Economic Growth Effect of Poverty Alleviation Policies: Evidence from China's Photovoltaic Industry

Jiang Hongze[1], Liang Pinghan[*2,3]
[1] School of Economics, Anhui University, Hefei, China
[2] Center for Chinese Public Administration Research, Sun Yat-sen University, Guangzhou, China
[3] School of Government, Sun Yat-sen University

Abstract: *In accordance with the directives of the Third Plenary Session of the 20th Central Committee of the Communist Party of China, it is essential to enhance policies for strategic emerging industries like photovoltaic energy and to establish localized mechanisms for developing new quality productive forces. Using a difference-in-differences (DID) approach on a panel data between 2010 and 2020, this study assesses the impact of China's photovoltaic (PV) poverty alleviation policies on county-level economic growth. The results show that the PV poverty alleviation policy leads to increases of 3.2% in GDP and 5.3% in GDP per capita, respectively, in targeted poverty counties. These findings are robust across multiple tests. The positive effects are particularly salient in regions with stronger central government support and higher solar radiation. Further analysis reveals that the beneficial effect of this policy is stronger in counties with higher share of poor villages and households, as well as larger coverage of PV station development. In terms of its impact mechanisms, the policy has provided new income sources, expanded employment opportunities, and enhanced market vitality through improvements in the electricity supply. This study offers theoretical insights for optimizing China's PV industry policy under its rural revitalization strategy, and contributes to building long-term sustainable development mechanisms in rural areas. It also advances our understanding of the poverty-reducing potential of new quality productive forces.*

Keywords: *New quality productive forces; Photovoltaic poverty alleviation; Economic growth; Poverty governance; Sustainable development*
JEL Classification Codes: L16; O11; R11
DOI: 10.19602/j. chinaeconomist.2025.09.02

1. Introduction

Poverty governance remains a pressing global challenge. According to the *United Nations 2021 Sustainable Development Goals Report*, the number of people living in poverty worldwide increased by nearly 120 million by the end of 2020, raising the extreme poverty rate to 9.3%. The report forecasts that the global poverty rate will still hover around 7% by 2030[1]. Reducing poverty continues to be a core objective of national and global governance. In stark contrast to the persistent global poverty

[*] CONTACT: Liang Pinghan, email: liangph5@mail. sysu. edu. cn.
Acknowledgement: Key Project of the National Social Science Fund of China "Research on Building and Consolidating a Close and Clean Government-Business Relationship" (Grant No.22AZD033); Youth Project of the Anhui Provincial Philosophy and Social Science Planning "Research on Impact Mechanism of Photovoltaic Industry Policies on Firm Entry and Policy Optimization in Anhui Province " (Grant No. AHSKYQ2023D060).
[1] United Nations, *The Sustainable Development Goals Report 2021*, https://unstats. un. org/sdgs/report/2021/, 2021.

trend, China has lifted over 700 million people out of poverty over the past four decades. Through the implementation of the largest and most intensive poverty alleviation campaign in human history—benefiting the greatest number of people—the Chinese government has created a globally recognized "miracle" in poverty reduction. As of February 2021, under the current national poverty standards, all rural poor in China had been lifted out of absolute poverty, completing a historic task.

A critical feature of China's poverty alleviation strategy is the prioritization of industrial poverty alleviation, particularly through the implementation of ten targeted programs, including photovoltaic (PV) poverty alleviation, e-commerce-driven development, and rural tourism. Among them, solar PV power generation gained widespread acceptance among rural households due to its abundant natural potential, low maintenance requirements, and stable income returns. Solar PV represents not only technological and energy innovation, but also exemplifies the role of new quality productive forces in driving the nation's coordinated economic, social, and environmental development. By the end of 2019, China had completed the construction of PV poverty alleviation power stations with a total capacity of 26.36 gigawatts, benefiting approximately 4.15 million poor households[2].

China's PV poverty alleviation policy aims to lift poor regions out of poverty and promote rural prosperity by building income-generating solar PV systems. This is achieved through distributed household-level installations and village-level PV power stations, both of which provide stable revenue streams. As a key mechanism for advancing targeted poverty reduction and stimulating rural economic development, PV power generation also offers advantages over traditional energy sources—particularly its environmental benefits and alignment with sustainability goals (Rabaia et al., 2021; Sharif et al., 2021; Wang et al., 2022; Sun & Zhan, 2023). Researchers have identified several key benefits of PV-based poverty alleviation (Wu, 2018; Guo & Bai, 2018). First, investing in PV stations that generate consistent returns enables the integration of poverty alleviation funds with renewable energy subsidies. This approach effectively channels resources into poor regions, improves livelihoods, and supports the achievement of poverty reduction targets. Second, solar PV systems contribute to universal electricity access by improving the reliability of energy supply for both households and businesses. By making efficient use of local solar resources, the policy enhances energy security, stimulates infrastructure development, and provides affordable energy for everyday use and economic activity. Third, the "PV + industry" model has introduced innovations in rural industrial development and brought spillover benefits to related sectors. For example, in the "PV + agriculture" model, PV greenhouses not only generate electricity via rooftop panels but also support agricultural or forestry production underneath, transforming previously fragmented land use into more integrated and productive systems.

Scholars have analyzed the pros and cons of PV poverty alleviation projects, exploring existing issues, primary challenges, and potential improvement strategies during policy implementation (Zou et al., 2019; Guo & Bai, 2018). Current policy evaluation research primarily examines the effectiveness of PV poverty alleviation policies through lenses such as carbon emission reduction, household income, and poverty alleviation outcomes (Zhang et al., 2020; Sharif et al., 2021; Liu et al., 2021). Yet, these studies often fall short of providing detailed empirical insights into the mechanisms driving poverty reduction. Furthermore, rising income levels do not guarantee improved welfare for the poor, as economic growth paired with unequal income distribution can result in unequal growth (Lopez, 2004). In this context, as China's rural focus shifts from targeted poverty alleviation to rural revitalization, understanding the impact and underlying mechanisms of PV poverty alleviation policies on economic growth in poor regions becomes critically important.

A clear grasp of the economic impacts of PV poverty alleviation policies can lay a strong theoretical

[2] *China Economic Herald*, "Photovoltaic Poverty Alleviation: Construction Tasks Fully Completed, Widely Welcomed Approach" October 29, 2020.

foundation for crafting and improving industrial poverty alleviation strategies, speeding up the development of new quality productive forces, and building durable mechanisms to prevent poverty relapse while advancing rural revitalization. This study leverages panel data from 832 national-level poverty-stricken counties between 2010 and 2020 designated under China's 2011 Poverty Alleviation Outline, using the late-2017 launch of the first batch of PV poverty alleviation projects under the "13th Five-Year Plan" as a quasi-natural experiment. Employing a difference-in-differences (DID) method, it assesses the impact and mechanisms of PV poverty alleviation on county-level economic growth. Findings reveal that, compared to non-priority counties, the policy significantly boosted economic development in key PV counties, with real GDP and real GDP per capita rising by 3.2% and 5.3%, respectively, post-implementation. These results hold steady when using pre-policy solar radiation intensity as an instrumental variable. The policy's effects are more significant in regions with stronger government support and higher solar intensity. Additionally, by innovatively constructing a policy intensity variable from PV project indicators, the study shows that counties with greater assistance to poor villages and households, and larger PV station scales, see stronger economic growth. The policy also drives impact by creating new income sources for residents, increasing local job opportunities, and boosting commercial activity through improved electricity access.

This study contributes to the literature on PV poverty alleviation policies in three main ways. First, it strengthens causal identification. Existing research on industrial poverty alleviation policies often struggles to isolate the effects of a specific policy due to the overlapping implementation of multiple measures, which can bias estimates. This study addresses this challenge by leveraging the pre-implementation level of solar irradiance as an instrumental variable for PV policy adoption, based on the technical requirements of the policy itself. This approach helps mitigate common endogeneity issues in policy evaluation and enhances the accuracy of causal inference. Building on the standard DID method, the study also constructs a policy intensity index and applies a generalized DID approach to assess the impact of PV poverty alleviation on economic growth. This allows for a better understanding of the policy's heterogeneous effects and offers insights for improving its implementation. Second, the study expands the evidence base on the effectiveness and mechanisms of PV poverty alleviation policies. While existing studies primarily focus on environmental and social welfare outcomes, they often overlook the economic consequences and offer limited discussion of the underlying mechanisms. Empirical analyses of how and why PV policies influence socio-economic outcomes in poor regions remain scarce (Zhang et al., 2020; Sharif et al., 2021; Liu et al., 2021; Xu et al., 2022; Li et al., 2022). This paper addresses this gap by not only evaluating the policy's impact on economic growth but also empirically examining the mechanisms at play—specifically, income generation, employment opportunities, and the entry of commercial entities. These insights provide a theoretical foundation for optimizing PV and other industrial poverty alleviation policies. Third, the study offers practical implications. Achieving common prosperity requires balanced regional development and improved income-generating capacity for the poor. By examining the role of PV policies in stimulating economic growth in underdeveloped areas, the study contributes to consolidating and extending the gains from China's poverty alleviation efforts. It complements the existing literature on poverty governance and provides actionable policy recommendations for integrating the PV industry into the rural revitalization strategy. These recommendations can support efforts to prevent the recurrence of poverty, promote sustainable rural development, and accelerate the formation of new quality productive forces.

