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Evaluating the effects of the targeted poverty alleviation programs on development: The case of China

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Abstract:

China eradicated absolute poverty recently. This research assessed the role of the targeted poverty alleviation program in fostering economic development in China. This study employed a difference-in-differences design and a propensity score matching estimation. It can be found that counties selected as targeted impoverished counties have significantly worse economic conditions than their counterparts. However, receiving policy treatment as targeted counties fosters economic development. There is little heterogeneity in the impact of the poverty alleviation program. Why the targeted poverty alleviation program has a significant role in eliminating absolute poverty in China will also be explained.

Keywords: Poverty alleviation; Targeted poverty alleviation program; Economic development; Difference-in-differences; China.

1 Introduction

A major component of human development, lowering poverty influences people's and communities' well-being and quality of life. Targeting poverty reduction helps nations foster stability, lower inequality, and stimulate sustainable growth. Moreover, decreasing poverty promotes long-term economic development since better-educated and healthier people help society more productively and creatively. Aiming to eradicate absolute poverty by 2020, China's targeted poverty alleviating program has grown to be among the biggest initiatives for poverty reduction worldwide since its introduction in 2013. The policy comprises several measures, including industrial support, education and training, health and ecological preservation. In this regard, maximizing poverty-reducing strategies and reaching sustainable development depends on evaluating these programs.

This paper uses the difference-in-differences (DiD) approach to evaluate, using China's targeted poverty-reducing program, economic development and poverty reduction. It especially answers these questions: How do focused poverty-reducing programs affect society and the economy? How may prejudices in policy assessments be reduced and these impacts quantified?

The main analytical instrument is the difference-in-differences method. The approach allows one to project the impacts of a policy by using the difference between the treatment and control groups before and after implementation outcomes. The study builds

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a model with a treatment group (targeted counties) and a control group (non-targeted counties) using national statistics and local government reports on poverty reduction to assess the total effects of the targeted poverty-alleviating program. According to the study, targeted countries had far worse economic situations at first than non-targeted ones. Still, the program has helped these places experience economic development and prosperity. With no indication of notable variation, the results also demonstrate that the effect of the policy is rather constant over areas. This consistency emphasizes how generally successful the program is in tackling financial difficulties in underdeveloped regions. The results imply that China's deliberate poverty reduction program has been crucial in helping millions of people escape poverty, promoting economic growth, and eradicating absolute poverty. The great popularity of this method also emphasizes its possible use as a template for poverty reduction plans abroad.

Using the DiD technique, this study mostly benefits academics by thoroughly evaluating the effects of China's focused poverty reduction policy and revealing any geographical or demographic variances in its influence. The study provides insightful information and theoretical analysis for the next policy changes by statistically evaluating the results. Moreover, it provides a platform for similar research in other nations and acts as a literature review assessing focused poverty reduction initiatives.

2 Literature Review

First, our work relates to earlier studies evaluating various effects of focused poverty reduction programs. Using regression analysis and propensity score matching, Li and Wang (2021) mostly assessed the policy impact using the household tracking survey data and National Bureau of Statistics statistics. It emphasizes the requirement of regional adaptive change and optimal allocation of resources in executing policies. Based on provincial panel data, Zhang and Liu (2020) investigate the several effects of policies on provinces and examine the dynamic changes in policy effects. The dynamic shift in policy influences the consequences of poverty decrease. Emphasizing the need for data integration and quality control, Chen and Li (2022) used big data technologies to examine the influence of poverty-reducing strategies. It implies that big information technologies had to be more thoroughly used in the next policy examination to acquire a more exact effect assessment. China's county-level data permit Wang and Huang (2019) an empirical investigation on the distribution and expenditure of hardship relief money at the county level and exposes an imbalance in the use of funds. According to the research, ideal cash distribution determines how efficient poverty-decreasing methods are. Yang and Sun (2023) use data to provide detailed insight into the policy implementation process through dynamic monitoring of policy implementation effects. Findings reveal that the policy has achieved positive results in improving the living conditions of poor households, but implementation differences and follow-up support still need attention. Overall, those studies provide a comprehensive perspective on the effect of China's poverty alleviation policies, reveal the successful experience and existing policy implementation problems, and provide valuable references for future policy adjustment and optimization.

