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Exploring the Impact of Rural Development Programs on Poverty Reduction in Chinese Counties: A Panel Data Analysis

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Abstract: In the backdrop of China's monumental challenge in poverty eradication, this study provides a critical evaluation of the rural development programs, particularly the targeted poverty reduction policy of 2013 which aimed at specialized interventions for 832 national poverty-stricken counties. Utilizing the Difference-in-Differences (DiD) methodology, the paper analyzes panel data from the China Statistical Yearbook (Township) between 2010 to 2019, contrasting the advancements in these designated counties against those not specifically targeted. Our findings reveal that, while the 2013 policy has made positive strides in enhancing the disposable incomes of residents in these counties, disparities persist. City-specific determinants emerged as key influencers, necessitating a tailored approach to future poverty alleviation strategies. The research underlines the success of China's poverty reduction efforts, whilst stressing the need for sustained, adaptive, and region-specific initiatives for more holistic and comprehensive poverty eradication in the future. Policymakers are thus advised to engage in continual policy introspection and refinement, acknowledging the intricate challenges and diversities within the nation.

Keywords: targeted poverty alleviation, rural development, DiD methodology, China's poverty, disposable incomes

1. Introduction

In recent decades, China's achievements in poverty reduction, particularly in its extensive rural regions, have garnered global attention. Given its status as the world's most populous nation, the magnitude of China's poverty challenge remains unparalleled. Central to its poverty alleviation approach are the rural development programs. Yet, the effectiveness of these initiatives, especially the targeted poverty reduction policies introduced in 2013, has spurred intense debate among experts, policymakers, and development practitioners.

This study delves into the effects of these rural development programs, placing specific emphasis on the policy that identified 832 national poverty-stricken counties for specialized interventions. Through a panel data analysis, the research critically evaluates the policy's results by contrasting the advancements in these counties with those not specifically targeted. The Difference-in-Differences (DiD) methodology underpins the analysis. This econometric tool facilitates an evaluation of the actual impact of the interventions, juxtaposing outcomes in treated and control groups over time, thereby isolating general influences and underscoring the policy's genuine effects.

Complemented by a thorough literature review and detailed model evaluations, this paper offers a comprehensive perspective on China's rural poverty alleviation endeavors. The focus remains on underscoring the importance of rigorous analytical methodologies in the creation and evaluation of potent policies, accentuating the transformative potential of knowledge-driven interventions.

2. Policy Interpretation

Before 2013, China's poverty alleviation strategies spanned several decades, beginning with the "Three-West" program in 1982 and the "8-7 National Poverty Reduction Program" in 1994, which targeted basic sustenance and clothing needs [1]. The focus was largely on broad strategies with villages and industrial sectors of central and western regions as key areas of emphasis.

In 2013, a transformative milestone was reached in China's longstanding battle against poverty. While visiting Shibadong Village, General Secretary Xi Jinping elucidated a paradigm shift in poverty alleviation tactics, unveiling the strategy of "Targeted Poverty Alleviation"[2]. This initiative underscored the importance of a nuanced, condition-specific approach, hinging on the mantra of "giving differentiated guidance for targeted poverty alleviation in line with local conditions by seeking truth from facts" [3]. Rather than a broad-brush method, the emphasis pivoted towards precision, with a particular focus on 832 pivotal poverty-stricken counties.

Xi's approach went beyond mere theory, establishing measurable, actionable standards. This encompassed not only ensuring necessities like food and clothing, but also included commitments to education, healthcare, and housing for the impoverished. Alongside these, China intensified industrial and employment-focused poverty alleviation, promoted relocation from ecologically sensitive areas, and emphasized health-related interventions [4].

The pivotal changes and enhanced focus initiated in 2013 mark an ideal starting point for this study, underscoring its significance in China's poverty alleviation journey. In 2020, the Communist Party of China declared an all-around victory over poverty, signifying the removal of all previously designated poverty-stricken counties from absolute poverty [5]. However, the battle against poverty remains ongoing. Disparities in economic conditions persist both within rural areas and in comparison, to urban populations. Evaluating the effectiveness of current poverty-reduction policies offers valuable insights for policymakers aiming to further reduce poverty.