The remainder of the paper is organized as follows: Section 2 introduces the operational mechanisms and policy background of PV poverty alleviation. Section 3 reviews the literature and presents the theoretical framework. Section 4 outlines the research design. Section 5 reports the empirical results. Section 6 explores the mechanisms of influence. Section 7 concludes with key findings and policy recommendations.

2. Operational Mechanisms and Policy Background of PV Poverty Alleviation

2.1 Operational Mechanisms

PV poverty alleviation in China is designed to install household PV power systems and construct village-level PV stations in sun-rich, underutilized areas of poor regions. The initiative is funded through a mix of four financial sources, including government poverty alleviation funds matched by household loans, corporate advance payments, local fiscal support, and investments from local development companies (Yang, 2017). This approach not only addresses electricity shortages in poor communities but also promotes the development and upgrading of the renewable energy sector. It serves as a key strategy for clean, low-carbon energy transition and has gradually evolved into a sustainable model for long-term poverty reduction. Under the "self-consumption, surplus-to-grid" model, households and village collectives—rural economic cooperatives that own and operate assets on behalf of all registered villagers—can reduce their electricity expenses while selling surplus electricity to the grid. They also receive subsidies from both national and local governments based on the amount of electricity fed into the grid. The income for households primarily consists of direct electricity sales revenue and a share of the income generated by the village collective. For example, in the PV poverty alleviation project implemented in Hefei, once construction costs were recouped and households' own power needs were covered, the average household earned over 3,000 yuan annually from selling surplus electricity and from collective revenue shares[3].

2.2 Policy Background

The policy framework for PV poverty alleviation was established through a series of national initiatives and progressively expanded over time. On October 11, 2014, the National Energy Administration (NEA) and the State Council Leading Group Office of Poverty Alleviation and Development jointly issued the *Notice on the Implementation Plan for Photovoltaic Poverty Alleviation Projects*. This document launched a six-year county-level initiative to promote PV industry-based poverty alleviation. The plan encouraged counties with suitable conditions to develop PV agriculture projects by utilizing barren hillsides, agricultural greenhouses, and other facility agriculture to construct PV power stations. The goal was to directly increase income for poor households. In March 2015, the NEA released the *Implementation Plan for PV Power Generation Projects*, which designated pilot poverty alleviation counties across six provinces—including Hebei, Shanxi, Anhui, Ningxia, Qinghai, and Gansu—for PV construction projects with a total allocated capacity of 1.5 gigawatts.

On March 23, 2016, China's National Development and Reform Commission (NDRC), the NEA, along with three other central government agencies, jointly issued the *Guidelines on Implementing PV Power Generation for Poverty Alleviation. This p*olicy marked a major step forward by mandating the implementation of PV poverty alleviation projects in all suitable poor areas across the country. It aimed to increase annual income by over 3,000 yuan per household for 2 million registered poor households without labor capacity—including people with disabilities—by the year 2020. Through a village-by-village rollout, the plan targeted approximately 35,000 registered poor villages across 471 national-level poverty-stricken counties in 16 provinces with favorable solar conditions. The *Guidelines* also required county-level investigations to assess the specific conditions of poverty-stricken households, the coordination of project construction funding, and the clarification of responsibilities and income distribution mechanisms among local governments, enterprises, financial institutions, and households. In October 2016, the NEA and the State Council Leading Group Office of Poverty Alleviation and Development issued the *Notice on the First Batch of Photovoltaic Poverty Alleviation Projects*,

[3] *People's Daily,* "Hefei's Solar Initiative: Over 6,400 PV Stations Empower Poverty Alleviation", http://energy.people.com.cn/n1/2018/1025/c71661-30363183.html, 2018.

allocating 5.16 gigawatts of PV projects across 14 provinces. Of this, 2.18 gigawatts were designated for village-level and household-based PV systems, while 2.98 gigawatts were allocated to centralized ground-mounted PV stations.

On December 29, 2017, the same agencies released the *Notice on the First Batch of "13th Five-Year Plan" Photovoltaic Poverty Alleviation Projects*. After evaluation, 236 out of 471 key poverty alleviation counties were deemed eligible. A total of 8,689 village-level PV stations were planned, with a combined installed capacity of 4.19 gigawatts. These projects, located in 14 provinces including Shanxi, Qinghai, and Gansu, aimed to benefit approximately 710,000 households in 14,600 registered poor villages. The notice emphasized the importance of local governments expediting project implementation, including site preparation, registration, and approvals, to ensure timely delivery and effectiveness.

On April 12, 2019, the NEA and the State Council Leading Group Office of Poverty Alleviation and Development issued the *Notice on the Second Batch of Photovoltaic Poverty Alleviation Projects under the 13th Five-Year Plan (2016-2020)*. After evaluation, 165 remaining key PV poverty alleviation counties were deemed eligible for project allocation. A total of 3,961 village-level PV stations were planned, with a combined installed capacity of 1.67 gigawatts, targeting support for 300,000 registered poor households across 3,859 poor villages. Building on the implementation of the first batch, the second round further expanded the scale of PV poverty alleviation, enabling more registered poor households to benefit from related policies. Upon completion of the second batch, it was officially announced that no additional PV poverty alleviation projects would be introduced under the national framework[4].

3. Literature Review and Theoretical Hypotheses

3.1 Literature Review

Poverty reduction remains one of the most pressing global governance challenges and continues to be a priority for governments around the world (Tollefson, 2015). Pro-poor growth theory posits that economic growth effectively reduces poverty by raising incomes of the poor, — meaning they disproportionately benefit from economic growth, such expansion is typically defined as "pro-poor" (Ravallion, 2001; Kakwani & Son, 2008). When the "trickle-down effect" of growth helps improve the opportunities and capabilities of the poor, allowing them to actively participate in and benefit from economic progress, pro-poor outcomes can be realized (Ravallion & Chen, 2007). However, practical experience in some countries suggests that in the context of significant income inequality, economic growth can lead to declining welfare among the poor—a phenomenon known as unequal growth (Lopez, 2004). As a result, research on pro-poor growth typically focuses on the relationship between economic growth, income distribution, and poverty, emphasizing the importance of sound policy frameworks. The key lies in establishing effective poverty reduction mechanisms whereby appropriate government interventions enable economic growth to benefit the broader population (Cai & Wang, 2005). In this regard, assessing the effectiveness of poverty alleviation policies is crucial to realizing the pro-poor potential of growth.

During China's targeted poverty alleviation campaign, the Party and the government introduced a series of coordinated poverty reduction measures. Existing studies have extensively evaluated initiatives such as the designation of national-level poverty-stricken counties, inter-provincial paired assistance programs, the Great Western Development Strategy, and poverty alleviation reform pilot zones (Xu & Liu, 2018; Huang, 2018; Zhang et al., 2019; Liu & Zhao, 2020). Over time, the country's poverty alleviation focus has shifted from addressing income poverty to tackling multidimensional poverty,

[4] See: National Rural Revitalization Administration & Huazhong University of Science and Technology Research Team, "Comprehensive Report on PV Poverty Alleviation Case Studies", http://www. banyuetan. org/fpdxal/detail/20210426/1000200033138961619407069478366150_1.html, 2021.

with governance evolving from broad-based approaches to targeted, precision strategies (Zhang et al., 2019). Among these efforts, industrial poverty alleviation has played a central role. Its core logic lies in leveraging industrial development to drive economic participation and income growth among poor populations. Shen & Peng (2016) point out that China's strong state capacity has allowed the government to use administrative measures to forge institutional linkages between industries and poor households. Research in this area has addressed several key dimensions, including the efficiency of industrial poverty alleviation in reducing poverty (Li, 2017; Zhao et al., 2023), the mechanisms through which it operates (Liu, 2016), the models adopted (Xu & Liu, 2011), and the practical challenges encountered during implementation (Li & Zuo, 2016). These studies collectively highlight the centrality of industrial policy in China's broader poverty alleviation strategy.

