Eradicating Poverty and Unshackling from Illness Expense: The Impact of Targeted Poverty Alleviation Policy on Medical Burden

Chao Jin[1,a,*]

[1]University of Toronto, Toronto, Canada, M5S 3G7
a. chao.jin@mail.utoronto.ca
**corresponding author*

Abstract: Health poverty alleviation is a crucial aspect of targeted poverty alleviation policy, with easing the medical burden being its primary goal. This study evaluates China's targeted poverty alleviation policy's impact on reducing the medical burden of impoverished households, using data from the China Health and Retirement Longitudinal Survey (CHARLS) for the years 2011, 2013, 2015, and 2018. Employing Difference-in-Differences (DID) methodology, this paper finds significant reductions in both the out-of-pocket to income ratio and catastrophic medical expenditure among targeted households. The policy's success is attributed to the "income effect", raising household income levels, and the "safety-net effect" increasing the reimbursement ratio for inpatient expenses. These results are valid across several robustness tests including propensity score matching (PSM-DID) and placebo test. The findings have implications for global health policy, suggesting that targeted poverty alleviation interventions can effectively alleviate medical burden and prevent poverty due to health expenses, offering a viable model for other developing countries facing similar challenges.

Keywords: Targeted Poverty Alleviation, Medical Burden, Catastrophic Medical Expenditure

1. Introduction

The strategy of targeted poverty alleviation has been central to China's efforts to achieve comprehensive societal prosperity, marking significant progress and offering insights into poverty reduction globally. World Bank data reveals a dramatic reduction in China's poverty rate, from 88.3% in late 1981 to just 0.5% by the close of 2016, amounting to an 87.8% decrease with an average yearly reduction of 2.5%. Comparatively, the worldwide rate of poverty declined from 42.7% to 9.7% over the same timeframe, showing an overall 33.0% drop at a rate of 0.9% annually. This demonstrates that China outpaced the global average in diminishing poverty, maintaining a significantly lower rate of poverty incidence. A major focus within the targeted poverty alleviation efforts has been on addressing healthcare burdens. The State Council's Poverty Alleviation Office's records indicate that by 2015's end, around 20 million individuals had fallen into or returned to poverty due to health issues, making up 44.1% of all impoverished individuals, with 7.34 million affected by severe or chronic health conditions [1,2]. Therefore, protecting the health rights of the impoverished population and preventing impoverishment due to illness have become important components of the targeted poverty alleviation strategy, making health poverty alleviation a key area in the fight against poverty.

The issue of medical burden is a concern for scholars worldwide. Basic medical insurance can reduce the medical burden for rural elderly with high income or high medical expenses, and long-term care insurance can also alleviate medical burden, but it may extend hospital stays [3]. However, medical insurance may lead to the waste of medical resources due to moral hazard. A study using a generalized linear medical expenditure model on the United States Medical Expenditure Panel Survey dataset, found that in the short run, changes in income rather than changes in health spending per se appeared to drive changes in the out-of-pocket burden [4]. Yet, there is a lack of causal evidence on the impact of income on medical burden. Additionally, Chinese scholars' research on the health effects of targeted poverty alleviation policies focuses on the utilization of medical services. Targeted poverty alleviation policies can improve the level of medical service utilization among the poor, but the increase in medical service utilization is partly due to the "work effect", i.e., people paying more attention to health rather than being sick, which cannot accurately measure the issue of family economic burden aggravated by illness [5,6]. Therefore, this paper uses the "out-of-pocket to income ratio" and "household catastrophic medical expenses" to measure medical burden, utilizing four waves of CHARLS data from 2011, 2013, 2015, and 2018, and employs a difference-in-differences approach to estimate the impact of targeted poverty alleviation policies on the medical burden of poor families. This provides causal evidence for the policy effects of preventing "returning to poverty due to illness", a perspective that is still rare in similar empirical studies, thereby further enriching the literature on medical burden.

This study also potentially offers the following marginal contributions: Besides exploring the impact of targeted poverty alleviation policies on family medical burden, it examines the mechanisms behind this effect and introduces, for the first time, the concept of a "safety-net effect" beyond income effects. This "safety-net effect," which helps to alleviate medical burden by increasing the reimbursement ratio for hospitalization expenses, corresponds in reality to the targeted poverty alleviation policy goals of making illnesses treatable and curable. Furthermore, as previously mentioned, research on the health effects of targeted poverty alleviation policies has focused on the utilization of medical services. Moreover, most studies on the effects of targeted poverty alleviation policies have concentrated on their direct objective—poverty alleviation—while this paper proposes the supplementary viewpoint of alleviating medical burden, aiming to eradicate poverty at its roots and free individuals from the constraints of illness, further affirming the superiority of targeted poverty alleviation policies. The remainder of this paper is organized as follows: The second section provides methodologies, including research design, background, data description, and identification strategies. The third section details the findings and analytical insights derived from the tests conducted. The fourth section delves into the underlying mechanisms through which the observed effects are realized. The concluding section summarizes the study's key takeaways.

