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ORIGINAL RESEARCH

A Counterfactual Assessment of Poverty Alleviation Sustainability on Multiple Non-equivalent Household Groups

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Abstract
Poverty has been a long-term global challenge, and China's Targeted Poverty Alleviation (TPA) Strategy has made considerable advances in recent years. Taking a poverty-stricken county in Southwest China as an example, this study evaluated the effectiveness of the TPA strategy using a propensity scoring weighting model for multiple non-equivalent household groups based on counterfactual inference. It was found that households who planned to be out of poverty earlier had significantly higher incomes than those later, with transfer incomes contributing substantially to the income gap. The non-poverty-stricken households had much higher total income and significantly lower transfer incomes than the poverty-stricken households, including those that planned to be out of poverty earlier and those later. A more nuanced analysis revealed that the income of the poverty-stricken households was not as sustainable as expected. Therefore, measures to improve the self-development capabilities of these poverty-stricken households were also proposed to ensure the poverty alleviation programs are more effective and sustainable.

Keywords Target poverty alleviation · Propensity score · Multiple non-equivalent groups · Household income

Introduction

Eradicating poverty in all its forms and dimensions is a significant global challenge and is indispensable for sustainable development (Arnold, 2018). China has made remarkable progress in its poverty alleviation efforts, with 98 million rural residents emerging from poverty between 2013 and 2020. As the key to consolidating these

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existing poverty alleviation achievements is preventing any backsliding (Deng et al., 2020) and informing the next set of global development goals and policies, regular evaluations of the anti-poverty policy successes and failures are needed to identify the deficiencies and learn from the lessons (Bray et al., 2020).

China's success with the Target Poverty Alleviation (TPA) strategy has been hailed worldwide (Zhou et al., 2018). To eliminate absolute poverty in China by the end of 2020, the TPA strategy was proposed in 2013. It classified all households with per capita annual net income below the poverty line in 2013 as poverty-stricken households (Liu et al., 2017) and the counties and villages with a high incidence of poverty-stricken households as poverty-stricken counties and poverty-stricken villages. The TPA strategy tried to classify the poverty-stricken households based on the environment of various poor areas and the situation of different poor households and take different assistance measures according to the poverty-stricken households with varying causes of poverty (Cheng et al., 2021). During the TPA implementation, the central government evaluated the poverty eradication effectiveness each year, which included an assessment of the reduction in the number of poverty-stricken villages and counties based on the percentage of households no longer classified as poverty-stricken (Zhou et al., 2018).

In practice, the local governments developed time goals for each poverty-stricken household to be lifted out of poverty to ensure that the poverty alleviation goals are achieved on time. Not surprisingly, some of the poverty-stricken households were lifted out of poverty earlier, while others were lifted out of poverty later. The central government allowed local governments to designate a certain percentage of poverty-stricken households to be lifted from poverty first. At the same time, it hoped that rather than receiving only monetary or material assistance, all poverty-stricken households would improve their development capacities and income sustainability. Whether government subsidies or improved ability leads to income growth can be analyzed by comparing the income sources of the group lifted out of poverty and those still poverty-stricken. Therefore, this study divides the poverty-stricken households into the households who planned to be out of poverty in or before 2018 and the households who planned to be out of poverty after 2018 and sought to identify the developmental differences in 2018 between them, which have not been paid attention to in previous studies. Following the TPA strategy's implementation after 4 years, this study can be viewed as providing a medium-term assessment of the TPA strategy.

As poverty alleviation sustainability has become a critical issue in long-term poverty alleviation (Mai et al., 2020), governments need to determine whether the households lifted out of poverty had sustainable incomes. Therefore, simply comparing whether poverty-stricken households had more significant income increases than non-poverty-stricken households without analyzing the actual household income structures would not identify the poverty alleviation sustainability. Besides, these three groups, households lifted from poverty, households that remained poverty-stricken, and non-poverty-stricken, were not equivalent. To evaluate the poverty alleviation effectiveness, this study compared three household income groups using counterfactual inferences. A propensity scoring weighting model was employed for multiple non-equivalent groups with doubly robust estimation on data from a poverty-stricken county in Southwest China.

The remainder of this study is organized as follows. Section 2 gives an overview of previous poverty alleviation evaluations, Section 3 describes the data and methodology employed in the analysis, Section 4 reports the empirical results, and Section 5 discusses the results and gives the conclusion.

Literature Review

Rural societies in developing countries face numerous challenges, such as poverty, inequality, vulnerability, and deprivation. A wide range of anti-poverty policies have been implemented worldwide (Ravallion, 2010), and follow-up evaluations have been conducted to assess their effectiveness (Gao et al., 2019; Prentice et al., 2020).

However, there are many challenges when seeking to assess the impacts of anti-poverty resilience interventions (Gertler et al., 2011), as many other external factors also affect the life and livelihoods of the participants. Therefore, as randomly assessing the subjects/households as required in authentic experimental designs is generally not applicable, quasi-experimental designs have usually been adopted (Béné et al., 2020). For example, Meng (2013) employed a regression discontinuity approach to evaluate the impacts of China's '8-7' plan poverty alleviation program and concluded that the program had had a positive impact on rural income from 1994 to 2000. Using a propensity scoring matching model, Tohari et al. (2019) evaluated Indonesia's three most extensive socially targeted poverty programs, finding that compared to the non-receiving households, the receiving households in all three programs had had household expenditure increases. Sotomayor (2021) used a difference-in-difference estimator to evaluate the effect of the higher minimum wages anti-poverty policy tool in Brazil and found that these increases had resulted in declines in poverty and income inequality.

Several empirical studies have evaluated the socioeconomic impacts of China's poverty alleviation programs since the implementation of the TPA, with most focusing on the effects of specific TPA poverty reduction measures. In particular, Liao et al. (2020) found that a higher labor transfer proportion positively impacted household per capita income. Liu et al. (2020) found that because of government subsidies and other income, participation in an ecological resettlement program had generally increased the income of the relocated households, reduced the poverty rate, and improved the living conditions and facilities. Le and Leshan (2020) evaluated the eco-compensation poverty reduction effects, one of the five major TPA approaches, and found that the eco-compensation program did not necessarily contribute to poverty reduction unless the eco-compensation schemes were purposely designed to do so. Wang et al. (2020) found that the investments in photovoltaic poverty alleviation projects had been effective, with the increase in the investment scale and property support further improving the poverty alleviation effects. However, while most of these studies focused on increases in total household income, few considered long-term income sustainability.

Therefore, examining poverty alleviation performances requires the assessment of both household livelihoods and income sustainability because only by ensuring a self-development route out of poverty and sustainable poverty alleviation can rural households avoid falling back into poverty (den Broeck and Maertens, 2017). Deng et al. (2020) found that rural household income sustainability in a poverty-stricken county in China was limited by the lack of livelihood resources, especially labor resources. Research primarily analyzed the impact of government policies on various dimensions of rural household livelihoods. It focuses on measuring and analyzing the differences in the rural household livelihoods before and after policy implementations focused on tourism industry development (Luo et al., 2019), industry-based poverty alleviation (Ding et al., 2020), and transnational labor migration (Sunam et al., 2021). Other studies investigating the impacts of livelihood capital on livelihood sustainability found that livelihood strategies affected revenue sources and welfare (Zhang and Fang, 2020). However, as livelihood is a complex term made of and affected by many systems, such as local ecology, the economy, the society, and institutions, measuring livelihood sustainability has been difficult (Deng et al., 2020). Objectively, income is the most direct indicator for assessing poverty, with income structures directly reflecting rural income stability; for example, income derived from a farmer's abilities and efforts is more sustainable than income obtained from government subsidies or aid.

