Essays in Environmental and Development Economics

A DISSERTATION

SUBMITTED TO THE FACULTY OF THE GRADUATE SCHOOL

OF THE UNIVERSITY OF MINNESOTA

BY

YANXU LONG

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

Advisors: Marc F. Bellemare & Stephen Polasky

February, 2025

Acknowledgements

There are many people to whom I owe my deepest gratitude for their support throughout my graduate studies. Their guidance, encouragement, and kindness have been invaluable, shaping both my academic work and personal growth.

First and foremost, I extend my deepest gratitude to my advisors, Dr. Marc F. Bellemare and Dr. Stephen Polasky, for their unwavering support throughout my Ph.D. journey. On my very first day in the program, Marc generously offered to serve as my advisor, assuring me, "happy to help in whatever way I can"—a promise he not only kept but exceeded. He guided me in selecting reforestation as my research focus, which evolved from my second-year paper into the central theme of this dissertation. His financial support, through a research assistantship, sustained me for nearly my entire program. Beyond academia, Marc's encouragement extended into my personal life—he was the one who suggested that my wife and I consider having a child, and his support throughout that journey left a lasting impact on our lives. His generosity and mentorship extended far beyond what I can put into words, for which I am truly grateful. He deeply appreciates every meal or dessert I prepare at home, and I always hope that one day he will enjoy my papers as much as my cooking.

I first met Steve before joining the graduate program, during his lecture on Making Nature Count. His insights immediately captivated me, sparking my deep interest in natural capital accounting—an interest that became the core of my research and continues to inspire my work. Steve exemplifies how to conduct meaningful research and teach with clarity and impact. His mentorship has been invaluable in shaping my academic path.

I am also deeply grateful to my committee members, Dr. Justin Johnson and Dr. Forrest Fleischman, for their guidance and constructive feedback. Justin trained me in working with big data, a skill that has been crucial to my research. With Forrest, I share a strong interest in forest studies, and his work has offered valuable insights that have enriched my understanding of forest conservation.

I have had the privilege of working with Dr. Jay Coggins for many years and deeply appreciate his mentorship. I am also profoundly grateful to Dr. Paul Glewwe for his unwavering support. Additionally, I thank Dr. Rodney Smith for his guidance and friendship. I would also like to extend my gratitude to Drs. Charlotte Ambrozek, Metin Çakır, Elizabeth Davis, Nicholas Gallagher, Frances Homans, Laura Kalambokidis, Jason Kerwin, Terrance Hurley, and Raahil Madhok in the Department of Applied Economics for their valuable insights and encouragement throughout my Ph.D. journey.

I am incredibly thankful for my study partners and office mates, Libby Kula and Ann Mellisa Perez. I am also grateful to my cohort members, including but not limited to Matt Braaksma, Matt Bombyk, Adriana Castillo Castillo, Qingyin Cai, Manlin Cui, Monique Davis, Haoyu Fang, Ryan McWay, Dr. Jhih-Yun Liu, Casey McNichols, Divya Pandey, Uma Parasuram, Isabel Pastoor, SongYi Paik, Stephen Pitts, Lifeng Ren, Becca

Weir, and Yang Wang. Their camaraderie, support, and shared experiences have made this journey all the more meaningful.

To my parents—When I was four or five years old, I would tell people I wanted to be a doctor, even though I had no real understanding of what a Ph.D. meant. Looking back, I realize that dream was deeply rooted in the value my parents placed on education. With unwavering love and unshakable belief, they supported me every step of the way, making this journey possible.

Finally, my deepest gratitude goes to my wife. Without her unwavering support, I could not have completed this journey. During graduate school, we welcomed our son into the world—a moment that brought immense meaning to my life and reminded me of what truly matters.

Dedication

To my parents, wife and son

Abstract

This dissertation explores the intersection of environmental and development economics through three essays, centering on forests as natural capital. It investigates human–forest interactions using rigorous econometric methods, including ordinary least squares, instrumental variables (IV), difference-in-differences (DID), and quantile regression. By integrating economic, geospatial, and ecological data, the research evaluates forest-related policies at both micro (household) and macro (county) levels. The findings offer policy insights for optimizing land use, public financial investments, and household decision-making, ultimately contributing to sustainable development by balancing economic growth with environmental conservation.

Essay 1 examines the effects of rural poverty alleviation on forest conservation. Using a high-resolution annual land cover dataset and a generalized DID approach, the study finds that poverty alleviation programs increased forest cover by 0.5% annually, with carbon storage benefits outweighing program costs. Rural relocation policies emerge as key drivers of conservation, highlighting a cost-effective strategy for integrating economic development with environmental restoration.

Essay 2 evaluates the economic and ecological impacts of large-scale tree planting from 2002 to 2019 using an IV approach. While afforestation enhances grain production—particularly four to eight years after planting—it negatively affects GDP in primary and secondary sectors. The findings reveal an inverted U-shaped relationship between plantation forest maturity and grain production, underscoring the need to

balance ecological benefits with economic trade-offs.

Essay 3 investigates the long-term effects of China's Grain for Green (GfG) program, which subsidizes farmers to convert cropland on steep slopes into forests. Using national survey data and a DID framework with multiple treatment periods, the study finds that GfG increases household income and expenditure, primarily through farm income growth and government subsidies. Households reallocate land from staple crops to soybeans and cash crops, improving soybean productivity.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Essay 1–Forest conservation is essential for combating climate change, as forests play a critical role in regulating the Earth's climate and mitigating global warming. However, poverty often drives deforestation, as economically disadvantaged populations may lack the resources, knowledge, or incentives to adopt sustainable forest management practices (Leichenko and Silva, 2014; World Bank, 2020). This raises a key question: can poverty alleviation and forest conservation be pursued simultaneously? Despite its importance, this relationship remains underexplored (Hubacek et al., 2017; Malerba, 2020).

To address this gap, I examine the impact of rural poverty alleviation on forest conservation. In 2011, China launched targeted poverty alleviation programs across 11 priority regions based on county-level GDP and farmers' income. The staggered implementation of these programs provides a quasi-experimental setting to evaluate their effects on forest cover. I use county-level classifications and high-resolution 30-m Land Use and Land Cover (LULC) data, employing a generalized difference-in-differences

(DiD) approach to identify the effects.

The results indicate that rural poverty alleviation contributes to a 0.5% annual increase in forest cover from 2011 to 2020. While spatial variations exist, the overall trend consistently supports the positive effect of poverty alleviation on forest conservation. The ecosystem service benefits of increased forest cover, estimated using the social cost of carbon, are approximately five times the cost of implementing poverty alleviation efforts, highlighting its cost-effectiveness. The primary mechanism driving this forest expansion is cropland conversion, reinforcing the link between rural poverty and agricultural land use. Additionally, relocation initiatives associated with poverty alleviation reduce pressure on cropland, facilitating reforestation.

This study contributes to the literature by providing empirical evidence linking poverty alleviation to forest conservation, diverging from previous research focused on tropical forests (Alix-Garcia, McIntosh, et al., 2013; Malerba, 2020; Wunder, 2001). It enriches discussions on inequality and environmental sustainability, supporting the Environmental Kuznets Curve (EKC) hypothesis, which suggests environmental degradation declines as income rises. It also highlights that poverty alleviation enhances ecosystem services, demonstrating benefits that extend beyond economic welfare to environmental gains. The findings offer valuable insights for policymakers seeking to integrate poverty reduction with environmental sustainability.

Essay 2–Tree planting plays a critical role in environmental conservation, climate change mitigation, and desertification control while also affecting local livelihoods (Bond, Millar, and Ramos, 2020; Deininger et al., 2001; Di Sacco et al., 2021; Newmark et al., 2017; Seymour, 2020). However, limited empirical evidence exists on the economic consequences of large-scale afforestation, particularly its effects on local economic development. It remains unclear whether afforestation fosters economic growth or imposes opportunity costs, making this study crucial for refining global afforestation strategies.

I examine the economic and ecological effects of large-scale tree planting in China, a country facing severe environmental challenges (J. Liu and Raven, 2010). Over decades, afforestation has been central to China's environmental policies, making it the world's largest contributor to forest expansion, accounting for 25% of the global net increase in leaf area from 2000 to 2017 (C. Chen et al., 2019; S. S. Peng et al., 2014). Given the scale of afforestation, assessing its economic consequences is crucial for balancing environmental restoration with rural development.

To estimate the direct effects of large-scale tree planting as a labor-intensive green infrastructure project on local economic development, I focus on GDP from the primary and secondary sectors. Additionally, I investigate its indirect effects on agricultural production and GDP, considering the ecological benefits of afforestation, such as wind erosion control and crop protection. I use the previous year's precipitation as an instrumental variable for tree planting, leveraging implementation rules from China's Three-North Shelterbelt Program. In arid and semiarid regions, where water availability is the primary constraint, afforestation planning considers precipitation levels from the preceding year. I provide evidence that higher precipitation leads to increased tree planting in subsequent years.

The results indicate that, contrary to policymakers' expectations, large-scale tree planting does not stimulate local economic growth. Instead, I find statistically significant negative effects on GDP from the primary and secondary sectors, likely due to tree planting being a low-value economic activity compared to manufacturing and agriculture. The substantial opportunity costs associated with afforestation—such as land use restrictions and labor reallocation—may further hinder economic expansion. These findings align with research highlighting the role of governance and environmental conditions in shaping afforestation outcomes (Yirenkyi-Boateng, 2001; Zinda and Z. Zhang, 2019).

In contrast, I find positive indirect effects on grain production, emerging six years after afforestation. This aligns with findings from carbon sequestration programs in the U.S. that show additional agricultural benefits from soil erosion reduction (Plantinga and J. Wu, 2003). However, this effect is limited to plain agricultural areas and follows an inverted U-shaped pattern, suggesting diminishing benefits as forests mature. I find no evidence of changes in other agricultural outputs (e.g., cotton, oil crops, or meat production) or GDP from the secondary sector.

Overall, large-scale tree planting negatively affects local GDP, with no evidence of economic spillovers beyond grain production. While afforestation may offer long-term environmental benefits, its economic trade-offs must be carefully considered. This study contributes to the empirical literature on afforestation's economic consequences in developing countries, highlighting the hidden opportunity costs of large-scale tree planting. Additionally, the findings contribute to research on nature's contribution to economic activity, particularly in the context of ecosystem services (Díaz et al., 2018).

Essay 3–Reforestation plays a crucial role in environmental conservation, climate change mitigation, and rural economic development (Bond, Millar, and Ramos, 2020; Deininger et al., 2001; Di Sacco et al., 2021; Newmark et al., 2017; Seymour, 2020). Payments for Ecosystem Services (PES) programs have emerged as key policy tools for promoting reforestation and curbing deforestation (Alix-Garcia and Wolff, 2014; Zilberman, Lipper, and McCarthy, 2009). However, their long-term effectiveness in improving rural livelihoods remains underexplored (Alix-Garcia and Wolff, 2014; Zilberman, Lipper, and Mccarthy, 2008), as these programs must balance environmental objectives with economic redistribution (Zilberman, Lipper, and Mccarthy, 2008). This study examines China's "Grain for Green" (GfG) program—one of the world's largest PES initiatives—to assess its impact on rural income and expenditure.

China's GfG program, launched in the late 1990s to combat soil erosion, incentivizes farmers to convert sloped cropland (>25 degrees) into forests or grasslands in exchange for financial subsidies (Z. Feng, Yanzhao Yang, et al., 2005). The *Notice of the China's State Council on Improving the Grain-for-Green Policy (2007)* outlines subsidy rates of 105 RMB per mu annually in the Yangtze River Basin and 70 RMB per mu in the Yellow River Basin. Participation is voluntary, allowing households to choose land conversion types best suited to their needs. While the program has significantly increased forest cover and enhanced soil and water conservation, its broader economic implications remain unclear.

To address potential endogeneity concerns, such as reverse causality and omitted variable bias, I use a Difference-in-Differences (DID) approach with staggered treatment timing. I incorporate household- and individual-level controls, including landholding, agricultural inputs, and demographics, and validate the parallel trends assumption through event study analysis. I also examine income distribution effects using quantile regressions and assess within-village inequality using the Gini index. This approach enables a robust analysis of GfG's long-term economic and distributional impacts.

I find that GfG participation significantly increases rural income and expenditure, primarily driven by farm income growth and government subsidies, while nonfarm business income and local wages remain unaffected. Households shift land use from staple crops to soybeans and cash crops, with soybean productivity improving. However, higher-income households benefit more, leading to a modest increase in local income inequality. Expenditure analysis shows increased spending on food, housing, and fuel, reflecting improved living conditions. These findings underscore both the economic benefits and distributional challenges of the GfG program.

This study contributes to the literature by providing a long-term, nationwide assessment of GfG's effects on rural livelihoods, addressing gaps in prior research focused on short-term, localized impacts (Z. Feng, Yanzhao Yang, et al., 2005; Uchida, Rozelle, and Jintao Xu, 2009). By decomposing income and expenditure, I identify key mechanisms—land use change, agricultural diversification, and government transfers—driving economic shifts. While the program successfully enhances rural incomes and living standards, limited impacts on nonfarm income suggest that complementary policies, such as financial access and vocational training, are needed to promote income diversification and equitable benefit distribution. These findings offer valuable insights for future PES policy design.

Chapter 2

Rural Poverty Alleviation and Forest Conservation

2.1 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 US $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

[1] At 2017 purchasing power adjusted prices.

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 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, 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 165.67 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 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)*[3], 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.

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

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

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 plays a pivotal role in China's rural poverty 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.

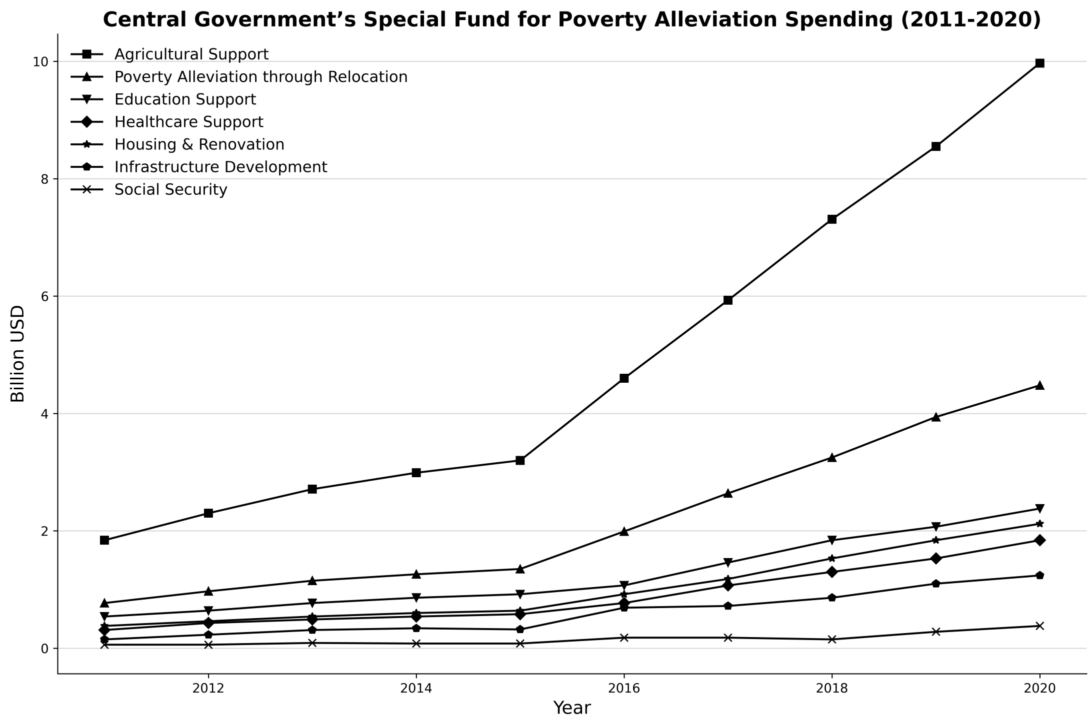


FIGURE 2.1: CENTRAL GOVERNMENT'S SPECIAL FUND FOR POVERTY ALLEVIATION SPENDING

Notes: This figure 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. 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%), poverty alleviation relocation (19.8%), education support (11.4%), healthcare support (8.1%), housing renovation (9.3%), infrastructure development (5.3%), and social security measures (1.4%). This comprehensive strategy aims to address immediate needs while promoting sustainable economic growth in poverty counties.

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.

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 N. 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, McIntosh, 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 Yuping 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 Jun 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 2.2 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.

2.2 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.

2.2.1 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[4] 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 China's State Council[5]. 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[6] 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

[4]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

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

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

counties within 10 contiguous areas[7] of extreme poverty. Figure 2.2 illustrates the geographic distribution of these 106 poverty counties, while Figure 2.4 displays the distribution across the 10 contiguous areas.

Data on the control group, comprising non-poverty counties [8] in 2011, was compiled from the comprehensive list of counties available in the *China County Statistical Yearbooks (2001–2021)*, published by the National Bureau of Statistics of China.[9] These yearbooks provide comprehensive socio-economic information for all counties across China, with further details discussed in Section 2.2.3. 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 2.2.

2.2.2 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

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

[8] 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.

[9] National Bureau of Statistics of China Website: https://www.stats.gov.cn/english/

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[10], 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 [11] from the National Platform for Common GeoSpatial Information Services[12]. 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 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,

[10]China's Land-Use/Cover Datasets (CLUDs) can be downloaded from Zenodo https://zenodo.org/record/5816591

[11]The official approval number of the county boundary map is GS (2020)4630.

[12]National Platform for Common GeoSpatial Information Services Website: https://www.tianditu.gov.cn/

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.

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[13] from the National Platform for Common GeoSpatial Information Services[14]. 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 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

[13] The official approval number of the county boundary map is GS (2020)4630.

[14] National Platform for Common GeoSpatial Information Services Website: https://www.tianditu.gov.cn/

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 2.2 illustrates forest share changes between 2011 and 2020 in treatment and control groups, as described in Section 2.2.1. 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 2.2 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.

Forest Share Change in Treatment and Control Groups in the Post-Period (2011-2020)

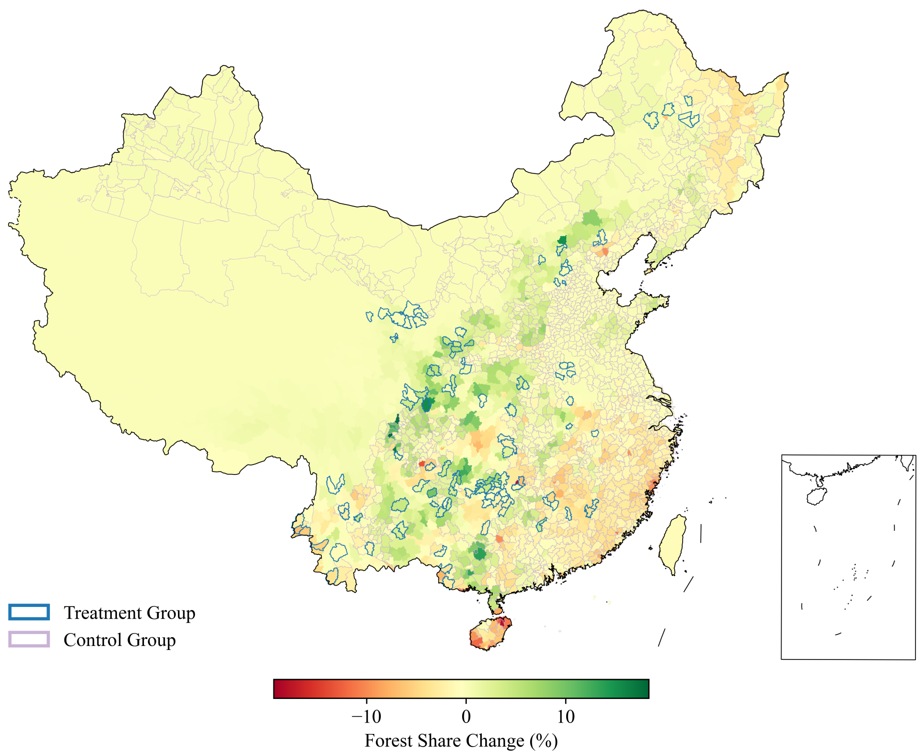


FIGURE 2.2: DISTRIBUTION OF TREATMENT GROUP AND CONTROL GROUP

Notes: This figure 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.

2.2.3 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[15].

2.2.4 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 2.2.2, 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[16]. 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

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

[16] 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.

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[17], 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 China[18]. Relief Degree of Land Surface is a comprehensive representation of regional altitude and surface cutting from You, Z. Feng, and Yanzhao Yang (2018)[19]. The nighttime light intensity data is sourced from the NOAA's Visible Infrared Imaging Radiometer Suite (VIIRS)[20].

2.2.5 Descriptive Statistics

Table 2.1 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,

[17] 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. From You, Z. Feng, and Yanzhao 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.

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

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

[20] 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

expenditure, GDP (both primary and secondary sectors), savings deposits in financial institutions, and nighttime light intensity. Appendix Tables A-2 and A-3 provide the descriptive statistics for all other 64 land use changes for both the treatment and control groups.

Table 2.1: Descriptive Statistics

Variable	Treatment Group Mean	Treatment Group SD	Contrl Group Mean	Contrl Group 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: This table presents county-level descriptive statistics for treatment and control groups, summarizing land use, economic conditions, and environmental dynamics.

2.3 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:

$$Y_{ct} = \alpha_c + \delta_t + \beta \times PovertyAlleviation_{ct} + \mathbf{X}_{ct} \times \boldsymbol{\psi} + \epsilon_{ct}, \tag{2.1}$$

where 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 2.1, with standard errors clustered at the county level.

Under the assumptions delineated in the preceding paragraph, the TWFE model facilitates the mitigation of various potential biases that could compromise the validity and robustness of the causal interpretation of the results. First, I can rule out concerns that the findings are driven by time-invariant differences in forest cover across regions. By including region fixed effects, I control for static differences. Second, I mitigate concerns that results may be driven by trends in forest cover evolving similarly across counties over time, unrelated to poverty alleviation efforts. The inclusion of year fixed effects helps control for such temporal shocks, isolating the specific impact of the poverty alleviation program on forest conservation.

Assuming parallel trends in forest cover between the 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 forest cover after the treatment. Figure 2.2 shows the trends of forest share in the treatment group and control group during the post-period (2011-2020).

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

$$Y_{ct} = \alpha_c + \delta_t + \beta_k \times \sum_{k=-11}^{9} D_{k(ct)} + \epsilon_{ct}, \tag{2.2}$$

where Y_{ct} is my outcome 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 heterogeneity of effects, I incorporate an interaction term into the baseline specification 2.1, 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. The modified empirical specification is:

$$Y_{ct} = \alpha_c + \delta_t + \sum_{r=1}^{10} (\beta_r \times \text{Poverty Alleviation}_{ct} \times \text{Region}_c) + \mathbf{X}_{ct} \times \boldsymbol{\psi} + \epsilon_{ct}, \quad (2.3)$$

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

2.4 Results

2.4.1 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 2.2 presents the estimates of β from Equation 2.1, utilizing various levels of fixed effects and control variables. The results consistently indicate a significant positive impact of poverty alleviation across all model specifications.

TABLE 2.2: 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, denoted as Forest Share, is defined as the proportion of forested land area to the total land area within a county, serving as a measure of the relative extent of forest coverage. 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 treatment effects on forest share, I implement an event-study regression as specified in Equation 2.2. Figure 2.3 presents the event-study estimates, revealing that poverty alleviation leads to a significant increase in forest share.

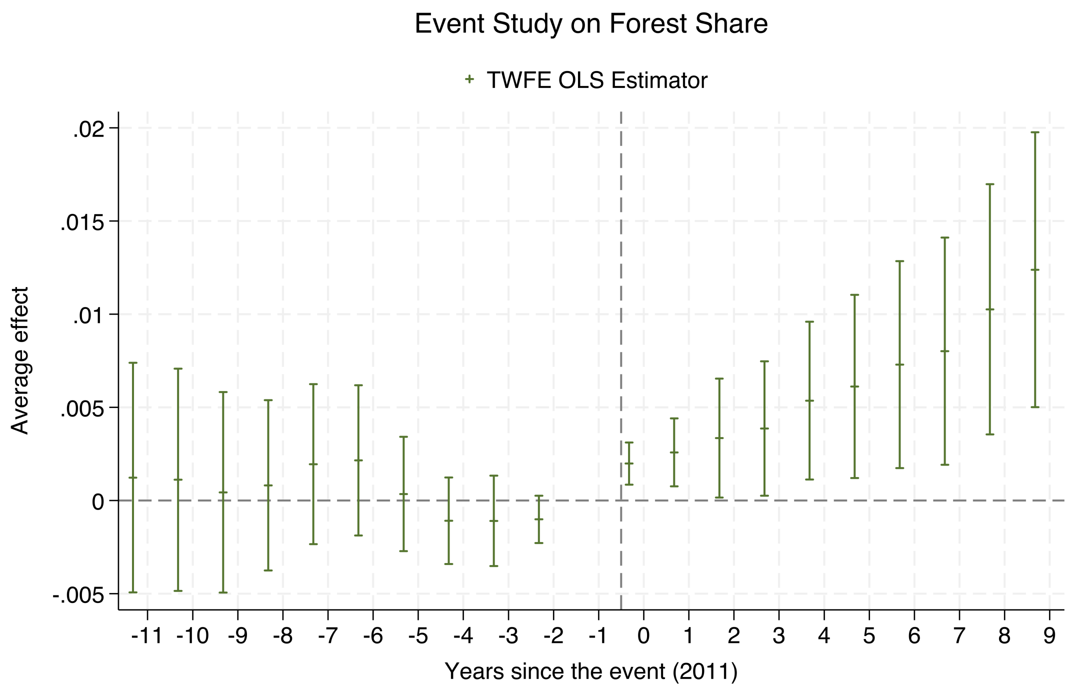


FIGURE 2.3: EFFECTS OF RURAL POVERTY ALLEVIATION ON FOREST SHARE: BEFORE AND AFTER INTERVENTION

Notes: Figure 2.3 presents the results of the event-study regression on forest share. The horizontal axis represents 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.

2.4.2 Spatial Heterogeneity

I also examine 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-4. This analysis evaluates how the impact of poverty alleviation varies across these geographic regions.

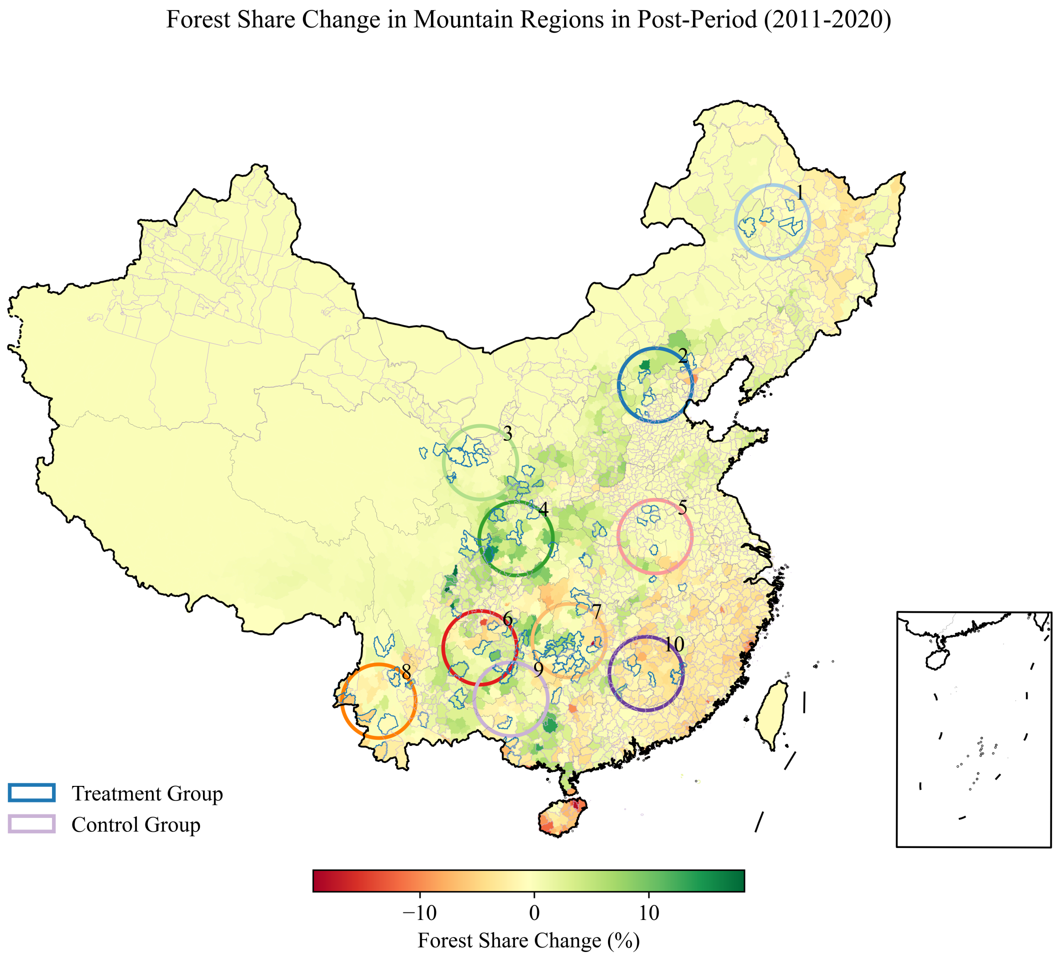


FIGURE 2.4: FOREST GAIN AND LOSS IN DIFFERENT MOUNTAINOUS AREAS

Notes: Figure 2.4 shows differences in forest share in China during the post-period (2011-2020). The circles with numbers represent different mountain regions. Green represents an increase in forest share, red indicates a decrease, and yellow signifies no change.

TABLE 2.3: 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)
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 dependent variable, forest share, is defined as the proportion of forested land area divided by the total land area within a given county.Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

2.4.3 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. 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-1 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)*[21] 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.

[21] 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

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 forested areas. Under the policy since 2018, farmers receive a subsidy of 1,600 RMB per mu[22] , which equates to approximately \$0.368 million per km^2 [23]. 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.

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

[23] 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.

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 2.4 provides detailed information on carbon pools across various ecosystems, illustrating differences in carbon storage capacity. With the forest carbon pool having

Table 2.4: 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 2.4 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.

a 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). 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, equivalent to approximately 5.5 times the associated costs.

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 2.4.4, 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 2.1, 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 2.4.1, incorporating province and prefectural city levels, county fixed effects, and relevant controls.

TABLE 2.5: 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 defined as the average carbon storage density (measured in tons of carbon per km^2),within a county. 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 2.5 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, 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.

In summary, the benefit-cost ratios of rural poverty alleviation range from 0.3 to 5.5, underscoring its substantial environmental benefits. The estimated direct costs, derived from central and provincial government expenditures, amount to \$19.18 million per poverty-designated county. These expenditures support poverty alleviation while indirectly promoting forest conservation. Benefits include an average increase of 18 km^2 in forest cover per county, with carbon sequestration as a key ecosystem service. Using a global Social Cost of Carbon (SCC) of \$185 per ton, carbon storage benefits are valued at \$93.31–\$104.90 million, significantly exceeding costs.These results highlight rural poverty alleviation as a cost-effective strategy for achieving both poverty reduction and environmental sustainability. Table 2.6 summarizes the cost-benefit analysis findings.

Table 2.6: Cost-Benefit Analysis Summary

	Replacement Cost Method	Carbon Storage Value (SCC)	
	PES for Reforestation	Direct Forest Expansion	Carbon Storage Density
Benefits (million USD)	6.6	104.90	93.31
Costs (million USD)		19.18	
Ratio	0.3	5.5	4.9

Notes: The benefit-cost ratios of rural poverty alleviation range from 0.3 to 5.5. The estimated direct costs, derived from central and provincial government expenditures, are \$19.18 million per poverty-designated county. These expenditures are allocated to poverty alleviation while also supporting forest conservation. Benefits include an average increase of 18 km^2 in forest cover per county, with carbon sequestration as a primary ecosystem service. Using a global Social Cost of Carbon (SCC) of \$185 per ton, carbon storage benefits are valued between \$93.31 million and \$104.90 million.

2.4.4 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 2.7: 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, defined as the change in the proportion of forested land area relative to the total land area within a county. 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 2.1 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 2.5 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.

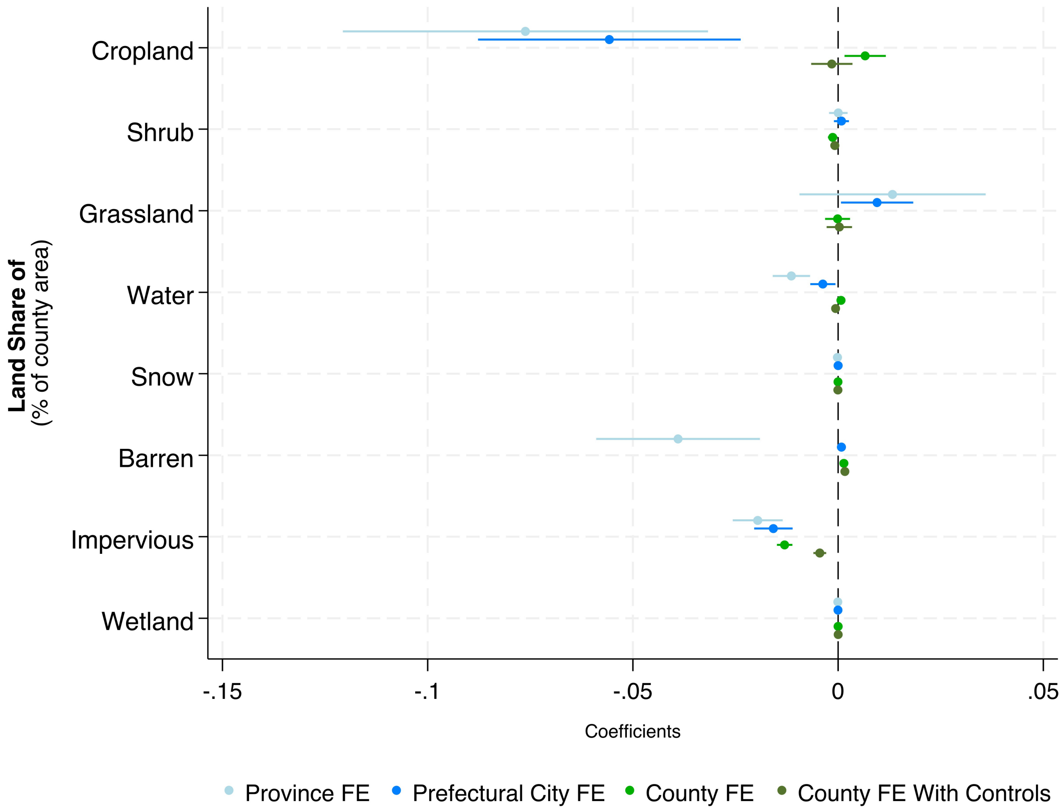


FIGURE 2.5: EFFECTS ON OTHER LAND USES

Notes: Figure 2.5 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 2.8: 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 defined as the average Normalized Difference Vegetation Index (NDVI) within a county, which serves as a proxy for vegetation density and health. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.5 Mechanisms

2.5.1 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 2.1, 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 2.6 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 significance 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.