3. Literature Review

Numerous studies by fellow scholars have delved into the topic of national poverty-stricken counties. Typically, researchers concentrate on the following areas: (i)Factors determining the distribution of these counties. For instance, Lei Zhou's team categorizes national poverty-stricken counties based on constraints such as terrain, cultivated land resources, water abundance, traffic conditions, and location indices, indicating the natural challenges faced by these counties [6]. (ii) The allocation and efficiency of poverty alleviation funds in these counties. As an example, Yanlei Zhang's research demonstrates that net fiscal expenditure positively impacts the long-term economic growth of poverty-alleviated counties, although variations exist among these counties. This growth is mainly driven by stimulating investment [7]. However, Xi Man's team also highlights how over-reliance on government funding can suppress the income levels of local agricultural sectors, emphasizing the dualism of policy outcomes in the long run [8]. (iii)The impact of policies on poverty reduction. Danmeng Feng's team confirms the efficacy of policies targeting impoverished areas but also notes that regional differences can result in varied policy outcomes [9].

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The majority of research confirms the validity of the national poverty-stricken policy as a measure of poverty reduction. They also consistently denote the severe regional difference in terms of policy efficiency. As Zhou claims that the uniqueness of geological features of different counties constrain the poverty reduction policy's development [6], highlighting the significance of the considering regionality in this research.

4. Research Design

4.1. Dataset

Data Source: All data utilized in this essay is derived from the China Statistical Yearbook (Township) [10], an official government publication issued annually from 2010 to 2020 by the national statistical bureau.

Time Span: This essay utilizes data from 2010 to 2019. Starting in 2013, the Chinese government initiated a targeted poverty reduction policy, designating 832 national poverty-stricken counties. Various measures were implemented to alleviate poverty in these counties. To examine the effectiveness of this policy, data from before and after its implementation is analyzed. It should be noted that due to the global economic recession caused by the COVID-19 pandemic, data beyond the year 2019 is not included in the scope of this essay.

Subject: This essay seeks to analyze the policy effects within the 832 counties, yet the dataset contains numerous missing values, posing challenges to data processing and analysis. For minor gaps, we employed interpolation—a method that estimates values by leveraging known data point relationships. However, counties with substantial missing values were infeasible to estimate and were thus excluded. Post these adjustments, this analysis covers 730 national poverty-stricken counties and 1,306 non-poverty-stricken counties (resulting in an unbalanced panel) with a total of 34,694 observational units.

4.2. Model and Variables

4.2.1. Define the Treatment and Control Groups

Treatment group: national poverty-stricken counties.

Control group: counties that are not included in national poverty-stricken counties.

4.2.2. Variables

Dependent Variable: Per capita disposable income of rural residents (in Chinese Yuan).

Control variable: Administrative Area (in Square Km), Registered Population (in Ten Thousand), and City.

Table 1 provides insight into basic statistics regarding these variables.

Table 1: Summary Statistics.

	Mean	Standard Deviation	Variance
Administrative Area (in Square Km)	4,024.96	9,757.00	95,199,130.00
Registered Population (in Ten Thousands)	47.90	35.13	1,234.05
Per capita disposable income of rural residents (in Chinese Yuan)	7,271.21	5,615.56	31,534,490.00

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4.2.3. Methodology

This research employs the Difference-in-Differences (DiD) approach, a quasi-experimental technique that captures the causal impact of interventions by contrasting changes in outcomes between treated and control groups over time. By controlling for unobserved fixed effects and time trends, DiD offers a robust method for policy evaluations. To quantify this effect and control for confounders, the study utilizes the Ordinary Least Squares (OLS) regression, a widely-used linear regression technique. OLS provides clear coefficient interpretations and is efficient under standard assumptions, making it an ideal choice for evaluating the impact of rural development programs on poverty reduction in Chinese rural areas.

$$\begin{aligned} Income_{it} = \alpha + \beta_1 \times treatment_i + \beta_2(treatment_i \times Post_t) + \beta_3 \times year\ 2010 \\ + \beta_4 \times year\ 2011 + \cdots + \beta_{12} \times year\ 2019 \\ + \gamma_1 \times Control_{it} + \gamma_2 \times City_{it} + \epsilon_{it} \end{aligned} \tag{1}$$

Definition of variables and coefficients are shown in Table 2.