Second, many developing countries have adopted similar protection policies to reduce poverty and improve living conditions, and all are grappling with policy implementation challenges. Olinto et al. (2009) studied the Bolsa Familia policy in Brazil and found that this policy significantly reduces poverty and improves health and educational outcomes for children from beneficiary families. Through conditional cash transfers, it enhanced the economic stability of lowincome households and effectively lowered income inequality. Imbert and Papp (2012) demonstrate that India's Mahatma Gandhi National Rural Guarantee Act (MGNREGA) policy has notably increased incomes and employment opportunities in rural areas, effectively reduced extreme poverty, and promoted infrastructure development. However, payment delays and corruption problems in implementation limit its overall effect. Hoddinott and Kelley (2008) corroborate that the Productive Safety Net Program (PSNP) policy has worked well in mitigating the impact of drought, reducing hunger, and improving food security. By providing public works and cash transfer support, the program has enhanced the economic stability of recipient households and improved community infrastructure. Samson et al. (2006), focusing on the social welfare in South Africa, including old age pensions and child grants, suggest that these policies have substantially impacted reducing poverty levels and improving quality of life. These allowances have helped reduce income inequality and enhance the economic security of have shown positive results in reducing poverty and improving children's education, increasing stability, reducing poverty persistence, and improving the quality of beneficiaries.

Third, this paper is based on the literature on the interactions between government policy and economic growth. Tobin (1964) argues that economic growth is always an important objective of government policies. King and Rebelo (1990) discuss that the answer can be found in the variation of national public policies that shape the incentives available for people to build up physical and human capital. Grossman (1988) indicates that government influences total economic output positively in the following ways. Pigovian public goods could improve the efficiency of the private sector's inputs and add to the total production. But then public decision-making is inefficient in the number of public goods in society. Finally, Adelman (2000) concludes that, unlike the later neoclassical development economists who believe there are few technological and institutional barriers to the required resource mobility, the classical development economists believe that technological and institutional rigidities constrain the resource mobility process. Heterogeneity of investments, underdeveloped structures, limited ability to predict, and missing markets create structural rigidities, prevent efficient resource mobility across sectors in response to individual profit-seeking, and form the basis of classical and structuralist theories of economic development.

The above literature underscores the complexity of poverty alleviation and the necessity for a comprehensive and tailored approach. Targeted poverty alleviation policies have significantly improved the living standards of impoverished populations. Nevertheless, some issues are still present and need to be solved, especially concerning the further development of these changes and the new aspects of poverty.

2.1 Targeted Poverty Evaluations in Impoverished Counties

China's technique to lower hardship has been based on many focused initiatives to address particular problems impacting undeveloped locations and counties. The intricacy of poverty has customized these techniques, which now suggest an intentional trend toward more customized and effective solutions. Formally, the Chinese government recommended deliberate hardship reduction in the 18th National Congress of the Communist Party of China in 2013. This method needs to concentrate on the causes of hardship in particular places and building techniques for removing hardship. Since it provides entire options that satisfy local requirements by finding and fixing the unique issues undeveloped areas suffer, this technique is crucial for China's poverty decrease initiatives.

Infrastructure development has become the front phase of China's initiatives to lower hardship. Roadways, water systems, and electrical energy tasks, to name a few infrastructure developments, have boosted living requirements and spurred financial growth. Though facilities advancement has been a crucial focus given that the early 2000s, under the "13th Five-Year Plan" starting in 2015, it accelerated sharply. These projects have connected far-off areas to economic centers and raised the basic quality of living. In impoverished regions, occupational and instructional advancement programs have been intended to increase employability and ability levels. Under the "National Education Reform Plan," which sought to enhance rural education and occupation training, resolving instructional inequalities and arming people with the skills needed for financial participation and individual development, academic reforms related to poverty reduction acquired momentum in 2015. Improvements in healthcare have also been a main focus of China's strategy for lowering poverty. Starting with the "New Healthcare Reform Plan" in 2009, which aimed to improve access to medical treatment, noteworthy changes began. This focus continued with the 2016 release of the "Healthy China 2030" plan, which particularly targeted healthcare improvements in rural and impoverished areas, improving health outcomes and providing required medical treatments to vulnerable people. Individuals and companies have been given financial help to boost economic activity and lower financial barriers, including low-interest loans and subsidies. Although China's poverty-reducing initiatives throughout the 2000s have included financial aid, under the "13th Five-Year Plan" in 2016, a more methodical strategy was used to boost financial support systems, fostering economic development. Improving rural livelihoods has also depended much on agricultural support. Policies with subsidies, encouragement of better farming methods, and market access have existed for decades. With the publication of the "No. 1 Central Document," which concentrated on rural revitalization and agricultural growth and sought to raise output and income for rural farmers, 2015 saw a notable surge. Efforts at poverty reduction are progressive, including environmental sustainability. In 2015, the "Ecological Civilization" plan underlined the need for sustainable development and environmental protection, assuring that poverty reduction efforts support long-term ecological stability and solve environmental problems in underdeveloped areas. Local government and community involvement have also changed to become the main components in decreasing poverty. Early in the 2000s, local governments' systems of operation have been reinforced, and their participation in decision-making procedures a growing number of highlighted. More official neighborhood involvement and governance methods were embraced in 2015 as part of China's larger poverty decrease strategy, ensuring the reliable application of policies and increasing regional participation.