Research on PV poverty alleviation policies primarily falls into two main strands. The first strand involves case-based evaluations of implemented PV projects, focusing on identifying challenges and offering policy recommendations. For example, Zou et al. (2019) conducted fieldwork in Fuyang City, Anhui, and Zuoquan County, Shanxi, to examine the construction processes, funding sources, subsidy distribution, and loan arrangements of completed and ongoing PV projects. Based on their findings, they proposed targeted improvements in areas such as subsidy delivery, bidding procedures, project supervision, and innovation mechanisms. In addition to empirical studies, some works adopt a normative analytical approach to assess PV poverty alleviation. Guo & Bai (2018) outlined several persistent issues, including excessive reliance on government subsidies, difficulties integrating PV output into the power grid, challenges in post-construction maintenance, and weak supervision mechanisms. They proposed comprehensive future strategies such as factoring in regional solar irradiance, encouraging diversified investment, promoting "PV + agriculture" business models, and improving income distribution systems. Similarly, Wu (2018) examined the goals, characteristics, and practical obstacles of PV poverty alleviation, summarizing four core challenges and offering forward-looking policy suggestions in areas such as benefit distribution, infrastructure systems, industrial support, and accountability mechanisms.

The second strand of literature focuses on evaluating the effectiveness of PV poverty alleviation policies through empirical methods. As a clean and renewable energy source, solar power generates neither carbon emissions nor solid or liquid waste. Compared to other energy-based poverty alleviation initiatives, PV systems offer notable environmental advantages (Rabaia et al., 2021; Sharif et al., 2021), particularly in addressing energy shortages in high-altitude regions (Liu et al., 2019). Researchers frequently employ the DID method to assess the socioeconomic effects of PV policies. For instance, Liu et al. (2021) analyzed data from 735 poor households and found that China's PV poverty alleviation programs effectively targeted rural families in need. The study reported significant reductions in poverty, along with improvements in household economic conditions and social capital, although it found no substantial effect on human capital development. Xu et al. (2022), using panel data from 852 counties over five years, identified a significant positive relationship between the duration of PV policy implementation and both income growth and poverty reduction in pilot areas. Their analysis also revealed notable positive spatial spillover effects. Similarly, Zhang et al. (2020) reported that PV poverty alleviation policies increased per capita disposable income in pilot counties by 7% to 8%, with the strongest effects observed in eastern and economically disadvantaged regions. Li Na et al. (2022) evaluated the broader socioeconomic impact of the policy by using the number of workers in secondary industries and residents' savings deposits as proxy variables. Their findings indicated that, in designated poor counties, PV poverty alleviation led to increases of 10.37% and 6.04% in these two indicators, respectively.

3.2 Theoretical Hypotheses

The PV poverty alleviation policy, designed to boost income and welfare for poor populations, involves multiple stakeholders, including local governments, power grid companies, enterprises, financial institutions, and low-income households. Drawing on pro-poor growth theory, the policy's impact on economic development in key poverty alleviation counties—compared to non-key counties—can be understood through several mechanisms. Under the "self-use, surplus-to-grid" arrangement, designated counties gain both a more reliable energy supply and direct cash income from selling excess electricity to the grid. This represents a direct contribution to local economic growth. Additionally, through the interaction of diverse stakeholders under coordinated policy and institutional frameworks, the policy promotes infrastructure improvements that enhance the foundational conditions for economic development. These developments may generate economic spillover effects (Wang & Shu, 2021). Furthermore, the PV poverty alleviation policy contributes to county-level industrial development. Tax reductions and credit incentives enhance the profitability and capital accumulation capacity of related enterprises, while R&D subsidies stimulate innovation among upstream and downstream PV firms, boosting local market vitality and contributing to growth through indirect channels (Lu & Du, 2024).

Based on these dynamics, this study proposes the following hypothesis:

Hypothesis 1: The PV poverty alleviation policy has a pro-poor effect, significantly promoting economic growth in key poverty alleviation counties compared to non-key counties.

This policy is likely to affect economic growth through three interrelated mechanisms.

First, by creating new income channels, the "self-consumption" model enables households and village collectives to reduce electricity expenditures by using self-generated power, while the "surplus-to-grid" arrangement allows them to sell excess electricity and receive national and local subsidies. These additional income streams support both consumption and savings, thereby stimulating economic activity in poor counties.

Second, the policy contributes to employment creation. The construction, operation, and maintenance of PV projects involve a wide range of job functions—from infrastructure building to technical maintenance and environmental monitoring—which directly absorb local labor and provide both short-term and long-term employment opportunities. In addition, technical training programs associated with PV projects improve the skill levels of local residents, enabling them to work not only in the renewable energy sector but also in other industries, thus expanding employment options and adaptability. According to an October 2020 briefing by the State Council Information Office, PV poverty alleviation efforts created 1.25 million public welfare jobs nationwide, helping over 116,000 poor individuals secure employment and contributing significantly to poverty reduction.

Third, the PV poverty alleviation policy further influences economic growth through enhanced market vitality. Regions with vibrant entrepreneurial activity typically exhibit stronger economic performance (Li & Jiang, 2020). A reliable power supply is a critical component of the business environment, recognized as one of the ten primary indicators in the World Bank's *Doing Business* survey. By delivering a more robust energy supply, the PV poverty alleviation policy reduces electricity costs for commercial entities, strengthens the local power supply environment, and stimulates entrepreneurial activity, thereby encouraging the entry of new businesses. For example, the "PV + industry" model fosters integrated development in key PV poverty alleviation areas by promoting PV agriculture alongside agricultural processing, warehousing, and logistics industries, or by advancing PV material processing, ultimately enhancing market vitality in poor regions (Zhu, 2020).

Hypothesis 2: The PV poverty alleviation policy drives economic growth in poverty-stricken counties by reducing residents' electricity expenditures and increasing generation subsidies.

Hypothesis 3: The PV poverty alleviation policy promotes economic growth in poverty-stricken counties by increasing residents' employment opportunities.

Hypothesis 4: The PV poverty alleviation policy fosters economic growth in poverty-stricken counties by facilitating the entry of commercial entities.

4. Research Design

4.1 Data Source

This study uses data from all 832 national-level poverty-stricken counties listed in the *China County Statistical Yearbook* from 2010 to 2020 to assess the economic impact of the PV poverty alleviation policy. The PV policy, implemented as a nationwide poverty alleviation initiative, is treated as a quasi-natural experiment. Focusing exclusively on national-level poverty-stricken counties allows both the treatment and control groups to be equally subject to other poverty alleviation policies, helping reduce estimation bias from omitted variables and more accurately identifying the net effects of the PV intervention. The treatment group consists of the 236 key poverty alleviation counties identified in the "Notice" issued at the end of 2017, while the remaining counties serve as the control group. This choice of policy document is supported by the 2019 publication *100 Questions and Answers on PV Poverty Alleviation Work* issued by the National Energy Administration (NEA) and the State Council Leading Group Office of Poverty Alleviation and Development, which confirms that PV poverty alleviation focused on 471 national-level poverty-stricken counties in 16 provinces with suitable sunlight conditions, as originally stated in the 2016 *Guidelines on Implementing Photovoltaic Power Generation for Poverty Alleviation*. The same document also clarifies that only village-level PV stations included in the first and second batches under the 13th Five-Year Plan (2016-2020) were eligible for subsidy benefits, supporting the use of the 2017 "Notice" to define the treatment group.

This study does not use the 471 counties listed in the 2016 *Guidelines* to define the treatment group, since that document was intended for preparatory work such as identifying target populations, determining suitable implementation models, and securing construction funds. The counties listed there still needed approval by the National Energy Administration (NEA) and the State Council Leading Group Office of Poverty Alleviation and Development. Therefore, the actual implementation of PV poverty alleviation projects should not be considered to have begun in 2016. Furthermore, the second batch of projects announced in 2019 did not include a detailed county-level list. Although it covered 165 counties, the exact county names were not disclosed, and 70 counties from the 2016 list ultimately did not pass the approval process. Because of this, the second batch cannot be reconstructed by subtraction or other methods. This study, therefore, focuses only on the first batch of PV projects, a practice consistent with existing research (Xu et al., 2022; Li et al., 2022).

4.2 Model Specification

To evaluate the causal impact of the PV policy, this study applies a DID approach, treating the implementation of the 13th Five-Year Plan's PV poverty alleviation policy as a quasi-natural experiment. The 236 key counties designated in the 2017 "Notice" constitute the treatment group, and the remaining counties serve as the control group. The econometric model is specified as follows:

$$Y_{it}=\beta_0+\beta_1 did_{it}+\gamma X_{it}+\mu_i+year_t+\varepsilon_{it} \tag{1}$$

$$did_{it}=D_i\times T_t \tag{2}$$

Here, Y_{it} represents the dependent variable, capturing the economic development level of county i in year t. Subscripts i and t denote county and year, respectively. X_{it} encompasses variables that may influence economic growth and vary with i and t. μ_i represents county fixed effects, $year_t$ captures year fixed effects, and ε_{it} is the error term. The interaction term did_{it}, which equals the interaction between D_i and T_t, captures the policy treatment effect, and its coefficient β_1 reflects the net policy impact on the treatment group after implementation. If Hypothesis 1 holds, β_1 is expected to be significantly positive. Since the policy intervention did_{it} occurs at the county level, all regression models adopt robust standard errors clustered at the county level, following Bertrand et al. (2004).