2. Methodology

2.1. Research Design

This paper begins by contextualizing the research question within the backdrop of China's significant achievements in targeted poverty alleviation. Most existing studies on targeted poverty alleviation have concentrated on its primary objective—poverty eradication. However, this study seeks to explore the effects of targeted poverty alleviation policies from the perspective of medical burden. To do this, it is essential first to define the variable of medical burden. This study measures it through the out-of-pocket to income ratio and catastrophic medical expenditure. Specifically, the out-of-pocket to income ratio is defined as the ratio of out-of-pocket medical expenses to total income,

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excluding household food consumption, serving as a proxy variable. Catastrophic medical expenditure is identified as a binary variable, where a household is deemed to have incurred such expenses when its out-of-pocket to income ratio surpasses a threshold of 0.4, assigning a value of 1 in such instances and 0 otherwise. Furthermore, this research utilizes the China Health and Retirement Longitudinal Survey (CHARLS) dataset, notable for its comprehensive inclusion of various characteristic indicators and the 2018 data's inclusion of a variable indicating whether a household is officially recognized as impoverished, which assists in identifying the treatment group. To investigate the causal impact of targeted poverty alleviation policies on medical burden, this study employs Difference-in-Differences (DID) model for identification and undertakes a series of robustness tests to ensure the validity of the results.

2.2. Background

Since the 18th National Congress, under Xi Jinping's leadership, China has placed rural poverty eradication at the forefront of its agenda to forge a universally prosperous society. This directive has positioned poverty alleviation as a cornerstone of national policy, catalyzing a concerted strategy that mobilizes the Communist Party, the nation, and all segments of society in a holistic campaign against poverty to fulfill the vision of a prosperous society.

Further, in April and June 2014, the State Council's Leading Group Office for Poverty Alleviation and Development launched detailed schemes for identifying needy populations through a meticulous registration and assessment process, introducing an indicator system for this purpose. This effort successfully cataloged 128,000 impoverished villages and nearly 29.48 million impoverished households, encapsulating approximately 89.62 million individuals, thereby creating a comprehensive national database for poverty alleviation—an unprecedented achievement.

Tackling poverty is pivotal for achieving a fully prosperous society, where health poverty alleviation emerges as a critical endeavor. The primary aim here is to elevate medical insurance coverage and significantly lighten the healthcare cost burden for the rural impoverished. Accordingly, the National Health and Family Planning Commission, alongside the State Council's poverty alleviation office and other relevant bodies, endorsed the "Guiding Opinions on Implementing the Health Poverty Alleviation Project". This guideline reaffirms the commitment to the "two no worries and three guarantees" principles of the poverty eradication campaign, focusing on ensuring "guaranteed basic medical care" for the impoverished. It integrates major strategic initiatives like Healthy China and Rural Revitalization, executing a "three batches" action plan tailored to provide targeted interventions for major illnesses, systematic management of chronic diseases, and comprehensive insurance coverage for severe conditions. This framework aims to ensure that impoverished communities are equipped to afford and access essential healthcare services, reflecting a nuanced and integrated approach to health poverty alleviation within the broader objective of national prosperity [7].

2.3. Data and Variable Descriptions

This investigation leverages data from the China Health and Retirement Longitudinal Survey (CHARLS), which is specifically designed to assemble a comprehensive micro-level dataset that encapsulates the demographic and socio-economic characteristics of Chinese households and individuals aged 45 and older. This rich dataset facilitates an in-depth exploration of the aging population's dynamics in China and supports a wide array of interdisciplinary scholarly inquiries. Executed through a meticulously designed multi-stage probability proportionate to size (PPS) sampling strategy, the CHARLS initiative spans across 150 counties and 450 villages in 28 provinces, capturing extensive data across five waves: 2011, 2013, 2015, 2018, and 2020. The survey's

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completion in 2018 yielded a substantive dataset encompassing 19,000 respondents across 12,400 households. The breadth of information collected includes, but is not limited to, demographic profiles, health statuses, medical insurance coverage, engagement with healthcare services, income and consumption patterns, employment and pension details, asset ownership, and local community infrastructure. Due to significant data fluctuations caused by the COVID-19 pandemic in 2020 and the missing variables compared to the previous four waves, the 2020 data were not included in this study. The four waves of data from 2011, 2013, 2015, and 2018 actually collected information for the years 2010, 2012, 2014, and 2017 for rural elderly individuals. Given that the targeted poverty alleviation policy was proposed at the end of 2013 and the comprehensive registration and identification were completed by the end of 2014, this study constructed a panel dataset consisting of four waves of data to better address the specific issue of the policy's impact on medical burden. After excluding samples with missing core variables, urban area samples, and unbalanced samples in the panel data, the final sample used in this study consists of 47,952 rural elderly individuals, equating to 11,988 individuals per wave.

