who work on land owned by others; (3) *household industry workers*, where the household industry refers to activities primarily conducted at home or within the village in rural areas, including food production, beverages, tobacco, textiles, wood products, and paper products, with household members typically serving as the main workforce; and (4) all *other* sectors, encompassing professions such as teachers, factory workers, miners, plantation workers, workers in the tourism industry, and construction workers.[19]

---

[17] This specification (corresponding to Eq. (2)) enables us to estimate the treatment coefficient, representing the difference between treatment and control villages in 1991. In contrast, the coefficients depicted in red (square symbol) are estimated using Eq. (1), which includes village fixed effects. Consequently, the treatment coefficient is not estimated in this specification.

[18] Table A-4 in the Appendix presents the estimated coefficients depicted in Fig. 2.

[19] Table A-3 in the Appendix provides additional details on this classification.

Table 2 presents the CBPS-weighted DID coefficients estimated using village fixed-effects models of Eq. (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.[20]

Columns 1 and 2 report the coefficients corresponding to the red (square) symbols in Fig. 2. Columns 3 through 6 estimate the differences in the share of year-round employment by sector between treatment and control villages in 2011. For cultivators – those working on their own or leased land – no significant difference in year-round employment is observed between treatment and control villages. However, in arguably more mobile sectors, significant differences emerge. Specifically, we find a shift away from agricultural labor and household industry work, with effect sizes of −3.08 percentage points (p-value = 0.053) and −0.97 percentage points (p-value < 0.001), respectively. In contrast, year-round employment in other sectors is 4.2 percentage points higher (p-value < 0.001) in treatment villages in 2011.

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 composition, with treated villages experiencing lower rates of year-round employment, particularly in the agricultural and household industry sectors. This shift is accompanied by an increase in employment in the non-farm sector, as indicated by the rise in the share of year-round workers in the "Other" sector. We explore this trend in greater detail in Section 3.1.4. The reduction in year-round employment is offset by an increase in marginal workers[21] – those employed for less than six months in the year, henceforth referred to as seasonal employment.[22]

The observed decrease in agricultural employment aligns with research on the impact of protected area establishment in other developing countries. Cheng et al. (2023) document a negative effect of Nature Reserves on county-level employment in China, along with shifts in the composition of employment, moving 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. Similarly, Clements and Milner-Gulland (2015) provide evidence from Cambodia showing that households near protected areas diversified their livelihoods post-conservation initiatives, engaging in non-agricultural activities like retail operations and service provision.

3.1.2. *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 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 estimate the labor market impacts of eco-development separately for each gender (see Panels B and C in Table 2).[23]

First, while overall workforce participation rates in 2011 do not differ between treatment and control villages, the gender-specific analysis reveals that female workforce participation is 1.9 percentage points higher in treatment villages (p-value = 0.052), while male participation remains unaffected.

Second, the decline in year-round employment in treatment villages relative to control villages is evident across both genders but differs in magnitude. For males, the decline is 4.37 percentage points (p-value = 0.001), whereas for females, it is 7.61 percentage points (p-value = 0.001), 1.7 times larger.

Third, sectoral shifts in year-round employment are more pronounced for women than for men. Female participation in agriculture declines by 5.22 percentage points (p-value = 0.004), while male participation remains relatively unchanged (−2.14 percentage points, p-value = 0.155). Similarly, household industry employment among women drops by 2.25 percentage points (p-value < 0.001), an effect nearly eight times larger than that for men, where the decline is only 0.28 percentage points (p-value = 0.099).

Furthermore, both female and male year-round workforce participation in *other* industries saw a significant increase in 2011 in treatment villages compared to control villages. The effect is nearly twice as large for women, with a 6.11 percentage point increase (p-value < 0.001), compared to a 3.10 percentage point increase for men (p-value < 0.001).

[20] Appendix Table A-10 presents the results of estimating Eq. (1) without the CBPS weights. These results are largely aligned in sign and significance with those in Table 2 (Panel A).

[21] The Census of India defines a "marginal worker" as a person who worked for less than six months in a given year.

[22] Due to lack of data availability for 1991, we cannot present the results of the differences-in-differences estimation for the sectoral composition of seasonal employment.

[23] The Indian Population Census provides detailed data on labor force participation and composition, both overall and by gender. For instance, the female workforce participation rate is calculated as the number of female workers divided by the total female population in a village. Similarly, the male workforce participation rate is calculated as the number of male workers divided by the total male population in a village.

Table 2
Changes in labor force participation and composition, 1991–2011.

	Workforce participation rate (1)	Share of year-round employment (2)	Share of year-round employment by sector			
			Cultivators (3)	Agricultural labor (4)	Household industry (5)	Other (6)
Panel A: All						
Post × Treatment	0.882	−6.079***	−0.152	−3.079*	−0.967***	4.198***
	(0.626)	(1.523)	(1.187)	(1.593)	(0.197)	(1.476)
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	0.686
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 Eq. (1) from the main text to measure the impact of eco-development on village-level labor market outcomes. The CBPS weights applied correspond to those analyzed in Table 1. Treatment villages are defined as those that lie between 0–1 km of the protected area. Control villages are villages located 20–50 km 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. The *Baseline mean* refers to the mean value of each outcome variable in the control villages in 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. Statistical significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

In summary, these findings highlight the gendered nature of labor market adjustments in response to eco-development initiatives. While both men and women experience shifts in employment patterns, the effects are notably more pronounced for women, particularly in agriculture and household industries.

3.1.3. Impacts between 1991–2001

Our main analysis examines changes in labor force participation over two decades, reflecting the long-term effects of eco-development programs, which began in 1991. To assess how quickly labor markets responded to these initiatives, we estimate our primary model at three key time points: 1991 (baseline), 2001 (midline), and 2011 (endline). This approach allows us to capture dynamic treatment effects for both 2001 and 2011.

Our findings indicate that significant differences in labor force participation between treatment and control villages emerged only over the long term, as seen by 2011 (see Appendix Table A-5). This suggests that the labor market effects of eco-development initiatives materialized gradually, rather than in the short term.

The lack of noticeable impact between 1991 and 2001 is not unexpected, given the slow and incremental rollout of eco-development programs. As detailed in Appendix Table A-2, considerable time and resources were devoted to preparatory activities, such as establishing village eco-development committees, providing training for alternative employment opportunities, initiating microenterprises, and building trust between protected area managers and local communities (Wildlife Institute of India, 2016).

These results highlight the importance of evaluating cumulative impacts over extended periods, as shifts in livelihood strategies driven by conservation initiatives often unfold gradually over several years (Reynaert et al., 2023; Beauchamp et al., 2018; Ferraro and Pressey, 2015).

