Towards Multidimensional Poverty Reduction: An Empirical Assessment on the Effectiveness of China's Targeted Poverty Alleviation Strategy

Wenguang Zhang[1], Yifang Zhou[1], Wenjing Han,[1*] & Yu Pang[1]

[1] *School of Government, Beijing Normal University, Beijing, PR China*

*Corresponding author: Dr. Wenjing Han

Email: hanwenjing@bnu.edu.cn

Abstract

From 2015 to 2020, under the implementation of the Targeted Poverty Alleviation (TPA) strategy, China eliminated absolute poverty, making a notable contribution to global poverty reduction efforts. This study develops a multidimensional poverty measurement system for rural households in China, based on the FAO's 2021 Rural Multidimensional Poverty Index (R-MPI). Utilizing data from a national household survey across 2012, 2014, 2018, and 2020, this study evaluates the performance of multidimensional poverty reduction in rural China. By employing OLS, PSM, and DID methods, this study systematically assesses the effectiveness of China's TPA strategy in reducing multidimensional poverty. Findings reveal that the TPA strategy has made significant strides in reducing multidimensional poverty among rural households, particularly in impoverished villages. The strategy effectively improved living standards and income, contributing to substantial progress in alleviating multidimensional poverty. However, challenges remain in ensuring food security, enhancing nutritional status, and promoting the sustainability of rural livelihoods. These insights not only deepen the understanding of multidimensional poverty in rural China but also provide valuable lessons for other developing countries facing similar challenges in poverty alleviation.

Keywords: multidimensional poverty; poverty reduction; Targeted Poverty Alleviation strategy; PSM-DID; rural China

Hacia la reducción multidimensional de la pobreza: una evaluación empírica sobre la eficacia de la estrategia china de alivio de la pobreza focalizada

Resumen

Entre 2015 y 2020, gracias a la implementación de la estrategia de Alivio de la Pobreza Dirigida (APD), China erradicó la pobreza absoluta, contribuyendo notablemente a los esfuerzos mundiales de reducción de la pobreza. Este estudio desarrolla un sistema de medición de la pobreza multidimensional para los hogares rurales de China, basado en el Índice de Pobreza Multidimensional Rural (IPMR) de la FAO de 2021. Utilizando datos de una encuesta nacional de hogares realizada en 2012, 2014, 2018 y 2020, este estudio evalúa el desempeño de la reducción de la pobreza multidimensional en la China rural. Mediante los métodos de mínimos cuadrados ordinarios (MCO), muestreo por puntuación de propensión (MPP) y diferencias en diferencias (DID), este estudio evalúa sistemáticamente la efectividad de la estrategia APD de China para reducir la pobreza multidimensional. Los resultados revelan que la estrategia APD ha logrado avances significativos en la reducción de la pobreza multidimensional entre los hogares rurales, especialmente en las aldeas más pobres. La estrategia mejoró eficazmente los niveles de vida y los ingresos, contribuyendo a un progreso sustancial en el alivio de la pobreza multidimensional. Sin embargo, persisten desafíos para garantizar la seguridad alimentaria, mejorar el estado nutricional y promover la sostenibilidad de los medios de vida rurales. Estos hallazgos no solo profundizan la comprensión de la pobreza multidimensional en la China rural, sino que también brindan valiosas lecciones para otros países en desarrollo que enfrentan desafíos similares en la reducción de la pobreza.

Palabras clave: pobreza multidimensional; reducción de la pobreza; estrategia de Alivio de la Pobreza Dirigida; PSM-DID; China rural

迈向多维减贫：中国精准扶贫战略的有效性评估

摘要

2015年至2020年，在精准扶贫战略实施背景下，中国消除了绝对贫困，为全球减贫事业作出了重要贡献。本文基于联合国粮农组织2021年提出的农村多维贫困指数（R-MPI），构建了中国农村家庭多维贫困测度体系，并利用2012年、2014年、2018年和2020年全国住户调查数据，评估中国农村多维减贫绩效。本文采用普通最小二乘法（OLS）、倾向得分匹配法（PSM）和双重差分法（DID），系统评估中国精准扶贫战略在降低多维贫困方面的有效性。研究发现，精准扶贫战略在降低农村家庭多维贫困方面取得了显著成效，尤其是在贫困村表现更为突出。该战略有效改善了农村家庭生活水平和收入状况，为缓解多维贫困作出了重要贡献。然而，在保障粮食安全、改善营养状况和促进农村生计可持续性方面仍面临挑战。本文不仅深化了对中国农村多维贫困问题的理解，也为其他面临类似减贫挑战的发展中国家提供了有益经验。

关键词：多维贫困；减贫；精准扶贫战略；倾向得分匹配-双重差分法；中国农村

---

1. Introduction

Following the United Nations' success in halving global extreme poverty by 2015, the eradication of poverty was reaffirmed as a central objective of international development under the Sustainable Development Goals (SDGs). In developing countries, rural poverty remains a persistent challenge (Singh & Chudasama, 2020). Poverty has traditionally been defined in monetary terms, based primarily on income levels (Ward, 2016; Liu et al., 2017). However, evolving development paradigms have led scholars to increasingly adopt a broader, multidimensional perspective that incorporates capability deprivation and social inequality (Sen, 1976; Gallardo, 2020; Zhou et al., 2023; Liu et al., 2023). Consequently, poverty is now widely understood not merely as insufficient income, but as a deprivation of the essential capabilities required to lead a valued life (Sen, 1999; Nussbaum, 2011).

As the world's largest developing country, China has experienced considerable changes in poverty reduction since the reform and opening-up in 1978. A notable adjustment in poverty governance has been the shift from broad welfare distribution to targeted interventions, represented by the Targeted Poverty Alleviation (TPA) strategy launched in 2013. Through operational measures such as the "Five Batch Initiatives"—which include industrial development, relocation, ecological compensation, education support, and social security—the TPA strategy sought to tailor poverty alleviation resources to the specific needs of rural households (World Bank, 2019). By 2020, 99 million rural residents in China had escaped poverty, placing China among developing countries that attained the SDG poverty reduction target ten years in advance (Yang & Liu, 2021).

Although existing studies have begun to examine the institutional innovations and heterogeneous effects of the TPA campaign (Liu et al., 2020; Zhou et al., 2018), a significant research gap remains in the rigorous causal evaluation of its impact on poverty reduction, particularly within a multidimensional framework. Most research relies either on descriptive analysis or on simple correlational methods such as OLS regression, which cannot adequately isolate the policy's effect from confounding factors or construct a reliable counterfactual for treated villages (Yu et al., 2023; Davie et al., 2021).Some scholars have also pointed out the need to shift policy research toward a broader perspective, such as learning from unintended negative policy outcomes, in order to advance collective solutions to public issues (Arnold, 2025). Specifically, there is a lack of studies that apply a standardized multidimensional poverty index within a rigorous quasi-experimental design to estimate the net effect of TPA village designation on household multidimensional poverty.

Against this research gap, we conduct empirical analysis to complement both theoretical and empirical deficiencies in existing studies. This study aims to empirically assess the extent to which China's Targeted Poverty Alleviation (TPA) strategy has reduced multidimensional poverty in rural areas, with particular attention to non-income dimensions. To this end, we adopt the Rural Multidimensional Poverty Index (R-MPI) proposed by the Food and Agriculture Organization (FAO) in 2021 to construct a comprehensive evaluation framework for rural households. Our analysis draws on nationally representative panel data from household surveys conducted in 2012, 2014, 2018, and 2020 by China's Ministry of Agriculture and Rural Affairs (MARA)—the country's highest authority in agricultural and rural policymaking. Using a combination of econometric methods—including Ordinary Least Squares (OLS), Propensity Score Matching (PSM), and Difference-in-Differences (DID)—we rigorously assess the impact of the TPA strategy.

This study extends the application of standardized multidimensional poverty assessment to the field of policy evaluation, and improves the theoretical interpretation of how targeted institutional arrangements shape rural household welfare beyond single income dimension. Meanwhile, it provides generalized theoretical implications for multidimensional poverty governance research across regions with similar institutional backgrounds. Methodologically and empirically, by integrating internationally recognized poverty metrics, authoritative national survey data and a rigorous quasi-experimental design, this paper also delivers novel empirical evidence on how precision-targeted institutional interventions improve comprehensive welfare and substantive living standards of rural populations.

