Rural Poverty Alleviation and Forest Conservation

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Abstract

While forests' contributions to livelihoods and poverty reduction are well-documented, the reciprocal impacts of poverty alleviation initiatives on forest conservation and sustainability remain underexamined. This relationship is particularly critical in the context of climate change.I estimate the impact of rural poverty alleviation on forest conservation by analyzing the implementation of a large-scale poverty alleviation effort in rural China, beginning in 2011. My analysis employs a high-resolution annual land cover dataset from 2000 to 2020, encompassing periods around the implementation of rural poverty alleviation, and applies a generalized difference-in-differences empirical strategy. I find that rural poverty alleviation had a positive impact on forest cover, with an annual marginal effect of an 18 km^2 increase in forest area. Whether assessing the carbon storage increase directly from the marginal effect of forest area alone or considering the land-use changes underlying the forest area increase, the value of marginal carbon storage—estimated using global social cost of carbon—is approximately five times greater than the cost of poverty alleviation. The primary mechanism behind the positive effects on forest conservation is largely attributable to relocation initiatives linked to rural poverty alleviation efforts. These findings highlight a novel, highly cost-effective approach to conserve forests through poverty alleviation efforts. By addressing extreme poverty, this strategy not only supports the well-being of impoverished rural communities but also promotes environmental restoration, creating a mutually reinforcing pathway for sustainable development.

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Keywords: Rural Poverty alleviation, Forest conservation, Land use change, Carbon storage

JEL Codes: O23,O43,P25,Q57

1 Introduction

Eliminating extreme poverty and addressing climate change represent two of the most significant global challenges of the contemporary era (IPCC, 2021; Nations, 2015; Sachs et al., 2019; World Bank, 2020) . In 2024, approximately 8.5% of the global population lives in extreme poverty, equating to 692 million individuals subsisting on less than $2.15 per person per day[1](World Bank, 2024). More than three-quarters of those living in extreme poverty reside in rural areas (United Nations, 2023). Meanwhile, 2023 marked the hottest year on record, accompanied by unprecedented increases in ocean heat, sea level rise, Antarctic sea ice loss, and glacier retreat, collectively highlighting the escalating impacts of climate change (Lopez, 2024; NOAA, 2024; WMO, 2024).

Forest conservation has become increasingly important in combating climate change, as forests play a critical role in regulating the Earth's climate and mitigating global warming. Nevertheless, poverty often drives deforestation and forest degradation, as economically disadvantaged populations may lack the resources, knowledge, or incentives required to adopt sustainable forest management practices (Leichenko and Silva, 2014; World Bank, 2020). Within this framework, poverty alleviation holds significant potential to advance forest conservation by reducing reliance on forest exploitation and promoting the adoption of sustainable practices. This dual dynamic raises a fundamental question: can the global challenges of poverty alleviation and forest conservation be addressed concurrently? Specifically, can efforts to lift millions of people out of poverty align with the goals of conserving forests? Despite its importance, the interplay between poverty alleviation and forest conservation remains insufficiently examined in the literature (Hubacek et al., 2017; Malerba, 2020).

I estimate the impact of rural poverty alleviation on forest conservation by utilizing the rollout of a comprehensive poverty alleviation initiative launched in 2011 across over 100 counties within contiguous areas of extreme poverty in rural China. Using a generalized difference-in-differences empirical approach that incorporates high-resolution (30m) land use and land cover data, I examine the effects of rural poverty alleviation initiatives on forest conservation. The analysis reveals that the implementation of these poverty alleviation programs led to a significant increase in forest share at the county level, suggesting positive environmental spillovers associated with economic

[1] at 2017 purchasing power adjusted prices.

interventions in impoverished rural areas. Additionally, my analysis shows that the implementation of rural poverty alleviation initiatives promoted land use transitions toward forests, accompanied by a decline in deforestation—though this reduction was not statistically significant. Although there is regional heterogeneity across contiguous areas of extreme poverty, all located in mountainous regions, the majority of areas exhibit positive outcomes from the poverty alleviation initiatives, while the remainder show effects close to zero but statistically insignificant.

In 2021, China declared success in its fight against extreme poverty, having lifted 122.38 million rural residents[2] out of poverty in the past decade (World Bank, 2022). To achieve this milestone, in 2011, the country designated 11 contiguous areas of extreme poverty as the main battleground[3] for a new phase of poverty alleviation efforts. This designation was based on indicators closely linked to poverty levels, including the three-year averages (2007-2009) of county-level per capita GDP, per capita general budget revenue, and per capita net income of farmers. These areas include the Southern Daxing'anling mountain area, Yanshan-Taihang mountain area, Liupan mountain area, Qinba mountain area, Dabie mountain area, Wumeng mountain area, Wuling mountain area, Western Yunnan border mountain area, Dian-Gui-Qian karst region, Luoxiao mountain area, and Lvliang mountain area. Guided by the *Outline for Poverty Alleviation and Development in Rural China (2011–2020)*[4], poverty alleviation efforts were carried out at the county level. The implementation of poverty alleviation programs at the county level across these designated areas created a quasi-experimental variation that can be leveraged to identify the impact of poverty alleviation on forest conservation.

The counties within these 11 contiguous areas of extreme poverty, referred to as poverty counties (or poverty-stricken or impoverished counties), serve as the central front in China's fight against extreme poverty.The designation of poverty counties play a pivotal role in China's rural poverty

[2]Using the extreme poverty line as incomes below US$1.90 per day, constant 2010 US $
Data Source: National Bureau of Statistics of China https://www.stats.gov.cn/sj/ndsj/2021/indexeh.htm

[3]The Southern area of Xinjiang (Kashgar, Hotan, and Kizilsu Kirgiz Autonomous Prefecture), Lvliang, the Tibetan areas across four provinces (Qinghai, Gansu, Sichuan, and Yunnan), and the Xizang Autonomous Region— all of which had received special support prior to 2011—also serve as key battlegrounds for poverty alleviation efforts.Including these three areas, the total comes to 14 designated areas of extreme poverty.However, since these areas had received poverty alleviation support—being "already treated" —before 2011, they were excluded from the study to maintain the treatment approach.

[4]See in Chinese: https://www.gov.cn/gongbao/content/2011/content_2020905.htm

alleviation efforts across different eras (World Bank, 2022). In 1986, as part of a strategic approach to poverty alleviation, China identified the most vulnerable counties and designated them as state poverty counties. The list was revised in 1994 and 2001 to better target poverty reduction efforts, and in 2011, the term ″poverty county″ was officially changed to ″key county for national poverty alleviation and development work″. To maintain the treatment approach, counties within these 11 contiguous areas of extreme poverty that were also classified as ″key counties for national poverty alleviation and development work″ were excluded from the study, as they had already begun implementing poverty alleviation measures prior to 2011.

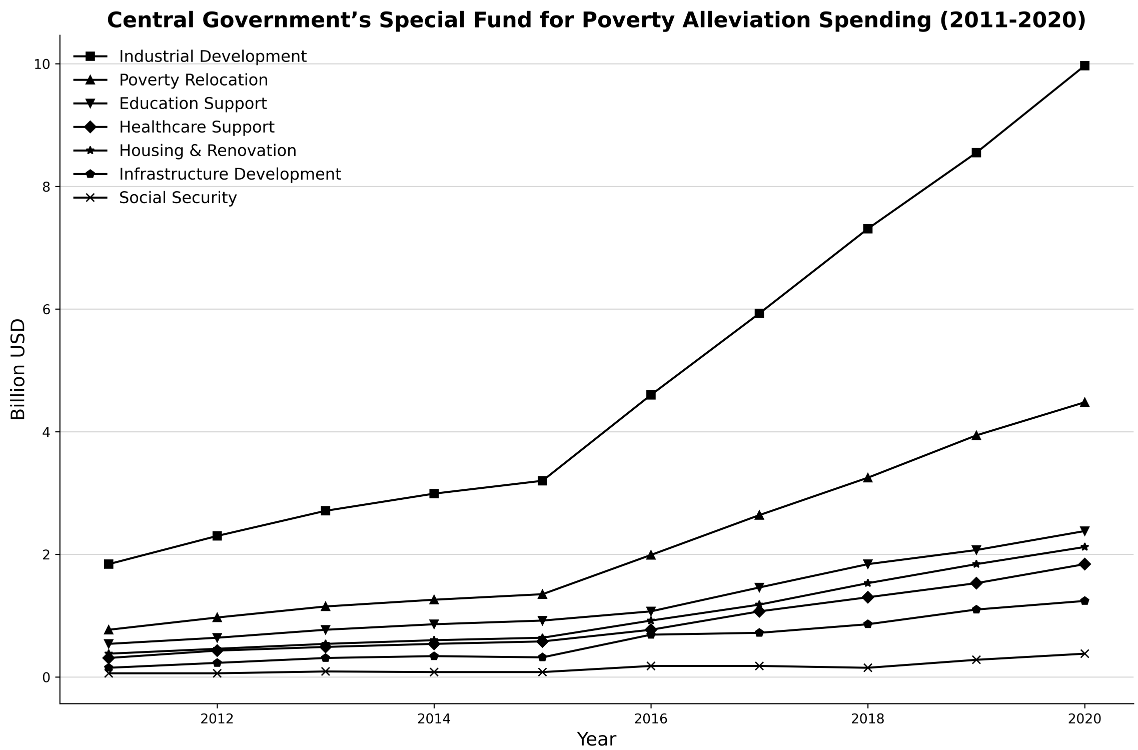

FIGURE 1: CENTRAL GOVERNMENT'S SPECIAL FUND FOR POVERTY ALLEVIATION SPENDING

Note: Figure 1 shows the main poverty alleviation programs and expenditures from the Chinese Central Government's Special Fund for Poverty Alleviation (in Billion USD) from 2011 to 2020. The USD conversion from RMB is based on the exchange rate as of December 31, 2020, at 6.5250 RMB/USD, as recorded by the Federal Reserve Bank of St. Louis. Source: China Rural Poverty Monitoring Reports (2011-2021).

Poverty alleviation funds for designated poverty counties primarily come from both central and provincial governments, with provincial governments often providing matching funds based on central allocations. Figure 1 outlines central government alleviation fund spending. Since 2011, the fund has increased each year from $4.05 billion to $22.40 billion, totaling $110.22 billion over the decade. These expenditures encompass a range of targeted areas, including industrial development (45.0%), which supports local industries, small enterprises, and agricultural modernization to generate employment and increase incomes; poverty alleviation relocation (19.8%), which relocates populations from resource-scarce regions to areas with improved economic opportunities and access to services, primarily transitioning the impoverished population from rural to urban areas. Figure 2 illustrates the contrasting living conditions of impoverished rural villagers from a specific village before and after the implementation of the poverty alleviation relocation program.Additionally, education support (11.4%) focuses on improving school attendance, educational quality, and vocational training. Healthcare support (8.1%) enhances access to medical services, mitigating health-related financial risks. Housing renovation (9.3%) provides subsidies for the construction or improvement of affordable homes, while infrastructure development (5.3%) emphasizes the construction and upgrading of roads, electricity, and water supplies in rural areas to improve connectivity and service access. Finally, social security measures (1.4%) extend minimum income guarantees, pensions, and welfare benefits to safeguard vulnerable populations This comprehensive strategy aims to address immediate needs while promoting sustainable economic growth in poverty counties.

Figure 2: Living Conditions Before and After Poverty Alleviation Relocation

Note: Figure 2 illustrates the contrasting living conditions of impoverished rural villagers before and after the implementation of a poverty alleviation relocation program. The upper image depicts a house in a mountainous, impoverished village prior to relocation. The lower image shows newly constructed white buildings, which are the replacement homes built for the villagers after their relocation. Source: https://english.news.cn/home.htm

This study employs two core datasets. The first dataset classifies counties into two distinct groups: those newly designated as poverty counties in 2011 and those that were not, with neither group having previously received such a designation.This classification enables a sharp analysis of the impact of rural poverty alleviation. The second dataset comprises Land Use and Land Cover (LULC) data, which provides detailed insights into the distribution of various land use categories and their temporal changes.

I employ a generalized difference-in-differences (DID) research framework that incorporates two dimensions of variation: the county's designation as a poverty county in 2011 and temporal variations in forest share, as captured by Land Use and Land Cover (LULC) data. Under the parallel trends assumption, the treatment—namely, the 2011 poverty county designation—facilitates the estimation of the impact of poverty alleviation policies on forest conservation outcomes. This empirical strategy addresses several potential confounding factors. First, it accounts for county-specific characteristics that remain constant over time (e.g., historical land use patterns or socio-economic characteristics). Second, it controls for temporal shocks that affect all counties uniformly (e.g., national economic trends or policy changes). Third, it accommodates differential yet smooth trends in land use change among counties that were designated as poverty-stricken and those that were not. I also address recent econometric concerns associated with the difference-in-differences designs by demonstrating robustness through the event study of various alternative estimators.

My primary findings indicate that rural poverty alleviation positively impacts forest share. Rural poverty alleviation contributes to approximately a 0.5% enhancement in forest cover during the post-period, specifically from 2011 to 2020. This aligns with the existing literature. Ran et al. (2022) discovered that China's poverty alleviation considerably enhances the ecological environment quality of poverty counties in the Qinghai-Tibet Plateau region, as evidenced by the use of the Remote Sensing Ecological Index as an environmental metric. Malerba (2020) similarly observed positive effects of poverty alleviation on forest cover through an analysis of the ″Familias en Acción″ program at the municipal level in Colombia, noting an annual increase of 0.5% in forest area.Fan, Bai, and Zhao (2022) found that average annual normalized difference vegetation index (NDVI) exhibited an increasing trend , increasing by 0.84% per year from 2000 to 2019 in poverty counties of 14 contiguous areas of dire poverty.

This study contributes to the literature in several significant ways. First, it provides evidence between poverty alleviation and forest conservation. The empirical results from this study, centered on China, diverge from prior research that specifically targeted tropical forests(Alix-Garcia et al., 2013; Malerba, 2020; Wunder, 2001). Second, this research contributes to the literature on inequality and environmental impacts. Most existing studies suggest that inequality, particularly income inequality, negatively impacts the environment, whereas reducing inequality can foster positive environmental outcomes (Ajide and Ibrahim, 2022; Baek and Gweisah, 2013; Berthe and Elie, 2015; W. Chen, S. Chen, and Tang, 2022; Heerink, Mulatu, and Bulte, 2001). This study provides additional evidence for this relationship: reducing income inequality through poverty alleviation has positive environmental effects, as seen in increased forest cover. The results of this study also align with the classic Environmental Kuznets Curve (EKC) hypothesis, which posits that environmental degradation decreases as per capita GDP rises beyond a certain income threshold. In my research, I observed an increase in forest cover following poverty alleviation, supporting the EKC hypothesis in this context. Third, this research addresses a gap in the literature on the relationship between poverty and ecosystem services,offering robust evidence to enhance our understanding of how poverty alleviation impacts ecosystem services. While many studies focus on how ecosystem services contribute to poverty alleviation (Cao, Ouyang, and Xu, 2022; Daw et al., 2011; Ferraro et al., 2015; Lehmann, Martin, and Fisher, 2018) or examine the trade-offs between poverty alleviation and ecosystem services (Jayachandran, 2023), this study shifts the perspective to assess the direct effects of poverty alleviation on ecosystem services. Specifically, I calculated the resulting carbon storage from both the direct increase in forest area and from land-use changes driven by shifts in forest share, attributable to rural poverty alleviation. This provides evidence that poverty alleviation has a positive effect on ecosystem services. Additionally, when valuing carbon storage using the social cost of carbon, the estimated value of carbon storage is five times the cost of poverty alleviation.