3.1.4. Dynamics of sectoral employment

In this section, we aim to identify the specific sectors contributing to the observed increase in the share of year-round employment within the “Other” sector, as discussed in Section 3.1.1. To do so, we analyze data from four rounds of the Indian Economic Census – 1990, 1998, 2005, and 2013 – to estimate sectoral differences in employment rates between treatment and control villages. It is important to note that the years covered by the Economic Census do not exactly coincide with those in our main analysis, though they do correspond to similar time periods. Additionally, the Economic Census does not differentiate between year-round and seasonal employment. Despite these limitations, the analysis can still provide valuable insights into the broader dynamics of employment by sector.

The dataset provides detailed documentation on employment in informal firms, service sector entities, and public sector establishments. However, due to changes in inclusion criteria and inconsistencies across census rounds, certain sectors – such as agricultural firms and those involved in government administration or defense – are excluded.[24]

To estimate the dynamic impacts of eco-development on labor employment by sector, we use a CBPS-weighted difference-in-differences model spanning four time periods, corresponding to the four waves of the Economic Census. The model incorporates village and year fixed effects, along with interaction terms between the treatment indicator and each of the four year dummies. Additionally, it includes interaction terms between each year dummy and the usual set of time-invariant village-level characteristics. Standard errors are clustered at the village level.

Using 1990 as the baseline, the estimated differences in sectoral employment between treatment and control villages for the years 1998, 2005, and 2013 are presented in Table A-8 in the Appendix. To inform the results of our main analysis from Section 3.1.1, we focus on sectors classified under the "Other" category.

By 2013, treatment villages saw significantly higher employment in the education and forestry sectors compared to control villages, with effect sizes of approximately 2.9 percentage points (p-value < 0.001) and 0.8 percentage points (p-value $= 0.083$), respectively. This trend mirrors the increases observed in 2005. These findings are consistent with qualitative evidence from the 2006–2014 Management Effectiveness Evaluation Report (Wildlife Institute of India, 2016) and various management plans (Appendix E), which highlight employment generation through eco-development activities by the state forest departments. These activities include habitat improvement, afforestation and reforestation, fire management, sapling revitalization, and trench digging for wildlife protection. The forest department also trains and recruits local residents for roles such as fire watchers, anti-poaching watchers, tourist guides, trekking guides, and drivers for safari vehicles.

Additionally, while positive effects in 2013 are observed for employment in the business, tourism, commerce, goods manufacturing, and transportation sectors, these results are not statistically significant.

While these results provide insights into the sectors contributing to the rise in year-round employment within the "Other" category, data limitations prevent a full understanding of these changes. Although the Economic Census aims to capture both formal and informal employment, informal jobs are likely underreported. For example, the 2006–2014 Management Effectiveness Evaluation report suggests that eco-development initiatives create employment in tourism-related activities (Wildlife Institute of India, 2016),[25] but our analysis does not detect significant changes in this sector. Additionally, plantation work, which falls under the "Other" category, is not captured in our dataset, limiting our ability to assess whether it was impacted.

3.1.5. National parks and wildlife sanctuaries

The literature consistently emphasizes that the effectiveness of conservation policies is highly contingent on specific contextual factors (for a review, see Börner et al., 2020). Notably, there are substantial variations in the environmental and socio-economic impacts of these policies, depending on the nature of the conservation program employed (Ferraro et al., 2013; Miranda et al., 2016; Sims and Alix-Garcia, 2017; Rico et al., 2023). Protected areas are categorized into different types based on the level of environmental protection they offer and the extent of restrictions imposed on economic activities. In this section, we investigate whether and to what extent the implementation of eco-development initiatives across different types of protected areas leads to divergent labor market outcomes.

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 restrictions placed on human activities. National Parks have a higher level of protection, prohibiting livestock grazing and private landholding within their boundaries. In contrast, Wildlife Sanctuaries allow for more flexibility; livestock grazing may be regulated, controlled, or prohibited depending on specific 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). Differences in protection also correspond to variations in geographical characteristics. Villages near National Parks are, on average, located at higher altitudes and on steeper slopes compared to those near Wildlife Sanctuaries (see Appendix Figure A-2). These geographical disparities may reflect differing biodiversity species and conservation priorities between the two types of protected areas.

We estimate a triple difference model, where we interact the type of protected area with the treatment indicator and the dummy variable representing the year 2011, as follows:

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

where all variables are defined as in the main model described in Eq. (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, there are a total of 1820 villages (343 treatment and 1477 control) near National Parks, and 4885 villages (992 treatment and 3963 control) near Wildlife Sanctuaries. As a result, the statistical power for estimating treatment effects is greater for Wildlife Sanctuaries compared to National Parks.

[24] The SHRUG dataset harmonizes NIC codes across various versions, covering 90 industrial codes. For this analysis, we aggregate these into 17 broader sectors, with definitions provided in Table A-7.

[25] Ecotourism creates employment opportunities for local residents, including positions such as canteen operators and roles in branding and selling local products and non-timber forest products through eco-shops authorized by protected area authorities.

Figure A-3 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 reduced impact of eco-development initiatives on workforce participation and composition in National Parks likely reflects their heightened protection status and the more stringent constraints on human and economic activities. In contrast, areas with less stringent regulations, such as Wildlife Sanctuaries, offer more flexibility, allowing eco-development initiatives to have a more pronounced effect on local labor markets. Differences in management effectiveness scores by protected area type further support this interpretation. National Parks generally score slightly higher in management effectiveness than Wildlife Sanctuaries (see Appendix Table A-1), suggesting they likely achieve better environmental protection outcomes.[26]

3.1.6. Robustness

Treatment definition. Our primary specification defines treatment villages as those located within 1 km of the protected area boundary. This choice aligns with the 2022 Supreme Court of India ruling, which mandates a minimum 1-kilometer eco-sensitive zone around protected areas.

To test robustness, we first narrow the treatment definition to include only villages located within the protected area boundary. Second, to account for earlier broader delineations of eco-sensitive zones and potential spillover effects on neighboring villages, we expand the treatment group to include villages within 5 and 10 km of the protected area boundary.[27]

We compute new CBPS weights for each treatment definition to ensure balance with control villages. Across all definitions, the CBPS-weighted DID coefficients show consistent signs and significance levels, similar to those in the main specification. The workforce participation rate remains comparable between treatment and control villages across all models.