Table 2: Definition of variables and coefficients.

Panel A: Variables	
Variables	Definition
$Income_{it}$	The per capita disposable income of rural residents in county i at year t.
$treatment_i$	A dummy variable that equals 1 if the county i is a national poverty-stricken county, and 0 otherwise.
$treatment_i \times Post_t$	Interaction term between the treatment group and post-intervention period. The coefficient β_2 will estimate the treatment effect of the rural development programs on poverty reduction in Chinese villages.
Year	dummy variables that take the value of 1 for observations from the respective years and 0 otherwise.
$Control_{it}$	control variables (administrative area and registered population) for county i at year t.
$City_{it}$	Dummy variable for county i at year t, which is 1 if it belongs to a specific city, and 0 otherwise.
ϵ_{it}	The error term.
Panel B: Coefficients	
Coefficients	Definition
α	Constant
β_1	β_1 measures the average difference in the per capita disposable income between the treatment (poverty-stricken counties) and control (non-poverty-stricken counties) groups before the intervention.
β_2	β_2 shows the interatcion between treatment and post-intervention.
$\beta_3 \sim \beta_{11}$	$\beta_3 \sim \beta_{11}$ are coefficients for year dummies. They capture year-specific deviations in the outcome variable relative to the reference year 2010.

Table 2: (continued).

β_{12}	β_{12} is the DiD estimator. It captures the differential impact of the intervention on the per capita disposable income of rural residents in the national poverty-stricken counties relative to the control counties.
γ_1 *and* γ_2	γ_1 *and* γ_2 are coefficients for the control variables. It measures the change in the dependent variable for a one-unit change in control variables, holding other factors constant.

4.2.4. Parellel Trend Analysis

Figure 1 below shows the parallel trend of the control and treatment groups.

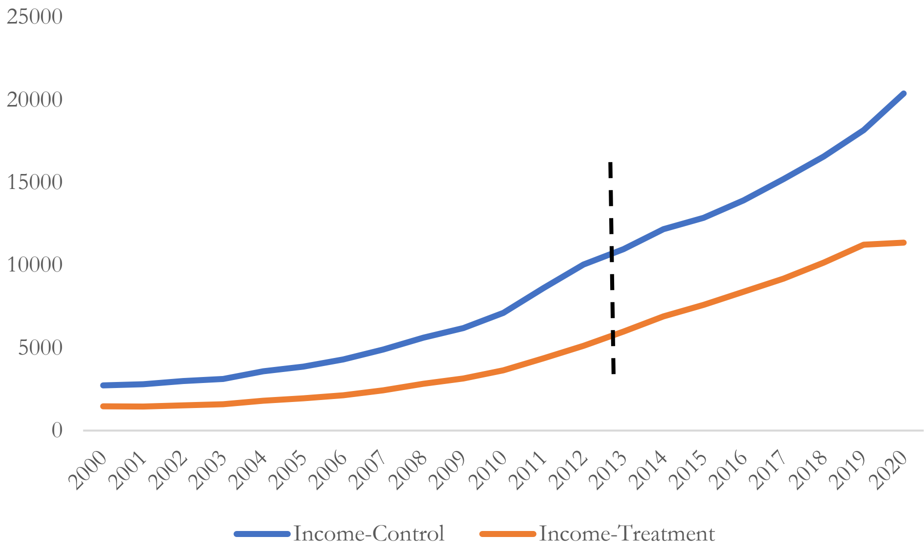

Figure 1: Parallel Trend.

Photo credit: Original

The graph illustrates the per capita income trends of two distinct groups from 2000 to 2020: the treatment group, comprising national poverty-stricken counties, and the control group, consisting of counties not designated as poverty-stricken. Over these two decades, both groups have observed growth in their per capita income. However, the treatment group, starting from a lower base, has consistently lagged behind the control group. Notably, the trends of the two groups seem parallel over the years, suggesting that the data might be suitable for a Difference-in-Differences (DiD) analysis. This parallelism is crucial for DiD, as it presupposes that, in the absence of treatment, the treatment group would have followed a similar trajectory to the control group.