Most existing studies have only examined the impacts of an anti-poverty policy by comparing program and non-program participant income (Liao et al., 2020; Liu et al., 2020; Le and Leshan, 2020). Although all poverty-stricken households were identified using the same standard, some were lifted out of poverty earlier than others due to faster income growth. Whether the income growth is sustainable determines whether the TPA strategy is long-acting characteristics. Besides, it is possible that some households who are scheduled to be out of poverty earlier were given priority, such as more transfers. Thus, to ensure that the households lifted out of poverty are now non-poor and their incomes are sustainable, the developmental differences between the relevant households must first be determined to reform and improve subsequent anti-poverty policies.

Therefore, further research on the effectiveness of China's TPA strategy for poverty alleviation is needed. Existing studies evaluated the effects of the poverty alleviation policies by comparing poverty-stricken and non-poverty-stricken household income without considering the development difference among poverty-stricken households. It is necessary to determine the assistance received by the different poverty-stricken households. Therefore, this study used a propensity scoring weighting model for multiple non-equivalent groups to compare and analyze the household incomes between households that lifted out of poverty, households that were still poverty-stricken, and non-poverty-stricken households. Meanwhile, previous studies have also focused on total rural household income without explicitly examining the income structures. Therefore, this study compared the income from different sources to determine whether these household incomes were sustainable and to reveal the income and livelihood differences between the households lifted out of poverty and the non-poverty-stricken households.

Materials and Methods

This section provided some basic contextual information on the target poverty alleviation strategy, sample collection, variable definition, and estimation method of treatment effect.

Target Poverty Alleviation Strategy in China

The targeted poverty alleviation (TPA) strategy was a series of poverty alleviation policy combinations that was initiated and promoted by the central government and cooperated by local governments. The strategy used scientific and practical procedures to accurately identify, assist and manage the poverty alleviation objects according to the environment of different poverty-stricken areas and the situation of different poverty-stricken households.

(1) *Accurately identify* The TPA strategy targeted poverty-stricken households using the income of households as the fundamental basis. Specifically, after publicizing the policy of accurate identification, the households voluntarily applied to be identified as poverty-stricken. Then, the township authorities and the village committee conducted the household investigation and checked each source of household income in detail, including wage income, family business income, property income, and transfer income. The household's per capita annual net income was obtained by dividing the total household income by the total number of registered residents of the household. And the households whose annual per capita net income was higher than the poverty line (2760 CNY in 2013) were excluded, forming the initial list of poverty-stricken households. After public announcement and democratic appraisal on the initial list, poverty-stricken households were identified. Besides, in the identification process, the causes of poverty and endowment resources of poverty-stricken households were investigated.
(2) *Accurately assist* The TPA strategy emphasized implementing different policies for different households. In particular, according to the causes of poverty in poverty-stricken households, the local government chose appropriate assistance to help them increase their income. Specifically, the central government had taken five unconventional measures to push forward the TPA strategy. The five measures include: (a) Supporting the poverty-stricken households who possess work ability and have productive skills to help them expand employment opportunities and develop their industries; (b) Relocating the poverty-stricken households in remote areas with fragile ecological environments and without primary development conditions to more livable villages; (d) Strengthening primary education and vocational education to improve local human capital and to prevent the intergenerational transmission of poverty; and (e) helping those who are totally or partially disabled from working out of poverty through the guarantee of social security (Zhou et al., 2018). In other words, appropriate assistance

methods were chosen to improve the endogenous development capacity of those who could work but lacked knowledge, technology, or funds. Social security would cover the expenses of those who were totally or partially unable to work in poverty-stricken households. Besides, apart from providing direct transfers to raise their incomes, the expenses were reduced through payment reductions, such as increasing the proportion of medical insurance reimbursement, waiving education expenses for young people of education age, and waiving various insurance premiums.

(3) *Accurately manage* A database management system, named national poverty alleviation and development information system, was built to keep poverty-stricken households' profiles, including basic family information, cause of poverty, production situation, life situation, house situation, household income, as well as a planned time of being lifted out of poverty. Besides, independent annual third-party poverty reduction evaluation groups by academic institutions and universities were assigned to evaluate the completion of local governments' annual poverty reduction tasks, including reducing the number of poverty-stricken households and villages. Poverty alleviation effectiveness evaluations had generally identified income above the poverty line, no worries about food and clothing, ensuring compulsory education, primary medical care, and safe housing as uniform benchmarking criteria.

Study Samples

This study evaluated the effectiveness of the TPA scheme in one of the nominated poverty-stricken counties in Southwest China. The central government recognized this remote county in a low mountain area as a "county in poverty." This county covers an area of 3903 square kilometers, is home to over 168,552 households, and has a population of 498,200 living in 294 villages (including 107 poverty-stricken villages). The TPA was implemented in 2018 for 4 years.

By stratified random sampling design and structured questionnaires for the rural households and communities, 1118 households from 25 villages were selected. First, based on the county's topographic and traffic maps and economic and social development data, the poverty-stricken villages were divided into villages in the county border zones and villages in the non-border zones. Second, using a simple random sampling method, nine villages were selected from the two poverty-stricken villages and two villages from the non-poverty-stricken villages. Third, from the selected survey villages, the poverty-stricken and non-poverty-stricken households were chosen at approximately 1:1 based on the household registration information from the local statistical bureau. Finally, the sample from the 25 villages comprised 502 non-poverty-stricken households and 616 poverty-stricken households (including 427 households that lifted out of poverty and 189 households that were still classified as poverty-stricken in 2018).

A trained team of investigators collected the survey data through face-to-face interviews in the household. The head of the household or a family member over 18 years old completes the interview. Each interview took about 40 min, for which two investigators were involved, with one recording, taking photos, and double-checking and the other conducting the interviews. The questionnaires were uploaded to a particular app. A professional would verify data and find outliers each evening to correct the data as soon as possible. After the 6-day field survey period, 1118 questionnaires on various aspects of the household economic situations were collected.

Variables

The selected variables are listed in Table 1. Specifically, household per capita income has always been a critical poverty indicator as it is considered highly representative. Several studies on the influencing factors of poverty reduction have employed income as a response variable (Bandiera et al., 2017; Liao et al., 2020).