In summary, China's poverty lowering program sticks out for its comprehensive and adaptable technique integrating targeted activities in numerous domains. China has made fantastic progress towards decreasing poverty and enhancing living requirements by addressing specific regional requirements, buying infrastructure, updating education

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and healthcare, and motivating community participation. That differed strategy displays a long-term commitment to managing hardship's complex and developing problems through constant and vibrant efforts.

3 Data

3.1 County Information

The county-level panel data from the China County Statistics Yearbooks from 2000 to 2022 was collected. This dataset contains annual observations of GDP growth, inflation, and unemployment rates over the past few decades.

Table 1 shows the summary statistics. In the sample, 25.9% of the counties are targeted poverty counties. The average Gross Domestic Product is approximately 140 million yuan, the maximum is 972 million yuan, and the minimum is 3.1 million yuan. The mean value of the gross domestic product is 140735.1 tons. The mean value of value-added of primary industry is estimated to be 174635.1 yuan. The mean value-added of the secondary sector is 65 million yuan, and the mean of the tertiary sector can also reach 56 million yuan. The average population is about 480000 people, ranging from a minimum of 2200 people to a maximum of 556700. In urban areas, the mean income of residents is 22861 yuan, while in rural areas, it is 7271 yuan.

Figure 1 presents the time trends of key socioeconomic outcomes of interest. In this figure, the red line represents the trend of non-targeted impoverished counties, while the blue line shows the trend for impoverished counties. From 2000 to 2020, non-targeted impoverished counties experienced consistent growth in per outcome despite improvements in the economic conditions of impoverished counties due to poverty alleviation policies. There has been a significant decline towards the end of the policy's implementation. This decline is because the economic benefits from the growth in these counties are relative to their past conditions, and those counties that remain on the list in the later stages of the policy already had very poor economic conditions to begin with.

Table 1 Statistics Summary

Variable	Obs	Mean	Std. dev.	Min	Max
1(Poverty county)	55,992	0.259	0.438	0	1
Gross Domestic Product	49,157	1407348	2464849	3102	9.27E+07
Value-added of Primary Industry	49,606	174635.1	182946.9	1	2096700
Value-added Of Secondary Industry	49,838	650300.2	1338049	1	5.83E+07
Value-added of Tertiary Industry	48,709	564538.7	1162534	1212	3.46E+07
Population	47,847	47.947	35.111	0.22	556.7
Income of Urban Residents	18,838	22861.51	10447.04	2514	80137
Income of Rural Residents	36,540	7271.212	5615.558	498	44117
Fiscal Revenue	51,693	87158.62	204150.8	6	6729838
Total Grain Production	45,526	238896.2	278733.4	0	3640712
Number of Elementary Schools	24,898	118.371	114.200	1	1441
Number of Middle Schools	24,455	26.952	19.240	1	260
Number of Hospital Beds	47,780	1445.476	1472.229	0	16669