Regardless of treatment definition, the share of year-round employment in treatment villages is significantly lower than in control villages by 2011. However, this difference diminishes as the treatment area expands further from the protected areas (see Appendix Figure A-5). In the primary specification (0–1 km), year-round employment in treatment villages is 6.09 percentage points lower than in control villages. Restricting treatment to villages within the protected area increases this gap to 6.36 percentage points. Expanding the treatment definition to 0–5 km and 0–10 km reduces the difference to 4.84 and 4.23 percentage points, respectively (all p-values < 0.001).

Overall, the evidence suggests that the impact of eco-development on labor force participation diminishes with distance from the protected areas but remains significant, extending beyond the immediate boundaries to affect neighboring villages, albeit to a lesser extent.

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-6).

Covariates and error clustering. We provide evidence that our main results are robust to estimating Eq. (1) without time-varying covariates and without time-invariant controls interacted with the *Post* (see Appendix Table A-11). Finally, results are robust to clustering the standard errors at higher administrative units, such as sub-district or district levels (see Appendix Table A-12 and Table A-13).

Placebo tests. To further assess the robustness of the estimated impacts of eco-development initiatives on labor market outcomes, we conduct a placebo test using the sample of six protected areas in the Western Ghats where these initiatives were not implemented during the study period and which have been excluded from our analysis thus far.

In this test, we replicate the steps of the main analysis, defining placebo-treated villages as those within 1 km of the six protected areas and control villages as those located 20 to 50 km away. We then compute new CBPS weights using the same set of covariates as in Table 1. However, it is important to note that the use of this sample of six protected areas offers limited statistical power.

The results of this analysis show an increase in the workforce participation rate in villages near protected areas where eco-development initiatives were not implemented, compared to villages farther away. Unlike in our main analysis, we find no statistically significant differences in the share of year-round employment, either in the aggregate or across employment sectors (see Appendix Table A-14). Additionally, the estimated coefficients display opposite signs to those in the main analysis, where year-round employment is significantly lower overall, with a clear shift from farm and household industry work to other forms of

[26] These scores are available for a single time period, which varies across protected areas depending on when the reports were completed. Consequently, we are unable to determine whether eco-development initiatives have influenced these scores or if the scores primarily reflect pre-existing differences between National Parks and Wildlife Sanctuaries.

[27] Prior to the 2022 ruling, India's 2002 Wildlife Conservation Strategy proposed designating land within a 10-kilometer radius of national parks and wildlife sanctuaries as Eco-Fragile Zones. This aimed to limit development near protected areas, but opposition from states led to a 2005 revision, suggesting site-specific eco-sensitive zones. For example, the Kalakad Mundanthurai National Park uses a 5-kilometer radius.

year-round employment (see Table 2). This stark contrast between the placebo test and the main findings strengthens the causal interpretation that eco-development initiatives have indeed affected the share of year-round employment in the targeted villages.

Estimator robustness. As an additional robustness check, we evaluate the average treatment effects of eco-development on labor market outcomes using the estimation method proposed by Callaway and Sant'Anna (2021). This DID estimator is particularly well-suited to our analysis, as it accommodates multiple time periods and allows conditioning on observed covariates. Specifically, we follow a similar approach to the analysis in Section 3.1.3, utilizing data from three time points: 1991 as the baseline year, with 2001 and 2011 serving as the midline and endline periods. Consistent with our baseline specification, we control for time-varying characteristics and include interaction terms between the 2001 and 2011 year dummies and the time-invariant village-level characteristics, while applying CBPS weights. The results of the estimated dynamic treatment effects using the Callaway and Sant'Anna (2021) estimator are presented in Appendix Table A-15. We find strong robustness in our main analysis estimators, both in terms of magnitude and statistical significance.

3.2. Mechanisms

In this section, we investigate the mechanisms through which eco-development initiatives have influenced shifts in labor market composition among the affected population. We focus on two key areas: first, changes in the socio-demographic characteristics of the population, and second, shifts in land use patterns.

3.2.1. Socio-demographic changes

Migration. Migration patterns are a key socio-demographic factor that can shape labor supply (*e.g.*, Bryan et al., 2014; Kleemans and Magruder, 2018). Eco-development initiatives could stimulate local economic activities and attract in-migration. Conversely, restrictions on agriculture and natural resource collection around protected areas may drive people away from agriculture and, without sufficient alternative employment opportunities, could lead to out-migration in search of better economic prospects. These migration trends could directly impact workforce participation and the composition of the labor market.

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 Eq. (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.[28]

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 $Post \times Treatment$ 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 DID 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. 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 A-9 in the Appendix illustrates the CBPS-weighted DID 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. It also corresponds with the observed increase in employment in the education sector.

In summary, our analysis finds no significant changes in migration patterns attributable to eco-development initiatives in protected areas, suggesting that migration is not a key mechanism affecting labor force participation during the study period. Instead,

[28] 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 Eq. (1). See Table A-3 for variable definitions. Treatment villages are defined as those that lie between 0–1 km of the protected area. Control villages are villages located 20–50 km 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-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. Statistical significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

the significant increase in literacy rates and the growing presence of industrial schools appear to be plausible channels facilitating the shift towards non-farm employment. This trend is consistent with qualitative findings from Cambodia, where households with higher education levels near protected areas were more likely to diversify into non-agricultural activities (Clements et al., 2014).

3.2.2. Changes in land use patterns

Eco-development initiatives are designed to involve the local population in a variety of activities that create alternative employment opportunities, thereby reducing dependency on protected area resources. These initiatives include interventions for habitat improvement, restoration of degraded areas, soil and water conservation, as well as afforestation and reforestation efforts (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 examine this mechanism by analyzing changes in land use distribution across various categories.[29] The estimation results, presented in Table 4, 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, we find that, in 2011, the proportion of forest land in treatment villages was approximately 2.5 percentage points higher than in control villages (p-value = 0.003). In our dataset, forest land includes all areas legally classified as forest, regardless of ownership, current tree cover, or whether the land is maintained as potential forest land. To ensure the robustness of our findings, we supplement our analysis with remotely-sensed data from Vancutsem et al. (2021), which provides annual village-level measurements of tropical moist forest (TMF) land from 1991 to 2021. Although TMF is the dominant forest type in the Western Ghats, other forest types are also present in the region (Reddy et al., 2016), but we lack data to assess changes in these other types. Details on the estimation and results regarding TMF can be found in Appendix Section A-4. The analysis shows that tropical moist forested land shares remained similar between treatment and control villages in the early years following the implementation of eco-development initiatives but began to increase significantly in treatment villages after 2005, with a consistent upward trend continuing through 2021. Notably, this effect is driven by an increase in TMF regrowth, rather than reductions in deforestation or forest degradation.[30] In summary, while eco-development does not seem to have altered TMF deforestation patterns, it contributed to an increase in TMF land through reforestation.