The remainder of this paper is organized as follows: Section 2 introduces the data used in the analysis; Section 3 outlines the empirical framework; Section 4 presents and discusses the regression results; Section 5 examines the underlying mechanisms; and finally, Section 6 concludes with a discussion of the findings.

2 Data

This section provides an overview of the primary datasets employed in the study. Data collection includes information on contiguous areas of extreme poverty and land use and land cover, such as forest share and other land use categories. Additionally, socio-economic indicators at the county level, as well as environmental and geographic variables, were gathered to provide a comprehensive dataset for analysis.

2.1 Contiguous Areas of Extreme Poverty

The initiative to implement poverty alleviation measures across contiguous areas of extreme poverty, recognized as the focal regions in China's campaign against extreme poverty, was inaugurated in 2011. The Chinese government designated a total of 11 contiguous areas[5] nationwide to address extreme poverty comprehensively.Among the contiguous areas, 680 counties have been officially designated as poverty counties. Data on poverty counties were sourced from the official website of the China's State Council [6]. Among these poverty counties, some had already been designated as ″key counties for national poverty alleviation and development″ or had implemented other specialized poverty alleviation policies [7] prior to 2011. I exclude counties that had already received poverty alleviation interventions from the set of all poverty counties within contiguous areas of extreme poverty. The treatment group ultimately consists of 106 poverty counties within 10 contiguous areas [8] of extreme poverty. Figure 3 illustrates the geographic distribution of these 106 poverty counties, while Figure 5 displays the distribution across the 10 contiguous areas.

Data on the control group, comprising non-poverty counties [9] in 2011, was compiled from the comprehensive list of counties available in the *China County Statistical Yearbooks (2001–2021)*,

[5] These areas include the Southern Daxing'anling mountain area, Yanshan-Taihang mountain area, Liupan mountain area, Qinba mountain area, Dabie mountain area, Wumeng mountain area, Wuling mountain area, Western Yunnan border mountain area, Dian-Gui-Qian karst region, Luoxiao mountain area, and Lvliang mountain area

[6] The State Council of China website: https://www.gov.cn/gzdt/2012-06/14/content_2161045.htm

[7] Data sourced from China's Poverty Alleviation Database: https://www.jianpincn.com/

[8] This excludes the Lvliang Mountain area from the original 11 designated contiguous areas of extreme poverty.

[9] Non-poverty counties are defined as those that are neither designated as "key counties for national poverty alleviation and development" nor classified as poverty counties within the 11 contiguous areas of extreme poverty.

published by the National Bureau of Statistics of China.[10] These yearbooks provide comprehensive socio-economic information for all counties across China, with further details discussed in Section 2.3. The control group was defined by excluding all counties designated as poverty-stricken, encompassing both "key counties for national poverty alleviation and development" and counties located within contiguous areas of extreme poverty. Consequently, the control group comprises relatively affluent counties that were not classified as poverty counties in 2011, totaling 1,284 counties. The distribution of the control group is presented in Figure 3.

2.2 Land Use Land Cover Data

I establish my outcomes of interest using Land Use Land Cover data from China's Land-Use/Cover Datasets (CLUDs), which provide detailed documentation of land-use and land-cover patterns across China from 1999 to 2020. The CLUDs are derived from remotely sensed products with a 30-meter resolution, generated through a combination of human-computer interaction and interpretation of Landsat imagery (Yang et al., 2021). The CLUDs utilize a classification system that includes nine major land cover types: cropland, forest, shrub, grassland, water, snow and ice, barren land, impervious surfaces, and wetland. Publicly accessible on Zenodo[11], the CLUDs serve as the core dataset for my analysis of land-use dynamics in China.

The outcomes of interest derived from the CLUDs include the shares of different land uses and the shares of changes in different land uses. To illustrate the deriving process, I use my baseline outcomes—forest share, along with forest gains and losses—as an example. First, I collected the county border shapefile [12] from the National Platform for Common GeoSpatial Information Services [13]. I then combined the county border shapefile with the CLUDs (1999-2020) for each year. For each county and each year, I calculate both the total area and the forest area. The forest share of a county in a given year is calculated by dividing the forest area of the county in that year by the total county area. Forest gains are derived by comparing land use and land cover between any two years

[10] National Bureau of Statistics of China Website: https://www.stats.gov.cn/english/
[11] China's Land-Use/Cover Datasets (CLUDs) can be downloaded from Zenodo https://zenodo.org/record/5816591
[12] The official approval number of the county boundary map is GS (2020)4630.
[13] National Platform for Common GeoSpatial Information Services Website: https://www.tianditu.gov.cn/

from 1999 to 2020, capturing land use changes over the study period (2000-2020). Forest gains are defined as areas classified as forest in the subsequent year that were not classified as forest in the previous year. The forest gains share of a county in a given year is calculated as the total forest gains in that year divided by the total county area. Using the same calculation method, I also determine the forest gains share originating from the other eight land uses, including cropland, shrub, grassland, water, snow and ice, barren land, impervious surfaces, and wetland. Similarly, forest losses are calculated, including the forest losses share and the share of losses originating from the other eight land uses. Forest losses are defined as areas classified as forest in the previous year that were no longer classified as forest in the subsequent year.

Figure 3 illustrates forest share changes between 2011 and 2020 in treatment and control groups, as described in Section 2.1. This period corresponds to the post-poverty alleviation phase for the treatment group, i.e. the poverty counties in the continuous areas of extreme poverty designated in 2011. Figure 3 shows that the treatment group demonstrates more green, indicating an increase in forest share, while the control group exhibits either more red or yellow, suggesting a decrease or no change in forest share.

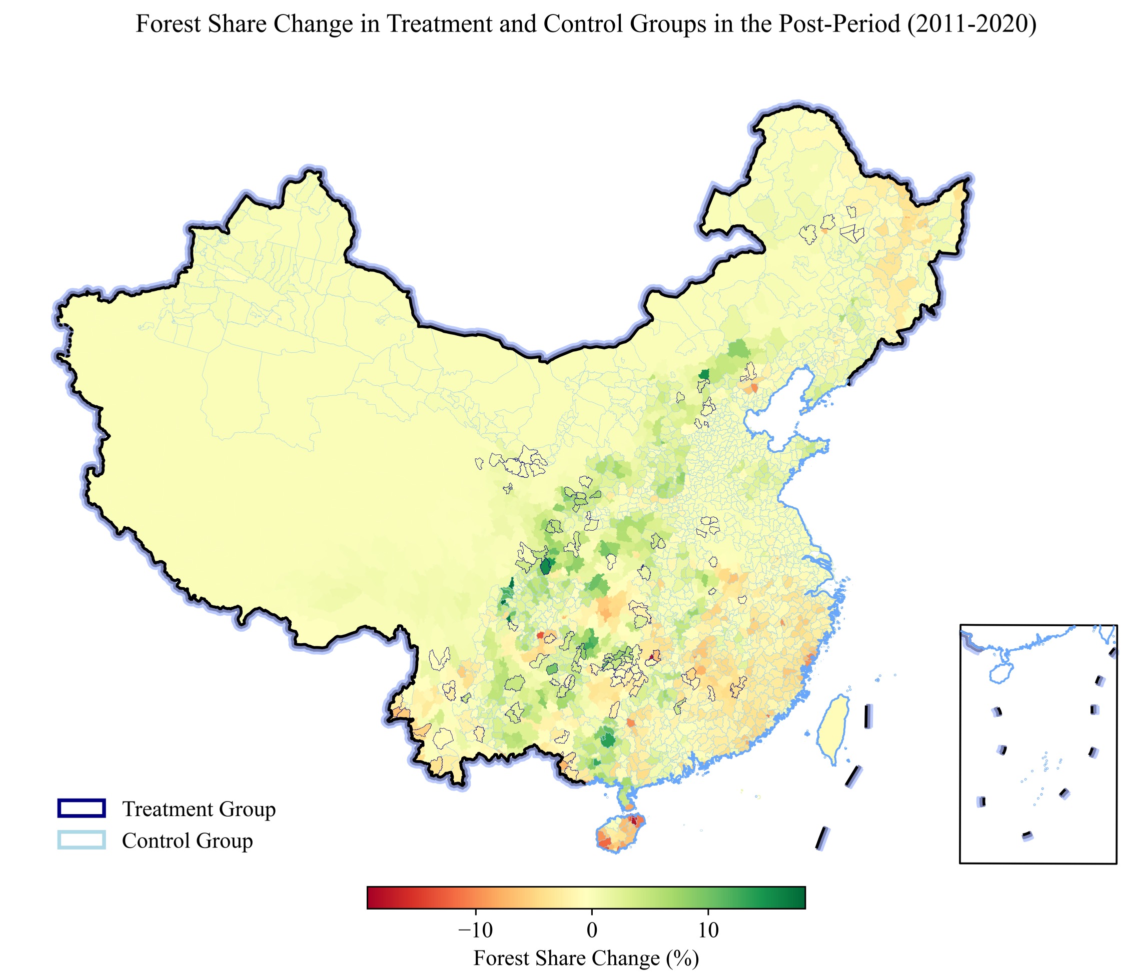

Figure 3: Distribution of Treatment Group and Control Group

Notes: Figure 3 shows the differences in forest share between the treatment and control groups during the post-period (2011-2020). The counties in the treatment group are outlined with navy borders, while those in the control group have light blue borders. Green represents an increase in forest share, red indicates a decrease, and yellow signifies no change.Black lines represent land borders, while light blue lines indicate ocean borders.

2.3 Socio-economic Data

I use various socio-economic variables as control factors in this study. The data is sourced from the *China County Statistical Yearbooks (2001-2021)*, which cover the period from 2000 to 2020 and are published by the National Bureau of Statistics of China (NBS). These yearbooks offer a comprehensive annual overview of each county, detailing variables related to economic development, agricultural production, industry and investments, education, health, and social welfare. The control variables include population, government revenue and expenditure, GDP from the primary sector, GDP from the secondary sector, and year-end savings deposits in financial institutions. All monetary variables have been adjusted for inflation using China's national Consumer Price Index (CPI), with 2010 as the base year (2010=100), sourced from the NBS website[14].

2.4 Other Data

In this study, I also include additional data, either as outcomes of interest or as control variables.

Other Outcomes of Interest.— Other outcomes of interest include the average NDVI per km^2, planted forest share and the number of rural villages. The NDVI data is sourced from the US NASS's MODIS Vegetation Index Products. Using the same county border shapefile as described in Section 2.2, I clip the NDVI data to the county level. The government-led planted forest share is defined as the planted forest area divided by the total county area and is sourced from the *China Forestry and Grassland Statistical Yearbooks (2001-2021)*, published by the National Forestry and Grassland Administration[15]. These yearbooks provide data on the area of government-led planted forests for each year during the study period. The number of rural villages is calculated from the Statistical Area Codes and Urban-Rural Classification Codes, which are published annually by the National Bureau of Statistics of China.

Other Control Variables.— The other control variables include annual average rainfall, relief degree of land surface [16], average nighttime light intensity, and average annual wind speed at the county level. The annual average rainfall is derived from the Precipitation Dataset of China, provided by the National Earth System Science Data Center, National Science & Technology Infrastructure of

[14] National Bureau of Statistics of China (NBS) website: http://www.stats.gov.cn/english/

[15] Part of the *China Forestry and Grassland Statistical Yearbooks* can be downloaded from the National Forestry and Grassland Administration website: http://www.forestry.gov.cn/c/www/tjnj.jhtml.

[16] Relief Degree of Land Surface (RDLS) is a comprehensive measure of regional altitude and the degree of surface dissection, with higher values indicating greater variation in elevation and surface ruggedness.
(Continued from the previous page) From You, Feng, and Y. Yang (2018), the equation is as follows:

$$\text{RDLS} = \frac{\text{Max}(H) - \text{Min}(H)}{\text{ALT}} \times \frac{P(A)}{A}$$

where RDLS is the relief degree of land surface; ALT is the average elevation in a grid cell (m); Max(H) and Min(H) represent the highest and lowest altitudes in this grid cell, respectively (m); $P(A)$ is the area of flat land (km^2); and A is the total area of the extraction unit.

China [17]. Relief Degree of Land Surface is a comprehensive representation of regional altitude and surface cutting from You, Feng, and Y. Yang (2018) [18].The nighttime light intensity data is sourced from the NOAA's Visible Infrared Imaging Radiometer Suite (VIIRS)[19].

2.5 Descriptive Statistics

Table 1 presents the main county-level descriptive statistics for both the treatment and control groups. It shows that the treatment group has a higher forest share and higher forest share change, but a lower cropland share, population, government revenue, expenditure, GDP (both primary and secondary sectors), savings deposits in financial institutions, nighttime light intensity. Appendix Tables A-1 and A-2 provide the descriptive statistics for all other 64 land use changes for both the treatment and control groups.