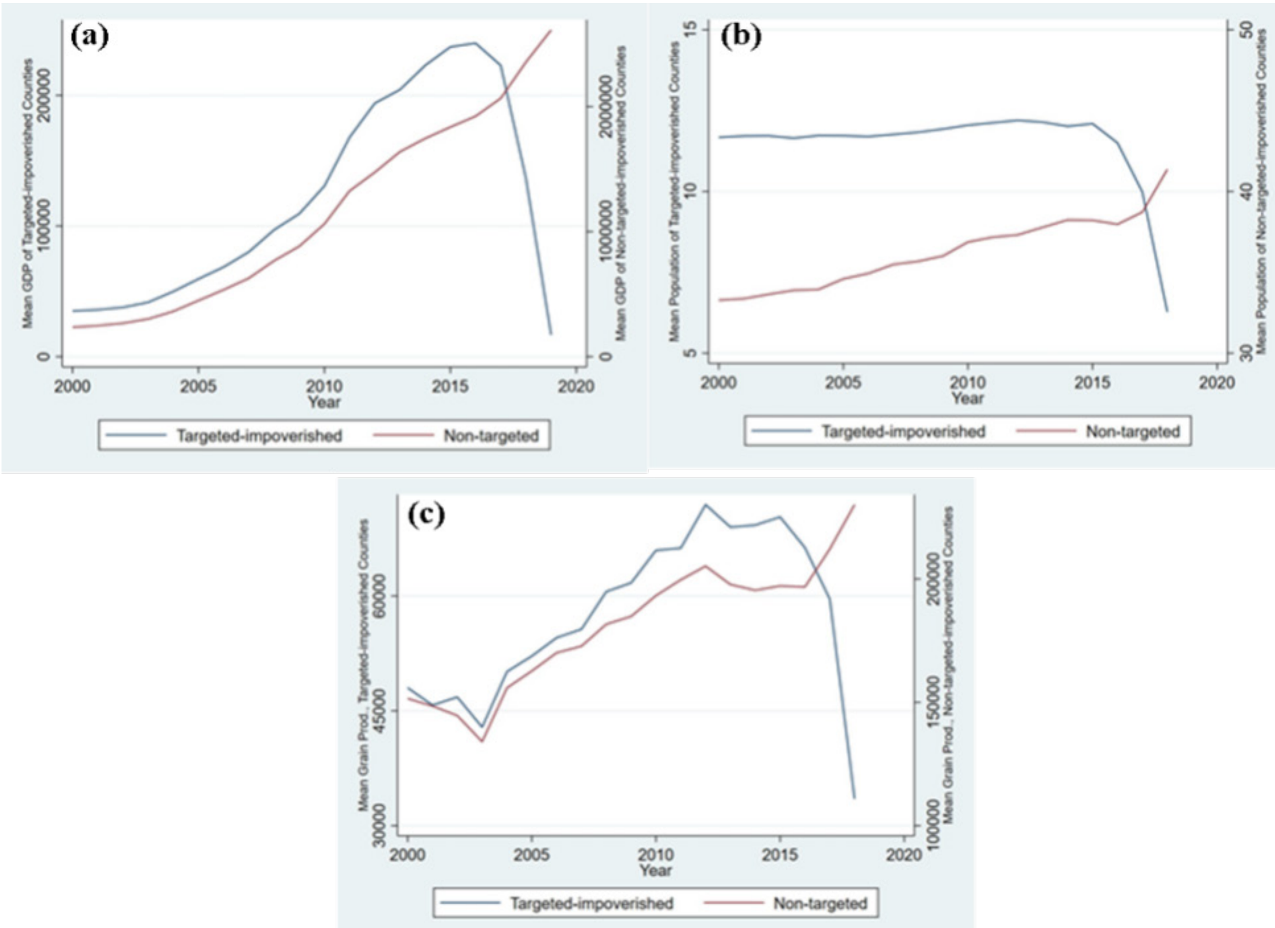

Fig. 1 Time trends of economic outcomes: 1

Figure 2 illustrates the new trends of key socioeconomic outcomes of interest, assuring that all counties listed in the targeted poverty county roster will consistently be considered. In this figure, the red line represents the trend of non-impoverished counties, while the blue line symbolizes impoverished counties. Under this assumption, it is evident that both groups of counties exhibit a clear and sustained upward trend in gross domestic product. In terms of population, impoverished counties exhibit a relatively stable trend, consistently remaining higher than non-impoverished counties. Conversely, non-impoverished counties show a trend of initially increasing, followed by a subsequent decline. The trends in grain production for both groups are generally similar. After 2005, the trends shifted from a decline to an increase, reaching a peak in 2010, and has since stabilized. The observed results are due to the assumption that the list of impoverished counties is fixed. Under the influence of poverty alleviation policies, targeted impoverished counties have generally shown positive economic development.

