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Governmental support and multidimensional poverty alleviation: efficiency assessment in rural areas of Vietnam

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Abstract
This paper provides evidence on the poverty-eradication effect of governmental support, broadly categorised into human support and living support. Following the doubly robust approach and using data collected from 1,538 households of mountainous ethnic minorities, the evidence indicates that current governmental support can help reduce the poor's multidimensional poverty. However, these supports cannot mitigate all of the deprivations the poor endure. The alleviation impact of human support is observed in education and health deprivations, but that of living support is limited to health deprivation. Employment and living standard deprivations appear to not be significantly influenced by both supports. The results on the effect of human support on education and of living support on health are robust to sensitivity checks, following a novel approach examining violations of unconfoundedness. These findings contribute to the literature on government policy efficacy and suggest a crucial policy adjustment area.

Keywords Governmental support · Multidimensional poverty · Propensity score · Doubly robust · Vietnam

JEL classification I32 · I38 · J15 · P46

1 Introduction

Despite notably positive signals in poverty eradication throughout the past decades, the year 2020 marked the recuperation of global poverty, igniting a phase of consecutive increases in the number of people living in poverty and extreme poverty (World Bank 2022). This situation is manifested through the reality of millions of people suffering from hunger, malnutrition, homelessness, stunting, and chronic diseases, among whom mountainous residents are regarded as the group possessing the greatest degree of vulnerability to these threats (Mohanty et al. 2018). It is viable that, notwithstanding years of experience fighting against poverty among nations, poverty alleviation remains an onerous long-term task, accentuating the need for the adoption of effective means (Pan et al. 2021a).

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Governmental anti-poverty and poverty-reduction programmes have been a long-standing approach to serving this purpose; nevertheless, there emerge controversies over whether such interventions are rightly efficacious (Ravallion 2007; Mohanty et al. 2018). The urgency of this matter upsurges due to the widespread recognition that poverty is indeed not merely an income-related issue but a far more sophisticated one. Poverty is a multifaceted issue that emerges as deprivation in several facets of life, including health, education, living standards, and work (Alkire and Foster 2011; Alkire and Santos 2014; Alkire et al. 2015). Therefore, concerning poverty eradication, government support measures cannot solely focus on income enhancement; they must also assist their disadvantaged people in overcoming the aforementioned deprivations. Insights into the mechanism through which governmental support helps lift inhabitants out of poverty are fundamental for the settlement of this dispute as well as for the establishment of a satisfactory poverty alleviation support framework.

In this paper, we concentrate on the poverty-alleviation effect of governmental support, broadly categorised into two types: human support (which fosters human capital) and living support (which facilitates production and employment). Impoverished individuals, particularly poor people living in distant places and belonging to ethnic minorities, confront several disadvantages, including geographical isolation, limited market access, social, cultural, and linguistic isolation, and limited access to high-quality land (Ravallion 2020; Churchill and Smyth 2017). If they rely exclusively on their own efforts, the majority of the poor can only undertake low-paying physical labour and produce agriculture on a modest scale. This can only assist them in maintaining a poor standard of living on a daily basis without helping them break their cycle of poverty. In contrast, government assistance can provide the impoverished with a solid platform for advancement (Hulme et al. 2014; Omar and Inaba 2020). Initially, the poor may be able to compete for higher-paying jobs and perform their current production activities on a greater scale due to increased human capacity and access to production-enhancing resources made available by effective poverty-reduction efforts (Chowdhury and Mukhopadhaya 2012; Pan et al. 2021b). In the long run, the poor may even be able to implement more self-sufficient solutions to poverty, such as commercialisation (Brown 2021).

The poverty-eradication impact of governmental support is estimated following the doubly robust counterfactual causation approach that combines regression adjustments and inverse probability weighting (IPW). This is to reduce estimation errors when estimating governmental support's causal effects, given their selection bias. Using data collected on the multidimensional poverty and deprivation status of 1,538 mountainous, ethnic households, we find that governmental support in Vietnam helps households escape multidimensional poverty, as evidenced by the reduction in their deprivations. Nevertheless, it is notable that it fails to cast the mitigation effect on all deprivations experienced by the poor. The alleviation effect of human support is evident in health and education deprivations, while that of living support exists merely in the deficiency of health. Deprivations concerning employment and living standards seem to be untapped by the impact of support policies, signifying existing shortcomings in the design of support policies. When it comes to the matter of income, human support and living support impose contradictory effects on the income per capita of poor household members, with human support being on the positive side.