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[17] National Earth System Science Data Center: http://www.geodata.cn

[18] The dataset can be downloaded from here: https://www.geodoi.ac.cn/WebEn/HTML_INFO.aspx?Id=d663c880-600e-47c4-9df1-19d9c3f86e68

[19] Visible Infrared Imaging Radiometer Suite (VIIRS) Website: https://www.nesdis.noaa.gov/my-satellites/currently-flying/joint-polar-satellite-system/visible-infrared-imaging-radiometer-suite-viirs

Table 1: Descriptive Statistics

	Treatment Group		Contrl Group	
Variable	Mean	SD	Mean	SD
Forest Share (%)	50.74	31.62	31.86	33.00
Forest Gains per km^2 (%)	0.40	0.46	0.24	0.42
Forest Losses per km^2 (%)	0.34	0.41	0.24	0.41
Forest Share Change (%)	0.06	0.59	0.00	0.54
Planted Forest Share (%)	1.58	1.48	1.25	2.11
Cropland Share (%)	35.92	24.55	48.04	28.87
Shrub Share (%)	0.86	1.63	0.19	0.78
Grassland Share (%)	9.42	20.97	7.42	18.22
Water Share (%)	0.64	1.47	2.66	5.26
Snow Share (%)	0.00	0.04	0.07	0.74
Barren Land Share (%)	0.11	0.64	2.89	13.28
Impervious Surface Share (%)	2.30	4.02	6.86	7.87
Wetland Share (%)	0.00	0.00	0.01	0.08
Carbon Storage Density (C ton/km^2)	20156.30	7165.95	14826.26	8323.45
Average NDVI per km^2	0.36	0.10	0.32	0.13
County Area (km^2)	2505.59	1337.95	3362.43	9179.46
Population (Thousand)	475.21	300.41	554.67	357.76
Gov't Revenue (Million USD)	49.26	56.94	162.02	328.52
Gov't Expenditure (Million USD)	237.79	230.58	325.56	403.98
GDP Primary (Million USD)	235.99	203.11	333.38	294.55
GDP Secondary (Million USD)	373.63	396.94	1282.99	2091.20
Number of Rural Villages	190.88	133.30	205.81	162.92
Relief Degree of Land Surface	1.23	0.95	0.61	0.73
Savings Deposit (Million USD)	778.80	856.48	1616.85	2472.62
Average NTL Intensity per km^2	0.08	0.16	0.46	1.33
Average Annual Precipitation (mm)	1024.56	365.40	993.32	471.70
Average Annual Wind Speed (mph)	3.87	0.97	4.80	1.28
Total Observations	2132		26193	
No. of Counties	106		1284	

Notes: Table 1 presents the main county-level descriptive statistics for both the treatment and control groups. These county-level, annual variables offer a detailed snapshot of land use, economic, and environmental conditions within each region over time. Forest Share (%) and Forest Share Change (%) capture the extent and shifts in forest cover, reflecting both natural dynamics and human interventions in forestry management. Forest Gains and Losses per km^2 (%) measure the rates of reforestation and deforestation, indicating the outcomes of conservation efforts and land use policies. The Planted Forest Share (%) represents the proportion of forest area in a county that is established through government-led tree planting programs. Land use shares across Cropland, Shrub, Grassland, Water, Snow, Barren Land, Impervious Surfaces, and Wetlands (%) reveal the diversity of landscapes and the intensity of human impacts. Economic indicators, such as sectoral GDP, Government Revenue and Expenditure, and Savings Deposits (Million USD), provide insights into each county's economic performance and fiscal resources. Savings Deposits (Million USD) specifically represent the total amount of deposits held in financial institutions within a county, offering a view into the financial resources available at the local level and reflecting both individual and institutional saving behaviors within the county.Demographic measures, including Population and Number of Rural Villages, highlight human settlement patterns. NDVI (Normalized Difference Vegetation Index) measures vegetation health by quantifying live green vegetation per km^2, aiding in assessments of ecosystem vitality and land productivity. Average NTL Intensity per km^2, representing the average nighttime light intensity within a county.

3 Empirical Strategy

The central objective of this study is to identify the impact of poverty alleviation on forest conservation. A simple correlation between poverty alleviation and forest conservation is likely to be influenced by severe endogeneity concerns, making it unsuitable for credible interpretation. To overcome these issues, I utilize the sharp rollout of the poverty alleviation program across counties beginning in 2011, which offers quasi-experimental variation. As discussed in the background section, I exclude counties in ethnic minority areas from the analysis due to the presence of distinct support policies that may independently affect forest outcomes. The final treatment group comprises 106 counties. For robust identification, the control group consists of ″never treated″ counties, defined as wealthier counties that have never participated in the program. The treatment variable is defined by enrollment in the state poverty alleviation program, which is a central element of China's poverty reduction strategy, as the program's initiatives are primarily implemented within these designated counties.

Using a generalized difference-in-differences strategy, I begin my analysis by estimating a two-way fixed effects (TWFE) model as the baseline specification:

$$Y_{ct} = \alpha_c + \delta_t + \beta \times PovertyAlleviation_{ct} + \mathbf{X}_{ct} \times \psi + \epsilon_{ct}, \tag{1}$$

y_{ct} represents the outcome of interest, such as forest share (expressed as a percentage of county area) in county c at year t; α_c denotes region fixed effects, including province, prefectural city, and county fixed effects. ;δ_t represents year fixed effects; $PovertyAlleviation_{ct}$ is an indicator that specifies whether county c participates in the poverty county program at time t; $\mathbf{X}_c$ represents a vector of county-level control variables. I employ ordinary least squares (OLS) to estimate Equation 1, with standard errors clustered at the county level.

Under the assumptions outlined in the previous paragraph, the two-way fixed effects (TWFE) model enables us to address various potential biases that could undermine the interpretation of my results. First, I can rule out concerns that the findings are driven by time-invariant differences in forest cover across regions. For instance, some counties may have had historically higher forest cover due to geographic or climatic factors, which could influence conservation outcomes regardless of poverty alleviation efforts. By including region fixed effects—encompassing province, prefectural city, and county levels—I control for such static differences. Second, I can mitigate concerns that the results may be driven by trends in forest cover that evolve similarly across counties over time, unrelated to poverty alleviation efforts. For example, national policy shifts or broader economic fluctuations could influence forest cover uniformly across all counties, irrespective of their treatment status. The inclusion of year fixed effects helps control for such common temporal shocks, allowing us to isolate the specific impact of the poverty alleviation program on forest conservation.

Assuming parallel trends in forest cover between treatment group (state poverty counties designated in 2011) and control group (non-poverty counties in 2011), and homogeneous average treatment effects across treated counties and over time, the coefficient β captures the average treatment effect on the treated (ATT) of the enrollment of state poverty counties on the forest cover after the treatment. Figure 3 shows the trends of forest share in treatment group and control group in the post-period (2011-2020).

The plausibility of the parallel trends assumption is the main concern. To examine the pre-treatment parallel trends, I conduct an event study using the following specification.

$$Y_{ct} = \alpha_c + \delta_t + \beta_k \times \sum_{k=-11}^{9} D_{k(ct)} + \epsilon_{ct} \tag{2}$$

where Y_{ct} is my outcomes of interest and $D_{k(ct)}$ is a set of indicator variables that take a value of one if poverty alleviation is implemented in county c in year t.

To assess the heterogeneity of effects, I incorporate an interaction term into the baseline specification 1, capturing whether a county is part of a contiguous area of extreme poverty. This approach allows us to examine whether the impacts of poverty alleviation programs vary based on the county's geographical characteristics, specifically comparing outcomes among different mountainous areas. The modified empirical specification is presented as follows:

$$Y_{ct} = \alpha_c + \delta_t + \sum_{r=1}^{10} (\beta_r \times \text{Poverty Alleviation}_{ct} \times \text{Region}_c) + \mathbf{X}_{ct} \times \psi + \epsilon_{ct}, \tag{3}$$

where $Region_c$ represents an indicator variable that identifies whether county c is classified as one of the 10 contiguous areas of extreme poverty. Standard errors are again clustered at the county level.

4 Results

4.1 Baseline Results

Baseline Estimates.—I find that poverty alleviation significantly increases the share of forest area (measured as a percentage of land area in a county). Table 2 presents the estimates of β from equation 1, utilizing various levels of fixed effects and control variables. The results consistently indicate a significant positive impact of poverty alleviation across all model specifications, although the magnitude of the effect diminishes as fixed effects shift from broader to more localized regions and additional controls are introduced. The treatment—defined as poverty alleviation—is implemented at the county level. In columns 1 and 2, the model includes time (year) fixed effects alongside broader regional fixed effects, such as those at the province and prefectural city levels, which exceed the treatment level in geographic scope. In columns 3 and 4, time fixed effects are paired with regional fixed effects at the county level, corresponding to the treatment area. Column 4 represents the preferred specification, incorporating time and county fixed effects, along with an expanded set of control variables. The results remain stable across specifications, with point estimates decreasing but remaining statistically significant at the 5% level or lower, along with improved R-squared values. Notably, the estimate in column 4 aligns closely with that in column 3, even after the inclusion of additional controls, demonstrating the robustness of the findings across alternative model specifications. Furthermore, the R-squared values in columns 3 and 4 are close to 1, indicating a strong explanatory power of the model and a high degree of fit to the observed data.

The analysis across all model specifications suggests that poverty alleviation has a statistically significant positive effect on forest conservation. In the preferred specification (column 4 of Table 2), the estimated effect size on forest share is 0.005, indicating that poverty alleviation initiatives lead to an average 0.5% annual increase in forest cover within the treatment group relative to the control group. Given that the mean county area is 3,298 km^2, this corresponds to an average annual increase of 18 km^2 in forest area. The point estimate reflects both the direct effects of poverty alleviation in treated counties—those actively implementing such programs—and the indirect effects in wealthier counties that have not engaged in large-scale poverty alleviation efforts.

Table 2: Baseline Results: Forest Share

	Forest Share			
	(1)	(2)	(3)	(4)
Post-Poverty Alleviation	0.1330***	0.0640***	0.0057**	0.0054**
	(0.0248)	(0.0172)	(0.0026)	(0.0027)
Marginal Forest Area (km^2)	439	211	19	18
Mean County Area (km^2)	3298	3298	3298	3298
Observations	28,305	28,304	28,300	23,467
R-squared	0.544	0.820	0.998	0.998
Province FE	✓			
Prefectural-City FE		✓		
County FE			✓	✓
Year FE	✓	✓	✓	✓
Controls				✓

Notes: This table presents the results of the Two-Way Fixed Effects (TWFE) regressions analyzing the impact of poverty alleviation on forest share at the county level. The dependent variable is the percentage of forest area. Column 1 includes province and year fixed effects, column 2 incorporates prefectural-city and year fixed effects, column 3 adds county and year fixed effects, while column 4 includes county and year fixed effects with additional control variables. Standard errors, shown in parentheses, are clustered at the county level. Control variables include total population, value-added of the primary and secondary sectors, relief degree of land surface, number of social welfare agents, government revenue, government expenditure, deposits and loans balance of financial institutions, mean nighttime light intensity, annual rainfall, square of annual rainfall, average annual wind speed, and square of average wind speed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Event Study Figures.— To assess the parallel trends assumption and investigate the dynamics of treatment effects on forest share, I implement an event-study regression, as specified in Equation 2. As discussed in Section 3, in addition to the TWFE specification, I also consider other specifications, including the proposed estimators from (Borusyak, Jaravel, and Spiess, 2024; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2020; Sun and Abraham, 2021), which account for heterogeneity in treatment effects over time and across treated units.

Figure 4 presents the event-study estimates revealing that poverty alleviation leads to a significant increase in forest share, measured as a percentage of county land area. The results demonstrate that the coefficients for the pre-treatment periods are close to zero, consistent with the parallel trends assumption. Following the introduction of poverty alleviation in poverty counties, there is a notable upward trend in the estimated coefficients after 3 years, indicating that the impact on forest cover becomes increasingly positive over time. This pattern suggests that the effects of poverty alleviation are not only immediate but also accumulate, becoming more pronounced in subsequent periods. The robustness of these findings is confirmed by similar trends across different specifications proposed by Borusyak, Jaravel, and Spiess (2024), Callaway and Sant'Anna (2021), de Chaisemartin and D'Haultfœuille (2020), and Sun and Abraham (2021), which account for heterogeneity in treatment effects over time and across treated units. Overall, the event-study results underscore the sustained and growing impact of poverty alleviation on forest cover over the study periods, affirming the effectiveness of such interventions in promoting forest conservation.

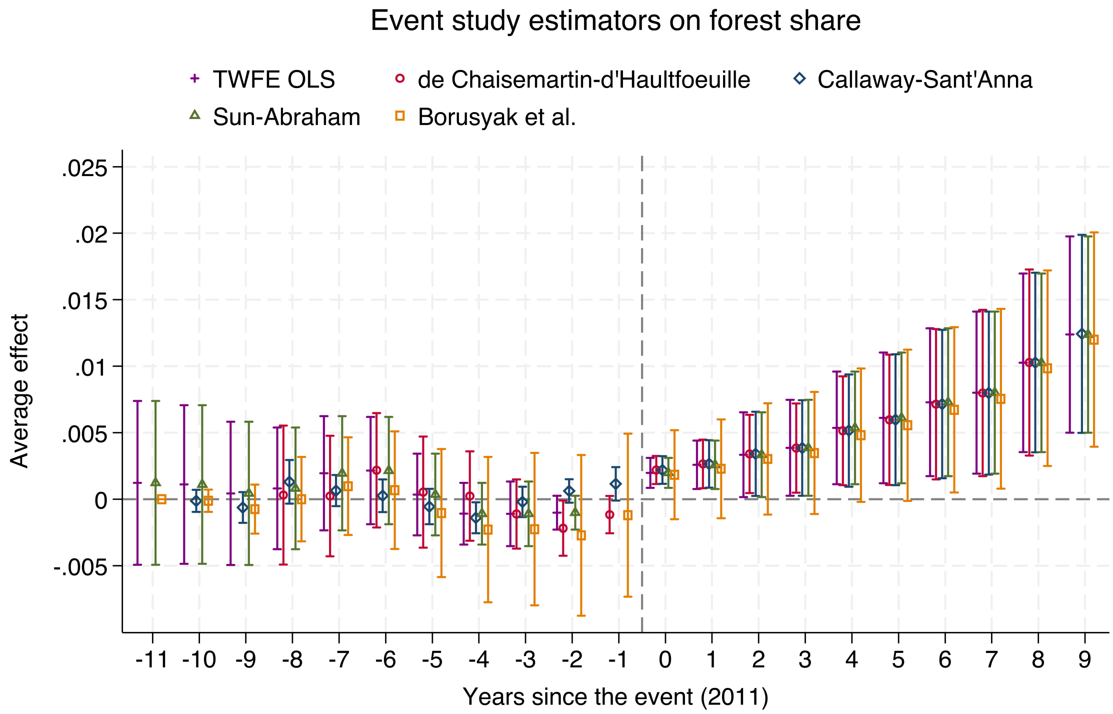

Figure 4: Effects of Rural Poverty Alleviation on Forest Share: Before and After Intervention

Notes: Figure 4 presents the results of the event-study regression on forest share, comparing outcomes across different model specifications, including the traditional TWFE model and alternative estimators proposed by Borusyak, Jaravel, and Spiess (2024), Callaway and Sant'Anna (2021), de Chaisemartin and D'Haultfœuille (2020), and Sun and Abraham (2021), which account for heterogeneity in treatment effects over time and among treated units. The horizontal axis represents the time periods, while the vertical axis shows the estimated effects on forest share, expressed as a percentage of county land area. The figure includes 95% confidence intervals for each estimate, illustrating the precision of the results over time.

4.2 Spatial Heterogeneity

I also examine the spatial heterogeneity of the treatment effect across 10 distinct mountainous areas included in the study. The summary statistics for these areas are presented in Appendix Table A-3. This analysis is conducted using Equation 3, which allows us to evaluate how the impact of poverty alleviation varies across these geographic regions.

Following the specification used in the baseline results, I employ various levels of fixed effects and control variables. The results consistently show a significant positive impact of poverty alleviation across most regions. Column 4 of Table 3 shows that 9 out of 10 mountainous regions display positive results, with 7 of these being significant at the 1 percent level. The effect sizes are all larger than the baseline estimates, with the Qinba Mountain Area showing the largest effect size at 0.044. The Luoxiao Mountain Area shows a non-zero effect, although the standard errors are missing. This may be explained by the fact that the Luoxiao Mountain area has the highest forest share and a strong reliance on the primary sector. The details about summary statistics within mountain areas can be found in Appendix Table A-3.