2. Research Context and Literature Review

2.1 Targeted Poverty Alleviation (TPA) strategy practices

In 2015, the Chinese government launched the Targeted Poverty Alleviation (TPA) strategy, representing an important stage in the nation's poverty reduction efforts. It is noteworthy that this policy was not implemented simultaneously in all impoverished villages in 2015, but rather followed a sequential coverage process based on a precise identification mechanism. The relevant policy framework was established between 2014 and 2015 and implemented nationwide in phases. Its target scope gradually refined from regions to villages, and ultimately detailed down to households through the establishment of a national poverty alleviation information system. Specifically, by 2015, the strategy targeted 832 impoverished counties and 128,000 villages, covering approximately 56.3 million people (Wu et al., 2022). Building on this foundational identification, the strategy advanced into a comprehensive implementation phase (2016–2020). During this period, local governments deployed a suite of targeted measures, including industrial revitalization, financial aid, education, and healthcare (Zhou et al., 2023; Guo et al., 2022), which were designed to enhance public services and support the self-reliance of recipients (Liu et al., 2020).

By the end of 2020, China eliminated absolute poverty under national standards, removing all impoverished counties from the official list and completing regional poverty elimination. Despite the international poverty line rising from US\$1.25/day to US\$1.9/day in 2015, the proportion of people living below this higher threshold decreased significantly between 2010 and 2022 (Table 1, Figure 1). Meanwhile, rural well-being improved markedly in areas such as education, healthcare, housing, and access to safe drinking water. According to the official report released by State Council of China, the disposable income for residents of rural areas classified as impoverished increased significantly from RMB 6,079 in 2013 to RMB 12,588 by 2019 (The State Council, 2019).

However, the execution of this targeting mechanism at the household level fell short of perfect precision. Empirical research confirms the presence of both inclusion errors, defined as the allocation of benefits to non-poor households, and exclusion errors, which refer to the omission of eligible poor households (Cheng, Wang, & Chen, 2022). Consequently, despite the broad gains in income and infrastructure, progress in alleviating multidimensional poverty has consistently lagged behind these advances.

Table 1. Proportion of population below international poverty line in China

Year	Poverty headcount ratio (%)	Standard
2010	13.9	$1.25/day
2011	10.2	$1.25/day
2012	8.5	$1.25/day
2013	2.9	$1.25/day
2014	2.1	$1.25/day
2015	1.2	$1.9/day
2016	0.8	$1.9/day
2017	0.7	$1.9/day
2018	0.4	$1.9/day
2019	0.2	$1.9/day
2020	0.2	$1.9/day
2021	0.2	$1.9/day
2022	0.1	$1.9/day
2023	0.8	$2.15/day

Notes: The data are sourced from Department of Economic and Social Affairs Statistics, United Nations (https://unstats.un.org/sdgs/dataportal/countryprofiles/chn)

2.2 Studies on multidimensional poverty measurement

Poverty remains a major barrier to growth and development, attracting extensive scholarly attention (Debebe & Wuletaw, 2022; Barati et al., 2022; Hamago et al., 2023; Long et al., 2021). The concept of poverty has gradually expanded from a one-dimensional to a multidimensional perspective (Kakwani & Son, 2026). Amartya Sen's concept of multidimensional poverty (1976) has become central to poverty research, leading to various measurement approaches, including the income-consumption criterion (Ravallion et al., 1991) and the Human Development Index (UNDP, 2010). Among these, the Alkire-Foster (A-F) method (Alkire & Foster, 2011) is widely recognized for assessing multidimensional poverty by capturing deprivations in health, education, and living standards. Unlike income-based measures, the A-F method provides a holistic view of poverty by aggregating multiple deprivations.

The Multidimensional Poverty Index (MPI), developed by the UNDP and Oxford Poverty and Human Development Initiative (OPHI), offers a rigorous alternative to traditional income metrics. Extensively used in developing countries, MPI supports poverty assessments and policy decisions (Alkire & Santos, 2014). Many nations have adapted MPI for rural poverty evaluation, such as studies on multidimensional poverty trends in Sub-Saharan Africa (Alkire & Housseini, 2014), poverty comparisons in China, Japan, and South Korea (Kayo Nozaki & Takashi Oshio, 2016), and links between poverty and disability in Cameroon and Guatemala (Pinilla-Roncancio et al., 2020). By 2018, 14 countries had established national multidimensional poverty indices to guide anti-poverty strategies (Shen & Zhan, 2018).

Despite MPI's widespread use, the Global Sustainable Development Index (UNDP, 2010) has been criticized for failing to account for rural household economies (OPHI, 2020). To address this, the UN's Food and Agriculture Organization (FAO) and OPHI introduced the Rural Multidimensional Poverty Index (R-MPI) in 2021. Incorporating dimensions like health, education, living standards, and rural livelihoods, R-MPI provides a more precise assessment of rural poverty, improving policy guidance and intervention strategies tailored to rural populations.

2.3 Studies on the Effects of the TPA Strategy

Targeted poverty alleviation, as a recent development in China's poverty reduction efforts and a key innovation in the poverty governance system, effectively tackles challenges such as the uneven distribution of the poor, the growing diversity of their needs, and the misalignment of targeting. It has comprehensively enhanced poverty reduction outcomes in terms of the actors involved, the scope of interventions, and the methods employed (Sun et al., 2019).

Scholars have examined China's poverty reduction from multiple perspectives, including fiscal policy allocation (Liu et al., 2019; Wang et al., 2020), insurance coverage (Huang, 2019), healthcare utilization (Sun et al., 2022; Xia et al., 2021), and access to credit (Zulher & Ratnasih, 2021). Huang and Zhu (2021) employed micro-level panel data on impoverished households to conduct a multidimensional evaluation of the targeted poverty alleviation policy. Their findings indicate that the policy exerts significant poverty reduction effects across multiple dimensions, with particularly pronounced improvements in income, labor capacity, and quality of life. Cai et al. (2021) further demonstrate that, beyond its direct benefits for impoverished populations, targeted poverty alleviation generates spillover effects on non-impoverished groups through improvements in infrastructure, the accumulation of social capital, and shifts in relative income positions. However, these studies typically focus on single-policy dimensions, lacking a holistic, multidimensional evaluation framework. Moreover, studies using large-scale, nationally representative household data remain limited.

3. Research Design

3.1 Data description

This study draws on empirical data from the National Rural Fixed Observation Point (NRFO) survey, administered by the Ministry of

Agriculture and Rural Affairs. As China's largest longitudinal household-level survey, initiated in 1986, the NRFO dataset offers several key advantages: (1) coverage of 375 villages across 31 provincial-level administrative units; (2) tracking of over 20,000 rural households with high-frequency data collection; and (3) inclusion of 136 core variables across 12 modules, including demographics, agricultural production, and household income-expenditure profiles. Given its extensive temporal span (1986–2022), panel structure, and comprehensive multidimensional poverty indicators-particularly those related to nutritional security, such as grain output and animal product consumption—this study selects four survey waves (2012, 2014, 2018, and 2020) to assess the poverty reduction effects of the Targeted Poverty Alleviation (TPA) strategy through a multidimensional poverty framework.

The data cleaning process followed these steps: (1) exclusion of households with missing values in key explanatory variables (TPA participation) or outcome variables (multidimensional poverty indicators); (2) removal of atypical households, such as those headed by students. The final analytical sample consists of an unbalanced panel dataset of 15,201 households across 375 villages, resulting in 34,738 observations across the four survey rounds.

3.2 Measurement of multidimensional poverty

The construction of the multidimensional poverty index in this study is guided by three interrelated principles to ensure theoretical rigor, international comparability, and empirical feasibility. First, it is grounded in Sen's capability approach, which conceptualizes poverty as the deprivation of essential capabilities rather than merely a lack of income. Accordingly, the index transcends a unidimensional, income-based perspective and captures deprivation across multiple domains, thereby reflecting the inherent complexity of rural poverty.

Second, to enhance comparability and methodological robustness, this study draws on the Rural Multidimensional Poverty Index (R-MPI), jointly developed by the FAO and OPHI, which is widely recognized as a standard framework for measuring rural poverty. This study employs the Rural Multidimensional Poverty Index (R-MPI) to measure rural poverty in China due to three main reasons. First, R-MPI integrates multiple dimensions, such as food security and nutrition, rural livelihoods and resources, living standards, and income, allowing for a more comprehensive reflection of the complexity and diversity of poverty. Second, the comprehensive nature of R-MPI enables the identification of different types and levels of poverty, thus providing a solid basis and direction for formulating more precise poverty alleviation policies. By focusing on health and living conditions, R-MPI not only takes economic factors into account but also reflects the intricate relationships among various socio-economic indicators, thereby revealing potential impacts of structural poverty. This provides sufficient evidence and support for evaluating rural poverty in China, ensuring that the research findings possess a certain degree of representativeness and policy relevance. Finally, as an internationally recognized measurement tool, R-MPI facilitates comparisons and learning between China and other countries regarding poverty alleviation practices and policy designs, thereby enhancing dialogue on poverty reduction experiences with other developing nations.

Third, the selection of dimensions and indicators is constrained by data availability from China's national rural fixed observation point survey; thus, all variables are required to be directly observable or reliably derived from the dataset, with proxy indicators employed where exact measures are unavailable.