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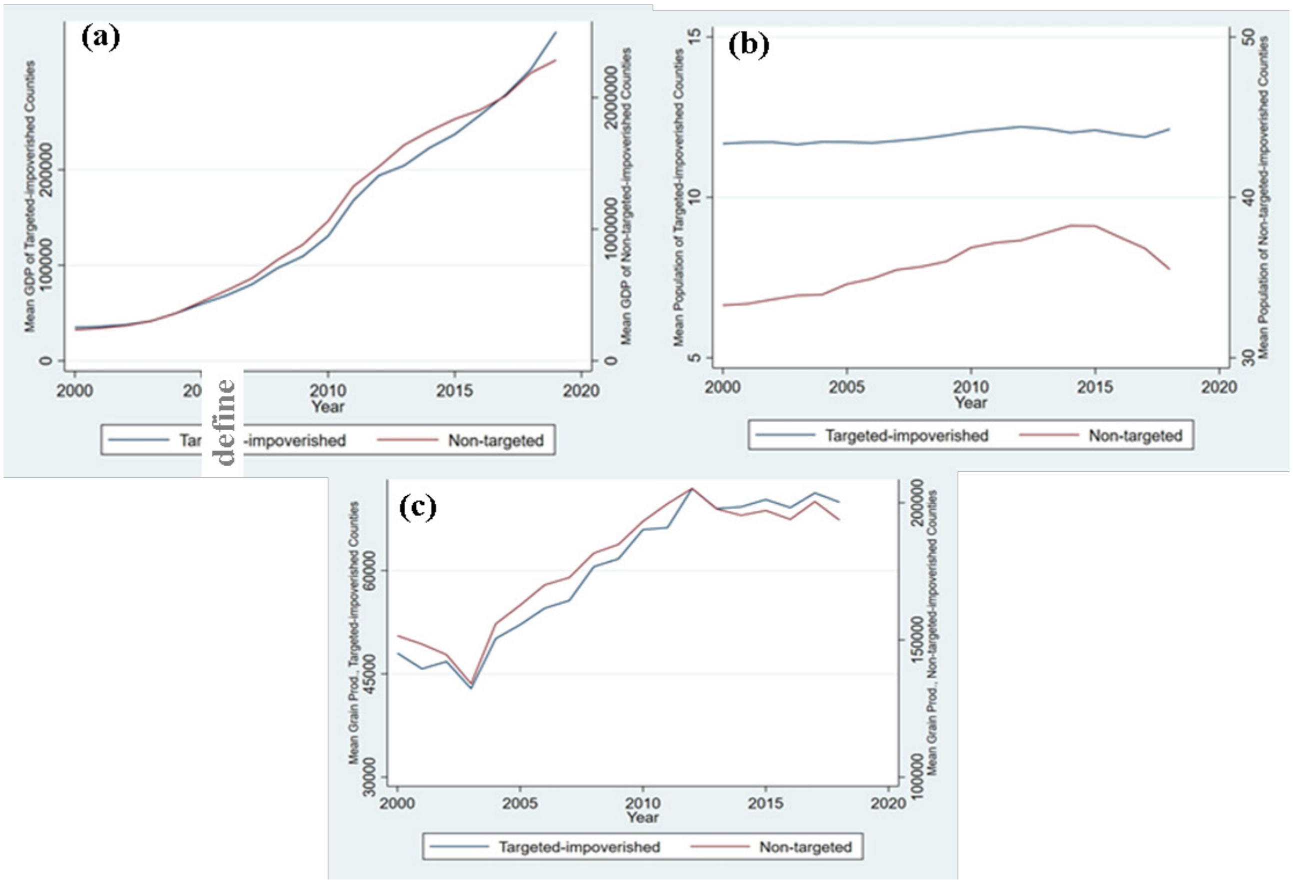

Fig. 2 Time trends of economic outcomes: 2

4 Empirical Analysis

4.1 Empirical Strategies

The main empirical analysis employed in this paper is the difference-in-differences method. I contrast the results of interests of targeted and non-targeted counties before and after the county alleviation poverty program. To be specific, we run the following specifications:

$$y_{it} = \alpha \times TargetedCounties_{it} + X_{it}\beta + \lambda_i + \lambda_t + u_{it}, \quad (1)$$

Where y_{it} is the outcome of interest, $TargetedCounties_{it}$ is a dummy variable of whether county i is a targeted county in year t, X_{it} is a vector of control variables, λ_i is county fixed effects, λ_t is year fixed effects, and u_{it} is the error term. The standard error at the county level was clustered. α is the parameter of interest. That is a standard difference-in-differences model with two-way fixed effects.

The key assumption of the difference-in-differences design is the assumption of common trends. That is, the impacts of the targeted alleviation program in equation (1) are not due to uncontrolled pre-treatment trends. To be more specific, I assumed the following specification:

$$y_{it} = \sum_{\tau \neq -1} \alpha_{\tau} \times TargetedCounties_i \times 1(t = t^* + \tau) + X_{it}\beta + \lambda_i + \lambda_t + u_{it} \quad (2)$$

Where t* is the starting year of the treatment, $TargetedCounties_i$ is a dummy variable of whether county i has ever been a targeted impoverished county. The parallel trend assumption requires that α_τs are not statically significant for $\tau < 0$ and that α_τ s are statically significant for $\tau \geq 0$ and have the same sign as α in equation (1). In equation (2), $\tau = -1$ is set as the base period, and $\alpha{-1}$ is normalized to zero. In equation (2), the rest of the variables are the same as in equation (1).

4.2 Empirical Results

4.2.1 Baseline Results

Table 2 acknowledges and assumes fixed effects for time and region. This regression analysis of 42,000 county-year observations from 2000 to 2021 examines the impact of being a targeted county (coded as 1) versus not being a targeted county (coded as 0) on several variables, including county and year-fixed effects. The regression specification is associated with equation (1).

The regression analysis shows that being classified as a targeted county is associated with a decline in per capita GDP. The poverty coefficient is -0.189 with a standard error of 0.0144, indicating that per capita GDP (Y1) is, on average, 1.87% lower in targeted counties compared to non-targeted ones after accounting for county and year fixed effects. There is statistical significance in the coefficient at 1%. The model explains 95.1% of the variations in per capita GDP.

For population (column (2)), the coefficient is 0.0617 with a standard error of 0.00673, suggesting that targeted counties see a 6.17% increase in population on average, holding other factors constant. The R-squared value of 0.998 shows that the model explains 99.8% of the variation in population, indicating a strong fit. Regarding per capita grain output (column (3)), the coefficient is -0.181 with a standard error of 0.0186, implying an 18.1% decrease in targeted impoverished counties compared to non-targeted ones. This effect shows significance (at the 1% level), with the model accounting for 90.8% of the variation in per capita grain output.