Forest Share Change in Mountain Regions in Post-Period (2011-2020)

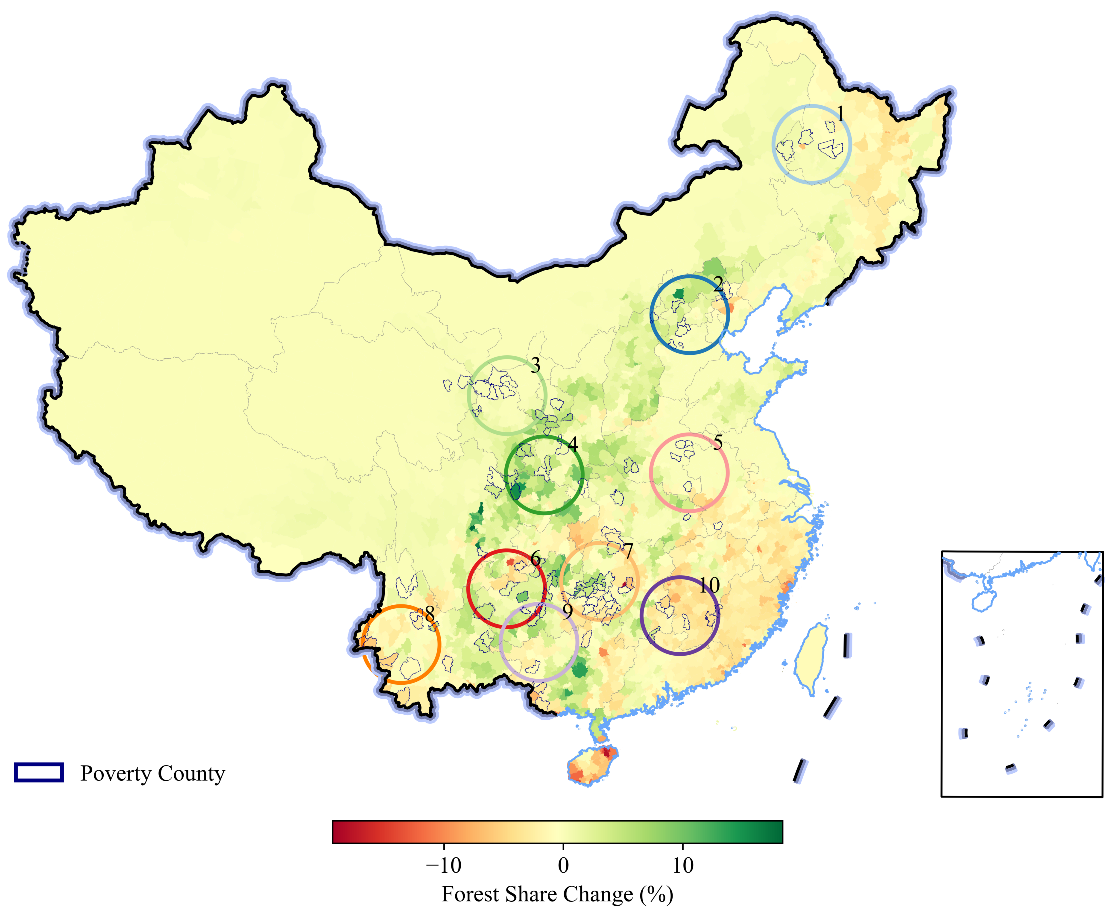

FIGURE 5: FOREST GAIN AND LOSS IN DIFFERENT MOUNTAINEOUS AREAS

Notes: Figure 5 shows the differences in forest share in China during the post-period (2011-2020). The circles with numbers represent different mountain regions. The treated counties in the mountain regions are outlined with navy borders. Green represents an increase in forest share, red indicates a decrease, and yellow signifies no change.Black lines represent land borders, while light blue lines indicate ocean borders. The Dabie Mountain Area consists of 7 poverty-stricken counties. The Dian-Gui-Qian Karst Region includes 13 such counties, while the Liupan Mountain Area has 14. Similarly, the Luoxiao Mountain Area contains 7 poverty counties. The Qinba Mountain Area also has 13, and the Southern Daxing'anling Mountain Area includes 6. The Western Yunnan Border Mountain Area comprises 11 poverty counties. The Wuling Mountain Area has the highest number, with 22 counties, and the Wumeng Mountain Area includes 6. Finally, the Yanshan-Taihang Mountain Area consists of 7 poverty-stricken counties.

4.3 Cost-benefit Analysis

Costs— The costs of rural poverty alleviation encompass both direct and indirect expenditures. However, due to challenges in estimating indirect costs, the analysis is limited to direct expenditures.

TABLE 3: HETEROGENEITY EFFECTS: FOREST SHARE

	Forest Share			
	(1)	(2)	(3)	(4)
Post-Poverty Alleviation ×				
Wumeng Mountain Area	0.018	0.041	0.040***	0.038***
	(0.034)	(0.030)	(0.014)	(0.014)
Liupan Mountain Area	0.042***	0.038***	0.040***	0.042***
	(0.010)	(0.010)	(0.010)	(0.011)
Southern Daxing'anling Mountain Area	0.019***	0.019***	0.019***	0.019***
	(0.006)	(0.006)	(0.006)	(0.006)
Dabie Mountain Area	0.019***	0.019***	0.019***	0.018***
	(0.006)	(0.006)	(0.006)	(0.006)
Wuling Mountain Area	0.018**	0.020**	0.016**	0.017**
	(0.009)	(0.010)	(0.008)	(0.008)
Dian-Gui-Qian Karst Region	0.018**	0.014*	0.015**	0.013
	(0.009)	(0.007)	(0.007)	(0.008)
Western Yunnan Border Mountain Area	0.004	0.006	0.006	0.006
	(0.010)	(0.009)	(0.009)	(0.009)
Yanshan-Taihang Mountain Area	0.025	0.047**	0.028***	0.029***
	(0.031)	(0.020)	(0.007)	(0.007)
Qinba Mountain Area	0.044***	0.045***	0.043***	0.044***
	(0.009)	(0.009)	(0.009)	(0.009)
Luoxiao Mountain Area	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Observations	28,305	28,304	28,300	23,467
R-squared	0.573	0.828	0.998	0.998
Province FE	✓			
Prefectural-City FE		✓		
County FE			✓	✓
Year FE	✓	✓	✓	✓
Controls				✓

Notes: The Dabie Mountain Area consists of 7 poverty-stricken counties. The Dian-Gui-Qian Karst Region includes 13 such counties, while the Liupan Mountain Area has 14. Similarly, the Luoxiao Mountain Area contains 7 poverty counties. The Qinba Mountain Area also has 13, and the Southern Daxing'anling Mountain Area includes 6. The Western Yunnan Border Mountain Area comprises 11 poverty counties. The Wuling Mountain Area has the highest number, with 22 counties, and the Wumeng Mountain Area includes 6. Finally, the Yanshan-Taihang Mountain Area consists of 7 poverty-stricken counties.

Furthermore, because of data availability constraints, only expenditures from central and provincial governments are included. As a result, the overall cost estimate may be understated. The average annual expenditure on poverty alleviation by the central and provincial governments is $15.96 billion over the study period. Appendix Table A-4 presents detailed information on poverty alleviation expenditures by central and provincial governments from 2011 to 2020, based on data sourced from the *Yearbook of China's Poverty Alleviation and Development (2021)*[20] published by the International Poverty Reduction Center in China. As outlined from *Yearbook of China's Poverty Alleviation and Development (2021)*, the 832 designated poverty counties receive the majority of the allocated poverty alleviation funds. For the purposes of this analysis, I assume that all poverty alleviation funds are allocated exclusively to these counties. Under this assumption, the average poverty alleviation expenditure for each county is approximately $0.01918 billion, or $19.18 million, representing the cost of rural poverty alleviation in the treated group.

Benefits—I employ two approaches to quantify the benefits of forest conservation resulting from rural poverty alleviation. The first approach assesses the costs associated with reforestation programs, while the second estimates the value of ecosystem services generated by forest conservation.
The cost of reforestation serves as a proxy to estimate the additional benefits associated with rural poverty alleviation. This approach operates under the premise that, in the absence of poverty alleviation efforts, reforestation programs would be required to achieve comparable gains in forest cover. Thus, the analysis assumes that the improvements in forest cover observed as a result of poverty alleviation would otherwise necessitate direct reforestation expenditures to produce similar outcomes. My findings on the relationship between rural poverty alleviation and forest conservation suggest that poverty reduction efforts can yield additional environmental benefits, specifically through enhanced forest conservation. The analysis reveals a marginal increase in forest area, with approximately 18 km^2 of expansion per county following the implementation of poverty alleviation measures. The cost of reforestation programs can be used as a proxy for calculating the economic benefits of forest conservation. The most well-known reforestation initiative in China is the Green for Grain Program, which provides subsidies to rural farmers to convert sloped farmland into

[20]The *Yearbook of China's Poverty Alleviation and Development (2021)* can be downloaded from the International Poverty Reduction Center in China website: https://yearbook.iprcc.org.cn/zggjfpzxnj/index.shtml

forested areas. Under this program, farmers receive a subsidy of 1,600 RMB per mu [21], which equates to approximately \$0.368 million per km^2[22]. Based on this cost, the additional benefits of poverty alleviation can be estimated at around \$6.6 million per county, corresponding to a marginal increase of 18 km^2 in forest area attributable to poverty alleviation efforts. While this approach provides a measure of the direct benefits, it likely underestimates the true value of forest conservation resulting from rural poverty alleviation.

To provide a more comprehensive measure of the additional benefits of forest conservation, I integrate the value of ecosystem services, or nature's contributions to people, generated by the increased forest cover resulting from rural poverty alleviation. Forests play a key role in various ecosystem services, such as carbon storage and soil erosion mitigation (Bonan, 2008; Dixon et al., 1994; Kumarasiri, Udayakumara, and Jayawardana, 2022; Pan et al., 2011; Tiemann and Ring, 2022; Yu et al., 2022). In this analysis, I focus specifically on carbon storage, given its critical importance in addressing climate change. Forests serve as the primary carbon pool(Dixon et al., 1994; Pan et al., 2011), and I use the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model (Sharp et al., 2014), developed by the Natural Capital Project, to calculate carbon storage. There are two approaches to estimating carbon storage resulting from forest conservation outcomes. The first approach involves a straightforward calculation of direct carbon storage based on the increased forest area and the carbon density of the forest ecosystem. This method estimates the total carbon sequestered by multiplying the additional forest cover resulting from rural poverty alleviation by the average carbon density per unit area. I use the carbon pool data from *2006 IPCC Guidelines for National Greenhouse Gas Inventories* (Penman et al., 2006) and *2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories* (Domke et al., 2019). The Intergovernmental Panel on Climate Change (IPCC) identifies four primary carbon pools in forest ecosystems—above-ground biomass, below-ground biomass, soil organic carbon, and dead wood—each contributing to total carbon storage. Table 4 provides detailed information on carbon pools across various ecosystems, illustrating differences in carbon storage capacity. With the forest carbon pool having a

[21] See in Chinese: http://www.forestry.gov.cn/main/4861/20211123/154111481329343.html

[22] 1 km^2 = 1,500 mu; 1 mu = 666.67 m^2. The exchange rate used is 6.5250 RMB/USD, as of December 31, 2020, as reported by the Federal Reserve Bank of St. Louis.

total carbon density of 315 tons of carbon per hectare (tC/ha), an increase of 18 km^2 in forest area can potentially sequester an additional 567,000 tons of carbon. The Social Cost of Carbon (SCC) is a widely used benchmark for carbon pricing (Nordhaus, 2017; Ricke et al., 2018). There is an ongoing debate over whether the SCC should be calculated on a global scale or tailored to individual countries. Using the global SCC valued at \$185 per ton (\$44–\$413 per tCO_2: 5%–95% range, 2020 US dollars) (Rennert et al., 2022), the additional benefits of poverty alleviation are estimated at \$104.90 million USD, equivalent to approximately 5.5 times the associated costs. In contrast, with a China-specific SCC of \$24 per ton (range: \$4–\$50 per tCO_2) (Ricke et al., 2018), the benefit is \$13.61 million USD, which is 0.71 times the associated costs. This analysis supports a global SCC framework, as climate change is a transboundary challenge requiring coordinated international efforts.

Table 4: Carbon Pools in Different Ecosystems

Ecosystem	C Above (ton/ha)	C Below (ton/ha)	C Soil (ton/ha)	C Dead (ton/ha)	Total (ton/ha)
Cropland	6	1.5	65	5	77.5
Forest	150	35	100	30	315
Shrubland	30	12.5	60	10	112.5
Grassland	6	11	115	5	137
Water	0	0	0	0	0
Snow	0	0	350	0	350
Barren	0	0	0	0	0
Impervious	0	0	0	0	0
Wetland	55	30	400	50	535

Notes: Table 4 presents carbon storage estimates across different ecosystems, based on the 2006 IPCC Guidelines for National Greenhouse Gas Inventories and its 2019 Refinement (Penman et al., 2006; Domke et al., 2019) . It includes four primary carbon pools: above-ground biomass, below-ground biomass, soil organic carbon, and dead wood, each measured in tons per hectare (ton/ha). The table covers nine ecosystem types—cropland, forest, shrubland, grassland, water, snow, barren land, impervious surfaces, and wetlands—revealing significant variations in carbon storage capacity. Forests and wetlands demonstrate the highest total carbon storage, with substantial contributions from all carbon pools, while snow-dominated areas exhibit high soil organic carbon due to accumulated organic matter. In contrast, croplands and grasslands show lower overall carbon storage, primarily concentrated in soil organic carbon. Ecosystems like water, barren land, and impervious surfaces contribute minimally across all carbon pools. The total column aggregates the carbon storage for each ecosystem, providing a comprehensive measure of carbon sequestration per hectare.

As discussed in Section 4.4, rural poverty alleviation, in relation to land uses other than forests, either exhibits no impact or fails to meet the parallel trends assumption. This indicates that the impact of rural poverty alleviation on land-use change is evident only through forests. In other words, the land-use change is primarily driven by changes in forest areas

The direct carbon storage benefits from increased forest areas, however, do not account for land-use changes, which may lead to an overestimation of carbon storage attributable to poverty alleviation. As discussed in Section 4.4, rural poverty alleviation, in relation to land uses other than forests, either exhibits no impact or fails to meet the parallel trends assumption. This indicates that the impact of rural poverty alleviation on land-use change is evident only through forests.Therefore, I rerun Equation 1, using average carbon storage density (measured in tons of carbon per km^2) as the outcome variable of interest, to estimate the overall effects of rural poverty alleviation on carbon storage. I first use the InVEST model(Sharp et al., 2014) to estimate the carbon storage across all land uses for each county. This total is then divided by the respective county area, yielding the average carbon storage density. I also employ the four specifications outlined in Section 4.1, incorporating province and prefectural city levels, county fixed effects, and relevant controls.