This paper focuses on the "medical burden issue" of impoverished households, using the "out-of-pocket to income ratio", which is the ratio of out-of-pocket medical expenses to total income excluding household food consumption, as a proxy variable. Additionally, another widely used international proxy variable, "catastrophic medical expenditure," is introduced to measure the medical burden. This variable is a binary variable where a household is considered to have incurred catastrophic medical expenditure when its out-of-pocket to income ratio exceeds the threshold of 0.4; the variable is assigned a value of 1 in such cases and 0 otherwise [8].

Based on the analytical framework of this paper, the selected control variables are as follows: age, square of age/100, education level, marital status, presence of hypertension, number of chronic diseases, self-rated health, poor memory, daily mobility, depression index, presence of medical insurance, and presence of pension insurance. Detailed variable descriptions are provided in Table 1.

Table 1: Variable Descriptions

Variables		Variable Description
Dependent Variables	Out-of-Pocket to Income Ratio	The ratio of out-of-pocket medical expenses to total income after excluding household food consumption
	Catastrophic Medical Expenditure	Assigned a value of 1 if the household's out-of-pocket to income ratio exceeds the threshold of 0.4, otherwise 0
Independent Variable	Targeted Poverty Alleviation Household	1 if the household is identified as impoverished in the official registration system, otherwise 0
Covariates	Age	Age as written on the respondent’s household registration
	Age Squared/100	Age squared divided by 100 to capture the changing marginal effects with increasing age
	Education	Less than primary=1, Primary=2, Middle school=3, High school and above=4
	Marital Status	Married=1, Others (including divorced, widowed, etc.)=0
	Self-Rated Health	Very poor=1, Poor=2, Fair=3, Good=4, Very good=5
	Hypertension	YES=1,NO=0

Table 1: (continued).

	Chronic Disease	YES=1,NO=0
	Episodic Memory	1-10 points, higher scores indicate better memory
	Depression Score	1-10 points, higher scores indicate worse mental health
	Cognitive Function	0-21 points, higher scores are better
	Daily Living Activities	0-6 points, higher scores indicate worse ability
	Pension Insurance	NO=0,YES=1
	Medical Insurance	NO=0,YES=1

2.4. Identification Strategy

This paper employs a Difference-in-Differences (DID) model to identify the impact of targeted poverty alleviation policies on medical burden:

$$\boldsymbol{Y}_{it} = \alpha + \beta Treat_{it} + \boldsymbol{X'}_{it}\boldsymbol{\gamma} + \omega_t + \varphi_i + \varepsilon_{it} \tag{1}$$

where $\boldsymbol{Y}_{it}$ represents both the "out-of-pocket to income ratio" and "catastrophic medical expenditure", with i and t denoting the individual and time, respectively. As mentioned earlier, the targeted poverty alleviation policy was proposed at the end of 2013 and the comprehensive registration and identification process was completed by the end of 2014. Therefore, the policy implementation year is set to 2014 in this study. The CHARLS 2018 data collection includes information on whether a household is targeted for poverty alleviation. Not only does the current questionnaire ask if a household is identified as impoverished in the official registration system, but it also inquires about the year the household was designated as such. Consequently, this paper constructs the $Treat_{it}$ variable, where $Treat_{it} = 1$ if the policy occurred after the household was identified as "impoverished" post-policy implementation, otherwise $Treat_{it} = 0$.

The main challenge of DID is that the subjects of targeted poverty alleviation are not randomly selected but are relatively low-income impoverished households [5]. Since impoverished households inherently differ from the control group samples in terms of medical burden, directly conducting DID would inevitably overestimate the policy effect. Hence, $\boldsymbol{X'}_{it}$ is introduced as a vector of covariates unaffected by the policy, including other factors mentioned earlier that influence medical burden. $\boldsymbol{\gamma}$ is the coefficient vector of covariates, and ε_{it} is the random error. The coefficient of interest, β, measures the difference in medical burden between impoverished households (treatment group) and non-impoverished households (control group) before and after the implementation of targeted poverty alleviation policies. If $\beta < 0$, it implies that the targeted poverty alleviation policy alleviates the medical burden of impoverished households.

3. Test Results and Analysis

3.1. Basic Regression

To accurately identify the reduction in medical burden brought about by the targeted poverty alleviation policy, Table 2 reports the basic regression results of the DID model.

Columns (1) and (3) present the regression results without covariates, while columns (2) and (4) include covariates.

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Table 2: The Impact of Targeted Poverty Alleviation Policy on Medical Burden: DID

	(1)	(2)	(3)	(4)
	Out-of-Pocket to Income Ratio	Out-of-Pocket to Income Ratio	Catastrophic Medical Expenditure	Catastrophic Medical Expenditure
Treat	-0.062***	-0.052***	-0.061***	-0.053***
	(0.009)	(0.011)	(0.009)	(0.012)
Control Variables	NO	YES	NO	YES
Year FE	YES	YES	YES	YES
ID FE	YES	YES	YES	YES
N	47952	28620	47952	28620
Adj. R^2	0.295	0.328	0.275	0.301

Note: Parentheses contain robust standard errors clustered at the household level, because "medical burden" is primarily a household issue [4,9], **p<0.1, **p<0.05, ***p<0.01*.