Based on these principles, several context-specific adjustments are made to the original R-MPI framework. While the original framework comprises five dimensions—food security and nutrition, education, living standards, rural livelihoods and resources, and risk exposure—the education dimension is excluded in this study. This is because China had achieved near-universal compulsory education coverage by 2010 (MOE, 2012), and the effects of educational deprivation typically manifest with a substantial intergenerational lag. In addition, aligning with China's "Two Assurances and Three Guarantees" strategy (The State Council, 2015), we omit risk and introduce an income dimension, drawing on multidimensional poverty metrics validated by Chinese scholars (Liu et al., 2023). Consequently, the revised R-MPI comprises: food security and nutrition, living standards, rural livelihoods and resources, and income, totaling 13 poverty indicators (Table 2).

In terms of threshold setting, most existing studies set 0.4–0.6 times the median per capita income as the relative poverty line (Chauvel 2013; Peichl et al. 2010; Eisenhauer 2011). The median reflects the central tendency of income distribution, whereas the lower quartile directly corresponds to the bottom 25% of the population in terms of income and welfare. Adopting the lower quartile as the threshold allows for more direct and stable identification of disadvantaged groups at the tail of the distribution. This approach also avoids the measurement bias, where the median itself is prone to distortion by extreme values and the overall distribution.

3.3 Empirical Strategy

3.3.1 Baseline regression model

China's targeted poverty alleviation strategy, launched in 2015, designated impoverished villages as priority units for coordinated interventions. Consequently, the assistance provided to farmers in impoverished and non-impoverished villages showed significant disparities in areas such as fiscal support, project supply, and human capital allocation. Therefore, this study designates farmers in impoverished villages as the experimental group and farmers in non-impoverished villages as the control group, in order to evaluate the TPA strategy.

Table 2. Multidimensional poverty index of rural households

Dimensions	Indicator	Deprived if	Weight
Food security and nutrition (1/4)	Food insecurity	The annual total household grain production is lower than the lower quartile of the overall population.	1/8
	malnutrition	The annual household primary food consumption of pork, beef, mutton, milk (cow and sheep), poultry, eggs, fish and shrimp, and fruits is lower than the lower quartile of the overall population.	1/8
Living standards (1/4)	Improved sanitation	If the sanitation facilities are not indoor toilets or outdoor toilets.	1/28
	Electricity	The household has no electricity energy.	1/28
	Drinking water	The household lacks access to potable drinking water sources, including piped water, water from deep wells, and water from shallow wells.	1/28
	Cooking fuel	The household uses firewood or coal for cooking.	1/28
	Internet	The household is devoid of internet connectivity.	1/28
	Housing	The housing is not a multistory building or brick bungalow.	1/28
	Assets	The household does not possess any two out of the 22 durable goods.	1/28
Rural livelihoods and resources (1/4)	Agricultural assets adequacy	The share of agricultural income in the total income of the household is equal to or exceeds 30%.	1/12
	Low wage	The family is officially recognized as a households covered under the Five Guarantees program*.	1/12
	Social protection	The household has no insurance expenses throughout the year	1/12
Income (1/4)	Annual household income	The household annual income is lower than the lower quartile of the overall population.	1/4

Note: *Five Guarantees Households refers to a specific social security system in rural China aimed at assisting individuals facing extreme poverty and lacking support. The Five Guarantees program is designed to help impoverished and vulnerable rural populations, ensuring basic guarantees in terms of survival, healthcare, housing, and education.

Firstly, we estimate a baseline Ordinary Least Squares (OLS) regression to examine the impact of residence in impoverished villages on rural households' multidimensional poverty. The model specification is:

$$Y_{it} = \alpha + \beta Poverty + \gamma X_{it} + \mu_i + \nu_t + \omega_{it} \quad (1)$$

In the regression model (1), Yit is the multidimensional poverty of rural households, indicates whether the village is identified as a impoverished village by Ministry of Civil Affairs of the People's Republic of China; Xit represents other control variables at village level, household level and household head level that change over time and affect the multidimensional poverty of farmers; μi represents the fixed effect of farmers' individuals; νt represents the fixed effect of years, and ωit is a random error term. In the empirical analysis, we utilized regression equation (1) to explore how various control variables impact the multidimensional poverty of rural households in impoverished villages compared to those in non-impoverished villages. The variables are described in Table 3.

Table 3. Variables description

Variable type	Variable name	Variable description	N	Mean	SD	Min	Max
Dependent variable	R-MPI	Multidimensional poverty index for households, range 0-1	35647	0.190	0.152	0	0.790
Independent variable	Poverty	1 if the household's village is a designated impoverished village; otherwise, 0	35647	0.100	0.300	0	1
Control variables	Edu	Years of education received by the household head	36448	7.020	2.449	0	18
	Gender	Gender of the household head, 1 if male, 2 if female	36844	1.049	0.215	1	2
	Labor	Number of working members in the household	36186	5.359	0.068	0	10
	Township	Whether the village hosts the township government: 1 if yes, 2 if no	36824	1.871	0.335	1	2
	Village PCI	Village level per capita income, measured in RMB	35833	10801.48	12091.27	0.758	181230

3.3.2 Robustness test with the propensity score matching method

Given the vast geographical disparities and significant differences in economic development levels across regions in China, and considering that the impoverished village designation involves some provincial autonomy, this study uses the propensity score matching method (PSM) (Heckman and Todd, 1997), alongside Rosenbaum and Rubin's (1983) research for supplemental improvements to the DID method. Specifically, this study calculated the conditional probability $P(D_i=1|X_i)$—the propensity score—that a household's village is designated as impoverished using a logit model based on characteristics at the village, household, and household head levels, along with whether the village is officially recognised as impoverished. For this study, comparable households from the treatment and control groups were paired together with careful consideration of their propensity scores.

Here, Treatment = 1 indicates that the household is from an impoverished village impacted by TPA strategy, representing the treatment group. Conversely, Treatment = 0 indicates households from non-impoverished villages, representing the control group. Therefore, we can evaluate how the targeted strategy to alleviate poverty affects the overall poverty of households in impoverished villages by using the following equation (2):

$$ATT = E(Y_1 \mid T = 1) - E(Y_0 \mid T = 1) = E(Y_1 - Y_0 \mid T = 1) \tag{2}$$

3.3.3 DID model

Examining the poverty reduction effects of the TPA strategy on rural households in impoverished areas requires comparing the differences in multidimensional poverty among rural households in impoverished villages before and after the implementation of these policies. In the data processing, we observed that after the implementation of the TPA strategy, the number of impoverished villages increased year by year due to precise identification. Therefore, we defined the treatment variable as residence in designated impoverished villages and adopted the criterion that villages initially identified as impoverished in 2012 were classified into the treatment group. Meanwhile, we distinguish the status effect from the inherent endowments of impoverished villages from TPA's actual implementation effect, and clarify that the estimated effect essentially captures the average effect of place-based bundled pro-poor policies. However, rural households' multidimensional poverty is influenced not only by TPA but also by time changes. The academic consensus supports using the difference-in-differences (DID) methodology to isolate "time effects" from "policy effects," minimizing evaluation bias (Abadie, 2010). Our study constructs the treatment group's counterfactual state using the control group and compares changes in the multidimensional poverty index between affected and unaffected rural households.The DID model established in this study is described as follows:

$$Y_{it} = \alpha + \beta_1 Poverty_i + \beta_2 Time_t + \beta_3 Poverty_i \times Time_t + \gamma X_{it} + \mu_i + \nu_t + \omega_{it} \quad (3)$$

In DID model (3), $_i$ represents the household, $_t$ represents time, and Y_{it} is the multidimensional poverty status of household $_i$ in year $_t$. $Poverty_i Time_t$ is the independent variable of this study, assigned a value of 1 if the household's village is designated as impoverished and the TPA strategy has been implemented in that year; otherwise, it is 0. During TPA strategy's implementation process, the official policy directive issued by China's Central Committee and State Council emphasized maintaining the status quo regarding poverty alleviation strategies for counties that had previously escaped the poverty trap. Additionally, they urged the formulation of post-alleviation national assistance policies to ensure sustained progress. Therefore, in subsequent years, the treatment group includes samples from villages that have successfully overcome poverty, meaning once a village is classified as impoverished, $Poverty_i Time_t$ = 1 in subsequent years. The coefficient β to be estimated represents the poverty reduction effect of the targeted assistance strategy. X_{it} denotes additional control variables that vary over time and influence the multidimensional poverty status of households, μ_i denotes individual fixed effects of the household, ν_t represents fixed effects for the year, and ω_{it} is the random error term.