Table 1 Variable definitions used for the inverse probability of treatment weighting (IPTW) impact evaluation

Variable	Definition
Dependent variables	
Total income	Per capita annual net total income of the surveyed household (CNY/person)
Transfer income	Per capita annual transfer payments to rural families, mainly from social security subsidies, ecological protection compensation, food compensation, etc (CNY/person)
Family business income	Per capita annual net income from family business income, mainly from agricultural cultivation and raising livestock (CNY/person)
Wage income	Per capita annual net income obtained through working locally or out of town (CNY/person)
Property income	Per capita annual net income from house rent, land transfer rent, or dividends and so on (CNY/person)
Treatment effects	
E-poor	Households with net per capita annual income lower than the poverty line in 2013 and
	having a goal to be out of poverty before or in 2018
Poor	Households with net per capita annual income lower than the poverty line in 2013 and
	having a goal to be out of poverty after 2018
Non-poor	Households with net per capita annual income higher than the poverty line in 2013
Covariates	
Labor	the number of working age people in a household
Farmer	The number of farmers in a household
Worker	The number of workers in a household
Old	Dummy variable. 1 if there was an old person (age > 60) in a household and 0 if not
Disabled	Dummy variable. 1 if there was a disabled person in a household and 0 if not
Illness	Dummy variable. 1 if there was a seriously ill person in a household and 0 if not

Similarly, this study used household per capita income as the dependent variable to analyze the role of TPA in reducing poverty. The difference in income structures among *e-poor* households, *poor* households, and *non-poor* households was determined, each of which is defined in Table 1. The *e-poor* were defined as those households with a net per capita annual income lower than the poverty line in 2013 and with the goal to be out of poverty before or in 2018. The *poor* were defined as households with a net per capita annual income lower than the poverty line in 2013 and with the goal to be out of poverty after 2018. The *non-poor* were defined as households with a net per capita annual income higher than the poverty line in 2013. Objectively, transfer income mainly included social security subsidies, ecological protection compensation, food compensation, etc. It is less stable than other income types such as family business income and wage income because transfer income is a direct government subsidy with no need for hard work (Deng et al., 2020). There were five total response variables: total income, transfer income; family business income; wage; and property income. Table 2 shows the mean and standard errors for the different income types for the groups.

As only observed data were available, the quasi-experiment format required a similar control group (Rubin, 2014). Potentially confounding variables that affected household type and household income was controlled. The poor household identification criterion was the farm household income in 2013, mainly influenced by the farming household's human and natural resources (Liu et al., 2021). As the county's natural resources were poor and almost all households were located in similar environments, there was little differentiation in their natural resources. Based on Schultz's theory of human capital (Schultz, 1993), poverty is mainly attributed to the quality of human capital. Thus, the following variables were selected to calculate the propensity scores and adjust the characteristic discrepancies between the three groups; *labor*, *farmer*, *worker*, *old*, *disabled*, and *illness*. The covariate definitions are as shown in Table 1. The *labor*, *farmer*, and *worker* variables were associated with the net per capita annual household income growth and relief from poverty. In contrast, the *old*, *disabled*, and *illness* variables hindered household income growth and being lifted from poverty. The covariates were centered using their unweighted overall sample means to obtain the mean estimates from the model that controlled for the covariates.

Table 2 The mean and standard error of different types of incomes for different groups

Variable	E-poor		Non-poor		Poor		Pooled sample	
	Mean	Std. error	Mean	Std. error	Mean	Std. error	Mean	Std. error
Total income	8517.14	4222.80	13367.68	45424.11	4211.50	1682.28	9967.24	30730.16
Transfer income	2792.67	2123.17	947.31	1522.82	2024.30	1763.90	1834.97	1998.64
Family business income	676.59	1134.00	1549.84	6017.41	529.41	912.54	1043.81	4133.12
Wage income	4905.13	4782.23	8771.77	9370.81	2367.27	10938.19	6212.28	8622.27
Property income	183.59	335.61	2082.89	44629.72	77.16	265.81	1018.41	29905.74

Estimating the Multiple Propensity Scores

Inverse probability of treatment weighting (IPTW) (Robins et al., 2000) was applied to reduce potential confounding and adjust for the group covariate differences when modeling the causal effects for the multiple non-equivalent groups. This study used the weighting algorithms implemented in the R-package twang (Burgette et al., 2014). As proposed in (Mccaffrey et al., 2015), an extension of the generalized boosted model (GBM) (Friedman, 2001) was used to estimate the propensity score weights when there were more than two treatments. Specifically, as the study was interested in determining the average treatment effects (ATEs), the GBM was used in the following way to obtain the weights. First, dummy indicators were developed for each of the three treatments (*e-poor*, *non-poor*, and *poor*). Then, separate GBMs were fitted to each dummy treatment indicator, and the estimated propensity score was obtained for the given treatment in question. Finally, the estimated propensity scores from each fitted GBM were used to compute the ATE weights needed to estimate the treatment effects. When estimating the weights for the average treatment effects for the treated (ATTs), the GBM method was fitted to the treatment indicator for $T = t'$ using only the subsample, with $T = t''$ and $T = t'$ using the standard stopping rules with a binary treatment to estimate the ATT. Then, the individuals in the treatment group t'' were assigned the ATT weights resulting from this binary fit. This procedure was repeated for all $t'' \neq t'$. The absolute standardized bias (SB) mean (also referred to as the absolute standardized mean difference) was utilized to select the optimal GBM iteration to estimate the propensity score weights. Although the proposed method for estimating the propensity score weights for multiple groups using GBM checks the group balance when fitting the GBM model, it is also important to have good diagnostic criteria for assessing the overall balance across the multiple groups. For the ATE and ATT estimations, overall summary balance measures were used by taking the maximum balance metrics for each group. Generally, standardized mean differences of less than 0.20 are considered small, 0.40 are considered moderate, and 0.60 are considered large (Cohen, 1988).

Estimating the Treatment Effect

The causal effect of interest for an individual was defined as the difference between the potential outcomes to compare the alternative treatments. Therefore, the possible causal effects of interest could be the relative effectiveness of all possible treatment pairs: *e-poor* versus *non-poor*, *e-poor* versus *poor*, and *non-poor* versus *poor*.

The average treatment effect (ATE): if μ_e, μ_n, and μ_p were defined as the mean outcomes for the entire population when treated with e-poor, non-poor, and poor households, that is, $\mu_e = E[Y(T = \text{e-poor})]$, $\mu_n = E[Y(T = \text{non-poor})]$, and $\mu_p = E[Y(T = \text{poor})]$, then the ATE for the e-poor households relative to the non-poor households was $\mu_e - \mu_n$, the ATE for the e-poor households relative to the poor households was $\mu_e - \mu_p$, and the ATE for the non-poor households relative to poor households was $\mu_n - \mu_p$ (shown in Table 3).

Table 3 Causal estimands for the effects of multiple treatments

Effect	ATE	ATT		
		E-poor case	Non-poor case	Poor case
Non-poor vs. e-poor	$\mu_n - \mu_e$	$\mu_{e,n} - \mu_{e,e}$	$\mu_{n,n} - \mu_{n,e}$	*
Poor vs. e-poor	$\mu_p - \mu_e$	$\mu_{e,p} - \mu_{e,e}$	*	$\mu_{p,p} - \mu_{p,e}$
Poor vs. non-poor	$\mu_p - \mu_n$	*	$\mu_{n,p} - \mu_{n,n}$	$\mu_{p,p} - \mu_{p,n}$

The average treatment effect between the treated (ATT): if $\mu_{e,p}$ was defined as the mean outcome that the e-poor households would have if they had been assigned as poor households instead, that is, $\mu_{e,p} = E[Y(p)|\mathrm{T}=\text{e-poor}]$. Then the ATT for the e-poor relative to the poor was $\mu_{e,p} - \mu_{e,e}$. The other definitions are similar, as shown in Table 3.