TABLE 5: CARBON STORAGE RESULTS

	Carbon Storage (ton C/km^2)			
	(1)	(2)	(3)	(4)
Post-Poverty Alleviation	3772.676***	1724.191***	214.786***	152.937**
	(608.833)	(428.717)	(59.952)	(61.943)
Mean County Area (km^2)	3298	3298	3298	3298
Observations	28,305	28,304	28,300	23,467
R-squared	0.522	0.814	0.998	0.998
Province FE	✓			
Prefectural-City FE		✓		
County FE			✓	✓
Year FE	✓	✓	✓	✓
Controls				✓

Notes: This table presents the results of the Two-Way Fixed Effects (TWFE) regressions analyzing the impact of poverty alleviation on forest share at the county level. The dependent variable is the average carbon storage density (measured in tons of carbon per km^2). Column 1 includes province and year fixed effects, column 2 incorporates prefectural-city and year fixed effects, column 3 adds county and year fixed effects, while column 4 includes county and year fixed effects with additional control variables. Standard errors, shown in parentheses, are clustered at the county level. Control variables include total population, value-added of the primary and secondary sectors, relief degree of land surface, number of social welfare agents, government revenue, government expenditure, deposits and loans balance of financial institutions, mean nighttime light intensity, annual rainfall, square of annual rainfall, average annual wind speed, and square of average wind speed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Similar to the baseline results, all results from the four specifications are positive and significant at least at the 5 percent level. Column 4 of Table 5 presents the results from the preferred specification, which includes year and county fixed effects, as well as controls. The results from the preferred specification indicate an increase of 152.937 tons per km^2 , attributable to the rural poverty alleviation. To further examine the effects of rural poverty alleviation on carbon storage, I conduct an event study following the methods described in Section4.1 in addition to the static analysis of carbon. Figure 6 presents the results, demonstrating compliance with the parallel trends assumption and showing an increase in carbon storage immediately following poverty alleviation. Given the mean county area of 3,298 km^2, the total increase in carbon storage is calculated as 504,386 tons, compared to 567,000 tons as estimated by the previous method. Using the global SCC valued at \$185 per ton as the carbon price (Rennert et al., 2022), the additional benefit of poverty alleviation is estimated at \$93.31 million USD, approximately 4.9 times the cost of implementing rural poverty alleviation. In contrast, with a county-level China SCC of \$24 per ton(Ricke et al., 2018), the benefit is estimated at \$12.10 million USD, equivalent to 0.63 times the associated costs. These benefit estimates align closely with calculations based directly on the increased forest area.

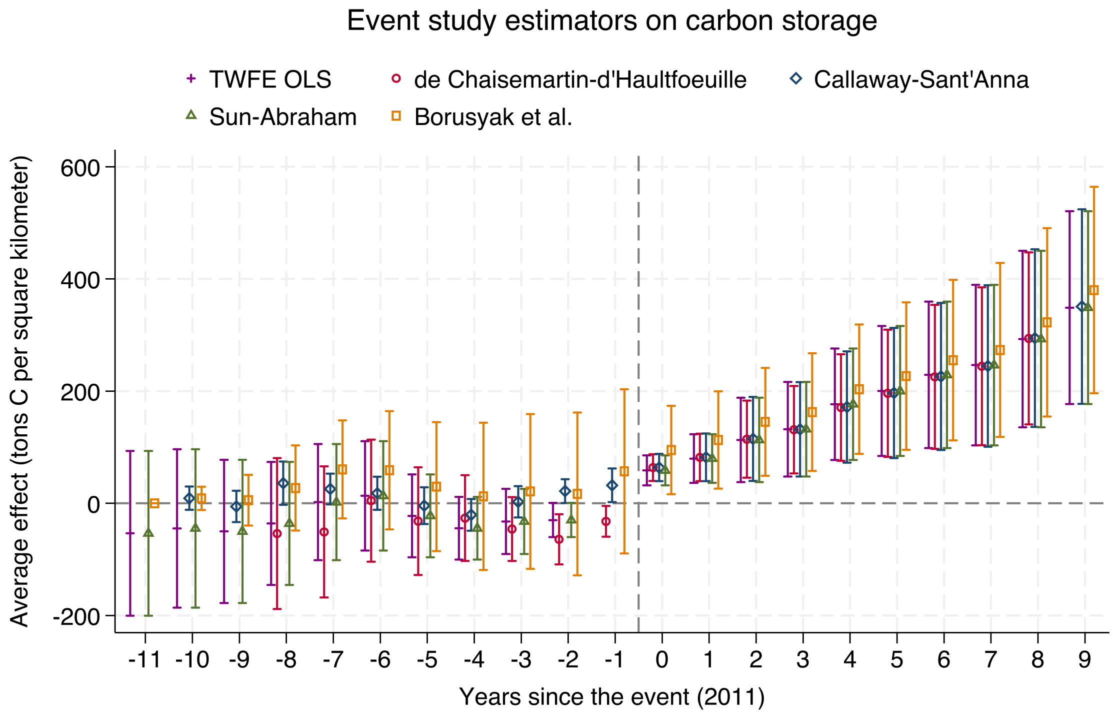

Figure 6: Effects of Rural Poverty Alleviation on Carbon Sotrage Density: Before and After Intervention

Notes: Figure 6 presents the results of the event-study regression on carbon storage density, comparing outcomes across different model specifications, including the traditional TWFE model and alternative estimators proposed by Borusyak, Jaravel, and Spiess (2024), Callaway and Sant'Anna (2021), de Chaisemartin and D'Haultfœuille (2020), and Sun and Abraham (2021), which account for heterogeneity in treatment effects over time and among treated units. The horizontal axis represents the time periods, while the vertical axis shows the estimated effects on forest share, expressed as a percentage of county land area. The figure includes 95% confidence intervals for each estimate, illustrating the precision of the results over time.

4.4 Robustness Checks

In addition to the baseline results, several robustness checks were conducted. In this section, I introduce two additional robustness checks, where the selection of both the treatment and control groups is adjusted. Specifically, I compare the treatment group with an already treated group that entered the program at an earlier stage. This approach enhances the reliability of the findings by verifying whether the observed impact of poverty alleviation remains consistent when using different comparison groups.

Forest Share Change—First, I use changes in forest share instead of forest share itself as the outcome of interest to conduct a robustness check. Changes in forest share represent the rate of increase in forest cover. Positive results in forest share change indicate greater forest cover, with larger values reflecting a faster rate of increase. Following the specifications in the baseline analysis, I obtained positive results at the 1 percent level for all specifications. This aligns with the baseline results, which indicate that poverty alleviation leads to an increase in forest share within the treatment group, further supporting the event study results from the baseline analysis. As the duration of poverty alleviation efforts extends, I observe an accelerated rate of increase in forest share.

Table 6: Robustness Check: Forest Share Change

	Forest Share Change			
	(1)	(2)	(3)	(4)
Post-Poverty Alleviation	0.001***	0.001***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	28,305	28,304	28,300	23,467
R-squared	0.043	0.100	0.142	0.149
Province FE	✓			
Prefectural-City FE		✓		
County FE			✓	✓
Year FE	✓	✓	✓	✓
Controls				✓

Notes: This table presents the results of the Two-Way Fixed Effects (TWFE) regressions analyzing the impact of poverty alleviation on forest share at the county level. The dependent variable is the forest share change. Column 1 includes province and year fixed effects, column 2 incorporates prefectural-city and year fixed effects, column 3 adds county and year fixed effects, while column 4 includes county and year fixed effects with additional control variables. Standard errors, shown in parentheses, are clustered at the county level. Control variables include total population, value-added of the primary and secondary sectors, relief degree of land surface, number of social welfare agents, government revenue, government expenditure, deposits and loans balance of financial institutions, mean nighttime light intensity, annual rainfall, square of annual rainfall, average annual wind speed, and square of average wind speed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Other Land Uses—As an additional robustness check, the analysis is extended to encompass regressions on land uses beyond forests, following Equation 1 with four distinct specifications. Consistent with the baseline results for forested areas, all dependent variables of interest are expressed as a share of the total land area.Figure 7 presents the results of the regressions for other land uses. Most coefficients indicate no significant effect, except for impervious surfaces, which exhibit a negative impact. While cropland shows a relatively large effect size, the results are inconsistent across the four specifications. In my preferred specification, the effect on cropland is not statistically different from zero.

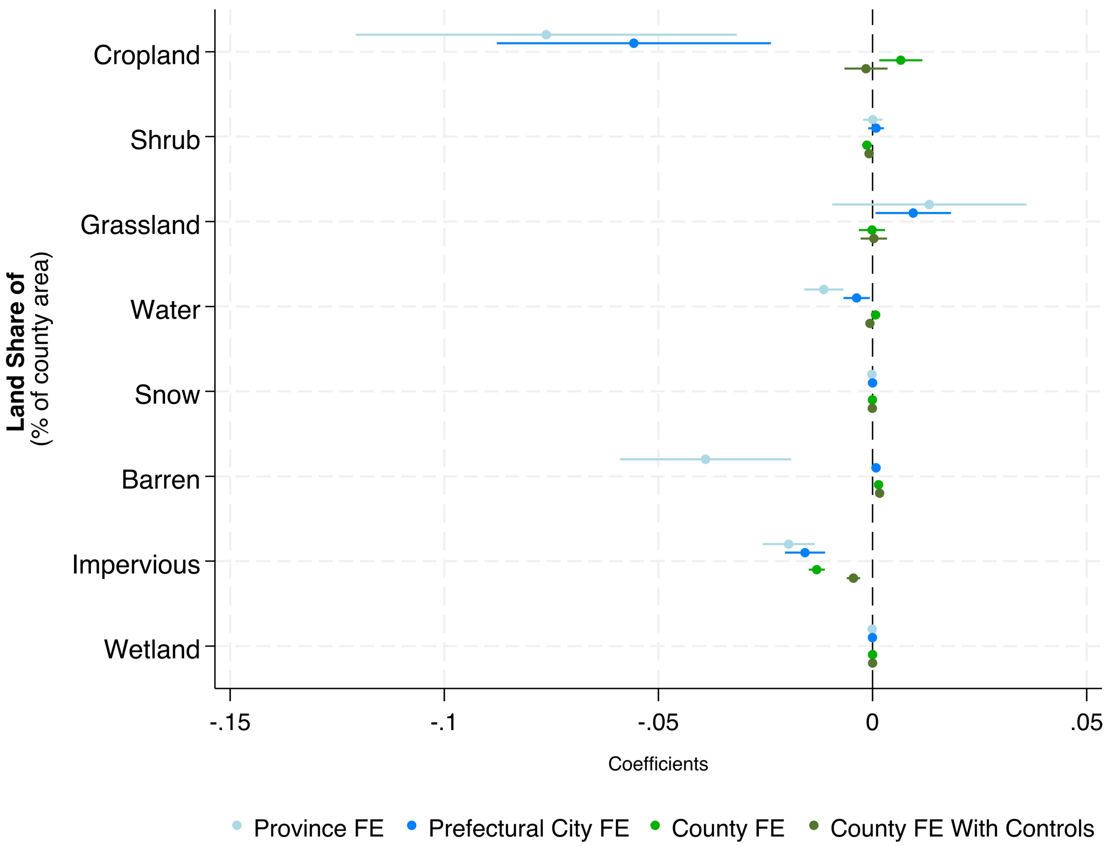

Figure 7: Effects on other land uses

Notes: Figure 7 depicts the treatment effects on shares of various other land uses, including cropland, shrub, grassland, water, snow including ice, barren land, impervious surface, and wetland.

Normalized Difference Vegetation Index—I use the Normalized Difference Vegetation Index (NDVI) as an alternative measure of vegetation cover to assess the impact of poverty alleviation. NDVI is a widely used satellite-derived indicator that serves as a proxy for changes in vegetation health and density. To address potential measurement errors, this alternative dataset enhances the reliability of the results by providing a more comprehensive view of vegetation dynamics. This approach helps validate the findings and minimizes the risk of bias due to data limitations or errors in measuring forest cover.

Table 7: Robustness Check Results: NDVI

	average NDVI			
	(1)	(2)	(3)	(4)
Post-Poverty Alleviation	0.051***	0.027***	0.009***	0.006*
	(0.008)	(0.006)	(0.003)	(0.004)
Mean County Area (km2)	3298	3298	3298	3298
Observations	26,952	26,950	26,946	22,389
R-squared	0.361	0.650	0.828	0.834
Province FE	✓			
Prefectural-City FE		✓		
County FE			✓	✓
Year FE	✓	✓	✓	✓
Controls				✓

Notes:This table presents the results of the Two-Way Fixed Effects (TWFE) regressions analyzing the impact of poverty alleviation on forest share at the county level. The dependent variable is the average NDVI. Column 1 includes province and year fixed effects, column 2 incorporates prefectural-city and year fixed effects, column 3 adds county and year fixed effects, while column 4 includes county and year fixed effects with additional control variables. Standard errors, shown in parentheses, are clustered at the county level. Control variables include total population, value-added of the primary and secondary sectors, relief degree of land surface, number of social welfare agents, government revenue, government expenditure, deposits and loans balance of financial institutions, mean nighttime light intensity, annual rainfall, square of annual rainfall, average annual wind speed, and square of average wind speed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Mechanisms

5.1 Forest Gains and Losses

To understand the mechanisms driving changes in forest cover, the analysis begins by examining forest gains and losses, followed by an evaluation of their sources. These sources include forest gains and losses from transitions involving cropland, shrubland, grassland, water bodies, snow, barren land, impervious surfaces, and wetlands. Following Equation 1, four model specifications are applied: province fixed effects, prefectural city fixed effects, county fixed effects, and county fixed effects with additional controls, with the latter serving as the preferred specification.

Figure 8 presents the results for total forest gains, losses, and the land use transitions involving forests, each measured as a percentage of county area. The analysis primarily emphasizes the preferred specification—county fixed effects with controls. The positive effects of rural poverty alleviation on total forest gains are evident across all model specifications with signicance at least 5% level. This consistent result suggests that poverty alleviation efforts may play a supportive role in promoting forest recovery and reforestation initiatives.

In this specification, results highlighted in dark green indicate an effect size of 0.0012 for total forest gains, with statistical significance at the 1% level. In contrast, forest losses show an effect size of -0.0003, which is not statistically significant. This yields a net forest gain effect size of 0.0015, which is also statistically significant at the 1% level.

In contrast, the analysis shows that forest losses to cropland have negative coefficients, though they are not statistically significant. This lack of significance suggests a possible trend of forest loss from cropland expansion, yet this trend is not robustly supported by the data. For other land use changes, such as transitions involving shrubland, grassland, and water bodies, the effect sizes tend to be minor. This contrast underscores a distinct difference in the factors influencing forest gains versus forest losses. Additionally, the observed gap between forest gains and losses aligns closely with a baseline value of -0.005. This proximity to the baseline highlights the stronger role of variability in influencing the patterns of forest change.

Compared to the baseline results, these findings demonstrate greater consistency in both effect size and significance level. The analysis underscores that increased forest gains, rather than reduced forest loss, are the primary driver of forest conservation. Among these gains, transitions involving cropland are particularly central. This focus on forest gains arising specifically from cropland conversions highlights a targeted mechanism, distinct from other possible channels, underscoring the significant role of reforesting cropland in contributing to net forest gains.