4. Descriptive Results

Table 4 & Figure 1 offers a synoptic view of the descriptive statistics associated with the core variables analyzed in the current research. The dataset encompasses observations from the years 2012, 2014, 2018, and 2020, comprising 34,738 samples, with 5,696 in the treatment group and 29,042 in the control group.

Table 4. Descriptive statistics

Variable Name	Definitions	N	Mean	SD	Min	Max
R-MPI	Multidimensional poverty index for households	34738	0.180	0.140	0	0.762
Food security and nutrition	Conditions of food insecurity and malnutrition in households	34738	0.198	0.287	0	1
Living standards	Poverty conditions related to household living standards	34738	0.219	0.118	0	0.857
Rural livelihoods and resources	Poverty conditions related to rural livelihood and resources	34738	0.149	0.169	0	1
Income	Poverty conditions related to annual total income for households	34738	0.154	0.361	0	1

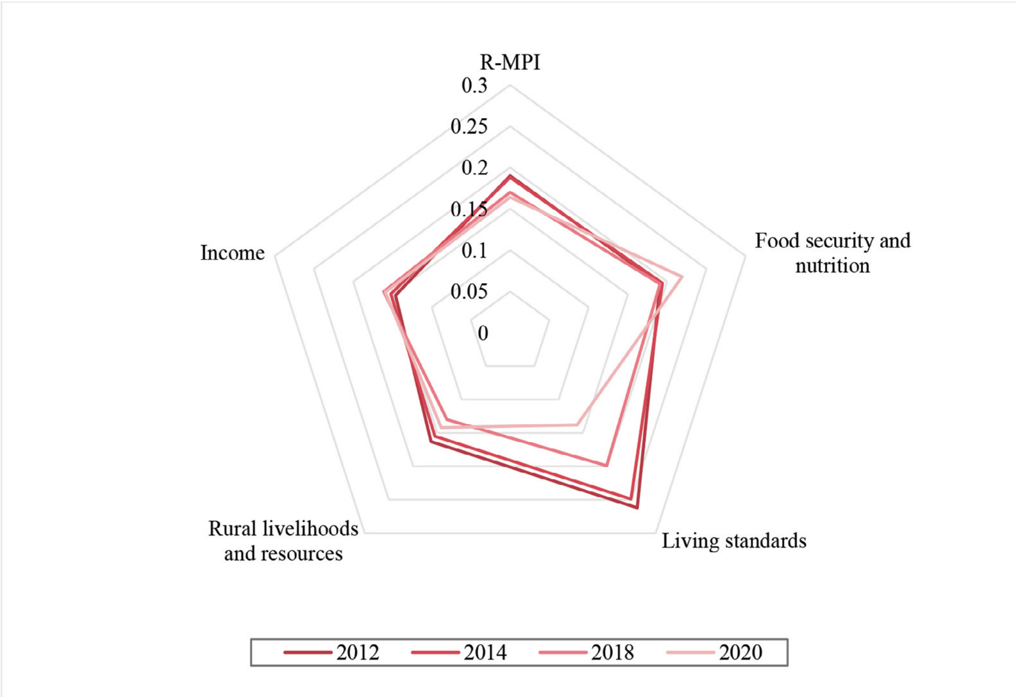

Figure 1. Changes in multidimensional poverty index across different dimensions

Table 5 lists the comparisons between the number of impoverished and non-impoverished villages identified in different years. The results show that the increasingly precise identification of poverty has led to a yearly increase in the number of impoverished village samples, particularly marked after the implementation of the registration and card system for targeted poverty alleviation in 2015, showing significant growth compared to the years 2012 and 2014.

Table 5. The number of households: impoverished vs. non-impoverished villages

Variable name	Number of households in impoverished villages	Number of households in non-impoverished villages	total
2012	1193	9036	10229
2014	1176	8191	9367
2018	1707	6368	8075
2020	1620	5447	7067
total	5,696	29042	34,738

Figure 2 illustrates the evolution of the R-MPI among households in impoverished villages, showing a decrease from 0.2162 in 2012 to 0.1816 by 2020. In contrast, the R-MPI for non-impoverished households demonstrates a more consistent downward trend, decreasing from 0.187 in 2012 to 0.1592 by 2020. Notably, the R-MPI for impoverished households consistently remained above 0.2 until 2018, while the R-MPI for non-impoverished households fell below this threshold in 2016. Before the TPA strategy was introduced in 2015, the R-MPI for households in impoverished villages exhibited stagnation with a slight increase. However, following the implementation, a notable downward trend in the R-MPI became apparent. In contrast, the R-MPI for households in non-impoverished areas displayed a steady decreasing trend over the years, indicating minimal impact from the TPA strategy.

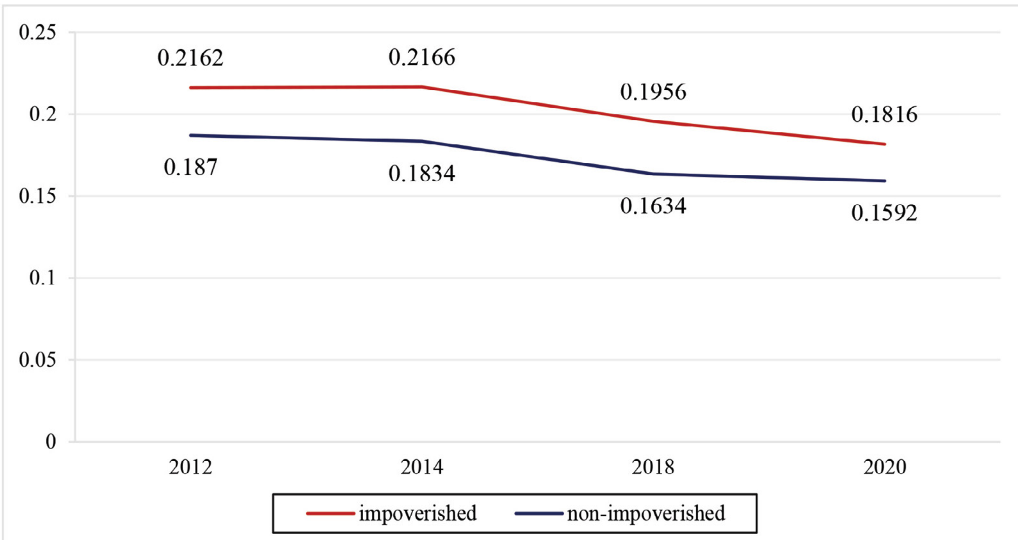

Figure 2. R-MPI change: impoverished vs. non-impoverished villages

Figure 3 reveals significant disparities in poverty across different dimensions between households in impoverished and non-impoverished villages. Households in impoverished villages notably face higher poverty levels in food security, nutrition, income, and living standards, with food security and nutrition showing the most pronounced gap, thereby reflecting the adverse impact of natural disasters and other risks (Hallege et al., 2020). Meanwhile, the lower R-MPI in rural livelihood and resources among impoverished households may stem from government agricultural subsidies targeting non-impoverished villages during the TPA period. Policies such as direct grain and agricultural input subsidies have contributed significantly to household income in impoverished villages, yet short-term agricultural earnings remain low. Additionally, the per capita net income of these households is less than 60% of the provincial average, which limits their disposable income and constrains ability to afford social insurance.

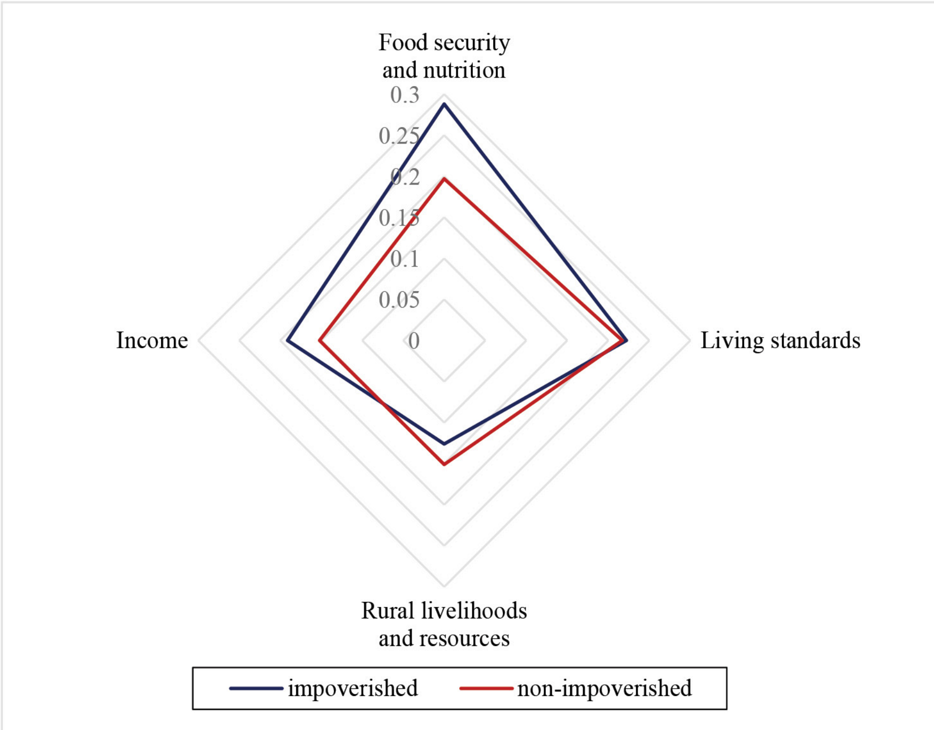

Figure 3. Poverty dimensions comparison: impoverished vs. non-impoverished villages