Results

First, the balanced property fulfillment assumptions for the propensity scoring weighting model are analyzed, after which the effectiveness of the poverty alleviation is discussed.

Study Profile and Covariates Balance

Household characteristics of human capital for the households lifted out of poverty earlier were likely to differ from those lifted out of poverty later (Table 4). Specifically, the number of laborers, farmer, and worker for the e-poor households are more

Table 4 Means for treatment groups (unweighted and ATE weighted) and the pooled sample (unweighted)

Covariates	Unweighted means			ATE weighted means			Pooled sample	
	Non-poor	Poor	E-poor	Non-poor	Poor	E-poor	Mean	SD
Labor	2.60	1.53	2.04	2.22	2.12	2.16	2.20	1.37
Farmer	1.26	0.56	1.01	1.07	1.06	1.04	1.05	0.87
Worker	1.32	0.95	1.11	1.17	1.04	1.14	1.18	1.09
Old	1.08	1.32	1.12	1.12	1.10	1.15	1.14	0.85
Disabled								
% Yes	0.11	0.18	0.2	0.16	0.15	0.15	0.15	0.33
% No	0.89	0.82	0.8	0.84	0.85	0.85	0.85	0.33
Illness								
% Yes	0.08	0.44	0.15	0.15	0.17	0.16	0.17	0.38
% No	0.92	0.56	0.85	0.85	0.83	0.84	0.83	0.38

than that for the poor households, and the proportions of older adults and illness for the e-poor households are less than that for the poor households. These results mean that the e-poor households usually have better human capital than the poor households.

Using the ATE Weights

The differences in the individual level characteristics were minor after the ATE weighting (Tables 4 and 5). For all covariates, the ATE weighted means for each group: the non-poor households, the poor households, and the e-poor households: were more similar to each other, and the unweighted overall pooled sample means than the unweighted means for each group (Table 4). Before the weighting, the non-poor household group was very different from the poor household group, with the effect size differences [absolute standardized bias (SB)] being more significant than 0.20 for all selected covariates. Compared to the poor households, the e-poor households had four covariates with effect size differences more significant than 0.20 before the weighting. Specifically, the poor household group had lower mean numbers for labor and farmers, a higher mean number of older adults, and a higher percentage of families with members suffering from serious illnesses. There were fewer laborers and farmers in the e-poor household group than in the non-poor household group. Before the weighting, the percentage of disabled people in the e-poor household group was higher than in the non-poor household group. However, the weighting removed these differences, after which all effect size differences were lower than 0.20 (Table 5).

Using the ATT Weights

When the e-poor and non-poor samples and the e-poor and poor samples were compared before and after the non-poor sample and poor sample were weighted, it was found that the balance for the six covariates improved after the weighting

Table 5 Effect size difference for treatment groups (unweighted and ATE weighted)

Covariates	Unweighted			ATE weighted		
	E-poor vs. non-poor	E-poor vs. poor	Non-poor vs. poor	E-poor vs. non-poor	E-poor vs. poor	Non-poor vs. poor
Labor	0.41*	0.37*	0.78*	0.04	0.03	0.07
Farmer	0.29*	0.52*	0.81*	0.03	0.03	0.01
Worker	0.19	0.15	0.34*	0.02	0.10	0.12
Old	0.05	0.24*	0.29*	0.04	0.06	0.02
Disabled	0.28*	0.06	0.22*	0.01	0.00	0.01
Illness	0.19	0.76*	0.95*	0.03	0.03	0.06

Cells marked with an * denote covariates for which effect size difference is more significant than 0.20 within a given program

Table 6 Means for treatment groups (unweighted and ATT weighted)

Covariates	Non-poor unweighted		ATT non-poor weighted means		Poor unweighted		ATT poor weighted means		E-poor unweighted		ATT e-poor weighted means	
	Mean	SD	Poor	E-poor	Mean	SD	Non-poor	E-poor	Mean	SD	Non-poor	Poor
Labor	2.60	1.42	2.48	2.51	1.53	1.20	1.51	1.52	2.04	1.24	2.03	2.04
Farmer	1.26	0.87	1.26	1.24	0.56	0.72	0.61	0.58	1.01	0.84	1.02	1.01
Worker	1.32	1.18	1.19	1.25	0.95	0.90	0.93	0.93	1.11	1.05	1.09	1.02
Old	1.08	0.84	0.97	1.11	1.32	0.79	1.31	1.35	1.12	0.88	1.11	1.12
Disabled												
% Yes	0.11	0.31	0.12	0.12	0.18	0.38	0.19	0.18	0.20	0.40	0.20	0.19
% No	0.89	0.31	0.88	0.88	0.82	0.38	0.81	0.82	0.80	0.40	0.80	0.81
Illness												
% Yes	0.08	0.27	0.08	0.08	0.44	0.50	0.41	0.43	0.15	0.36	0.15	0.16
% No	0.92	0.27	0.92	0.92	0.56	0.50	0.59	0.57	0.85	0.36	0.85	0.84

(Table 6 and Fig. 1). As expected, when using the ATT weights to make the non-poor and poor group households appear to be e-poor households, the ATT e-poor weighted covariate means for the non-poor and poor households were very similar to the unweighted means for the e-poor (Table 6), and there was a significant reduction in the effect size differences (Fig. 1).

After the weighting, the significant differences in the covariate means between the non-poor and weighted e-poor samples and between the non-poor and poor samples were significantly reduced (Table 6). The samples were very different before the weighting, with the standard bias for all selected covariates between the non-poor and poor households being more significant than 0.20 and the standard bias between the non-poor and e-poor households being more significant than 0.20 for four of the six covariates. The weighting removed these differences; the effect size differences for the six covariates between the non-poor and e-poor households were lower than 0.10. Only two of the six covariates between the non-poor and poor households were more significant than 0.10; 0.11 for *Farmer* and 0.13 for *Old* (Table 7).

The e-poor and non-poor samples matched the poor samples very well after the weighting. The poor households had similar means on all six covariates to the e-poor and non-poor households after the ATT weighting when the poor households were the target population (Table 6). The weightings fully corrected the differences with no common biases greater than 0.10 (Fig. 2).

However, as the weights could not wholly remove the differences between the covariate distributions, a doubly robust modeling strategy was utilized to estimate the ATEs and ATTs that controlled for both the propensity score weights and the six covariates in which imbalances still existed after the weighting.