From the Difference-in-Differences (DID) results, both the out-of-pocket to income ratio and the occurrence of catastrophic medical expenditure significantly decreased at the 1% level after the implementation of the targeted poverty alleviation policy. This indicates that the policy significantly alleviates the medical burden on impoverished households. Furthermore, in the regression without covariates, the medical burden also significantly decreased at the 1% level, but the coefficients are larger in absolute value compared to those in the regression with covariates included. This supports the earlier assertion that conducting DID without including covariates would inevitably overestimate the policy effect.

3.2. Robustness Test

3.2.1. Parallel Trends Test

The purpose of using the Difference-in-Differences method to identify policy effects is to eliminate other non-treatment policy factors that might affect the dependent variable. Central to the DID approach is the assumption of parallel trends, necessitating that, prior to the enactment of the policy, both the treatment and control groups exhibit similar trajectories of change. The DID model can only reveal causal effects under the premise of satisfying the common trends assumption: in this study, that is, before the targeted poverty alleviation policy was implemented, the treatment and control groups should have the same trend of changes in the outcome variables. Given that the policy point is set to 2014, 2013 is set as the base period in the figure. Since the parallel trends test examines pre-treatment trends, only data from 2011, 2013, and 2015 are included in the test. In the parallel trends test graph, if the effect before the policy occurs is around zero, and the effect after the policy implementation significantly deviates from zero, it indicates that the empirical analysis can be conducted through DID following a parallel trends test. See Figure 1 for details.

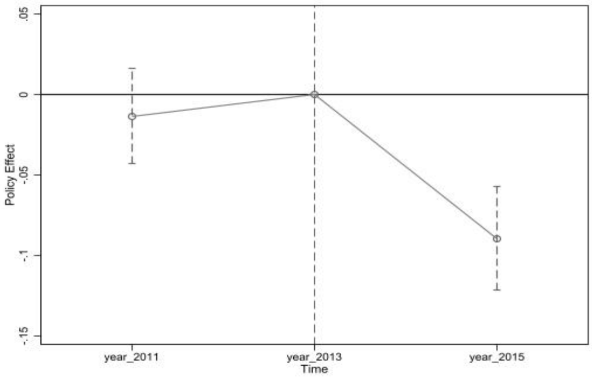
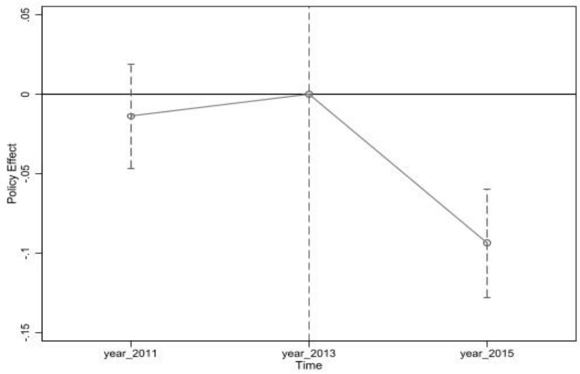


Figure 1: (a) Parallel trends test: Out-of-pocket to income ratio



(b) Parallel trends test: catastrophic medical expenditure

From the figure, the coefficients before the policy implementation are not significant and close to zero, preliminarily verifying the assumption of parallel trends before the intervention. However, due to the limited sample size and data years in the CHARLS dataset (with only two waves of data in 2011 and 2013 before the policy point in 2014), the parallel trends test graph for this paper can only be presented in the form of Figure 1.

3.2.2. Abadie SDID Re-weighted Regression

The credibility of DID conclusions depends on the premise of parallel trends. Therefore, to enhance the credibility of DID conclusions, this paper refers to the re-weighted semiparametric difference-in-difference method (Semiparametric Difference-in-Difference, SDID) proposed by Abadie [10] for robustness testing. This method allows for a more balanced characteristic between the treatment and control group samples by weighting in cases with two-period balanced panel data. It assesses the impact of the policy by evaluating the differential in outcome variables across two periods between the adjusted treatment group and control group. This technique is capable of yielding robust insights, even in instances where the parallel trends precondition may not be entirely met. The formulation for estimating the average effect of the treatment under the Semi-parametric Difference-in-Differences (SDID) framework is given by:

$$E\left[\frac{\Delta Y_t}{P(d_t=1)}\cdot\frac{d_t-\pi(X_b)}{1-\pi(X_b)}\right] \tag{2}$$

where d_t represents whether it is the treatment group in period t. $P(d_t=1)$ represents the probability of being in the treatment group, and $\pi(X_b)$ is the Abadie weight, which can be calculated through the linear probability model $\pi(X_b)=P(d_t=1|X_b)$.