5. Empirical Result

5.1. Overview

To rigorously evaluate the impact of China's targeted poverty reduction policy on the per capita disposable income of rural residents, a panel data analysis was conducted using three distinct Ordinary Least Squares (OLS) regression models. The OLS.1 model captures the year effect, illuminating time-specific variations. Building upon this, the OLS.2 model integrates control variables, namely the administrative area and registered population, to account for county-specific characteristics that might influence income levels. The OLS.3 model, as the most comprehensive framework, adds a city effect to capture potential variations across different cities. These incremental model structures offer a nuanced understanding of the policy's implications, ensuring that results remain robust across various specifications and potential confounding factors. The subsequent Table 3 provides a general overview of the empirical result:

Table 3: Regression results.

VARIABLES	(1) OLS Income	(2) OLS Income	(3) OLS Income
Treat	-0.6640***	-0.6185***	-0.3801***
	(0.0137)	(0.0147)	(0.0135)
Treat × Post	0.1581***	0.1456***	0.1412***
	(0.0089)	(0.0088)	(0.0078)
Constant	7.8782***	8.0165***	8.1548***
	(0.0104)	(0.0735)	(0.0751)
Observations	34,694	34,694	34,694
R-squared	0.8491	0.8566	0.9433
Year	Yes	Yes	Yes
Controls	No	Yes	Yes
City	No	No	Yes

5.2. Empirical Results Interpretation

5.2.1. OLS.1 Model (Year Effect Only)

The treatment variable coefficient (β_1) is -0.6640, significant at the 1% level. This implies that with everything else being constant, national poverty-stricken counties experienced a dip in per capita disposable income by 0.6640 units relative to their counterparts. This preliminary finding underscores the economic challenges faced by these counties even before the targeted interventions.

The interaction term coefficient (β_1) is valued at 0.1581 (significant at the 1% level), this coefficient is a testament to the policy's success. It indicates that post-2013, the designated counties saw an incremental positive shift in disposable incomes, averaging 0.1581 units annually, outpacing the counties not under this policy's purview.

The model's R2 value is 0.8491, suggesting that the model variables account for approximately 84.91% of the variability in disposable income. This high value underscores the model's robustness in capturing the major factors influencing income levels.

5.2.2. OLS.2 Model (Year Effect + Control Variables)

The treatment variable coefficient: At -0.6185, this figure is slightly less negative than the basic model. This hints at the possibility that when we factor in the administrative area and registered population, the economic divide between poverty-stricken and other counties narrows down.

Interaction Term Coefficient: With a value of 0.1456, it suggests a marginally reduced policy impact after considering the control variables. This could be attributed to variations in administrative areas and population densities across counties, which might influence income levels.

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The R2 value is 0.8566, which is a slight improvement from the basic OLS model. This means that approximately 85.66% of the variation in income is explained when we include the control variables.

5.2.3. OLS.3 Model (Year Effect + Control Variables + City)

The treatment variable coefficient is −0.3801. This value is significantly higher than the previous models, indicating that when we account for the city effect along with other controls, the disadvantage of being in a poverty-stricken county reduces considerably.

The interaction term coefficient is 0.1412, suggesting that the positive effect of the policy remains largely consistent even after accounting for the city effect.

The R2 value for this model is 0.9433, a substantial increase from the previous models. This indicates that approximately 94.33% of the variation in income is explained by this model, suggesting that the inclusion of the city variable provides a much better fit to the data.

5.3. Deep Dive: Implications

Upon rigorous examination of regression models, the enduring positive coefficient of the interaction term warrants attention, signaling the tangible benefits of the targeted poverty reduction initiative for the residents of designated counties. Nevertheless, this benefit's magnitude is nuanced, showing variations based on the specific model under consideration, indicative of the multifaceted challenges these counties confront.