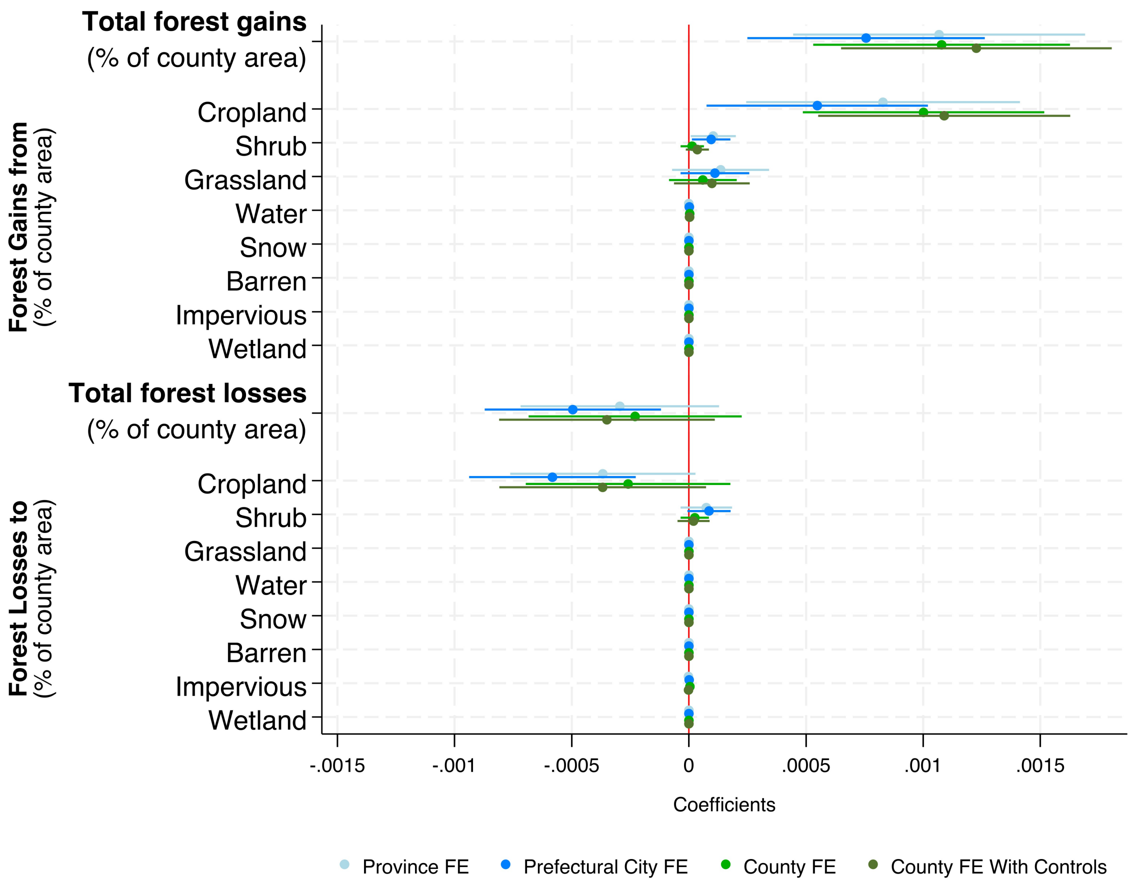

FIGURE 8: EFFECTS ON FOREST GAINS AND LOSSES FROM OTHER LAND USES

Notes: Figure 8 displays the results for total forest gains, losses, and transitions between forest and other land use types, all measured as a percentage of county area. The bars represent 95 percent confidence intervals. Standard errors are clustered at the county level.

5.2 Government Forestation Program

The previous section establishes that forest gains are the primary driver of increased forest cover. A plausible explanation for this trend could be the government's implementation of forest restoration programs specifically targeting poverty-stricken counties. In this section, I examine this hypothesis; however, the findings indicate that this assumption is not supported by the data. This suggests that the observed forest gains may arise from factors beyond the scope of these targeted forest restoration interventions.

China has launched several forest restoration programs aimed at expanding forest cover, enhancing ecological resilience, and mitigating environmental degradation. These initiatives include large-scale projects such as the Grain for Green Program, which incentivizes farmers to convert marginal agricultural lands back into forests, and the Natural Forest Conservation Program, which halts logging and promotes natural regeneration in critical areas. Additionally, the Three-North Shelterbelt Program, also known as the ″Green Great Wall″, seeks to combat desertification by establishing an extensive network of protective forests across northern China. Together, these programs boost carbon sequestration, improve biodiversity, and contribute to sustainable development, positioning China as a global leader in forest restoration efforts.

Table 8: Government Forestation Program

	Planted Forest Share from Gov't Forestation Program			
	(1)	(2)	(3)	(4)
Post-Poverty Alleviation	0.001	0.001	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Mean County Area (km2)	3298	3298	3298	3298
Observations	23,017	23,015	23,012	19,375
R-squared	0.074	0.165	0.265	0.446
Province FE	✓			
Prefectural-City FE		✓		
County FE			✓	✓
Year FE	✓	✓	✓	✓
Controls				✓

Notes:Table 2 presents the TWFE regression results examining the impact of poverty alleviation, with a particular focus on the effect of participation in the program on forest conservation. The table provides estimates of the coefficient β from equation (1), using forest cover at the county level as the outcome variable. Columns 1 to 4 show regressions with different fixed effects: column 1 includes province fixed effects, column 2 adds mountain region fixed effects, column 3 includes county fixed effects, and column 4 incorporates both county fixed effects and controls. Column 4 is the preferred specification.

I rerun Equation 1 using the same four model specifications as outlined in Section 4.1. Table 8 displays zero effects across all four specifications, suggesting that the observed forest gains may stem from factors beyond the government-led reforestation programs. In the following section, I continue exploring aother channel that may contribute to the observed forest gains.

5.3 Relocation

Relocation for poverty alleviation functions as a potential mechanism for forest conservation. Funding for designated poverty counties primarily comes from central and provincial governments, with provinces often matching central allocations. As shown in Figure 1, key spending areas include relocating residents to economically viable areas (urban centers or well-connected rural regions), supporting agriculture and related industries, and enhancing education, healthcare, housing, infrastructure, and social security. However, aside from relocation, these initiatives are unlikely to encourage the conversion of cropland to forests, which remains a key driver of forest conservation. Figure 9 illustrates the satellite imagery and land use changes in a poverty-stricken village before and after relocation.

Poverty alleviation relocation or relocation for poverty alleviation is a key aspect of China's rural poverty alleviation efforts. By relocating rural populations from areas with harsh living conditions, this initiative fundamentally improves their living and development environments. As shown in Figure 1, the average annual spending on poverty alleviation relocation is approximately 2.1 million US dollars, accounting for about 20% of the overall annual central government's special fund for poverty alleviation spending from 2011 to 2020. In this period, 13.54 million rural residents, accounting for approximately 11.1% of the total, were lifted out of poverty through relocation to urban areas or other rural villages with reliable transportation access within their original counties. According to the Poverty Alleviation Relocation Plans (2011-2020)[23] developed by China's National Development and Reform Commission, origin areas of relocated rural residents are reclaimed as croplands or forests, providing a potentially crucial channel for forest conservation. Although, according to the plan, poverty alleviation relocation had been primarily implemented in contiguous areas of extreme poverty, exact data on relocation, including population and expenditures at the county level, is unavailable. Hence, I examine the poverty alleviation relocation channel on forest conservation through the change in number of rural villages.

[23] The official names are the 12th and 13th Five-Year Plans for Poverty Alleviation Relocation. They can be downloaded from China's National Development and Reform Commission Website: https://www.ndrc.gov.cn/xxgk/zcfb/tz/201209/W020190905511496633388.pdf and https://www.ndrc.gov.cn/xxgk/zcfb/ghwb/201610/t20161031_962201.html

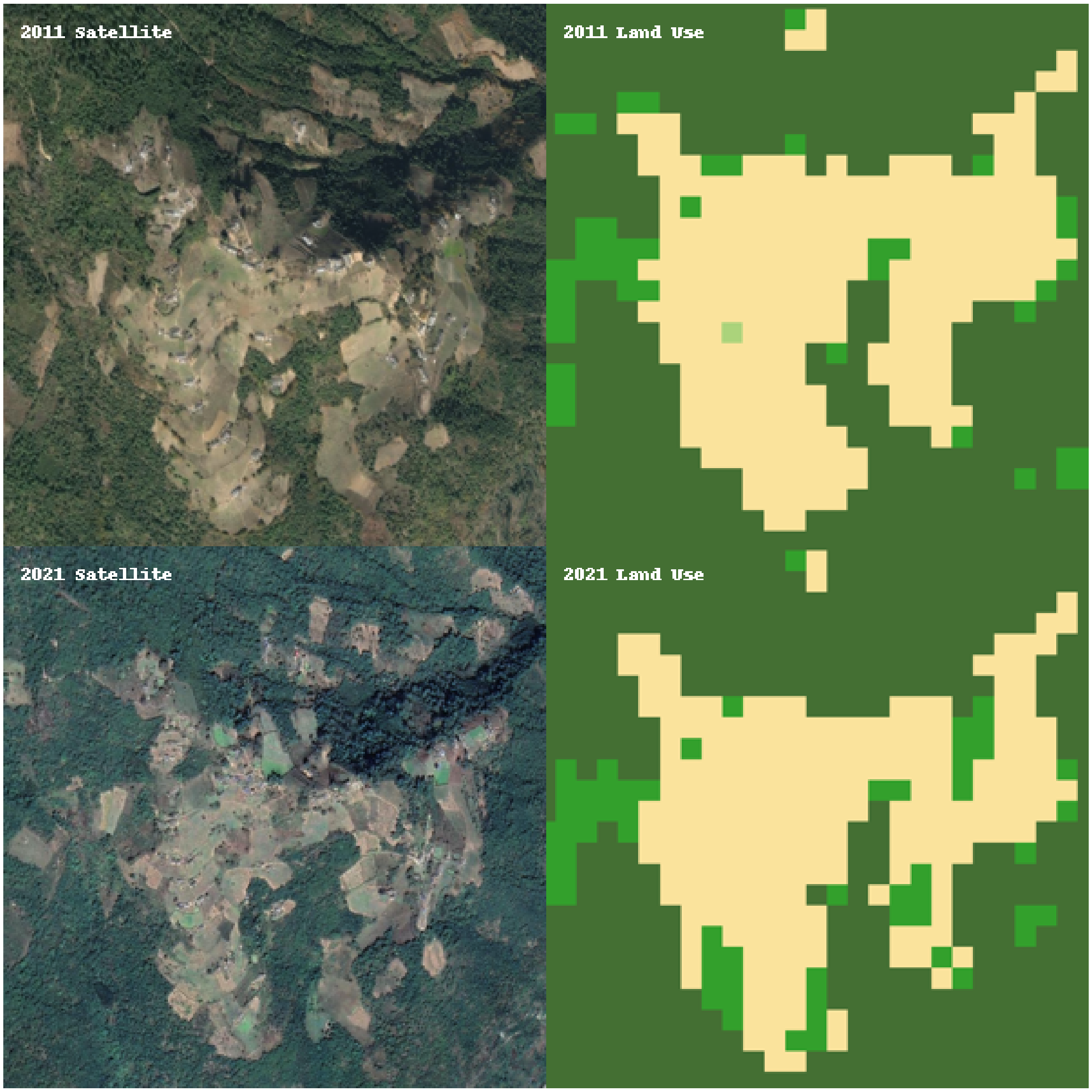

Figure 9: Satellite Imagery and Land Use Changes in a Poverty-Stricken Village Before and After Relocation

Notes: Figure 9 presents the satellite imagery and land use changes observed in a poverty-stricken village before and after relocation. The village under study is Tuoping Village, situated in Pihe Nu Ethnic Township, Fugong County, Yunnan Province, China.
Source: The satellite imagery is sourced from Google Earth: https://earth.google.com/web/@26.51304429,98.89005585,1730.90171071a,2014.16286627d,35y,-12.99646073h,13.99993393t,-0r/data=CgRCAggBQgIIAEoNCP___________wEQAA. The land use data corresponds to the land use and land cover dataset employed in this study.

Table 9: Changes in Rural Village Numbers

	Number of Rural Villages			
	(1)	(2)	(3)	(4)
Post-Poverty Alleviation	13.927	5.458	-7.426	-11.205**
	(10.561)	(10.016)	(5.429)	(5.260)
Observations	15,027	15,026	15,013	14,077
R-squared	0.422	0.641	0.929	0.928
Province FE	✓			
Prefectural City FE		✓		
County FE			✓	✓
Year FE	✓	✓	✓	✓
Controls				✓

Notes: This table presents the results of Two-Way Fixed Effects (TWFE) regressions analyzing the impact of poverty alleviation on the number of rural villages at the county level. The dependent variable, the number of rural villages, serves as a proxy for the rural poverty population change in this analysis, reflecting relocation of rural poverty population at the county level. Column 1 includes province and year fixed effects, column 2 incorporates prefectural-city and year fixed effects, column 3 adds county and year fixed effects, while column 4 includes county and year fixed effects with additional control variables. Standard errors, shown in parentheses, are clustered at the county level. Control variables include total population, value-added of the primary and secondary sectors, relief degree of land surface, number of social welfare agents, government revenue, government expenditure, deposits and loans balance of financial institutions, mean nighttime light intensity, annual rainfall, square of annual rainfall, average annual wind speed, and square of average wind speed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The changes in rural village numbers reflect the relocation population at the county level, which in turn can verify the impact of this relocation channel on forest conservation. I rerun Equation 1 with four distinct specifications, using the number of rural villages at the county level as the outcome. Table 9 shows the estimated results. The results are not significant with only region and time fixed effects shown in Columns 1-3 of Table 9. When adding controls, the preferred specification — the one with county and time fixed effects in Column 4 of Table 9 — shows a significant and negative result. This indicates that, following poverty alleviation efforts, the number of rural villages decreased in the treatment group compared to control group.

To confirm the above finding of a negative impact on the number of rural villages, I conduct an event study as specified in Equation 2. This event-study regression, discussed in Section 3, includes a traditional TWFE specification as well as alternative specifications proposed from Borusyak, Jaravel, and Spiess (2024), Callaway and Sant'Anna (2021), de Chaisemartin and D'Haultfœuille (2020), and Sun and Abraham (2021). Figure 10 shows the results of the event study. Due to data availability, the pre-parallel trend is examined only up to two years before rural poverty allevaition. In the first three years following rural poverty alleviation, the effect on the number of rural villages remains zero. Then, in the subsequent two years, a positive effect emerges. This is followed by a sustained negative effect over the next four years, continuing until the final year of observation. Figure 10 confirms the pre-parallel trend and illustrates the dynamic effects underlying the overall negative impact.