5. Empirical Results and Discussion

5.1 Baseline regression results

Table 6(a) details the control variables selected for this study and their differing impacts on the multidimensional poverty index-(R-MPI) of households in impoverished and non-impoverished villages. Notably, in Column (1), the gender of the household head, the number of family labor force members, and whether the township government provides assistance significantly influence the multidimensional poverty index of households in non-impoverished villages. Furthermore, in Column (2), it is evident that the township government's assistance and village per capita income have a substantial effect on the multidimensional poverty index of households in impoverished villages. These findings underscore the importance of such variables in understanding the dynamics of poverty across different village types.

Table 6(b) examines the influence of accounting for village-level, family, and household leadership attributes on the distinct components of poverty within households residing in impoverished communities. The analysis reveals pronounced disparities in the manner in which control variables exert their effects across the various aspects of multidimensional poverty within this demographic. Firstly, the number of family labourers significant-

Table 6. Baseline regression results

(a) All households

Variable name	(1) R-MPI (impoverished)	(2) R-MPI (non-impoverished)
Gender	0.0120 (0.0045)	0.0289*** (0.0108)
Labor	-0.0033 (0.0050)	-0.0083*** (0.00086)
Edu	-0.0008 (0.0012)	-0.0014 (0.0009)
Township	0.0400*** (0.0093)	0.0276*** (0.0054)
Village PCI	-0.00001*** (0.00001)	0.00001 (0.00001)
Constant	0.1728*** (0.0304)	0.1552*** (0.0122)
Controls	YES	YES
Individual FE	YES	YES
Year FE	YES	YES
Observations	5572	28817
R-squared	0.0460	0.0420

***p<0.01, **p<0.05, *p<0.1

ly negatively impacts living standards poverty and income poverty. Secondly, our analysis demonstrates the presence of township governments significantly influences farmers' food security and nutrition, as well as their overall living standards. The township government office typically functions as a central nexus for the concentration of administrative resources, where policy implementation tends to be more efficient and effective. Local governments are better positioned to directly deliver agricultural support to farmers, including subsidies, agricultural technical training, and access to agricultural loans. The enthusiasm and capacity for policy execution at the local level can have a direct impact on farmers' agricultural productivity, thereby influencing their food security. The timeliness and precision of policy implementation are pivotal in determining whether farmers receive timely support, which, in turn, affects their productive capacity and overall living standards.

(b) Impoverished village households

	(1)	(2)	(3)	(4)	(5)
Variable name	R-MPI	Food security and nutrition	Living standards	Rural livelihoods and resources	Income
Gender	0.0120 (0.0045)	0.0239 (0.0477)	-0.0048 (0.0190)	0.0111 (0.0248)	0.0178 (0.0638)
Labor	-0.0033 (0.0050)	0.0192*** (0.0055)	-0.0045** (0.0021)	-0.0029 (0.0029)	-0.0251*** (0.0073)
Edu	-0.0008 (0.0012)	-0.0064 (0.0040)	-0.0021 (0.0014)	0.0009 (0.0020)	0.0043 (0.0053)
Township	0.0400*** (0.0093)	0.4234*** (0.0199)	0.0615*** (0.0022)	-0.3445*** (0.0092)	0.0197 (0.0261)
Village PCI	-0.00001*** (0.00001)	-0.00001*** (0.00001)	-0.00001 (0.00001)	0.00001** (0.00001)	0.00001** (0.00001)
Constant	0.1728*** (0.0304)	-0.5239*** (0.0658)	-0.1998*** (0.0227)	0.7646*** (0.0316)	0.2506*** (0.0871)
Controls	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	5572	5572	5572	5572	5572
R-squared	0.0460	0.0020	0.1453	0.0029	0.0438

***p<0.01, **p<0.05, *p<0.1

Table 6(c) presents the effects of accounting for characteristics specific to villages, families, and household heads on the multidimensional poverty status of households residing in non-impoverished villages. Firstly, compared to households in impoverished village areas, household head's gender characteristics significantly impact households in non-impoverished villages. Meanwhile, whether the village hosts the township government is also a key factor affecting poverty issues among households in non-impoverished villages. Secondly, the number of family labourers also significantly negatively impacts the overall multidimensional poverty, living standards poverty, rural livelihood and resources poverty, and income poverty of households in non-impoverished villages. Lastly, the years of education of the household head have an impact on the income of families in non-impoverished villages.

Specifically, the longer the household head's education, the more likely it is to reduce income poverty, which provides some empirical support for the significant positive role of increasing the educational level of household heads in alleviating rural household poverty (Bigsten et al., 2003).

(c) Non-impoverished village households

Variable name	(1) R-MPI	(2) Food security and nutrition	(3) Living standards	(4) Rural livelihoods and resources	(5) Income
Gender	0.0289*** (0.0108)	0.0297 (0.0192)	-0.0041 (0.0072)	-0.0025 (0.0101)	0.0922*** (0.0274)
Labor	-0.0083*** (0.00086)	0.0001 (0.0055)	-0.0025*** (0.0008)	-0.0051*** (0.0011)	-0.0257*** (0.0022)
Edu	-0.0014 (0.0009)	-0.0009 (0.0018)	-0.0011 (0.0008)	0.0007 (0.0009)	-0.0044* (0.0088)
Township	0.0276*** (0.0054)	0.0411*** (0.0199)	0.0152** (0.0064)	0.0305*** (0.0067)	0.0237* (0.0129)
Village PCI	0.00001 (0.00001)	0.00001 (0.00001)	0.00001*** (0.00001)	-0.00001 (0.00001)	0.00001 (0.00001)
Constant	0.1552*** (0.0122)	0.0925*** (0.0249)	-0.2390*** (0.0137)	0.1232*** (0.0147)	0.1661*** (0.0302)
Controls	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	28817	28817	28817	28817	28817
R-squared	0.0420	0.0002	0.1661	0.0192	0.0431

***p<0.01, **p<0.05, *p<0.1

5.2 Results of the PSM method

To construct potential outcomes similar to those of the treatment group, the PSM method was employed to extract observations from the common support region, which is the overlapping area of the propensity scores (PS). Initially, the PS, the predicted probability of being included in the treatment group, was calculated for households in impoverished villages. Given the results of the baseline regression, variables such as whether the village hosts the township government, number of family labourers, and the gender, and education of the household head were identified as good predictors. Therefore, employing a logistic regression analytical framework, we construct the PS by incorporating above variables.

The retention rate of 99.97% (34,388 / 34,389) significantly surpasses the 95% threshold for robust causal inference in observational studies (Caliendo and Kopeinig, 2008) (See Appendix Table 1). Furthermore, as shown in Table 7, the pseudo R^2 for the matched data decreased to 0 ($p = 0.999$), indicating that the matched data distribution achieved a high level of model fit. The mean bias was significantly reduced, dropping from 17.5% to 0.4%, which not only falls far below the 5% bias threshold but also provides robust evidence of effective control over sample selection bias. Additionally, the standardized bias was optimized from 55.1 to 1.01, satisfying Rubin's criterion for approximate normality of the matched distribution ($B < 1.25$) (Rubin, 2001). These results demonstrate that the PSM method performs exceptionally well in controlling sample selection bias and enhancing the robustness of causal effect estimation, thereby providing a reliable foundation for subsequent causal inference.

Table 8 presents the estimated results for the Average Treatment Effect on the Treated (ATT). The results show that the impoverished village exerts a significant positive effect on the outcome variable R-MPI, which aligns with the baseline results. Specifically, villages classified as impoverished, as indicated by a higher R-MPI, experience a deeper level of poverty.