This paper contributes to several strands of literature, with the first relating to the literature that examines the poverty-eradication effect of governmental support. Previous studies before 2010 often investigated the impact of governmental poverty-reduction efforts by assessing a certain kind of anti-poverty policy or programme, with the conclusion only

concerning the rise or decline in the income-based poverty status of the poor (Gebregziabher et al. 2009; Hanjra et al. 2009; Rao et al. 2009). More recent scholarly efforts have taken a further step, examining the effects of these policies and programmes not only on the income of the poor but also on the deprivations that they experience. It has been argued that effective poverty reduction requires government aid aimed at fostering human capital, as this is what enables individuals to participate in economic progress and obtain its benefits (Olopade et al. 2019). Two components of human capital, namely education and health, have been shown to have positive interacting effects, which increase the likelihood of opportunity equality by increasing total factor productivity (Larionova and Varlamova 2015; Olopade et al. 2019). The impact of education and training on family planning and gender roles contributes to increases in per capita income. Employment is also viewed as a crucial link between economic expansion and poverty reduction. If they have access to productive and well-paid employment, the poor are more likely to enjoy the benefits of economic progress (Yunus 2009). In a number of nations, government assistance aimed at diversifying livelihoods, promoting employment opportunities, and enhancing production has resulted in significant poverty reduction achievements. Examples include cash subsidies and microfinance, which are reported to have helped the poor get access to money and expand their enterprises, resulting in better wages and more discretionary expenditure on items such as health care, education, and food for themselves and their families (Félix and Belo 2019).

Due to the efficacy of social protection programmes, health, education, and living-standard disparities encountered by the poor are reduced, which is considered a major cause for the fall in poverty rates and intensities (Borga and D'Ambrosio 2021). Despite differences in research subjects and samples, particularly in Vietnam, several previous studies have proved the positive impact of poverty-reduction measures (Cuong et al. 2015; Mu and Van de Walle 2011; Van den Berg and Cuong 2011; Cuong et al. 2011; Wagstaff 2010; Cuong 2008; Van de Walle 2002). Nonetheless, it has also been argued that the efficacy of government interventions designed to reduce poverty is questionable. Some have argued that not all poverty-reduction initiatives are effective at enhancing the lives of the poor and that the rate at which poverty falls varies depending on the conditions (Borga and D'Ambrosio 2021; Jha et al. 2009). This research contributes to the resolution of this academic debate and adds to what is already known by providing more evidence of how governmental support affects multidimensional poverty and explaining how the path breaks down in the Vietnamese context.

It also contributes to empirical evidence of a novel approach to sensitivity analysis, which is proposed by (Masten et al. 2024). This procedure employs fully non-parametric bounds, which are then estimated using flexible parametric estimators of the propensity score and the quantile regression of outcomes on treatment and covariates. This procedure also considers estimation and inference of the average treatment effect (ATE) and average treatment effect on the treated (ATET) bounds, which are so-called additional parameters of interest. The ground for this shift to non-parametric estimators relies on the fact that in the case of parametric estimators, "the asymptotic distribution theory is non-standard, complicated, and at the frontier of current research" (Masten et al. 2024). The adoption of this new approach lends greater credibility to our conclusions and offers a more apparent picture of the treatment effects compared to its predecessors. It is also worth noting that this procedure has never been applied in the research field of multidimensional poverty before.

Finally, this paper also signifies a critical area for policy adjustment in Vietnam by revealing areas untapped by the effect of governmental support. It can be seen in this study

that, notwithstanding positive signals in the multidimensional poverty status of the poor, their deprivations in employment and living standards have not been mitigated, which indicates the unsustainable nature of these poverty-reduction achievements. The objective of Vietnam's subsequent poverty reduction phase is to achieve the Sustainable Development Goals (SDGs) and Millennium Development Goals (MDGs), with a greater emphasis on reducing the multidimensional poverty of ethnic minorities residing in disadvantaged regions (Decision 880/QD-TTg issued in July 2022). Consequently, the development of living conditions and employability among the poor is crucial for targeted individuals to transcend poverty and then to maintain that position on their own, avoiding sliding back into the poverty trap.

The remainder of the paper would be organised as follows: Section 2 would present the data and context of the research. The counterfactual causality estimation strategy will be shown in Section 3. Section 4 reports on the results and Section 5 discusses them. Finally, Section 6 concludes the study.