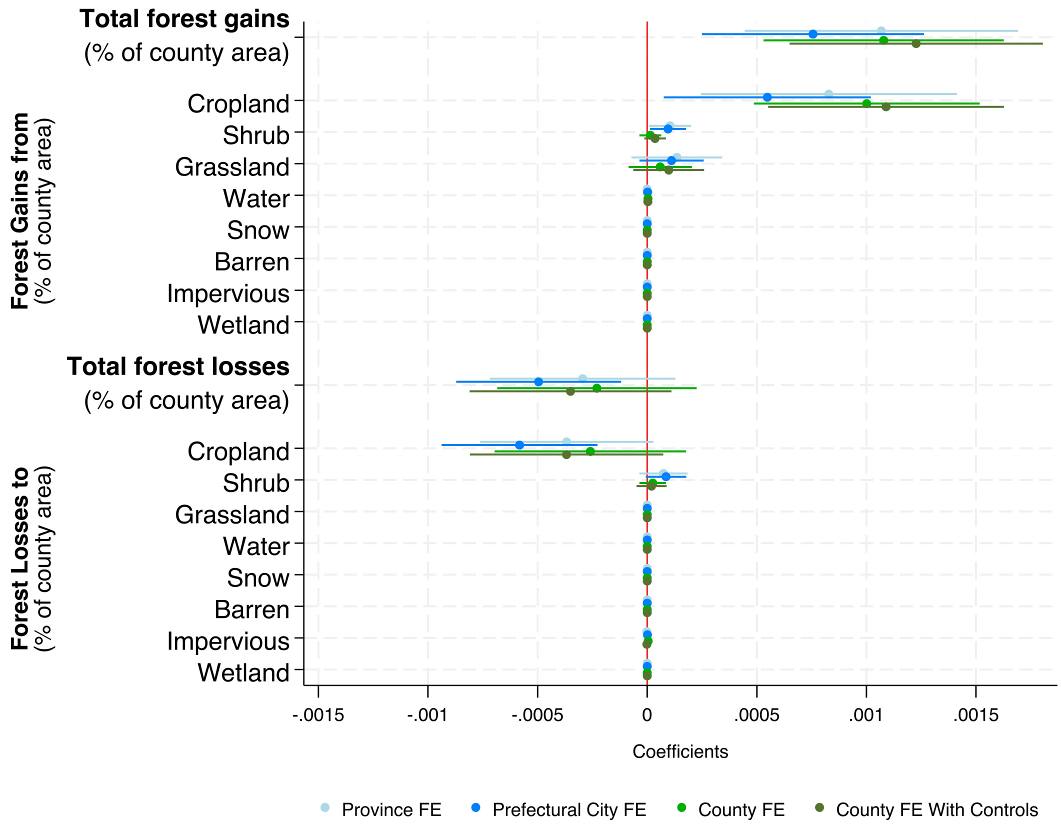


FIGURE 2.6: EFFECTS ON FOREST GAINS AND LOSSES FROM OTHER LAND USES

Notes: Figure 2.6 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.

2.5.2 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 2.9: 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 2.2 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 2.1 using the same four model specifications as outlined in Section 2.4.1. Table 2.9 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 another channel that may contribute to the observed forest gains.

2.5.3 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 2.1, 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 2.7 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 2.1, 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)[24], 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

[24]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

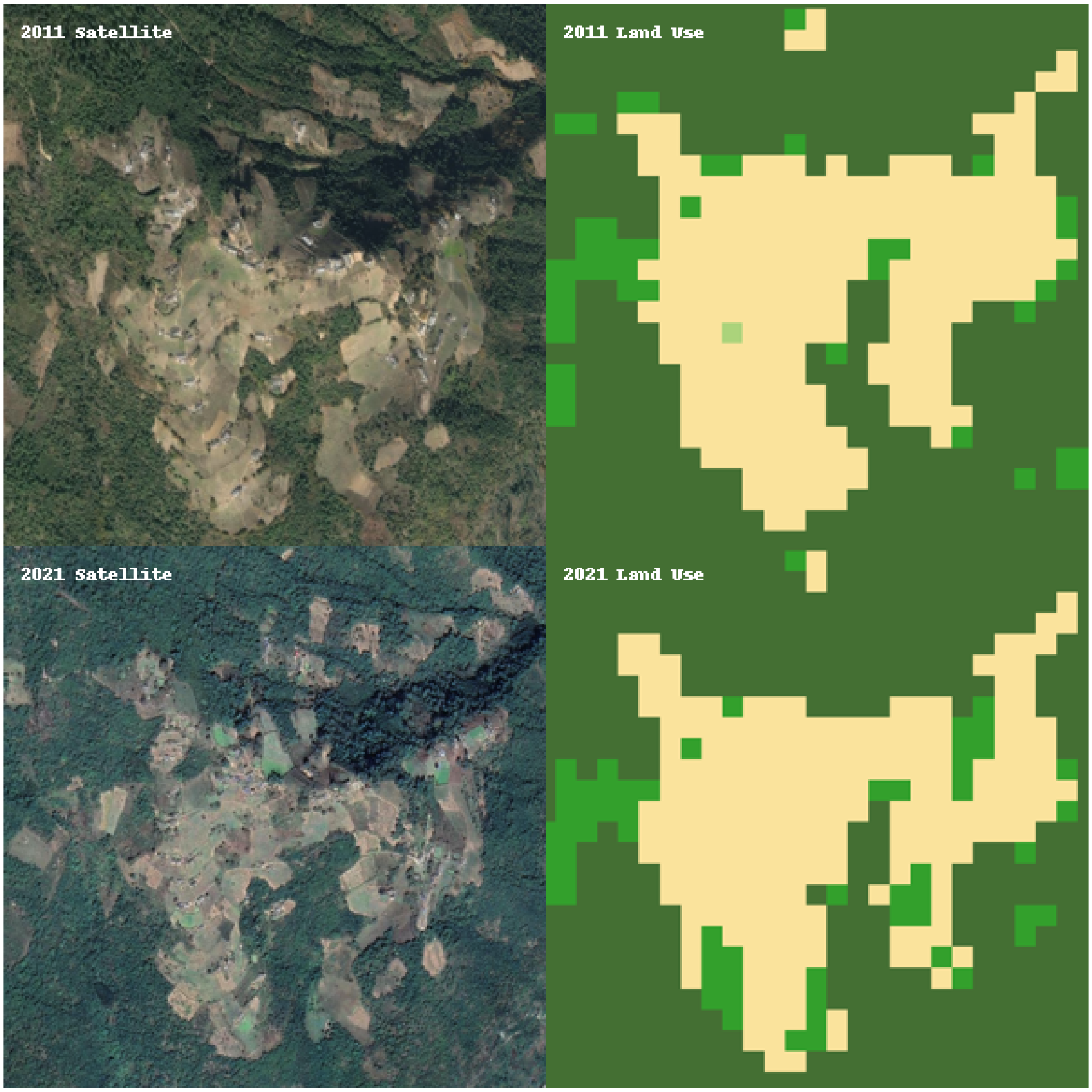


FIGURE 2.7: SATELLITE IMAGERY AND LAND USE CHANGES IN A POVERTY-STRICKEN VILLAGE BEFORE AND AFTER RELOCATION

Notes: This figure 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. The land use data corresponds to the land use and land cover dataset employed in this study.

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 the number of rural villages.

TABLE 2.10: 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 2.1 with four distinct specifications, using the number of rural villages at the county level as the outcome. Table 2.10 shows the estimated results. The results are not significant with only region and time fixed effects shown in Columns 1-3 of Table 2.10. When adding controls, the preferred specification — the one with county and time fixed effects in Column 4 of Table 2.10 — 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 the control group.

Figure 2.8 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 alleviation. 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 2.8 confirms the pre-parallel trend and illustrates the dynamic effects underlying the overall negative impact.

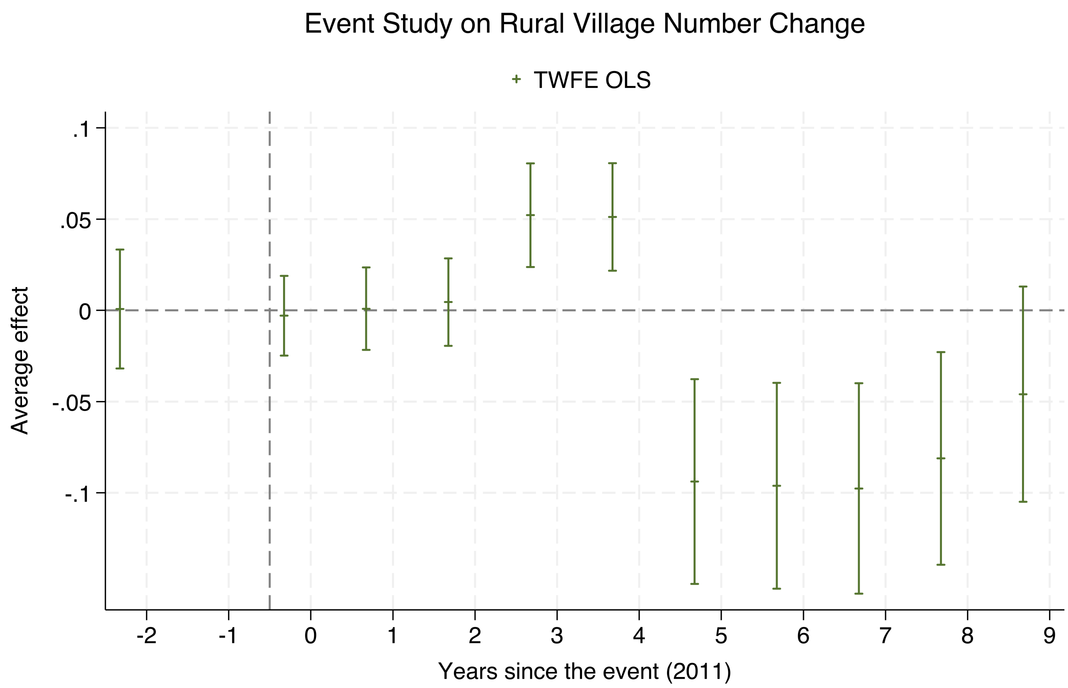


Figure 2.8: Effects of Rural Poverty Alleviation on Number of Rural Villages: Before and After Intervention

Notes: This figure presents the results of the event-study regression on the number of rural villages. 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 2.9 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).

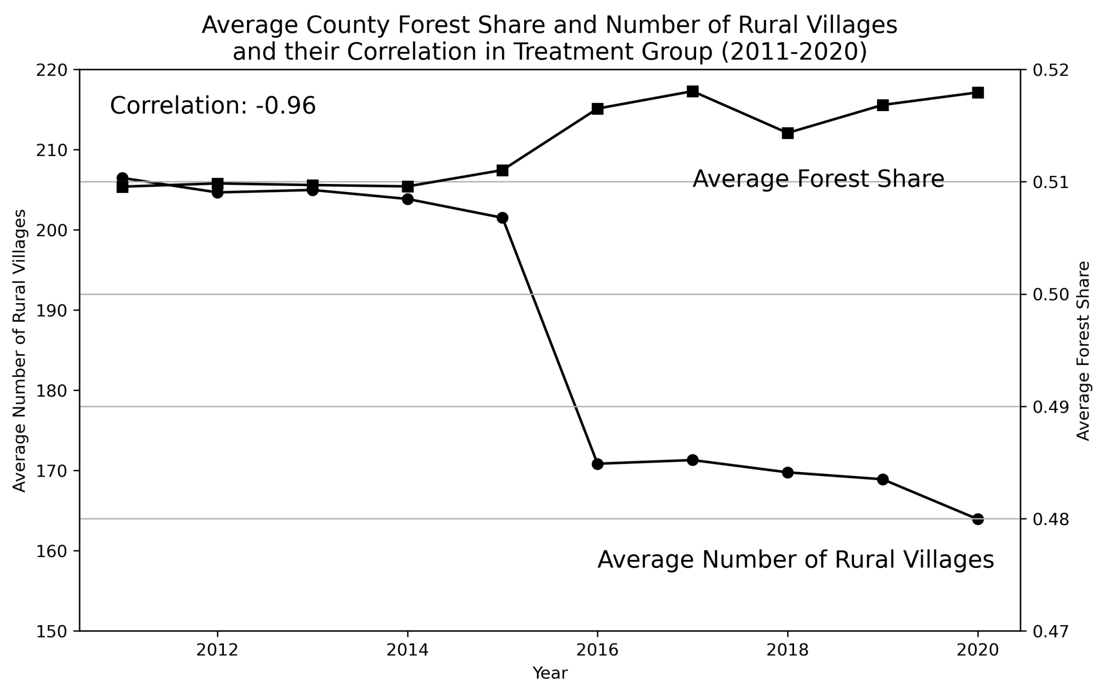


FIGURE 2.9: CORRELATION BETWEEN NUMBER OF RURAL VILLAGES AND FOREST SHARE IN THE TREATMENT GROUP

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.

2.6 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 addresses 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 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, McIntosh, 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 alleviation 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.

Chapter 3

Economic and Ecological Effects of Large-scale Tree Planting on Local Economic Development

3.1 Introduction

Tree planting has been recognized as a means to conserve the environment, mitigate climate change, combat desertification, and support local livelihoods (Bond, Millar, and Ramos, 2020; Deininger et al., 2001; Di Sacco et al., 2021; Newmark et al., 2017; Seymour, 2020). However, there remains a dearth of empirical evidence regarding the economic outcomes of tree planting, particularly on a large scale. This lack of empirical data leaves the question unanswered as to whether tree planting can effectively drive local economic development or not. The limited empirical evidence regarding the economic consequences of tree planting holds significant implications for its adoption as a global strategy to address environmental challenges and for the design of policies such as payments for ecosystem services (PES).

This paper aims to examine the impact of large-scale tree planting, a commonly employed strategy to address environmental degradation, on local economic development. The main objective is to assess the economic effects of implementing labor-intensive green infrastructure projects, such as large-scale tree planting, on local economic development in China. This approach not only generates substantial employment opportunities but also encourages public investments. The focus of this study is on evaluating the influence of tree planting on the Gross Domestic Product (GDP) within the primary and secondary sectors. Additionally, the secondary objective is to explore the ecological effects of tree planting on agricultural production and GDP within the primary and secondary sectors. These effects are examined to the ecological impacts of plantation forests, which include preventing wind erosion and safeguarding crops.

My study focuses on the empirical context of China, a country that has demonstrated strong political support and ambitious goals for tree planting over the past four decades. China has faced significant environmental challenges, surpassing those of many other nations (J. Liu and Raven, 2010). Large-scale tree planting has been a central component of China's environmental efforts for many years (S. S. Peng et al., 2014; Xi et al., 2022). China boasts the largest forested area globally (S. S. Peng et al., 2014) and has contributed to 25% of the global net increase in leaf area from 2000 to 2017 (C. Chen et al., 2019). These endeavors have been spearheaded by the central government and implemented at all levels of governance. The Three-North Shelterbelt Program

(TNSFP), initiated by the Chinese government in 1978, holds a prominent position in China's large-scale ecological construction efforts. It is considered the world's best ecological project and encompasses regions in Northwest China, North China, and Northeast China, collectively known as the Three-North region or Northern China. The program aims to combat desertification and mitigate dust storms in the arid, semiarid, and dry sub-humid areas of Northern China (Chu et al., 2019; Han Li et al., 2021). Building on the early success of the TNSFP, additional tree-planting initiatives were launched in the 1980s, including the Sand Source Control Program around Beijing and Tianjin, the Nature Forest Conservation Program, and the Grain for Green Program. These programs have significantly contributed to the acceleration of greening efforts in the Three-North region. Over the past 40 years, the total area of tree planting in this region has surpassed 46.14 million hectares, leading to an increase in forest coverage from 5.05% to 13.57% by 2018 (CAS, 2018, October). Satellite imagery provides visual evidence of the successful tree planting endeavors in Northern China (Macias-Fauria, 2018).

In addition to China, large-scale tree planting projects have been implemented worldwide over the past century, particularly gaining momentum after 2000, with the aim of environmental conservation and supporting local livelihoods. Notable examples include the Great Plains Shelterbelt program initiated by the United States in 1934, which later became the Prairie States Forestry Project. This project was a response to the devastating dust storms of the Dust Bowl, which caused severe soil erosion and drought. The shelterbelts planted throughout the Great Plains provide wind protection for homes, farms, ranches, livestock, and crops, and serve as habitats for numerous wildlife species (Orth, 2007). Another significant initiative is the Great Green Wall of the Sahara and the Sahel (GGWSSI) project led by the African Union, which commenced in 2007. The objective of this project is to combat desertification in the Sahel region and halt the expansion of the Sahara by creating a wall of trees stretching across the entire Sahel (Campos-Filho, Junqueira, and Nicola Costa, 2014).In 2021, Vietnam approved the "Planting one billion trees from 2021 to 2025" project. The primary goals of this project are to protect the ecological environment, enhance the landscape, address climate change, improve people's quality of life, and foster sustainable development within the country (Vietnam's MARD, 2021). Increasing afforestation and reforestation efforts are also recognized globally as part of Goal 15 of the United Nations' Sustainable Development Goals (United Nations, 2015).

Given the increasing global adoption of large-scale tree planting as a primary strategy to combat climate change and achieve carbon neutrality in the coming decades, this analysis holds valuable lessons for countries worldwide and researchers studying the evolving dynamics of natural resources.

Examining the economic effects of large-scale tree planting as a green infrastructure investment presents inherent challenges due to the intricate nature of the relationship between infrastructure and economic output (Esfahani and Ramírez, 2003; Fedderke and Bogetić, 2009). This analysis is further complicated by the presence of reverse causality, where both large-scale tree planting and local economic development mutually influence each other. Moreover, the selective implementation of tree-planting initiatives in politically significant areas, such as minority-inhabited regions, frontier areas, and poverty-stricken areas in China, introduces unpredictable selection biases when comparing areas with and without tree-planting programs. Additionally, as large-scale tree-planting activities are inherently intertwined with economic activity, it becomes challenging to disentangle their specific effects on economic outcomes. Consequently, conducting a comprehensive evaluation requires a meticulous approach, employing robust research methods that address endogeneity, account for selection biases, and carefully analyze the distinct contributions of tree planting to local economic development.

In this paper, an instrumental variable empirical strategy is employed to examine the economic effects of large-scale tree planting, with careful consideration given to endogenous tree planting placement and potential confounding economic trends. The study takes advantage of the implementation rules specific to the study area, namely the Three-North region, where water availability poses a significant barrier to tree planting due to its predominantly arid or semiarid nature. The artificial afforestation technical regulations stipulate that afforestation construction design should be developed and approved one year before the actual afforestation process, taking into account local precipitation. Building upon this, the paper utilizes the precipitation levels of the previous year as an instrumental variable to capture tree planting in the subsequent year. The argument is made and supported by evidence that higher precipitation in the preceding year leads to a greater number of trees being planted in the following year.

As a supplementary approach to the primary analysis, a fixed-effects strategy is employed to estimate the economic effects of large-scale tree planting on specific economic outcomes, namely GDP from the primary and secondary sectors. To account for potential confounding factors and regional variations, county-level fixed effects and prefecture-level city fixed effects are incorporated into the analytical framework. In the context of China, it is important to note that a prefecture-level city comprises multiple counties [1]. This consideration allows for a more comprehensive and nuanced understanding of the relationship between tree planting and economic outcomes at both the county and prefecture levels.

After estimating the economic effects of large-scale tree planting, the analysis shifts focus to investigating the ecological effects of this strategy, particularly to improving the local climate, controlling wind erosion, conserving water, and protecting crops. Given the time required for fast-growing plantation trees to mature, as prescribed by the Artificial afforestation technical regulations, the study considers six years as the average growth age for exploring the ecological effects of tree planting in the t-6 year. Additionally, to delve deeper into the ecological effects of tree planting on grain output, a regression analysis is conducted, incorporating the forestation area as a percentage of land area from year t-3 to year t-10. This approach allows for a comprehensive examination of the broader impacts of tree planting on ecological and agricultural aspects, shedding light on the potential benefits and considerations associated with large-scale tree-planting initiatives.

Contrary to expectations of significant economic benefits, the results of this study indicate that large-scale tree planting does not lead to accelerated local economies. Instead, there is evidence of negative effects on local GDP from both the primary and secondary sectors. This challenges the notion that tree planting is a high-value economic activity compared to other sectors such as manufacturing and agriculture. Moreover, the

[1] According to the National Bureau of Statistics of China (https://data.stats.gov.cn/english/), there were 293 prefecture-level cities and 2844 counties in 2020.

study suggests that the opportunity costs associated with implementing large-scale tree-planting programs should not be overlooked. The findings align with the perspective of Yirenkyi-Boateng (2001), who argue that inadequate attention to the conceptualization and impact assessment of rural development projects, particularly to forestry practices, can hinder their effectiveness. Additionally, Zinda and Z. Zhang (2019) emphasize the influence of local governance behavior and environmental conditions on the contributions of afforestation and land-use patterns.These findings highlight the complexities and trade-offs inherent in large-scale tree-planting initiatives. It is crucial to have a comprehensive understanding of the economic implications of such projects and consider the contextual factors that shape their outcomes. Policymakers and researchers should carefully assess the costs and benefits associated with tree planting programs, taking into account the specific socio-economic and environmental conditions of the target area.

Regarding the ecological effects of large-scale tree planting, the study reveals that after six years of initial tree planting, there is an increase in grain production. This finding is consistent with research on a carbon sequestration program in Wisconsin, USA, which demonstrates the additional benefits of reduced soil erosion in agriculture (Plantinga and J. Wu, 2003). Additionally, the study uncovers an inverted U-shaped relationship between the maturity of plantation forests and their ecological impact on grain production. However, these effects are primarily observed in plain agricultural areas, with no significant changes detected in other agricultural products such as cotton, oil crops, and meat production. Furthermore, the study finds no overall effects on GDP from the primary sector, but significant variations in different subregions. Importantly, there are no ecological effects on GDP from the secondary sector observed in the analysis.These findings highlight the specific influence of large-scale tree planting on grain production, particularly in plain agricultural areas. The lack of substantial effects on other agricultural outputs and GDP from the primary and secondary sectors suggests the need for careful consideration of the economic implications and regional variations when implementing large-scale tree-planting initiatives.

In summary, the study reveals that large-scale tree planting has adverse effects on local economic development, leading to a decrease in GDP from both the primary and secondary sectors. After six years following tree planting, the main ecological effect of mature plantation forests is limited to facilitating grain production, exhibiting an inverted U-shaped relationship with the maturation of the forests. However, no significant changes are observed in other agricultural outputs or GDP from the secondary sector. These findings underscore the complexities and nuanced outcomes associated with large-scale tree-planting initiatives, emphasizing the need for a comprehensive understanding of their economic impacts and sector-specific considerations.

In conclusion, this paper makes valuable contributions to the existing literature in several ways. Firstly, it adds to the growing body of empirical research on the economic consequences of large-scale tree planting in developing countries. The findings highlight the negative economic effects, indicating that such initiatives can have detrimental impacts on the local economy. This sheds light on the cost considerations associated with tree planting, encompassing both visible labor and material costs, as well as the less tangible opportunity costs of dedicating substantial efforts to these programs.

Secondly, the study's analysis of the ecological effects reveals that mature plantation forests can effectively enhance grain production six years after the initial tree planting. This finding contributes to the literature on nature's contribution to people, as it underscores the role of large-scale tree planting in promoting agricultural productivity. The insights gained from this research further enhance our understanding of the intricate relationships between tree planting, ecosystem services, and human well-being, as explored in the literature on nature's contributions to people (Díaz et al., 2018).

Overall, this paper provides important empirical evidence and insights into the economic and ecological effects of large-scale tree planting, informing policymakers, researchers, and practitioners involved in environmental management and economic development.

The remaining sections of this paper are structured as follows: Section 2 provides an introduction to the background of large-scale tree planting in Northern China. Section 3 discusses the relevant data used in the analysis. Section 4 presents the empirical framework employed in the study. Section 5 presents the regression results and provides a detailed analysis of the estimation findings. Finally, Section 6 concludes by discussing the implications of the study's findings and their policy relevance.

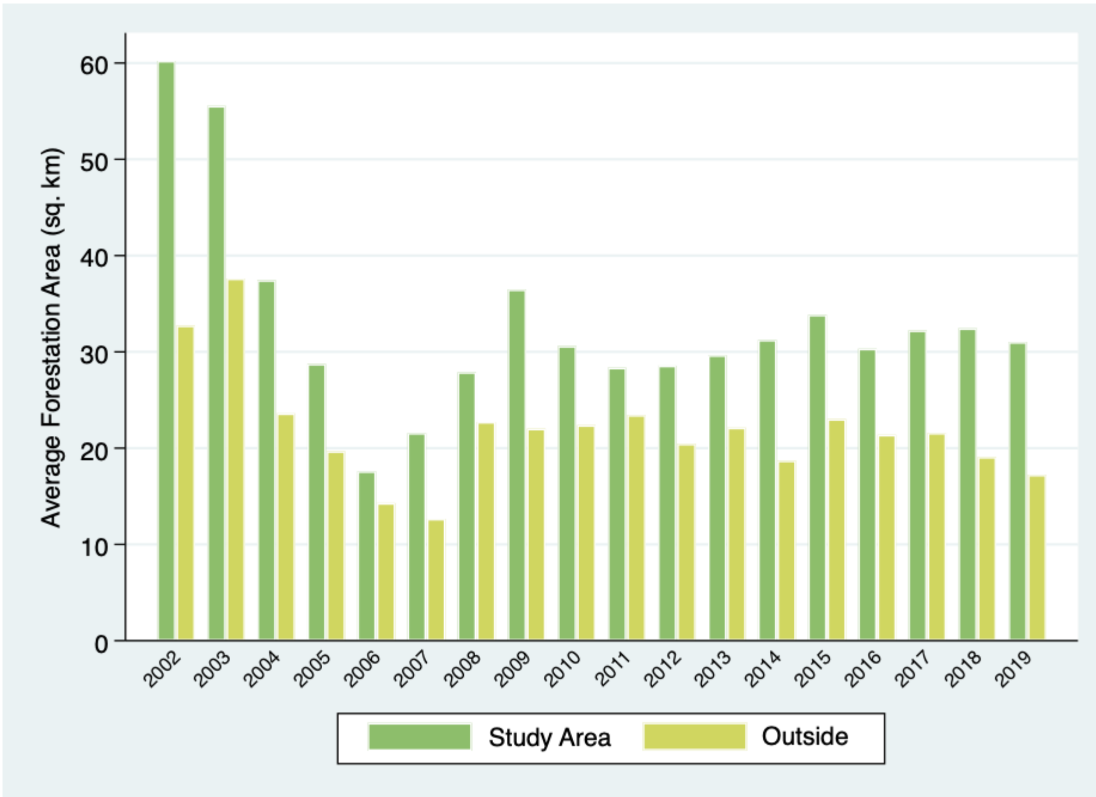
3.2 Background

China has undertaken extensive tree-planting efforts over the past four decades to combat desertification and control wind erosion, primarily focusing on Northwest China, North China, and Northeast China, collectively known as the Three-North region or Northern China. In 1978, the Chinese government initiated the Three-North Shelter

Forest Program (TNSFP), which marked the first large-scale tree-planting initiative. The TNSFP aimed to establish a vast sheltered forest area in the Three-North region. Subsequently, China implemented various other tree-planting programs to address the escalating environmental challenges in this region.

Building upon the early success of the TNSFP, several additional tree-planting programs were launched, including the Sand Source Control Program around Beijing and Tianjin, the Forest Program for Nature Conservation, and the Grain for Green Program. These programs were initiated in the 1980s and played a significant role in accelerating the process of greening in the Three-North region. Over the past 40 years, the cumulative tree planting in this area has surpassed 46.14 million hectares, resulting in a substantial increase in forest coverage from 5.05% to 13.57% by 2018 (CAS, 2018, October). The Three-North region has emerged as a leader in the greening efforts of China, as revealed by satellite imagery (Y. Zhang et al., 2015) and highlighted in Figure 3.2, which illustrates the average forestation area in counties within and outside the Three-North region.

Figure 3.2: The County Average Forestation Area in and outside the Three-North Region (2002-2019)



Notes: The study area for this research is focused on the Three-North region, which includes Northwest China, North China, and Northeast China. The comparison is made between this specific region and other regions within China. The data used in this study is derived from the China Forestry and Grassland Statistical Yearbooks, covering the period from 2002 to 2019. The author conducted the analysis and created the comparison based on the data obtained from these sources.

The Three-North region serves as a unique battleground for tree planting in China due to its challenging ecological conditions. The region has been plagued by environmental disasters such as drought, sandstorms, and soil erosion, which have significantly hindered economic and social development, leading to long-term poverty and backwardness among its inhabitants. This situation presents a major challenge to China's overall economic growth.In the majority of the Three-North region, the annual precipitation is less than 500 mm, and approximately 85% of the land is classified as desert-type, encompassing arid and semiarid lands spanning over 1.6 million km^2 (X. M. Wang et al., 2010). Furthermore, the area is heavily affected by soil erosion, with an estimated erosion area of 554,000 square kilometers, particularly prominent in the Loess Plateau Hilly and Gully Area (Chang et al., 2012). The region is also subjected to severe sandstorms caused by winds originating from Siberia on an annual basis (X. Liu et al., 2004).

Large-scale tree planting plays a decisive role in improving the ecological environment of this region. Overall, TNSFP aims to combat desertification, control wind erosion, and protect crops by planting trees in the wasteland. In addition, according to the Three-North Shelter Forest Program Planning[2], there are different focuses in different subregions. The construction of Soil and Water Conservation Forests is the main focus in the Loess Plateau Hilly and Gully Area to control severe soil erosion. In the Northeast and North China Plain Agricultural Area, the aim is to construct farmland protection forests. The main goal in the Northwest Desert Area is to plant shelterbelt forests to protect oases. In the Wind-blown Sand Area, the primary objective is to combat desertification through tree planting.

Several regional or nationwide forest programs in the area also have different project goals. The Sand Source Control Program around Beijing and Tianjin forest program

[2]This includes Three-North Shelter Forest Program Planning (Phase 4 and Phase 5) from China's National Forestry and Grassland Administration. http://www.forestry.gov.cn/

aims to reduce desertification and dust storms and improve the environment in the upwind area of Beijing and Tianjin in this region (Shan et al., 2015). The Nature Forest Conservation Program is a nationwide forest program that focuses on improving the fragile and unstable ecological environment by conserving natural forests (Huang et al., 2019). The Grain for Green forest program, another nationwide initiative, aims to control the country's soil erosion problems by converting sloping farmland into forests (Deng, Shangguan, and R. Li, 2012).

To implement large-scale tree planting, China has issued several laws, such as the Forest Law of the People's Republic of China[3], regulations, such as the Artificial Afforestation Technical Regulations, and guidance to manage and monitor tree planting activities. Local governments are required to comply with the relevant laws, regulations, and guidance and fulfill the assigned tree-planting tasks from higher government authorities.

According to the Artificial Afforestation Technical Regulations, there are three methods for forestation in China: artificial afforestation, aerial afforestation, and reforestation by closing mountains or hills. Among these methods, artificial afforestation is the primary approach. The implementation of forestation by artificial afforestation must adhere to the principle of selecting suitable tree species for specific locations. The following criteria should be met:i. The planned land should have a soil layer of no less than 30 cm. ii. The slope of the land should be gentle, generally below 25 degrees. iii. The gravel content in the soil should generally be below 30%. Aerial afforestation is employed in remote mountainous areas and sandy regions where the terrain is relatively

[3]Forest Law of the People's Republic of China: https://english.mee.gov.cn/Resources/laws/

rugged. The altitude difference should not exceed the requirements for aircraft operation, and this method is suitable for afforestation in forests, barren hills, and wastelands. Reforestation by closing mountains or hills focuses on areas with sparse forests, logging sites, mountains, and steep slopes.

China has made significant investments in the implementation of large-scale tree-planting initiatives. In 2018, the total forestation area exceeded 7.3 million hectares across the country. According to the *China Forestry and Grassland Development Report* (2018)[4], the cumulative nationwide investment for tree planting reached 481.7 billion RMB (US$74.10 billion) in the same year. It is worth noting that a portion of this investment is allocated towards payments for ecosystem services.

3.3 Data

This subsection offers a concise overview of the primary datasets employed in the analysis. To leverage the variation in large-scale tree planting at the county level, I integrate county-level administrative data on such activities with various external datasets encompassing socio-economic, meteorological, and topographic information within northern China. As previously mentioned, the Three-North region exhibits the most rapid growth in terms of tree planting. Consequently, the study concentrates on the Three-North region, which comprises four subregions and spans 13 provinces. Figure 3.1 illustrates the geographical location of this study area and its four subregions.

[4]From China's National Forestry and Grassland Administration: http://www.forestry.gov.cn/

3.3.1 Tree-planting Data

I collected county-level tree-planting data from the China Forestry and Grassland Statistical Yearbooks between 2002 and 2019 published by China's National Forestry and Grassland Administration and stored in China National Knowledge Infrastructure. This dataset includes forestation areas by different forestation methods, including forestation by artificial afforestation, aerial afforestation, and reforestation by closing the mountains or hills covering all more counties in China. I created several variables from these measures. The annual forestation area (sq. km) in the county is calculated by summing up the artificial afforestation area (sq. km), aerial afforestation area (sq. km), and reforestation area (sq. km) by closing the mountains or hills in the county. I calculated the annual forestation area (% of land area) by dividing the county's annual forestation area by the county's land area multiplied by 100[5]. Similarly, I also calculated the annual artificial afforestation area (% of land area), the annual aerial afforestation area (% of land area), and the reforestation area (% of land area) by closing the mountains or hills for the analysis.

Relevant program planning information is from China's National Forestry and Grassland Administration Website[6]. Table 3.1 shows the descriptive statistics.

The county-level tree-planting data used in this study were obtained from the China Forestry and Grassland Statistical Yearbooks published by China's National Forestry and Grassland Administration. These yearbooks are stored in the China National Knowledge

[5] The annual forestation area (% of land area) is calculated as $\frac{\text{the county's annual forestation area (sq. km)}}{\text{the county's land area (sq. km)}} \times 100$.