Secondly, we find that the proportion of cultivated land is 4.3 percentage points lower in treatment villages compared to control villages in 2011 (p-value < 0.001). This reduction aligns with the observed decrease in year-round farm employment. 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 observe no significant differences in the overall proportion of non-cultivated land. However, the share of non-agricultural land is significantly higher in treatment villages compared to control villages in 2011, with an effect size of +1.6 percentage points (p-value = 0.043). This finding aligns with the observed increase in year-round non-farm employment and reflects the broader objectives of the eco-development initiatives.

Collectively, our findings demonstrate that eco-development initiatives in protected areas have influenced land use patterns for various economic activities. These effects are evident in two key ways. First, treatment villages exhibit higher shares of forested

[29] The land use data from the Census of India is sourced from land records maintained by various state government departments.

[30] The dataset provided by Vancutsem et al. (2021) identifies tropical forests, primarily located in the central and southern regions of the Western Ghats. However, other forest types are not classified as forest in this dataset. To address this limitation, we also analyze the share of land not covered by tropical forests or water, which would include other (non-tropical) forest types if present. The results indicate a decline in land used for other purposes.

Table 4
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 Eq. (1). Treatment villages are defined as those that lie between 0–1 km of the protected area. Control villages are villages located 20–50 km 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-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 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. Statistical significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

land, consistent with the broader goals of biodiversity conservation as well as soil conservation and erosion control in these regions. Second, the proportion of cultivated land is significantly lower in treatment villages compared to control villages, primarily due to a smaller share of irrigated agricultural land, partially offset by a higher share of rainfed land.

These results align with the observed differences in employment patterns, where treatment villages show a lower rate of year-round employment in the agricultural sector and a higher rate of year-round non-farm employment, as documented in Table 2. First, the higher share of forested land in treatment villages corresponds with the greater employment in the forestry sector. According to Wildlife Institute of India (2016), eco-development initiatives generate job opportunities in areas such as forest protection, maintenance, afforestation and reforestation, fire management, anti-poaching efforts, and habitat restoration, many of which are likely to be seasonal. However, the link between higher village-level forest cover and greater employment in the forestry sector should be interpreted with caution. The observed employment differences might also reflect jobs located within protected areas but outside village boundaries.

Second, the higher share of rainfed agriculture in treatment villages may help explain the significantly greater seasonal employment observed. Irrigation, being less reliant on precipitation patterns, enables crop production 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 highlights the restriction on irrigated agricultural land as a key mechanism through which eco-development initiatives in protected areas significantly reshape the composition of the labor force in nearby communities, alongside other contributing factors. 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.

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, 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 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 km, we differentiate between villages with higher irrigation potential (distances less than 10 km) and villages with lower irrigation potential (distances greater than 10 km). The choice of cutoff reflects the severe restrictions on irrigation for villages located more than 10 km 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 largest source of irrigation after

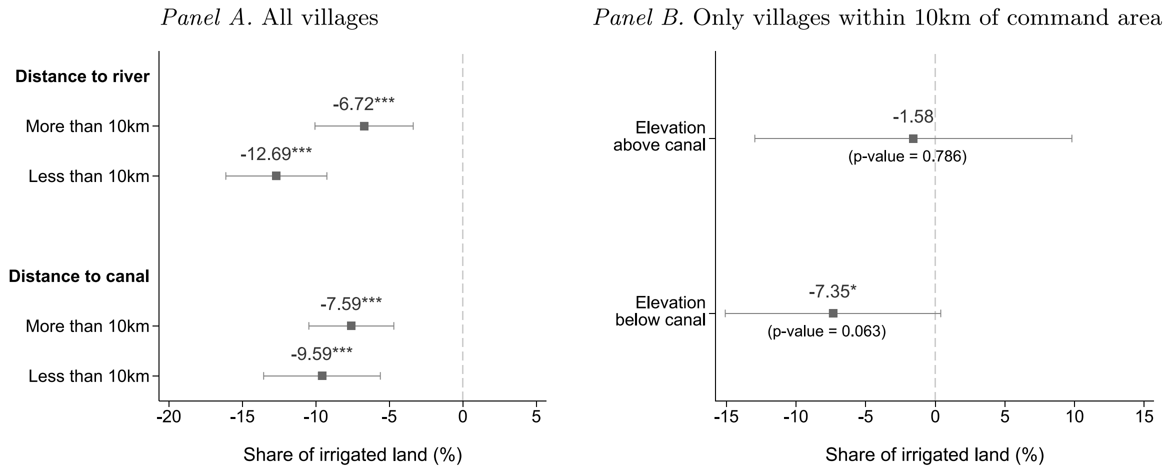

Fig. 3. Changes in the share of irrigated area in treatment villages compared to control villages in 2011, by access to irrigation source.
Notes: This figure presents estimates of Eq. (4) from the main text. The dependent variable is the share of irrigated land of a village. *Panel A* employs the entire sample for estimation and utilizes the CBPS weights described in Table 1. *Panel B* restricts the sample to villages located within 10 km of distance and within 50 m of elevation from the command area of a canal, excluding villages within 2.5 m 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 CBPS-weighted DID coefficient *Treatment* × *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. Statistical significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

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 km of the protected area boundary and 0 for control villages, as defined above. Close_i is the indicator for a village located within 10 km 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 Fig. 3. 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 km 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 km 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.

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 m from the canal. Thirdly, to account for villages with parts both above and below the canal, we exclude villages within 2.5 m in elevation of the nearest canal in either direction.

Following this restriction process, we retain a sample of 1872 villages, comprising 265 villages located within 1 km of a protected area boundary and 1607 control villages.[31] 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 Eq. (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 Eq. (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 Fig. 3 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 had a share of irrigated land that was 7.35 percentage points lower (p-value = 0.063) than that of control villages with direct access to irrigation. In contrast, for villages without direct access to irrigation, the difference was minimal, at −1.58 percentage points (p-value = 0.786), an effect that is 4.7 times smaller.

In summary, this section provides robust evidence that eco-development initiatives have resulted in a reduced share of irrigated land compared to control villages, while the opposite effect is observed for rainfed land. Along with seasonal jobs created through eco-development initiatives, these changes emerge as plausible mechanisms driving the higher levels of seasonal employment in treatment villages.

3.3. 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 present descriptive evidence to assess whether socio-economic disparities exist between the treatment and control villages at the end of the study period. 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_i 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 5 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 Committee definition. Furthermore, this is reflected in lower levels of per capita consumption, with an average annual disparity of 1281 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.[32]

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 6 presents the estimation results of CBPS-weighted linear regressions over 6 outcome

[31] 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, 1066 villages are located above the canal, with 541 villages below the canal.