2 Background, data collection, and key measurements

2.1 Poverty-reduction support in Vietnam

In order to eradicate poverty, governments usually give precedence to the development of policies that help people earn more income, foster human capital, and improve their quality of life. This is true for all nations, including Vietnam. The target beneficiaries of these policies are typically identified in three ways: geographical targeting, special group targeting, and needs targeting. Concerning geographical targeting, to aid the greatest number of people, aid might be provided to rural areas, where the majority of the poor reside. It is advised that regions with high levels of poverty execute integrated rural and regional development initiatives that emphasise the provision of social services, the improvement of infrastructure, and the expansion of agricultural output. Additionally, depending on the local context, aid programmes may target certain populations, such as ethnic minorities, women, the homeless, or the unemployed. To ensure their participation in the benefits given by growth, efforts geared specifically to address the obstacles faced by these groups are essential. Overcoming deficiencies in living conditions might also be a key objective of assistance. This can be achieved by providing food, shelter, clothing, and other basics in addition to critical community amenities such as clean water, sanitation, educational institutions, health care, and public transportation. Table 1, which enumerates the most prevalent support policies administered to the residents of Ha-Giang province, the study area, is a testament to this backdrop. The Ministry of Labour, Invalids, and Social Affairs (MOLISA) is primarily responsible for determining the real beneficiaries of efforts designed to reduce poverty. Since 2015, MOLISA has followed the multidimensional poverty approach to compile the list of poor households (Decision No. 59/2015/QD-TTg). Through two-phase questionnaires, data is aggregated from the village or commune level to the level of the district and then to the level of the province. The list is discussed and validated by the relevant community at each tier (Pham et al. 2020).

Overall, the Vietnamese government currently employs two categories of targeted policies: unconditional transfers and public works. The first type hosts the majority of programmes, including periodic cash transfers, tuition or health care fee exemptions, or financial support for housebuilding and other expenses. These programmes also make in-kind

Table 1 List of support policies in studied areas

Policy name	Beneficiary	Eligibility criteria	Support content
Decree No. 116/2016/ND-CP	Poor students or students in extremely difficult regions	Education; Distance to school; Poverty group	Financial support for food and housing; In-kind food support
Decree No. 146/2018/ND-CP	Poor people	Poverty group	Health insurance premiums; Medical cost deduction
Decree No. 20/2021/ND-CP	People under social protection	Education; Age; Health; Dependant ratio; Poverty group	Monthly social allowance; Funeral cost; In-kind food support
Decree No. 81/2021/ND-CP	Public education participants	Education; Age; Dependant ratio; Poverty group	Tuition fee deduction; Direct financial support
Document No. 4242/BHXH-TST	Poor people	Poverty group	Health insurance card
Decision No. 32/2016/QD-TTg	Poor people and ethnic minorities	Poverty group	Legal advice and representation
Resolution 30a/2008/NQ-CP	People in poor areas	Poverty group; Borrowing; Cultivated land area; Capital lack; Production lack	Financial support; In-kind food support; Interest rate deduction for loans; Financial support for land reclamation and land restoration; Fertiliser subsidies; Farming facilities subsidies
Decision No. 2086/QD-TTg	Poor people and ethnic minorities	Poverty group; Cultivated land area; Capital lack; Production lack	Breeds and seeds; Livestock vaccines; Financial support for land reclamation; Financial support for capacity building; Public official trainings
Circular No. 01/2022/TT-BXD	Poor people	Poverty group; Unstable housing; Housing area per capita	Financial support; Provision of designs, and construction brigade supervision; Supervision of construction work
Decision No. 2621/QD-TTg	People in poor areas	Poverty group; Borrowing; Cultivated land area; Capital lack; Production lack	Financial support; Interest rate deduction; Financial support for land reclamation and land restoration; Fertiliser subsidies; Farming facility subsidies; Livestock vaccines subsidies
Decision No. 60/2014/QD-TTg	People in social protection	Poverty group; Dependant ratio; Production lack; Spending ratio	Financial support for electricity cost
Resolution No. 102/2009/QD-TTg	Poor people	Poverty group; Dependant ratio; Distance to center; Distance to market	Financial support; In-kind support of plant varieties, livestock breeds, veterinary medicine, and iodized salt

Table 1 (continued)

Policy name	Beneficiary	Eligibility criteria	Support content
Decision 755/QD-TTg	Poor people and ethnic minorities	Poverty group; Borrowing; Housing area per capita; Capital lack; Production lack	Capital support of production land; Financial support for production; Financial support for education; Financial support for water-related construction
Decision No. 2086/QD-TTg	Poor people and ethnic minorities	Poverty group	In-kind support of plant varieties, facilities, livestock; Capital support for production land

transfers such as seeds, fertilisers, or livestock. The public work category includes programmes that provide the poor with forestry and agriculture land slots for maintenance and production. These programmes are often rolled out with the double aim of improving the poor's livelihood as well as protecting the forests from encroachment. Other than these two categories targeting the poor, the Vietnamese government also rolled out social protection programmes to a wider range of beneficiaries, including the poor. Since these programmes deliver unconditional monthly cash transfers to the targeted groups, they can be put into the first category. Among these policies, it can be said that the Vietnamese government provides two primary types of aid to the poor: aid to stimulate the growth of human capital (human support) and aid to generate livelihoods and improve people's living situations (living support). This is stated in Decision No. 90/QD-TTg approving the national target programme on sustainable poverty reduction for the 2021–2025 period.