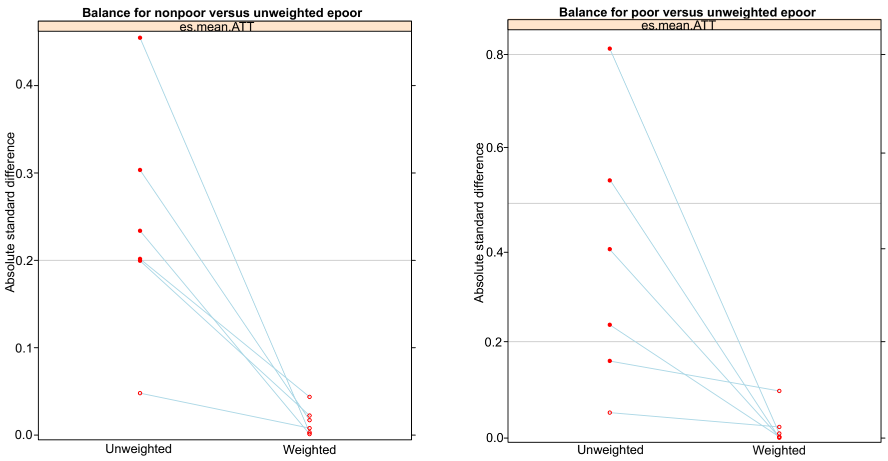

Fig. 1 Effect size plots for assessing the covariates balance to make the non-poor and poor group households appear to be e-poor households to estimate the e-poor group's pairwise ATT effects

Table 7 Effect size difference for assessing the balance between groups on pretreatment variables before and after ATT weighting when non-poor households are the target population

Covariates	Unweighted		ATT weighted	
	Non-poor vs. e-poor	Non-poor vs. poor	Non-poor vs. e-poor	Non-poor vs. poor
Labor	0.40*	0.76*	0.06	0.09
Farmer	0.29*	0.81*	0.02	0.00
Worker	0.18	0.32*	0.06	0.11
Old	0.05	0.29*	0.03	0.13
Disabled	0.30*	0.24*	0.00	0.03
Illness	0.27*	1.36*	0.00	0.01

Cells marked with an * denote covariates for which effect size difference is greater than 0.20 within a given program

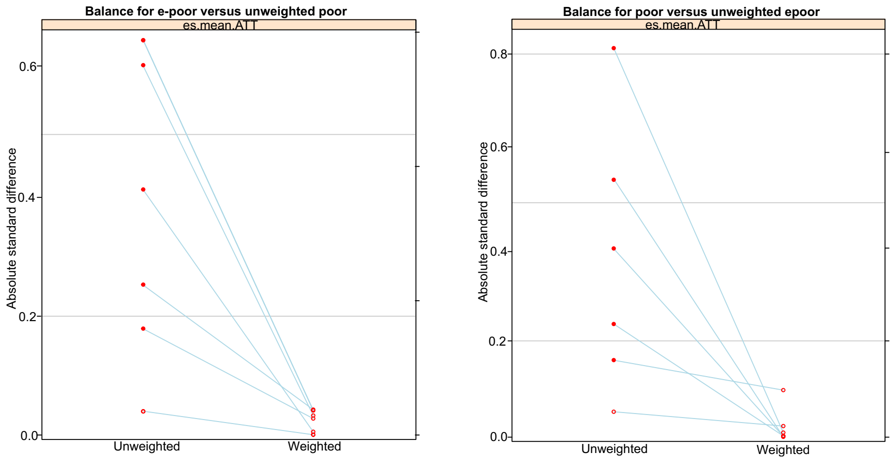

Fig. 2 Effect size plots for assessing the covariates balance to make the non-poor and e-poor group households appear to be poor households to estimate the poor group's pairwise ATT effects

Effect of the TPA on Household Income

The Income Gap Between the Poor and the E-poor

There were no significant differences between the unweighted outcomes for the e-poor and poor households ($p = 0.1405$). After the sample was weighted to control the covariate differences and the treatment effect estimations for the pooled sample, it was found that the estimated effects were much larger than the basic differences and were statistically significant. The e-poor households were found to have a higher per capita annual net total income than the poor households ($p < 0.001$, $\text{Income}_{\text{e-poor}} = 8465.65$, $\text{Income}_{\text{poor}} = 4232.603$). The total income estimated for the e-poor households was 4197.31 if they had received the poor household treatment instead (i.e., the ATT weighted mean for the poor sample). It was notably lower than the estimated 8517.14 when following the e-poor group (Difference = −4319.83, Std. Error = 256.60, $p < 0.001$, as shown in Table 8). The total income estimated for the poor households was 8207.408 if they had been recognized as e-poor households (i.e., the ATT weighted mean for the e-poor sample). It was notably higher than the estimated 4211.504 outcomes when following the poor group (Difference = 3995.904, Std. Error = 330.11, $p < 0.001$, as shown in Table 8).

Before the weighting, there were significant differences in the transfer incomes between the poor households and the e-poor households (Difference = −1173.3, Std. Error = 146.47, $p < 0.001$). The doubly robust estimation (ATE) showed that, on average, the e-poor households had 1091.692 (Std. Error = 162.9) higher transfer incomes than the poor households at $p < 0.001$. The counterfactual outcomes gave greater detail. The households that had planned to escape poverty before and in 2018 would have had around 1695.698 CNY transfer income if they had planned to escape poverty after 2018, which was 1096.973 lower than the e-poor group transfer income at $p < 0.001$. Similarly, if the current poor households had been e-poor households, they would have obtained 1311.559 higher transfer income than they obtained at $p < 0.001$.

The income from wages made up the most significant share of total income for most households, with the e-poor households earning higher income from wages than the poor households (Table 10). Specifically, based on the results after the ATE weighting, the e-poor households earned 2994.008 CNY more in wages than

Table 8 Treatment group means and pairwise ATEs and ATTs for annual net total household income per capital before and after weighting

	Non-poor	Poor	E-poor	Difference (Std. Error)	Pr (> $\|t\|$)
Unweighted					
Non-poor vs. E-poor	13391.700		8452.900	4938.800 (2072.40)	0.017**
Poor vs. E-poor		4292.600	8452.900	−4160.300 (2820.80)	0.141
Non-poor vs. Poor	13391.700	4292.600		9099.100 (2916.60)	0.002***
ATE weighted					
Non-poor vs. E-poor	14174.208		8465.650	5708.558 (3418.65)	0.095*
Poor vs. E-poor		4232.603	8465.650	−4233.046 (377.18)	< 0.001***
Non-poor vs. Poor	14174.208	4232.603		9941.605 (3433.94)	0.004***
ATT weighted to match e-poor household sample					
Non-poor vs. E-poor	14897.360		8517.140	6380.220 (4115.70)	0.121
Poor vs. E-poor		4197.310	8517.140	−4319.830 (256.60)	< 0.001***
ATT weighted to match non-poor household sample					
Non-poor vs. E-poor	13367.681		8565.149	4802.532 (2076.90)	0.021*
Non-poor vs. Poor	13367.681	3919.055		9448.600 (2310.00)	< 0.001***
ATT weighted to match poor household sample					
Poor vs. E-poor		4211.504	8207.408	−3995.904 (330.10)	< 0.001***
Poor vs. Non-poor	12836.998	4211.504		−8625.494 (3526.00)	0.015**

Significance level: *10%, **5%, ***1%

the poor households ($p < 0.001$). The pairwise ATT analyses targeting the e-poor household sample were very different from ATT analyses targeting the poor households. The estimated effect of the e-poor households relative to the poor households on the e-poor household sample was 1827.418, which was 3077.700 lower than the e-poor wage income at $p < 0.001$. After weighing and controlling the unbalanced covariates, the estimated effect of the poor households relative to the e-poor households was substantial (Difference = −2531.178, Std. Error = 311.015, $p < 0.001$). It again indicated significant wage income differences between these two groups.