Table 7. Comparative statistical analysis by group: unmatched vs matched

Sample	PsR2	LRchi2	p>chi2	Mean Bias	Med Bias	B	R	%Var
Unmatched	0.046	1405.06	0.000	17.5	14.8	55.1*	1.36	67
Matched	0.000	0.38	0.999	0.4	0.4	1.01	0	

*if B>25%, R outside [0.5;2]

Table 8. ATT estimation results

Sample	Treated	Controls	Difference	S.E.	T-stat
Unmatched	0.1991	0.1756	0.0235	0.0020	11.44
ATT	0.1991	0.1869	0.0122	0.0172	0.71

5.3 Results of the effectiveness of TPA strategy

After completing the sequence matching process, we proceeded with a difference-in-differences (DID) analysis of the sample data, adhering to the research design outlined previously. Furthermore, we conducted rigorous robustness checks, including parallel trend validation and placebo tests, to ensure the reliability of our difference-in-differences (DID) estimates. Specifically, the parallel trend assumption was validated through a dynamic event study approach, while placebo tests were implemented by randomly assigning pseudo-treatment timing across 1,000 iterations. Both procedures confirmed the absence of pre-treatment divergence and spurious policy effects, thereby reinforcing the robustness of our causal inferences (See Appendix Figure 1 & 2).

Table 9 summarises the findings of the regression analysis. The significantly negative coefficient of the DID items in columns (1) and (2) of Table 9 indicates that TPA strategy successfully reduced the R-MPI for households in impoverished areas. This finding provides strong evidence of the strategy's positive impact on poverty reduction and the improvement of living conditions for these vulnerable communities. Similarly, the results in Columns (4), and (6), like those in Column (1), show that the DID items is also significantly negative, reflecting significant enhancements in living standards and income as a result of the TPA strategy. This aligns with findings by Yin & Guo (2021), who observed that TPA strategy's effects as a whole on improving the poor's material living standards.

The data in Columns (3) and (5) show that the poverty reduction approach aimed at specific targets actually worsened the situation for those in poverty, particularly concerning food security, nutrition, and the living conditions and resources of life in rural areas for families living in impoverished villages. This does not imply that the TPA strategy failed to implement grain production support; on the contrary, during this period, local finance invested substantial funds in grain-producing households to ensure national food security. However, most households in impoverished villages in China operate on a small, dispersed scale, and grain production is less profitable compared to cash crops and external employment. The contradiction between increasing grain production and promoting income growth among farmers is a key factor exacerbating the multidimensional poverty in food security and nutrition dimensions.

Additionally, considering that the main strategy goal during China's TPA strategy implementation period was to eliminate absolute poverty with a focus on industrial and social security poverty alleviation, aiming to provide a safety net for impoverished households, as shown in Column (6), the TPA strategy significantly narrowed the income disparity between households in impoverished and non-impoverished villages. The overall income increases among impoverished village households mainly stemmed from the development of local speciality industries, agricultural processing, and rural tourism, which boosted non-agricultural income for these households, while significant growth in agricultural income was not achieved. In the dimension of rural livelihood and resources, people in disaster-prone impoverished areas are more likely to rely on the government to cover losses, showing a lack of insurance awareness and a low willingness to spend on insurance (Wang et al., 2012), increasing the likelihood that households go through a year without any insurance expenditure.

Table 9. The effectiveness of TPA strategy with PSM-DID method

Variable name	(1) R-MPI (1)	(2) R-MPI (2)	(3) Food security and nutrition	(4) Living standards	(5) Rural livelihoods and resources	(6) Income
DID (Poverty*Time)	-0.0070** (0.0035)	-0.0093*** (0.0035)	0.0327*** (0.0076)	-0.0161*** (0.0029)	0.0132*** (0.0040)	-0.0576*** (0.0094)
Constant	0.16262*** (0.0114)	0.1839*** (0.0010)	0.0989*** (0.0238)	0.2426*** (0.0126)	0.1224*** (0.0137)	0.1867*** (0.0282)
Control	YES	NO	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
R-squared	0.0425	0.0022	0.0025	0.1543	0.0192	0.0472

***p<0.01, **p<0.05, *p<0.1

6. Discussion

Our analysis reveals two key features in rural China's multidimensional poverty transformation. First, households in impoverished villages experience more severe multidimensional poverty than those in non-impoverished villages. Second, the R-MPI in economically disadvantaged communities has declined significantly since the introduction of the TPA strategy in 2015, indicating stronger poverty-reducing effects where need is greatest. When examining specific dimensions, we found poverty remains highest in income, living standards, food security and nutrition, while dimensions such as rural livelihoods and resource access showed comparatively smaller gains. This discrepancy aligns with Bellon et al. (2020), who attribute persistent deprivation to geographical isolation and low agricultural output, especially in remote, mountainous areas.

OLS regression results indicate that in non-impoverished villages, household factors—such as the number of laborers, village administrative status, and the gender of the household head—significantly influence multidimensional poverty outcomes. In contrast, in impoverished villages, only village administrative status remains statistically significant, suggesting that at high poverty levels, institutional or governance characteristics are the dominant drivers—a finding echoing Ma et al. (2018). Applying a PSM-DID approach, we confirm that TPA has significantly reduced multidimensional poverty, particularly in terms of living standards and income. This is consistent with findings from Liu et al. (2023) on relocation-based poverty relief. Moreover, our results are consistent with similar targeted interventions abroad: Mexico's Community Forestry Program, which seeks to build local capacity, has also improved incomes in forest communities (Torres-Rojo et al., 2019), Rwanda's plant clinic model has enhanced food security and reduced poverty (Tambo et al., 2020), and India's National Rural Employment Guarantee Act (NREGA) provided a legal guarantee for wage employment, which improved rural household income and food security (Klonner & Oldiges, 2022).

However, we also observe that TPA's impact on food security, nutrition, rural livelihoods and resource access is comparatively limited. As pre-TPA policies emphasized grain subsidies (Liu et al., 2023), and TPA subsequently focused on increasing income level through industrialization and social security (Yang et al., 2020), agricultural livelihoods have remained structurally constrained, particularly for smallholder farmers. Additionally, China's reliance on small-scale farming means that while TPA's employment assistance programs offer higher-income non-agricultural jobs, their effect on diversifying rural livelihoods remains constrained (Lei et al., 2016; Wang et al., 2019). This pattern can be further explained by examining regional disparities in household income structure and agricultural production models. Previous studies also reveal significant regional differences in rural household income composition across China, Zhang et al. (2025) based on CFPS data found that the poverty reduction effects of different income sources vary considerably by region, with operating income demonstrating the most pronounced impact on poverty alleviation across all areas. And the income sources of farmers in central and western China are relatively more homogeneous and exhibit greater dependence on household operating income compared to eastern region (Shi & Huang, 2023). This process has direct consequences for food security and nutrition, when households reduce their engagement in food production, they will lose the buffer provided by home-grown food stocks, the increase in income may not indicate on improvement in the overall living conditions. This trade-off between income growth and food security is not unique to rural China; in many sub-Saharan African countries, agricultural interventions that prioritized cash crops or off-farm employment over staple food production have inadvertently exacerbated household food insecurity, as smallholders allocate less labor and land to subsistence crops (Nyambo, P. et al., 2022). These domestic and international experience suggest that the trade-off between income growth and food security is a structural challenge in contexts where smallholder agriculture predominates and safety nets for nutrition are weak. Addressing it requires deliberate policy design that integrates nutrition-sensitive agriculture with income support, rather than only considering income growth. In addition, the long-term sustainability of poverty reduction should be linked to broader agricultural transformation, since low-carbon and resource-efficient agricultural development can help reconcile livelihood improvement, food security, and environmental resilience in rural China (Wu et al., 2024).

By revealing the TPA's uneven effects—stronger in income and living standards but weaker in food security and rural livelihood sustainability. Our study highlights the urgent need for context-sensitive, integrated poverty interventions that address the full breadth of rural poverty.

7. Conclusion, Implications and Limitations

7.1 Conclusion

By 2021, China had eradicated absolute poverty, marking a significant achievement among developing nations (Chen et al., 2021). This accomplishment reflects the effectiveness of institutionalized strategies like Targeted Poverty Alleviation (TPA), which have reshaped China's approach to poverty governance. This study, using a multidimensional poverty perspective and the UNFAO's R-MPI framework, analyzed rural panel data from 2012, 2014, 2018, and 2020 through PSM-DID. Our results reveal a complex picture: the TPA strategy significantly alleviated multidimensional poverty in officially designated impoverished villages. However, its effects were more pronounced in improving income and living standards than in addressing persistent deprivations such as food security, nutrition, and livelihood sustainability.

7.2 Implications

Based on these findings, we propose the following policy recommendations. First, poverty alleviation strategies should move beyond income-centered approaches toward a more comprehensive welfare framework. While TPA has significantly improved income and living standards, its negative effects on food security and nutrition highlight critical shortcomings in non-income dimensions. In the context of rural revitalization, policy design should incorporate multidimensional poverty indicators to guide resource allocation and project implementation, with particular emphasis on integrating food security and nutrition monitoring into evaluation systems.