Transitioning to the urban landscape, a salient observation from the OLS.3 model emerges with the noticeable elevation in the R2 value. This metric unequivocally emphasizes the substantive role that city-specific factors play in determining disposable incomes. From a policy standpoint, this underscores the necessity for future poverty alleviation initiatives to be meticulously tailored, taking into account the unique contexts of individual cities to optimize efficacy.

Progressing further in the analysis, the steadfast positive value of the interaction term, even amidst the integration of diverse controls, corroborates the robust effectiveness of the targeted policy. This empirical finding fortifies the claims of policy success, presenting a robust validation to stakeholders.

However, it is paramount to address a lingering concern. The persistent negative coefficient associated with the treatment variable across models signals an undeniable challenge. Despite strategic interventions, the designated poverty-stricken counties continue to exhibit economic vulnerabilities. This observation accentuates the intricate nature of rural poverty in China, advocating for a holistic and sustained strategic approach in subsequent policy formulations.

6. Discussion

6.1. The Problem of Current Poverty Reduction Policy

China's ambitious poverty reduction endeavors, particularly the targeted poverty alleviation strategy, have undeniably yielded impressive results. However, a closer inspection reveals potential challenges intrinsic to the present policy framework.

Firstly, the application of a singular system across diverse regions presents evident challenges. A case in point is the country's overarching emphasis on tourism as a primary poverty alleviation tool. The strategy to capitalize on local culture, through homestays and showcasing intangible cultural heritage, while commendable, has led to several unintended consequences. Most counties have adopted this model, and while it has brought prosperity to some, it has simultaneously given rise to significant homogeneity with counties. There's an evident narrow radiating area of resources, which means only certain pockets within these counties are benefiting, leading to an obvious gap between

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the affluent and the poor. Furthermore, with most counties employing similar strategies, there is a glaring problem of homogeneity. The single form of tourism, primarily centered around local culture and homestays, has led to serious similarities in offerings across different regions [11]. This not only dilutes the unique appeal of individual counties but also raises concerns about the sustainability of such a model in the long run.

Secondly, the heavy reliance on government funding poses a substantial concern. While the influx of government funds has been instrumental in initiating and sustaining many of the poverty alleviation projects, it has also made these counties disproportionately dependent on external aid. Such a model can be susceptible to changes in political priorities or fiscal constraints. Over-reliance on government funding can also stifle local innovation and entrepreneurship, as regions might be less incentivized to develop self-sustaining economic models. In the longer term, for these counties to truly thrive and ensure that the gains from poverty alleviation are not merely transient, they would need to develop diversified and self-reliant economic frameworks.

6.2. Policy Recommendation

In light of the identified challenges with China's current poverty reduction policy, it is pivotal to adopt a more diversified and region-specific approach. While the emphasis on tourism has borne fruit in certain regions, it's crucial to assess the unique strengths and challenges of each county. A multi-pronged economic development strategy, integrating sectors like agri-business, digital entrepreneurship, and sustainable energy, should be explored. Regional training programs can be instituted to upskill the local populace, aligning their capabilities with emerging industries. Furthermore, to reduce over-reliance on government funds, mechanisms should be established to foster public-private partnerships. Private enterprises can be incentivized through tax breaks or subsidies to invest in infrastructure and skill development in these counties. Lastly, a continuous feedback loop, incorporating data analytics and ground-level feedback, should be instituted. This would ensure that policies remain dynamic, adjusting to the changing needs and challenges of the targeted regions, thereby ensuring sustained growth and genuine poverty eradication.

7. Conclusion

In examining China's ongoing efforts to combat poverty, this research offers robust empirical support for the government's claims of successful poverty alleviation, particularly in terms of enhancing disposable incomes. Yet, the intricate landscape of poverty becomes evident with the diverse results across models, underscoring its multifaceted nature and the indispensability of multi-variable considerations in policy crafting.

The study's methodological rigor, particularly the adept application of the Difference-in-Differences approach, elucidates the profound impact of the targeted interventions rolled out in 2013 on the designated poverty-stricken counties. The findings distinctly spotlight the genuine benefits experienced by residents within these counties. Nevertheless, the challenges persist. The positive interactions across the models contrast with certain negative coefficients, revealing that while the policy has catalyzed beneficial shifts, these impoverished regions haven't fully bridged the gap with their non-designated counterparts. The pronounced influence of city-specific determinants on disposable incomes serves as a compelling testament to the need for tailoring poverty alleviation initiatives. A blanket, one-size-fits-all approach might not fully capture the complexities inherent in such a vast and diverse nation.