4.3 Selection of Variables

4.3.1 Dependent Variable

To measure county-level economic development, this study draws on the approaches of Zhang et al. (2019) and Liu & Zhao (2020), using the logarithm of real regional GDP (lngdp), and the logarithm of real per capita regional GDP (lnpgdp). Real GDP is derived by deflating each county's nominal GDP using the provincial GDP deflator indexed to 2010.

4.3.2 Explanatory variable

Regarding the key explanatory variable, since the "Notice" was issued at the end of December 2017, it is reasonable to assume that PV project construction began in 2018. Therefore, T_t equals 1 when $t \geq 2018$ and 0 otherwise. A dummy variable D_i is defined to distinguish the treatment group from the control group: if county i is listed in the first batch of key counties from the 2017 "Notice", then D_i=1; otherwise, D_i=0. The interaction term did_{it} (interaction term between D_i and T_t) is then constructed to serve as the core explanatory variable, with its estimated coefficient representing the treatment effect of the PV poverty alleviation policy — that is, the policy's economic growth impact.

4.3.3 Control variables

Drawing on Zhang et al. (2019), Zhang et al. (2020), and Xu et al. (2022), this study selects control variables related to regional economic growth, encompassing industrial structure, local fiscal capacity, population density, human capital investment, and financial support. Industrial structure is captured by the shares of primary (*prir*) and secondary (*secr*) industry value added in GDP. Local fiscal capacity is reflected by the shares of general budget revenue (*govr*) and expenditure (*gove*) in GDP . Population density is measured as the ratio of registered (*hukou*) population to administrative land area (*pden*). Human capital investment is gauged by the proportions of enrolled primary (*ppr*) and middle school (*mpr*) students to the registered population, controlling for the impact of basic education on local economic development. Financial support is assessed using the natural logarithm of year-end loan balances from financial institutions (*lfin*), accounting for financial influences on economic growth. All nominal variables are adjusted to real values using the 2010-base-year GDP deflator.

4.3.4 Mechanism variables

Mechanism variables include urban and rural residents' savings deposits, rural and urban per capita disposable income to reflect income levels, the number of employed persons and urban on-the-job staff to reflect employment levels, and the number of registered industrial and commercial enterprises to reflect the entry of commercial entities. Definitions and descriptive statistics of all variables are provided in Table 1.

Table 1: Variables and Definitions

Variable category	Primary indicator	Secondary indicator	Variable symbol	Description
Dependent variables	Economic development	Real GDP	*lngdp*	Natural logarithm of actual regional gross domestic product
		Per capita real GDP	*lnpgdp*	Natural logarithm of per capita actual regional gross domestic product
Explanatory variables	Policy variables	Policy dummy variable	*did*	$D \times T$
		Regional dummy variable	*D*	0 for non-pilot counties, 1 for pilot counties
		Time dummy variable	*T*	0 before policy implementation, 1 after policy implementation
Control variables	Industrial structure	Primary industry share	*prir*	Value-added of primary industry / Regional GDP
		Secondary industry share	*secr*	Value-added of secondary industry / Regional GDP

Table 1 Continued

Variable category	Primary indicator	Secondary indicator	Variable symbol	Description
Control variables	Fiscal revenue & expenditure	Fiscal revenue share	*govr*	Local general public budget revenue / Regional GDP
		Fiscal expenditure share	*gove*	Local general public budget expenditure / Regional GDP
	Population	Population density	*pden*	Registered population (in 10,000s) / Area of jurisdiction (sq km)
	Human capital	Primary school student share	*ppr*	Number of students in regular primary schools / Registered population
		Middle school student share	*mpr*	Number of students in regular middle schools / Registered population
	Financial support	Financial loans	*lfin*	Natural logarithm of outstanding loans from financial institutions at year-end
Mechanism variables	Income level	Deposit balance	*deposit*	Natural logarithm of urban and rural household savings deposit balance
		Rural disposable income	*rlincome*	Natural logarithm of rural residents' per capita disposable income
		Urban disposable income	*tlincome*	Natural logarithm of urban residents' per capita disposable income
	Employment level	Total employment	*lemploy*	Natural logarithm of the number of formally employed persons
		Urban employment	*ltemploy*	Natural logarithm of the number of urban employees on job
	Market vitality	Business entity entry	*lentry*	Natural logarithm of the number of industrial and commercial registered enterprises plus 1

5. Empirical Results

5.1 Baseline Regression Analysis

The regression results from Equation (1) are presented in Table 2. Columns (1) to (3) take the logarithm of real GDP as the dependent variable, while columns (4) to (6) use the logarithm of real GDP per capita. Columns (1) and (4) do not include any control variables. Columns (2) and (5) add the control variables discussed earlier, such as industrial structure, fiscal revenue and expenditure, population density, human capital investment, and financial support. Columns (3) and (6) further control for county-fixed effects and year-fixed effects. According to the estimates in columns (3) and (6), after accounting for both county and year fixed effects, the PV poverty alleviation policy increased real GDP and real GDP per capita in the treatment group by 3.2% and 5.3%, respectively, compared to the control group. These effects are statistically significant at the 1% level, supporting Hypothesis 1. This indicates that the PV poverty alleviation policy has a pro-poor effect, significantly promoting economic growth in key poverty-stricken counties relative to other counties, and playing an important role in poverty reduction.

Table 2: Baseline Regression Results

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	lngdp			*lnpgdp*		
did	0.048***	0.057**	0.032***	0.017	0.065***	0.053***
	(0.015)	(0.022)	(0.011)	(0.016)	(0.014)	(0.012)
D	-0.289***	0.023		0.103**	0.121***	
	(0.074)	(0.031)		(0.042)	(0.035)	
T	0.401***	0.105***		0.444***	0.445***	
	(0.009)	(0.026)		(0.008)	(0.019)	
Fixed effects	No	No	Yes	No	No	Yes
Sample size	8860	8608	8604	8792	8601	8596
R^2 value	0.047	0.848	0.992	0.132	0.429	0.968

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors clustered at the county level are reported in parentheses.

5.2 Parallel Trends Test

The use of the DID method relies on the parallel trends assumption, rather than strict random assignment of the policy (Huang et al., 2022). To verify whether this assumption holds prior to policy implementation, this study follows Sun & Abraham (2021) and adopts an event study framework to evaluate the dynamic effects of the PV poverty alleviation policy. To avoid perfect multicollinearity, and in line with Chen (2017), the year before policy implementation (2017) is set as the baseline period, with the remaining years serving as event windows. The policy is considered to have taken effect starting in 2018, providing eight pre-treatment periods and two post-treatment periods. The econometric model is specified as follows:

$$Y_{it}=\beta_0+\sum_{j=-M}^{N}\delta_j did_{ij}+\eta X_{it}+\mu_i+\nu_t+\varepsilon_{it} \quad (3)$$

In the model, M and N represent the event time indicators for the 8 years prior to the policy implementation and the 2 years after it, respectively. X_{it} denotes a set of control variables that may affect the regression outcomes, consistent with those used in the baseline regression. did_{ij} is a dummy variable indicating whether a county is subject to the PV poverty alleviation policy in a given period; its coefficient δ_j measures the difference between the treatment and control groups in period j. Once county i becomes part of the PV poverty alleviation pilot program, the policy variable did_{ij} takes a value of 1; otherwise, it is 0. δ_{-8} through δ_{-2} capture the effects from the 8 pre-policy years to the second year before policy implementation. δ_0 reflects the effect in the implementation year (2018), while δ_1 and δ_2 reflect the policy effects in the first and second years after implementation (2019 and 2020, respectively). If the coefficients from δ_{-8} to δ_{-2} are not statistically significant, it suggests that there were no systematic differences between the treatment and control groups prior to the policy, thereby satisfying the parallel trends assumption. In addition, the model in Equation (3) also controls for county and year fixed effects.