[32] Table A-16 and Table A-17 show qualitative robustness of these results when standard errors are clustered at the sub-district and district levels, accordingly.

Table 5
Poverty and consumption estimates, 2011.

	World Bank poverty rate (1)	Tenduklar poverty rate (2)	Per capita consumption (annual INR) (3)	Nightlights index (4)	Share of households with solid roof (5)	Share of households with solid walls (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	6161	6161	6161	6161	6161	6161
adj. R^2	0.400	0.411	0.272	0.226	0.164	0.259

Notes: This table presents CBPS-weighted estimates of Eq. (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 0–1 km of the protected area. Control villages are villages located 20–50 km 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. Statistical significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Table 6
Ownership shares, 2011.

	Enterprise (1)	Agricultural equipment (2)	Mechanized agricultural equipment (3)	Irrigation equipment (4)	Vehicle with 2 or 3 wheels (5)	Vehicle with 4 wheels (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	6161	6161	6161	6161	6161	6161
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 ownership shares 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 0–1 km of the protected area. Control villages are villages located 20–50 km 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. Statistical significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

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, our findings indicate higher poverty rates and lower consumption levels among populations residing near protected areas two decades after the commencement of eco-development initiatives. We also observe a decline in the ownership of assets typically associated with agricultural employment, such as vehicles and agricultural and irrigation equipment. These findings are consistent with our main results, which suggest that exposure to eco-development initiatives has shifted the labor force away from the agricultural sector and limited the proportion of irrigated land. However, these results should be interpreted with caution, as the absence of baseline data for these outcomes in 1991 limits our ability to draw causal conclusions about the impacts of eco-development initiatives on the overall well-being of the affected population.

4. Discussion and conclusions

For protected areas in developing countries to serve as effective policy tools for safeguarding biodiversity, it is essential to balance the developmental needs of rural communities with conservation goals (Adams et al., 2023). 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).

We find robust evidence that eco-development initiatives influenced labor markets between 1991 and 2011. By the end of the study period, while workforce participation rates remained comparable, villages within or near protected areas exhibited a lower share of year-round employment and a higher proportion of seasonal employment compared to more distant villages. The sectoral composition of year-round employment shifted away from agriculture and household industries towards other occupations, particularly in forestry and education. Additionally, treatment villages have a smaller share of irrigated agricultural land compared to control villages, partially offset by a higher share of rainfed agriculture, which is more conducive to seasonal employment.

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 this shift is accompanied by an increase in the share of seasonal workers it may imply irregular incomes, increasing the vulnerability of the local population. Additionally, the differences in forested land, alongside the higher share of rainfed agriculture in treatment villages compared to control villages, present a complex scenario regarding the population's well-being and resilience to climate change. Consequently, further research is needed to accurately assess these effects and, if necessary, to develop strategies that ensure eco-development initiatives effectively support stable incomes and climate resilience.

One positive outcome evident in our analysis is the increase in literacy rates across both genders, accompanied by the establishment of a greater number of industrial schools. This trend further aligns with the higher levels of employment in the education sector. Although we note that by 2011, affected villages 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 offers valuable insights into the labor market impacts of eco-development initiatives in protected areas, it is important to recognize several limitations. First, although our main dataset spans three decades, it lacks coverage for periods prior to 1991 and after 2011. While the CBPS-weighted DID approach ensures comparability at baseline between treatment and control areas, these data limitations restrict our ability to empirically verify the parallel trends assumption for the period before the initiation of eco-development activities. Moreover, we are unable to examine recent labor market developments. The absence of higher-frequency data also limits our ability to estimate more granular dynamic effects of eco-development. Second, the overlapping timing of various eco-development activities across protected areas constrains our analysis to average aggregate effects, preventing us from isolating the impacts of specific initiatives. Third, as with many empirical studies, our findings are region-specific. We focus on the Western Ghats in India, an area crucial for biodiversity conservation, which limits the generalizability of our results to other regions. Finally, while we explore several mechanisms through which eco-development initiatives could affect labor market outcomes, there may be additional channels that we have not investigated. For instance, the promotion of seasonal employment on plantations, either within or outside village boundaries, could play a significant role in shaping local employment patterns. Unfortunately, the data necessary to test such mechanisms are unavailable.

CRediT authorship contribution statement

Anca Balietti: Writing – review & editing, Writing – original draft, Formal analysis, Methodology, Investigation, Conceptualization. **Sreeja Jaiswal:** Writing – review & editing, Writing – original draft, Funding acquisition, Formal analysis, Methodology, Data curation, Investigation, Conceptualization. **Daniel Schäffer:** Software, Resources, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Sreeja Jaiswal gratefully acknowledges the financial support of the Alexander von Humboldt Foundation.

The authors are grateful for the very helpful comments and suggestions from the co-editor and the reviewers. We would like to thank Gunther Bensch for his suggestions on improving the methodology of the paper, Karina Kindler for her research assistance, the participants at the seminar in University of Manchester and Heidelberg for their comments and suggestions and academics and policymakers in India who helped in understanding the context and implementation of eco-development.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2024.103070.

References

Adams, Vanessa M., Chauvenet, Alienor L.M., Stoudmann, Natasha, Gurney, Georgina G., Brockington, Dan, Kuempel, Caitlin D., 2023. Multiple-use protected areas are critical to equitable and effective conservation. One Earth 6 (9), 1173–1189.

Akram, Agha Ali, Chowdhury, Shyamal, Mobarak, Ahmed Mushfiq, 2017. Effects of emigration on rural labor markets.

Alix-Garcia, Jennifer M., Sims, Katharine R.E., Orozco-Olvera, Victor H., Costica, Laura E., Fernández Medina, Jorge David, Romo Monroy, Sofía, 2018. Payments for environmental services supported social capital while increasing land management. Proc. Natl. Acad. Sci. 115 (27), 7016–7021.

Alix-Garcia, Jennifer M., Sims, Katharine R.E., Yañez-Pagans, Patricia, 2015. Only one tree from each seed? Environmental effectiveness and poverty alleviation in Mexico's payments for ecosystem services program. Amer. Econ. J.: Econ. Policy 7 (4), 1–40.

Alkon, Meir, 2018. Do special economic zones induce developmental spillovers? Evidence from India's states. World Dev. 107, 396–409.

Anand, M.O., Krishnaswamy, Jagdish, Kumar, Ajith, Bali, Archana, 2010. Sustaining biodiversity conservation in human-modified landscapes in the western ghats: remnant forests matter. Biol. Cons. 143 (10), 2363–2374.