[6] National Forestry and Grassland Administration Website Address: http://www.forestry.gov.cn

Infrastructure (CNKI) [7], a prominent national research and information publishing platform in China. The dataset includes information on forestation areas using different methods, such as artificial afforestation, aerial afforestation, and reforestation by closing mountains or hills. It covers numerous counties across China, providing comprehensive coverage of tree planting activities.

From this dataset, several variables were derived for analysis. The annual forestation area (measured in square kilometers) for each county was calculated by summing up the areas of artificial afforestation, aerial afforestation, and reforestation by closing mountains or hills within the county. To assess the scale of tree planting relative to the county's land area, the annual forestation area was expressed as a percentage. This percentage was obtained by dividing the county's annual forestation area (in square kilometers) by the county's land area (in square kilometers) and multiplying by 100. Similarly, the annual artificial afforestation area, annual aerial afforestation area, and reforestation area by closing mountains or hills were also calculated as percentages of the respective county's land area. These variables provide valuable insights into the extent of tree planting activities at the county level and their relative proportions compared to the land area.

Table 3.1 presents the descriptive statistics related to the variables used in the analysis.

[7] China National Knowledge Infrastructure (CNKI) is a key national research and information publishing platform in China, led by Tsinghua University, and supported by China's Ministry of Education and Ministry of Science. According to its introduction, CNKI provides professional software products and services of various resources with unified search, unified navigation, online reading, and download, such as Chinese academic literature, foreign literature, dissertations, newspapers, conference proceedings, yearbooks, reference books, and so on. https://cdi.cnki.net.

3.3.2 Socio-economic Data

The socio-economic data used in this study were obtained from the China County Statistical Yearbooks published by the National Bureau of Statistics of China (NBS) and accessed through the CNKI website. These yearbooks provide comprehensive information on economic development, agricultural production, industry and investments, education, health, and social welfare and security at the county level. The variables included in the dataset comprise county-level indicators such as GDP, GDP from the primary and secondary sectors, county area (sq. km), population, government expenditure, loan balance in financial institutions, agricultural production (including grain output, oil crops output, cotton output, and meat output), power of agricultural machinery per worker (kWh), student enrollment in primary and middle schools, and the number of telephone users. These variables offer a holistic perspective for analyzing the relationship between tree-planting activities and various socio-economic factors at the county level.

I adjusted all the monetary variables for inflation using China's national CPI (2010=100) that is collected from the NBS's website[8]. I also converted all the monetary variables in Chinese Yuan into U.S. dollars using the 2010 average annual exchange rate provided on the People's Bank of China's website[9].

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

[9]People's Bank of China's website: http://www.pbc.gov.cn/en/

3.3.3 Meteorological and topographic data

I collected meteorological data, including annual precipitation and average land surface wind speed, as well as topographic data indicating the relief degree of the land surface (RDLS). The meteorological data are sourced from the China Meteorological Data Service Center [10]. The RDLS data, obtained from the Journal of Global Change Data & Discovery[11], provides a comprehensive representation of regional altitude and surface roughness (You, Z. Feng, and Yanzhao Yang, 2018). RDLS is calculated using the following formula: RDLS = altitude/1000 + [max(altitude) - min(altitude)] × [1 - proportion of flat area / total area]/500. RDLS is an interesting parameter that has been applied in various disciplines. For instance, Z. Feng, Yan Tang, et al. (2008) investigated its influence on population distribution, while Yang et al. (2021) studied its impact on urban street network complexity.

[10] China Meteorological Data Service Center website: https://data.cma.cn/en

[11] Journal of Global Change Data & Discovery: According to its website, the Journal of Global Change Data & Discovery is sponsored by the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences (IGSNRR/CAS) and Geographical Society of China, and co-sponsored by CODATA Task Group of Preservation of and Open Access to S&T Data in Developing Countries (CODATA-PASTD), Jomo Kenyatta University of Agriculture and Technology of Kenya (JKUAT), and Digital Lin Chao Geomuseum.

TABLE 3.1: DESCRIPTIVE STATISTICS OF DATA USED IN ANALYSIS (2000–2020)

Variables	Control		Treatment		Difference
	Mean	SD	Mean	SD	
Forest Cover (%)	32.03	33.05	55.52	30.62	-23.49***
Reforestation (%)	1.22	2.08	1.53	1.46	-0.30***
County Area (Sq. km)	3520.30	9645.81	2846.78	1731.01	673.53***
Cropland (%)	47.55	28.84	30.93	22.63	16.62***
Barren (%)	2.95	13.39	0.12	0.69	2.84***
Population (Thousand)	553.14	360.08	437.39	279.15	115.75***
Gov't Expenditure (Billion RMB)	1.99	2.25	1.44	1.25	0.55***
GDP (Secondary) per cap (RMB)	1.53	2.32	0.45	0.40	1.08***
GDP (Primary) per cap (RMB)	0.42	0.34	0.31	0.18	0.11***
Nighttime Light Mean Value	0.48	1.34	0.09	0.28	0.39***
Average Annual Precipitation (mm)	989.69	473.13	1053.70	358.34	-64.01***
Average Annual Wind Speed (KPH)	2.15	0.57	1.69	0.47	0.46***
Obs	23537		3006		
No. of Counties	1277		163		

*Notes:*The table presents mean values for Treatment Group (poverty counties designated in 2011) and Control Grop (non-poverty counties in 2011)'s characteristics between 2000 and 2020.

3.4 Empirical Strategy

This section utilizes the aforementioned database to estimate the effects of large-scale tree planting on local economic development in a cross-section of counties in northern China. Specifically, it examines the impact on local GDP in the primary and secondary sectors, as well as agricultural production.

Measuring the effects of large-scale tree planting presents challenges for economists due to at least two reasons. Firstly, tree planting, as an investment, is not exogenous to rural economic development. The implementation of large-scale tree planting initiatives creates substantial job opportunities for residents and can stimulate the growth of related industries such as the tree seed industry. Secondly, plantation forests, which serve as a technology to control wind erosion, require a considerable amount of time after tree planting before they become fully functional.

3.4.1 Economic effects

My first objective is to estimate the economic effect of large-scale tree planting on local economic development. Given that large-scale tree-planting initiatives in China, particularly in Northern China, have been implemented for over four decades, it is now possible to observe the resulting local economic development. In this study, I intend to leverage cross-sectional variation to capture the short-term economic consequences of large-scale tree planting on local economic outcomes across counties in China's Three-North region. To estimate the economic effect of local large-scale tree planting on local economic development, I employ the following baseline specification:

$$Y_{ct} = \beta \times \text{Forestation}_{ct} + X_{ct} \times \zeta + \gamma_c + \delta_t + \epsilon_{ct}. \tag{3.1}$$

In Equation (3.1), Y_{ct} represents the outcome variable (GDP from the primary and secondary sectors) for county c in year t. Forestationct indicates the tree planting activities, such as the annual forestation area (sq. km), in county c in year t. Xct denotes other controlled variables, including population, K-12 students ratio, per capita loan balance in financial institutions at the end of the year, hospital beds per capita, power of agricultural machinery per capita, average relief degree of the land surface, precipitation, and annual average wind speed. γ_c and δ_t represent the county or prefecture-level city fixed effects and year-fixed effects, respectively. ϵ_{ct} is the error term with a mean of zero.

One of the critical challenges in identifying the economic effects of large-scale tree planting is the issue of simultaneity. Large-scale tree planting can both influence local economic development and be influenced by it, creating an endogeneity problem. The relationship between forest cover and economic development exhibits a strong interaction (Ewers, 2006). For instance, using satellite data on forest cover, Crespo Cuaresma et al. (2016) finds that income per capita is a robust determinant of cross-border variations in forest cover.

To address these identification challenges, I employ an instrumental variable approach by using precipitation in the previous year as an instrument for local tree planting activity. This choice is motivated by the fact that tree planting plans for a county are formulated based on the precipitation experienced in the year prior. The instrumental variable strategy relies on the assumption that conditional on other controlled variables, the precipitation in the previous year only affects the economic development of the next year through the large-scale tree planting activity.

However, it is important to acknowledge a potential concern that, even when considering other controlled variables, the precipitation in the previous year could have an impact on local economic development through channels other than tree planting.

To address this concern, I run an additional specification using the following equation (Equation 3.2) as an exogenous check on the instrumental variable, i.e., the precipitation in the previous year:

$$Y_{ct} = \beta_p \times Precipitation_{ct-1} + \mathbf{X}_{ct} \times \boldsymbol{\zeta_p} + \gamma_c + \delta_t + \epsilon_{ct}. \tag{3.2}$$

The analysis reveals that the precipitation in the previous year has minimal or negligible effects on all the local economic outcomes of interest examined in this paper. For further details on the results, please refer to Section 3.5.3.

Using the precipitation in the previous year as the instrumental variable, the system of equations to be estimated is as follows:

$$\text{Forestation}_{ct} = \alpha \times \text{Precipitation}_{ct-1} + \mathbf{Z}_{ct} \times \boldsymbol{\varphi} + \gamma_c + \delta_t + \epsilon_{ct} \tag{3.3}$$

$$\text{Y}_{ct} = \beta_{\text{iv}} \widehat{\text{Forestation}}_{ct} + \mathbf{X}_{ct} \times \boldsymbol{\theta} + \gamma_c + \delta_t + \epsilon_{ct} \tag{3.4}$$

In Equation (3.3), Forestation_{ct} represents one of the measures for large-scale tree planting, such as the annual forestation area in square kilometers. Additionally, to account for the varying levels of exposure to large-scale tree planting within the local economy, two alternative measures are used: the annual forestation area as a percentage of land area and the annual forestation area per capita (measured in mu, where 1 mu = 1/15 ha).

Conditional on the validity of the instrumental variable, β_{iv} captures the local average treatment effect (LATE) of large-scale tree planting on county-level economic development. The equation (3.4) represents the outcome variable Y_{ct} as a function of the estimated instrumental variable $\widehat{\text{Forestation}}_{ct}$, along with other control variables denoted by $\mathbf{X}_{ct}$. The county fixed effects γ_c, year fixed effects δ_t, and the error term ϵ_{ct} are included to account for unobserved heterogeneity and potential time-varying factors.

3.4.2 Ecological effects

To estimate the ecological effects of large-scale tree planting on local economic development, I focus on the tree planting's impact on local economic outcomes after six years. In the Three-North region, fast-growing trees, with a growth cycle of approximately 4-8 years, are the primary species planted. Therefore, I consider six years as the average growth cycle of plantation forests in the study area.

To account for the survival rate of planted trees, which is approximately 80% according to the technical regulation for afforestation (State Forestry Administration of the People's Republic of China, 1982) and relevant guidance on tree planting, I incorporate the survival rate into the following specification to be estimated:

$$Y_{ct} = \beta_{mf}(\text{Forestation}_{ct-6} \times 80\%) + \mathbf{X}_{ct} \times \boldsymbol{\eta} + \gamma_c + \delta_t + \epsilon_{ct} \tag{3.5}$$

In Equation (3.5), the outcome of interest Y_{ct} is a function of the annual plantation forest expansion area, i.e., 80% of the tree planting area in the year t-6, denoted as Forestation Area$t - 6$. The vector Xct represents other controlled variables, such as population, K-12 students ratio, per capita loan balance in financial institutions at the end of the year, hospital beds per capita, power of agricultural machinery per capita, average relief degree of the land surface, precipitation, and annual average wind speed. The county or prefecture-level city fixed effects are denoted by γ_c, the year fixed effects by δ_t, and the error term by ϵ_{ct}.

To account for potential spatial heterogeneity in the ecological effects of large-scale tree planting, I introduce an interaction term between tree planting and different subregions in Equation (3.6). The equation is as follows:

$$Y_{ct} = \beta_{mr}(Forestation_{ct-6} \times 80\%) \cdot Subregion_i + \mathbf{X}_{ct} \times \boldsymbol{\kappa} + \gamma_c + \delta_t + \epsilon_{ct} \tag{3.6}$$

In Equation (3.6), the outcome of interest Y_{ct} is determined by the interaction between the annual plantation forest expansion area (80% of the tree planting area in the year $t-6$), denoted as $Forestation_{ct-6}$, and the subregion indicator $Subregion_i$. The subregion indicator takes the following values: 1 for the Loess Plateau Hilly and Gully Area, 2 for the Northeast and North China Plain Agricultural Area, 3 for the Northwest Desert Area, and 4 for the Wind-blown Sand Area. The locations of these different subregions can be observed in Figure 3.1. The vector $\mathbf{X}_{ct}$ represents other controlled variables, including population, K-12 students ratio, per capita loan balance in financial institutions at the end of the year, hospital beds per capita, power of agricultural machinery per capita, average relief degree of land surface, precipitation, and annual average wind speed. The county or prefecture-level city fixed effects are denoted by γ_c, the year fixed effects by δ_t, and the error term by ϵ_{ct}.By including the interaction term in Equation (3.6), the analysis considers the potential spatial variation in the ecological effects of large-scale tree planting across different subregions.

3.5 Results and Discussion

3.5.1 Economic effects

Coefficients from ordinary least squares (OLS) and instrumental variable (IV) regressions of local economic development are presented in Table 3.2 for GDP from the primary and secondary sectors. The table reports estimated coefficients for various measures of large-scale tree planting, along with robust standard errors for control variables clustered at the county or prefecture-level city level.

Table 3.2 provides the results for GDP from the primary and secondary sectors. In Columns 1-4, the regressions use the log of GDP from the primary sector as the main explanatory variable. Columns 1-2 correspond to OLS estimates, while Columns 3-4 represent IV estimates. The first-stage F-statistics for the IV estimates range from 10.4423 to 28.5224, all exceeding the threshold of 10. Columns 1 and 3 include county fixed effects, while Columns 2 and 4 include fixed effects at the prefecture-level city level.

Panel A of the table presents the results for the annual forestation area in square kilometers within a county. Only in Columns 2 and 4, which incorporate prefecture-level city fixed effects, are the coefficients significant at the 5 percent level. However, it is worth noting that the signs of the coefficients in Columns 2 and 4 differ between OLS and IV regressions. This is expected since OLS estimates the average treatment effect, while IV regression estimates the local average treatment effect (Imbens and

Angrist, 1994). Another possible explanation for the differing signs between OLS and IV estimates is the measure of tree planting used, which is forestation area in square kilometers. This measure does not consider the relationships between forestation area and land area within a county (as shown in Panel B of Table 3.2), or between forestation area and population within a county (as shown in Panel C of Table 3.2), both of which incorporate county-fixed effects.

The IV regression results indicate a significant positive relationship between an increase in forestation area and local GDP from the primary sector. This aligns with the intuition that tree planting, as an economic activity within the primary sector, can increase local GDP from that sector, regardless of the relative relationships among forestation area, total land area, and population. The coefficient in Column 4 represents the local average treatment effect of large-scale tree planting on GDP from the primary sector: an increase of one square kilometer in the tree-planting area leads to an approximately 0.859% decrease in GDP from the primary sector within the same year. This is considered the preferred estimate.

Panels B and C provide results for the annual forestation area as a percentage of land area and the annual forestation area per capita (in mu) within a county, respectively. In Columns 1-4 of both panels, all coefficients are negative, indicating a negative correlation between large-scale tree planting and local GDP from the primary sector. The coefficient (-0.293) in Column 4 of Panel B suggests that the conversion of one percent of the land area into forests within a county leads to a 25% ($1 - \exp(-0.293) \approx 0.25$) decrease in GDP from the primary sector. Similarly, the coefficient (-1.173762) in Column 4 of Panel C indicates an increase of one mu in forestation area (according to the National Bureau of Statistics of China, the average arable land per capita is about 1.35 mu in China from 2002 to 2019) within a county leads to a 69% ($1 - \exp(-1.173762) \approx 0.69$) decrease in GDP from the primary sector.

In Columns 5-8 of Table 3.2, the regressions focus on the log of GDP from the secondary sector as the main explanatory variable. Columns 5 and 6 present OLS estimates, while Columns 7 and 8 present IV estimates. The first-stage F-statistics for the IV estimates range from 9.90779 to 28.0664. Only the first-stage F-statistics in Panel B (9.90779 and 9.91162) are slightly smaller than 10 but still very close to 10. Columns 5 and 7 include county fixed effects, while Columns 6 and 8 include fixed effects at the prefecture-level city level.

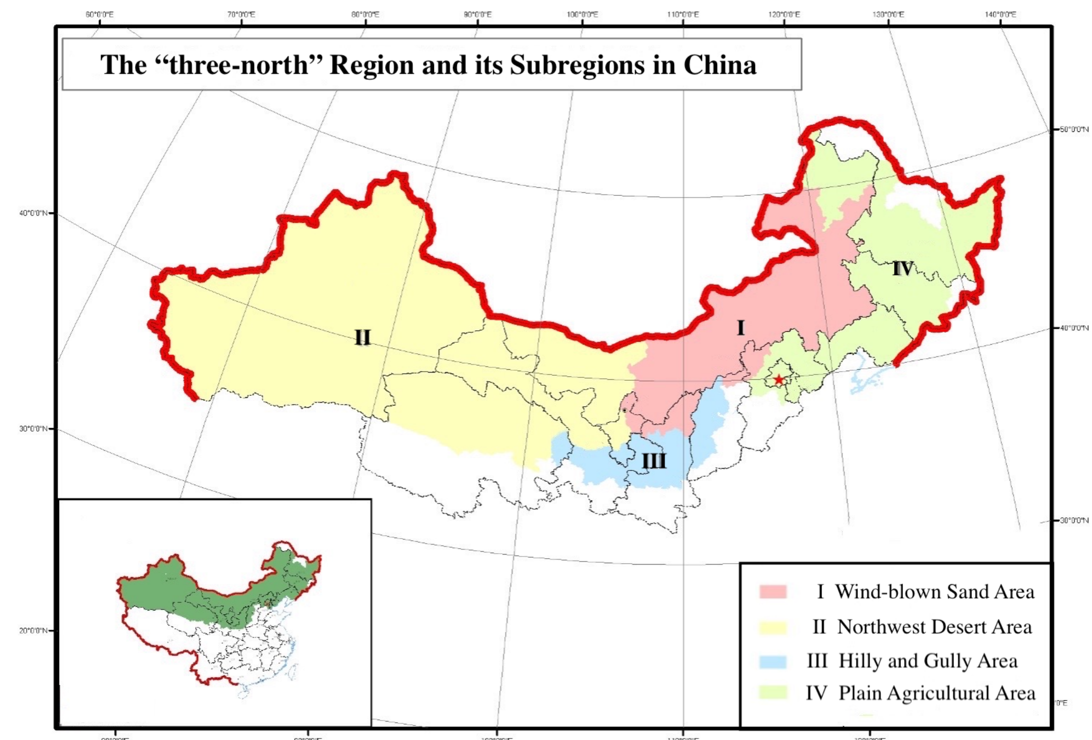
Panel A of the table displays the results for the annual forestation area in square kilometers within a county. Only in Column 8, which incorporates prefecture-level city fixed effects, is the coefficient negative and significant at the 1 percent level. The sign of the coefficient from OLS estimates is opposite to that from IV regression in Column 8, but it is not statistically significant. The signs of the coefficients in Columns 5 and 7 align with Column 8, but they are not statistically significant. The coefficient in Column 8 represents the local average treatment effect of large-scale tree planting on GDP from the secondary sector: an increase of one square kilometer in the tree-planting area leads to an approximate 3.658% decrease in GDP from the secondary sector within the same year. This is considered the preferred estimate for GDP from the secondary sector.

Panels B and C present the results for estimating the effects of the annual forestation area as a percentage of land area and the annual forestation area per capita (in mu) within a county, respectively, on GDP from the secondary sector. Similarly, all coefficients in Columns 5-8 of both panels are negative, indicating a negative correlation between large-scale tree planting and local GDP from the secondary sector. The coefficients in Columns 5 and 6 of Panel B suggest that the conversion of one percent of the land area into forests within a county leads to approximately a 1.4% or 3.1% decrease in GDP from the secondary sector. The coefficients in Columns 5 and 6 of Panel C indicate that an increase of one mu in forestation area per capita leads to about a 3% to 25% decrease in GDP from the secondary sector. The coefficients in Column 8 of both Panel B and Panel C demonstrate that one percent of land area converted into forests or one mu of forestation area per capita increase leads to a significant proportionate decrease in GDP from the secondary sector.

Contracting with the significant economic benefits anticipated by policymakers, it is evident that large-scale tree planting does not lead to an acceleration of local GDP in the primary and secondary sectors. My analysis reveals statistically significant evidence suggesting a negative impact of large-scale tree planting on local GDP by sector. This finding aligns with existing literature in the field.

For instance, Fan (2000) investigates the effects of investment in soil and water conservation in India using state-level data from 1970 to 1993. The study concludes that such investments have only modest effects on growth and poverty reduction. Similarly, Yirenkyi-Boateng (2001) argues that rural development projects in underdeveloped regions often fail to achieve their desired outcomes due to inadequate attention given to the initial problem of conceptualization. In the case of rural forestry practices, this lack of attention hinders the ability to assess their effects on the desired outcomes. Furthermore, Zinda and Z. Zhang (2019) posits that the contributions of afforestation programs are contingent upon the behavior of local governance and environmental conditions, which in turn shape different land-use patterns. These findings highlight the dependence of afforestation outcomes on contextual factors. One possible explanation for the observed phenomenon is that tree planting represents a low-value economic activity compared to manufacturing or even agricultural production. Implementing large-scale tree-planting programs entails significant opportunity costs.

Figure 3.1: The location of the Three-North region and its subregions in China



Notes: This Figure shows the location of the Three-North region and its four subregions, including the Loess Plateau Hilly and Gully Area, Northeast and North China Plain Agricultural Area, Northwest Desert Area, and Wind-blown Sand Area. This region covers 13 province-level prefectures, including Heilongjiang, Jilin, Liaoning, Hebei, Shanxi, Shaanxi, Gansu, Qinghai provinces, Tianjin City, Beijing City, the Inner Mongolia, Ningxia, and Xinjiang autonomous regions, as well as 600 counties between 2002 and 2019. The region is approximately 4,069,000 km^2 in size, occupying more than 40% of the total territory of China. The author created this Figure based on the original figure from the Fifth Phase Project Planning of the Construction of the Three-North Shelter Forest System.

Table 3.2: Economic Effects of Forestation Area on GDP from the primary and secondary sectors

Dependent Variables:	Log GDP from the Primary Sector				Log GDP from the Secondary Sector			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Forestation area (sq.km)							
Forestation area (sq.km)	-0.00003	0.00038**	-0.00057	-0.00859**	-0.00022	0.00048	-0.00035	-0.03658***
	(0.000)	(0.000)	(0.001)	(0.004)	(0.000)	(0.000)	(0.003)	(0.012)
R-squared	0.968	0.842	0.968	0.756	0.924	0.692	0.924	0.512
First-stage F			28.5224	14.1447			28.0664	13.7292
	Panel B: Forestation area (% of land area)							
Forestation area (% of land area)	-0.009***	-0.017***	-0.027	-0.293**	-0.014***	-0.031***	-0.015	-1.259***
	(0.002)	(0.005)	(0.055)	(0.138)	(0.005)	(0.009)	(0.121)	(0.442)
R-squared	0.969	0.842	0.968	0.755	0.924	0.692	0.924	0.581
First-stage F			10.5221	10.4423			9.90779	9.91162
	Panel C: Forestation area (mu) per Capita							
Forestation area (mu) per Capita	-0.01037*	-0.25159***	-0.07367	-1.73762***	-0.03015**	-0.25323***	-0.05262	-4.33138***
	(0.006)	(0.014)	(0.136)	(0.541)	(0.013)	(0.022)	(0.295)	(1.289)
R-squared	0.968	0.735	0.968	0.250	0.924	0.633	0.924	0.498
First-stage F			21.931	12.4059			21.7520	12.2591
Controls	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	No	YES	No	YES	No	YES	No
Prefecture FE	No	YES	No	YES	No	YES	No	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,588	6,588	6,588	6,588	6,594	6,594	6,594	6,594

Notes: This table presents OLS and IV regression estimates from the main estimating equation of the direct effect of large-scale tree planting on GDP from the primary and secondary sectors. I have three panels for three different measures of tree planting activities including the annual forestation area (sq.km) in Panel A,annual forestation area (% of land area) in Panel B and annual forestation area (mu) per Capita in Panel C.Mu is the unit of area used in China and 1 mu = 1/15 ha. Odd columns are with county-fixed effects, and even columns are with prefecture-level city fixed effects. The prefecture-level city is a bigger division than a county in China; a prefecture-level city usually consists of several counties. See Tables A-8, A-7, A-9 for details.Standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

3.5.2 Ecological effects

Table 3.3 presents the estimates of the ecological effects of tree planting on various aspects of agricultural production, such as grain output, oil crops output, cotton output, and meat output, as well as GDP from the primary and secondary sectors. These effects are evaluated based on the ecological impacts of plantation forests, specifically after six years of their growth. The table is divided into two panels: Panel A represents the results of the pooled model, while Panel B presents the results of the regionally disaggregated model.

Given the close relationship between agricultural production, GDP from the primary sector, and land area, my analysis primarily focuses on the measure of tree planting, namely the forestation area (% of land area). This measure gauges the extent to which agricultural production and GDP from the primary and secondary sectors are exposed to large-scale tree planting.

The first four columns of the table display the effects of mature forestation area (% of land area) on agricultural production. The last two columns demonstrate the effects of mature forestation area (% of land area) on GDP from the primary sector. Notably, the results indicate that a one percent increase in forestation area after six years leads to a statistically significant 1.4 percentage point increase in grain output overall. However, the regional regression model reveals that this statistically significant effect is observed specifically in the plain agricultural area, where it translates into an approximate 5 percentage point increase. This outcome aligns with the fact that the primary objective of large-scale tree planting in the plain agricultural area is to protect farmland.

Interestingly, large-scale tree planting after six years has a negative impact on cotton production overall. Nevertheless, the coefficient of 0.613 in Column 2 demonstrates that it results in an 85% increase in cotton production specifically in the plain agricultural area. This finding is consistent with the results for grain production in the same area significant effects on oil crops are observed, which might be attributed to the fact that oil crops are less susceptible to wind erosion. In terms of meat production, no overall effects are found. However, large-scale tree planting after six years does lead to a statistically significant increase of approximately 3.1 percentage points at a 5% significance level in the plain agricultural area.

In other areas, including hilly and gully areas, desert areas, and wind-blown sand areas, large-scale tree planting does not have any statistically significant effects on agricultural production.

To further investigate the ecological effects of tree planting on grain output, I conducted a regression analysis using the specification outlined in Equation 3.5. The regression considered the forestation area (% of land area) from year $t-3$ to year $t-10$. Figure 3.3 presents the coefficients and their corresponding 95% confidence intervals obtained from these regressions. The coefficients of forestation area (% of land area) in years $t-4$ to $t-8$ were found to be statistically significant. Notably, the magnitude of the coefficient in year $t-6$ is approximately equal to the average magnitude of the coefficients observed in years $t-4$ to $t-8$. This suggests a consistent relationship between the maturation of plantation forests and their ecological effect on grain production. Additionally, the relationship between the maturation of plantation forests and their ecological effect on grain production exhibits an inverted U-shaped pattern. However, the results were not statistically significant in years $t-3$, $t-9$, and

$t-10$. For more detailed estimates of these regressions, please refer to Appendix Table A-12.

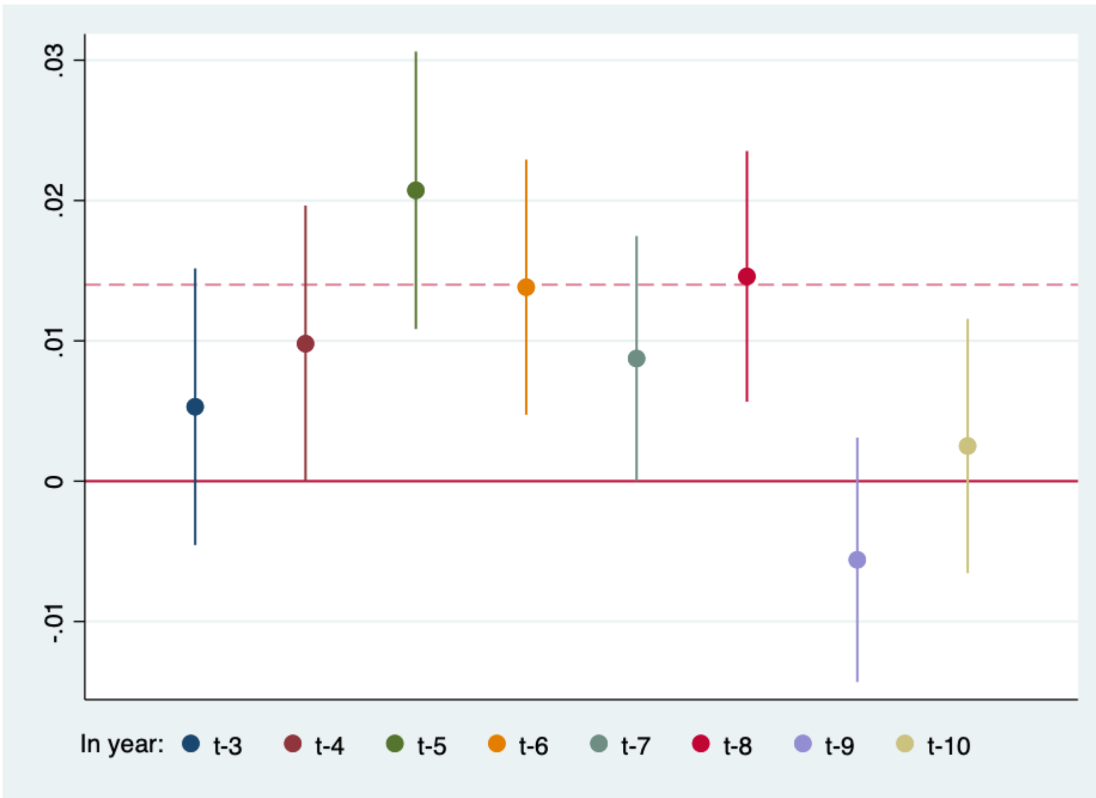
Column 5 of the regression results focuses on the log of GDP from the primary sector as the main explanatory variable, while Column 6 examines the log of GDP from the secondary sector. The findings regarding GDP from the primary sector are noteworthy. Although no significant overall effects are observed, all four subregions in the regional regression model exhibit significant coefficients at a 1% level of significance. Specifically, in the Hilly and Gully Area, the impact of large-scale tree planting on GDP from the primary sector is negative. A conversion of one percent of the land area into mature forestation area leads to an approximate 1.2 percentage point decrease in GDP from the primary sector. In contrast, in other areas, large-scale tree planting has positive effects on GDP from the primary sector. These effects translate into an approximately 2.2 to 3.6 percentage point increase in GDP from the primary sector. On the other hand, no effects are found on GDP from the secondary sector, both overall and regionally. This aligns with the expectation that tree planting does not impact sectors such as logging industries in the medium run.

Table 3.3: Ecological Effect of Mature Forestation Area (% of Land Area) on Local Economic Development

Dependent Variables:	*Log Agricultural Production*				Log GDP	Log GDP
	Grain	Cotton	Oil Crops	Meat	(Primary)	(Secondary)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full Sample						
Mature planted forest area (% of land area)	0.014***	-0.059*	-0.001	-0.003	0.001	-0.004
	(0.005)	(0.031)	(0.016)	(0.006)	(0.003)	(0.006)
Panel B: Subregions by Geography						
(Mature planted forest area (% of land area)×Hilly and Gully Area	0.008	-0.131	0.008	-0.009	-0.012***	-0.004
	(0.006)	(0.144)	(0.020)	(0.007)	(0.004)	(0.008)
(Mature planted forest area (% of land area))×Plain Agricultural Area	0.050***	0.613**	-0.004	0.031**	0.036***	-0.016
	(0.012)	(0.275)	(0.039)	(0.013)	(0.007)	(0.016)
(Mature planted forest area (% of land area))×Desert Area	-0.010	-0.112	-0.031	0.025	0.024***	0.020
	(0.014)	(0.470)	(0.067)	(0.023)	(0.008)	(0.018)
(Mature planted forest area (% of land area))×Wind-blown Sand Area	0.007	-0.148	-0.042	-0.010	0.022***	-0.004
	(0.012)	(0.309)	(0.043)	(0.015)	(0.008)	(0.017)
Observations	2,820	1,497	1,412	1,497	4,003	3,996
R-squared	0.154	0.036	0.031	0.152	0.666	0.424
Number of cntyid	442	435	419	435	443	443
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: This table presents the OLS regression estimates from the main estimating equation of the indirect effect of large-scale tree planting on agricultural production, including grain,cotton, oil crops and meat outputs, and GDP by sector (primary and secondary sector). The variable of interest is the forestation (% of land area) in t-6 year times the average survival rate of planted trees as the measure of mature plantation forests. Panel A shows the regression estimates for the full sample. Panel B shows the regression estimates of regional models. See Tables A-10 and A-11 for details.Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 3.3: Estimates of the Ecological Effect of Forestation Area (% 0f Land Area) in t-3 to t-10 year on Grain Output and their 95% Confidence Intervals



Note: Figure 3.3 plots estimates of Forestation Area (% of Land Area) in t-3 to t-10 year and 95% confidence intervals using the specifications in Equation 3.5. Other estimates of these regressions are shown in Appendix Table A-12.

3.5.3 Robustness

This section aims to address identification and bias concerns raised in previous sections by conducting various robustness tests. These tests provide additional evidence to support the validity and reliability of the findings.

One potential concern regarding the research design used to investigate the economic effects of large-scale tree planting on GDP from the primary and secondary sectors is the issue of selection bias in the instrumental variable (IV), which in this case is the precipitation in the previous year. There is a possibility that the precipitation in the previous year may not be relevant to tree planting in the subsequent year.

Table 3.4 presents the first-stage estimates for large-scale tree planting using Equation 3.3, with the outcome variables being the three measures of large-scale tree planting used to estimate the economic effects. The coefficients associated with precipitation in the previous year are positive and statistically significant at a 1% level. These findings indicate that precipitation in the last year is strongly and positively related to tree planting in the next year. In other words, higher levels of precipitation in the previous year are associated with increased tree planting in the following year.

Furthermore, when comparing the sizes of the coefficients across columns, it can be observed that they are very similar to the coefficients obtained when incorporating county fixed effects or prefecture-level city fixed effects. This suggests that the positive relevance of precipitation in the previous year to tree planting in the next year remains consistent, irrespective of the inclusion of these fixed effects.