The analysis also finds that targeted counties experience a 2.70% decline in per capita oil output (column (4)), with a coefficient of -0.270 and a standard error of 0.0390. There is statistical significance in the coefficient at 1%. The model explains 85.6% of the variation in per capita oil output. Moreover, per capita meat output (column (5)) is also lower in poorer counties, with a coefficient of -0.208 and a standard error of 0.0361, translating to a 20.8% decrease. There is statistical significance in the coefficient at 1%. This result shows significance, and the model accounts for 85.7% of the per capita meat output variability.

The analysis reveals that per capita middle school enrollment (column (6)) is 1.87% lower in targeted counties, with a coefficient of -0.0187 and a standard error of 0.00664. There is statistical significance in the coefficient at 1%. The model explains 74.8% of the variation in enrollment rates.

When a county is designated as targeted, per capita hospital beds (column (7)) decrease by 12.2%, with a standard error of 0.0154; the coefficient is statistically significant at 1%. The model explains 82.3% of the variation in this outcome. In addition, per capita fiscal revenue (column (8)) is 5.36% lower in poorer counties, with a standard error of 0.0186, and the model explains 92.7% of the variation in fiscal revenue. There is statistical significance in the coefficient at 1%.

The transition to a targeted county results in a 14.8% decrease in per capita fiscal expenditures (column (9)), with a standard error of 0.0122. The model explains 96.9% of the variation in budgetary spending. There is statistical significance in the coefficient at 1%.

The regression analysis reveals that targeted counties face significant declines across various economic and social indicators. Lower per capita GDP suggests reduced economic productivity and wealth, while meat output and school enrollment declines indicate limited access to resources and educational opportunities. These findings underscore poverty's profound and widespread impact, as it adversely affects multiple dimensions of county life. The high R-squared values show that poverty status explains a substantial portion of the variability in these outcomes, highlighting the critical role of poverty in driving economic and social disparities.

Table 2 Baseline Results

	(1)	(2)	(3)
	log per capita GDP	log population	log per capita grain output
1(Targeted county)	-0.189***	0.0617***	-0.181***
	(0.0144)	(0.00673)	(0.0186)
County FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	43,464	47,842	43,770
R-squared	0.951	0.988	0.908
	(4)	(5)	(6)
	log per capita oil output	log meat output	log per capita middle school
1(Targeted county)	-0.270***	-0.208***	-0.0187***
	(0.0390)	(0.0361)	(0.00664)
County FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	43,007	40,776	23,562
R-squared	0.856	0.857	0.748
	(7)	(8)	(9)
	log per capita hospital bed	log per capita fiscal revenue	log per capita fiscal expenditure

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1(Targeted county)	-0.122*** (0.0154)	-0.0536*** (0.0186)	-0.148*** (0.0122)
County FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	42,447	45,915	45,876
R-squared	0.823	0.927	0.969

4.2.2 Robustness Checks

In Table A6, the data from the sample period of 2014 to 2021 was chosen because 2014 is the first year the poverty alleviation policy was launched. Overall, the results are qualitatively and quantitatively consistent with Table 2. Except for the population variable, which shows an increase, all other social and economic indicators are declining when transitioning from non-targeted to targeted poverty counties. Finally, in Table 3, the dataset spans from 2014 to 2020. By augmenting the analysis with county and city-year fixed effect, the log per capita GDP, log population, and log per capita grain production, the outcomes maintain consistency with Table 2.

Table 3 Adding city-year fixed effects and control variables

	(1)	(2)	(3)
	log per capita GDP	log population	log per capita grain output
1(Targeted county)	-0.0760*** (0.00863)	0.0311*** (0.00453)	-0.0406*** (0.0113)
County FE	Y	Y	Y
City-Year FE	Y	Y	Y
Controls	Y	Y	Y
Observations	13,124	13,354	12,299
R-squared	0.979	0.994	0.984
	(4)	(5)	(6)
	log per capita oil output	log meat output	log per capita middle school
1(Targeted county)	-0.0680*** (0.0238)	-0.114*** (0.0244)	-0.00347 (0.00398)
County FE	Y	Y	Y
City-Year FE	Y	Y	Y
Controls	Y	Y	Y
Observations	12,402	9,483	4,922
R-squared	0.964	0.966	0.948
	(7)	(8)	(9)
	log per capita hospital bed	log per capita fiscal revenue	log per capita fiscal expenditure
1(Targeted county)	-0.0349*** (0.0105)	-0.0250 (0.0156)	-0.0552*** (0.00926)
County FE	Y	Y	Y
City-Year FE	Y	Y	Y
Controls	Y	Y	Y
Observations	12,135	13,181	13,085
R-squared	0.901	0.956	0.956