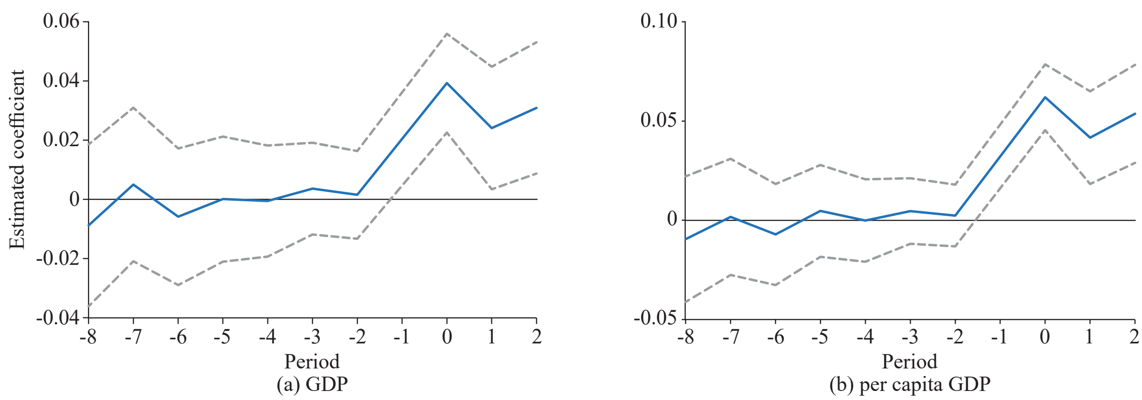

Figure 1: Dynamic Effects

Figure 1 presents the estimation results using the event study approach. It plots the estimated coefficients did_{ij} and their 95% confidence intervals based on the logarithm of real GDP and real GDP per capita. The results show that in the years prior to the implementation of the PV poverty alleviation policy, the estimated coefficients for both real GDP and per capita real GDP remain statistically insignificant and close to zero within the 95% confidence interval. This suggests that there were no significant differences between the treatment and control groups before the policy was introduced, thereby satisfying the parallel trends assumption. In contrast, from the year of implementation (2018) onward, the coefficients become significantly positive at the 5% level, indicating that the policy had a notable and statistically significant positive effect on economic growth in poverty-stricken counties from 2018 through 2020.

5.3 Robustness Checks

5.3.1 Placebo test

To ensure the robustness of causal identification and eliminate concerns about the influence of other policies or unobservable omitted variables, a placebo test is conducted. A placebo treatment indicator was generated by randomly assigning the ‘policy treatment’ status to 236 counties—matching the size of the actual treatment group. This randomization process was replicated 1,000 times using Monte Carlo simulations. The resulting 1,000 estimated coefficients are used to generate a kernel density distribution, with each regression’s p-value also shown. As illustrated in Figure 1, the distribution of these coefficients for both GDP and GDP per capita approximates a normal distribution with a mean of 0.0001, indicated by the dashed vertical line. This stands in sharp contrast to the baseline regression coefficients of 0.032 and 0.053, marked by solid vertical lines, with the corresponding p-value of the baseline shown as a dashed horizontal line. The baseline estimates are clear outliers in this distribution, confirming that the observed effects of the PV poverty alleviation policy are unlikely to be driven by chance or omitted variables.

5.3.2 Shortened duration

To further address potential disruptions caused by the sudden global public health crisis that began in early 2020, the study narrows the time window to the pre-pandemic years. Specifically, it limits the sample to the five-year period from 2015 to 2019. The main regression results based on this restricted window, presented in Table 2, columns (1) and (2), show that the PV poverty alleviation policy significantly improved economic development in the treatment group at the 1% level, consistent with the conclusions drawn from the baseline analysis.

5.3.3 Replacement of dependent variable

In addition, this study replaces the dependent variable with economic growth rate to test the robustness of the results. As a dynamic indicator, the economic growth rate reflects the pace of economic development in a given region, and prior studies (e. g., Liu & Li, 2017) often use GDP growth rate and GDP per capita growth rate as key measures. Drawing on this approach, the study re-estimates Equation (1) using GDP growth rate and GDP per capita growth rate as dependent variables. The regression results, reported in Table 2, columns (3) and (4), show that, after controlling for other variables, the PV poverty alleviation policy increased the GDP growth rate and GDP per capita growth rate in key poverty counties by 5.5% and 5.4%, respectively—both statistically significant at the 1% level. These findings indicate that the policy not only expanded the total economic output in targeted counties but also accelerated their economic growth, further confirming Hypothesis 1.

5.3.4 Excluding the influence of other PV poverty alleviation policies

Between 2010 and 2020, China implemented a series of PV poverty alleviation policies, including the central government “Notice”. To enhance the credibility of the estimation results, this study systematically examines the potential influence of these other policies on the conclusions. First, we exclude the six provinces identified in the 2015 “Notice on the Implementation Plan for Photovoltaic Power Generation Construction” as pilot regions for PV poverty alleviation projects. These provinces may have influenced the composition of the treatment group, and results after their exclusion are presented in Table 3, columns (1) and (2). Second, we exclude the counties listed in the 2016 “Notice on Issuing the First Batch of Photovoltaic Poverty Alleviation Projects”, which includes 14 provinces.

The results of this exclusion are shown in Table 3, columns (3) and (4). Third, we remove counties not included in the first batch of PV key poverty alleviation counties under the 13^{th} Five-Year Plan. Of the 471 counties mentioned in the 2016 "Guidelines", 236 were officially designated in the first batch on December 29, 2017, while another 165 were included in the second batch on April 12, 2019. However, 70 counties ultimately did not receive approval. Since the list of the second batch is not publicly available, the baseline regression may inadvertently include some of these 165 second-batch counties in the control group. This inclusion could lead to underestimation of the policy effects after 2019, as a portion of the control group would have been subject to the policy. To address this, we remove the 235 counties (471 minus 236) not included in the first batch. The regression results, presented in Table 3, columns (5) and (6), show that the estimated coefficients are slightly larger than those in the baseline regression, but remain robust. Finally, we simultaneously apply all three exclusion criteria above. In Table 3, columns (7) and (8), we incorporate these adjustments together. The estimated coefficients increase further, confirming the earlier hypothesis and supporting Hypothesis 1.

5.4 Endogeneity Issues

The above analyses show that the implementation of the PV poverty alleviation policy significantly enhanced economic growth in the treatment group. However, since other targeted poverty alleviation policies were also implemented during the same period, the treatment group may have been simultaneously affected by multiple policy interventions, leading to potential estimation bias due to omitted variables.

To address this endogeneity concern and disentangle the effect of the PV policy, we employ an instrumental variable (IV) approach, using sunshine intensity in the year prior to policy implementation. According to the 2016 "Guidelines", PV poverty alleviation was to be implemented in 471 national-level poverty counties across 16 provinces with favorable sunlight conditions. Thus, pre-policy sunshine levels are strongly correlated with the likelihood of policy implementation, satisfying the relevance condition for a valid instrument. Additionally, the sunshine conditions in a county during the year before implementation are unlikely to directly affect short-term economic growth through other channels, thereby meeting the exogeneity requirement. Since the sunshine data from the year before implementation are cross-sectional, we construct a panel-format instrumental variable by interacting this data with the policy time node. The core explanatory variable thus takes the value zero before the policy and becomes observable only after implementation. As a robustness check, we also use the three-year average of sunshine intensity prior to policy implementation as an alternative instrument. The regression results, shown in Table 4, remain positively significant at the 1% level. This confirms that, even accounting for the potential influence of concurrent policies, the estimated effect of the PV policy on economic growth remains robust after addressing omitted variable bias.

5.5 Heterogeneity Analysis

5.5.1 Heterogeneity of support intensity

This section explores heterogeneity in the effects of the PV poverty alleviation policy, focusing on differences in assistance intensity and sunshine intensity.

The "Three Regions and Three Prefectures[5]" (*Sanqu Sanzhou*) are considered some of the most challenging areas in China's poverty alleviation campaign. Due to their high poverty incidence, deep

[5] The "three regions" are the Xizang Autonomous Region, the Tibetan-inhabited areas of Sichuan, Yunnan, Gansu and Qinghai provinces, and the four prefectures in southern Xinjiang (Hotan, Aksu, Kashi and the Kizilsu Kirgiz Autonomous Prefecture). The "three prefectures" are Liangshan in Sichuan, Nujiang in Yunnan and Linxia in Gansu.

levels of poverty, weak infrastructure, and severely underdeveloped economies, these areas have been designated by the central government as key targets for poverty alleviation. In this analysis, counties within the “Three Regions and Three Prefectures” are treated as key assistance areas, while counties in the same six provinces but outside these regions are classified as non-key areas. Regression results in Table 3 show that the PV poverty alleviation policy increased GDP and GDP per capita in the key assistance areas by 3.4% and 4.6%, respectively, with both effects statistically significant at the 10% level. In contrast, the policy’s impact on non-key assistance areas is not statistically significant. This indicates that the state’s concentrated support can significantly enhance the effectiveness of the PV poverty alleviation policy.

A plausible explanation is the presence of a “siphon effect”. As priority regions, the “Three Regions and Three Prefectures” receive more favorable support, including larger fiscal subsidies, better talent recruitment, enhanced technical guidance, and stronger policy incentives. These advantages may attract labor and enterprises from other counties within the same provinces, thereby diluting the policy effects in non-priority areas and rendering them statistically insignificant.