TABLE 3.4: LARGE-SCALE TREE PLANTING:FIRST STAGE OLS ESTIMATES

Dependent Variables:	Forestation area (sq.km)		Forestation area (% of land area)		Forestation area ((mu) per Capita)	
	(1)	(2)	(3)	(4)	(5)	(6)
Precipitation (in t-1 year)	0.029*** (0.006)	0.022*** (0.006)	0.0007*** (0.0002)	0.0007*** (0.0002)	0.00004*** (0.00001)	0.00003** (0.00001)
Controls	YES	YES	YES	YES	YES	YES
Observations	6,599	6,599	6,597	6,597	6,599	6,599
R-squared	0.567	0.380	0.583	0.455	0.568	0.388
County FE	YES	No	YES	No	YES	No
Prefecture FE	No	YES	No	YES	No	YES
Year FE	YES	YES	YES	YES	YES	YES

*Notes:*This table presents first-stage OLS estimates of the instrument variable used in the study, the precipitation in the previous year. The dependent variables are three measures of tree planting activities including the annual forestation area (sq.km),annual forestation area (% of land area) and annual forestation area (mu) per Capita in a county. Odd columns are with the county fixed effects and even columns with prefecture-level city fixed effects. The prefecture-level city is a bigger division than a county in China; a prefecture-level city usually consists of several counties.I also add control variables in the regression. See Table A-6 for details. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

To address the concern that precipitation in the previous year may have effects on GDP from the primary and secondary sectors through channels other than tree planting in the next year, I conducted an exogenous check on the instrumental variable. I employed the following specification, Equation 3.2, to investigate this issue. The results of this exogenous check on the instrumental variable are presented in Table 3.5.

The coefficients obtained from the analysis suggest that conditional on other controlled variables, precipitation in the previous year has minimal effects on the local economic outcomes examined in this study. Specifically, the coefficients for precipitation in the previous year on GDP from the primary sector and GDP from the secondary sector are statistically non-significant. This finding aligns with the identification assumption made in the analysis.

One possible explanation for the negligible effects of precipitation in the previous year on local GDP through channels other than tree planting is that the Three-North region has adapted to the semi-arid and arid climate conditions, particularly concerning the impact of precipitation in the previous year. However, it should be noted that according to the technical regulation for afforestation (State Forestry Administration of the People's Republic of China, 1982) and relevant guidance on tree planting, the precipitation in the previous year does influence tree planting in the subsequent year.

Table 3.5: Exogenous Check on Instrumental Variable

Dependent Variables:	Log GDP (Primary) (1)	Log GDP (Secondary) (2)
Precipitation in t-1 year	-0.000009	-0.000007
	(0.000)	(0.000)
Constant	11.350***	12.092***
	(0.097)	(0.203)
Controls	YES	YES
Observations	7,211	7,217
R-squared	0.965	0.919
County FE	YES	YES
Year FE	YES	YES

*Notes:*The table presented below displays the results of the exogenous check conducted on the instrumental variable employed in the study, namely the precipitation in the previous year. The dependent variables in this analysis are the measures of local economic development, specifically the Gross Domestic Product (GDP) from the primary and secondary sectors within a county. The regression models include additional control variables to account for potential confounding factors. See Table A-5 for details. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

3.5.4 Limitations

The empirical analysis in this study is constrained by data limitations, preventing the examination of the distinct effects of various tree-planting programs, such as the Green for Grain program. This particular program aims to convert sloping farmland into forests within the study area. Additionally, the absence of data on land use change precludes the estimation of the effects associated with converting different land types, particularly farmland, into forest land through tree planting. It is important to acknowledge that diverse land use changes resulting from tree planting may yield varying impacts on local economic development.

To address these limitations, future research can consider leveraging remote satellite data and employing spatial econometric methods. Remote sensing technology can provide valuable insights into land use changes, enabling a more comprehensive analysis of the impacts of distinct tree-planting programs and land use conversions on local economic development. Moreover, the incorporation of spatial econometric techniques can account for the spatial interdependence among observations, yielding a more precise understanding of the relationships between tree planting, land use change, and economic outcomes. By adopting these approaches, researchers can overcome data constraints and acquire deeper insights into the specific effects of different tree-planting programs and land use changes on local economic development.

This paper primarily examines the short-run and medium-run effects of tree planting, as data limitations prevent the estimation of long-run effects. However, it is important to acknowledge that in the long run, tree planting can potentially impact GDP from the secondary sector through the provision of wood as a source of energy or construction material.

According to a study by Ramage et al. (2017), it is projected that planted trees will contribute up to 80% of global annual wood harvests by 2030. This highlights the potential significance of tree planting in meeting the future demand for wood resources. However, the specific long-run effects on GDP from the secondary sector are not directly estimated in this paper due to the aforementioned data limitations.

Future research could explore the long-term impacts of tree planting on GDP from the secondary sector by incorporating comprehensive data and considering the role of wood supply in various industries. Understanding the long-run effects of tree planting is essential for assessing the sustainability and economic benefits of such initiatives.

3.6 Conclusion

This study examines the economic consequences of large-scale tree planting as a strategy to address environmental degradation. To provide a comprehensive and robust analysis, a rich dataset of administrative data from China is employed. The study employs an instrumental variable (IV) empirical strategy to estimate the economic impacts of tree planting and utilizes fixed effects models to investigate the ecological effects.

Contrary to the anticipated substantial economic benefits, the findings reveal statistically significant evidence of the negative effects of large-scale tree planting on local GDP from both the primary and secondary sectors. This suggests that tree planting, in comparison to manufacturing and agricultural production, is a low-value economic activity with significant opportunity costs associated with its implementation.

Additionally, the study demonstrates that large-scale tree planting leads to an increase in grain production after six years after the initial tree planting. Furthermore, an inverted U-shaped relationship is observed between the maturation of plantation forests and their ecological effects on grain production through ecosystem services. However, these ecological effects are primarily limited to the plain agricultural areas. No significant changes are observed in other agricultural production sectors, such as cotton, oil crops, and meat production. Regarding GDP from the primary sector, no overall effects are identified, although significant results are found when examining different subregions. Similarly, there are no ecological effects observed on GDP from the secondary sector.

These findings highlight the complex dynamics and diverse impacts of large-scale tree planting on local economies. The study emphasizes the importance of considering the economic value, opportunity costs, and regional variations associated with implementing large-scale tree-planting programs.

The analysis presented in this study has important implications for ongoing policy debates in two main areas. Firstly, the study provides credible empirical evidence on the negative economic effects of large-scale tree planting. While such initiatives can create significant employment opportunities and attract public investments to local economies, the overall impact on GDP from the primary and secondary sectors is found to be negative. This finding suggests that tree planting, in comparison to manufacturing and even agricultural production, may be a low-value economic activity with substantial opportunity costs. Policymakers and relevant stakeholders should carefully consider the opportunity costs associated with large-scale tree-planting projects.

Secondly, the study highlights the benefits of mature plantation forests on grain production, aligning with the intentions of policymakers. However, these positive effects are primarily observed in plain agricultural areas, with minimal effects in other regions. This variation in effects may be attributed to differences in the main objectives of tree planting programs in different areas. Furthermore, the study does not find strong evidence to suggest that mature plantation forests have significant effects on other crops or meat production. This raises concerns about potential inequities within local communities resulting from large-scale tree-planting initiatives. Policymakers need to acknowledge the heterogeneity of ecological effects related to tree planting and address any potential equity issues that may arise.

Overall, this research provides valuable insights for policymakers by shedding light on the negative economic effects of large-scale tree planting, the limited ecological effects on specific agricultural sectors, and the importance of considering opportunity costs and regional variations in implementing such programs.

Chapter 4

Payments for Ecosystem Services and Rural Household Welfare: A Comprehensive Analysis of China's Grain for Green Program

4.1 Introduction

China's Grain for Green (GfG) program is the world's largest Payments for Ecosystem Services (PES) initiative (Gauvin et al., 2010; Hua et al., 2016). Since its implementation in 1999, the program has garnered significant attention, with numerous studies examining its environmental and economic impacts (He et al., 2023; X. Wu, S. Wang, Fu, X. Feng, and Chen, 2019; Zeng et al., 2022). Many studies highlight its environmental benefits, including reductions in soil erosion (H. Zhao et al., 2022), enhanced carbon sequestration (Deng, Shangguan, and R. Li, 2012; X. Song et al., 2014), and improvements in other ecosystem services (Xiaoqian Hu et al., 2021; Wang et al., 2007).Nevertheless, its economic impact—particularly on participants' welfare—remains debated (Giefer and An, 2022; Treacy et al., 2018). Most existing studies focus on specific regions (König et al., 2014), such as the Loess Plateau (Q. Li et al., 2018), or rely on case studies (H. Peng et al., 2007; Wang et al., 2007), lacking a comprehensive national-level assessment of its welfare effects (Z. Wu et al., 2021), primarily due to data limitations. This paper addresses this gap by utilizing a detailed national dataset to conduct a comprehensive evaluation of the GfG program's impact on rural household welfare across China. Additionally, it investigates whether the GfG program affects income inequality and explores the underlying mechanisms in depth, resolving inconsistencies in the existing literature. It offers insights into the program's broader economic implications and provides policy recommendations for improving PES design.

Following the catastrophic floods of 1998, the GfG program, also known as the Sloping Land Conversion Program or the Conversion of Cropland to Forest Program, was launched in 1999 as a pilot in three provinces and expanded nationwide in 2002 to combat severe soil erosion and environmental degradation. It incentivizes farmers to convert steeply sloped croplands into forests or grasslands by providing financial subsidies. According to China's *Regulations on Restoring Farmland to Forest (2002)*[1], only sloping and desertified farmland with severe soil erosion and low, unstable grain yields qualifies for conversion. Initially, farmers received both grain and cash subsidies,

[1] State Council of China, *Regulations on Restoring Farmland to Forest*, 2002, available at: https://www.gov.cn/gongbao/content/2016/content_5139491.htm

with grain subsidies ranging from 100 to 150 kg per mu, depending on the region, and a cash subsidy of 20 RMB per mu. The subsidy duration varied by land conversion type: grassland restoration was subsidized for 2 years, economic forest restoration for 5 years, and ecological forest restoration for 8 years.

Initially, the program primarily focused on environmental benefits, despite claims of addressing household welfare. Jintao Xu et al. (2010) found that income effects were not robust enough to support government claims of substantial economic gains, particularly when assessing the program's early years in 2003. To address potential livelihood challenges for participating farmers, the GfG program underwent a major policy reform in 2007, replacing its mixed grain-and-cash subsidies with a fully cash-based compensation system. According to the *Notice of the China's State Council on Improving the Grain-for-Green Policy (2007)*, annual payments ranged from 70 to 105 RMB per *mu*, depending on the region, with an additional 20 RMB allocated for livelihood support. The subsidy duration remained unchanged: grassland restoration continued for 2 years, economic forest restoration for 5 years, and ecological forest restoration for 8 years. Participation remained voluntary, allowing rural households to independently decide on enrollment and select land conversion options—such as forests, orchards, or grasslands—based on their needs and ecological conditions. This flexible approach enabled households to optimize land use while benefiting from financial incentives and contributing to environmental restoration.

The GfG program serves as a pioneering model for environmental restoration, offering a valuable framework for evaluating the impacts of PES programs on rural household welfare (Z. Feng, Yanzhao Yang, et al., 2005; Uchida, Rozelle, and Jintao Xu, 2009). Its voluntary participation structure, however,complicates causal inference, particularly due to endogeneity concerns such as reverse causality, as poorer households are more likely to enroll. To address these challenges, I leverage the program's staggered participation and employ a Difference-in-Differences (DID) approach with multiple treatment periods to compare income and expenditure trends between participating and non-participating households. Recognizing the importance of accounting for household heterogeneity in the GfG program (Liang et al., 2012), I incorporate household- and individual-level controls—including landholding, agricultural inputs, and demographic characteristics—to mitigate pre-existing differences. To ensure the validity of my identification strategy, I conduct an event study analysis to test the parallel trends assumption. Additionally, I examine distributional effects across income and expenditure quantiles to assess whether the program exacerbates inequalities or produces unintended consequences.

I find that the GfG program significantly improves rural households' economic welfare, leading to higher income and expenditure. Using a DID approach, I estimate that participation increases household income by approximately 5.9% (about RMB 2,840 [2]) and expenditure by 5.2% (about RMB 1,869[3]). Event study analyses confirm the parallel trends assumption, showing stable pre-trends and positive post-treatment effects, though income gains fluctuate over time while expenditure remains more stable. Quantile regression results indicate no significant impact across income distribution.

The main results align with the majority of the literature, indicating that the GfG

[2]This is based on the dependent mean and is equivalent to USD 438.42 based on the exchange rate at the end of 2015. Exchange rate data is from the Federal Reserve Bank of St. Louis: https://fred.stlouisfed.org/series/DEXCHUS.

[3]Equivalent to USD 288.36 based on the end-2015 exchange rate. Source: Federal Reserve Bank of St. Louis.

program improves total household income without exacerbating income inequality. B. Jin and H. Wang (2024) conducted a systematic review of empirical research on PES programs and rural household income in China. Among the 28 studies reviewed, 24 examined the GfG program, with 15 reporting positive effects on total household income. All 15 studies referenced are summarized in Table 4.1. Specifically, Uchida, Jintao Xu, and Rozelle (2005) found that average household income increased after participation through a before-and-after comparison of 144 participating households from 16 randomly selected villages in two western provinces. Likewise, Jintao Xu et al. (2010) conducted a comprehensive study on the GfG program in the Yellow River Basin, covering Shaanxi, Gansu, and Sichuan provinces, and found that the program positively impacted household income. A more recent study by J. Peng et al. (2022) used a structural equation model to compare household income before (2000) and after (2014), overlapping with this study on the GfG program, and also found that farm households experienced income growth following participation. In addition to the main income findings, 19 out of 24 studies report no evidence of the GfG program exacerbating income inequality, as shown in Table 4.1.

TABLE 4.1: SUMMARY OF THE GFG PROGRAM'S IMPACTS ON HOUSEHOLD INCOME IN THE LITERATURE

Effects	**No. of Papers**
Increased Total Income	**15** (Uchida, Jintao Xu, and Rozelle (2005), X. Chen et al. (2009), Yao, Guo, and Huo (2010), J. Li et al. (2011), W. Yang et al. (2013), Lin and Yao (2014), C. Song et al. (2014), Yin, C. Liu, et al. (2014), Zhen et al. (2014), Duan, Lang, and Wen (2015), Chengchao Wang, Pang, and Hong (2017), Yin, H. Liu, et al. (2018), Xujun Hu et al. (2020), Yu Yang et al. (2020), J. Peng et al. (2022))
Increased Agricultural Income	**6** (Jintao Xu et al. (2010), W. Yang et al. (2013), Lin and Yao (2014), Zhen et al. (2014), Duan, Lang, and Wen (2015), Yin, H. Liu, et al. (2018))
No evidence of income inequality	**19** (Uchida, Jintao Xu, and Rozelle (2005)X. Chen et al. (2009)Jintao Xu et al. (2010)Yao, Guo, and Huo (2010)J. Li et al. (2011)Chunmei Wang and Maclaren (2012)W. Yang et al. (2013)Lin and Yao (2014)C. Song et al. (2014)Zhen et al. (2014)Duan, Lang, and Wen (2015)Hua Li et al. (2015)Chengchao Wang, Pang, and Hong (2017)Yin, H. Liu, et al. (2018)X. Wu, S. Wang, Fu, Y. Zhao, and Wei (2019)Yu Yang et al. (2020)Lingchao Li et al. (2021)X. Wu, S. Wang, and Fu (2021)Ying Wang et al. (2021))

Notes: This Table summarizes the GfG program's impact on household income as documented in the literature, revised from Table 1 of B. Jin and H. Wang (2024), which examines all Payments for Ecosystem Services (PES) programs in China. Additional details are provided in Appendix Table A-13.

The findings on household expenditure and income inequality provide a nuanced comparison with existing literature, as summarized in Table 4.1. While most studies focus on income effects, relatively few examine the GfG program's influence on household spending (Lu and Yin, 2020). Z. Liu and Henningsen (2016) found that GfG participation increased total consumption only in certain regions.

To understand the mechanisms driving these effects, I analyze land use changes, income sources, and expenditure patterns. First, I find that the program significantly increases forested areas, aligning with its environmental objectives, while its impact on orchard and pasture expansion is modest. Next, I decompose household income to identify the primary drivers of economic change. The results show that GfG participation significantly increases farm income and government subsidies, with farm income growth driven by a shift from staple crops—such as wheat, rice, and corn—to higher-value activities like soybean and cash crop farming. This reallocation of land use, coupled with improved soybean productivity, contributes to the observed income gains. Additionally, government subsidies provide direct financial support, further boosting household income. As documented by B. Jin and H. Wang (2024), 13 out of 24 studies on the GfG program find no evidence of increased agricultural income (see Appendix Table A-13). This may stem from the absence of long-term impact assessments or the lack of comprehensive national-level analyses. For instance, Uchida, Jintao Xu, and Rozelle (2005) examined only the years 1999 and 2000, focusing on two provinces in western China, which restricts the ability to capture long-term shifts in agricultural practices.

Beyond agricultural income, the GfG program's economic impact appears concentrated in agriculture and government transfers, as non-farm business income and local wage income remain largely unaffected. I also examine household expenditure patterns to assess how income gains are utilized. The results indicate that GfG participation leads to significant increases in operating expenditures and living expenses, reflecting higher spending on agricultural operations and daily consumption. A closer look at expenditure decomposition reveals that households allocate more resources toward staple and non-staple food, clothing, housing, and fuel, indicating improved living standards. These findings highlight how the GfG program reshapes rural household economic behavior through land use changes, agricultural diversification, and government subsidies, ultimately enhancing income and well-being.

This study contributes to the literature in several ways. First, it provides a national-level analysis of the GfG program's impact on rural welfare, whereas existing research has largely focused on localized or regional effects and short-term outcomes (Z. Feng, Yanzhao Yang, et al., 2005; Uchida, Rozelle, and Jintao Xu, 2009). This paper examines GfG participants across 30 of the 31 provinces in mainland China, offering a more comprehensive evaluation of the program's broader economic implications.

Second, while most studies focus on income as the primary measure of household welfare, this paper also examines expenditure effects, providing a more holistic perspective on how the program influences rural livelihoods. Lei et al. (2023) investigated the impact of GfG on medical expenses, whereas this study extends the analysis to overall household expenditure patterns, capturing broader economic implications.

Third, by decomposing income and expenditure effects, this study identifies key mechanisms—such as land use changes, agricultural diversification, and government subsidies—through which the program affects rural households. By systematically analyzing these pathways, this paper enhances the understanding of how PES programs influence household welfare beyond aggregate income measures, offering insights into both direct financial benefits and broader economic adjustments.

Given the above findings, policy recommendations should focus on enhancing the GfG program's effectiveness and equity. To maximize long-term benefits, policymakers should introduce complementary measures that support income diversification, such as improved access to financial services, agricultural technology, and vocational training. Strengthening PES design through targeted interventions can further enhance income gains, particularly by promoting high-value crop production. Additionally, ensuring equitable benefit distribution is crucial, as lower-income households may face greater challenges in improving their welfare post-participation.

The remainder of this paper is structured as follows. Section 2 describes the data sources and key variables. Section 3 outlines the identification strategy, addressing potential endogeneity concerns. Section 4 presents the main results, while Section 5 explores the decomposition of income and expenditure effects and examines the underlying mechanisms. Finally, Section 6 concludes with policy implications and directions for future research.

4.2 Data

I rely on China's National Rural Fixed Point (NRFP) Survey, a longitudinal panel survey initiated in 1986 and conducted by the Chinese Ministry of Agriculture. The NRFP Survey provides comprehensive micro-level data at the village, household, and individual levels, including detailed information on income, expenditure, and agricultural production. With its broad national coverage and long-term perspective, the NRFP Survey has been widely utilized in empirical research on rural China (Banerjee, Duflo, and Qian, 2020; Kinnan, S. Y. Wang, and Yongxiang Wang, 2018; Lingyan Li et al., 2024).

For this study, I use NRFP survey data from 2009 to 2015 to ensure data consistency, as the survey questionnaire underwent major revisions in 2009, and data availability is limited beyond 2015. The year 2009 serves as the baseline, and only households surveyed in that year are included in the analysis to maintain consistency. To define treatment status clearly, I restrict the sample to households that began participating in the GfG program in 2010 or later, excluding those that participated in 2009, as their initial enrollment timing cannot be determined with certainty, given that GfG program payments can last up to eight years. The final sample consists of 5,471 households across all 31 mainland provinces of China. Figure 4.1 illustrates the participation dynamics of these households over the study period. By the end of the period, 706 households had enrolled in the GfG program, representing approximately 12.9 percent of the sample.

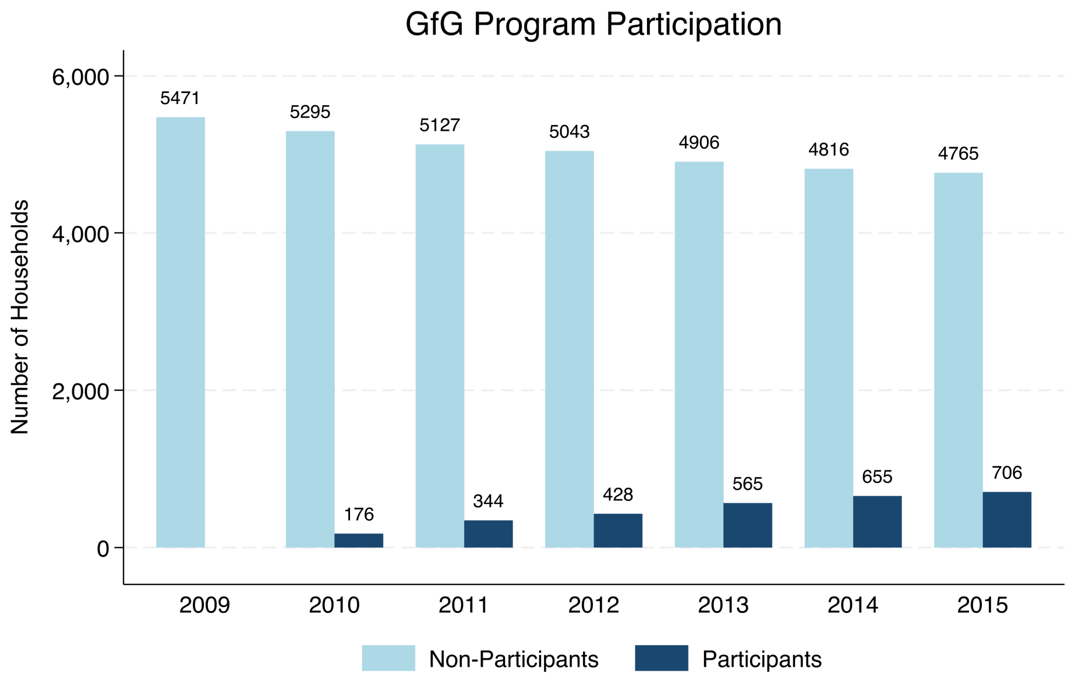


FIGURE 4.1: HOUSEHOLD PARTICIPATION IN THE GFG PROGRAM

Note: This figure illustrates the number of households that participated in the GfG program. The sample consists of 5,471 households surveyed from 2009 to 2015, covering all 31 mainland provinces of China. By the end of the period, 706 households had enrolled in the program, representing approximately 12.9 percent of the sample. Households that participated in the GfG program in 2009 were excluded to ensure a clear treatment definition.
Source: China's National Rural Fixed Point Survey

Table 4.2 and Table 4.3 provide a comparative analysis of rural household income and expenditure between participants and non-participants in the GfG program. Table 4.2 presents summary statistics on household income, comparing participants and non-participants in the GfG program. Total income is slightly lower among participating households, averaging 45,528 RMB compared to 47,606 RMB for non-participants, primarily due to lower farm income. However, participants receive higher government subsidies, including an average of 178 RMB in GfG-specific payments. Migrant wage income is also slightly higher among participants, while local wage income and non-farm business income remain comparable between the two groups. Regarding farm income composition, participants earn less from staple crops such as wheat, rice, and corn, consistent with the program's objective of converting cropland into forests. In contrast, forestry income is slightly higher among participants. Income from orchards, cash crops, and livestock farming shows no significant differences, whereas fishery income is notably lower for participants. Net income follows a similar pattern, with participating households earning slightly less on average.

Table 4.2: Summary of Household Income (RMB)

	Participation		Non-Participation	
	Mean	SD	Mean	SD
Incomes				
Total Income	45,527.61	58,417.79	47,606.05	52,604.82
Farm Income	15,123.01	27,700.05	18,351.98	38,985.02
Non-Farm Income	11,255.77	55,163.89	10,432.27	76,976.74
Local Wage Income	6,258.02	12,370.18	6,071.13	13,098.57
Migrant Wage Income	12,551.18	20,611.76	11,928.47	19,008.80
Government Subsidies	1,045.89	2,493.66	840.10	1,554.38
- GfG Subsidies	178.08	485.96	0.00	0.00
Other Income	1,592.73	7,621.63	1,758.61	9,045.21
Main Farm Income				
Wheat Income	791.02	1,685.08	1,161.22	2,435.08
Rice Income	1,615.95	4,465.40	2,277.96	7,536.27
Corn Income	3,412.20	8,939.79	4,447.30	10,087.38
Soybean Income	206.85	1,529.71	613.20	4,027.33
Forestry Income	477.23	2,267.05	406.73	3,411.36
Orchard Income	1,849.62	10,600.36	1,862.16	8,352.08
Cash Crop Income	2,382.50	8,844.15	3,088.04	14,499.56
Livestock Income	3,585.37	21,286.50	3,677.43	30,469.13
Fishery income	55.68	706.66	603.60	10,752.50
Net Income	34,982.60	27,877.76	36,440.73	29,285.76
Observations	4942		33355	
Households	706		4765	

Notes: This table presents summary statistics on household income, comparing households that participated in the GfG program with those that did not. All income values are reported in RMB and adjusted for inflation using the Consumer Price Index (CPI), with 2009 as the baseline year.
Source: China's National Rural Fixed Point Survey

These income differences are reflected in household expenditure patterns, as shown in Table 4.3. Total expenditure is slightly lower among participants, averaging 34,695 RMB compared to 35,351 RMB for non-participants. This difference is mainly driven by lower village fees and tax expenditures among participants. Living expenditures are comparable between the two groups, though participants spend slightly more on staple food and medical expenses, while non-participants allocate more to housing and fuel. Operating expenses and productive asset expenditures are similar across both groups, though non-participants report marginally higher spending on other investments. These findings indicate that while participation in the GfG program does not substantially alter overall spending patterns, it slightly reduces tax and village fee burdens while shifting expenditure composition in certain categories.

Table 4.3: Household Income (RMB) and Expenditure (RMB)

	Participation		**Non-Participation**	
	Mean	SD	Mean	SD
Expenditures				
Total Expenditure	34,695.04	58,253.04	35,351.08	59,910.75
Total Living Exp.	21,756.76	28,443.03	21,420.62	29,414.75
Operating Exp.	10,424.83	43,622.89	10,983.21	36,522.60
Productive Asset Exp.	835.03	12,062.45	785.68	27,395.62
Other Investment Exp.	154.56	3,845.97	200.88	7,214.95
Tax Expenditure	56.12	943.64	68.97	1,528.37
Village Fees	36.04	513.15	68.63	1,045.32
Living Expenditure				
Staple Food Exp.	1,973.42	1,622.99	1,838.35	1,340.40
Non-Staple Food Exp.	3,915.34	4,109.84	3,994.99	3,898.92
Clothing Expenditure	1,251.88	1,565.36	1,276.95	1,272.23
Housing Expenditure	4,214.54	23,059.05	3,795.93	22,325.78
Fuel Expenditure	867.62	851.45	827.91	778.94
Medical Expenses	1,281.20	5,244.46	1,170.29	5,680.07
Observations	4942		33355	
Households	706		4765	

*Notes:*This table presents summary statistics on household expenditure, comparing households that participated in the GfG program with those that did not. All expenditure values are reported in RMB and adjusted for inflation using the Consumer Price Index (CPI), with 2009 as the baseline year.
Source: China's National Rural Fixed Point Survey

Table 4.4 presents summary statistics on household characteristics, including fixed capital, operational inputs, and household head attributes, for both GfG program participants and non-participants.On average, participating households are slightly larger but cultivate smaller cropland areas compared to non-participants. However, they manage a greater number of land plots, indicating higher land fragmentation. Despite having less cropland, GfG participants report higher productive asset values. In terms of operational inputs, participating households use fewer agricultural inputs, including fertilizer, diesel, and pesticides, than non-participants. This pattern aligns with the program's objective of reducing agricultural intensity through reforestation and land conversion. Regarding household head characteristics, GfG participants tend to be younger and have lower levels of education. The gender distribution is similar across both groups, with the majority of household heads being male. Notably, the composition of primary income sources and business types is highly similar between participants and non-participants, with family farming as the dominant income source and agriculture as the most common business type.

TABLE 4.4: HOUSEHOLD CHARACTERISTICS AND DEMOGRAPHICS

	Participation		Non-Participation	
	Mean	SD	Mean	SD
Fixed Capital & Operational Inputs				
Household Size	4.00	1.60	3.90	1.73
Cropland Area (mu)	8.19	11.13	9.16	15.49
Forest Area (mu)	6.35	18.15	4.26	19.61
Orchard Area (mu)	1.06	2.84	0.59	2.18
Pasture Area (mu)	0.08	0.86	0.30	13.32
Number of Land Plots	5.26	4.97	4.44	4.80
Productive Asset Value (RMB)	12,006.71	32,832.42	10,713.08	60,047.15
Fertilizer (kg)	639.72	2,550.57	717.94	907.78
Agricultural Diesel (kg)	19.46	86.10	27.85	185.02
Pesticides (kg)	17.20	99.88	25.43	1,384.08
Household Head				
Age	53.69	13.09	54.45	24.38
Gender (1=Male,2=Famale)	1.05	0.28	1.04	0.34
Years of Education	6.06	3.06	6.55	3.41
Primary Income Source	Obs	Ratio	Obs	Ratio
Family Farming	3,592	72.68%	24,063	72.14%
Private Enterprise Ownership	70	1.42%	755	2.26%
Labor Wage	974	19.71%	6,391	19.16%
Government Employment	50	1.01%	319	0.96%
Management Wage	108	2.19%	608	1.82%
Other Sources	148	2.99%	1,216	3.65%
Primary Business Type	Obs	Ratio	Obs	Ratio
Agriculture	3,937	79.66%	26,396	79.14%
Forestry	209	4.23%	1,486	4.46%
Livestock	103	2.08%	862	2.58%
Fishery	25	0.51%	143	0.43%
Manufacturing	62	1.25%	396	1.19%
Construction	81	1.64%	671	2.01%
Others	525	10.62%	3,401	10.20%
Observations	4942		33355	

Notes: This table presents summary statistics on household characteristics for both GfG program participants and non-participants. *Source:* China's National Rural Fixed Point Survey

4.3 Identification Strategy

The primary objective of this study is to evaluate the impact of the GfG program on rural livelihoods.A simple correlation between program participation and household income is likely to suffer from severe endogeneity concerns, rendering it inappropriate for causal interpretation. Key sources of endogeneity include reverse causality—where households with lower income may be more likely to enroll in the program—and omitted variable bias, in which unobserved factors, such as broader economic conditions, could simultaneously influence both program participation and household income.

To address these endogeneity concerns, I leverage the sharp and staggered rollout of the GfG program across households in different regions of China, as illustrated in Figure 4.1. This quasi-experimental variation provides a more credible causal identification strategy under a set of assumptions. Specifically, I employ a DID design with multiple treatment periods, comparing changes in household income and expenditure over time between participants and non-participants. The DID approach has been widely applied to assess the impacts of the GfG program (Uchida, Rozelle, and Jintao Xu, 2009; Yan, 2019; Zheng et al., 2013), as it facilitates a more rigorous estimation of treatment effects. By exploiting this staggered implementation, I aim to isolate the program's causal effect while mitigating biases from time-invariant unobserved heterogeneity and common economic shocks.

As a baseline specification, I estimate the following model:

$$Y_{it} = \alpha_i + \delta_t + \beta \times \text{GfG}_{it} + \mathbf{X}_{it} \times \gamma + \epsilon_{it}, \tag{4.1}$$

where Y_{it} denotes an outcome of interest—such as income or expenditure—for household i in year t; GfG_{it} is an indicator variable denoting whether household i participated in the GfG program in year t; β estimates the effect of participation in the GfG program, representing the Average Treatment Effect on the Treated (ATT);α_i captures village fixed effects; δ_t represents year fixed effects; and . The vector X_{it} includes household- and individual-level controls, as shown in Figure 4.4, that may influence the outcomes of interest. These controls encompass household fixed capital—such as household size, cropland area, number of land plots, and productive asset value—which capture variations in household resources and landholding structures. Additionally, operational inputs, including fertilizer usage, agricultural diesel consumption, and pesticide application, reflect differences in agricultural production intensity. Household head characteristics—such as age, squared age, gender, and years of education—are included to account for demographic factors that may shape household decision-making and economic behavior. Collectively, these controls help ensure that the estimated effects of the GfG program are not confounded by pre-existing differences in household endowments, production capacity, and socioeconomic characteristics.

The primary concern in implementing the DID design is the plausibility of the parallel trends assumption, which requires that, in the absence of the GfG program, the outcomes of participating and non-participating households would have followed a similar trajectory over time. If this assumption does not hold, the estimated treatment effects may be biased due to pre-existing differences in trends between the two groups.

To assess the validity of this assumption, I conduct an event study analysis using the following specification:

$$Y_{ct} = \alpha_c + \delta_t + \sum_{k=-5}^{5} \beta_k D_{k(ct)} + \epsilon_{ct} \tag{4.2}$$

where Y_{ct} represents the outcome of interest for household c in year t, and $D_{k(ct)}$ is a set of indicator variables that take a value of one if the household participates in the GfG program in period k, where $k = 0$ denotes the year of program adoption.

This approach allows me to examine whether systematic differences in income and expenditure trends existed between participants and non-participants before the introduction of the program. By estimating the dynamic effects of GfG participation over multiple periods, the event study framework provides a more nuanced understanding of how household economic outcomes evolved relative to the treatment timing. This helps to rule out potential confounders and reinforces the credibility of the DID identification strategy.

In addition to the conventional two-way fixed effects (TWFE) estimator, I also adopt the estimator proposed by Borusyak, Jaravel, and Spiess (2024) to address concerns regarding the reliability of the TWFE estimator in the presence of treatment effect heterogeneity. This alternative estimator mitigates bias by preventing contamination from 2×2 DID comparisons involving already-treated units. By employing these estimator, I ensure that the estimated effects of the GfG program remain robust even when treatment effects vary across time and treated units.