There were no statistically significant differences between the e-poor and poor households regarding family business income either before or after the weighting (Table 9). Further, the e-poor and poor households had very little property income (below 300 CNY on average, Table 11). The property income also contributed less to the income inequality between the poverty-stricken households.

Income Gap Between the *Poor/E-poor*, and *Non-poor*

The ATE and ATT estimations showed that the non-poor households had significantly higher total household, farm, and wage incomes than the e-poor or poor households at a 5% significance level (Table 8). Wage income was the most significant contributor to income difference as it comprised the most outstanding share of total income in most households. Before and after the weighting, it was found that the e-poor/poor households had statistically significantly lower wage incomes

Table 9 Treatment group means and pairwise ATEs and ATTs for annual net family business income per capital before and after weighting

	Non-poor	Poor	E-poor	Difference (Std. Error)	Pr (> t)
Unweighted					
Non-poor vs. E-poor	1444.102		670.075	774.027 (277.62)	0.005***
Poor vs. E-poor		824.983	670.075	154.909 (377.87)	0.682
Non-poor vs. Poor	1444.102	824.983		619.119 (390.70)	0.113
ATE weighted					
Non-poor vs. E-poor	1401.616		680.116	721.500 (240.81)	0.003***
Poor vs. E-poor		558.914	680.116	−121.202 (113.25)	0.284
Non-poor vs. Poor	1401.616	558.914		842.702 (257.38)	0.001***
ATT weighted to match e-poor household sample					
E-poor vs. Non-poor	1460.273		676.589	783.684 (285.92)	0.006***
E-poor vs. Poor		574.318	676.589	−102.271 (113.49)	0.368
ATT weighted to match non-poor household sample					
Non-poor vs. E-poor	1549.843		737.114	812.729 (266.69)	0.002***
Non-poor vs. Poor	1549.843	556.995		992.848 (300.71)	0.001***
ATT weighted to match poor household sample					
Poor vs. E-poor		529.411	544.716	−15.305 (94.06)	0.871
Poor vs. Non-poor	898.455	529.411		369.044 (155.80)	0.018**

Significance level: *10%, **5%, ***1%

than the non-poor households (Table 10). When weighted, significant differences were found in the family business incomes between the non-poor households and the e-poor and poor households at a 5% significance level (Table 9). The property income was the lowest in the total income for most households, and there were no statistically significant differences in property incomes found between the non-poor and e-poor (or poor) households (Table 11).

However, it was found that the non-poor households had significantly lower transfer income than the poverty-stricken households (Table 12). Specifically, before the weighting, there were significant transfer income differences found between the poor/e-poor households and the non-poor households ($Income_{poor} = 1521.23$, $Income_{e\text{-}poor} = 2692.53$, $Income_{non\text{-}poor} = 1224.85$), and when randomly assigned to the three groups, the ATE estimations showed that the non-poor households earned about −1495.638 CNY ($p < 0.001$) and −403.945 CNY ($p = 0.013$) less than the e-poor and poor households earned on average, respectively. Besides, the estimate of the mean transfer income for non-poor households had they instead received the e-poor household treatment was 2441.224 CNY, which was 1490.815 CNY ($p < 0.001$) higher than the estimate for this household's outcomes following the non-poor households. The mean transfer income for the non-poor households had they instead received the poor household treatment was 1384.059 CNY, which was 436.75 CNY ($p = 0.003$) higher than estimated for these households' outcomes following the non-poor households. The mean transfer income estimate for e-poor households had they received the non-poor treatment was 1271.427 CNY, which

Table 10 Treatment group means and pairwise ATEs and ATTs for annual net wage income per capital before and after weighting

	Non-poor	Poor	E-poor	Difference (Std. Error)	Pr (> t)
Unweighted					
Non-poor vs. E-poor	8264.800		5102.800	3162.000 (434.90)	< 0.001***
Poor vs. E-poor		2481.500	5102.800	−2621.300 (591.90)	< 0.001***
Non-poor vs. Poor	8264.800	2481.500		5783.300 (612.00)	< 0.001***
ATE weighted					
Non-poor vs. E-poor	7110.875		4043.969	3066.906 (404.47)	< 0.001***
Poor vs. E-poor		1049.961	4043.969	−2994.008 (289.61)	< 0.001***
Non-poor vs. Poor	7110.875	1049.961		6060.914 (417.47)	< 0.001***
ATT weighted to match e-poor household sample					
E-poor vs. Non-poor	7869.354		4905.128	2936.800 (400.40)	< 0.001***
E-poor vs. Poor		1827.418	4905.128	−3077.700 (258.00)	< 0.001***
ATT weighted to match non-poor household sample					
Non-poor vs. E-poor	8771.773		5308.333	3463.440 (454.70)	< 0.001***
Non-poor vs. Poor	8771.773	2148.949		6622.824 (449.60)	< 0.001***
ATT weighted to match poor household sample					
Poor vs. E-poor		1581.559	4112.737	−2531.178 (311.015)	< 0.001***
Poor vs. Non-poor	6403.853	1581.559		4822.294 (488.25)	< 0.001***

Significance level: *10%, **5%, ***1%

Table 11 Treatment group means and pairwise ATEs and ATTs for annual net property income per capital before and after weighting

	Non-poor	Poor	E-poor	Difference (Std. Error)	Pr (> t)
Unweighted					
Non-poor vs. E-poor	2444.100		25.160	2418.980 (2033.63)	0.235
Poor vs. E-poor		−524.400	25.160	−549.570 (2768.01)	0.843
Non-poor vs. Poor	2444.100	−524.400		2968.500 (2862.00)	0.300
ATE weighted					
Non-poor vs. E-poor	3515.932		144.048	3371.884 (3425.66)	0.325
Poor vs. E-poor		59.380	144.048	−84.669 (233.16)	0.717
Non-poor vs. Poor	3515.932	59.380		3456.553 (3439.63)	0.315
ATT weighted to match e-poor household sample					
E-poor vs. Non-poor	4281.201		183.594	4097.607 (4135.90)	0.322
E-poor vs. Poor		101.870	183.594	81.724 (36.31)	0.025**
ATT weighted to match non-poor household sample					
Non-poor vs. E-poor	2082.906		114.036	1968.870 (2035.30)	0.334
Non-poor vs. Poor	2082.906	−169.953		2252.853 (2274.00)	0.322
ATT weighted to match poor household sample					
Poor vs. E-poor		77.161	259.404	−182.243 (43.13)	< 0.001***
Poor vs. Non-poor	3724.123	77.161		3646.962 (3524.00)	0.301

Significance level: *10%, **5%, ***1%

Table 12 Treatment group means and pairwise ATEs and ATTs for annual net transfer income per capital before and after weighting