In particular, human support includes support with access to education; provision of vocational training for employment transition; incentives in medical examination and treatment; legal advice and representation regarding personal issues; and support with market access and production techniques. In particular, within the context of Vietnam's programmes and strategies for reducing poverty, the poor are eligible for full or partial exemptions on medical examination and treatment charges and tuition fees at public institutions, as well as cash aid for purchasing necessary school supplies. In addition to aiding in gaining entry to general education, the poor also receive funding to cover the cost of short-term apprenticeships at the primary vocational level to enhance their capacity to find or switch occupations. The government offers training classes on contemporary farming and production practices, as well as market access tactics, to ensure that poor households have the knowledge and skills necessary to increase productivity, product quality, and production scale. To protect their legitimate legal rights and interests, the poor are also entitled to legal advice and free legal representation in some legal proceedings, such as contract signing, complaint filing, and complicated or typical cases. The recipients of human support are frequently determined by the following factors: education, age, health, dependent ratio (number of household members), and poverty group. This can be seen in Table 1, Eq. 6, and Table 2.

On the other hand, government assistance in the form of land allocation, agricultural production resource provision, financial support for housing construction and repair, subsidised electricity bills, and low-interest credit grants is referred to as living support. Concerning the allocation of land to the poor, the state distributes households a particular piece of forest land for one of two purposes: the conservation of forest land or the conversion of forest land into useful land for agriculture and animal husbandry. The allocated land area will depend on the state of the local land fund and the real circumstances of the household based on the subsidy eligibility criteria.

The state then provides in-kind support, such as food (rice), plant varieties, machinery, agricultural tools, and medications for livestock and poultry, so that people can cultivate the provided land and raise livestock there. In addition, qualifying households may receive direct support payments for the purpose of repairing or building new permanent residences or paying monthly energy bills. The objective is to establish a safe environment where people can improve their standard of living, thus boosting their prospects of escaping low-income conditions. In addition, the state also provides households with government-backed agriculture loans at low interest rates and with longer payback terms. The following factors are used to determine who receives this kind of support: dependent ratio, number of household members, poverty group, borrowing, and unstable housing. This is demonstrated in Table 1, Eq. 7, and Table 3.

Table 2 Determining components of human support

	(1)		(2)		(3)	
Education	0.210***	(0.049)	0.106**	(0.051)	0.098*	(0.052)
Age	−0.013***	(0.004)	−0.016***	(0.005)	0.050**	(0.024)
Perceived health	−0.167***	(0.044)	−0.217***	(0.047)	−0.205***	(0.047)
Dependant ratio	0.285	(0.183)	0.347*	(0.189)	0.577***	(0.215)
No. of member	0.103***	(0.026)	0.103***	(0.027)	0.078***	(0.028)
Near poor	−0.434***	(0.086)	−0.643***	(0.095)	−0.506***	(0.114)
Escapee	−0.790***	(0.121)	−0.942***	(0.119)	−1.430***	(0.219)
Participate in union(s)			0.973***	(0.089)	0.990***	(0.137)
Age × Age					−0.001***	(0.000)
Near poor × Participate in union(s)					−0.325*	(0.189)
Escapee × Participate in union(s)					0.763***	(0.284)
Constant	−0.097	(0.341)	0.144	(0.354)	−0.802	(0.494)
Observations	1197		1197		1197	
Outcome mean	0.343		0.343		0.343	
Log pseudolikelihood	−707.639		−644.068		−631.711	
Pseudo R2	0.080		0.163		0.179	

(1) is with base covariates without Participate in union(s), (2) is with base covariates, (3) is with interaction terms

Robust standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 3 Determining components of living support

	(1)		(2)		(3)	
Borrowing	0.691***	(0.109)	0.663***	(0.111)	0.691***	(0.113)
Unstable housing	−0.696***	(0.117)	−0.694***	(0.117)	−0.711***	(0.118)
Dependant ratio	0.336	(0.238)	0.395*	(0.240)	0.646	(0.520)
No. of member	−0.019	(0.036)	−0.021	(0.036)	0.008	(0.073)
Near poor	−1.213***	(0.145)	−1.252***	(0.152)	−1.133***	(0.171)
Escapee	−1.436***	(0.190)	−1.452***	(0.185)	−1.789***	(0.270)
Participate in union(s)			0.229	(0.143)	0.195	(0.182)
Dependant ratio × No. of member					−0.068	(0.139)
Near poor × Participate in union(s)					−0.312	(0.331)
Escapee × Participate in union(s)					0.865**	(0.401)
Constant	−0.446**	(0.206)	−0.493**	(0.208)	−0.592**	(0.294)
Observations	936		936		936	
Outcome mean	0.159		0.159		0.159	
Log pseudolikelihood	−315.362		−314.014		−310.466	
Pseudo R2	0.231		0.235		0.243	

(1) is with base covariates without *Participate in union(s)*, (2) is with base covariates, (3) is with interaction terms.