While PES programs like GfG aim to provide both environmental and economic benefits, they may also generate unintended consequences or exacerbate existing inequalities (Alix-Garcia and Wolff, 2014; Yan, 2019; Zilberman, Lipper, and McCarthy, 2009). To examine the distributional effects of GfG participation on income and expenditure, I estimate the following conditional quantile function:

$$Q_\tau(Y_{it}|GfG_{it}, \mathbf{X}_{it}, \alpha_i, \lambda_t) = \mathbf{X}_{it}'\beta_\tau + \gamma_\tau GfG_{it} + \alpha_i + \lambda_t + \epsilon_{it,\tau}, \tag{4.3}$$

where $Q_\tau(\cdot)$ denotes the conditional quantile of Y_{it} at quantile τ, and Y_{it} represents the outcome of interest, either household income or expenditure. The model conditions on GfG program participation (GfG_{it}), household characteristics ($\mathbf{X}_{it}$), village fixed effects (α_i), and year fixed effects (λ_t). The coefficient γ_τ captures the heterogeneous effects of GfG participation across different points in the income, allowing for a more nuanced understanding of how the program impacts households at varying levels of economic well-being.

4.4 Results

4.4.1 Main Results

I first establish that the GfG program significantly enhances rural households' economic well-being, as measured by income and expenditure, following program participation. Table 4.5 presents estimates of β from Equation 4.1, evaluating the impact of GfG participation on household total income and expenditure. Column (1) reports results from a baseline specification with year and village fixed effects, while Column (2) adds household type fixed effects and additional controls, including household fixed capital, operational inputs, and household head characteristics. Columns (3) and (4) follow the same structure for total expenditure. The results remain highly significant at the 1 percent level across all specifications, with point estimates slightly decreasing after accounting for household type fixed effects and controls. Standard errors are clustered at the village level, and all dependent variables are log-transformed for interpretation in percentage terms. These findings provide strong evidence that GfG participation leads to significant increases in household income and expenditure.

Table 4.5: Baseline Regression Results

	Log Total Income		Log Total Expenditure	
	(1)	(2)	(3)	(4)
GfG	0.077***	0.059***	0.069***	0.052***
	(0.015)	(0.013)	(0.016)	(0.014)
Mean(Y)	47,338	47,338	35,266	35,266
Observations	38,297	38,297	38,297	38,297
R-squared	0.355	0.528	0.344	0.491
Year-Village FEs	✓	✓	✓	✓
Household Type FEs		✓		✓
Controls		✓		✓

Notes: This table presents baseline regression estimates of the impact of GfG participation on log-transformed household income and expenditure. All dependent variables are log-transformed to allow for interpretation in percentage terms. Columns (1)–(2) report results for total income, while columns (3)–(4) examine total expenditure. Specifications in (1) and (3) include year and village fixed effects, while (2) and (4) additionally incorporate household type fixed effects and other controls. Household type fixed effects account for differences in primary income sources, such as household business, village employment, and government employment. Additional controls include household fixed capital, operational inputs, and household head characteristics. Mean(Y) represents the average values of total income or expenditure. Standard errors are reported in parentheses and clustered at the village level. Detailed regression results are provided in Appendix Table A-14. Statistical significance is denoted as follows:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results indicate that GfG participation significantly increases both household income and expenditure across all specifications. In my preferred model—which includes household type fixed effects and additional controls—the estimated impact on total income is 0.060[4], while the effect on total expenditure is 0.053, both statistically significant at the 1 percent level. These estimates suggest that program participation raises household income by approximately RMB 2,840[5] and household expenditure by RMB 1,869[6]. The relatively larger impact on income than expenditure suggests that households may initially allocate additional earnings toward savings or investment before increasing consumption.

4.4.2 Event Study

To assess the plausibility of the parallel trends assumption, I estimate an event-study version of the TWFE model, as specified in Equation 4.2, to examine the impact of the GfG program on rural household income and expenditure. In addition to the TWFE estimator, I employ the approach proposed by Borusyak, Jaravel, and Spiess (2024), which accounts for heterogeneous treatment effects in staggered DID designs, thereby mitigating potential biases in conventional regression-based estimators. This specification is preferred for the event study analysis, as it provides a more robust assessment of treatment dynamics. The event study framework further allows for an examination of the persistence of these effects over time, offering insights into both the immediate and long-term impacts of GfG participation.

Figure 4.2 presents event-study estimates of the GfG program's effect on rural household income, illustrating its dynamic impacts over time. To ensure consistency with the baseline results, the dependent variable is log-transformed total household income.

[4] Transformed as $e^{0.059} - 1$, hereafter, $e^{\hat{\beta}} - 1$ for interpretation of log-transformed dependent variables.
[5] Computed as RMB 47,338 $\times$ 0.060.
[6] Computed as RMB 35,266 $\times$ 0.053.

The treatment follows a staggered adoption design, with the first implementation occurring in 2010.The estimates across both specifications indicate a stable pre-trend, with coefficients on pre-treatment periods remaining close to zero, providing strong support for the parallel trends assumption. In the post-treatment period, the estimated effects on income remain positive, though statistical significance falls below the 5 percent level in the third year after participation and the final year.Additionally, the results highlight the evolution of treatment effects over time. The observed positive income effects post-treatment suggest that program benefits may accumulate gradually, potentially driven by increased household adaptation to the program and the reallocation of resources toward more productive activities.

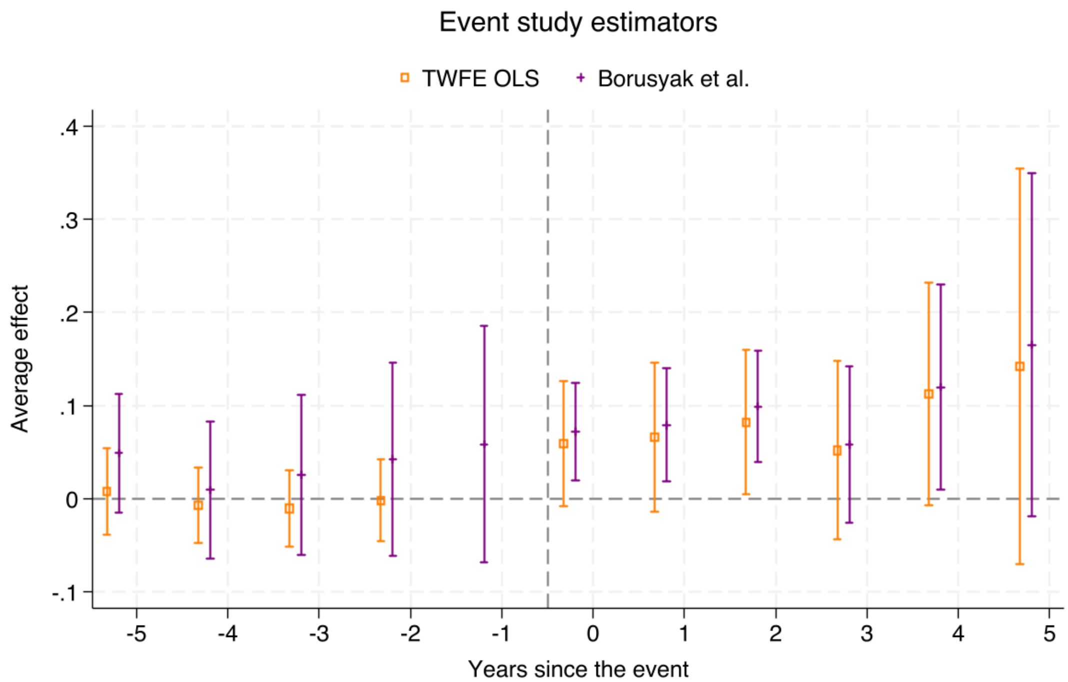


Figure 4.2: Effects of GfG on Household Income Before and After Participation

Note: This figure presents event-study estimates of the GfG program's effect on rural household income from 2009 to 2015, with the first treatment occurring in 2010. Estimates are obtained using the TWFE estimator and the method proposed by Borusyak, Jaravel, and Spiess (2024), as specified in Equation 4.2. The dependent variable is log-transformed total household income. Point estimates are shown with 95 percent confidence intervals represented by lines.

Figure 4.3 presents the event-study estimates of the GfG program's effect on rural household expenditure, complementing the findings on income dynamics. Similar to the income estimates, the results indicate a stable pre-trend, with expenditure trajectories remaining parallel across treatment and control groups before program participation, reinforcing the validity of the parallel trends assumption. In the post-treatment period, the estimated effects on expenditure remain consistently positive, though statistical significance fluctuates across years. Compared to income effects, expenditure responses appear more stable over time, suggesting that while households experience income gains, they may smooth consumption rather than immediately adjusting their spending patterns.

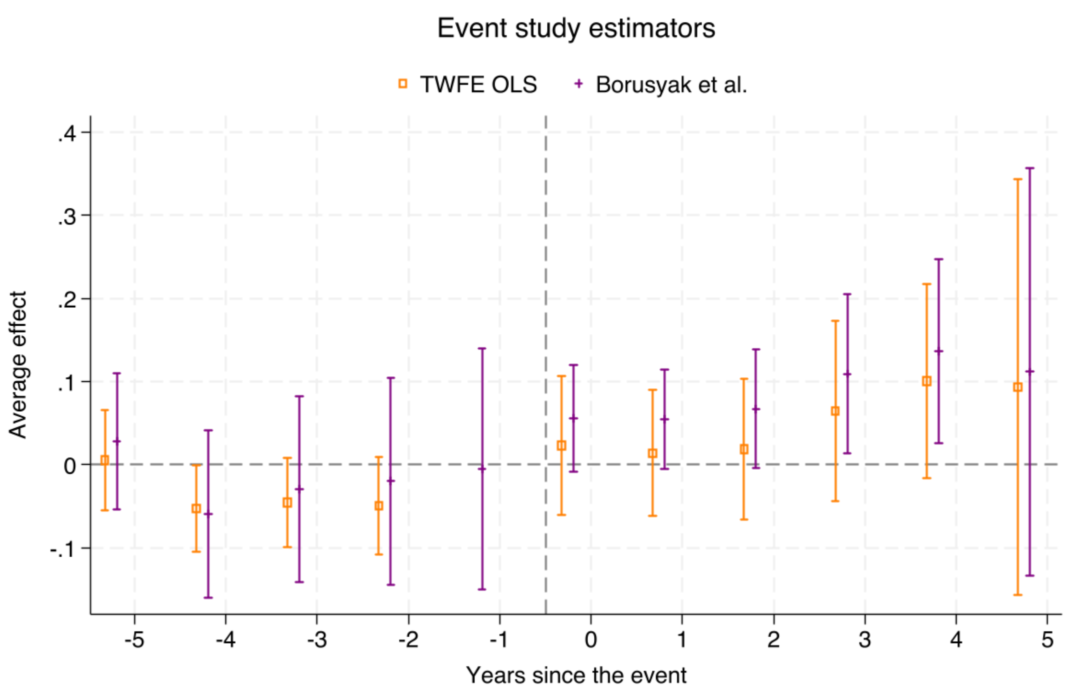


Figure 4.3: Effects of GfG on Household Expenditure Before and After Participation

Note: This figure presents event-study estimates of the GfG program's effect on rural household expenditure from 2009 to 2015, with the first treatment occurring in 2010. Estimates are obtained using the TWFE estimator and the method proposed by Borusyak, Jaravel, and Spiess (2024), as specified in Equation 4.2. The dependent variable is log-transformed total household expenditure. Point estimates are shown with 95 percent confidence intervals represented by lines.

4.4.3 Equality Impact

To evaluate the distributional effects of the GfG program, I conduct an equity impact assessment, focusing exclusively on household income. Since household expenditures may be influenced by external factors unrelated to program participation, income serves as a more direct measure of economic disparities. I employ quantile regression to examine how the effect of GfG participation varies across different points of the income distribution, assessing whether the benefits are more pronounced among lower- or higher-income households.

Table 4.6 presents the quantile regression estimates of the impact of GfG participation across different points of the income distribution. Column (1) reports the ordinary least squares (OLS) estimate from Equation 4.1, while columns (2)–(6) provide quantile regression estimates for the 10th, 25th, 50th (median), 75th, and 90th quantiles, as specified in Equation 4.3. The effect of GfG participation on household income exhibits a slight upward trend from the 10th to the 90th quantile, indicating that higher-income households experience relatively greater income gains from program participation. The estimated coefficients remain consistently positive and statistically significant at the 1 percent level across all quantiles. Standard errors are clustered at the village level, and all specifications include year and village fixed effects, household type fixed effects, and additional controls.

TABLE 4.6: Quantile Regression Results for Total Income

	Dependent Variable: Log Total Income					
		Quantile				
	OLS	0.1	0.25	0.5	0.75	0.9
	(1)	(2)	(3)	(4)	(5)	(6)
GfG	0.05925***	0.05877***	0.05901***	0.05926 ***	0.05949***	0.05969***
	(0.01269)	(0.01900)	(0.01474)	(0.01261)	(0.01364)	(0.01658)
Observations	38,297	38,297	38,297	38,297	38,297	38,297
Year-Village FEs	✓	✓	✓	✓	✓	✓
HH Type FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Notes: This table presents the quantile regression results estimating the impact of GfG participation on household income. Column (1) reports the ordinary least squares (OLS) estimate, while columns (2)–(6) provide quantile regression estimates for the 10th, 25th, 50th (median), 75th, and 90th quantiles. All specifications include year and village fixed effects, household type fixed effects, and additional controls. Standard errors are clustered at the village level.Statistical significance is denoted as follows:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5 Decompositions and Mechanisms

After presenting the main findings, I further explore the mechanisms driving the positive effects of the GfG program on rural household well-being. First, I examine the direct benefits stemming from the program's "Green" component, which may yield immediate financial gains for participating households. Next, I conduct a detailed decomposition analysis to disentangle the effects of GfG participation across various income and expenditure components, identifying the primary drivers of economic changes. Finally, I assess the channels implied by the decomposition results, offering a comprehensive perspective on how the GfG program influences rural household livelihoods.

4.5.1 Land Use Change

To evaluate the GfG program's effectiveness in driving land use transformation, I analyze changes in forest, orchard, and pasture areas among participating households. The program provides subsidies for converting cropland into these land categories, granting households the flexibility to select their preferred transition. Table 4.7 presents the estimated effects of program participation on these land use changes. All specifications include year and village fixed effects to control for unobserved regional characteristics. Additionally, household-level controls are incorporated in columns (2), (4), and (6) to account for variations in household attributes that may influence land use decisions. Standard errors are clustered at the village level to address potential within-village correlations, ensuring the robustness of the results.

Table 4.7: GfG Program Effects on Land Use Change

	Log Forest Area		Log Orchard Area		Log Pasture Area	
	(1)	(2)	(3)	(4)	(5)	(6)
GfG	0.907***	0.897***	0.170	0.153	0.108***	0.108***
	(0.117)	(0.117)	(0.107)	(0.106)	(0.037)	(0.037)
Mean(Y)	4.53	4.53	0.65	0.65	0.27	0.27
Observations	38,297	38,297	38,297	38,297	38,297	38,297
R-squared	0.794	0.795	0.679	0.682	0.629	0.630
Year-Village FEs	✓	✓	✓	✓	✓	✓
Household Type FEs		✓		✓		✓
Controls		✓		✓		✓

*Notes:*This table presents baseline regression estimates of the impact of GfG participation on log-transformed land use outcomes. All dependent variables are log-transformed to allow for interpretation in percentage terms. Columns (1)–(2) report results for forest area, columns (3)–(4) examine orchard area, and columns (5)–(6) assess pasture area. Specifications in (1), (3), and (5) include year and village fixed effects, while (2), (4), and (6) additionally incorporate household type fixed effects and other controls. Household type fixed effects account for differences in land use preferences and farming practices. Additional controls include household fixed capital, operational inputs, and household head characteristics. Mean(Y) represents the average values of each land category. Standard errors are reported in parentheses and clustered at the village level. Detailed regression results are provided in Appendix Table A-15.Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

This analysis underscores the GfG program's substantial role in promoting large-scale reforestation, while its impact on orchard and pasture expansion remains relatively modest. Columns (1) and (2) of Table 4.7 reveal a significant increase in forested areas, with estimated coefficients of 0.907 and 0.897, both highly significant at the 1 percent level. These estimates correspond to approximately 148 percent and 145 percent increases in forest area, respectively, highlighting the program's strong incentive for reforestation in line with its core environmental objectives. In contrast, Columns (3) and (4) show a positive but statistically insignificant effect on orchard area, suggesting that program participation does not substantially encourage orchard cultivation. Meanwhile, Columns (5) and (6) indicate a modest yet statistically significant expansion in pasture area, with coefficients of 0.108, equating to an 11.4 percent increase, implying some degree of cropland conversion into grassland. However, given the relatively small mean pasture area, this effect remains limited in magnitude.

4.5.2 Income Decompositions and Mechanisms

To further examine the channels through which the GfG program influences household income, I conduct a multi-level income decomposition analysis. This method disaggregates the program's effects across various income sources, providing a more granular understanding of the mechanisms driving the observed changes in total income. Specifically, this analysis assesses whether the financial benefits of program participation arise from shifts in agricultural production, increased government subsidies, or changes in household labor allocation. By distinguishing between these potential drivers, the study offers deeper insights into how the GfG program reshapes rural household economic behavior.

Overall Income Decompositions

I begin by decomposing rural household total income into key components: farm income, nonfarm business income, local and non-local wages, government subsidies, and other income sources. Table 4.8 presents the estimated effects of program participation on these income sources. Columns (1)–(2) report estimates for farm income, columns (3)–(4) analyze nonfarm business income, columns (5)–(6) examine local wage income, columns (7)–(8) assess non-local wage income, columns (9)–(10) estimate government subsidies, and columns (11)–(12) capture other income sources. Odd-numbered columns present the baseline specification, which includes only year and village fixed effects, while even-numbered columns report the preferred specification, which further incorporates household type fixed effects and additional controls.

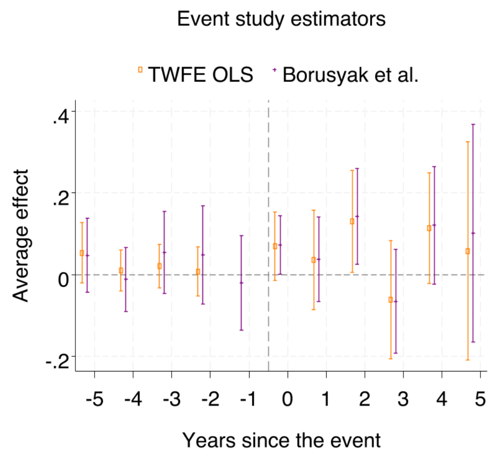
Table 4.8: Household Income Decomposition Results

	Log Farm Income		Log Non-farm Business Income		Log Local Wage Income		Log Non-local Wage Income		Log Gov't Subsidies		Log Other Incomes	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GfG	0.047**	0.046***	-0.126	-0.146	0.042	0.008	-0.228	-0.309**	0.779***	0.787***	0.203	0.223*
	(0.018)	(0.016)	(0.146)	(0.138)	(0.147)	(0.146)	(0.153)	(0.149)	(0.053)	(0.053)	(0.130)	(0.130)
Mean(Y)	17,935	17,935	10,539	10,539	6,095	6,095	12,009	12,009	867	867	1,737	1,737
Observations	36,971	36,971	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297
R-squared	0.499	0.619	0.338	0.416	0.243	0.256	0.239	0.295	0.496	0.510	0.412	0.419
Year-Village FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
HH Type FEs		✓		✓		✓		✓		✓		✓
Controls		✓		✓		✓		✓		✓		✓

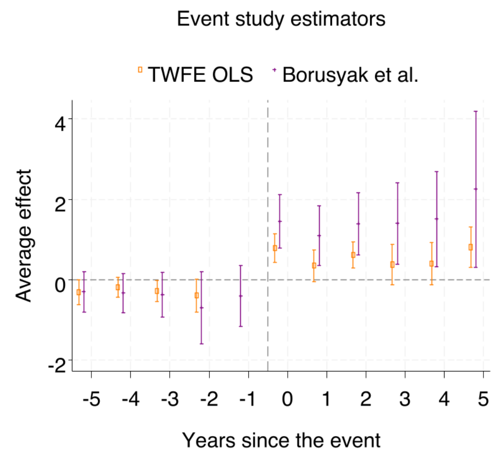
*Notes:*This table presents the estimated effects of GfG participation on household income decomposition using log-transformed dependent variables. Columns (1)–(2) report estimates for farm income, columns (3)–(4) analyze nonfarm business income, columns (5)–(6) examine local wage income, columns (7)–(8) assess non-local wage income, columns (9)–(10) estimate government subsidies, and columns (11)–(12) capture other income sources. The specification in odd-numbered columns includes year and village fixed effects, while even-numbered columns incorporate household type fixed effects and additional controls.Household type fixed effects account for differences in primary income sources, such as household business, village employment, and government employment. Additional controls include household fixed capital, operational inputs, and household head characteristics. Mean(Y) represents the average values of each income component. Standard errors are reported in parentheses and clustered at the village level. All dependent variables are log-transformed. Detailed regression results are provided in Appendix Table A-16.Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

The results from Table 4.8 indicate that the GfG program has heterogeneous effects across different income sources. Participation in the program is associated with a statistically significant increase in farm income and government subsidies in all specifications, with significance at the 5 percent level or higher. In the preferred specification, non-local wage income and other income sources also exhibit statistically significant increases at the 5 percent and 10 percent levels, respectively. In contrast, nonfarm business income and local wage income do not show significant changes, suggesting that the program's economic impact is primarily driven by agriculture, government transfers, and non-local wage employment rather than non-farm business or local wage income.

I conduct an event study on the income sources included in the income decomposition analysis to assess the validity of the parallel trends assumption, following Equation 4.2. I employ both the TWFE specification and the approach proposed by Borusyak, Jaravel, and Spiess (2024) to ensure robustness. Figure 4.4 confirms that household farm income and government subsidies exhibit a stable parallel pre-trend prior to GfG program participation. After participation, the estimated effects on farm income remain positive, though statistical significance fluctuates across years, as shown in Panel A of Figure 4.4. Meanwhile, Panel B of Figure 4.4 illustrates a stable and sustained increase in government subsidies following program implementation, which aligns with the program's intended financial support structure. Additionally, Figure A-1 in the appendix provides further evidence of parallel pre-trends for other income sources, reinforcing the credibility of the identification strategy.



(A) Event Study on Farm Income



(B) Event Study on Gov't Subsides

FIGURE 4.4: EFFECTS OF GFG PROGRAM ON THE FARM INCOME AND GOVERNMENT SUBSIDIES BEFORE AND AFTER PARTICIPATION

Notes: This figure presents event-study estimates of the GfG program's effect on household farm income and government subsidies from 2009 to 2015, with the first treatment occurring in 2010. Estimates are obtained using the TWFE estimator and the method proposed by Borusyak, Jaravel, and Spiess (2024), as specified in Equation 4.2. The dependent variables are log-transformed farm income (Panel A) and government subsidies (Panel B). Point estimates are shown with 95 percent confidence intervals represented by lines.

The positive effect on farm income is unexpected, given that the program encourages the conversion of cropland into forests, orchards, and pastures. In the preferred specification, which includes year and village fixed effects, household type fixed effects, and additional controls, the estimated effect size is 0.047, as shown in Table 4.8.

This estimate closely aligns with the coefficient from the baseline regression on total income, suggesting that the observed increase in farm income may stem from shifts in agricultural productivity and diversification into higher-value crops.

Farm Income Decompositions

To further investigate the unexpected increase in farm income, I conduct a detailed decomposition by disaggregating farm income into its key components: grain production—including staple crops such as wheat, rice, and corn,—as well as soybean and cash crops, forestry and orchard farming, livestock farming, and fishery.

Table 4.9 focuses on the first thematic component of the GfG program—its impact on grain, soybean and cash crops production. The results indicate a significant decline in income from wheat, rice, and corn farming, aligning with the program's objective of reducing cultivation on sloped land. In the preferred specification, which includes year and village fixed effects, household type fixed effects, and additional controls, the estimated effect on rice income is negative but not statistically significant. This suggests that while the program may have influenced rice farming, the effect is relatively weak compared to other staple crops.

In contrast, income from soybean and cash crops exhibits a significant increase, suggesting that some participating households may be shifting towards higher-value agricultural activities. The estimated effect size for soybean income in the preferred specification, which includes year and village fixed effects as well as household type fixed effects and additional controls, is 0.519. Given the average soybean income of 561 RMB, this translates to an approximate increase of 291.7 RMB. Similarly, the estimated effect on cash crop income is 0.272, reflecting a notable expansion in these farming activities. Given the average cash crop income of 2,997 RMB, this corresponds to an approximate increase of 815.2 RMB. These findings suggest that while the GfG program reduces income from staple crops, it may encourage diversification into more profitable agricultural sectors.

Table 4.9: Household Farm Income Decomposition Results (1)

	Log Income from Wheat Farming		Log Income from Rice Farming		Log Income from Corn Farming		Log Income from Soybean Farming		Log Income from Cash Crop Farming	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GfG	-0.436***	-0.433***	-0.132*	-0.093	-0.223***	-0.202***	0.494***	0.519***	0.285***	0.272***
	(0.065)	(0.065)	(0.076)	(0.072)	(0.070)	(0.068)	(0.071)	(0.071)	(0.031)	(0.030)
Mean(Y)	1,113	1,113	2,193	2,193	4,314	4,314	561	561	2,997	2,997
Observations	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	20,749	20,749
R-squared	0.823	0.825	0.749	0.770	0.734	0.748	0.527	0.537	0.598	0.633
Year-Village FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Household Type FEs		✓		✓		✓		✓		✓
Controls		✓		✓		✓		✓		✓

*Notes:*This table presents the estimated effects of GfG program participation on household farm income decomposition using log-transformed dependent variables. Columns (1)–(2) report estimates for income from wheat farming, columns (3)–(4) analyze income from rice farming, columns (5)–(6) examine income from corn farming, columns (7)–(8) assess income from soybean farming, and columns (9)–(10) estimate income from cash crop farming.Specifications in odd-numbered columns include year and village fixed effects to account for time-invariant regional factors, while even-numbered columns additionally incorporate household type fixed effects and other controls to address potential heterogeneity in income sources. Household type fixed effects control for systematic differences in primary income sources, such as household business, village employment, and government employment. Additional controls include household fixed capital, operational inputs, and household head characteristics. Mean(Y) represents the average income value for each farm income source. Standard errors are reported in parentheses and clustered at the village level. All dependent variables are log-transformed.Detailed regression results are provided in Appendix Table A-17. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 4.10 examines the second thematic component of the GfG program—its impact on forestry and orchard farming, as well as livestock farming, and fishery activities. The results indicate a negligible and statistically insignificant effect on forestry and orchard farming income, suggesting that program participation does not lead to substantial revenue generation from these activities. The estimated effect for orchard farming is negative, though not statistically significant, indicating that the program has not substantially influenced the expansion of orchard-related income. Given the program's emphasis on land conservation and afforestation, this finding suggests that while households may be shifting land use towards these categories, the short-term income effects remain limited.

The findings reveal a significant increase in income from livestock farming, with an estimated coefficient of 0.176 in the preferred specification, which includes year and village fixed effects, household type fixed effects, and additional controls. Given an average livestock farming income of 3,666 RMB, this corresponds to an approximate increase of 645.2 RMB. (Uchida, Jintao Xu, Z. Xu, and Rozelle, 2007) also found that the GfG program positively impacts income from livestock activities. This suggests that some households may be reallocating resources toward livestock production as an adaptive response to cropland conversion. A key factor facilitating this shift could be the GfG program's policy of permitting livestock rearing within reforested land under the livestock-forest integration framework.

By contrast, the program's effect on fishery income appears negligible, as the estimated coefficient is negative but not statistically significant. This indicates that participation in the GfG program does not substantially influence income from fishing activities.

TABLE 4.10: Household Farm Income Decomposition Results (2)

	Log Income from Forestry		Log Income from Orchard Farming		Log Income from Livestock Farming		Log Income from Fishery	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GfG	0.027	0.034	-0.025	-0.076	0.176*	0.176*	-0.048	-0.047
	(0.068)	(0.068)	(0.059)	(0.057)	(0.096)	(0.094)	(0.032)	(0.032)
Mean(Y)	416	416	1,861	1,861	3,666	3,666	533	533
Observations	38,297	38,297	6,093	6,093	38,297	38,297	38,297	38,297
R-squared	0.734	0.736	0.649	0.669	0.488	0.512	0.273	0.283
Year-Village FEs	✓	✓	✓	✓	✓	✓	✓	✓
HH Type FEs		✓		✓		✓		✓
Controls		✓		✓		✓		✓

*Notes:*This table presents the estimated effects of GfG program participation on household farm income decomposition using log-transformed dependent variables. Columns (1)–(2) report estimates for income from forestry, columns (3)–(4) analyze income from orchard farming, columns (5)–(6) examine income from livestock farming, and columns (7)–(8) assess income from fishery activities. Specifications in odd-numbered columns include year and village fixed effects to control for time-invariant regional factors, while even-numbered columns additionally incorporate household type fixed effects and other controls to account for heterogeneity in income sources. Household type fixed effects control for systematic differences in primary income sources, such as household business, village employment, and government employment. Additional controls include household fixed capital, operational inputs, and household head characteristics. Mean(Y) represents the average income value for each farm income source. Standard errors are reported in parentheses and clustered at the village level. Detailed regression results are provided in Appendix Table A-18.Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Mechanisms of Income Change

To explore the mechanisms through which the GfG program affects farm income, particularly from grain, soybean, and cash crop farming, I analyze shifts in agricultural land use and productivity. This approach offers deeper insights into how program participation influences income dynamics, whether through changes in crop allocation, increased efficiency, or adaptations in farming practices.

Table 4.11: GfG Program Effects on Agricultural Land Allocation

	Log Planted Area of Wheat		Log Planted Area of Rice		Log Planted Area of Corn		Log Planted Area of Soybeans		Log Planted Area of Cash Crops	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GfG	-0.725***	-0.717***	-0.205*	-0.145	-0.366***	-0.334***	0.731***	0.772***	0.334**	0.374***
	(0.109)	(0.108)	(0.118)	(0.113)	(0.109)	(0.106)	(0.121)	(0.121)	(0.131)	(0.128)
Mean(Y)	1.53	1.53	2.00	2.00	4.95	4.95	1.10	1.10	2.36	2.36
Observations	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297
R-squared	0.813	0.816	0.746	0.766	0.739	0.751	0.521	0.531	0.604	0.623
Year-Village FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
HH Type FEs		✓		✓		✓		✓		✓
Controls		✓		✓		✓		✓		✓

*Notes:*This table presents the estimated effects of GfG program participation on agricultural land allocation using log-transformed dependent variables. Columns (1)–(2) report estimates for the planted area of wheat, columns (3)–(4) analyze the planted area of rice, columns (5)–(6) examine the planted area of corn, columns (7)–(8) assess the planted area of soybeans, and columns (9)–(10) estimate the planted area of cash crops.Specifications in odd-numbered columns include year and village fixed effects to control for time-invariant regional factors, while even-numbered columns additionally incorporate household type fixed effects and other controls to account for heterogeneity in land allocation. Household type fixed effects control for systematic differences in primary income sources, such as household business, village employment, and government employment. Additional controls include household fixed capital, operational inputs, and household head characteristics.Mean(Y) represents the average planted area for each crop type. Standard errors are reported in parentheses and clustered at the village level.Detailed regression results are provided in Appendix Table A-19. Statistical significance is denoted as follows * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 4.11 presents the estimated effects of GfG program participation on agricultural land allocation. Specifically, it examines changes in the planted area of major crops, including wheat, rice, corn, soybeans, and cash crops. The results indicate a significant reduction in the cultivated area of staple crops such as wheat, rice, and corn, aligning with the program's goal of converting cropland into forests, orchards, and pastures. Meanwhile, the planted areas of soybeans and cash crops exhibit a notable expansion, suggesting that participating households are shifting toward higher-value agricultural activities. This pattern is consistent with the observed increase in income from soybean and cash crop farming.These findings suggest that the GfG program not only reduces reliance on staple crops but also encourages diversification into more profitable agricultural alternatives, supporting the broader goal of improving rural livelihoods while promoting sustainable land use.

Beyond agricultural land allocation, the increase in farm income may also result from productivity improvements and price changes. However, evidence suggests that the GfG program has no effect on prices (Z. Xu et al., 2006). Therefore, I focus solely on productivity. Table 4.12 presents the estimated effects of GfG program participation on agricultural productivity, measured as yield (kg per mu[7]) for key staple crops, including wheat, rice, corn, and soybeans. Due to data limitations, cash crop productivity is not included in the analysis. The results indicate no significant changes in the productivity of wheat, rice, and corn, as evidenced by the statistically insignificant coefficients. However, soybean productivity significantly increases under the GfG program, with an estimated effect of 11% in the preferred specification, which includes year and village

[7] 1 mu = 1/15 hectare

fixed effects, household type fixed effects, and additional controls. Given an average soybean yield of 201.30 kg per mu, this translates to an approximate increase of 22.14 kg per mu.

TABLE 4.12: GfG Program Effects on Agricultural Productivity

	Log Wheat Productivity		Log Rice Productivity		Log Corn Productivity		Log Soybeans Productivity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GfG	0.004	0.004	-0.001	-0.003	0.010	0.009	0.113***	0.105***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.012)	(0.012)	(0.032)	(0.032)
Mean(Y)	356.55	356.55	500.55	500.55	514.20	514.20	201.30	201.30
Observations	13,456	13,456	14,077	14,077	23,243	23,243	6,035	6,035
R-squared	0.598	0.600	0.402	0.405	0.416	0.419	0.435	0.439
Year-Village FEs	✓	✓	✓	✓	✓	✓	✓	✓
HH Type FEs		✓		✓		✓		✓
Controls		✓		✓		✓		✓

*Notes:*This table presents the estimated effects of GfG program participation on agricultural productivity using log-transformed dependent variables. Columns (1)–(2) report estimates for wheat productivity, columns (3)–(4) analyze rice productivity, columns (5)–(6) examine corn productivity, and columns (7)–(8) assess soybean productivity. Agricultural productivity is measured in kilograms per mu (1 mu = 1/15 hectare). Specifications in odd-numbered columns include year and village fixed effects to control for time-invariant regional factors, while even-numbered columns additionally incorporate household type fixed effects and other controls to account for heterogeneity in agricultural productivity. Household type fixed effects control for systematic differences in primary income sources, such as household business, village employment, and government employment. Additional controls include household fixed capital, operational inputs, and household head characteristics. Mean(Y) represents the average productivity (kg per mu) for each crop type.Detailed regression results are provided in Appendix Table 4.12. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

The analysis reveals that the positive effect of GfG participation on total income is primarily driven by increases in farm income and government subsidies. The rise in farm income stems largely from the expansion of soybean farming and cash crop cultivation, which offsets the decline in staple crop production, particularly wheat, rice, and corn.