	Non-poor	Poor	E-poor	Difference (Std. Error)	Pr (> t)
Unweighted					
Non-poor vs. E-poor	1224.850		2692.530	−1467.680 (107.68)	< 0.001***
Poor vs. E-poor		1521.230	2692.530	−1171.300 (146.47)	< 0.001***
Non-poor vs. Poor	1224.850	1521.230		−296.380 (151.48)	0.051*
ATE weighted					
Non-poor vs. E-poor	1220.101		2715.738	−1495.638 (124.74)	< 0.001***
Poor vs. E-poor		1624.046	2715.738	−1091.692 (162.90)	< 0.001***
Non-poor vs. Poor	1220.101	1624.046		−403.945 (162.88)	0.013**
ATT weighted to match e-poor household sample					
E-poor vs. Non-poor	1271.427		2792.671	−1521.244 (126.39)	< 0.001***
E-poor vs. Poor		1695.698	2792.671	−1096.973 (168.37)	< 0.001***
ATT weighted to match non-poor household sample					
Non-poor vs. E-poor	947.309		2441.224	−1490.815 (115.14)	< 0.001***
Non-poor vs. Poor	947.309	1384.059		−436.750 (146.22)	0.003***
ATT weighted to match poor household sample					
Poor vs. E-poor		2024.297	3335.856	−1311.559 (197.58)	< 0.001***
Poor vs. Non-poor	1814.148	2024.297		−210.149 (235.30)	0.372

Significance level: *10%, **5%, ***1%

was significantly less than the estimated 1521.244 CNY for these households if following the e-poor households ($p < 0.001$). Differences were also found between the ATT weighted transfer income mean for the non-poor households (1814.148 CNY) and the transfer income mean for the poor households (2024.297 CNY); however, these differences were not significant ($p = 0.372$).

Robustness Check

The robustness of the findings was checked by using another measurement of household income other than per capita annual net household income. Considering the influence of family size and composition, the simplified "OECD equivalent scale" formula given in Anyaegbu (2010) was used to adjust the household incomes as follows:

$$\text{Income}_{\text{adj}} = \text{Income}/(a_1 + 0.5a_2 + 0.3a_3 + 0.3a_4),$$

where *Income* responds to the total income, transfer income, family business income, wage income, and property income of the surveyed household, $a_1 = 1$ when there were adults in the family, and 0 otherwise, a_2 equaled the number of extra adults in the household, and a_3 and a_4 , respectively, equaled the number of children (0–16 years old) and the number of elderly (over 65 years old).

Tables 13, 14, 15, 16 and 17 report the estimates and similar results were found. On the one hand, non-poor households, not surprisingly, had a total household income among the three groups, and e-poor households had significantly more than poor households. On the other hand, e-poor households had the most transfer income among the three groups, while non-poor households had the least. Wage income made up the most significant share of total income

Table 13 Robustness check when using OECD equivalent scale to adjust total income

	Non-poor	Poor	E-poor	Difference (Std. Error)	Pr (> |t|)
ATE weighted					
Non-poor vs. E-poor	18464.823		11608.287	7033.633 (3481.95)	< 0.001***
Poor vs. E-poor		5576.735	11608.287	−6153.981 (426.49)	< 0.001***
Non-poor vs. Poor	18464.823	5576.735		13187.614 (3478.31)	< 0.001***
ATT weighted to match e-poor household sample					
Non-poor vs. E-poor	19126.66		11501.97	7625 (4367.00)	< 0.001***
Poor vs. E-poor		5304.01	11501.97	−6198.0 (386.60)	< 0.001***
ATT weighted to match non-poor household sample					
Non-poor vs. E-poor	18335.61		11934.41	6401.2 (2117.3)	< 0.001***
Non-poor vs. Poor	18335.61	5654.53		12681.1 (2161.8)	< 0.001***
ATT weighted to match poor household sample					
Poor vs. E-poor		5068.48	10420.11	−5351.6 (621.4)	< 0.001***
Poor vs. Non-poor	15109.70	5068.48		10100 (3211)	0.002***

Significance level: *10%, **5%, ***1%

Table 14 Robustness check when using OECD equivalent scale to adjust transfer income

	Non-poor	Poor	E-poor	Difference (Std. Error)	Pr (> |*t*|)
ATE weighted					
Non-poor vs. E-poor	678.935		1381.836	−702.901 (80.86)	< 0.001***
Poor vs. E-poor		822.375	1381.836	−559.461 (104.43)	< 0.001***
Non-poor vs. Poor	678.935	822.375		−143.440 (107.21)	< 0.001***
ATT weighted to match e-poor household sample					
Non-poor vs. E-poor	706.340		1435.016	−728.68 (97.54)	< 0.001***
Poor vs. E-poor		918.816	1435.016	−516.2 (125.4)	< 0.001***
ATT weighted to match non-poor household sample					
Non-poor vs. E-poor	503.377		1218.769	−715.39 (79.50)	< 0.001***
Non-poor vs. Poor	503.377	725.900		−222.5 (118.9)	0.0617*
ATT weighted to match poor household sample					
Poor vs. E-poor		1129.683	1830.241	−700.6 (190.4)	< 0.001***
Poor vs. Non-poor	1175.177	1129.683		45.67 (266.4)	0.864

Significance level: *10%, **5%, ***1%

Table 15 Robustness check when using OECD equivalent scale to adjust family business income

	Non-poor	Poor	E-poor	Difference (Std. Error)	Pr (> |*t*|)
ATE weighted					
Non-poor vs. E-poor	701.370		314.196	387.174 (161.75)	0.016**
Poor vs. E-poor		246.056	314.196	−68.140 (60.94)	0.263
Non-poor vs. Poor	701.370	246.056		455.314 (176.09)	0.009***
ATT weighted to match e-poor household sample					
Non-poor vs. E-poor	772.371		328.574	443.8 (205.4)	0.031**
Poor vs. E-poor		288.029	328.574	−40.54 (71.51)	0.571
ATT weighted to match non-poor household sample					
Non-poor vs. E-poor	721.864		335.915	385.95 (147.06)	0.009***
Non-poor vs. Poor	721.864	288.005		433.86 (166.74)	0.009***
ATT weighted to match poor household sample					
Poor vs. E-poor		256.192	273.003	−16.81 (57.44)	0.77
Poor vs. Non-poor	456.877	256.192		200.7 (109.6)	0.067*

Significance level: *10%, **5%, ***1%

no matter which groups of households, and property income made up the smallest share. There were significantly different in wage income among the three groups. The wage income of non-poor households was more than that of e-poor households, and both were more than that of poor households. And there were almost no significantly different in property income among the three groups. Non-poor households had significantly higher family business income than e-poor or poor households, and there were no significant differences in family

Table 16 Robustness check when using OECD equivalent scale to adjust wage income

	Non-poor	Poor	E-poor	Difference (Std. Error)	Pr (> |t|)
ATE weighted					
Non-poor vs. E-poor	3486.848		2060.516	1426.333 (257.14)	< 0.001***
Poor vs. E-poor		947.471	2060.516	−1113.044 (251.69)	< 0.001***
Non-poor vs. Poor	3486.848	947.471		2539.377 (322.93)	< 0.001***
ATT weighted to match e-poor household sample					
Non-poor vs. E-poor	3589.003		2105.734	1483.3 (313.2)	< 0.001***
Poor vs. E-poor		886.531	2105.734	−1219.2 (249.0)	< 0.001***
ATT weighted to match non-poor household sample					
Non-poor vs. E-poor	3614.267		2039.760	1574.5 (241.5)	< 0.001***
Non-poor vs. Poor	3614.267	948.5025		2665.8 (315.4)	< 0.001***
ATT weighted to match poor household sample					
Poor vs. E-poor		875.356	1658.773	−783.4 (277.2)	0.005***
Poor vs. Non-poor	2867.007	875.356		1991.7 (451.3)	< 0.001***