4.2.3 Event Study Analysis

Table 4 analyzes the impact of transitioning from a non-targeted impoverished county to a targeted impoverished county on various economic and demographic factors. The variables under examination are binary indicators of whether a county is a targeted impoverished county (with 1 indicating targeted impoverished counties). This table corresponds to the estimation results of equation (2). Additional variables were considered to delve deeper into the impact, including log per capita GDP, log population, log per capita grain, etc. In my initial assumptions and previous research, the statistically significant increase in the coefficients post-policy suggests the policy's effectiveness in targeting poverty. However, these findings deviate significantly from those assumptions. A dataset from 2000 to 2020 reveals that, before the policy implementation, most variables demonstrated a negative and statistically significant coefficient. However, following the policy implementation, most indicators exhibited a positive correlation and statistical significance. For example, I observed an unexpected increase in the log per capita GDP coefficient, which rose from a pre-policy range of -0.0533 to 0.458 to at least 0.127 post-policy, contradicting my initial assumptions.

Table 5 provides the findings of propensity score matching estimation. The coefficients for variable log per capita, log per capita grain output, log per capita oil put, etc., all significant at 1%, indicating a strong and statistically significant positive impact on the dummy variable. That suggests that an increase in these social and economic variables is associated with the outcome variables, with a high confidence level. The results align with the initial hypothesis in Table 2.

Table 4 Event Study Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	log p.c. GDP	log population	log per capita grain	log p.c. oil	log p.c. meat	log p.c. middle school	log p.c. hospital bed	log p.c. fis. rev.	log p.c. fis. exp.
Pre 6	0.0458***	-0.0293***	-0.00833	-0.208***	-0.0254	-0.0106	0.0214	0.0508***	-0.0609***
	(0.0127)	(0.00367)	(0.0159)	(0.0302)	(0.0185)	(0.00690)	(0.0145)	(0.0195)	(0.00966)
Pre 5	-0.0399***	-0.00119	-0.0659***	-0.154***	-0.0259**	0.00907*	0.00713	-0.0925***	-0.0300**
	(0.00861)	(0.00351)	(0.0147)	(0.0310)	(0.0127)	(0.00512)	(0.0153)	(0.0169)	(0.0126)
Pre 4	-0.0533***	-0.00374	-0.0345***	-0.159***	-0.0257**	0.00933**	-0.00552	-0.106***	-0.0232**
	(0.00706)	(0.00294)	(0.0112)	(0.0268)	(0.0113)	(0.00472)	(0.0150)	(0.0152)	(0.0105)
Pre 3	-0.0433***	-0.00300	-0.0526***	-0.0726***	-0.00886	-0.00691*	0.00320	-0.0765***	-0.0258***
	(0.00636)	(0.00251)	(0.0101)	(0.0200)	(0.00936)	(0.00396)	(0.0134)	(0.0124)	(0.00947)
Pre 2	-0.0130***	-0.000180	-0.0292***	-0.0716***	-0.00521	0.00195	0.0268**	-0.0372***	0.0149**
	(0.00426)	(0.00187)	(0.00811)	(0.0162)	(0.00770)	(0.00268)	(0.0114)	(0.0109)	(0.00693)
Post 1	0.0298***	-0.00213	0.0378***	0.0306**	0.0234***	0.00713***	0.0446***	0.0368***	0.0327***
	(0.00483)	(0.00186)	(0.00646)	(0.0149)	(0.00567)	(0.00261)	(0.0104)	(0.0133)	(0.00629)
Post 2	0.0515***	-0.000702	0.0329***	0.0500**	0.0414***	0.0176***	0.0421***	0.106***	0.0659***
	(0.00730)	(0.00254)	(0.00983)	(0.0212)	(0.00875)	(0.00489)	(0.0123)	(0.0172)	(0.00891)
Post 3	0.131***	-0.0453***	0.0880***	0.0695**	0.120***	0.0386***	0.111***	0.173***	0.0920***
	(0.0122)	(0.00546)	(0.0120)	(0.0281)	(0.0122)	(0.00627)	(0.0166)	(0.0212)	(0.0110)
Post 4	0.127***	-0.0729***	0.134***	0.257***	0.151***	0.0364***	0.129***	0.135***	0.132***
	(0.0143)	(0.00693)	(0.0168)	(0.0397)	(0.0309)	(0.00693)	(0.0181)	(0.0230)	(0.0123)
Post 5	0.127***	-0.0590***	0.141***	0.244***	0.0250	0.0357***	0.131***	0.0645**	0.176***
	(0.0184)	(0.00795)	(0.0229)	(0.0492)	(0.0394)	(0.00824)	(0.0217)	(0.0255)	(0.0159)
Post 6	0.310***	-0.0624***	0.0663*	0.256***	0.182**	0.0416***	0.286***	-0.0135	0.341***
	(0.0453)	(0.0182)	(0.0391)	(0.0843)	(0.0888)	(0.0147)	(0.0688)	(0.0519)	(0.0342)
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	43,464	47,842	43,770	43,007	40,776	23,562	42,447	45,915	45,876
R-squared	0.951	0.988	0.908	0.857	0.857	0.750	0.823	0.928	0.969