Participating households reallocate land away from staple crops toward more profitable agricultural activities, leading to significant increases in the planted areas of soybeans and cash crops. This shift aligns with the program's goal of reducing cultivation on sloped land while promoting afforestation and alternative income-generating activities. In addition to land reallocation, improvements in agricultural productivity—particularly in soybean production—contribute to farm income growth. The findings indicate a statistically significant increase in soybean yield following GfG implementation, suggesting that the program may incentivize better land management, investment in higher-yield varieties, or improved farming practices. However, no significant changes are observed in the productivity of wheat, rice, or corn, reinforcing the idea that the income gains from these crops are primarily driven by land use changes rather than efficiency improvements. Beyond farm income, government subsidies represent another major channel through which GfG participation influences total income. The program provides direct financial support to households transitioning their land use, which helps compensate for potential income losses from staple crop reduction. This additional source of income may also reduce the need for households to engage in non-local wage employment, leading to shifts in labor allocation and potential long-term adjustments in rural household economic strategies.

Overall, these findings highlight that GfG participation reshapes rural household economic behavior through multiple mechanisms: incentivizing land reallocation, enhancing soybean productivity, and providing financial support through government subsidies. The program effectively reduces reliance on staple crop farming while fostering diversification into higher-value agricultural activities. However, its impact on other non-farm income sources remains limited, suggesting that complementary policy measures may be necessary to further promote rural income diversification and long-term economic resilience.

4.5.3 Expenditure Decompositions

Overall Expenditure Decompositions

I also conduct a detailed decomposition of total expenditure into key categories. These include operating expenditure,productive asset investment, other investments, tax payments, village fees, and living expenditure. This analysis provides insights into how program participation affects household spending patterns and resource allocation, shedding light on whether income gains are primarily used for consumption, reinvestment in agricultural activities, or other economic priorities.

Table 4.13 presents the estimated effects of GfG participation on various expenditure components. Columns (1)–(2) report estimates for operating expenditures, columns (3)–(4) analyze productive asset investments, columns (5)–(6) examine other investments, columns (7)–(8) assess tax payments, columns (9)–(10) estimate village fees, and columns (11)–(12) capture living expenditures. Odd-numbered columns include only year and village fixed effects, while even-numbered columns incorporate household type fixed effects and additional controls to account for heterogeneity in household spending behavior.

TABLE 4.13: Household Expenditure Decomposition Results

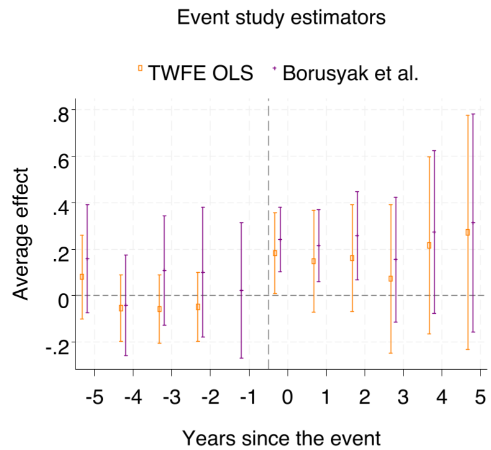
	Log Operating Exp.		Log Productive Asset Exp.		Log Other Investment Exp.		Log Tax Exp.		Log Village Fees		Log Living Exp.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GfG	0.191***	0.194***	-0.020	-0.034	0.082	0.083	-0.004	-0.009	0.320***	0.307***	0.062***	0.047***
	(0.054)	(0.053)	(0.157)	(0.156)	(0.068)	(0.068)	(0.065)	(0.063)	(0.112)	(0.112)	(0.016)	(0.014)
Mean(Y)	10,911	10,911	792	792	195	195	67	67	64	64	21,464	21,464
Observations	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297
R-squared	0.215	0.271	0.101	0.114	0.052	0.054	0.238	0.274	0.482	0.484	0.283	0.375
Year-Village FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Household Type FE		✓		✓		✓		✓		✓		✓
Controls		✓		✓		✓		✓		✓		✓

*Notes:*This table presents the estimated effects of GfG participation on household income decomposition using log-transformed dependent variables. Columns (1)–(2) report estimates for farm income, columns (3)–(4) examine non-farm business income, columns (5)–(6) analyze local wage income, columns (7)–(8) assess other wage income, columns (9)–(10) estimate government subsidies, and columns (11)–(12) capture other income sources. Specifications in odd-numbered columns include year and village fixed effects to control for time-invariant regional factors, while even-numbered columns additionally incorporate household type fixed effects and other controls to account for heterogeneity in agricultural productivity. Household type fixed effects control for systematic differences in primary income sources, such as household business, village employment, and government employment. Additional controls include household fixed capital, operational inputs, and household head characteristics. Mean(Y) represents the average expenditure for each category.Detailed regression results are provided in Appendix Table A-21.Statistical significance is denoted as follows: $*p < 0.10$, $** \ p < 0.05$, and $*** \ p < 0.01$.

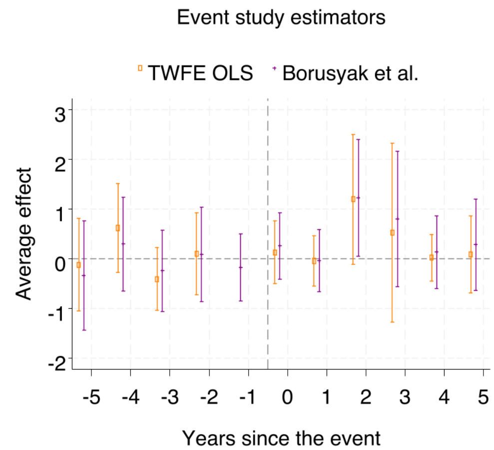
The results from Table 4.13 indicate that GfG program participation has heterogeneous effects across different expenditure categories. Participation in the program is associated with a statistically significant increase in operating expenditures and living expenses across all specifications, with significance at the 1 percent level. The estimated coefficients for operating expenditures and living expenses are 0.194 and 0.047, respectively. Given the average operating expenditure of 10,911 RMB and the average living expenditure of 21,464 RMB, these estimates correspond to approximate increases of 2,114 RMB and 1,009 RMB, respectively. This suggests that program participation leads to higher spending on agricultural operations and household consumption, potentially reflecting adjustments in production activities and improvements in living standards. Village fees also exhibit a significant increase at the 1 percent level, suggesting that program participation may lead to greater contributions to local community obligations. However, given the relatively low average village fee of 64 RMB, the estimated effect translates into only a marginal increase, .

In contrast, the estimated effects on productive asset investment, other investments, and tax expenditures are not statistically significant, indicating that GfG participation does not substantially alter household investment behaviors or tax burdens. These findings suggest that while the program influences household spending patterns, its economic impact is primarily concentrated in operational and consumption-related expenditures rather than in long-term investments or tax-related payments. This implies that participating households may prioritize short-term financial adjustments, such as covering increased operating costs and meeting daily living expenses, rather than allocating resources toward capital accumulation or tax obligations.

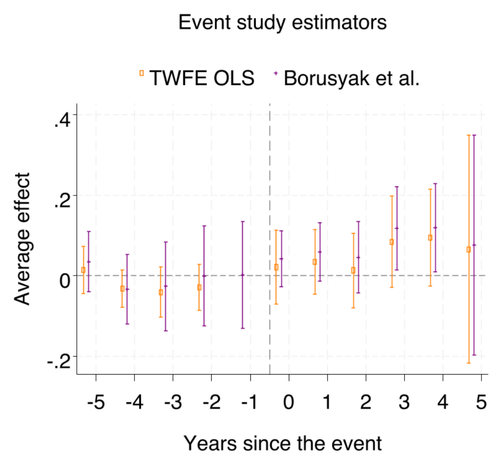
Similar to the event study analysis conducted for income, Figure 4.5 further validates the parallel pre-trend assumption for operating expenditures, living expenses, and village fees. The results indicate that these expenditure categories followed a stable trajectory prior to GfG program participation, reinforcing the causal interpretation of the observed post-treatment effects.



(A) Event Study on Operating Expenditure



(B) Event Study on Village Fees



(C) Event Study on Livelihood Expenditure

FIGURE 4.5: EFFECTS OF GFG PROGRAM ON OPERATING EXPENDITURE, VILLAGE FEES, AND LIVING EXPENDITURES BEFORE AND AFTER PARTICIPATION

Living Expenditure Decompositions

I further examine the effects of the GfG program on household consumption by decomposing living expenditure into staple food, non-staple food, clothing, housing, fuel, and medical expenses. Table 4.14 presents the estimated impacts of the program on these expenditure categories.

Table 4.14: Household Living Exp. Decomposition Results

	Log Staple Food Exp.		Log Non-staple Food Exp.		Log Clothing Exp.		Log Housing Exp.		Log Fuel Exp.		Log Medical Exp.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GfG	0.097***	0.086***	0.084***	0.077***	0.384***	0.349***	0.796***	0.758***	0.519***	0.507***	0.005	0.017
	(0.034)	(0.033)	(0.030)	(0.030)	(0.079)	(0.077)	(0.161)	(0.160)	(0.112)	(0.112)	(0.249)	(0.249)
Mean(Y)	1,856	1,856	3,985	3,985	1,274	1,274	3,850	3,850	833	833	1,185	1,185
Observations	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297
R-squared	0.150	0.168	0.238	0.255	0.099	0.129	0.578	0.581	0.395	0.397	0.289	0.293
Year-Village FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
HH Type FE		✓		✓		✓		✓		✓		✓
Controls		✓		✓		✓		✓		✓		✓

Notes: This table presents the estimated effects of GfG program participation on household living expenditure decomposition using log-transformed dependent variables. Columns (1)–(2) report estimates for staple food expenditure, columns (3)–(4) analyze non-staple food expenditure, columns (5)–(6) examine clothing expenditure, columns (7)–(8) assess housing expenditure, columns (9)–(10) estimate fuel expenditure, and columns (11)–(12) capture medical expenses. Specifications in odd-numbered columns include year and village fixed effects to control for time-invariant regional factors, while even-numbered columns additionally incorporate household type fixed effects and other controls to account for heterogeneity in expenditure patterns. Household type fixed effects control for systematic differences in primary income sources, such as household business, village employment, and government employment. Additional controls include household fixed capital, operational inputs, and household head characteristics. Mean(Y) represents the average expenditure value for each category.Standard errors are reported in parentheses and clustered at the village level. All dependent variables are log-transformed. Detailed regression results are provided in Appendix Table A-22.Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

The results from Table 4.13 indicate that participation in the GfG program significantly impacts household living expenditures across multiple categories. Specifically, expenditures on staple and non-staple food, clothing, housing, and fuel increase, suggesting that participating households allocate more resources toward essential consumption and improved living conditions. These findings imply that the program enhances household well-being by facilitating greater spending on daily necessities and housing-related expenses.In contrast, medical expenses do not exhibit a statistically significant change, indicating that the financial benefits of the program do not directly translate into increased healthcare spending. This suggests that the additional income generated through the program is primarily directed toward improving food security, housing quality, and other essential needs rather than healthcare.

Overall, the results indicate that the GfG program leads to a significant increase in expenditures on food, clothing, housing, and fuel, underscoring its role in improving household living conditions. However, there is no strong evidence that the program affects medical expenses. These findings provide further insights into the broader economic implications of the GfG program on rural livelihoods.

4.6 Conclusion

This study examines the economic impacts of China's GfG program, one of the world's largest Payments for Ecosystem Services programs, on rural households. I analyze how participation in the GfG program influences household income and expenditure.

The analysis uses household-level data from the NRFP Survey, a nationally representative panel covering rural economic activities. I focus on 2009–2015 to ensure data consistency, resulting in a sample of 5,471 households across 31 provinces, including 706 GfG participants. The empirical strategy exploits the program's staggered rollout, applying a DID framework with year and village fixed effects to control for unobserved heterogeneity. An event study confirms parallel pre-treatment income and expenditure trends between participants and non-participants.

The results indicate that participation in the GfG program significantly increases total household income and expenditure. I assess the income equity implications of GfG participation using quantile regression at the household level. The results indicate no significant impact across income distribution. The income increase is primarily driven by farm income and government subsidies, while nonfarm business income and local wage earnings remain unchanged. The decomposition analysis reveals that farm income gains stem from a shift in land allocation, with households reducing staple crop cultivation and increasing the planted areas of soybeans and cash crops. Additionally, soybean productivity improves following program participation, contributing further to income growth. The program also provides direct financial support through government subsidies, helping to offset potential losses from reduced staple crop farming.

The findings have two implications for PES program design. First, the effectiveness of financial incentives depends on households' ability to adjust agricultural practices. PES programs should consider providing additional technical support or training to facilitate the transition to higher-value crops. Second, since the subsidies alone do not fully offset income losses for all participants, payment structures should be adjusted to account for variations in household capacity and local agricultural conditions. These insights can help refine PES programs to better balance environmental goals with rural economic development.

This study contributes to the literature in three key ways. First, while existing research on the GfG program has largely focused on localized impacts and short-term effects, typically within a two-year timeframe (Z. Feng, Yanzhao Yang, et al., 2005; Uchida, Rozelle, and Jintao Xu, 2009), this study provides a comprehensive assessment of its long-term and national-level consequences for rural livelihoods. Second, although prior studies extensively examine the program's effects on income, employment, food security, land access, social equity, and migration, relatively little attention has been given to household expenditure. By addressing this gap, this study offers new insights into how GfG participation reshapes spending patterns, highlighting broader economic adjustments. Third, through a detailed decomposition of both income and expenditure, this study uncovers the specific channels through which the program influences rural households, enhancing understanding of financial decision-making and informing policy design for future PES initiatives.

These findings demonstrate that the GfG program enhances rural well-being by increasing farm income, promoting environmental restoration, and boosting household consumption. However, its limited impact on nonfarm business and wage income highlights the lack of income diversification. To maximize long-term benefits, policymakers should introduce complementary measures that support alternative income sources. Additionally, the decomposition analysis reveals that farm income gains primarily result from land reallocation, as households shift away from staple crops toward soybean and cash crop production, with improved soybean productivity further driving income growth. Strengthening PES design through targeted interventions could enhance these effects and improve overall program effectiveness. Ensuring equitable distribution of benefits is also essential, as lower-income households may face greater barriers to participation. This study contributes to the broader understanding of PES initiatives by demonstrating their potential to balance environmental and economic objectives while emphasizing the need for inclusive growth strategies and complementary interventions for sustainable rural development.

This study has several limitations that future research should address. First, while it examines the welfare effects of the GfG program, it does not integrate its environmental befinits, which could indirectly affect household income. Ideally, studies on PES programs should integrate both environmental and economic benefits, as demonstrated by Zheng et al. (2013). In this study, reduced soil erosion from land conversions may enhance agricultural productivity on flatter land. Second, although the DID approach mitigates endogeneity concerns, this study does not account for participation intensity, which may vary across households. Future research could explore alternative identification strategies, such as regression discontinuity design, given that recent GfG policies restrict land conversion on slopes exceeding 25 degrees. Third, this analysis focuses on medium-term effects, leaving longer-term dynamics—such as potential land-use reversals or shifts in labor allocation—largely unexplored. Addressing these gaps would provide a more comprehensive understanding of the program's long-term implications.

Bibliography

Ajide, K. B., & Ibrahim, R. L. (2022). Environmental impacts of income inequality: evidence from G7 economies. *Environmental Science and Pollution Research*, *29*(2). https://doi.org/10.1007/s11356-021-15720-6

Alix-Garcia, J., McIntosh, C., Sims, K. R. E., & Welch, J. R. (2013). The ecological footprint of poverty alleviation: Evidence from mexico's oportunidades program. *Review of Economics and Statistics*, *95*(2). https://doi.org/10.1162/REST{_}a{_}00349

Alix-Garcia, J., & Wolff, H. (2014). Payment for ecosystem services from forests. *Annual Review of Resource Economics*, *6*(1), 361–380. https://doi.org/10.1146/annurev-resource-100913-012524

Baek, J., & Gweisah, G. (2013). Does income inequality harm the environment?: Empirical evidence from the United States. *Energy Policy*, *62*. https://doi.org/10.1016/j.enpol.2013.07.097

Banerjee, A., Duflo, E., & Qian, N. (2020). On the road: Access to transportation infrastructure and economic growth in China. *Journal of Development Economics*, *145*, 102442. https://doi.org/10.1016/J.JDEVECO.2020.102442

Berthe, A., & Elie, L. (2015). Mechanisms explaining the impact of economic inequality on environmental deterioration. https://doi.org/10.1016/j.ecolecon.2015.04.026

Bonan, G. B. (2008). Forests and climate change: Forcings, feedbacks, and the climate benefits of forests. https://doi.org/10.1126/science.1155121

Bond, J., Millar, J., & Ramos, J. (2020). Livelihood benefits and challenges of community reforestation in Timor Leste: implications for smallholder carbon forestry schemes. *Forests Trees and Livelihoods*, *29*(3), 187–204. https://doi.org/10.1080/14728028.2020.1798817

Borusyak, K., Jaravel, X., & Spiess, J. (2024). Revisiting Event-Study Designs: Robust and Efficient Estimation. *Review of Economic Studies*. https://doi.org/10.1093/restud/rdae007

Campos-Filho, E. M., Junqueira, R. P., & Nicola Costa, J. (2014). The Xingu Seed Network and mechanized direct seeding Native seed technology for ecological restoration View project PCI-MT View project. https://www.researchgate.net/publication/302527492

Cao, P., Ouyang, X., & Xu, J. [Jun]. (2022). How Do Ecosystem Services Affect Poverty Reduction Efficiency? A Panel Data Analysis of State Poverty Counties in China. *International Journal of Environmental Research and Public Health*, *19*(3). https://doi.org/10.3390/ijerph19031886

CAS. (2018, October). Three-North Shelterbelt Program Completed Afforestation of 46.14 Million Hectares Over the Past 40 years. https://english.cas.cn/newsroom/archive/news_archive/nu2018/201812/t20181228_202988.shtml

Chang, R., Fu, B., Liu, G., Wang, S., & Yao, X. (2012). The effects of afforestation on soil organic and inorganic carbon: A case study of the Loess Plateau of China. https://doi.org/10.1016/j.catena.2012.02.012

Chen, C., Park, T., Wang, X., Piao, S., Xu, B., Chaturvedi, R. K., Fuchs, R., Brovkin, V., Ciais, P., Fensholt, R., Tømmervik, H., Bala, G., Zhu, Z., Nemani, R. R., & Myneni, R. B. (2019). China and India lead in greening of the world through land-use management. *Nature Sustainability*, *2*(2), 122–129. https://doi.org/10.1038/s41893-019-0220-7

Chen, W., Chen, S., & Tang, Y. [Yuping]. (2022). Does Income Inequality Harm Green Growth? the BRICS Experience. *Journal of Environmental and Public Health*, *2022*. https://doi.org/10.1155/2022/7046208

Chen, X., Lupi, F., He, G., Ouyang, Z., & Liu, J. (2009). Factors affecting land reconversion plans following a payment for ecosystem service program. *Biological Conservation*, *142*(8), 1740–1747. https://doi.org/10.1016/J.BIOCON.2009.03.012

Chu, X., Zhan, J., Li, Z., Zhang, F., & Qi, W. (2019). Assessment on forest carbon sequestration in the Three-North Shelterbelt Program region, China. *Journal of Cleaner Production*, *215*, 382–389. https://doi.org/10.1016/j.jclepro.2018.12.296

Crespo Cuaresma, J., Danylo, O., Fritz, S., Mccallum, I., Obersteiner, M., See, L., & Walsh, B. (2016). Economic Development and Forest Cover: Evidence from Satellite Data OPEN. https://doi.org/10.1038/srep40678

Daw, T., Brown, K., Rosendo, S., & Pomeroy, R. (2011). Applying the ecosystem services concept to poverty alleviation:The need to disaggregate human well-being. *Environmental Conservation*, *38*(4). https://doi.org/https://doi.org/10.1017/S0376892911000506

Deininger, K., FEDER World Bank, G., Deininger, K., & Feder, G. (2001). *Land Institutions and Land Markets* (tech. rep.).

Deng, L., Shangguan, Z. p., & Li, R. (2012). Effects of the grain-for-green program on soil erosion in China. *International Journal of Sediment Research*, *27*(1), 120–127. https://doi.org/10.1016/S1001-6279(12)60021-3

Di Sacco, A., Hardwick, K. A., Blakesley, D., Brancalion, P. H. S., Breman, E., Cecilio Rebola, L., Chomba, S., Dixon, K., Elliott, S., Ruyonga, G., Shaw, K., Smith, P., Smith, R. J., & Antonelli, A. (2021). Ten golden rules for reforestation to optimize carbon sequestration, biodiversity recovery and livelihood benefits. *Global Change Biology*, *27*(7), 1328–1348. https://doi.org/10.1111/gcb.15498

Díaz, S., Pascual, U., Stenseke, M., Martín-López, B., Watson, R. T., Molnár, Z., Hill, R., Chan, K. M. A., Baste, I. A., Brauman, K. A., Polasky, S., Church, A., Lonsdale, M., Larigauderie, A., Leadley, P. W., Van Oudenhoven, A. P. E., Van Der Plaat, F., Schröter, M., Lavorel, S., . . . Shirayama, Y. (2018). Assessing nature's contributions to people: Recognizing culture, and diverse sources of knowledge, can improve assessments. *Science*, *359*(6373), 270–272. https://doi.org/10.1126/SCIENCE.AAP8826/SUPPL{_}FILE/AAP8826-DIAZ-SM.PDF

Dixon, R. K., Brown, S., Houghton, R. A., Solomon, A. M., Trexler, M. C., & Wisniewski, J. (1994). Carbon pools and flux of global forest ecosystems. *Science*, *263*(5144). https://doi.org/10.1126/science.263.5144.185

Domke, G., Brandon, A., Diaz-Lasco, R. D.-L., Federici, S., Garcia-Apaza, E., Grassi, G., Gschwantner, T., Herold, M., Hirata, Y., Kasimir, Å., Kinyanjui, M. J., Krisnawati, H., Lehtonen, A., Malimbwi, R. E., Niinistö, S., Ogl, S. M., Paul, T., Ravindranath, N. H., Rock, J., . . . Zhu, J. (2019). IPCC 2019 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Agriculture, Forestry and Other Land Use. *Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories*, *4*.

Duan, W., Lang, Z., & Wen, Y. (2015). The Effects of the Sloping Land Conversion Program on Poverty Alleviation in the Wuling Mountainous Area of China. *Small-scale Forestry*, *14*(3), 331–350. https://doi.org/10.1007/S11842-015-9291-0

Esfahani, H. S., & Ramírez, M. T. (2003). Institutions, infrastructure, and economic growth. *Journal of Development Economics*, *70*(2), 443–477. https://doi.org/10.1016/S0304-3878(02)00105-0

Ewers, R. M. (2006). Interaction effects between economic development and forest cover determine deforestation rates. *Global Environmental Change*, *16*(2), 161–169. https://doi.org/10.1016/j.gloenvcha.2005.12.001

Fan, Z., Bai, X. Y., & Zhao, N. (2022). Explicating the responses of NDVI and GDP to the poverty alleviation policy in poverty areas of China in the 21st century. *PLoS ONE*, *17*(8 August). https://doi.org/10.1371/journal.pone.0271983

Fedderke, J. W., & Bogetić, Ž. (2009). Infrastructure and Growth in South Africa: Direct and Indirect Productivity Impacts of 19 Infrastructure Measures. *World Development*, *37*(9), 1522–1539. https://doi.org/10.1016/J.WORLDDEV.2009.01.008

Feng, Z., Tang, Y. [Yan], Yang, Y., & Zhang, D. (2008). Relief degree of land surface and its influence on population distribution in China. *J. Geogr. Sci*, *18*, 237–246. https://doi.org/10.1007/s11442-008-0237-8

Feng, Z., Yang, Y. [Yanzhao], Zhang, Y., Zhang, P., & Li, Y. (2005). Grain-for-green policy and its impacts on grain supply in West China. *Land Use Policy*, *22*(4), 301–312. https://doi.org/10.1016/j.landusepol.2004.05.004

Ferraro, P. J., Hanauer, M. M., Miteva, D. A., Nelson, J. L., Pattanayak, S. K., Nolte, C., & Sims, K. R. (2015). Estimating the impacts of conservation on ecosystem services and poverty by integrating modeling and evaluation. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(24). https://doi.org/10.1073/pnas.1406487112

Gauvin, C., Uchida, E., Rozelle, S., Xu, J., & Zhan, J. (2010). Cost-effectiveness of payments for ecosystem services with dual goals of environment and poverty alleviation. *Environmental Management*, *45*(3). https://doi.org/10.1007/s00267-009-9321-9

Giefer, M. M., & An, L. (2022). Divergent impacts of the grain to green program, landholdings, and demographic factors on livelihood diversification in rural China. *World Development*, *156*, 105917. https://doi.org/10.1016/J.WORLDDEV.2022.105917

He, W., Di, B., Zeng, Y., Duan, Y., Li, J., Qiu, L., Balikuddembe, J. K., Peng, Q., Zeng, W., Stamatopoulos, C. A., Luo, B., & Pan, J. (2023). Reconsidering the eco-economic benefits of Grain for Green Program in Sichuan Province, China. *Ecological Indicators*, *157*. https://doi.org/10.1016/j.ecolind.2023.111225

Heerink, N., Mulatu, A., & Bulte, E. (2001). Income inequality and the environment: Aggregation bias in environmental Kuznets curves. *Ecological Economics*, *38*(3). https://doi.org/10.1016/S0921-8009(01)00171-9

Hu, X. [Xiaoqian], Li, Z., Chen, J., Nie, X., Liu, J., Wang, L., & Ning, K. (2021). Carbon sequestration benefits of the grain for Green Program in the hilly red soil region of southern China. *International Soil and Water Conservation Research*, *9*(2). https://doi.org/10.1016/j.iswcr.2020.11.005

Hu, X. [Xujun], Zhang, H., Hao, H., Feng, D., Liu, H., & Zhang, Q. (2020). Understanding the relationships between poverty alleviation and ecosystem conservation: empirical evidence from western China. *Frontiers of Earth Science*, *14*(1), 209–220. https://doi.org/10.1007/S11707-019-0764-X/METRICS

Hua, F., Wang, X., Zheng, X., Fisher, B., Wang, L., Zhu, J., Tang, Y., Yu, D. W., & Wilcove, D. S. (2016). Opportunities for biodiversity gains under the world's largest reforestation programme. *Nature Communications*, *7*. https://doi.org/10.1038/ncomms12717

Huang, L., Wang, B., Niu, X., Gao, P., Song, Q., & Bing Wang, C. (2019). Changes in ecosystem services and an analysis of driving factors for China's Natural Forest Conservation Program. https://doi.org/10.1002/ece3.4925

Hubacek, K., Baiocchi, G., Feng, K., & Patwardhan, A. (2017). Poverty eradication in a carbon constrained world. *Nature Communications 2017 8:1*, *8*(1), 1–9. https://doi.org/10.1038/S41467-017-00919-4

Imbens, G. W., & Angrist, J. D. (1994). Identification and Estimation of Local Average Treatment Effects. *Econometrica*, *62*(2), 467–475.

IPCC. (2021). IPCC: Summary for Policymakers. *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*.

Jayachandran, S. (2023). The inherent trade-off between the environmental and anti-poverty goals of payments for ecosystem services. *Environmental Research Letters*, *18*(2). https://doi.org/10.1088/1748-9326/acb1a7

Jin, B., & Wang, H. (2024). A Systematic Review of Empirical Research on Payment of Ecosystem Services and Farm Household Income in China. *SAGE Open*, *14*(4). https://doi.org/10.1177/21582440241301426/ASSET/IMAGES/LARGE/10.1177{_}21582440241301426-FIG5.JPEG

Kinnan, C., Wang, S. Y., & Wang, Y. [Yongxiang]. (2018). Access to migration for rural households. *American Economic Journal: Applied Economics*, *10*(4). https://doi.org/10.1257/app.20160395

König, H. J., Zhen, L., Helming, K., Uthes, S., Yang, L., Cao, X., & Wiggering, H. (2014). Assessing the impact of the sloping land conversion programme on rural sustainability in Guyuan, Western China. *Land Degradation and Development*, *25*(4). https://doi.org/10.1002/ldr.2164

Kumarasiri, A. D. T. N., Udayakumara, E. P. N., & Jayawardana, J. M. C. K. (2022). Impacts of soil erosion and forest quality on water quality in Samanalawewa watershed, Sri Lanka. *Modeling Earth Systems and Environment*, *8*(1). https://doi.org/10.1007/s40808-021-01082-y

Lehmann, I., Martin, A., & Fisher, J. A. (2018). Why Should Ecosystem Services Be Governed to Support Poverty Alleviation? Philosophical Perspectives on Positions in the Empirical Literature. https://doi.org/10.1016/j.ecolecon.2018.03.003

Lei, Q., Qi, C., Ye, C., & Fang, G. (2023). Health shock, the Green for Grain Program and medical expenses: Empirical Evidence on the well-being of Chinese Farmers. *Economic Analysis and Policy*, *78*, 406–418. https://doi.org/10.1016/j.eap.2023.03.015

Leichenko, R., & Silva, J. A. (2014). Climate change and poverty: Vulnerability, impacts, and alleviation strategies. *Wiley Interdisciplinary Reviews: Climate Change*, *5*(4). https://doi.org/10.1002/wcc.287

Li, H. [Han], Xu, F., Li, Z., You, N., Zhou, H., Zhou, Y., Chen, B., Qin, Y., Xiao, X., & Dong, J. (2021). Forest Changes by Precipitation Zones in Northern China after the Three-North Shelterbelt Forest Program in China. *Remote Sensing*, *13*(4), 543. https://doi.org/10.3390/rs13040543

Li, H. [Hua], Yao, S., Yin, R., & Liu, G. (2015). Assessing the decadal impact of China's sloping land conversion program on household income under enrollment and earning differentiation. *Forest Policy and Economics*, *61*, 95–103. https://doi.org/10.1016/J.FORPOL.2015.07.008

Li, J., Feldman, M. W., Li, S., & Daily, G. C. (2011). Rural household income and inequality under the sloping land conversion program in Western China. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(19). https://doi.org/10.1073/pnas.1101018108

Li, L. [Lingchao], Liu, C., Liu, J., & Cheng, B. (2021). Has the Sloping Land Conversion Program in China impacted the income and employment of rural households? *Land Use Policy*, *109*, 105648. https://doi.org/10.1016/J.LANDUSEPOL.2021.105648

Li, L. [Lingyan], Xia, H., Chen, Z., Duan, M., & Pei, J. (2024). Spatiotemporal characteristics and driving mechanisms of household energy transition in rural China: Micro-evidence from 2005 to 2017. *Science of the Total Environment*, *909*. https://doi.org/10.1016/j.scitotenv.2023.168554

Li, Q., Amjath Babu, T. S., Sieber, S., & Zander, P. (2018). Assessing divergent consequences of payments for ecosystem services on rural livelihoods: A case-study in China's Loess Hills. *Land Degradation and Development*, *29*(10). https://doi.org/10.1002/ldr.3082

Liang, Y., Li, S., Feldman, M. W., & Daily, G. C. (2012). Does household composition matter? The impact of the Grain for Green Program on rural livelihoods in China. *Ecological Economics*, *75*. https://doi.org/10.1016/j.ecolecon.2012.01.019

Lin, Y., & Yao, S. (2014). Impact of the Sloping Land Conversion Program on rural household income: An integrated estimation. *Land Use Policy*, *40*, 56–63. https://doi.org/10.1016/J.LANDUSEPOL.2013.09.005

Liu, J., & Raven, P. H. (2010). China's Environmental Challenges and Implications for the World. *Critical Reviews in Environmental Science and Technology*, *40*, 823–851. https://doi.org/10.1080/10643389.2010.502645

Liu, X., Yin, Z.-Y., Zhang, X., & Yang, X. (2004). Analyses of the spring dust storm frequency of northern China in relation to antecedent and concurrent wind, precipitation, vegetation, and soil moisture conditions. https://doi.org/10.1029/2004JD004615

Liu, Z., & Henningsen, A. (2016). The effects of China's Sloping Land Conversion Program on agricultural households. *Agricultural Economics*, *47*(3), 295–307. https://doi.org/10.1111/AGEC.12230

Lopez, N. (2024). Copernicus: 2023 is the hottest year on record, with global temperatures close to the 1.5°C limit. *Copernicus*.

Lu, G., & Yin, R. (2020). Evaluating the Evaluated Socioeconomic Impacts of China's Sloping Land Conversion Program. *Ecological Economics*, *177*, 106785. https://doi.org/10.1016/J.ECOLECON.2020.106785

Macias-Fauria, M. (2018). Satellite images show China going green. *Nature*, *553*(7689), 411–413. https://doi.org/10.1038/d41586-018-00996-5

Malerba, D. (2020). Poverty alleviation and local environmental degradation: An empirical analysis in Colombia. *World Development*, *127*, 104776. https://doi.org/10.1016/J.WORLDDEV.2019.104776

Nations, U. (2015). *Transforming our world: the 2030 Agenda for Sustainable Development* (tech. rep.).

Newmark, W. D., Jenkins, C. N., Pimm, S. L., McNeally, P. B., & Halley, J. M. (2017). Targeted habitat restoration can reduce extinction rates in fragmented forests. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(36), 9635–9640. https://doi.org/10.1073/pnas.1705834114

NOAA. (2024). 2023 was the world's warmest year on record, by far.

Nordhaus, W. D. (2017). Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(7). https://doi.org/10.1073/pnas.1609244114

Orth, J. (2007). The Shelterbelt Project: Cooperative Conservation in 1930s America. *81*(3), 333–357. https://www.jstor.org/stable/20454725?seq=1&cid=pdf-

Pan, Y., Birdsey, R. A., Fang, J., Houghton, R., Kauppi, P. E., Kurz, W. A., Phillips, O. L., Shvidenko, A., Lewis, S. L., Canadell, J. G., Ciais, P., Jackson, R. B., Pacala, S. W., McGuire, A. D., Piao, S., Rautiainen, A., Sitch, S., & Hayes,

D. (2011). A large and persistent carbon sink in the world's forests. *Science*, *333*(6045). https://doi.org/10.1126/science.1201609

Peng, H., Cheng, G., Xu, Z., Yin, Y., & Xu, W. (2007). Social, economic, and ecological impacts of the "Grain for Green" project in China: A preliminary case in Zhangye, Northwest China. *Journal of Environmental Management*, *85*(3). https://doi.org/10.1016/j.jenvman.2006.09.015

Peng, J., Lü, H., Qiao, R., Yu, S., Xu, Z., & Wu, J. (2022). Farm households' willingness to participate in China's Grain-for-Green Program under different compensation scenarios. *Ecological Indicators*, *139*. https://doi.org/10.1016/j.ecolind.2022.108890

Peng, S. S., Piao, S., Zeng, Z., Ciais, P., Zhou, L., Li, L. Z. X., Myneni, R. B., Yin, Y., & Zeng, H. (2014). Afforestation in China cools local land surface temperature. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(8), 2915–2919. https://doi.org/10.1073/pnas.1315126111

Penman, J., Gytarsky, M., Hiraishi, T., Irving, W., & Krug, T. (2006). *2006 IPCC - Guidelines for National Greenhouse Gas Inventories*.