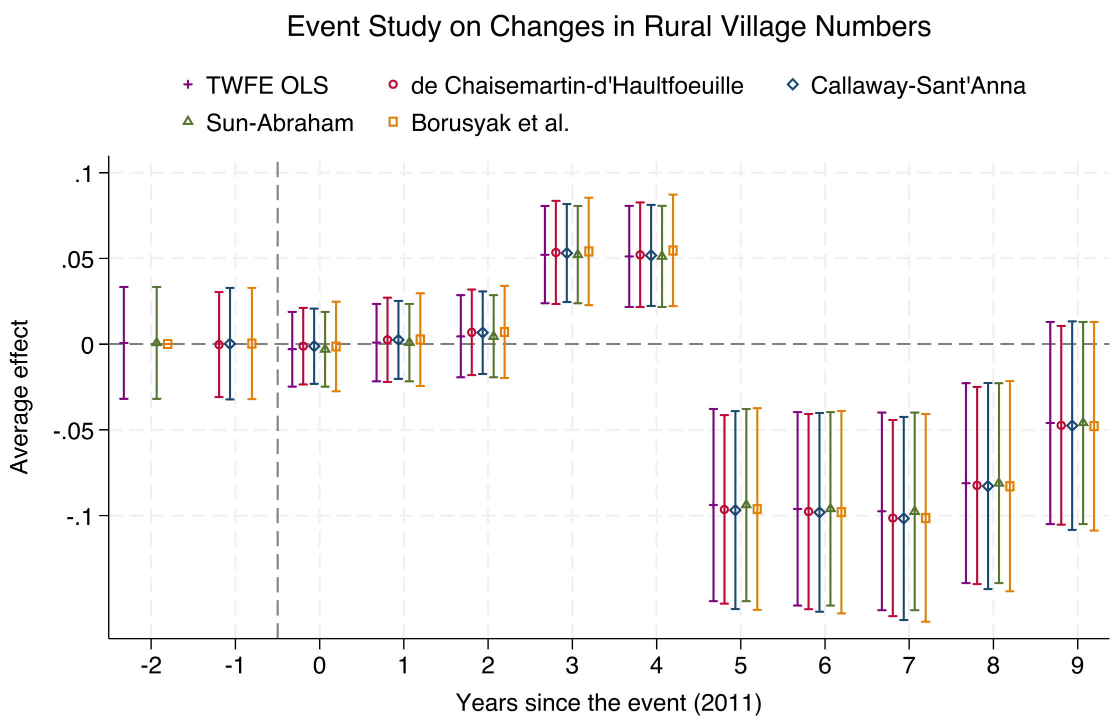

FIGURE 10: EFFECTS OF RURAL POVERTY ALLEVIATION ON NUMBER OF RURAL VILLAGES:BEFORE AND AFTER INTERVENTION

Notes: Figure 6 presents the results of the event-study regression on number of rural villages, comparing outcomes across different model specifications, including the traditional TWFE model and alternative estimators proposed by Borusyak, Jaravel, and Spiess (2024), Callaway and Sant'Anna (2021), de Chaisemartin and D'Haultfœuille (2020), and Sun and Abraham (2021), which account for heterogeneity in treatment effects over time and among treated units. The horizontal axis represents the time periods, while the vertical axis shows the estimated effects on forest share, expressed as a percentage of county land area. The figure includes 95% confidence intervals for each estimate, illustrating the precision of the results over time.

From the event study, the negative effect of poverty alleviation on the number of rural villages is robust. The parallel trend is confirmed In the first three years following poverty alleviation, the effect is zero. Then, in the subsequent two years, a positive effect emerges. This phenomenon likely involves the establishment of new settlements or divisions of existing ones, while the original village remains intact. This is followed by a sustained negative effect over the next four years, continuing until the final year of observation.

With the findings on the negative effect of rural poverty alleviation on the number of rural villages, which likely reflects the relocation of the rural poverty population, I examine the correlation between the number of rural villages and forest share. Figure 11 illustrates the strong negative correlation (-0.96) between the average county forest share and the number of rural villages in the treatment group in the post-period (2011-2020). Appendix Figure A-1 depicts the negative correlation (-0.07) between county forest share and the number of rural villages in the treatment group during the post-period, disregarding the time trend. This verify the channel that the positive effect of poverty avelleviation is driven by relocation of rural poverty population.

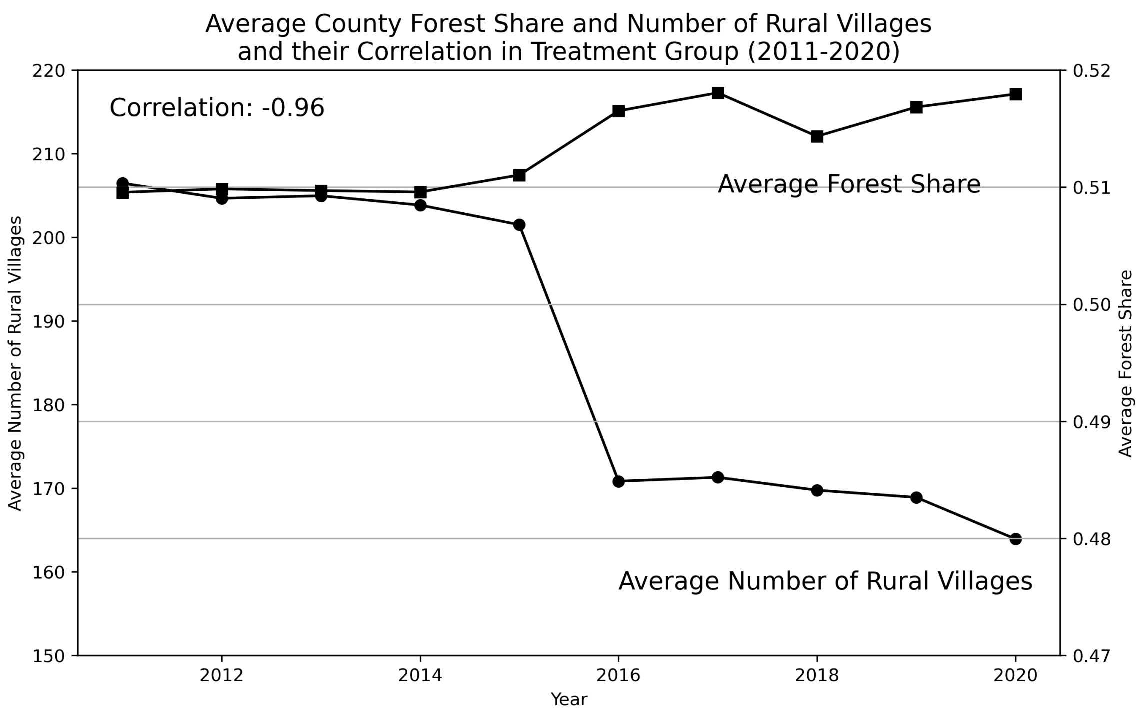

FIGURE 11: CORRELATION BETWEEN NUMBER OF RURAL VILLAGES AND FOREST SHAREIN TREATMENT GROUP

In conclusion, for the mechanisms examined, evidence suggests that the effect of rural poverty alleviation is likely driven by poverty alleviation relocation. I analyze this relocation mechanism through changes in the number of rural villages. Both the overall analysis and the event study reveal a negative effect of poverty alleviation on the number of rural villages. Additionally, changes in impervious surfaces further confirm the reduction in rural villages following the implementation of rural poverty alleviation in the treatment group. The negative correlation between the number of rural villages and forest share completes the final step in demonstrating the mechanism.

6 Conclusion

In 2024, approximately 8.5% of the global population lives in extreme poverty, equating to 692 million individuals (World Bank, 2024). More than three-quarters of those living in extreme poverty reside in rural areas (United Nations, 2023). Climate change is becoming increasingly severe and 2023 marked the hottest year on record (WMO, 2024). It is urgent to address these two global challenges.

I conduct a human-forest-human analysis, linking rural poverty alleviation to forest conservation. This approach is linked to addressing two global challenges: alleviating extreme poverty and combating climate change. I provide quasi-experimental estimates of the impact on forest conservation by exploring the implementation of rural poverty alleviation across more than 100 counties in China. I find that rural poverty alleviation has a positive impact on forest share, contributing to approximately a 0.5% increase in forest cover during the post-period, specifically from 2011 to 2020.The annual marginal effect equates to an 18 km^2 increase in forest area. Although there is spatial heterogeneity across different regions, almost all results from different regions consistently confirm the positive effects of rural poverty alleviation.

I further assess the contribution of increased forest share to human well-being by accounting for its valuation of ecosystem services. Whether measuring the carbon storage increase from the marginal effect of forest area alone or considering the land-use changes underlying the increase in forest share, the value of marginal carbon storage—estimated using the social cost of carbon—is approximately five times the cost of poverty alleviation.

I provide additional evidence to explore the potential mechanisms. The effect on forest conservation is primarily driven by forest gains converted from cropland, rather than from other types of land use changes. This further suggests that the channel for forest conservation operates through rural poverty alleviation, as most rural poverty is linked to farming activities on croplands. By examining the changes in the number of rural villages and the share of impervious surfaces, the evidence suggests that the results are driven by relocation efforts associated with poverty alleviation.

This study contributes to the literature in three key ways. First, it provides evidence linking poverty alleviation and forest conservation, diverging from previous studies focused on tropical forests (Alix-Garcia et al., 2013; Malerba, 2020; Wunder, 2001). Second, it adds to research on inequality and environmental impacts, showing that reducing income inequality through poverty alleviation can increase forest cover, aligning with the Environmental Kuznets Curve (EKC) hypothesis that environmental degradation declines as income rises. Third, this study fills a gap in understanding poverty alleviation's direct effects on ecosystem services, offering robust evidence that poverty reduction supports ecosystem benefits like carbon storage, with a value five times the cost of poverty alleviation.

This study links rural poverty alleviation to forest conservation, addressing poverty and climate change together. Using a generalized difference-in-differences approach with the poverty allevaition efforts across more than 100 counties in rural China, findings show that poverty alleviation resulted in a 0.5% increase in forest cover (18 km^2 annually) from 2011 to 2020. The value of this added carbon storage is estimated to be five times the cost of poverty alleviation. Forest gains are primarily from cropland conversion, suggesting that poverty alleviation supports conservation, especially through rural poverty relocation. These findings highlight a sustainable development path where poverty reduction and environmental conservation reinforce each other, enhancing rural well-being and supporting global ecological goals.

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7 Appendix

TABLE A-1: DESCRIPTIVE STATISTICS (LAND USE CHANGE: PART 1)

	Treatment		Contrl Group	
Variable	Mean	SD	Mean	SD
Cropland to Forest (%)	0.32	0.43	0.21	0.41
Cropland to Shrub (%)	0.01	0.04	0.00	0.02
Cropland to Grassland (%)	0.15	0.37	0.09	0.27
Cropland to Water (%)	0.01	0.04	0.04	0.17
Cropland to Snow (%)	0.00	0.00	0.00	0.00
Cropland to Barren (%)	0.00	0.00	0.00	0.00
Cropland to Impervious (%)	0.05	0.08	0.15	0.23
Cropland to Wetland (%)	0.00	0.00	0.00	0.00
Forest to Cropland (%)	0.32	0.39	0.23	0.40
Forest to Shrub (%)	0.03	0.07	0.01	0.03
Forest to Grassland (%)	0.00	0.00	0.00	0.00
Forest to Water (%)	0.00	0.00	0.00	0.00
Forest to Snow (%)	0.00	0.00	0.00	0.00
Forest to Barren (%)	0.00	0.00	0.00	0.00
Forest to Impervious (%)	0.00	0.00	0.00	0.01
Forest to Wetland (%)	0.00	0.00	0.00	0.00
Shrub to Cropland (%)	0.02	0.06	0.00	0.02
Shrub to Forest (%)	0.04	0.08	0.01	0.04
Shrub to Grassland (%)	0.01	0.03	0.00	0.02
Shrub to Water (%)	0.00	0.00	0.00	0.00
Shrub to Snow (%)	0.00	0.00	0.00	0.00
Shrub to Barren (%)	0.00	0.00	0.00	0.00
Shrub to Impervious (%)	0.00	0.00	0.00	0.00
Shrub to Wetland (%)	0.00	0.00	0.00	0.00
Grassland to Cropland (%)	0.14	0.34	0.10	0.29
Grassland to Forest (%)	0.04	0.13	0.02	0.09
Grassland to Shrub (%)	0.01	0.03	0.00	0.01
Grassland to Water (%)	0.00	0.00	0.00	0.01
Grassland to Snow (%)	0.00	0.00	0.00	0.00
Grassland to Barren (%)	0.01	0.06	0.02	0.14
Grassland to Impervious (%)	0.00	0.01	0.01	0.03
Grassland to Wetland (%)	0.00	0.00	0.00	0.00
Water to Cropland (%)	0.01	0.04	0.04	0.12
Water to Forest (%)	0.00	0.00	0.00	0.00
Water to Shrub (%)	0.00	0.00	0.00	0.00
Water to Grassland (%)	0.00	0.00	0.00	0.01

Table A-2: Descriptive Statistics (Land Use Change: Part 2)

	Treatment		Contrl Group	
Variable	Mean	SD	Mean	SD
Water to Snow (%)	0.00	0.00	0.00	0.00
Water to Barren (%)	0.00	0.00	0.00	0.02
Water to Impervious (%)	0.00	0.01	0.01	0.06
Water to Wetland (%)	0.00	0.00	0.00	0.00
Snow to Cropland (%)	0.00	0.00	0.00	0.00
Snow to Forest (%)	0.00	0.00	0.00	0.00
Snow to Shrub (%)	0.00	0.00	0.00	0.00
Snow to Grassland (%)	0.00	0.00	0.00	0.00
Snow to Water (%)	0.00	0.00	0.00	0.00
Snow to Barren (%)	0.00	0.00	0.00	0.02
Snow to Impervious (%)	0.00	0.00	0.00	0.00
Snow to Wetland (%)	0.00	0.00	0.00	0.00
Barren to Cropland (%)	0.00	0.00	0.00	0.02
Barren to Forest (%)	0.00	0.00	0.00	0.00
Barren to Shrub (%)	0.00	0.00	0.00	0.00
Barren to Grassland (%)	0.01	0.06	0.03	0.17
Barren to Water (%)	0.00	0.00	0.00	0.05
Barren to Snow (%)	0.00	0.01	0.00	0.02
Barren to Impervious (%)	0.00	0.00	0.00	0.06
Barren to Wetland (%)	0.00	0.00	0.00	0.00
Impervious to Cropland (%)	0.00	0.00	0.00	0.00
Impervious to Forest (%)	0.00	0.00	0.00	0.00
Impervious to Shrub (%)	0.00	0.00	0.00	0.00
Impervious to Grassland (%)	0.00	0.00	0.00	0.00
Impervious to Water (%)	0.00	0.01	0.01	0.03
Impervious to Snow (%)	0.00	0.00	0.00	0.00
Impervious to Barren (%)	0.00	0.00	0.00	0.00
Impervious to Wetland (%)	0.00	0.00	0.00	0.00
Wetland to Cropland (%)	0.00	0.00	0.00	0.01
Wetland to Forest (%)	0.00	0.00	0.00	0.00
Wetland to Shrub (%)	0.00	0.00	0.00	0.00
Wetland to Grassland (%)	0.00	0.00	0.00	0.00
Wetland to Water (%)	0.00	0.00	0.00	0.00
Wetland to Snow (%)	0.00	0.00	0.00	0.00
Wetland to Barren (%)	0.00	0.00	0.00	0.00
Wetland to Impervious (%)	0.00	0.00	0.00	0.00