5.5.2 Heterogeneity of sunlight intensity

To further isolate the effect of the PV policy and investigate the heterogeneity of its outcomes, this study examines variation in sunshine intensity. The rationale is that if the observed benefits are indeed due to the PV policy—and not other concurrent poverty alleviation policies—then the effects should be more significant in areas where sunlight is more abundant. PV projects operate by converting solar energy into electricity; therefore, regions with greater sunshine exposure are expected to yield greater benefits from such projects. In contrast, other poverty alleviation programs (e. g., appointment of capable government officials, vocational training, relocation, or e-commerce assistance) are unlikely to be directly influenced by local sunshine conditions in the short term. To quantify sunshine intensity, we use the natural logarithm of the total annual sunshine hours (lnSun) in each county. Annual sunshine hours refer to the number of hours in which direct solar irradiance meets or exceeds 120 watts per square meter. Table 4 presents the results of this heterogeneity analysis. The interaction term between the policy indicator and sunshine intensity (did×lnSun) is significantly positive at the 10% level. This finding suggests that the pro-poor effects of the PV poverty alleviation policy are stronger in areas with greater sunshine intensity. Accordingly, the observed economic growth in counties implementing PV policies is primarily attributable to the PV policy itself, rather than to other unrelated poverty alleviation measures.

Table 3: Heterogeneity in Assistance Intensity

Variables	(1)	(2)	(3)	(4)
	lngdp		*lnpgdp*	
	Key assisted regions	Non-key assisted regions	Key assisted regions	Non-key assisted regions
did	0.034* (0.018)	0.013 (0.026)	0.046* (0.026)	0.020 (0.028)
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Sample size	1,827	1,743	1,827	1,743
R^2	0.988	0.988	0.966	0.975

Note: Same as Table 2.

Table 4: Heterogeneity in Irradiance Intensity

Variables	(1)	(2)
	lngdp	*lnpgdp*
did	-0.760*	-0.909*
	(0.457)	(0.463)
ln*Sun*	0.020	0.052***
	(0.018)	(0.020)
did×ln*Sun*	0.101*	0.123**
	(0.058)	(0.059)
Control variables	Yes	Yes
Fixed effects	Yes	Yes
Sample size	8593	8585
R^2	0.992	0.968

Note: The sunshine intensity variable (lnSun) is a panel data variable that varies across time and counties. Other specifications follow those in Table 2.

5.6 Analysis of Poverty Alleviation Policy Intensity

The standard DID method estimates the average treatment effect on the treated group. However, even under the same policy framework, the intensity of implementation can differ significantly across regions within the treatment group. As highlighted in the *Guidelines*, targeted poverty alleviation should be tailored to local conditions, including sunshine availability. The implementation document for the first batch of PV poverty alleviation projects provides a detailed list of participating counties along with specific planned indicators. These offer a solid empirical foundation for analyzing the intensity of the PV poverty alleviation policy.

This study further examines the impact of PV poverty alleviation policy on county-level economic growth. Drawing on the *13th Five-Year Plan: First Batch of PV Poverty Alleviation Projects*, data were collected for 236 designated poverty-stricken counties. Four planned indicators are used in the analysis: the number of registered poor villages, which are identified based on fixed per capita net income, household income, and other characteristics such as assets and health status; the number of assisted households covered by the project; the number of planned PV power stations; and the planned installed capacity, measured in kilowatts. These four indicators are synthesized into a policy intensity index system. At the first level, the index includes two dimensions: the "Village/Household Assistance Ratio" and the "Power Station Coverage Scale". These dimensions are further disaggregated into four second-level indicators: the proportion of poverty alleviation villages, the proportion of poverty alleviation households, the average number of PV power stations per village, and the average installed capacity per household. The structure and definitions of these indicators are presented in Table 5.

Table 5: Policy Intensity Indicators

Primary indicator	Secondary indicator	Variable symbol	Description
Village/household assistance ratio	Share of designated poor villages	*villagerate*	Number of officially designated poor villages / number of village committees
	Share of assisted households	*householdrate*	Number of assisted households / number of rural households
Power station coverage scale	Average number of power stations per village	*perstation*	Number of power stations / number of village committees
	Average installed capacity per household	*perscale*	Construction scale (installed capacity) / number of rural households

Under the "Extent of Village and Household Assistance" dimension, this study defines the first policy intensity indicator, *villagerate*, as the ratio of the number of registered poverty-stricken villages in each pilot county to the number of village committees. This indicator reflects the extent of poverty within a county, with higher values indicating a larger share of poor villages. The second indicator, *householdrate*, is calculated by dividing the number of assisted households by the total number of rural households in the county. This measure captures the scale of targeted support; the higher its value, the greater the share of households benefiting from the policy. Under the "Extent of Power Station Coverage" dimension, the third indicator, *perstation*, is computed as the number of PV power stations divided by the number of village committees. This metric represents the average number of power stations per village, with higher values indicating broader infrastructure coverage. The fourth indicator, *perscale*, is calculated as the total planned installed capacity divided by the number of rural households, reflecting the average PV capacity allocated per household. A higher value implies more capacity per household, signaling a more intensive implementation of the policy. These four secondary indicators collectively capture the implementation intensity of the PV poverty alleviation policy. Among counties participating in the PV program, a higher intensity score suggests a stronger pro-poor impact.

Following the methodology of Nunn & Qian (2011), this study adopts a Generalized Differences-in-Differences (DID) approach to estimate the effect of policy intensity on county-level economic growth. Building on Equation (1), the estimation model is specified as Equation (4):

$$Y_{it}=\beta_0+\beta_1 I_i\times T_t+\gamma X_{it}+\mu_i+year_t+\varepsilon_{it} \tag{4}$$

In Equation (4), which builds on Equation (1), the term did_{it} is replaced by $I_i\times T_t$, where I_i represents the four policy intensity variables: the proportion of poverty-stricken villages (*villagerate*), the proportion of assisted households (*householdrate*), the average number of PV power stations per village (*perstation*), and the average installed capacity per household (*perscale*). The coefficient of this interaction term β_1 measures the impact of increased policy intensity on county-level economic growth. The variable T_t equals 1 for years $t\geq 2018$, and 0 otherwise. All other variables remain consistent with those in Equation (1).

As shown in Table 6, regardless of whether economic development is measured by GDP or GDP per capita, the estimated coefficients on policy intensity across columns (1) to (8) are all positively significant at the 1% confidence level. This confirms that greater policy intensity amplifies the poverty-alleviation effect of the PV initiative. Specifically, a one standard deviation increase in *villagerate* (0.198) is associated with a 3.56% increase in GDP and a 4.63% increase in GDP per capita. Similarly, a one standard deviation increase in *householdrate* (0.049) raises GDP and GDP per capita by 3.34% and 3.84%, respectively. For *perstation* (0.295), the corresponding increases are 4.97% and 6.50%, while for *perscale* (0.189), they are 2.11% and 2.53%. These results suggest that counties with higher proportions of targeted villages and households, more power stations per village, and greater installed capacity per household experience significantly stronger economic growth effects from the PV poverty alleviation policy.

Table 6: Policy Intensity Regression Results

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	lngdp				*lnpgdp*			
villagerate×T	0.157***				0.215***			
	(0.036)				(0.040)			
householdrate×T		0.709***				0.837***		
		(0.249)				(0.253)		
prestation×T			0.145***				0.205***	
			(0.039)				(0.043)	

Table 6 Continued

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	lngdp				*lnpgdp*			
prescale×T				0.120*** (0.041)				0.143*** (0.043)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	4183	4140	4183	4140	4175	4140	4175	4140
R^2	0.993	0.993	0.993	0.993	0.983	0.983	0.982	0.983

Note: Due to significant missing values for the number of village committees and rural households in the county statistical yearbooks, this study, in unreported results, measures the intensity of poverty alleviation by dividing the number of registered poor villages, assisted households, power stations, and construction capacity by population. The results remain robust. Other model specifications are consistent with those in Table 2.

6. Mechanisms Analysis

To test Hypotheses 2, 3, and 4, this section analyzes three transmission mechanisms: resident income channels, employment opportunities, and the entry of commercial entities, forming the logical chain: Photovoltaic Poverty Alleviation Policy → Resident Income / Employment Opportunities / Entry of Commercial Entities → County-Level Economic Growth.

6.1 Photovoltaic Poverty Alleviation and Resident Income Channels

Expanding income channels promotes economic development by stimulating consumption and investment, while higher income levels serve as a fundamental guarantee for stable and sustained growth. To examine the impact of the photovoltaic poverty alleviation (PVPA) policy on residents' income levels, this study uses the savings deposit balance of urban and rural residents, rural per capita disposable income, and urban per capita disposable income as proxy variables for income channel changes, replacing the dependent variable in the baseline model. Data are drawn from the *China County Statistical Yearbook*. Real income values are obtained by deflating the nominal figures using the GDP deflator with 2010 as the base year, followed by logarithmic transformation. All other variables are consistent with those used in the baseline regression.