Andam, Kwaw S., Ferraro, Paul J., Sims, Katharine R.E., Healy, Andrew, Holland, Margaret B., 2010. Protected areas reduced poverty in Costa Rica and Thailand. Proc. Natl. Acad. Sci. 107 (22), 9996–10001. http://dx.doi.org/10.1073/pnas.0914177107, URL https://www.pnas.org/content/107/22/9996.

Angrist, Josh, 2002. How do sex ratios affect marriage and labor markets? Evidence from America's second generation. Q. J. Econ. 117 (3), 997–1038.
Arkhangelsky, Dmitry, Athey, Susan, Hirshberg, David A., Imbens, Guido W., Wager, Stefan, 2021. Synthetic difference-in-differences. Amer. Econ. Rev. 111 (12), 4088–4118.
Asher, Sam, Lunt, Tobias, Matsuura, Ryu, Novosad, Paul, 2021. Development research at high geographic resolution: an analysis of night-lights, firms, and poverty in India using the shrug open data platform. The World Bank Econ. Rev. 35 (4).
Asher, Sam, Novosad, Paul, 2020. Rural roads and local economic development. Amer. Econ. Rev. 110 (3), 797–823.
Athey, Susan, Imbens, Guido W., 2017. The state of applied econometrics: Causality and policy evaluation. J. Econ. Perspect. 31 (2), 3–32.
Barboni, Giorgia, Agarwal, Parul, 2023. How do flexible microfinance contracts improve repayment rates and business outcomes? Experimental evidence from India. SSRN (February 14, 2023).
Bauer, Michal, Chytilová, Julie, Morduch, Jonathan, 2012. Behavioral foundations of microcredit: Experimental and survey evidence from rural India. Amer. Econ. Rev. 102 (2), 1118–1139.
Beauchamp, Emilie, Clements, Tom, Milner-Gulland, E.J., 2018. Assessing medium-term impacts of conservation interventions on local livelihoods in Northern Cambodia. World Dev. 101, 202–218. http://dx.doi.org/10.1016/j.worlddev.2017.08.008, URL https://www.sciencedirect.com/science/article/pii/S0305750X17302796.
Beck, Thorsten, Levine, Ross, Loayza, Norman, 2000. Finance and the sources of growth. J. Financ. Econ. 58 (1–2), 261–300.
Bensch, Gunther, Kluve, Jochen, Stöterau, Jonathan, 2021. The market-based dissemination of energy-access technologies as a business model for rural entrepreneurs: Evidence from Kenya. Resour. Energy Econ. 66, 101248.
Berman, Eli, Bui, Linda T.M., 2001. Environmental regulation and labor demand: Evidence from the South Coast air basin. J. Public Econ. 79 (2), 265–295.
Bhagwat, Shonil A., Kushalappa, Cheppudira G., Williams, Paul H., Brown, Nick D., 2005. The role of informal protected areas in maintaining biodiversity in the Western Ghats of India. Ecol. Soc. 10 (1).
Blakeslee, David, Dar, Aaditya, Fishman, Ram, Malik, Samreen, Pellegrina, Heitor S., Bagavathinathan, Karan Singh, 2023. Irrigation and the spatial pattern of local economic development in India. J. Dev. Econ. 161, 102997.
Börner, Jan, Schulz, Dario, Wunder, Sven, Pfaff, Alexander, 2020. The effectiveness of forest conservation policies and programs. Annu. Rev. Resour. Econ. 12 (1), 45–64.
Breza, Emily, Kaur, Supreet, Shamdasani, Yogita, 2021. Labor rationing. Amer. Econ. Rev. 111 (10), 3184–3224.
Breza, Emily, Kinnan, Cynthia, 2021. Measuring the equilibrium impacts of credit: Evidence from the Indian microfinance crisis. Q. J. Econ. 136 (3), 1447–1497.
Bryan, Gharad, Chowdhury, Shyamal, Mobarak, Ahmed Mushfiq, 2014. Underinvestment in a profitable technology: The case of seasonal migration in Bangladesh. Econometrica 82 (5), 1671–1748.
Callaway, Brantly, Sant'Anna, Pedro H.C., 2021. Difference-in-differences with multiple time periods. J. Econometrics 225 (2), 200–230.
Caloffi, Annalisa, Freo, Marzia, Ghinoi, Stefano, Mariani, Marco, Rossi, Federica, 2022. Assessing the effects of a deliberate policy mix: The case of technology and innovation advisory services and innovation vouchers. Res. Policy 51 (6), 104535.
Chaudhuri, Tapoja, 2013. From policing to'social fencing': shifting moral economies of biodiversity conservation in a South Indian Tiger Reserve. J. Political Ecol. 20 (1), 376–394.
Cheng, Audrey T., Sims, Katharine R.E., Yi, Yuanyuan, 2023. Economic development and conservation impacts of China's nature reserves. J. Environ. Econ. Manag. 121, 102848.
Cincotta, Richard P., Wisnewski, Jennifer, Engelman, Robert, 2000. Human population in the biodiversity hotspots. Nature 404 (6781), 990–992. http://dx.doi.org/10.1038/35010105, URL https://www.nature.com/articles/35010105.
Clements, Tom, Milner-Gulland, E.J., 2015. Impact of payments for environmental services and protected areas on local livelihoods and forest conservation in northern Cambodia. Conserv. Biol. 29 (1), 78–87. http://dx.doi.org/10.1111/cobi.12423, URL http://doi.wiley.com/10.1111/cobi.12423.
Clements, Tom, Suon, Seng, Wilkie, David S., Milner-Gulland, E.J., 2014. Impacts of protected areas on local livelihoods in Cambodia. World Develop. 64, S125–S134.
Curtis, E. Mark, 2018. Who loses under cap-and-trade programs? The labor market effects of the NOx budget trading program. Rev. Econ. Stat. 100 (1), 151–166.
Estifanos, Tafesse Kefyalew, Polyakov, Maksym, Pandit, Ram, Hailu, Atakelty, Burton, Michael, 2020. The impact of protected areas on the rural households' incomes in Ethiopia. Land Use Policy 91, 104349. http://dx.doi.org/10.1016/j.landusepol.2019.104349, URL https://linkinghub.elsevier.com/retrieve/pii/S0264837719306222.
Fafchamps, Marcel, 2013. Credit constraints, collateral, and lending to the poor. Revue d'économie du développement 21 (2), 79–100.
Ferraro, Paul J., Hanauer, Merlin M., 2011. Protecting ecosystems and alleviating poverty with parks and reserves: 'Win-Win' or Tradeoffs? Environ. Resour. Econ. 48 (2), 269–286. http://dx.doi.org/10.1007/s10640-010-9408-z, URL http://link.springer.com/10.1007/s10640-010-9408-z.
Ferraro, Paul J., Hanauer, Merlin M., 2014. Quantifying causal mechanisms to determine how protected areas affect poverty through changes in ecosystem services and infrastructure. Proc. Natl. Acad. Sci. 111 (11), 4332–4337.
Ferraro, Paul J., Hanauer, Merlin M., Miteva, Daniela A., Canavire-Bacarreza, Gustavo Javier, Pattanayak, Subhrendu K., Sims, Katharine R.E., 2013. More strictly protected areas are not necessarily more protective: evidence from Bolivia, Costa Rica, Indonesia, and Thailand. Environ. Res. Lett. 8 (2), 025011. http://dx.doi.org/10.1088/1748-9326/8/2/025011, URL https://iopscience.iop.org/article/10.1088/1748-9326/8/2/025011.
Ferraro, Paul J., Hanauer, Merlin M., Sims, Katharine R.E., 2011. Conditions associated with protected area success in conservation and poverty reduction. Proc. Natl. Acad. Sci. 108 (34), 13913–13918.
Ferraro, Paul J., Pressey, Robert L., 2015. Measuring the difference made by conservation initiatives: protected areas and their environmental and social impacts. Phil. Trans. R. Soc. B 370 (1681), 20140270. http://dx.doi.org/10.1098/rstb.2014.0270, URL https://royalsocietypublishing.org/doi/10.1098/rstb.2014.0270.
Ferris, Ann E., Frank, Eyal G., 2021. Labor market impacts of land protection: The northern spotted owl. J. Environ. Econ. Manag. 109, 102480.
Ferris, Ann E., Shadbegian, Ronald J., Wolverton, Ann, 2014. The effect of environmental regulation on power sector employment: Phase I of the title IV SO2 trading program. J. Assoc. Environ. Resour. Econ. 1 (4), 521–553.
Fink, Günther, Jack, B. Kelsey, Masiye, Felix, 2020. Seasonal liquidity, rural labor markets, and agricultural production. Amer. Econ. Rev. 110 (11), 3351–3392.
Fukumoto, Kentaro, McClean, Charles T., Nakagawa, Kuninori, 2021. No causal effect of school closures in Japan on the spread of COVID-19 in spring 2020. Nature Med. 27 (12), 2111–2119.
Gomez, Matthieu, Landier, Augustin, Sraer, David, Thesmar, David, 2021. Banks' exposure to interest rate risk and the transmission of monetary policy. J. Monetary Econ. 117, 543–570.
Goodair, Benjamin, Reeves, Aaron, 2022. Outsourcing health-care services to the private sector and treatable mortality rates in England, 2013–20: an observational study of NHS privatisation. The Lancet Public Health 7 (7), e638–e646.
Gubbi, Sanjay, Linkie, Matthew, Leader-Williams, Nigel, 2008. Evaluating the legacy of an integrated conservation and development project around a tiger reserve in India. Environ. Conserv. 35 (04), 331. http://dx.doi.org/10.1017/S0376892908005225, URL http://www.journals.cambridge.org/abstract_S0376892908005225.
Gubbi, Sanjay, MacMillan, Douglas C., 2008. Can non-timber forest products solve livelihood problems? A case study from Periyar Tiger Reserve, India. Oryx. 42 (2), 222–228. http://dx.doi.org/10.1017/S0030605308071111, URL https://www.cambridge.org/core/journals/oryx/article/can-nontimber-forest-products-solve-livelihood-problems-a-case-study-from-periyar-tiger-reserve-india/A400EAB9D3F23117390B90E712295530.
Hafstead, Marc A.C., Williams III, Roberton C., 2018. Unemployment and environmental regulation in general equilibrium. J. Public Econ. 160, 50–65.