Plantinga, A. J., & Wu, J. (2003). Co-benefits from Carbon Sequestration in Forests: Evaluating Reductions in Agricultural Externalities from an Afforestation Policy in Wisconsin. *Land Economics*, *79*(1), 74–85. http://login.ezproxy.lib.umn.edu/login?url=https://www.proquest.com/scholarly-journals/co-benefits-carbon-sequestration-forests/docview/56162331/se-2?accountid=14586%20http://primo.lib.umn.edu/openurl/TWINCITIES/TWINCITIES_SP?url_ver=Z39.88-2004&rft_val_fmt=info:ofi/fmt:kev:mtx:journal&genre=article&sid=ProQ:ProQ%3Aeconlit&atitle=Co-benefits+from+Carbon+Sequestration+in+Forests%3A+Evaluating+Reductions+in+Agricultural+Externalities+from+an+Afforestation+Policy+in+Wisconsin&title=Land+Economics&issn=00237639&date=2003-02-01&volume=79&issue=1&spage=74&au=Plantinga%2C+Andrew+J%3BWu%2C+JunJie&isbn=&jtitle=Land+Economics&btitle=&rft_id=info:eric/0643026&rft_id=info:doi/

Ramage, M. H., Burridge, H., Busse-Wicher, M., Fereday, G., Reynolds, T., Shah, D. U., Wu, G., Yu, L., Fleming, P., Densley-Tingley, D., Allwood, J., Dupree, P., Linden, P. F., & Scherman, O. (2017). The wood from the trees: The use of timber in construction. *Renewable and Sustainable Energy Reviews*, *68*, 333–359. https://doi.org/10.1016/J.RSER.2016.09.107

Ran, R., Ni, Z., Hua, L., & Li, T. (2022). Does China's poverty alleviation policy improve the quality of the ecological environment in poverty-stricken areas? *Frontiers in Environmental Science*, *10*. https://doi.org/10.3389/fenvs.2022.1067339

Rennert, K., Errickson, F., Prest, B. C., Rennels, L., Newell, R. G., Pizer, W., Kingdon, C., Wingenroth, J., Cooke, R., Parthum, B., Smith, D., Cromar, K., Diaz, D., Moore, F. C., Müller, U. K., Plevin, R. J., Raftery, A. E., Ševčíková, H., Sheets, H., . . . Anthoff, D. (2022). Comprehensive evidence implies a higher social cost of CO2. *Nature*, *610*(7933). https://doi.org/10.1038/s41586-022-05224-9

Ricke, K., Drouet, L., Caldeira, K., & Tavoni, M. (2018). Country-level social cost of carbon. *Nature Climate Change*, *8*(10). https://doi.org/10.1038/s41558-018-0282-y

Sachs, J. D., Schmidt-Traub, G., Mazzucato, M., Messner, D., Nakicenovic, N., & Rockström, J. (2019). Six Transformations to achieve the Sustainable Development Goals. *Nature Sustainability*, *2*(9). https://doi.org/10.1038/s41893-019-0352-9

Seymour, F. (2020). Seeing the Forests as well as the (Trillion) Trees in Corporate Climate Strategies. *One Earth*, *2*(5), 390–393. https://doi.org/10.1016/j.oneear.2020.05.006

Shan, N., Shi, Z., Yang, X., Gao, J., & Cai, D. (2015). Spatiotemporal trends of reference evapotranspiration and its driving factors in the Beijing–Tianjin Sand Source Control Project Region, China. *Agricultural and Forest Meteorology*, *200*, 322–333. https://doi.org/10.1016/J.AGRFORMET.2014.10.008

Sharp, R., Tallis, H. T., Ricketts, T., Guerry, A. D., Wood, S. A., Chaplin-Kramer, R., Nelson, E., Ennaanay, D., Wolny, S., Olwero, N., et al. (2014). InVEST user's guide. *The Natural Capital Project, Stanford*.

Sheng, J., Qiu, H., & Zhang, S. (2019). Opportunity cost, income structure, and energy structure for landholders participating in payments for ecosystem services: Evidence from Wolong National Nature Reserve, China. *World Development*, *117*. https://doi.org/10.1016/j.worlddev.2019.01.016

Song, C., Zhang, Y., Mei, Y., Liu, H., Zhang, Z., Zhang, Q., Zha, T., Zhang, K., Huang, C., Xu, X., Jagger, P., Chen, X., & Bilsborrow, R. (2014). Sustainability of Forests Created by China's Sloping Land Conversion Program: A comparison among three sites in Anhui, Hubei and Shanxi. *Forest Policy and Economics*, *38*, 161–167. https://doi.org/10.1016/j.forpol.2013.08.012

Song, X., Peng, C., Zhou, G., Jiang, H., & Wang, W. (2014). Chinese Grain for Green Program led to highly increased soil organic carbon levels: A meta-analysis. *Scientific Reports 2014 4:1*, *4*(1), 1–7. https://doi.org/10.1038/SREP04460

Tiemann, A., & Ring, I. (2022). Towards ecosystem service assessment: Developing biophysical indicators for forest ecosystem services. *Ecological Indicators*, *137*. https://doi.org/10.1016/j.ecolind.2022.108704

Treacy, P., Jagger, P., Song, C., Zhang, Q., & Bilsborrow, R. E. (2018). Impacts of China's Grain for Green Program on Migration and Household Income. *Environmental Management*, *62*(3). https://doi.org/10.1007/s00267-018-1047-0

Uchida, E., Rozelle, S., & Xu, J. [Jintao]. (2009). Conservation payments, liquidity constraints, and off-farm labor: Impact of the grain-for-green program on rural households in China. *American Journal of Agricultural Economics*, *91*(1). https://doi.org/10.1111/j.1467-8276.2008.01184.x

Uchida, E., Xu, J. [Jintao], & Rozelle, S. (2005). Grain for green: Cost-effectiveness and sustainability of China's conservation set-aside program. *Land Economics*, *81*(2). https://doi.org/10.3368/le.81.2.247

Uchida, E., Xu, J. [Jintao], Xu, Z., & Rozelle, S. (2007). Are the poor benefiting from China's land conservation program? *Environment and Development Economics*, *12*(4). https://doi.org/10.1017/S1355770X07003713

United Nations. (2015). Transforming Our World: the 2030 Agenda for Sustainable Development United Nations United Nations Transforming Our World: the 2030 Agenda for Sustainable Development. *United Nations*.

United Nations. (2023). *Eradicating rural poverty to implement the 2030 Agenda for Sustainable Development Report of the Secretary-General* (tech. rep.).

Vietnam's MARD. (2021). Approved the project "Planting one billion trees in the period of 2021 - 2025". https://www.mard.gov.vn/en/Pages/approved-the-project-planting-one-billion-trees-in-the-period-of-2021--2025-.aspx

Wang, C., Ouyang, H., Maclaren, V., Yin, Y., Shao, B., Boland, A., & Tian, Y. (2007). Evaluation of the economic and environmental impact of converting cropland to forest: A case study in Dunhua county, China. *Journal of Environmental Management*, *85*(3). https://doi.org/10.1016/j.jenvman.2006.04.025

Wang, C. [Chengchao], Pang, W., & Hong, J. (2017). Impact of a regional payment for ecosystem service program on the livelihoods of different rural households. *Journal of Cleaner Production*, *164*, 1058–1067. https://doi.org/10.1016/j.jclepro.2017.07.002

Wang, C. [Chunmei], & Maclaren, V. (2012). Evaluation of economic and social impacts of the sloping land conversion program: A case study in Dunhua County, China. *Forest Policy and Economics*, *14*(1), 50–57. https://doi.org/10.1016/j.forpol.2011.06.002

Wang, X. M., Zhang, C. X., Hasi, E., & Dong, Z. B. (2010). Has the Three Norths Forest Shelterbelt Program solved the desertification and dust storm problems in arid and semiarid China? *Journal of Arid Environments*, *74*(1), 13–22. https://doi.org/10.1016/J.JARIDENV.2009.08.001

Wang, Y. [Ying], Zhang, Q., Li, Q., Wang, J., Sannigrahi, S., Bilsborrow, R., Bellingrath-Kimura, S. D., Li, J., & Song, C. (2021). Role of social networks in building household livelihood resilience under payments for ecosystem services programs in a poor rural community in China. *Journal of Rural Studies*, *86*. https://doi.org/10.1016/j.jrurstud.2021.05.017

WMO. (2024). State of the Global Climate 2023. https://wmo.int/publication-series/state-of-global-climate-2023

World Bank. (2020). Reversals of Fortune (Poverty and Shared Prosperity 2020). *The World Bank-Washington DC-USA*, (March).

World Bank. (2022). *Four decades of poverty reduction in China: Drivers, insights for the world, and the way ahead*. https://elibrary.worldbank.org/doi/abs/10.1596/978-1-4648-1877-6

World Bank. (2024). *Pathways Out of the Polycrisis* (tech. rep.).

Wu, L., & Jin, L. (2020). How eco-compensation contribute to poverty reduction: A perspective from different income group of rural households in Guizhou, China. *Journal of Cleaner Production*, *275*. https://doi.org/10.1016/j.jclepro.2020.122962

Wu, X., Wang, S., & Fu, B. (2021). Multilevel analysis of factors affecting participants' land reconversion willingness after the Grain for Green Program. *Ambio*, *50*(7). https://doi.org/10.1007/s13280-020-01475-w

Wu, X., Wang, S., Fu, B., Feng, X., & Chen, Y. (2019). Socio-ecological changes on the Loess Plateau of China after Grain to Green Program. *Science of the Total Environment*, *678*. https://doi.org/10.1016/j.scitotenv.2019.05.022

Wu, X., Wang, S., Fu, B., Zhao, Y., & Wei, Y. (2019). Pathways from payments for ecosystem services program to socioeconomic outcomes. *Ecosystem Services*, *39*. https://doi.org/10.1016/j.ecoser.2019.101005

Wu, Z., Dai, X., Li, B., & Hou, Y. (2021). Livelihood consequences of the Grain for Green Programme across regional and household scales: A case study in the Loess Plateau. *Land Use Policy*, *111*. https://doi.org/10.1016/j.landusepol.2021.105746

Wunder, S. (2001). Poverty alleviation and tropical forests-what scope for synergies? *World Development*, *29*(11). https://doi.org/10.1016/S0305-750X(01)00070-5

Xi, Y., Peng, S., Liu, G., Ducharne, A., Ciais, P., Prigent, C., Li, X., & Tang, X. (2022). Trade-off between tree planting and wetland conservation in China. *Nature Communications*, *13*(1), 1967. https://doi.org/10.1038/s41467-022-29616-7

Xu, J. [Jintao], Tao, R., Xu, Z., & Bennett, M. T. (2010). *China's Sloping Land Conversion Program: Does Expansion Equal Success?* (Tech. rep. No. 2). https://www.jstor.org/stable/27821421

Xu, Z., Xu, J., Deng, X., Huang, J., Uchida, E., & Rozelle, S. (2006). Grain for Green versus grain: Conflict between food security and conservation set-aside in China. *World Development*, *34*(1). https://doi.org/10.1016/j.worlddev.2005.08.002

Yan, Y. (2019). Unintended Land Use Effects of Afforestation in China's Grain for Green Program. *American Journal of Agricultural Economics*, *101*(4), 1047–1067. https://doi.org/10.1093/ajae/aay107

Yang, Jiang, L., Chao, Y., Li, Y., & Liu, P. (2021). Geo-Information Influence of Relief Degree of Land Surface on Street Network Complexity in China. https://doi.org/10.3390/ijgi10100705

Yang, W., Liu, W., Viña, A., Luo, J., He, G., Ouyang, Z., Zhang, H., & Liu, J. (2013). Performance and prospects of payments for ecosystem services programs: Evidence from China. *Journal of Environmental Management*, *127*, 86–95. https://doi.org/10.1016/J.JENVMAN.2013.04.019

Yang, Y. [Yu], Wu, F., Zhang, Q., Hong, J., & Dong, C. (2020). Is It Sustainable to Implement a Regional Payment for Ecosystem Service Programme for 10 Years? An Empirical Analysis From the Perspective of Household Livelihoods. *Ecological Economics*, *176*, 106746. https://doi.org/10.1016/J.ECOLECON.2020.106746

Yao, S., Guo, Y., & Huo, X. (2010). An empirical analysis of the effects of china's land conversion program on farmers' income growth and labor transfer. *Environmental Management*, *45*(3). https://doi.org/10.1007/s00267-009-9376-7

Yin, R., Liu, C., Zhao, M., Yao, S., & Liu, H. (2014). The implementation and impacts of China's largest payment for ecosystem services program as revealed by longitudinal household data. *Land Use Policy*, *40*, 45–55. https://doi.org/10.1016/J.LANDUSEPOL.2014.03.002

Yin, R., Liu, H., Liu, C., & Lu, G. (2018). Households' Decisions to Participate in China's Sloping Land Conversion Program and Reallocate Their Labour Times: Is There Endogeneity Bias? *Ecological Economics*, *145*, 380–390. https://doi.org/10.1016/J.ECOLECON.2017.11.020

Yirenkyi-Boateng, S. (2001). Rural afforestation programmes for sustainable rural development: how realist conceptualisation can help. *Development Southern Africa*, *18*(3). https://doi.org/10.1080/03768350120070000

You, Z., Feng, Z., & Yang, Y. [Yanzhao]. (2018). Relief Degree of Land Surface Dataset of China (1km). *Digital Journal of Global Change Data Repository*. https://doi.org/10.3974/geodb.2018.03.16.V1

Yu, Z., Ciais, P., Piao, S., Houghton, R. A., Lu, C., Tian, H., Agathokleous, E., Kattel, G. R., Sitch, S., Goll, D., Yue, X., Walker, A., Friedlingstein, P., Jain, A. K., Liu, S., & Zhou, G. (2022). Forest expansion dominates China's land carbon sink since 1980. *Nature Communications*, *13*(1). https://doi.org/10.1038/s41467-022-32961-2

Zeng, Y., Ran, L., Fang, N., Wang, Z., Xu, Z., Lu, X., Yu, Q., Wang, L., Yu, S., & Shi, Z. (2022). How to Balance Green and Grain in Marginal Mountainous Areas? *Earth's Future*, *10*(5). https://doi.org/10.1029/2021EF002552

Zhang, Y., Peng, C., Li, W., Tian, L., Zhu, Q., Chen, H., Fang, X., Zhang, G., Liu, G., Mu, X., Li, Z., Li, S., Yang, Y., Wang, J., & Xiao, X. (2015). Multiple afforestation programs accelerate the greenness in the 'Three North' region of China from 1982 to 2013. *Ecological Indicators*, *61*, 404–412. https://doi.org/10.1016/j.ecolind.2015.09.041

Zhao, H., Wu, R., Yang, F., Hu, J., Wang, J., Guo, Y., Feng, Z., Zhang, C., Wang, Y., & Zhou, J. (2022). Spatiotemporal patterns of vegetation conversion under the Grain for Green Program in southwest China. *Conservation Science and Practice*, *4*(2). https://doi.org/10.1111/csp2.604

Zhen, N., Fu, B., Lü, Y., & Zheng, Z. (2014). Changes of livelihood due to land use shifts: A case study of Yanchang County in the Loess Plateau of China. *Land Use Policy*, *40*. https://doi.org/10.1016/j.landusepol.2013.05.004

Zheng, H., Robinson, B. E., Liang, Y. C., Polasky, S., Ma, D. C., Wang, F. C., Ruckelshaus, M., Ouyang, Z. Y., & Daily, G. C. (2013). Benefits, costs, and livelihood implications of a regional payment for ecosystem service program. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(41). https://doi.org/10.1073/pnas.1312324110

Zilberman, D., Lipper, L., & McCarthy, N. (2009). *Putting payments for environmental services in the context of economic development* (tech. rep.).

Zilberman, D., Lipper, L., & Mccarthy, N. (2008). When could payments for environmental services benefit the poor? *Environment and Development Economics*, *13*(3), 255–278. https://doi.org/10.1017/S1355770X08004294

Zinda, J. A., & Zhang, Z. (2019). Explaining heterogeneous afforestation outcomes: How community officials and households mediate tree cover change in China. *World Development*, *122*, 385–398. https://doi.org/10.1016/j.worlddev.2019.05.020

Appendix A

Appendix

A.1 Supplemental Material: Essey 1

Table A-1: Poverty Alleviation Funds (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

Notes: This table presents major poverty alleviation programs and expenditures (in billion USD) from the Chinese Central Government and Provincial Special Fund (2011–2020). USD values are converted from RMB using the exchange rate of 6.5250 RMB/USD as of December 31, 2020 (Federal Reserve Bank of St. Louis).
Source: China Rural Poverty Monitoring Reports (2011-2021).

TABLE A-2: DESCRIPTIVE STATISTICS (LAND USE CHANGE: PART 1)

Variable	Treatment Mean	SD	Contrl Group 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-3: DESCRIPTIVE STATISTICS (LAND USE CHANGE: PART 2)

Variable	Treatment Mean	SD	Contrl Group 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-4: 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	Western Yunnan Border	Wuling Mountain Area	Wumeng Mountain Area	Yanshan -Taihang Mountain	Control Group
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 (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
RDLS	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
Avg. 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
Avg. Annual Precipitation (mm)	1053.92	1276.17	545.82	1562.46	874.15	551.49	1079.88	13112	1063.95	568.15	993.32
Avg. 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

A.2 Supplemental Material: Essey 2

TABLE A-5: EXOGENOUS CHECK ON INSTRUMENTAL VARIABLE

Dependent Variables:	Log GDP (Primary) (1)	Log GDP (Secondary) (2)
Precipitation in t-1 year	-0.000009	-0.000007
	(0.000)	(0.000)
Population	0.002612***	0.005404***
	(0.001)	(0.001)
K-12 Students per Capita	-1.035643***	-0.979732***
	(0.111)	(0.233)
Loan Balance per Capita	-0.000001***	0.000002***
	(0.000)	(0.000)
Agriculture Machine Power per Capita	0.061116***	0.060486***
	(0.006)	(0.013)
Hospital beds per Capita	1.088285	2.613476
	(2.575)	(5.409)
Relief degree of land surface	-0.087804	-0.799155**
	(0.158)	(0.333)
Precipitation in t year	0.000084**	0.000078
	(0.000)	(0.000)
Land surface wind speed	-0.056083***	-0.002117
	(0.014)	(0.030)
Constant	11.350063***	12.092686***
	(0.097)	(0.203)
Controls	YES	YES
Observations	7,211	7,217
R-squared	0.965	0.919
County FE	YES	YES
Year FE	YES	YES

*Notes:*The table presented below displays the results of the exogenous check conducted on the instrumental variable employed in the study, namely the precipitation in the previous year. The dependent variables in this analysis are the measures of local economic development, specifically the Gross Domestic Product (GDP) from the primary and secondary sectors within a county. The regression models include additional control variables to account for potential confounding factors. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A-6: Large-scale tree planting:First Stage OLS Estimates

Dependent Variables:	Forestation area (sq.km)		Forestation area (% of land area)		Forestation area (mu) per Capita	
	(1)	(2)	(3)	(4)	(5)	(6)
Precipitation in t-1 year	0.029***	0.022***	0.0007***	0.0007***	0.00004***	0.00003**
	(0.006)	(0.006)	(0.0002)	(0.0002)	(0.00001)	(0.00001)
Population	-0.142	0.037	-0.0009	-0.0099***	-0.00044**	-0.00121***
	(0.094)	(0.033)	(0.0032)	(0.0011)	(0.00022)	(0.00008)
K-12 Students per Capita	-21.684	-13.969	0.9819*	1.8418***	0.00053	-0.17137***
	(16.841)	(15.834)	(0.5792)	(0.5200)	(0.03924)	(0.03672)
Loan Balance per Capita	0.000**	0.000	0.0000	0.0000	0.00000	-0.00000***
	(0.000)	(0.000)	(0.0000)	(0.0000)	(0.00000)	(0.00000)
Power of Ag. Machinery per Capita	-1.268	4.481***	-0.0616*	-0.1481***	0.00298	0.00814***
	(0.973)	(0.778)	(0.0335)	(0.0256)	(0.00227)	(0.00181)
Hospital beds per Capita	-667.098*	-2,834.836***	-1.1886	-5.4743	-3.70397***	-2.33438***
	(396.640)	(301.444)	(13.6412)	(9.8996)	(0.92411)	(0.69897)
Relief degree of land surface	101.243***	-1.927**	-0.7007	-0.1661***	0.06512	-0.00366
	(23.109)	(0.963)	(0.7948)	(0.0316)	(0.05384)	(0.00223)
Precipitation	0.015**	0.008	0.0004*	0.0004**	0.00002	0.00001
	(0.006)	(0.006)	(0.0002)	(0.0002)	(0.00001)	(0.00001)
Land surface wind speed	3.836*	-1.378	-0.1085	0.0848*	0.00008	0.00290
	(2.263)	(1.486)	(0.0778)	(0.0488)	(0.00527)	(0.00345)
Constant	26.483*	45.283***	2.2860***	2.4813***	0.05989*	0.16977***
	(14.325)	(11.247)	(0.4927)	(0.3694)	(0.03338)	(0.02608)
Observations	6,599	6,599	6,597	6,597	6,599	6,599
R-squared	0.567	0.380	0.583	0.455	0.568	0.388
County FE	YES	No	YES	No	YES	No
Prefecture FE	No	YES	No	YES	No	YES
Year FE	YES	YES	YES	YES	YES	YES

*Notes:*This table presents first-stage OLS estimates of the instrument variable used in the study, the precipitation in the previous year. The dependent variables are three measures of tree planting activities including the annual forestation area (sq.km),annual forestation area (% of land area) and annual forestation area (mu) per Capita in a county. Odd columns are with county fixed effects, and even columns are with prefecture-level city fixed effects. The prefecture-level city is a bigger division than a county in China; a prefecture-level city usually consists of several counties. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A-7: Economic Effect of Forestation area (sq.km) on GDP from the primary and secondary sectors

Dependent Variables:	Log GDP from the Primary Sector				Log GDP from the Secondary Sector			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Forestation area (sq.km)	-0.00003	0.00038**	-0.00057	-0.00859**	-0.00022	0.00048	-0.00035	-0.03658***
	(0.000)	(0.000)	(0.001)	(0.004)	(0.000)	(0.000)	(0.003)	(0.012)
Population	0.00224***	0.02834***	0.00216*	0.02865***	0.00336**	0.02926***	0.00334***	0.03049***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
K-12 Students per Capita	-1.01447***	-0.40432**	-1.02551***	-0.52508*	-0.72287***	1.82203***	-0.72546**	1.32423*
	(0.110)	(0.193)	(0.156)	(0.308)	(0.237)	(0.376)	(0.324)	(0.742)
Loan Balance per Capita	-0.00000***	-0.00000***	-0.00000***	-0.00000**	0.00000***	0.00001***	0.00000***	0.00001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Power of Ag. Machinery per Capita	0.06239***	0.23975***	0.06182***	0.28043***	0.05586***	-0.03882**	0.05573***	0.12840**
	(0.006)	(0.010)	(0.007)	(0.023)	(0.014)	(0.019)	(0.015)	(0.065)
Hospital beds per Capita	0.98610	-78.95253***	0.55657	-104.98634***	8.17911	79.00235***	8.07803	-28.35620
	(2.580)	(3.696)	(2.798)	(14.996)	(5.579)	(7.197)	(6.507)	(37.117)
Relief degree of land surface	0.00150	-0.12798***	-4.67548***	-0.14138***	-0.68653**	-0.03821*	-6.34363***	-0.09425***
	(0.148)	(0.012)	(0.435)	(0.020)	(0.320)	(0.023)	(0.352)	(0.034)
Precipitation	0.00005	-0.00014*	0.00006	-0.00007	0.00017**	-0.00070***	0.00017**	-0.00035
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Land surface wind speed	-0.05123***	-0.24930***	-0.04944***	-0.26457***	-0.01514	-0.15282***	-0.01473	-0.21646***
	(0.015)	(0.018)	(0.016)	(0.024)	(0.032)	(0.035)	(0.033)	(0.073)
Constant	11.48137***	10.04337***	15.01952***	11.38308***	12.35182***	9.84419***	16.91401***	12.41652***
	(0.090)	(0.132)	(0.478)	(0.359)	(0.195)	(0.257)	(0.340)	(0.586)
Observations	6,588	6,588	6,588	6,588	6,594	6,594	6,594	6,594
R-squared	0.968	0.842	0.968	0.756	0.924	0.692	0.924	0.512
County FE	YES	No	YES	No	YES	No	YES	No
Prefecture FE	No	YES	No	YES	No	YES	No	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
First-stage F			28.5224	14.1447			28.0664	13.7292

Notes: This table provides the OLS and IV regression estimates derived from the primary estimating equation, aiming to assess the direct impact of large-scale tree planting on the Gross Domestic Product (GDP) of both the primary and secondary sectors. The variable of interest in this analysis is the annual forestation area, measured in square kilometers, within a given county. County fixed effects are incorporated in the odd-numbered columns, while prefecture-level city fixed effects are introduced in the even-numbered columns. It is important to note that, within the Chinese administrative framework, a prefecture-level city represents a larger division encompassing multiple counties. See Tables A-8, A-7, A-9 for details.Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A-8: ECONOMIC EFFECT OF FORESTATION AREA (% OF LAND AREA) ON GDP FROM THE PRIMARY AND SECONDARY SECTORS

Dependent Variables:	Log GDP from the Primary Sector				Log GDP from the Secondary Sector			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Forestation area (% of land area)	-0.009***	-0.017***	-0.027	-0.293**	-0.014***	-0.031***	-0.015	-1.259***
	(0.002)	(0.005)	(0.055)	(0.138)	(0.005)	(0.009)	(0.121)	(0.442)
Population	0.002***	0.028***	0.002*	0.025***	0.003**	0.029***	0.003***	0.017***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.005)
K-12 Students per Capita	-1.006***	-0.376*	-0.987***	0.135	-0.705***	1.873***	-0.704**	4.149***
	(0.110)	(0.193)	(0.156)	(0.409)	(0.237)	(0.376)	(0.331)	(1.276)
Loan Balance per Capita	-0.000***	-0.000***	-0.000***	-0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Power of Ag. Machinery per Capita	0.062***	0.239***	0.061***	0.198***	0.055***	-0.041**	0.055***	-0.222***
	(0.006)	(0.010)	(0.008)	(0.025)	(0.014)	(0.019)	(0.016)	(0.071)
Hospital beds per Capita	0.967	-80.173***	0.894	-82.243***	8.282	77.393***	8.278	68.536***
	(2.576)	(3.668)	(2.641)	(7.251)	(5.575)	(7.142)	(6.250)	(15.723)
Relief degree of land surface	-0.011	-0.131***	-4.653***	-0.174***	-0.720**	-0.044*	-6.329***	-0.233***
	(0.148)	(0.012)	(0.427)	(0.029)	(0.320)	(0.023)	(0.304)	(0.075)
Precipitation	0.000	-0.000*	0.000	-0.000	0.000**	-0.001***	0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Land surface wind speed	-0.052***	-0.249***	-0.054***	-0.228***	-0.017	-0.151***	-0.018	-0.060
	(0.015)	(0.018)	(0.017)	(0.026)	(0.032)	(0.035)	(0.035)	(0.086)
Constant	11.504***	10.115***	15.002***	11.686***	12.380***	9.959***	16.901***	13.714***
	(0.090)	(0.133)	(0.468)	(0.427)	(0.195)	(0.258)	(0.280)	(0.983)
Observations	6,588	6,588	6,588	6,588	6,594	6,594	6,594	6,594
R-squared	0.969	0.842	0.968	0.755	0.924	0.692	0.924	0.581
County FE	YES	No	YES	No	YES	No	YES	No
Prefecture FE	No	YES	No	YES	No	YES	No	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
First-stage F			10.5221	10.4423			9.90779	9.91162

Notes: This table displays the results of OLS and IV regression analyses, focusing on the direct effect of large-scale tree planting on GDP from the primary and secondary sectors. The key independent variable of interest is the annual forestation area expressed as a percentage of land area. The odd-numbered columns present results with county fixed effects, while the even-numbered columns include prefecture-level city fixed effects. In China, prefecture-level cities are larger administrative divisions that typically encompass multiple counties. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A-9: Economic Effect of Forestation area (mu) per Capita on GDP from the primary and secondary sectors

Dependent Variables:	Log GDP from the Primary Sector				Log GDP from the Secondary Sector			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Forestation area (mu) per Capita	-0.01037*	-0.25159***	-0.07367	-1.73762***	-0.03015**	-0.25323***	-0.05262	-4.33138***
	(0.006)	(0.014)	(0.136)	(0.541)	(0.013)	(0.022)	(0.295)	(1.289)
K-12 Students per Capita	-1.05588***	-0.38226	-1.05146***	-2.03834**	-0.78066***	1.85059***	-0.77909**	-2.69238
	(0.109)	(0.250)	(0.156)	(0.829)	(0.236)	(0.411)	(0.321)	(1.780)
Loan Balance per Capita	-0.00000***	-0.00000***	-0.00000***	-0.00000***	0.00000***	0.00001***	0.00000***	-0.00000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Power of Ag. Machinery per Capita	0.05884***	0.12446***	0.06041***	0.25190***	0.05106***	-0.15753***	0.05162***	0.19173
	(0.006)	(0.012)	(0.008)	(0.061)	(0.014)	(0.020)	(0.016)	(0.146)
Hospital beds per Capita	0.15335	-109.23230***	-1.28887	-120.54897***	6.73575	47.50341***	6.22360	16.52989
	(2.579)	(4.724)	(4.067)	(12.731)	(5.574)	(7.756)	(8.910)	(23.864)
Relief degree of land surface	-0.15792	-0.28104***	-4.74616***	-0.24786***	-0.93516***	-0.19652***	-6.54642***	-0.10567**
	(0.142)	(0.015)	(0.447)	(0.026)	(0.306)	(0.024)	(0.401)	(0.046)
Precipitation	0.00005	-0.00037***	0.00006	-0.00019	0.00017**	-0.00093***	0.00017**	-0.00043
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Land surface wind speed	-0.05329***	-0.36070***	-0.05342***	-0.29109***	-0.01883	-0.26825***	-0.01889	-0.07732
	(0.015)	(0.023)	(0.016)	(0.044)	(0.032)	(0.038)	(0.032)	(0.103)
Constant	11.69643***	13.11087***	15.17908***	14.44531***	12.67152***	13.01489***	17.21703***	14.97275***
	(0.069)	(0.162)	(0.460)	(0.194)	(0.149)	(0.266)	(0.195)	(0.376)
Observations	6,588	6,588	6,588	6,588	6,594	6,594	6,594	6,594
R-squared	0.968	0.735	0.968	0.250	0.924	0.633	0.924	0.498
County FE	YES	No	YES	No	YES	No	YES	No
Prefecture FE	No	YES	No	YES	No	YES	No	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
First-stage F			21.931	12.4059			21.7520	12.2591

Notes: This table displays the results of OLS and IV regression estimates derived from the main estimating equation, examining the direct impact of large-scale tree planting on the Gross Domestic Product (GDP) within the primary and secondary sectors. The variable of interest in this analysis is the annual forestation area per capita, measured in mu, which is the standard unit of area used in China. It is important to note that 1 mu is equivalent to 1/15 hectare.The regression estimates presented in the table are organized in a panel format, with odd-numbered columns representing estimates with county fixed effects and even-numbered columns incorporating prefecture-level city fixed effects. In the Chinese administrative system, a prefecture-level city represents a larger division that typically encompasses several counties. This distinction is considered to capture the hierarchical administrative structure and provide a comprehensive analysis of the data. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A-10: Ecological Effect of Plantation Forest Area on Agricultural Production

	Log Agricultural Production				Log GDP	Log GDP
Dependent Variables:	Grain	Cotton	Oil Crops	Meat	(Primary)	(Secondary)
	(1)	(2)	(3)	(4)	(5)	(6)
Forestation area (% of land area) in t-6 year × 80%	0.014***	-0.059*	-0.001	-0.003	0.001	-0.004
	(0.005)	(0.031)	(0.016)	(0.006)	(0.003)	(0.006)
Population	0.002	-0.009	-0.006	0.006	0.009***	0.008***
	(0.002)	(0.021)	(0.014)	(0.005)	(0.001)	(0.002)
County Area (sq.km)	-0.000	-0.000	0.000	0.000	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gov. Expenditure per Capita	0.000	0.000	0.000	-0.000**	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
K-12 Students per Capita	-0.323	-3.727	-2.103	-0.819	-0.201	0.245
	(0.307)	(4.005)	(1.564)	(0.530)	(0.154)	(0.348)
Loan Balance per Capita	-0.000***	0.000	-0.000***	0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Power of Ag. Machinery per Capita	0.060***	0.596*	0.005	0.015	0.041***	0.062***
	(0.018)	(0.354)	(0.077)	(0.026)	(0.008)	(0.019)
Precipitation	0.000***	-0.002***	-0.000	0.000***	0.000***	0.000***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Land surface wind speed	-0.089***				-0.018	-0.089**
	(0.034)				(0.017)	(0.038)
Constant	11.699***	8.794***	8.570***	9.362***	10.659***	11.253***
	(0.123)	(1.388)	(0.607)	(0.206)	(0.068)	(0.152)
Observations	2,820	465	1,411	1,496	4,002	3,995
R-squared	0.147	0.112	0.030	0.147	0.666	0.424
Number of counties	442	145	419	435	443	443
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

*Notes:*This table displays the OLS regression estimates derived from the main estimating equation, aiming to examine the indirect effect of large-scale tree planting on agricultural production and sectoral Gross Domestic Product (GDP). The analysis includes various outputs such as grain, cotton, oil crops, and meat, as well as GDP from the primary and secondary sectors. The variable of interest in this study is the forestation expressed as a percentage of the total land area, specifically from t-6 years, multiplied by the average survival rate of planted trees. This measure serves as an indicator of mature plantation forests. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A-11: Ecological Effect of Plantation Forest Area on Agricultural Production