Given that Abadie SDID requires two-period panel data and considering the targeted poverty alleviation policy began in 2014, with no pilot targeted poverty alleviation policy in 2011 and surveys in 2018 asking whether a household was registered as impoverished, by which time the targeted poverty alleviation policy had entered a mature phase, this paper selects data from 2011 and 2018 to form a balanced panel and conduct SDID regression. The results, as shown in Table 3, indicate that the coefficients of the interaction terms are significantly negative, consistent with the findings previously discussed.

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Table 3: SDID Result

	(1)	(2)
	Out-of-Pocket to Income Ratio	Catastrophic Medical Expenditure
DID	-0.089***	-0.087***
	(0.012)	(0.013)
N	7284	7284

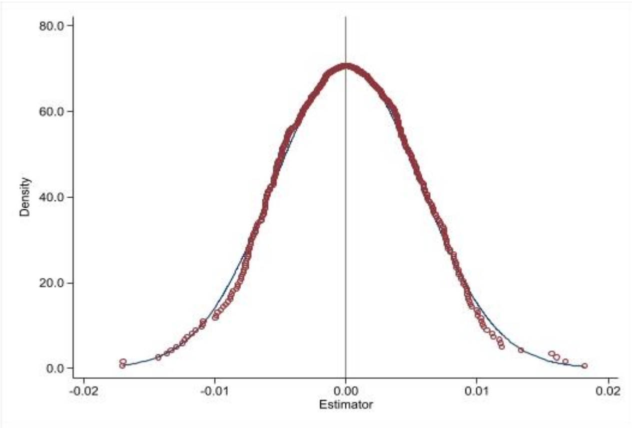
Note: Parentheses contain robust standard errors clustered at the household level., **p<0.1, **p<0.05, ***p<0.01*.

3.2.3. Placebo Test

To mitigate the potential influence of random variables on the outcomes of this study, a placebo test will be employed. Utilizing the permutation test as a placebo testing technique enables the determination of whether the observed results hold statistical significance or arise from random chance [11]. Within the context of the permutation test, it is hypothesized that the targeted poverty alleviation policy exerts no significant impact on the healthcare burden faced by impoverished households. Assuming this null hypothesis, it posits that the coefficients derived from the empirical data might be random instances within the overall distribution, allowing for statistical inferences to be drawn from this distribution as determined through the permutation test. The procedure involves randomly allocating the status of being affected by the targeted poverty alleviation policy to participants within the survey and subsequently assigning individuals to the treatment group on a random basis. Drawing on the methodologies established by Ferrara et al. [12], Liu and Lu [13], Zhou Mao et al. [14], and Song Hong et al. [15], this investigation adopts an indirect approach to the placebo test. Following Equation (1), it calculates the estimated coefficient $\hat{\beta}$ as:

$$\hat{\beta} = \beta + \rho \frac{cov(Treat, \varepsilon|V)}{var(Treat|V)} \tag{3}$$

where V represents all other control variables and fixed effects, ρ is the impact of unobserved factors on the medical burden of impoverished households. If $\rho = 0$, then unobserved factors do not affect the estimation results, proving $\hat{\beta}$ is unbiased. Since it's impossible to directly verify whether ρ is zero, this paper adopts an indirect placebo test. The logic is to randomize the targeted poverty alleviation policy, i.e., find a theoretically ineffective variable $Treat'$ to replace $Treat$. Since $Treat'$ is randomly generated, the actual effect of the targeted poverty alleviation policy $\beta = 0$. Under this premise, if the estimated $\hat{\beta}$ is not zero, it implies ρ is not zero, indicating the estimation results of this paper are biased. Specifically, this paper randomly generates a treated group of registered impoverished households, thus producing an erroneous estimate $\hat{\beta}'$, and repeats this process 500 times, plotting the distribution of 500 $\hat{\beta}'$ s. According to the results of the placebo test in Figure 2, it can be seen that $\hat{\beta}'$ is concentrated around zero and follows a normal distribution. The actual estimated coefficients (-0.052 and -0.053) are clearly outliers and conform to the expectations of the placebo test. Since the actual estimated coefficients significantly deviate, they are not marked in the figure.