Estimation results are presented in Table 7. Column (1) uses the savings deposit balance of urban and rural residents as the dependent variable, Column (2) uses rural per capita disposable income, and Column (3) uses urban per capita disposable income. After controlling for other variables, the PVPA policy significantly increases income levels in the treatment group relative to the control group, with coefficients statistically significant at the 1% level. Specifically, after the implementation of the PVPA policy, the savings deposit balance of urban and rural residents in counties with PVPA increased by 9.7%, rural per capita disposable income rose by 6.8%, and urban per capita disposable income increased by 7.5%. These findings confirm Hypothesis 2. According to the theoretical framework of this study, under the "self-consumption with surplus electricity fed into the grid" model, the PVPA policy reduces household electricity costs through self-consumption, while surplus power sales enable residents to obtain generation subsidies, thereby diversifying income sources and increase earnings.

Table 7: Household Income Mechanism

Variables	(1)	(2)	(3)
did	0.097*** (0.019)	0.068*** (0.011)	0.075*** (0.014)
Control variables	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
Sample size	8567	4480	6072
R^2	0.977	0.939	0.950

Note: Same as Table 2.

6.2 Photovoltaic Poverty Alleviation and Employment Opportunities

Employment is a key driver of economic growth. The implementation of the photovoltaic poverty alleviation (PVPA) policy has generated substantial short-term and long-term job opportunities in key poverty-stricken counties, spanning the planning, construction, and maintenance stages. Additionally, associated technical and skills training has enhanced the employability of local residents and broadened their access to job opportunities. To evaluate the impact of the PVPA policy on employment, this study replaces the dependent variable in the baseline model with two indicators: the number of formally employed persons and the number of urban employees on post. The relevant data are sourced from the *China County Statistical Yearbook*.

As shown in Table 8, column (1) uses the number of formally employed persons as the dependent variable, while column (2) uses the number of urban employees on post. After controlling for other variables, the PVPA policy significantly increased employment in the treatment counties. Specifically, the number of formally employed persons rose by 15.9%, and the number of urban employees on post increased by 11.6%. These findings support Hypothesis 3.

Table 8: Employment Mechanism

Variables	(1)	(2)
did	0.159*** (0.059)	0.116** (0.048)
Control variables	Yes	Yes
Fixed effects	Yes	Yes
Sample size	3093	1867
R^2	0.950	0.921

Note: Same as Table 2.

6.3 Photovoltaic Poverty Alleviation and Business Entry

This study examines the impact of the photovoltaic poverty alleviation (PVPA) policy on the entry of business entities. Following Li et al. (2022), the logarithm of the number of new business entities in each region plus one is used as the dependent variable, with other variables consistent with the baseline regression. The data are drawn from a full-sample dataset of industrial and commercial registrations, which includes both enterprises and individual businesses (Dong et al., 2021). Drawing on the method used by Li et al. (2022), this study identifies each business entity's registration time, location (at the county or district level), and industry type, and matches this information with panel data from 2010 to 2020 to construct a measure of business entry at the county level. According to the *National Economic Industry Classification* (GB/T 4754-2022), business entities are categorized into 20 major industry divisions.

Table 9 presents the estimation results. Column (1) reports the effect of the policy on total business entity entry across all divisions. Columns (2) to (5) examine specific sectors that are more likely to be influenced by the policy: agriculture, forestry, animal husbandry, and fisheries; manufacturing; finance; and all other sectors excluding the above three. The results show that the PVPA policy significantly promoted business entity entry in counties where it was implemented. On average, the number of new entities increased by 9.1% following the policy. Specifically, entries rose by 9.2% in agriculture, forestry, animal husbandry, and fisheries; by 5.1% in manufacturing; and by 11.9% in finance. No significant effect was observed in other sectors. These results provide empirical support for Hypothesis 4.

These findings are consistent with real-world developments. The widespread adoption of PV equipment has reduced electricity costs and improved the stability of energy supply for both local businesses and farmers. In agriculture-related industries, PV systems support key production activities such as spring plowing, irrigation, and greenhouse farming, thereby enhancing productivity and lowering operational costs (Guo & Bai, 2018). The policy has also stimulated the development of the photovoltaic industrial chain, particularly in manufacturing. Furthermore, the installation of household PV systems and village-level power stations—financed through a variety of mechanisms including poverty-targeted loans, corporate advances, and local investment funds—has driven rapid expansion in the financial sector due to the close involvement of financial institutions.

Table 9: Business Entry Mechanism

Variables	(1)	(2)	(3)	(4)	(5)
	Total	Agriculture, forestry, livestock and fishery	Manufacturing	Finance	Others
did	0.091*** (0.031)	0.092** (0.039)	0.051* (0.029)	0.119*** (0.038)	-0.007 (0.027)
Control variables	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes
Sample size	8603	8603	8605	8605	8605
R^2	0.926	0.890	0.888	0.394	0.895

Note: Same as Table 2.

7. Conclusions and Policy Recommendations

During a symposium on advancing comprehensive revitalization in Northeast China in September 2023, President Xi Jinping emphasized that it is essential to "actively cultivate strategic emerging industries such as new energy, new materials, advanced manufacturing, and electronic information; vigorously foster future industries to accelerate the formation of new quality productive forces characterized by innovation; and inject new momentum into development". Solar PV power generation is an integral part of these new quality productive forces, while the implementation of the PV poverty alleviation policy represents a major initiative by the Chinese government in its poverty eradication campaign. A clear understanding of the policy's economic impact can offer empirical evidence for evaluating how such new productive forces contribute to poverty alleviation. Using panel data from national-level poverty counties between 2010 and 2020, this study investigates the economic effects of the PV poverty alleviation policy and finds that it has significantly promoted economic development in poor areas. This effect is primarily driven by three mechanisms: improvements in resident income levels, expansion of employment opportunities, and increased entry of business entities. The policy's pro-poor impact is especially evident in counties receiving stronger national poverty alleviation support and those with higher solar irradiation intensity. Moreover, the policy demonstrates greater effectiveness in counties with higher proportions of targeted poor villages and households, as well as larger scales of PV station construction and coverage.

These findings provide several policy implications for institutionalizing and improving PV-related industrial policies under the current rural revitalization strategy.

Policy Recommendation 1: Plan Photovoltaic Deployment Based on Local Solar Resource Endowments. The implementation and promotion of PV poverty alleviation policies should be guided by the solar resource endowments of each locality and follow a framework of scientific and rational planning. Since PV systems rely on converting solar radiation into electricity, local solar conditions directly influence the efficiency and economic viability of PV generation. This study also finds that the pro-poor effect of the PV poverty alleviation policy is significantly affected by the level of regional solar irradiation. Therefore, when deciding whether to install PV systems, households and village collectives should be well-informed about local solar exposure. Installation methods should be adapted to regional conditions, and eligibility criteria for users should be clearly defined to prevent the over-deployment of PV infrastructure in areas with insufficient sunlight, where low returns may reduce the policy's intended economic impact. During the operational phase, attention must also be paid to routine maintenance. Regular cleaning of dust and debris from PV modules, as well as minimizing shading, is necessary to ensure optimal electricity generation efficiency and long-term stable system performance.

Policy Recommendation 2: Enhance Regional Collaboration and Support for Key Poverty Areas. This study finds that the photovoltaic poverty alleviation (PVPA) policy produces a more significant pro-poor effect in nationally designated key poverty alleviation regions. To further amplify this effect, it is essential to ensure the free flow of production factors and poverty alleviation resources across regions, thereby promoting the efficient allocation and utilization of those resources. Institutional barriers that hinder urban-rural integration and regional coordination should be dismantled. Strengthening collaboration among local governments, public service institutions, and region-specific PV-related enterprises will allow for complementary advantages, mutual support, and shared benefits. Establishing multi-level, synergistic partnerships can ensure that poverty alleviation resources are precisely targeted to the areas of greatest need, driving high-quality, coordinated regional development and advancing the broader goal of common prosperity.

Policy Recommendation 3: Actively Explore "PV+ Industry" Development Models. Given the clean, accessible, and cost-effective nature of PV technology, its deployment significantly reduces electricity and production costs for both residents and businesses. Local governments should leverage regional industrial strengths to promote the integration of the PV sector with other industries, fostering new development models under the "PV+" framework. Such models may include "PV + Agriculture", "PV + Fishery", "PV + Infrastructure", and "PV + Energy Storage", creating new engines of economic growth through self-sustaining poverty alleviation that enables expanded reproduction based on existing industrial capacities. This study further finds that the PVPA policy significantly increases business entity entry in sectors such as agriculture, manufacturing, and finance, indicating that it facilitates the growth of related industries. In response, local governments should focus on cultivating a favorable business and entrepreneurial environment to enhance the entrepreneurial and industrial spillover effects generated by the policy.