Heckman, James J., Vytlacil, Edward J., 2007. Econometric evaluation of social programs, part I: Causal models, structural models and econometric policy evaluation. Handb. Econom. 6, 4779–4874.

Hertzberg, Andrew, Liberman, Andres, Paravisini, Daniel, 2018. Screening on loan terms: evidence from maturity choice in consumer credit. Rev. Financ. Stud. 31 (9), 3532–3567.

Imai, Kosuke, Ratkovic, Marc, 2014. Covariate balancing propensity score. J. R. Stat. Soc. Ser. B Stat. Methodol. 76 (1), 243–263.

Imai, Kosuke, Ratkovic, Marc, 2015. Robust estimation of inverse probability weights for marginal structural models. J. Amer. Statist. Assoc. 110 (511), 1013–1023.

Imbens, Guido W., Rubin, Donald B., 2015. Causal Inference in Statistics, Social, and Biomedical Sciences. Cambridge University Press.

Imbert, Clement, Papp, John, 2015. Labor market effects of social programs: Evidence from India's employment guarantee. Am. Econ. J. Appl. Econ. 7 (2), 233–263.

Jayachandran, Seema, 2015. The roots of gender inequality in developing countries. Annu. Rev. Econ. 7 (1), 63–88.

Jones, Kendall R., Venter, Oscar, Fuller, Richard A., Allan, James R., Maxwell, Sean L., Negret, Pablo Jose, Watson, James EM, 2018. One-third of global protected land is under intense human pressure. Science 360 (6390), 788–791.

Kale, Manish P., Chavan, Manoj, Pardeshi, Satish, Joshi, Chitiz, Verma, Prabhakar A., Roy, P.S., Srivastav, S.K., Srivastava, V.K., Jha, A.K., Chaudhari, Swapnil, et al., 2016. Land-use and land-cover change in Western Ghats of India. Environ. Monit. Assess. 188, 1–23.

Karanth, Krithi K., Gopalaswamy, Arjun M., DeFries, Ruth, Ballal, Natasha, 2012. Assessing patterns of human-wildlife conflicts and compensation around a central Indian protected area. PLoS One 7 (12), e50433.

Karanth, Krithi K., Nepal, Sanjay K., 2012. Local residents perception of benefits and losses from protected areas in India and Nepal. Environ. Manag. 49, 372–386.

Kaur, Supreet, 2019. Nominal wage rigidity in village labor markets. Amer. Econ. Rev. 109 (10), 3585–3616.

Kleemans, Marieke, Magruder, Jeremy, 2018. Labour market responses to immigration: Evidence from internal migration driven by weather shocks. Econ. J. 128 (613), 2032–2065.

Kranker, Keith, 2019. PSWEIGHT: Stata module to perform IPW- and CBPS-type propensity score reweighting, with various extensions. URL https://ideas.repec.org/c/boc/bocode/s458657.html.