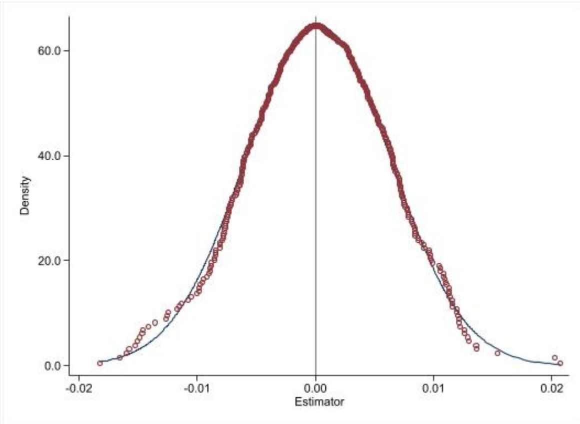


Figure 2: (a). Placebo Test:Out-of-pocket to income ratio

(b). Placebo Test:Catastrophic Medical Expenditure

3.2.4. PSM-DID Test

Despite satisfying both the parallel trends and placebo criteria, the distinction in sample attributes could still engender a selection bias between the treatment and comparison groups. This issue is particularly pertinent given the non-random allocation of the targeted poverty alleviation intervention, which relies on a comprehensive array of criteria to ascertain a household's poverty status. To mitigate the inherent selection bias between the treatment (impoverished households) and control (non-impoverished households) cohorts, this investigation adopts the Propensity Score Matching (PSM) combined with Difference-in-Differences (DID) analytical framework. It first matches the impoverished group with the non-impoverished group using 1-to-1 nearest neighbor matching with a caliper to ensure the quality of the matches. Then, it uses the Difference-in-Differences method to estimate the impact of targeted poverty alleviation on the medical burden of impoverished households.

Propensity score matching requires passing two tests:

(1) Balancing Test

Table 4 shows the results of the balance test for covariates pre and post matching between the treatment and control groups. The first two columns present the mean test results of variables between the two groups before matching. The results show that before matching, there were significant differences between the treatment and control groups in aspects such as squared age/100, age, daily living activities, mental health, social security, chronic diseases, marital status, self-rated health, memory ability, cognitive ability, and education level. Therefore, it can be concluded that there were indeed significant differences between the treatment and control group samples before matching. The last two columns present the mean test results of variables between the two groups after matching, indicating that there were no significant differences in all covariates between the treatment and control groups after matching. This suggests that the matched samples have good balance, and the overall matching effect is satisfactory.

Table 4: Balancing Test

Variable	Unmatched		Matched	
	t-value	p-value	t-value	p-value
Age^2/100	16.53	0.000	0.81	0.415
Age	15.34	0.000	0.95	0.342
Daily-life activity	12.55	0.000	-0.46	0.645

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Table 4: (continued).

Cesd	11.52	0.000	-0.12	0.907
Social pension	6.40	0.000	-0.00	1.000
Chronic disease	3.14	0.002	0.62	0.535
Hypertension	0.29	0.772	-0.01	0.989
Medical insurance	-0.26	0.794	-0.39	0.698
Married	-1.85	0.065	-0.49	0.627
Self-rated health	-8.56	0.000	0.01	0.995
Memory	-11.26	0.000	-0.69	0.490
Cognition	-14.98	0.000	-1.42	0.157
Education	-15.39	0.000	-0.17	0.867

In addition to the results presented above, this paper also provides a graphical illustration of the balance test, as shown in Figure 3.

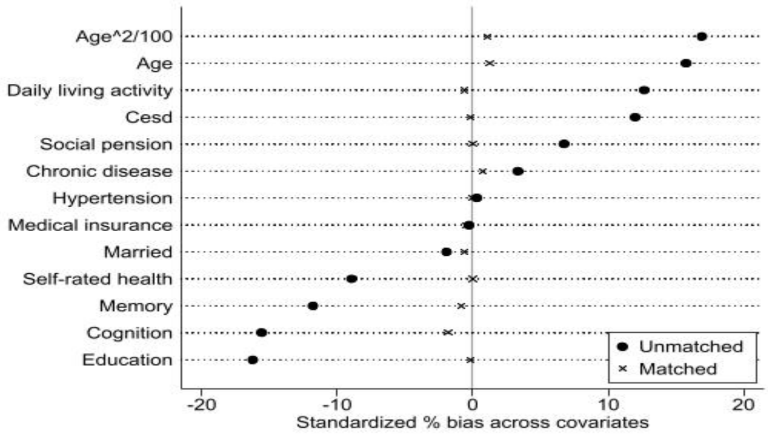

Figure 3: Balancing Test

All covariates exhibit a % bias of less than 10%, and the % bias is significantly lower than before matching. Thus, the balance test is passed.

(2) Common Support Test

Propensity score matching requires meeting the common support assumption, meaning that the propensity scores of the treatment and control groups need to encompass a common range of values. To this end, this study presents a graph of the common range of propensity scores for both the treatment and control groups, as shown in Figure 4:

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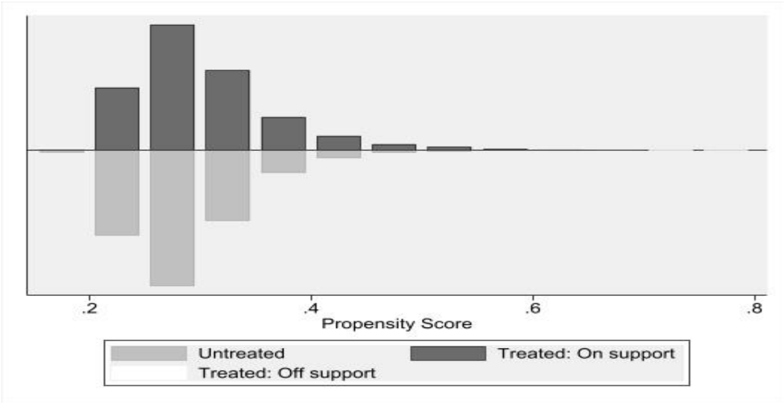

Figure 4: Common Support Test

From this figure, it's evident that the vast majority of samples from both the treatment and control groups fall within the common support range. Samples outside this range tend to have more extreme propensity score values, thus satisfying the common support assumption.