Policy Recommendation 4: Prevent and Mitigate Risks in PV Deployment. While advancing PV construction in an orderly manner, governments and stakeholders must remain vigilant to potential risks that arise in practice. Empirical evidence suggests that when electricity generation from PV stations exceeds local demand, grid systems may be unable to fully absorb the surplus, resulting in power curtailment and energy waste (Guo & Bai, 2018). To avoid this, policy implementation should be aligned with actual electricity demand across regions. In areas with relatively low electricity consumption, small- and medium-sized distributed PV projects should be prioritized. For surplus electricity, cross-regional transmission channels should be established, taking into account both transmission costs and power generation returns. In parallel, the development of energy storage systems and ultra-high-voltage (UHV) transmission infrastructure should be promoted to enhance the capacity to absorb and utilize excess electricity, thereby improving the efficiency and sustainability of PV deployment.

References:

Bertrand M., Duflo E., Mullainathan S. How Much Should We Trust Differences-in-differences Estimates [J]. Quarterly Journal of Economics, 2004(1), 249-275.

Cai F., Wang D. Changes in the Components of Economic Growth and the Sources of Farmers' Income [J]. Journal of Management World, 2005(5):77-83.

Chen S. X. The Effect of a Fiscal Squeeze on Tax Enforcement: Evidence from a Natural Experiment in China [J]. Journal of Public Economics, 2017, 147, 62-76.

Dong L., Yuan X., Li M., Ratti C., Liu Y. A Gridded Establishment Dataset as a Proxy for Economic Activity in China [J]. Scientific Data, 2021(1), 5.

Guo J., Bai T. The Discussion of Sustainability of Poverty Alleviation by Industrial Development in China: Taking Photovoltaic Poverty Alleviation as an Example [J]. Economic Review Journal, 2018(7):109-116.

Huang W., Zhang Z., Liu A. From Difference-in-Differences to Event Study [J]. Review of Industrial Economics, 2022(2):17-36.

Huang Z. Does the Establishment of National Poverty-stricken Counties Promote Local Economic Development? An Empirical Analysis Based on PSM-DID Methods [J]. Chinese Rural Economy, 2018 (5):98-111.

Kakwani N., Son H. H. Pro-poor Growth: The Asian Experience [A]. In Nissanki M. and Thorbeck E. (eds.), Globalization and the Poor in Asia: Can Shared Growth be Sustianed? [C]. New York: Palgrave Macmillan, 2008.

Li B., Zuo T. Discussion about the Implementation Logic in Poverty Alleviation Through Rural Industrialization from the Perspective of Precise Poverty Alleviation— A Case Study of Greenhouse Vegetable Industry in Y Village [J]. Journal of Southwest University(Social Sciences Edition), 2016(4):66-73+190.

Li K., Jiang W. Market Entry and Economic Growth: Evidence from Chinese Manufacturing Industry [J]. Economic Research Journal, 2015(5):48-60.

Li N., Zhang G. L., Zhou Y. H., Wu W. J. China’s Experience of Poverty Alleviation: Socioeconomic Effect of Rural “Photovoltaic Poverty Alleviation” Policy [J]. Journal of China Agricultural University, 2022(2): 294-310.

Li S., Wang M., Zhang D. Environmental Inspection and Firm Entry: Evidence from Firm Registration Data [J]. The Journal of World Economy, 2022(1): 110-132.

Li Z. Capital Transfer or Cash Transfer: Path Analysis of Chinese Industry Precision Poverty Alleviation and Its Policy Simulation [J]. Journal of Finance and Economics, 2017(4): 68-81.

Liu J., Huang F., Wang Z., Shuai C. What Is the Anti-poverty Effect of Solar PV Poverty Alleviation Projects? Evidence from Rural China [J]. Energy, 2021, 218, 119498.

Liu J., Xu M. Whether the Partner Assistance Policies Work? ——Natural Experiment Evidence from Partner Assistance of 19 Provinces & Cities [J]. World Economic Papers, 2017(4): 43-61.

Liu R., Zhao R. Government Support, Institutional Change and Academic Journal Progress — Evidence from China’s “Famous Journal Project” [J] China Economic Quarterly, 2020(2): 473-498.

Liu S. Empirical Analysis on the Targeting Mechanism and Performance Evaluation of Microfinance for Poverty Alleviation — Based on the Data of County R in Sichuan Province [J]. Southwest Finance, 2016(9): 12-14.

Liu Y., Li Y. High-speed Rails and City Economic Growth in China [J]. Journal of Financial Research, 2017(11): 18-33.

Liu Z., Wu D., He B. J., Wang Q., Yu H., Ma W., Jin, G. Evaluating Potentials of Passive Solar Heating Renovation for the Energy Poverty Alleviation of Plateau Areas in Developing Countries: A Case Study in Rural Qinghai-Tibet Plateau, China [J]. Solar Energy, 2019, 187, 95-107.

Lopez J. H. Pro-poor Growth: A Review of What We Know (and of What We Don’t) [M]. Washington: World Bank, 2004.

Lu Z., Du Y. The Impact of Tax Incentives on Innovation Performance of New Energy Companies—Taking Shanghai and Shenzhen A-share New Energy Listed Companies as An Example [J]. China Journal of Economics, 2024(1): 349-370.

Nunn N., Qian N. The Potato’s Contribution to Population and Urbanization: Evidence from a Historical Experiment [J]. Quarterly Journal of Economics, 2011(2), 593-650.

Rabaia M. K. H., Abdelkareem M. A., Sayed E. T., Elsaid K., Chae K. J., Wilberforce T., Olabi A. G. Environmental Impacts of Solar Energy Systems: A Review [J]. Science of The Total Environment, 2021, 754, 141989.

Ravallion M., Chen S. China's (Uneven) Progress Against Poverty[J]. Journal of Development Economics, 2007(1), 1-42.

Ravallion M. Growth, Inequality and Poverty: Looking Beyond Averages[J]. World Development, 2001(11), 1803-1815.

Sharif A., Meo M. S., Chowdhury M. A. F., Sohag K. Role of Solar Energy in Reducing Ecological Footprints: An Empirical Analysis [J]. Journal of Cleaner Production, 2021, 292, 126028.

Shen Y., Peng X. Chain Financing Mode and the Effects of Precision Poverty Alleviation: Empirical Study Based on Quasi Experiment [J]. Journal of Finance and Economics, 2016(9):4-15.

Sun C., Zhan Y. The Impact of Electricity Price Subsidy on Technological Innovation of New Energy Manufacturing Enterprises: Evidence from the Wind Power and Solar PV Equipment Manufacturing Industry[J]. Journal of Quantitative & Technological Economics, 2023(2): 158-180.

Sun L., Abraham S. Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects [J]. Journal of Econometrics, 2021(2), 175-199.

Tollefson J. Can Randomized Trials Eliminate Global Poverty [J]. Nature, 2015, 524, 150-153.

Wang H., Zhu X., Yin C. Research on the Development and the Feed-in Tariff Policy Impact of China's Photovoltaic Industry [J]. Journal of Quantitative & Technological Economics, 2022(7): 90-112.

Wang Y., Shu Q. The Spillover Effects of China's Targeted Poverty Alleviation Practice [J]. Journal of the Party School of the Central Committee of the C. P. C. (Chinese Academy of Governance), 2021(2): 49-57.

Wu S. High-Quality Development of Poverty Alleviation Through Photovoltaic Power Program Under the Background of Targeted Poverty Reduction [J]. Studies on Socialism with Chinese Characteristics, 2018 (5): 41-46.

Xu X., Cui X., Chen X., Zhou Y. Impact of Government Subsidies on the Innovation Performance of the Photovoltaic Industry: Based on the Moderating Effect of Carbon Trading Prices [J]. Energy Policy, 2022, 170, 113216.

Xu X., Liu E. Research on the Innovation of Financing Models for Industrial Poverty Alleviation [J]. Economic Review Journal, 2011(7): 85-88.

Yang K. Innovate Poverty Alleviation Models and Solve Financing Problems [N]. China Electric Power News, 2017-05-20(009).

Zhang G. J., Tong M. H., Li H., Chen F. Evaluation of Economic Growth Effect and Policy Effectiveness in Pilot Poverty Alleviation Reform Zone [J]. China Industrial Economics, 2019(8): 136-154.

Zhang H., Wu K., Qiu Y., Chan G., Wang S., Zhou D., Ren X. Solar Photovoltaic Interventions Have Reduced Rural Poverty in China [J]. Nature Communications, 2020, 11, 1969.

Zhao S., Zhou B., Zhou Z. Can the Development of E-Commerce Reduce Poverty Incidence? —— Evidence from China's Rural E-Commerce Demonstration Counties Project [J]. Statistical Research, 2023(2): 89-100.

Zhu L. Photovoltaic Poverty Alleviation: The Sun Shines on the Fields of Hope [N]. China Electronics News, 2020-05-19(001).

Zou L., Chen P., Wang H., Wu Y. Analysis and Optimization Path of Photovoltaic Poverty Alleviation Project Based on Field Investigation in Fuyang and Zuoquan [J]. China Soft Science, 2019(10): 50-60.