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Table 5 Results of propensity score matching estimation

	(1)	(2)	(3)
	Propensity score matching estimation (nearest neighbors)		
1(Targeted county)	log per capita GDP	log population	log per capita grain output
	0.0327***	0.0512**	0.0422***
	(0.00472)	(0.0268)	(0.0113)
County FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	43,464	47,842	43,770
	(4)	(5)	(6)
	Propensity score matching estimation (nearest neighbors)		
1(Targeted county)	log per capita oil output	log meat output	log per capita middle school
	0.0186***	0.0621***	0.106***
	(0.00472)	(0.0130)	(0.0151)
County FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	43,007	40,776	23,562
	(7)	(8)	(9)
	Propensity score matching estimation (nearest neighbors)		
1(Targeted county)	log per capita hospital bed	log per capita fiscal revenue	log per capita fiscal expenditure
	0.0659***	0.00713***	0.0446***
	(0.00864)	(0.00261)	(0.0104)
County FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	42,447	45,915	45,876

4.2.4 Heterogeneity Analysis

The effects of the targeted impoverished county program do not exhibit regional heterogeneity. Table 6 divides China into six geographical regions (Huabei, Dong-bei, Huadong, Xinan, Huanan, and Xibei) and detects that the overall impact of policies is greatest in the East, Southwest, and South China regions. For example, in column (2), the coefficient on the dummy variable of the targeted county is 0.135 and shows significance at a 5% level. In column (9), the coefficient on the dummy variable of the targeted county is 0.0600 and shows significance at a 1% level. In column (15), the coefficient on the dummy variable of the targeted county is 0.0888 and shows significance at a 1% level.

Table 6 Regional heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
	log per capita GDP					
	Propensity score matching estimation (nearest neighbors)					
	Huabei	Dongbei	Huadong	Xinan	Huanan	Xibei
1(Targeted county)	0.0937***	0.135**	0.0835**	0.0900***	0.0249**	0.0839***
	(0.0219)	(0.0612)	(0.0425)	(0.0143)	(0.0125)	(0.0251)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	2,122	883	2,219	3,048	2,857	1,995
	(7)	(8)	(9)	(10)	(11)	(12)
	log population					
	Propensity score matching estimation (nearest neighbors)					
	Huabei	Dongbei	Huadong	Xinan	Huanan	Xibei
1(Targeted county)	0.0113*	0.0124	0.0600***	0.0268***	0.0283***	0.0412***
	(0.00605)	(0.0293)	(0.0131)	(0.00669)	(0.00750)	(0.0135)
County FE	Y	Y	Y	Y	Y	Y

Year FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	2,157	883	2,359	3,061	2,868	2,026
	(13)	(14)	(15)	(16)	(17)	(18)
	log per capita grain output					
	Propensity score matching estimation (nearest neighbors)					
	Huabei	Dongbei	Huadong	Xinan	Huanan	Xibei
1(Targeted county)	0.0162	0.0273	0.0888***	0.0414***	0.0476**	0.0343
	(0.0295)	(0.0427)	(0.0166)	(0.0129)	(0.0215)	(0.0300)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	2,093	872	1,974	3,034	2,587	1,739

5 Conclusion

China recently reached a significant milestone by eradicating absolute poverty. This paper aims to assess the effectiveness of the targeted poverty alleviation program on economic growth in China with special reference to different regions. This study employed difference-in-differences with propensity score matching estimation and compared economic outcomes between counties designated as targeted poverty areas and those that were not. The analysis shows that the targeted counties initially faced significantly worse economic conditions than non-targeted ones. However, the policy intervention tied to their targeted status has promoted economic growth and development in these regions. Moreover, the results indicate that the program's effects are relatively uniform across regions, with little evidence of variation. This consistency emphasizes the program's broad success in addressing the economic difficulties targeted impoverished counties face. The targeted poverty alleviation program has been crucial to China's achievement in eradicating absolute poverty, being a major contributor to economic development and reducing the poverty level of millions of people. The program's extensive impact highlights its potential as a model for poverty reduction strategies in other contexts. A limitation of this paper is the lack of micro-level data, such as firm-level or individual survey data. As a result, the analysis focuses on the macro-level aggregate effects of the program. Future research could explore the micro-level impacts using more detailed data.

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