Moreover, this study further examines the common support assumption by comparing the kernel density distribution of propensity scores for the treatment and control groups before and after matching, as shown in Figures 5(a) and 5(b):

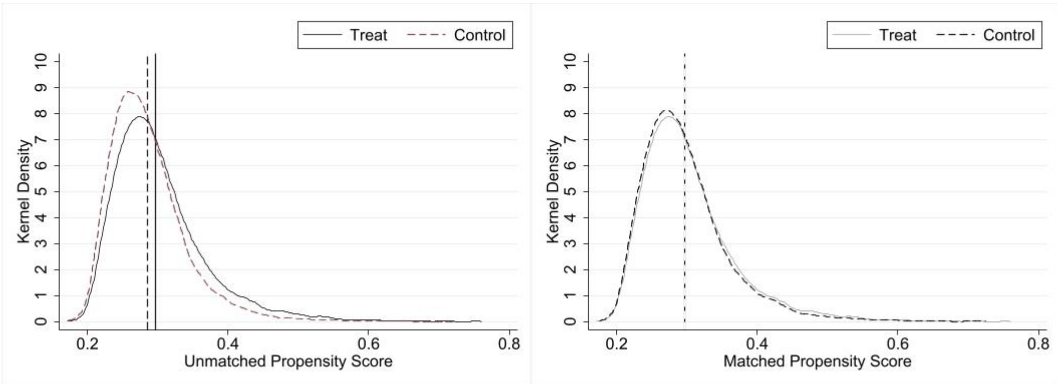

Figure 5: (a) Kernel Density: Unmatched (b) Kernel Density: Matched

Exactly, the visual evidence from the graphs clearly demonstrates the effectiveness of the matching process. Before matching, there was a noticeable difference between the treatment and control groups, indicating variation in their characteristics. However, after matching, the two groups closely align, nearly overlapping in the kernel density plots. This substantial improvement post-matching confirms that the samples satisfy the common support assumption, ensuring that the treatment and control groups are comparable for the analysis.

(3) PSM-DID Results

Using the samples after propensity score matching (PSM), this study conducts a Difference-in-Differences (DID) analysis, with the targeted poverty alleviation policy as the independent variable and both the out-of-pocket to income ratio and catastrophic medical expenditure as dependent variables. The regression results are as shown in Table 5:

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Table 5: The Impact of Targeted Poverty Alleviation Policy on Medical Burden: PSM-DID

	(1)	(2)
	Out-of-Pocket to Income	Catastrophic Medical Expenditure
Treat	-0.059***	-0.06***
	(0.009)	(0.010)
Control Variables	YES	YES
Year FE	YES	YES
ID FE	YES	YES
N	37546	37546
Adj. R^2	0.3285	0.3014

Note: Parentheses contain robust standard errors clustered at the household level., *$p<0.1$, **$p<0.05$, ***$p<0.01$.*

After controlling for covariates, year fixed effects, and individual fixed effects, the impact of the targeted poverty alleviation policy on reducing medical burden for economically disadvantaged families remains markedly significant. Post-policy enactment, there was a notable reduction in the ratio of out-of-pocket healthcare expenses to total income by 5.9%, a figure that holds statistical significance at the 1% level. Similarly, catastrophic health spending saw a 6% decline, also achieving significance at the 1% threshold. When juxtaposed with the pre-match findings presented in Table 2, the post-matching effect of the poverty alleviation initiative on mitigating healthcare expenses is accentuated. This congruence between the propensity score matched Difference-in-Differences analysis outcomes and the initial findings not only underscores the policy's efficacy but also affirms the robustness of the study's core conclusions

4. Mechanism Analysis

4.1. Income Effect

The direct objective of targeted poverty alleviation policies is evidently poverty eradication, with the primary manifestation being an increase in the income levels of impoverished households. Furthermore, based on the definition of medical burden used in this study, an increase in income levels, with out-of-pocket expenses remaining constant, necessarily leads to a decrease in medical burden. Thus, this section replaces the dependent variable with the logarithmic forms of household annual income and per capita annual income to perform a difference-in-differences analysis. This analysis controls for factors that may influence income, such as age, household size, employment status, productive fixed assets, per capita land value, and educational level. The results are as shown in Table 6:

Table 6: Impact of Targeted Poverty Alleviation Policy on Income: DID

	(1)	(2)
	Household Annual Income	Per Capita Annual Income
Treat	0.092**	0.096**
	(0.044)	(0.044)
Control Variables	YES	YES
Year FE	YES	YES
ID FE	YES	YES
N	30261	30261
Adj. R2	0.4749	0.4469

Note: Parentheses contain robust standard errors clustered at the household level, *$p<0.1$, **$p<0.05$, ***$p<0.01$.*

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The results indicate that the targeted poverty alleviation policy increased household annual income levels by 8.2% at the 10% significance level and per capita annual income levels by 8.7% at the 5% significance level. This suggests that the targeted poverty alleviation policy effectively raised the overall income levels of impoverished families, providing a fundamental condition for alleviating their medical burden.