Robust standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Tables 1, 2 and 3 are, *de jure*, criteria for a household to receive support. These determinants are also highly correlated with households' MPI, as that was initially the point: support is targeted at those in need. Thus, we can control for these lists of criteria to achieve conditional independence (see Section 3). However, de facto, these determinants are not definitive, as there are reported cases of policy profiteering via local capture, embezzling, or altering the poverty revision list. Given that, there are cases of both Type I and Type II targeting errors, meaning that there are poor households that were not supported and non-poor households that were supported. The same issue can also be observed between two supports, as households that should have been eligible for both might just receive one (Appendix Table 20). If this practice is prominent enough, our policy effect estimations might not be reliable. Thus, controlling for variables that capture these cases would help reflect the treatment assignment mechanism better and reduce the possibility of failing conditional independence, increasing the robustness of our evaluations.

Therefore, besides the determinants of governmental support that are specified within the eligibility criteria of the policies, we also add *Participate in union(s)* as a driver. This dummy variable takes the value of 1 when a household has members participating in unions or organisations, including Fatherland Front, Farmer's Union, Women's Union, Ho Chi Minh Communist Youth Union, or Veteran's Union. These are influential unions in Vietnam, especially in rural or far-flung areas such as Ha Giang Province, since they play an important role in conveying and implementing the state's policies. Thus, households with members participating in these unions can be considered to have better political connections than those without (To-The and Tran-Nam 2015). Moreover, within the procedure of reviewing poor households, representatives from these unions also form a part of the reviewing board (Appendix Fig. 11). Thus, we posit that political connections may make way for local and elite capture, causing imperfect targeting.

Previous studies also provided evidence that local or elite capture can be prevalent sometimes and that households with better political connections can opt in for target programmes where they initially are not the beneficiaries (Pan and Christiaensen 2012; Caeyers and Dercon 2012; Panda 2015). Even when these connections cannot directly alter the target via favouritism, households can still take advantage of higher social capital to manipulate target results (Cheng et al. 2022), and this is sensible in the context where union representatives hold voting power in reviewing household status.

Currently, about 35.2% of households have members in unions (Table 4), and this variation has strong explanatory power as a driver of human support. Adding this variable can significantly increase the pseudo-R^2 of the base covariates model from 8.1% to 16.7% (Table 2). The variable also shows statistical significance in its singular and interaction terms. Regarding living support, although adding *union participation* does not increase the model's explanatory power, its interaction with *poverty group* does show a strong and significant magnitude (Table 3).

2.2 Study areas and households survey

Ha-Giang is one of the poorest mountain provinces in Vietnam. In 2016, around 43.65% of the total population in this province was poor, as per the national multidimensional poverty standard. By 2020, this figure had dropped to around 22%; however, it remains the poorest province in the country in terms of headcount share. There are two major reasons behind this. First, more than 88% of the total population in Ha-Giang are ethnic minorities who have lower human capacity and access to developed facilities than the Kinh, the ethnic

Table 4 Variable description

Variable		Obs	Mean	Std. dev.	Min	Max
MPI		1,538	0.328	0.122	0.031	0.813
Multidimensionally poor		1,538	0.499	0.500	0	1
Income per capita (million VND per annum)		1,538	9.981	7.592	0.137	61.253
Income per capita (log term)		1,538	2.021	0.801	−1.990	4.115
MPI components	Job	1,538	0.143	0.227	0.000	1.000
	Education	1,538	0.459	0.216	0.000	1.000
	Health	1,538	0.258	0.282	0.000	1.000
	Living standard	1,538	0.452	0.143	0.125	1.000
Poverty group	Poor	1,538	0.548	0.498	0	1
	Near poor	1,538	0.298	0.457	0	1
	Escapee	1,538	0.154	0.361	0	1
Supports	Living	1,538	0.222	0.416	0	1
	Human	1,538	0.391	0.488	0	1
Borrowing		1,538	0.422	0.494	0	1
Agriculture ratio		1,538	0.358	0.313	0.000	1.000
Spending ratio		1,538	0.223	0.180	0.000	0.977
Education (Household average)		1,538	2.161	0.911	0.000	7.000
Gender (Female ratio)		1,538	0.514	0.196	0.000	1.000
Age (Household average)		1,538	28.374	11.172	10.200	80.000
Perceived health (Household head)		1,538	4.249	0.941	1	5
No. of members		1,538	4.479	1.624	1	9
Dependant ratio		1,538	0.394	0.243	0.000	1.000
Participate in union(s)		1,538	0.352	0.478	0	1
Perceived connectedness (Household head)		1,538	3.752	1.293	0	5
Unstable housing		1,538	0.687	0.464	0	1
Housing area per capita (m^2)		1,538	17.072	18.568	0.000	300.000
Cultivated land area (m^2)		1,538	4644.845	7925.307	10.000	250,230.000
Cultivated land area (log term)		1,538	7.665	1.555	2.303	12.430
Capital lack (PCA value)		1,538	−0.034	1.149	−2.286	3.503
Production lack (PCA value)		1,538	−0.205	2.047	−7.848	2.089
Perceived natural condition (PCA value)		1,538	0.205	1.423	−3.008	2.947
Distance to centre (km)		1,538	3.914	15.459	0.000	600.000
Distance to market (km)		1,538	7.919	6.675	0.200	56.000
Distance to road (km)		1,538	2.571	24.541	0.000	800.000
Distance to school (km)		1,538	3.545	10.662	0.000	400.000