	Log Agricultural Production				Log	Log
Dependent Variables:	Grain	Cotton	Oil Crops	Meat	Primary	Secondary
	(1)	(2)	(3)	(4)	(5)	(6)
(Forestation Area (% of land area)$_{t-6}$ × 80%)						
× Hilly and Gully Area	0.008	-0.131	0.008	-0.009	-0.012***	-0.004
	(0.006)	(0.144)	(0.020)	(0.007)	(0.004)	(0.008)
× Plain Agricultural Area	0.050***	0.613**	-0.004	0.031**	0.036***	-0.016
	(0.012)	(0.275)	(0.039)	(0.013)	(0.007)	(0.016)
× Desert Area	-0.010	-0.112	-0.031	0.025	0.024***	0.020
	(0.014)	(0.470)	(0.067)	(0.023)	(0.008)	(0.018)
× Wind-blown Sand Area	0.007	-0.148	-0.042	-0.010	0.022***	-0.004
	(0.012)	(0.309)	(0.043)	(0.015)	(0.008)	(0.017)
Population	0.002	-0.022	-0.006	0.007	0.009***	0.008***
	(0.002)	(0.101)	(0.014)	(0.005)	(0.001)	(0.002)
K-12 Students per Capita	-0.075	-5.288	-2.149	-0.704	-0.069	0.205
	(0.310)	(11.044)	(1.570)	(0.531)	(0.157)	(0.352)
Loan Balance per Capita	-0.000***	0.000	-0.000***	0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Power of Ag. Machinery per Capita	0.060***	0.753	0.006	0.018	0.042***	0.063***
	(0.018)	(0.544)	(0.077)	(0.026)	(0.008)	(0.019)
Precipitation	0.000***	-0.003**	-0.000	0.000***	0.000***	0.000***
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Land surface wind speed	-0.091***				-0.019	-0.090**
	(0.034)				(0.017)	(0.038)
Gov. Expenditure per Capita		0.000	0.000	-0.000**	0.000***	0.000**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	11.673***	-13.927***	8.580***	9.353***	10.786***	11.351***
	(0.123)	(4.208)	(0.602)	(0.202)	(0.063)	(0.141)
Observations	2,820	1,497	1,412	1,497	4,003	3,996
R-squared	0.154	0.036	0.031	0.152	0.666	0.424
Number of cntyid	442	435	419	435	443	443
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

*Notes:*This table presents the OLS regression estimates from the main estimating equation of the indirect effect of large-scale tree planting on agricultural production, including grain,cotton, oil crops and meat outputs, and GDP by sector (primary and secondary sector) within different subregions. The variable of interest is the forestation (% of land area) in t-6 year times the average survival rate of planted trees as the measure of mature plantation forests. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A-12: Ecological Effect of Plantation Forest Area in t-3 to t-10 years on Grain Output

	Dependent Variables:Log Grain Output							
After	3 yrs	4 yrs	5 yrs	6 yrs	7 yrs	8 yrs	9 yrs	10 yrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Forestation area (% of land area)	0.005	0.010*	0.021***	0.014***	0.009**	0.015***	-0.006	0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
Population	0.001	0.001	0.001	0.002	-0.001	-0.000	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
County Area (sq.km)	-0.000*	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gov. Expenditure per Capita	0.000**	0.000	0.000	0.000	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
K-12 Students per Capita	-0.514*	-0.781***	-1.148***	-0.323	-0.402	-0.353	-0.319	0.611
	(0.267)	(0.267)	(0.283)	(0.307)	(0.280)	(0.316)	(0.361)	(0.499)
Loan Balance per Capita	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Power of Ag. Machinery per Capita	0.065***	0.061***	0.078***	0.060***	0.050***	0.041***	0.041***	0.080***
	(0.017)	(0.013)	(0.013)	(0.018)	(0.012)	(0.014)	(0.015)	(0.028)
Precipitation	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Land surface wind speed	-0.118***	-0.108***	-0.118***	-0.089***	-0.097***	-0.067*	-0.164***	-0.209***
	(0.033)	(0.035)	(0.036)	(0.034)	(0.033)	(0.036)	(0.040)	(0.045)
Constant	11.786***	11.866***	11.741***	11.699***	11.885***	12.011***	12.015***	11.814***
	(0.109)	(0.109)	(0.112)	(0.123)	(0.149)	(0.163)	(0.191)	(0.213)
Observations	4,042	3,637	3,227	2,820	2,423	2,001	1,613	1,309
R-squared	0.241	0.212	0.219	0.147	0.152	0.107	0.129	0.090
Number of counties	442	442	442	442	441	436	364	298
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table displays the OLS regression estimates derived from the main estimating equation, aiming to examine the indirect effect of large-scale tree planting on agricultural production and sectoral Gross Domestic Product (GDP). The analysis includes various outputs such as grain, cotton, oil crops, and meat, as well as GDP from the primary and secondary sectors. The variable of interest in this study is the forestation expressed as a percentage of the total land area, specifically from t-6 years, multiplied by the average survival rate of planted trees. This measure serves as an indicator of mature plantation forests. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.3 Supplemental Material: Essey 3

TABLE A-13: STUDIES SUMMARY OF THE GFG PROGRAM

Authors	**Increased Total Income**	**Increased Agricultural Income**	**Increased Off-Farm Income**
Uchida, Jintao Xu, and Rozelle (2005)	Yes	No	Yes
X. Chen et al. (2009)	Yes	No	Yes
Jintao Xu et al. (2010)	No	Yes	Yes
Yao, Guo, and Huo (2010)	Yes	Mixed	Yes
J. Li et al. (2011)	Yes	No	No
Chunmei Wang and Maclaren (2012)	No	No	No
W. Yang et al. (2013)	Yes	Yes	Yes
Lin and Yao (2014)	Yes	Yes	Yes
C. Song et al. (2014)	Yes	No	Yes
Yin, C. Liu, et al. (2014)	Yes	No	Yes
Zhen et al. (2014)	Yes	Yes	Yes
Duan, Lang, and Wen (2015)	Yes	Yes	Yes
Hua Li et al. (2015)	NA	No	Yes
Chengchao Wang, Pang, and Hong (2017)	Yes	No	Yes
Yin, H. Liu, et al. (2018)	Yes	Yes	Yes
Sheng, Qiu, and S. Zhang (2019)	NA	NA	Yes
X. Wu, S. Wang, Fu, Y. Zhao, and Wei (2019)	NA	No	Yes
Xujun Hu et al. (2020)	Yes	NA	NA
L. Wu and L. Jin (2020)	No	NA	NA
Yu Yang et al. (2020)	Yes	No	Yes
Lingchao Li et al. (2021)	No	No	Yes
X. Wu, S. Wang, and Fu (2021)	NA	No	Yes
Ying Wang et al. (2021)	No	No	Yes
J. Peng et al. (2022)	Yes	NA	NA

Notes: This table is adapted from B. Jin and H. Wang (2024).

Table A-14: Baseline Regression Results

	Log Total Income		Log Total Expenditure	
	(1)	(2)	(3)	(4)
GfG	0.077***	0.059***	0.069***	0.052***
	(0.015)	(0.013)	(0.016)	(0.014)
Household Size		0.133***		0.120***
		(0.008)		(0.007)
Year-end Cropland Area (mu)		0.011***		0.011***
		(0.002)		(0.002)
Number of Land Plots		0.009***		0.010***
		(0.001)		(0.001)
Productive Fixed Assets (RMB)		0.000***		0.000***
		(0.000)		(0.000)
Fertilizer Purchased (kg)		0.000*		0.000*
		(0.000)		(0.000)
Agricultural Diesel Purchased (kg)		0.000		0.000
		(0.000)		(0.000)
Pesticides Purchased (kg)		0.000***		0.000*
		(0.000)		(0.000)
Age of Household Head		-0.005***		-0.005***
		(0.000)		(0.000)
Squared Age of Household Head		0.000***		0.000***
		(0.000)		(0.000)
Gender of Household Head		-0.010		-0.010
		(0.009)		(0.008)
Years of Education of Household Head		0.018***		0.018***
		(0.006)		(0.007)
Mean(Y)	47,338	47,338	35,266	35,266
Observations	38,297	38,297	38,297	38,297
R-squared	0.355	0.528	0.344	0.491
Year-Village FEs	✓	✓	✓	✓
Household Type FEs		✓		✓
Controls		✓		✓

Notes: This table presents baseline regression estimates of the impact of GfG participation on log-transformed household income and expenditure. All dependent variables are log-transformed to allow for interpretation in percentage terms. Standard errors are reported in parentheses and clustered at the village level. Statistical significance is denoted as follows:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A-15: GfG Program Effects on Land Use Change

	Log Forest Area		Log Orchard Area		Log Pasture Area	
	(1)	(2)	(3)	(4)	(5)	(6)
GfG	0.907***	0.897***	0.170	0.153	0.108***	0.108***
	(0.117)	(0.117)	(0.107)	(0.106)	(0.037)	(0.037)
Household Size		0.051***		0.074***		-0.003
		(0.012)		(0.014)		(0.003)
Year-end Cropland Area (mu)		0.002		-0.002		-0.000
		(0.002)		(0.004)		(0.001)
Number of Land Plots		0.033***		0.051***		0.000
		(0.006)		(0.007)		(0.001)
Productive Asset Value (RMB)		0.000		0.000		0.000**
		(0.000)		(0.000)		(0.000)
Fertilizer Purchased (kg)		-0.000***		0.000		-0.000
		(0.000)		(0.000)		(0.000)
Agricultural Diesel Purchased (kg)		-0.000*		0.000**		0.000*
		(0.000)		(0.000)		(0.000)
Pesticides Purchased (kg)		0.000		0.000		-0.000
		(0.000)		(0.000)		(0.000)
Age of Household Head		0.003*		0.001		0.001**
		(0.002)		(0.002)		(0.000)
Squared Age of Household Head		-0.000*		-0.000		-0.000***
		(0.000)		(0.000)		(0.000)
Gender of Household Head		-0.046		-0.064		-0.012
		(0.052)		(0.062)		(0.009)
Years of Education of Household Head		0.013**		0.013		0.001
		(0.007)		(0.015)		(0.001)
Mean(Y)	4.53	4.53	0.65	0.65	0.27	0.27
Observations	38,297	38,297	38,297	38,297	38,297	38,297
R-squared	0.794	0.795	0.679	0.682	0.629	0.630
Year-Village FEs	✓	✓	✓	✓	✓	✓
Household Type FEs		✓		✓		✓
Controls		✓		✓		✓

*Notes:*This table presents baseline regression estimates of the impact of GfG participation on log-transformed land use outcomes. Standard errors are reported in parentheses and clustered at the village level.Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

TABLE A-16: Household Income Decomposition Results

	Log Farm Income		Log Non-farm Business Inc.		Log Local Wage		Log Non-local Wage		Log Gov't Subsidies		Log Other Incomes	
GfG	0.047**	0.046***	-0.126	-0.146	0.042	0.008	-0.228	-0.309**	0.779***	0.787***	0.203	0.223*
	(0.018)	(0.016)	(0.146)	(0.138)	(0.147)	(0.146)	(0.153)	(0.149)	(0.053)	(0.053)	(0.130)	(0.130)
Household Size		0.063***		0.295***		0.157***		0.725***		0.048***		-0.104***
		(0.004)		(0.032)		(0.022)		(0.043)		(0.008)		(0.021)
Year-end Cropland Area (mu)		0.020***		-0.015***		-0.001		-0.003		0.022***		-0.016***
		(0.004)		(0.004)		(0.003)		(0.003)		(0.003)		(0.005)
Number of Land Plots		0.044***		-0.017*		-0.001		0.021**		0.047***		-0.048***
		(0.002)		(0.010)		(0.009)		(0.010)		(0.004)		(0.009)
Productive Asset Value (RMB)		0.000		0.000***		-0.000**		-0.000		-0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Fertilizer Purchased (kg)		0.000		-0.000		0.000		-0.000***		0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Agricultural Diesel Purchased (kg)		0.000		0.000		-0.000*		-0.000		-0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Pesticides Purchased (kg)		0.000**		-0.000		0.000***		-0.000***		0.000		-0.000**
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Age of Household Head		-0.000		-0.019***		-0.030***		-0.032***		0.005***		0.030***
		(0.000)		(0.003)		(0.003)		(0.003)		(0.001)		(0.003)
Squared Age of Household Head		0.000		0.000***		0.000***		0.000***		-0.000***		-0.000***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Gender of Household Head		-0.049		-0.089		-0.044		0.275		-0.075		0.134
		(0.033)		(0.072)		(0.071)		(0.170)		(0.047)		(0.088)
Years of Education of Household Head		0.010***		0.047**		0.035**		0.057***		0.002		-0.017**
		(0.003)		(0.020)		(0.015)		(0.018)		(0.004)		(0.008)
Observations	36,971	36,971	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297
R-squared	0.499	0.619	0.338	0.416	0.243	0.256	0.239	0.295	0.496	0.510	0.412	0.419
Year-Village FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Household Type FE		✓		✓		✓		✓		✓		✓
Controls		✓		✓		✓		✓		✓		✓

Notes: Standard errors are reported in parentheses and clustered at the village level. Statistical significance : * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A-17: Household Farm Income Decomposition Results (1)

	Log Income from Wheat		Log Income from Rice		Log Income from Corn		Log Income from Soybean		Log Income from Cash Crop	
GfG	-0.436***	-0.433***	-0.132*	-0.093	-0.223***	-0.202***	0.494***	0.519***	0.285***	0.272***
	(0.065)	(0.065)	(0.076)	(0.072)	(0.070)	(0.068)	(0.071)	(0.071)	(0.031)	(0.030)
Household Size		0.057***		0.066***		0.082***		0.051***		0.041***
		(0.009)		(0.010)		(0.012)		(0.010)		(0.006)
Year-end Cropland Area (mu)		0.010***		0.019***		0.044***		0.029***		0.007**
		(0.002)		(0.004)		(0.008)		(0.005)		(0.003)
Number of Land Plots		0.037***		0.181***		0.087***		0.059***		0.020***
		(0.004)		(0.008)		(0.007)		(0.005)		(0.002)
Productive Asset Value (RMB)		-0.000		-0.000*		-0.000**		0.000*		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Fertilizer Purchased (kg)		0.000		-0.000		0.000		-0.000**		0.000***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Agricultural Diesel Purchased (kg)		-0.000*		-0.000		-0.000*		-0.000**		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Pesticides Purchased (kg)		0.000		-0.000*		0.000		0.000		0.000*
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Age of Household Head		0.003**		-0.004**		0.002		0.008***		0.000
		(0.001)		(0.001)		(0.002)		(0.001)		(0.001)
Squared Age of Household Head		-0.000**		0.000**		-0.000		-0.000***		-0.000***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Gender of Household Head		-0.133*		-0.109		-0.002		-0.132***		0.005
		(0.074)		(0.067)		(0.107)		(0.035)		(0.026)
Years of Education of Household Head		-0.001		-0.000		0.002		-0.004		0.004***
		(0.003)		(0.004)		(0.005)		(0.004)		(0.002)
Observations	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	20,749	20,749
R-squared	0.823	0.825	0.749	0.770	0.734	0.748	0.527	0.537	0.598	0.633
Year-Village FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Household Type FEs		✓		✓		✓		✓		✓
Controls		✓		✓		✓		✓		✓

Notes: Standard errors are reported in parentheses and clustered at the village level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A-18: Household Farm Income Decomposition Results (2)

	Log Income from Forestry		Log Income from Orchard Farming		Log Income from Livestock Farming		Log Income from Fishery	
GfG	0.027	0.034	-0.025	-0.076	0.176*	0.176*	-0.048	-0.047
	(0.068)	(0.068)	(0.059)	(0.057)	(0.096)	(0.094)	(0.032)	(0.032)
Household Size		0.033***		0.064***		0.160***		0.012**
		(0.007)		(0.009)		(0.017)		(0.005)
Year-end Cropland Area (mu)		-0.001		0.001		0.005		0.003
		(0.001)		(0.003)		(0.005)		(0.002)
Number of Land Plots		0.034***		-0.004		0.131***		0.007*
		(0.004)		(0.005)		(0.008)		(0.004)
Productive Asset Value (RMB)		-0.000*		0.000***		0.000**		0.000**
		(0.000)		(0.000)		(0.000)		(0.000)
Fertilizer Purchased (kg)		-0.000**		0.000**		-0.000		-0.000*
		(0.000)		(0.000)		(0.000)		(0.000)
Agricultural Diesel Purchased (kg)		0.000		0.000		-0.000***		-0.000**
		(0.000)		(0.000)		(0.000)		(0.000)
Pesticides Purchased (kg)		-0.000		0.000**		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Age of Household Head		0.002**		0.024***		0.022***		0.000
		(0.001)		(0.004)		(0.002)		(0.001)
Squared Age of Household Head		-0.000**		-0.000***		-0.000***		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Gender of Household Head		-0.141*		-0.154***		-0.393**		-0.068*
		(0.073)		(0.045)		(0.198)		(0.036)
Years of Education of Household Head		-0.003		0.005		-0.007		0.002
		(0.003)		(0.006)		(0.006)		(0.002)
Observations	38,297	38,297	6,093	6,093	38,297	38,297	38,297	38,297
R-squared	0.734	0.736	0.649	0.669	0.488	0.512	0.273	0.283
Year-Village FEs	✓	✓	✓	✓	✓	✓	✓	✓
Household Type FEs		✓		✓		✓		✓
Controls		✓		✓		✓		✓

Notes: Standard errors are reported in parentheses and clustered at the village level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A-19: GfG Program Effects on Agricultural Land Allocation

	Log Planted Area of Wheat		Log Planted Area of Rice		Log Planted Area of Corn		Log Planted Area of Soybeans		Log Planted Area of Cash Crops	
GfG	-0.725***	-0.717***	-0.205*	-0.145	-0.366***	-0.334***	0.731***	0.772***	0.334**	0.374***
	(0.109)	(0.108)	(0.118)	(0.113)	(0.109)	(0.106)	(0.121)	(0.121)	(0.131)	(0.128)
Household Size		0.086***		0.092***		0.117***		0.090***		0.144***
		(0.015)		(0.016)		(0.018)		(0.016)		(0.028)
Year-end Cropland Area (mu)		0.015***		0.026***		0.064***		0.043***		0.042***
		(0.004)		(0.006)		(0.011)		(0.007)		(0.010)
Number of Land Plots		0.059***		0.270***		0.129***		0.112***		0.184***
		(0.007)		(0.012)		(0.010)		(0.009)		(0.012)
Productive Asset Value (RMB)		-0.000		-0.000*		-0.000**		0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Fertilizer Purchased (kg)		0.000		-0.000		0.000		-0.000**		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Agricultural Diesel Purchased (kg)		-0.000		-0.000		-0.001*		-0.000***		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Pesticides Purchased (kg)		0.000		-0.000		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Age of Household Head		0.005**		-0.005**		0.002		0.013***		0.018***
		(0.002)		(0.002)		(0.002)		(0.002)		(0.003)
Squared Age of Household Head		-0.000***		0.000**		-0.000		-0.000***		-0.000***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Gender of Household Head		-0.222*		-0.159		-0.007		-0.218***		0.014
		(0.123)		(0.100)		(0.156)		(0.056)		(0.070)
Years of Education of Household Head		-0.001		-0.002		-0.004		-0.007		0.013
		(0.006)		(0.006)		(0.007)		(0.007)		(0.008)
Observations	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297
R-squared	0.813	0.816	0.746	0.766	0.739	0.751	0.521	0.531	0.604	0.623
Year-Village FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Household Type FEs		✓		✓		✓		✓		✓
Controls		✓		✓		✓		✓		✓

Notes: Standard errors are reported in parentheses and clustered at the village level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A-20: GfG Program Effects on Agricultural Productivity

	Log Wheat Productivity		Log Rice Productivity		Log Corn Productivity		Log Soybeans Productivity	
GfG	0.004	0.004	-0.001	-0.003	0.010	0.009	0.113***	0.105***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.012)	(0.012)	(0.032)	(0.032)
Household Size		0.000		0.004**		-0.001		0.007
		(0.002)		(0.002)		(0.002)		(0.005)
Year-end Cropland Area (mu)		-0.003		-0.001***		-0.002***		0.001
		(0.002)		(0.000)		(0.001)		(0.001)
Number of Land Plots		0.001		-0.001*		-0.001		-0.003
		(0.002)		(0.001)		(0.001)		(0.002)
Productive Asset Value (RMB)		0.000**		0.000		0.000**		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Fertilizer Purchased (kg)		0.000		0.000***		0.000***		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Agricultural Diesel Purchased (kg)		0.000		0.000		0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Pesticides Purchased (kg)		-0.000		-0.000		0.000***		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Age of Household Head		0.001***		-0.001*		0.001***		-0.000
		(0.000)		(0.001)		(0.000)		(0.001)
Squared Age of Household Head		-0.000***		0.000		-0.000***		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Gender of Household Head		-0.004		-0.008		0.002		-0.076**
		(0.013)		(0.014)		(0.006)		(0.034)
Years of Education of Household Head		0.003**		-0.000		0.003**		-0.004
		(0.001)		(0.001)		(0.001)		(0.003)
Observations	13,456	13,456	14,077	14,077	23,243	23,243	6,035	6,035
R-squared	0.598	0.600	0.402	0.405	0.416	0.419	0.435	0.439
Year-Village FEs	✓	✓	✓	✓	✓	✓	✓	✓
Household Type FEs		✓		✓		✓		✓
Controls		✓		✓		✓		✓

Notes: Standard errors are reported in parentheses and clustered at the village level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A-21: Household Expenditure Decomposition Results

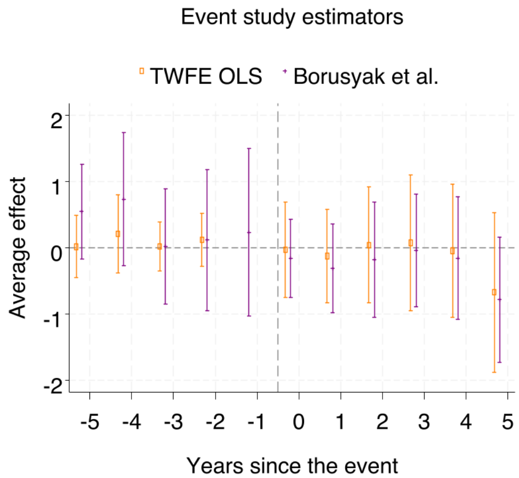
	Log Operating Expenditure		Log Productive Asset Expenditure		Log Other Investment Expenditure		Log Tax Expenditure		Log Village Fees		Log Living Expenditure	
GfG	0.047**	0.046***	-0.126	-0.146	0.042	0.008	-0.228	-0.309**	0.779***	0.787***	0.203	0.223*
	(0.018)	(0.016)	(0.146)	(0.138)	(0.147)	(0.146)	(0.153)	(0.149)	(0.053)	(0.053)	(0.130)	(0.130)
Household Size		0.063***		0.295***		0.157***		0.725***		0.048***		-0.104***
		(0.004)		(0.032)		(0.022)		(0.043)		(0.008)		(0.021)
Year-end Cropland Area (mu)		0.020***		-0.015***		-0.001		-0.003		0.022***		-0.016***
		(0.004)		(0.004)		(0.003)		(0.003)		(0.003)		(0.005)
Number of Land Plots		0.044***		-0.017*		-0.001		0.021**		0.047***		-0.048***
		(0.002)		(0.010)		(0.009)		(0.010)		(0.004)		(0.009)
Productive Asset Value (RMB)		0.000		0.000***		-0.000**		-0.000		-0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Fertilizer Purchased (kg)		0.000		-0.000		0.000		-0.000***		0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Agricultural Diesel Purchased (kg)		0.000		0.000		-0.000*		-0.000		-0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Pesticides Purchased (kg)		0.000**		-0.000		0.000***		-0.000***		0.000		-0.000**
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Age of Household Head		-0.000		-0.019***		-0.030***		-0.032***		0.005***		0.030***
		(0.000)		(0.003)		(0.003)		(0.003)		(0.001)		(0.003)
Squared Age of Household Head		0.000		0.000***		0.000***		0.000***		-0.000***		-0.000***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Gender of Household Head		-0.049		-0.089		-0.044		0.275		-0.075		0.134
		(0.033)		(0.072)		(0.071)		(0.170)		(0.047)		(0.088)
Years of Education of Household Head		0.010***		0.047**		0.035**		0.057***		0.002		-0.017**
		(0.003)		(0.020)		(0.015)		(0.018)		(0.004)		(0.008)
Observations	36,971	36,971	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297
R-squared	0.499	0.619	0.338	0.416	0.243	0.256	0.239	0.295	0.496	0.510	0.412	0.419
Year-Village FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Household Type FE		✓		✓		✓		✓		✓		✓
Controls		✓		✓		✓		✓		✓		✓

Notes: Standard errors are reported in parentheses and clustered at the village level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

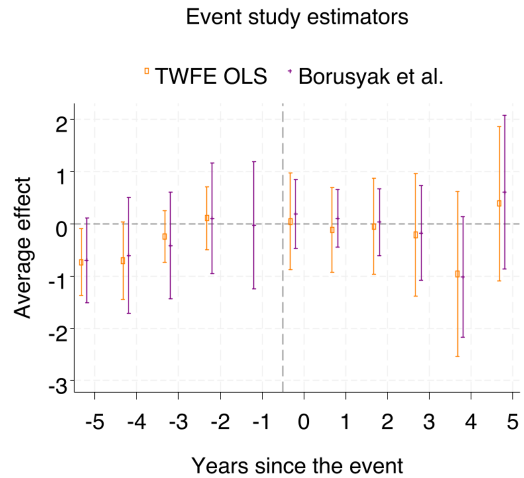
Table A-22: Household Living Expenditure Decomposition Results

	Log Staple Food Expenditure		Log Non-staple Food Expenditure		Log Clothing Expenditure		Log Housing Expenditure		Log Fuel Expenditure		Log Medical Expenses Expenditure	
GfG	0.047**	0.046***	-0.126	-0.146	0.042	0.008	-0.228	-0.309**	0.779***	0.787***	0.203	0.223*
	(0.018)	(0.016)	(0.146)	(0.138)	(0.147)	(0.146)	(0.153)	(0.149)	(0.053)	(0.053)	(0.130)	(0.130)
Household Size		0.063***		0.295***		0.157***		0.725***		0.048***		-0.104***
		(0.004)		(0.032)		(0.022)		(0.043)		(0.008)		(0.021)
Year-end Cropland Area (mu)		0.020***		-0.015***		-0.001		-0.003		0.022***		-0.016***
		(0.004)		(0.004)		(0.003)		(0.003)		(0.003)		(0.005)
Number of Land Plots		0.044***		-0.017*		-0.001		0.021**		0.047***		-0.048***
		(0.002)		(0.010)		(0.009)		(0.010)		(0.004)		(0.009)
Productive Asset Value (RMB)		0.000		0.000***		-0.000**		-0.000		-0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Fertilizer Purchased (kg)		0.000		-0.000		0.000		-0.000***		0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Agricultural Diesel Purchased (kg)		0.000		0.000		-0.000*		-0.000		-0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Pesticides Purchased (kg)		0.000**		-0.000		0.000***		-0.000***		0.000		-0.000**
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Age of Household Head		-0.000		-0.019***		-0.030***		-0.032***		0.005***		0.030***
		(0.000)		(0.003)		(0.003)		(0.003)		(0.001)		(0.003)
Squared Age of Household Head		0.000		0.000***		0.000***		0.000***		-0.000***		-0.000***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Gender of Household Head		-0.049		-0.089		-0.044		0.275		-0.075		0.134
		(0.033)		(0.072)		(0.071)		(0.170)		(0.047)		(0.088)
Years of Education of Household Head		0.010***		0.047**		0.035**		0.057***		0.002		-0.017**
		(0.003)		(0.020)		(0.015)		(0.018)		(0.004)		(0.008)
Observations	36,971	36,971	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297	38,297
R-squared	0.499	0.619	0.338	0.416	0.243	0.256	0.239	0.295	0.496	0.510	0.412	0.419
Year-Village FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Household Type FE		✓		✓		✓		✓		✓		✓
Controls		✓		✓		✓		✓		✓		✓

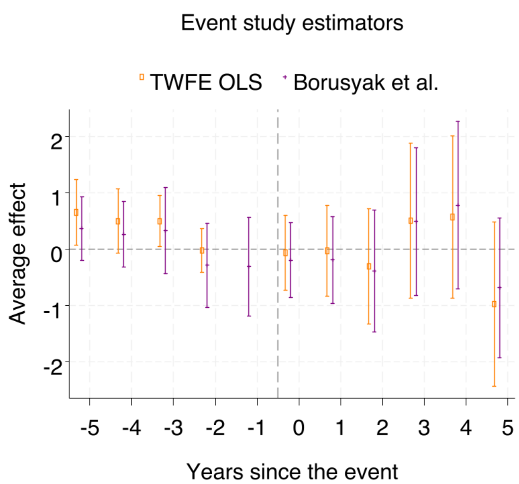
Notes: Standard errors are reported in parentheses and clustered at the village level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.



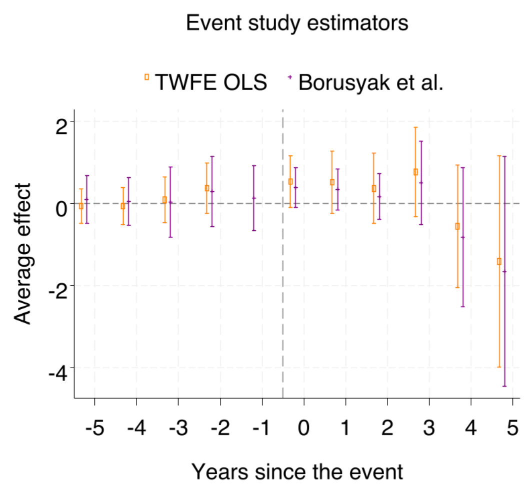
(A) Event Study on Non-Farm Income



(B) Event Study on Local Wage Income)

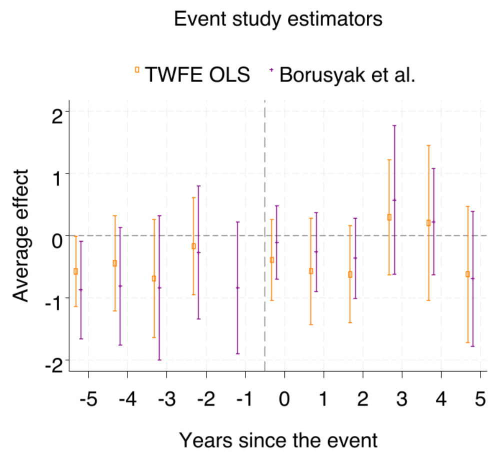


(C) Event Study on Non-local Wage Income

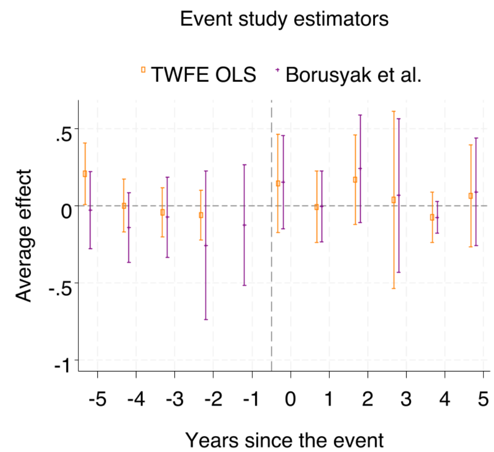


(D) Event Study on Other Sources)

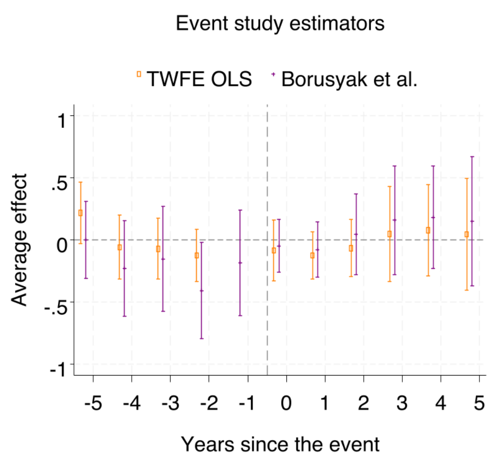
FIGURE A-1: EFFECTS OF GFG PROGRAM ON THE OTHER INCOME SOURCES FROM INCOME DECOMPOSITIONS BEFORE AND AFTER PARTICIPATION



(A) Event Study on Production Expenditure

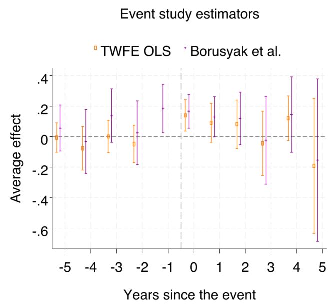


(B) Event Study on Management Expenditure

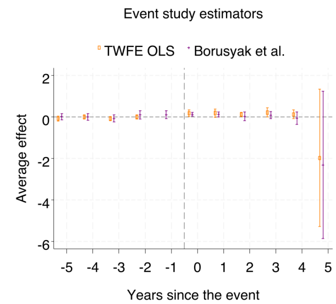


(C) Event Study on Tax Expenditure

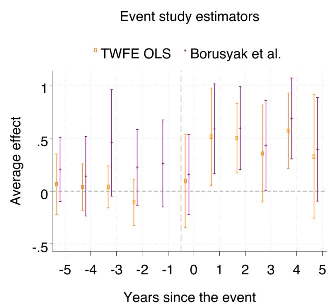
Figure A-2: Effects of GFG Program on Production, Management, and Tax Expenditures Before and After Participation



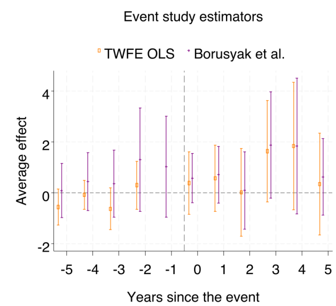
(A) Event Study on Staple Food Expenditure



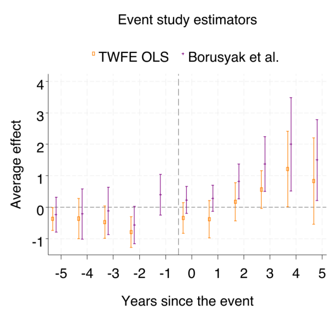
(B) Event Study on Non-Staple Food Expenditure



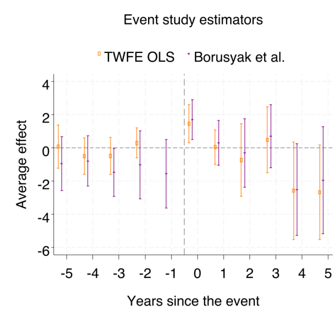
(C) Event Study on Clothing Expenditure



(D) Event Study on Housing Expenditure



(E) Event Study on Fuel Expenditure



(F) Event Study on Medical Expenses

FIGURE A-3: EFFECTS OF GFG PROGRAM ON HOUSEHOLD EXPENDITURES BEFORE AND AFTER PARTICIPATION