Table A-3: Summary Statistics within Mountain Areas

Variable	Dabie Mountain Area	Dian-Gui-Qian Karst Region	Liupan Mountain Area	Luoxiao Mountain Area	Qinba Mountain Area	Southern Daxing'anling Mountain Area	Western Yunnan Border Mountain Area	Wuling Mountain Area	Wumeng Mountain Area	Yanshan -Taihang Mountain Area	Control Group
	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Forest Share(%)	4.32	66.39	11.71	75.53	65.75	3.01	72.36	70.46	60.65	30.69	31.86
Forest Gains per km^2(%)	0.09	0.63	0.23	0.33	0.52	0.14	0.34	0.51	0.76	0.2	0.24
Forest Loss per km^2 (%)	0.06	0.64	0.02	0.46	0.25	0.11	0.43	0.53	0.55	0.09	0.24
Forest Share Change (%)	0.03	-0.01	0.21	-0.14	0.28	0.03	-0.1	-0.02	0.21	0.11	0.0
Planted Forest Share (%)	1.08	1.4	1.89	1.56	1.18	1.05	1.17	1.81	2.22	2.54	1.25
Cropland Share(%)	81.34	29.01	32.25	21.56	30.06	86.89	20.72	27.77	34.62	39.99	48.04
Shrub Share(%)	0.0	3.08	0.54	0.03	0.16	0.0	1.89	0.27	1.82	0.52	0.19
Grassland Share(%)	0.02	0.68	53.5	0.1	1.81	5.87	4.34	0.05	2.23	18.92	7.42
Water Share(%)	3.17	0.38	0.3	0.52	0.34	0.47	0.46	0.69	0.33	0.39	2.66
Snow Share(%)	0.0	0.0	0.01	0.0	0.01	0.0	0.03	0.0	0.0	0.0	0.07
Barren Land Share(%)	0.01	0.0	0.76	0.0	0.04	0.03	0.03	0.0	0.0	0.01	2.89
Impervious Surface Share(%)	11.14	0.46	0.93	2.25	1.82	3.72	0.17	0.76	0.34	9.48	6.86
Wetland Share(%)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.01
Carbon Storage Density (C ton/km^2)	7665.71	23599.31	13581.35	25482.35	233117	8487.49	25216.17	24384.72	22299.7	15418.83	14826.26
Average NDVI per km^2	0.32	0.34	0.29	0.41	0.39	0.38	0.46	0.34	0.35	0.38	0.32
County Area (km^2)	1334.95	2312.35	2618.76	1985.13	28867	3211.35	3711.43	2108.96	3055.28	1875.38	3362.43
Population (Thousand)	1008.26	360.35	318.39	514.27	444.56	410.25	298.95	510.51	801.32	418.48	554.67
Gov't Revenue (Million USD)	57.69	55.87	25.65	77.7	41.63	26.92	44.77	50.93	99.07	40.06	162.02
Gov't Expenditure (Million USD)	328.46	207.69	188.46	261.63	229.59	2275	208.8	253.3	379.11	173.51	325.56
GDP Primary (Million USD)	470.03	206.67	126.47	2078	216.24	282.33	236.61	237.19	342.13	197.12	333.38
GDP Secondary (Million USD)	713.16	371.06	257.53	452.0	446.99	179.44	239.23	347.22	588.6	316.68	1282.99
Number of Rural Villages	316.39	104.76	137.2	174.67	245.73	108.7	82.23	257.44	212.57	233.29	205.81
Relief Degree of Land Surface	0.06	1.13	1.92	0.62	1.86	0.2	2.43	0.79	1.68	0.63	0.61
Savings Deposit (Million USD)	1371.86	496.45	604.78	1072.36	831.65	493.77	505.52	825.22	1070.65	955.87	1616.85
Average NTL Intensity per km^2	0.13	0.11	0.09	0.07	0.05	0.04	0.06	0.08	0.09	0.16	0.46
Average Annual Precipitation (mm)	1053.92	1276.17	545.82	1562.46	874.15	551.49	1079.88	13112	1063.95	568.15	993.32
Average Annual Wind Speed (mph)	4.4	4.04	4.31	3.5	3.48	5.9	3.47	3.14	3.63	4.64	4.8
Observations	147	267	282	147	270	126	219	435	115	124	26193
No. of Counties	7	13	14	7	13	6	11	22	6	7	1284

Table A-4: Poverty Alleviation Funds from Central and Provincial Gov'ts (2011-2020)

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Central Government Poverty Alleviation Fund (Billion USD)										
Industrial Development	1.84	2.30	2.71	2.99	3.20	4.60	5.93	7.31	8.55	9.97
Poverty Relocation	0.77	0.97	1.15	1.26	1.35	1.99	2.64	3.25	3.94	4.48
Education Support	0.54	0.64	0.77	0.86	0.92	1.07	1.46	1.84	2.07	2.38
Healthcare Support	0.31	0.43	0.49	0.54	0.58	0.77	1.07	1.30	1.53	1.84
Housing & Renovation	0.38	0.46	0.54	0.60	0.64	0.92	1.18	1.53	1.84	2.12
Infrastructure Development	0.15	0.23	0.31	0.34	0.32	0.69	0.72	0.86	1.10	1.24
Social Security	0.06	0.06	0.09	0.08	0.08	0.18	0.18	0.15	0.28	0.38
Subtotal	4.05	5.09	6.26	6.67	7.09	10.22	13.18	16.26	19.31	22.41
Provincial Governments' Poverty Alleviation Funds (Billion USD)										
Hebei Province	0.03	0.12	0.17	0.16	0.17	0.31	0.15	0.63	0.84	1.07
Shanxi Province	0.07	0.09	0.12	0.12	0.17	0.30	0.28	0.38	0.41	0.43
Heilongjiang Province	0.01	0.02	0.02	0.02	0.03	0.11	0.14	0.17	0.32	0.34
Anhui Province	0.02	0.14	0.15	0.06	0.15	0.26	0.33	0.41	0.50	0.21
Jiangxi Province	0.03	0.09	0.11	0.15	0.19	0.27	0.37	0.43	0.51	0.62
Henan Province	0.04	0.07	0.10	0.12	0.13	0.19	0.27	0.32	0.40	0.50
Hubei Province	0.35	0.41	0.93	1.06	4.47	4.57	5.02	7.04	7.27	7.27
Hunan Province	0.03	0.04	0.06	0.07	0.13	0.37	0.51	0.58	0.70	0.78
Guangxi Province	0.04	0.05	0.07	0.11	0.16	0.28	0.37	0.60	0.82	0.93
Sichuan Province	0.12	0.16	0.16	0.22	0.29	0.40	0.54	0.83	0.98	1.26
Guizhou Province	0.10	0.22	0.27	0.38	0.45	0.69	0.84	0.97	1.20	1.49
Yunnan Province	0.12	0.15	0.17	0.21	0.20	0.46	0.50	0.70	0.97	1.17
Shaanxi Province	0.10	0.12	0.14	0.18	0.13	0.19	0.35	0.46	0.55	0.66
Gansu Province	0.04	0.05	0.07	0.17	0.18	0.27	0.29	0.70	0.92	1.10
Qinghai Province	0.02	0.04	0.06	0.10	0.13	0.13	0.16	0.22	0.37	0.28
Subtotal	1.76	2.18	2.96	4.69	5.60	8.21	10.20	12.20	11.57	11.57
Total	4.86	6.49	7.82	8.85	10.05	14.91	18.78	24.34	29.53	33.98

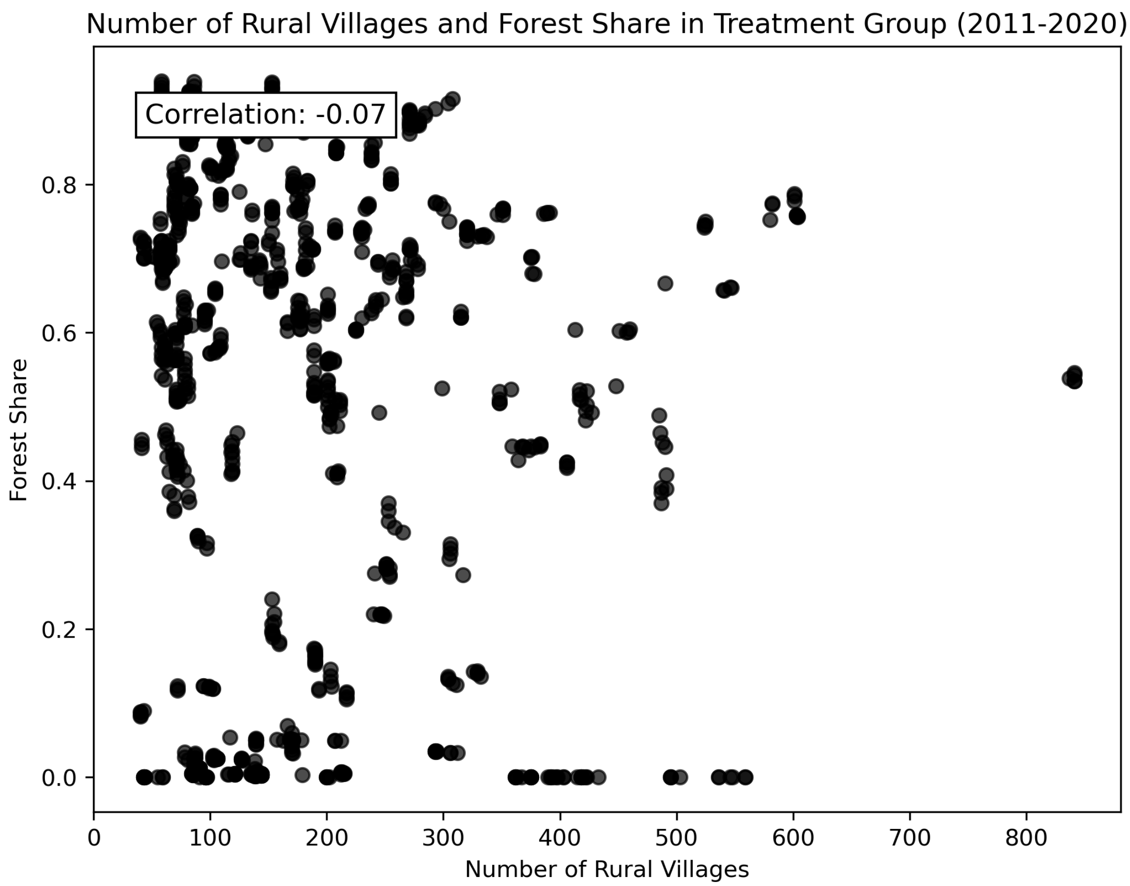

FIGURE A-1: EVENT STUDY ON IMPERIOUS SURFACE SHARE

A Additional Analysis on Village Number Change

Changes in impervious surfaces can also serve as an indicator of shifts in number of rural villages. In China, villages are defined as contiguous zones characterized by impervious surfaces, surrounded by other forms of land use, such as cropland and forests. To examine these changes, an event study approach is employed. It is important to emphasize that this event study does not aim to establish a causal relationship between poverty alleviation and changes in impervious surfaces. The prefered specification, i.e, the TWFE estimator, and other two estimtors from de Chaisemartin and D'Haultfœuille (2020) and Sun and Abraham (2021) show prior to the implementation of poverty alleviation measures in 2011 in poverty counties, the share of impervious surfaces was rising, albeit at a diminishing rate. However, following 2011, the impervious surface share began to decline, with the rate of decline accelerating over time. Given that impervious surfaces in urban areas of China tend to remain stable or increase, this observed reduction is likely attributable to rural areas. This trend suggests a corresponding decline in the number of rural villages, implying the poverty alleviation relocation.

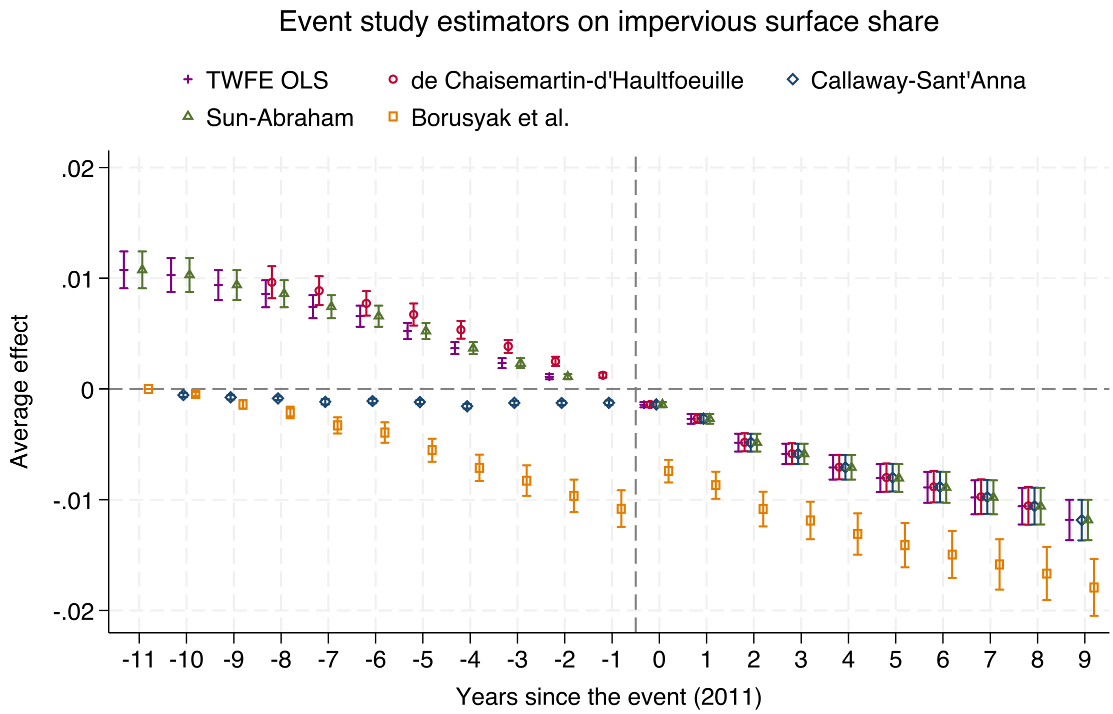

Figure A-2: Effects of Rural Poverty Alleviation on Imperious Surface Share:Before and After Intervention

Notes: Figure 6 presents the results of the event-study regression on imperious surface share, comparing outcomes across different model specifications, including the traditional TWFE model and alternative estimators proposed by Borusyak, Jaravel, and Spiess (2024), Callaway and Sant'Anna (2021), de Chaisemartin and D'Haultfœuille (2020), and Sun and Abraham (2021), which account for heterogeneity in treatment effects over time and among treated units. The horizontal axis represents the time periods, while the vertical axis shows the estimated effects on forest share, expressed as a percentage of county land area. The figure includes 95% confidence intervals for each estimate, illustrating the precision of the results over time.