majority. Given the diverse set of cultures and languages, poverty alleviation efforts among these groups would encounter more difficulties that require specific adjustments. Second, Ha-Giang is a remote province with difficult mountainous terrain that hinders its access to outer areas and the mass production of agriculture. People's livelihoods in this province, thus, are unsustainable and cannot rely solely on one single source of output. Given the difficulties, Ha-Giang is the target province for almost all of the Vietnamese government's anti-poverty policies. For these reasons, we chose Ha-Giang to study the efficiency

of governmental support for the poor. Due to the characteristics of the province, this paper can look further into the poverty status of ethnic minorities and those from the far-flung areas of Vietnam.

Our final survey data consists of 494 questions, of which 164 are for demographic information about each member of the household (up to 9); 88 are about production activities and asset holding; 161 are about support policies; 20 are about income sources; 27 are about daily expenses and food consumption; and 34 are about perceptions about surrounding favours and difficulties. We exclude responses from households that received both types of support because we seek to estimate the causal effect of each support independently rather than differentiating the effect of human support and living support. We maintain the responses of households that received only human support, only living support, or no support at all. The final dataset contains 1,538 observations after data cleaning and is divided into two subsets for subsequent data analysis. To determine the effect of human support, we compare only the observations that received human support to those that received no support at all. The same applies to living support.

Data summaries for variables used in this paper, excluding ones for MPI measurement, can be seen in Table 4. Certain variables require further explanation. Among the variables, there are three calculated from principal component analyses (PCA),[1] namely capital lack, production lack, and perceived natural condition. The first variable addresses a lack of financial capital and stable housing, while the second addresses a lack of agricultural production land, knowledge of production technology and schemes, linkage and market orientation, production electricity, proper production infrastructure, a risk-free production environment, and production labor. The variable of perceived natural condition is created from three original variables, namely favorable natural conditions, advantages of local and specialty product development, and tourism development potential. These PCAs help us reduce the unnecessary dimensionality of our data while still depicting a general perception of households about their needs and surrounding conditions.

In addition, "human support" and "living support" variables are dummy variables whose values are 0 and 1. A household is categorised as having received human support or living support when that household has received any kinds of human support or living support policies at least once during the past 12 months. This categorisation is deemed suitable because, in this article, we want to delve into the question of whether a household has received any human or living support. This approach has been argued to be a better one in the field since people are more likely to indicate whether they receive a particular type of support than how much they receive. Surveys that ask the former question tend to elicit a higher proportion of truthful responses (Livani and Graham 2019). Among our observations, 22.2% and 39.1% of households are provided with human and living support.

As for the financial status of the participants, it is reported that 42.2% of the surveyed households hold at least one unpaid debt. Their monthly agricultural production income and spending account for 35.8% and 22.3% of their total monthly income and spending, respectively. Notable is also the poor educational attainment of the local populace, with the majority of individuals having completed merely the lower secondary level. The problems of gender imbalance and an ageing population are not serious in this region, with the female ratio being 51.4% and the average age of household members being approximately

[1] The PCAs are the first principal components of the data from the corresponding lists. Since these variables were fundamentally designed to reflect shared contents, we reduced the dimensions in order not to include unnecessary variation in the final estimators.

28 years old. On average, a household has four members, and dependent members account for 39.4% of the total number of household members. From the perception of the household heads, the connection among communal dwellers is fairly strong, with an average corresponding rate of 3.752 on a scale from 1 to 5.

In addition, even though the housing area per capita is not low (17.1 m2), a large number of households (68.7%) here suffer from a lack of stable shelters. On average, each household possesses a cultivated land area of 4644.845m^2; nevertheless, the shortage of capital and production resources still exists, as reflected in the values of two principal components, capital lack and production lack. According to the household heads, with respect to natural factors, the natural conditions of the region are quite acceptable. On average, the distances from the household location to the centre, road, and closest school are 3.914 km, 2.571 km, and 3.545 km, respectively. Nevertheless, this ease of access cannot be found when the local residents want to travel to the closest market, with the average distance to the market being 7.9 km.