Second, policy priorities should shift from short-term poverty reduction to long-term resilience and livelihood sustainability. The limited impact of TPA on rural livelihoods and resources in impoverished villages, suggests that current interventions remain insufficient for building endogenous development capacity. Future policies should strengthen productive capabilities through targeted agricultural support, expanded access to subsidized insurance, and the promotion of diversified livelihood strategies, including high-value agriculture, cooperative development, and rural entrepreneurship.

Third, differentiated and capacity-oriented interventions should replace uniform policy approaches. The results indicate that multidimensional poverty in impoverished villages is primarily shaped by structural and governance factors, whereas in non-impoverished villages it is more closely associated with household-level characteristics. Accordingly, policy design should adopt a stratified approach: that prioritizes improvements in institutional capacity and governance in severely impoverished areas, while focusing on human capital accumulation and labor mobility support in relatively better-off regions.

7.3 Limitations

This study is subject to several limitations. First, data constraints pose a fundamental limitation. The use of confidential data restricts the sample period to 2020 and limits the inclusion of potentially important confounding variables, which may affect both the assessment of long-term policy effectiveness and the robustness of causal identification. Future research should leverage updated panel data and incorporate richer contextual variables to strengthen empirical inference. Second, the measurement of multidimensional poverty remains imperfect. Although the R-MPI framework is refined, data limitations may hinder its ability to fully capture the complexity and heterogeneity of rural poverty. Further improvements in indicator design and dimensional coverage are therefore needed. Third, the analysis focuses on average treatment effects and does not sufficiently explore heterogeneity across household groups and policy implementation modes. Future studies should adopt a more disaggregated approach to uncover the differentiated impacts of TPA across regions, household structures, and intervention types.

Disclosure Statement

There are no conflicts of interest to declare.

Data Availability

The data supporting this study were obtained from the Ministry of Agriculture and Rural Affairs of China and contain confidential information. Due to legal restrictions, the raw data cannot be publicly disclosed.

References

Abadie, A. (2010). Semiparametric difference-in-differences estimators. *Review of Economic Studies, 72*(1), 1-19. https://doi.org/10.1111/0034-6527.00321.

Alkire, S., & Foster, J. (2011). Counting and multidimensional poverty measurement. *Journal of public economics*, *95*(7-8), 476-487.

Alkire, S. & Housseini, B. (2014). Multidimensional poverty in sub-Saharan Africa: Levels and trends. In M. Nissanke & M. Ndulo (Eds.), *Poverty reduction in the course of African development* (102-109). Oxford Academic. https://doi.org/10.1093/acprof:oso/9780198797692.003.0005

Alkire, S. & Santos, M. E. (2014). Measuring acute poverty in the developing world: Robustness and scope of the multidimensional poverty index. *World Development*, *59*, 251-274. https://doi.org/10.1016/j.worlddev.2014.01.026

Arnold, G. (2025). Human agency, negative cases, and public problem-solving: Priorities for public policy scholarship in China and globally in the 21st century. China Policy Journal, 4(1), Article 2. https://doi.org/10.18278/cpj.4.1.2

Klonner, S. & Oldiges, C. (2022). The welfare effects of India's rural employment guarantee. *Journal of Development Economics*, 157. https://doi.org/10.1016/J.JDEVECO.2022.102848.

Barati, A. A., Zhoolideh, M., Moradi, M. Mollayousef, E. S, & Fürst, C. (2022). Multidimensional poverty and livelihood strategies in rural Iran. *Environment, Development, and Sustainability, 24*, 12963-12993. https://doi.org/10.1007/s10668-021-01977-x

Nyambo, P., Nyambo, P., Mavunganidze, Z., & Nyambo, V. (2022). Sub-Saharan Africa smallholder farmers agricultural productivity: risks and challenges. In Food security for African smallholder farmers (pp. 47-58). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-16-6771-8_3

Bellon, M. R., Kotu, B. H., Azzarri, C., & Caracciolo, F. (2020). To diversify or not to diversify, that is the question. Pursuing agricultural development for smallholder farmers in marginal areas of Ghana. *World Development*, *125*, 104682.

Bigsten, A., Kebede, B., Shimeles, A., & Taddesse, M. (2003). Growth and poverty reduction in Ethiopia: Evidence from household panel surveys. *World Development*, *31*(1), 87-106. https://doi.org/10.1016/S0305-750X(02)00175-4

Cai, Y. H., Huang, Y., & Zheng, X. Y. (2021). Spillover effects of poverty alleviation policies: A study based on the impact on life satisfaction of non-poor households. China Industrial Economics, (11), 24-43. https://doi.org/10.19581/j.cnki.ciejournal.2021.11.002

Caliendo, M., & Kopeinig, S. (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys, 22*(1), 31–72. https://doi.org/10.1111/j.1467-6419.2007.00527.x

Chang, Q., Ma, W., Vatsa, P., & Li, J. (2022). Has the Targeted Poverty Alleviation program improved household welfare in rural China? *Journal of Policy Modeling, 44*(5), 1041-1056.

Chauvel, L. (2013). Welfare regimes, cohorts and the middle classes. In J. Gornick & M. Jäntti (Eds.), *Income inequality: Economic disparities and the middle class in affluent countries* (pp. 115–141). Stanford, CA: Stanford University Press.

Chen, S. & Ravallion, M. (2021). Reconciling the conflicting narratives on poverty in China. *Journal of Development Economics*, *153*, Article 102711. https://doi.org/10.1016/j.jdeveco.2021.102711

Cheng, X., Wang, J., & Chen, K. Z. (2022). Does villager social capital hinder poverty targeting? Evidence from poverty-stricken county of Western China. *China Economic Review, 71*, 101728.

China Statistical Yearbook—2020. (2020). National Bureau of Statistics of China. https://www.stats.gov.cn.

Davie, G., Wang, M., Rogers, S., & Li, J. (2021). Targeted poverty alleviation in China: A typology of official–household relations. *Progress in Development Studies, 21*(3), 244-263.

Debebe, S., & Wuletaw, T. (2022). Comparative analysis of rural to urban multidimensional poverty and its correlates at household level in Gamo Zone of Southern Ethiopia. *Social Indicators Research, 162*(1), 107-121. https://doi.org/10.1007/s11205-021-02833-1

Eisenhauer, J. G. (2011). The rich, the poor, and the middle class: Thresholds and intensity indices. *Research in Economics,65*(4), 294–304.

Gallardo, M. (2020). Measuring Vulnerability to Multidimensional Poverty. *Social Indicators Research*, *148*, 67-103. https://doi.org/10.1007/s11205-019-02192-y

Guo, Y., Zhou, Y., & Liu, Y. (2022). Targeted poverty alleviation and its practices in rural China: A case study of Fuping County, Hebei Province. *Journal of Rural Studies, 93*, 430-440. https://doi.org/10.1016/j.jrurstud.2019.01.007

Hamago, J., Burton, J., Owen, J., & Bainton, N. (2023). Multidimensional poverty and small-scale mining in the shadow of large-scale mines in Papua New Guinea. *Journal of Rural Studies*, *101*, Article 103045. https://doi.org/10.1016/j.jrurstud.2023.103045

Huang, W. (2019). Insurance policy and poverty reduction with Chinese characteristics: Experience, dilemma and path optimization. *Management World*, 35(1), 135-150. https://doi.org/10.19744/j.cnki.11-1235/f.2019.0010 (in Chinese).

Huang, W., & Zhu, W. (2021). Multidimensional evaluation of targeted support policies: Empirical analysis based on poverty alleviation practice in B city, G province. *Management World*, 37(10), 111-128. https://doi.org/10.19744/j.cnki.11-1235/f.2021.0158 (in Chinese).

Liu, A., Shang, C., & Li, Y. (2023). Research on the impact of targeted poverty alleviation policies on rural family education investment. *Economic Theory and Business Management, 43*(8), 99-112. http://jjll.ruc.edu.cn/EN/Y2023/V43/I8/99

Liu, M., Wu, X., & Chen, J. (2023). Income, deprivation, and social exclusion: toward a comprehensive poverty measurement in Hong Kong. *Journal of Asian Public Policy,* 1-22. https://doi.org/10.1080/17516234.2023.2221977

Liu, M., Feng, X., Wang, S., & Qiu, H. (2020). China's poverty alleviation over the last 40 years: Successes and challenges. *Australian Journal of Agricultural and Resource Economics 64*(1), 209-228. https://doi.org/10.1111/1467-8489.12353

Liu, M., Feng, X., Zhao, Y., & Qiu, H. (2023). Impact of poverty alleviation through relocation: from the perspectives of income and multidimensional poverty. *Journal of Rural Studies*, *99,* 35–44. https://doi.org/10.1016/j.jrurstud.2023.02.009.