Ma, Ben, Cai, Zhen, Zheng, Jie, Wen, Yali, 2019. Conservation, ecotourism, poverty, and income inequality – a case study of nature reserves in Qinling, China. World Dev. 115, 236–244. http://dx.doi.org/10.1016/j.worlddev.2018.11.017, URL http://www.sciencedirect.com/science/article/pii/S0305750X18304236.

Maan, S.J., Chaudhry, P., 2019. People and protected areas: some issues from India maan, SJ chaudhry, p.. Animal Biodivers. Conserv. 42 (1), 79–90.

Mansourian, Stephanie, Belokurov, Alexander, Stephenson, P.J., 2009. The role of forest protected areas in adaptation to climate change. URL https://api.semanticscholar.org/CorpusID:130776484.

Meiyappan, P., Roy, P.S., Soliman, A., Li, T., Mondal, P., Wang, S., Jain, A.K., 2018. India village-level geospatial socio-economic data set: 1991, 2001. http://dx.doi.org/10.7927/H4CN71ZJ, Place: Palisades, NY.

Ministry of Environment and Forest, Government of India, 1992. Annual report 1991-92. http://moef.gov.in/wp-content/uploads/2018/04/AR-91-92.pdf.

Ministry of Environment and Forest, Government of India, 2002. Annual report 2001-02. http://moef.gov.in/wp-content/uploads/report/0102/con0102.html.

Ministry of Rural Development, Government of India, 2011. Socio economic and caste census.

Miranda, Juan José, Corral, Leonardo, Blackman, Allen, Asner, Gregory, Lima, Eirivelthon, 2016. Effects of protected areas on forest cover change and local communities: evidence from the Peruvian Amazon. World Develop. 78, 288–307.

Myers, Norman, Mittermeier, Russell A., Mittermeier, Cristina G., Da Fonseca, Gustavo A.B., Kent, Jennifer, 2000. Biodiversity hotspots for conservation priorities. Nature 403 (6772), 853–858.

Pfaff, Alexander, Robalino, Juan, Herrera, Diego, Sandoval, Catalina, 2015. Protected areas' impacts on Brazilian Amazon deforestation: examining conservation–development interactions to inform planning. PLoS One 10 (7), e0129460.

Pramova, Emilia, Locatelli, Bruno, Djoudi, Houria, Somorin, Olufunso A., 2012. Forests and trees for social adaptation to climate variability and change. Wiley Interdiscip. Rev. Clim. Change 3, URL https://api.semanticscholar.org/CorpusID:130301468.

Reddy, C. Sudhakar, Jha, C.S., Dadhwal, V.K., 2016. Assessment and monitoring of long-term forest cover changes (1920–2013) in Western Ghats biodiversity hotspot. J. Earth Syst. Sci. 125 (1), 103–114. http://dx.doi.org/10.1007/s12040-015-0645-y.

Reynaert, Mathias, Souza-Rodrigues, Eduardo, van Benthem, Arthur A., 2023. The environmental impacts of protected area policy. Reg. Sci. Urban Econ. 103968.

Reynaert, Mathias, Souza-Rodrigues, Eduardo, van Benthem, Arthur A., 2024. The environmental impacts of protected area policy. Reg. Sci. Urban Econ. 107, 103968.

Rico, Jimena, Wang, Zhenhua, Pfaff, Alexander, 2023. Comparing protection types in the peruvian amazon multiple-use protected areas did no worse for forests. Available at SSRN 4540784.

Rico-Straffon, Jimena, Wang, Zhenhua, Panlasigui, Stephanie, Loucks, Colby J, Swenson, Jennifer, Pfaff, Alexander, 2023. Forest concessions and eco-certifications in the peruvian amazon: Deforestation impacts of logging rights and logging restrictions. J. Environ. Econ. Manag. 118, 102780.

Robalino, Juan, Villalobos, Laura, 2015. Protected areas and economic welfare: an impact evaluation of national parks on local workers' wages in Costa Rica. Environ. Dev. Econ. 20 (3), 283–310. http://dx.doi.org/10.1017/S1355770X14000461, URL https://www.cambridge.org/core/journals/environment-and-development-economics/article/protected-areas-and-economic-welfare-an-impact-evaluation-of-national-parks-on-local-workers-wages-in-costa-rica/8E2867F9DE9EC8B073E3F82F9A3544E6.

Sims, Katharine R.E., 2010. Conservation and development: Evidence from Thai protected areas. J. Environ. Econ. Manag. 60 (2), 94–114. http://dx.doi.org/10.1016/j.jeem.2010.05.003, URL http://www.sciencedirect.com/science/article/pii/S0095069610000586.

Sims, Katharine R.E., Alix-Garcia, Jennifer M., 2017. Parks versus PES: Evaluating direct and incentive-based land conservation in Mexico. J. Environ. Econ. Manag. 86, 8–28.

Srivastava, A., Rajeevan, M., Kshirsagar, S., 2009. Development of a high resolution daily gridded temperature data set (1969–2005) for the Indian region. Atmospheric Sci. Lett. 10, 249–254. http://dx.doi.org/10.1002/asl.232.

Srivathsa, Arjun, Majgaonkar, Iravatee, Sharma, Sushma, Singh, Priya, Punjabi, Girish Arjun, Chawla, Malaika Mathew, Banerjee, Aditya, 2020. Opportunities for prioritizing and expanding conservation enterprise in India using a guild of carnivores as flagships. Environ. Res. Lett. 15 (6), 064009.

Vancutsem, Christelle, Achard, Frédéric, Pekel, J.-F., Vieilledent, Ghislain, Carboni, Silvia, Simonetti, Dario, Gallego, Javier, Aragao, Luiz E.O.C., Nasi, Robert, 2021. Long-term (1990–2019) monitoring of forest cover changes in the humid tropics. Sci. Adv. 7 (10), eabe1603.

Waldron, Anthony, Miller, Daniel C., Redding, Dave, Mooers, Arne, Kuhn, Tyler S., Nibbelink, Nate, Roberts, J. Timmons, Tobias, Joseph A., Gittleman, John L., 2017. Reductions in global biodiversity loss predicted from conservation spending. Nature 551 (7680), 364–367.

Walker, W. Reed, 2013. The transitional costs of sectoral reallocation: Evidence from the clean air act and the workforce. Q. J. Econ. 128 (4), 1787–1835.

Wildlife Institute of India, 2016. Management effectiveness evaluation (MEE) of national parks and wildlife sanctuaries in India. https://wii.gov.in/images/images/documents/publications/t_manual_2016_mee_2016.pdf.

Wildlife Protection Act, 1972. https://tribal.nic.in/downloads/FRA/Concerned%20Laws%20and%20Policies/Wildlife%20Protection%20Act,%201972.pdf.