2.3 Multidimensional poverty measurement

Our measurement of MPI is adapted from Alkire and Foster (2011), Alkire et al. (2015), and UNDP and OPHI (2021)'s structure with adjustments according to Decree 07/ND-CP[2] issued by the Vietnamese government regulating the multidimensional poverty assessment framework for 2021–2025. This adaptation allows us to better evaluate MPI with regard to the empirical context in Vietnam. The original MPI measuring framework (Alkire and Foster 2011; Alkire et al. 2015) calculates the weighted deprivation of households by 10 indicators falling into three dimensions, including education, health, and standard of living. Yet, this list of indicators and dimensions can be adaptive to changes and the addition of dimensions such as quality of work, empowerment, physical safety, social contentedness, and psychological well-being and happiness (Alkire et al. 2015). Decree No. 07 by the Vietnamese government thus adds the "Job" component,[3] represented by two indicators related to joblessness and household dependent ratio. Other than this addition, due to data availability, we made several changes to the original MPI structure. This results in a set of four dimensions and 14 indicators contributing to MPI, as shown in Table 5.

MPI is calculated as:

$$MPI = \frac{\sum_{i=1}^{n} z_i w}{n}$$

where z_i is the deprivation cut-off of household i, w is the weight, and n is the total number of households included in the study. Following Alkire and Foster (2011), we choose the equal weight w for each component of the index. This is a common practice, as it can ease the interpretation of indicators and keep our MPI calculation consistent with that in other contexts. We also follow Alkire et al. (2015) and choose 1/3 as the threshold; if households fall below this, they can be identified as multidimensionally poor.

[2] Decree 07/ND-CP, issued on January 27, 2021, stipulates the criteria for measuring multidimensional poverty; standards of poor households, near-poor households, households with average living standards, and responsibility for implementing poverty reduction in the period of 2021–2025.

[3] In this paper, "dimension" and "component," when referred to as part of MPI, can be used interchangeably.

Table 5 MPI measuring structure

Dimension	Indicator	Weight (w)	Deprivation cut-off (z)
Job	Joblessness	1/8	Any household member who is of working age and able to work but has no job
	Dependant ratio	1/8	The household has more than 50% of its total members as dependents (children under 16 years old, elderly, disabled members)
Health	Nutrition	1/8	The household's total nutrition input is less than 50% of its demand
	Insurance	1/8	Any six-year-old or older household member has no health insurance
Education	Years of schooling	1/8	No household member over 10 years old has finished primary education
	School attendance	1/8	Any 6–14-year-old household member does not attend school
Standards of living	Electricity	1/32	The household has no electricity
	Sanitation	1/32	The household's sanitation facility is not improved, or it is shared with other households
	Water	1/32	The household does not have access to safe drinking water
	Cooking fuel	1/32	The household cooks with dung, wood, or charcoal as fuel
	Housing	1/32	The household lives under primitive housing, semi-permanent housing, or no house
	Housing area	1/32	The household's living area is less than $8m^2$ per capita
	Internet	1/32	The household has no internet access
	Assets	1/32	The household has no car, motorbike, or has less than one TV, music system, refrigerator, air conditioner, dryer, water heater, microwave oven, computer, laptop, or phone

2.4 Theoretical background on the effect of support policies

Within the poverty literature, many studies have discovered and emphasised the poverty trap as an important reason why people still stay poor even in good conditions of positive overall economic growth (Banerjee et al. 2021; Balboni et al. 2021; Page and Pande 2018). This opens up the main argument for programmes such as targeted transfers, social works, or social protection programmes to lift the poor out of poverty. The most important role of these programmes is to redistribute resources to the poor so that they can keep up with the non-poor. Additionally, these anti-poverty policies also aim to enable greater access for the poor to the market via low-interest loans, free insurance, or skill trainings, and to improve their access to public services like healthcare and education (Ghatak 2015).

In the case of unconditional transfer programmes, where the poor receive some amount of money without any requirement, the immediate effect would be a direct increase in their disposal income. The same thing can be inferred from conditional transfers, where the recipients must ensure certain behaviours, such as sending children to school or health check-ups. This leads to an increase in the poor's consumption (Fiszbein and Schady 2009; Balboni et al. 2021), households' assets (Blattman et al. 2020; Cuong et al. 2015), and food security (Banerjee et al. 2021). However, the most important impact of transfers that can lift the poor out of poverty comes from their occupation switches afterward. With large enough transfers, households would be able to move away from casual labour tos working on their own farms and livestock (Balboni et al. 2021; Banerjee et al. 2021). Yet, this effect does not come from any transfer but only from a large one that can offer a "big push" to households to cross the threshold of the poverty trap (Banerjee et al. 2015). Thus, the poor can benefit more from large and time-limited transfers than from small, long-term programmes, and the governments may also save their fiscal resources with the former as well (Balboni et al. 2021).