Liu, X., Lin, J., Hu, J., Lu, H., & Cai, J. (2019). Economic transition, technology change, and energy consumption in China: A provincial-level analysis. *Energies*, *12*, 2581. https://doi.org/10.3390/en12132581

Long, Y., Lu, H., Sangui, W., & Li, M. (2021). Mobile Internet use and multidimensional poverty: Evidence from a household survey in rural China. *Social Indicators Research, 158*(3), 1065-1086.

Ma, Z., Chen, X., & Chen, H. (2018). Multi-scale spatial patterns and influencing factors of rural poverty: A case study in the Liupan Mountain Region, Gansu Province, China. *Chinese Geographical Science*, *28*, 296-312.

Ministry of Education of the People's Republic of China. (2012, September 10). *A miracle in the history of human education: A report on the popularization of nine-*

year compulsory education and the elimination of illiteracy among young and middle-aged adults in China [Report]. *China Education Daily*. http://www.moe.gov.cn/jyb_xwfb/s5147/201209/t20120910_142013.html

Nussbaum, M. C. (2011). Creating Capabilities: The Human Development Approach. *Cambridge*, MA: Harvard University Press.

Kakwani, N., & Son, H. H. (2026). Multidimensional poverty: A New perspective on measurement. *The Journal of Development Studies, 62*(3), 445-459.

Kayo Nozaki & Takashi Oshio. (2016). Multidimensional poverty and perceived happiness: Evidence from China, Japan and Korea. *Asian Economic Journal*, *30*(3), 275-293.

Peichl, A., Schaefer, T., & Scheicher, C. (2010). Measuring richness and poverty: A micro data application to Europe and Germany. *Review of Income and Wealth,56*(3), 597–619.

Pinilla-Roncancio, M., Mactaggart, I., Kuper, H., Dionicio, C., Naber, J., Murthy, G.V.S., & Polack, S. (2020). Multidimensional poverty and disability: A case control study in India, Cameroon, and Guatemala. *SSM - Population Health*, *11*, Article 100591. https://doi.org/10.1016/j.ssmph.2020.100591

Qunfang, G., & Xiaobing, H. (2024). The effect of targeted poverty alleviation on consumption of poor rural households in China. *Heliyon, 10*(10).

The State Council Information Office of the People's Republic of China. (2021). Poverty Alleviation: China's Experience and Contribution. *Rural Revitalization*, (5)1.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41-55.

Rubin, D. B. (2001). Using propensity scores to help design observational studies: application to the tobacco litigation. *Health Services and Outcomes Research Methodology*, *2*, 169-188. https://doi.org/10.1023/A:1020363010465

Sen, A. (1976). Poverty: an ordinal approach to measurement. *Econometrica: Journal of the Econometric Society*, *44*(2), 219-231.

Sen, A. (1999). Development as Freedom. New York: Alfred A. Knopf.

Shen, Y. Y., Zhan, P., & Li, S. (2018). Evolution of poverty alleviation policies and multidimensional poverty in rural China. *Economic Perspectives*, (7), 53-66 (in Chinese).

Shi, P. F., & Huang, J. K. (2023). Rural transformation, income growth, and poverty reduction by region in China in the past four decades. *Journal of Integrative Agriculture, 22*(12), 3582-3595.

Singh, P. K. & Chudasama, H. (2020). Evaluating poverty alleviation strategies in a developing country. *PloS one*, *15*(1), Article e0227176. https://doi.org/10.1371/journal.pone.0227176

Sun, D. C., Zhou, Y. Y., & Hu, C. M. (2019). Basic experiences, challenges and prospects of "China-style poverty reduction" over 70 years: From the three-dimensional perspective of subject–content–method. *Journal of Social Sciences*, (09), 31-42.

Sun, J. L., Tao, R., Wang, L., & Jin, L.-M. (2022). Does social medical insurance achieve a poverty reduction effect in China? *Frontiers in Public Health*, *9*, Article 800852. https://doi.org/10.3389%2Ffpubh.2021.800852

Tambo, J. A., Uzayisenga, B., Mugambi, I., Bundi, M., & Silvestri, S. (2020). Plant clinics, farm performance and poverty alleviation: Panel data evidence from Rwanda. *World Development*, *129*, 104881.

The Communist Party of China Central Committee, & State Council of the People's Republic of China. (2015). Decision on winning the battle against poverty. Retrieved from https://www.gov.cn/zhengce/202203/content_3635198.htm

The State Council Information Office of the People's Republic of China. Poverty Alleviation: China's Experience and Contribution. Available online: https://english.www.gov.cn/archive/whitepaper/202104/06/content_WS606bc77ec6d0719374afc1b9.html (accessed on 6 April 2019).

Tsui, K. Y. (2002). Multi-dimensional poverty indices. *Social choice and welfare, 19*(1), 69-93.

Torres-Rojo, J. M., Moreno-Sánchez, R., & Amador-Callejas, J. (2019). Effect of capacity building in alleviating poverty and improving forest conservation in the communal forests of Mexico. *World Development*, *121*, 108-122.

United Nations Development Programme. Evaluation Office. (2010). *Assessment of Development Results: Evaluation of UNDP Contribution. Cambodia.* UN.

Wang, H., Zhao, Q., Bai, Y., Zhang, L., & Yu, X. (2020). Poverty and subjective poverty in rural China. *Social Indicators Research*, *150*, 219-242. https://doi.org/10.1007/s11205-020-02303-0

Wang, M., Liao, C., Yang, S., Zhao, W., Liu, M., & Shi, P. (2012). Are people willing to buy natural disaster insurance in China? Risk awareness, insurance acceptance, and willingness to pay. *Risk Analysis: An International Journal*, *32*(10), 1717-1740. https://doi.org/10.1111/j.1539-6924.2012.01797.x

Wang, P., Yan, J., Hua, X., & Yang, L. (2019). Determinants of livelihood choice and implications for targeted poverty reduction policies: A case study in the YNL river region, Tibetan Plateau. *Ecological Indicators*, *101*, 1055-1063.

Wu, B., Geng, B., Wang, Y., McCabe, S., Liao, L., Zeng, L., & Deng, B. (2022). Reverse entrepreneurship and integration in poor areas of China: Case studies of tourism entrepreneurship in Ganzi Tibetan Region of Sichuan. *Journal of Rural Studies, 96*, 358-368.

Wu, J.; Xu, Y.; Liu, Z (2024). A comprehensive review on agricultural greenhouse gas emission reductions in China: opportunities and challenges. Carbon Footprints, 3, 17.

Xia, Q., Wu, L., Tian, W., Miao, W., Zhang, X., Xu, J., Li, Y., Shi, B., Wang, N., Yang, H., Huang, Z., Yang, H., Li, Y., Shan, L. & Wu, Q. (2021). Ten-year poverty alleviation effect of the medical insurance system on families with members who have a non-communicable disease: evidence from Heilongjiang Province in China. *Frontiers in Public Health*, *9*: Article 705488 https://doi.org/10.3389/fpubh.2021.705488

Yang, Y., de Sherbinin, A., & Liu, Y. (2020). China's poverty alleviation resettlement: Progress, problems and solutions. *Habitat International*, *98*, 102135.

Yang, Y. & Liu, Y. (2021). The code of targeted poverty alleviation in China: A geography perspective. *Geography and Sustainability*, *2*(4), 243-253. https://doi.org/10.1016/j.geosus.2021.09.004

Yu, W., Wang, Q., Wang, Y., Guan, G., & Gao, Y. (2023). Does targeted poverty alleviation policy reduce poverty? Evidence from Rural China. *SAGE Open, 13*(4), 21582440231197281.

Zhang, J. H., Zhao, Z. J., & Song, Y.X. (2025). Income growth and inequality reduction through rural industrial integration: Evidence from small-scale farmers in China. *Journal of Asian Economics,100*,102009-102009. https://doi.org/10.1016/J.ASIECO.2025.102009.

Zhou, Y., Guo, Y., Liu, Y., Wu, W., & Liu, Y. (2018). Targeted poverty alleviation and land policy innovation: Some practice and policy implications from China. *Land Use Policy*, *74*, 53-65. https://doi.org/10.1016/j.landusepol.2017.04.037

Zhou, Y., Zhong, Z., Cheng, G. (2023). Cultivated land loss and construction land expansion in China: Evidence from national land surveys in 1996, 2009, and 2019. *Land Use Policy*, *125*, Article 106496. https://doi.org/10.1016/j.landusepol.2022.106496

Zhou, Y., Huang, X., Shen, Y., & Tian, L. (2023). Does targeted poverty alleviation policy lead to happy life? Evidence from rural China. *China Economic Review*, *81*, Article 102037. https://doi.org/10.1016/j.chieco.2023.102037

Zulher, Z. & Ratnasih, C. (2021). Financial development and poverty reduction in developing countries. *Accounting*, *7*(3), 667-674. https://doi.org/10.5267/j.ac.2020.12.010