Significance level: *10%, **5%, ***1%

Table 17 Robustness check when using OECD equivalent scale to adjust property income

	Non-poor	Poor	E-poor	Difference (Std. Error)	Pr (> |t|)
ATE weighted					
Non-poor vs. E-poor	3487.749		92.115	3395.634 (3423.03)	0.321
Poor vs. E-poor		−5.723	92.115	−97.837 (246.91)	0.692
Non-poor vs. Poor	3487.749	−5.723		3493.471 (3486.27)	0.317
ATT weighted to match e-poor household sample					
Non-poor vs. E-poor	4425.066		102.090	4323 (4360)	0.322
Poor vs. E-poor		63.549	102.090	−38.54 (26.61)	0.148
ATT weighted to match non-poor household sample					
Non-poor vs. E-poor	2034.245		86.051	1948.19 (1991.08)	0.328
Non-poor vs. Poor	2034.245	62.202		1972.04 (1991.63)	0.322
ATT weighted to match poor household sample					
Poor vs. E-poor		46.056	144.476	−98.420 (28.645)	0.001***
Poor vs. Non-poor	3167.515	46.056		3121.5 (3060.2)	0.308

Significance level: *10%, **5%, ***1%

business income between e-poor households and poor households. These findings were the same as the primary analysis above, which means that this paper's estimation is robust.

Discussion and Conclusion

This study provides empirical evidence on the impacts of the TPA strategy on poverty reduction in a poverty-stricken county in Southwest China. Using data from a detailed household survey and employing a propensity scoring analysis with multiple non-equivalent groups, this study compared the income levels and structures of the e-poor, poor, and non-poor households. Several inconsistencies were identified between the expectations of the central government and the local governments' implementation, giving several policy suggestions to enable more effective policy evaluations.

Different Development Among the Poverty-Stricken Households

It was found that the household incomes of the e-poor were significantly higher than for the poor, which meant that the household income of e-poor households has indeed been improved. The poverty alleviation policy has been effective. These results also indicated that there had been an unfair development between the poor and e-poor households, which was reflected in the transfer income. The e-poor household transfer income was much higher than the poor household. This income difference was partly due to the wage incomes, with the e-poor household wage income significantly higher than the poor household. The average level of the human capital of the e-poor groups was higher than that of the poor households. Thus, e-poor households were better able to leverage assistance to their advantage and increase wage income. However, with higher human capital, the transfer income of e-poor households was higher than that of poor households, which was not in line with the logic of poverty alleviation. Usually, in a targeted poverty alleviation policy, more transfer payments as a bottom-up assistance policy should be paid to households with poorer resource endowments (Zheng et al., 2022). And this means that the e-poor group was given more significant assistance and transfer payments than the poor group.

It was surmised from these results that economic growth and sound macroeconomic management had contributed enormously to this success. The local government schedules developed for each poverty-stricken household partly accounted for the income gap. In 2013, both the e-poor and poor households were classified as poverty-stricken as both groups had incomes less than the local poverty line (2760 CNY). However, 4 years later, the incomes of the e-poor households were significantly higher than the incomes of the poor households. Inconsistent support efforts, such as giving more transfer payments, raise inequality between the e-poor and poor households. Therefore, it was necessary to examine these differences as they could lead to social problems and increase social inequality.

Insufficient Endogenous Development Capacity in the Poverty-Stricken Households

Family business income was closely related to local agricultural and industrial development (Yang et al., 2020). There was no statistically significant difference in the family business income among the e-poor households, the non-poor households, and the poor households. All shares of business income in total income were low, which meant that the local agricultural and industrial development was slow. The contribution of family business income to households' poverty alleviation was limited.

On average, the e-poor households had significantly higher (about 1.7 times) transfer incomes than the poor households, at about 30% of total income, which also indicated that the e-poor households moving out of poverty was partly because of the transfer income. Besides, the non-poor households had the lowest transfer incomes of the three groups, so the local government gave more significant financial assistance to the poverty-stricken households than the non-poverty-stricken households. The solid political nature of the TPA's mechanism brought the challenge of sustainability to a certain extent. To achieve the poverty reduction goal, the local government gave more transfer income to the e-poor households, thus increasing their income. Although the vulnerable groups whose income was slightly higher than the absolute poverty line have been lifted out of absolute poverty, they would return to poverty immediately after deducting the transfer income. And the acquisition of transfer income did not require farmers' efforts and labor skills. Compared with the income growth mechanism such as wage income and family business income, the sustainability of the external compensation mechanism of transfer income was relatively weaker (Deng et al., 2020). The poverty alleviation led by transfer income faced a more significant risk of returning to poverty. Therefore, although transfer incomes could be effective in the short term, they could not provide sustainability for poor households as they ignored the poor's endogenous motivation and inevitably led to a "reliance" on the government. These results revealed that the current effectiveness of poverty alleviation was relatively fragile and not yet adequately sustainable.

Policy Implications

The findings in this study have significant policy implications for the design of future anti-poverty projects in China and other similar developing countries. All anti-poverty policies have the common goal of seeking to improve incomes in poverty-stricken households continually. Therefore, the critical focus is whether these households have sustainable livelihoods and a sufficient endogenous development capacity to ensure income sustainability. While initially, transfer income can assist, it is not conducive to self-development improvements as it could result in poverty-stricken households becoming dependent on government aid, which is contrary to the original intention of poverty alleviation schemes. Some social issues, such as fairness, must be addressed during the anti-poverty policy implementation. If some poverty-stricken households are focused on and given priority care, such as higher transfer income, the households not included in these plans would feel they were being unfairly treated. Therefore, rather than increasing subsistence allowances, local governments must support all poor households by involving them in different income-generating activities. By analyzing the income gaps between the e-poor and non-poor households in the same environment, the local government could develop some favorable conditions to help the e-poor households improve their livelihoods and break out of the poverty cycle. For example, they could encourage them to join agricultural cooperatives or give them more excellent employment support to increase their wage incomes.

Limitations and Future Work

Caution should be taken in interpreting these findings because of the data limitations. First, cross-sectional data prevented us from capturing the dynamic household income changes. Second, there could have been observable features in the surveyed households that could have affected their poverty status identification, resulting in some selection bias in the estimated results. Also, the village development level could have affected the household type and income identification. These issues will be addressed in future research. The counterfactual poverty reduction effect of households could also be discussed using a multilevel model to circumvent the random effects between the villages. The counterfactual poverty reduction effect of marginal non-poor households could also be discussed using quantile regression models. In closing, we hope the findings of this study enhance the understanding of the status of Chinese efforts at poverty reduction, assist local governments, and strengthen future policy development.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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