4.2. Safety-Net Effect

Following the same logic, this section investigates whether the targeted poverty alleviation policy alleviates medical burden by increasing the reimbursement ratio of out-of-pocket expenses, referred to as the safety-net effect. The logic here is that direct medical costs resulting from seeking medical treatment are a major risk factor for impoverishment [16]. If the targeted poverty alleviation policy intensifies reimbursement efforts and provides a safety net for the medical treatment of impoverished households, it would have a significant impact on easing their medical burden. Due to the limitations of the CHARLS dataset, this study uses the proportion of out-of-pocket expenses as a proxy for the reimbursement ratio, as these two are inversely related. The dependent variables are changed to the ratios of total medical expenses out-of-pocket, outpatient expenses out-of-pocket, and inpatient expenses out-of-pocket. Control variables are added for a DID analysis, with results as shown in Table 7:

Table 7: Impact of Targeted Poverty Alleviation Policy on Reimbursement Ratio: DID

	(1)	(3)	(4)
	Total Expense Out-of-Pocket Ratio	Doctor Visit Out-of-Pocket Ratio	Hospitalization Out-of-Pocket Ratio
Treat	-0.082*	-0.084	-0.245**
	(0.056)	(0.06)	(0.106)
Control Variables	YES	YES	YES
Year FE	YES	YES	YES
ID FE	YES	YES	YES
N	2297	1350	735
Adj. R2	0.1930	0.1556	0.1479

Note: Parentheses contain robust standard errors clustered at the household level, **p<0.1, **p<0.05, ***p<0.01*.

The results show that the targeted poverty alleviation policy significantly reduced the total out-of-pocket medical expense ratio, implying that the policy increased the medical expense reimbursement ratio, thereby easing the medical burden on impoverished households. Specifically, the policy did not reduce the outpatient out-of-pocket ratio but significantly lowered the out-of-pocket hospitalization expense ratio, meaning that the targeted poverty alleviation policy primarily eases medical burden by reducing inpatient out-of-pocket expenses. This aligns with logic, as general outpatient visits do not lead to medical burden that could cause impoverishment due to illness. Instead, the significant medical burden mainly arises from hospitalizations for serious illnesses [17]. Therefore, by providing a safety net for serious illnesses among impoverished households, the state can alleviate their medical burden, aligning with the primary objectives of health poverty alleviation.

5. Conclusion

Health poverty alleviation is an integral part of the targeted poverty alleviation strategy, with easing the medical burden on impoverished households being its primary goal. In reality, comprehensively improving the health levels of the impoverished population is a long and arduous process. Given the limitations of dataset years, the lag in microdata, and the subjectivity of residents' self-assessments, it's challenging to empirically verify whether a policy can enhance health levels. However, the impact on medical burden is immediate. If medical burden is relieved, this provides a fundamental material basis for impoverished households to afford and recover from illnesses, which in turn can have a long-term effect on their health levels.

Therefore, utilizing the CHARLS datasets from 2011, 2013, 2015, and 2018, and based on the quasi-natural experiment of implementing the targeted poverty alleviation policy in China, this paper finds through a difference-in-differences model that the targeted poverty alleviation policy helps alleviate the medical burden on impoverished households. It not only reduces the out-of-pocket to income ratio for impoverished households but also their catastrophic medical expenditure. The empirical results have passed a series of robustness tests. Additionally, this paper confirms that the targeted poverty alleviation policy alleviates the medical burden on impoverished households through both the "income effect" and the "safety-net effect", i.e., by increasing the income level of impoverished households and the reimbursement ratio for hospitalization expenses. These conclusions are crucial for clarifying policy effects and responding to policy goals.

Furthermore, the conclusions of this paper may offer guidance for other developing countries around the world in alleviating the medical burden on their populations. As reported by the World Health Organization in 2017, approximately 800 million individuals globally allocate a minimum of 10% of their household budget to healthcare expenses, pushing nearly 100 million into extreme poverty [18]. China's targeted poverty alleviation policy not only lifted 98.99 million rural impoverished people out of poverty but also significantly alleviated their medical burden, preventing the occurrence of falling back into or being impoverished due to illness. Therefore, other countries grappling with the heavy burden of medical expenses can learn from China's approach, addressing the root causes of poverty to fundamentally solve the issue of medical burden.

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