Despite its depth, the study isn't without its limitations. The temporal scope of the data, capped at 2019, overlooks subsequent policy impacts and misses the potential repercussions of unforeseen global events, notably the COVID-19 pandemic that emerged post-2019. On the methodological front, handling missing values, especially from certain omitted counties, might have introduced nuances not captured in the current analysis. Additionally, while the models were comprehensive, they did not account for a few influential variables, such as health, education, and access to vital resources. These factors could deeply impact rural residents' disposable income and overall well-being.

Conclusively, while China has achieved remarkable strides in its journey toward poverty eradication, the marathon continues. The complexity of the challenge necessitates sustained, adaptive efforts with a commitment to continual policy introspection and refinement. In this grand tapestry of development, this research stands not just as a validation of past interventions, but more crucially, as a guidepost, illuminating the intricate path ahead and the imperative of targeted, informed strategies.

References

[1] *Li, Q. (2022). Research on spatial differentiation and influencing factors of relative poverty in China (translated by author). CNKI. https://kns.cnki.net/KCMS/detail/detail.aspx?dbname=CMFD202301&filename=1022075261.nh*
[2] *From Shibadong Village to UN Resolution. (2022, August 30). Www.fmprc.gov.cn. https://www.fmprc.gov.cn/mfa_eng/topics_665678/zggcddwjw100ggs/xsd/202208/t20220830_10757745.html*
[3] *Hua, X. (2021, April 6). Poverty Alleviation: China's Experience and Contribution - Xinhua | English.news.cn. Www.xinhuanet.com. http://www.xinhuanet.com/english/2021-04/06/c_139860414.htm*
[4] *Xie, Q., & Huang, J. (2018, August 19). China releases guideline on winning battle against poverty. English.www.gov.cn. http://english.www.gov.cn/policies/latest_releases/2018/08/19/content_281476267628020.htm*
[5] *Xia, H. (2021, February 26). Xi declares "complete victory" in eradicating absolute poverty in China - Xinhua | English.news.cn. Www.xinhuanet.com. http://www.xinhuanet.com/english/2021-02/26/c_139767705.htm*
[6] *Zhou, Zhen, Wang, & Xiong. (2019). Modeling the Spatial Formation Mechanism of Poverty-Stricken Counties in China by Using Geographical Detector. Sustainability, 11(17), 4752. https://doi.org/10.3390/su11174752*
[7] *Zhang, Y. (2023). The Long-run Impact of Financial Supports on the Former Poverty Counties' Economic Growth ——The Case of Henan Province - CNKI. Cnki.net. https://kns.cnki.net/kcms/detail/11.1010.F.20230419.1510.002.html*
[8] *Xi, M., Fu, W., & Fan, Y. (2021). Fiscal Dependence and Regional Poverty Reduction and Income Increase——An Empirical Study Based on Panel Data of National Poor Counties. Public Finance Research, 66-79(1003-2878(2021)07-0066-14). https://doi.org/10.19477/j.cnki.11-1077/f.2021.07.005.*
[9] *Feng, D., Chen, W., & Chu, X. (2016). Study of Comprehensive Evaluation of Poverty Reduction Effect for Chinese Poverty-Stricken Areas-Based on the Data of Chinese 14 Contiguous Poor Areas. Applied Economics and Finance, 3(3). https://doi.org/10.11114/aef.v3i3.1480*
[10] *China. (2010-2020). China statistical yearbook 201-2020. China Statistics Press.*
[11] *Wang, L., & Du, P. (2021). A study on the intervention of rural tourism in poverty alleviation in national-level poo r counties -- A case study of Nanjiang County, Sichuan Province (translated by author). Modernizing Agriculture, 643000(5), 37–40. https://kns.cnki.net/kcms/detail/detail.aspx?FileName=XDHY202105021&DbName=CJFQ2021*