Recently, Banerjee et al. (2021) also added more to the literature that, given an effective transfer, the poor can even move further to non-farm microenterprises and, later, wage labour thanks to better access to capital. This result supports the view that transfer can indirectly improve human capital, or at least reduce the mismatches between talent and occupations, as the poor normally do not have access to jobs that they can be most productive in (Balboni et al. 2021). With better-wage jobs, the livelihoods of households' dependents will improve, such as when the elderly can reduce their labour supply and the children can go to school. Therefore, transfers can impose different effects on members of a household. Banerjee et al. (2021) found that after ten years, households receiving transfers will enjoy higher wages from migrants working in farther cities than those not. Also, in Vietnam, Nguyen and Tarp (2023) indicated that transfers can reduce the labour force participation of old members, and since they can now help with more housework and childcare, their children can better improve their wage labour. The increasing income of parents will eventually reduce the opportunity cost of sending children to school, encouraging them to drop child labour (Fiszbein and Schady 2009) and enrol in school. Afridi et al. (2016) elaborated on this via the channel of increasing the mother's position in the family, thus increasing investment in children.

However, because transfer programmes, even conditional ones, cannot directly improve poor capabilities so that they can make significant occupational shifts right away, a combination of interventions has been shown to be more effective. Bandiera et al. (2013) found that "sizable" asset transfer coupled with skill training in Bangladesh

will help the poor shift from farming to running small businesses. Blattman et al. (2014) showed the same effect among Ugandan women, as cash transfers and business training can be "very effective". Berhane et al. (2014) also concluded that combining a public work and food transfer programme will be better for the poor than delivering either of them in Ethiopia.

Regarding public work programmes, the effects can be simply expected to come from three channels: wages from the work, skills obtained, and the productive assets created, although the poor may focus less on the third effect. In terms of the first two, public work programmes can directly improve the poor's disposal income, hence their consumption and possibly their investment. There's an opportunity cost argument that the income effect may not hold when the programmes pay below-average wages or when the poor had other jobs before the programme. But as, by nature, public works programmes are self-targeted and the wages tend not to pay above-market wages (Gehrke and Hartwig 2018), participants will benefit from the programme rather than other market jobs. As people are exposed to organised jobs with better income, they are more likely to make investments with higher risk-taking willingness (Banerjee et al. 2015; Gertler et al. 2012; Andersson et al. 2011). Additionally, formal or on-the-job training can help increase the poor's skills so that they can sustain their lives with better market jobs. In that case, income from public works might act as a safety net that allows them to make larger investments in their farms (Gehrke and Hartwig 2018). There is some evidence that longer-term public work programmes can help increase consumption and food security (Beierl and Grimm 2019) and raise the quality of labour supply (Lal et al. 2010).

Finally, there are social protection programmes whose effects are simple and straightforward. As these are considered the safety net for the vulnerable, the main effect of social protections comes directly from increasing transferred income (Borga and D'Ambrosio 2021). Unlike transfers, which are designed to offer a push to the poor to get out of the poverty trap, social protection programmes often aim to mitigate difficult circumstances in which people cannot sustain themselves. Therefore, the effect of these programmes is observed most clearly for the ultra-poor (Borga and D'Ambrosio 2021), who are beneficiaries for a longer period of time (Berhane et al. 2014). To support this, Porter and Goyal (2016) showed that the Ethiopia Productive Safety Net Programme could help cushion children from nutritional vulnerabilities, but the effect is different for different ages.

With this understanding of the conceptual frameworks related to government support programmes, we can see how these interventions can reduce poverty. The four dimensions of deprivation within MPI are alleviated in different stages upon receiving support. And as MPI is the identity of these four components, it is unambiguous that improvement of each or multiple components will result in a reduction of MPI. Increasing disposal income will be the direct effect of these programmes, which will lead to effects on asset accumulation, livestock, and other living standards indicators (Borga and D'Ambrosio 2021). Consumption and nutrition in households will also be improved, not just in quantity but also in quality (Fiszbein and Schady 2009). Combined with supports directed towards healthcare costs, insurances, and education costs, household members, especially children, would enjoy better health and higher school enrollment (Giang and Nguyen 2017). Eventually, given enough multifaceted supports, the poor's labour skills will be improved and they will have adequate resources to make occupational shifts to higher income, which will sustain their path out of poverty (Banerjee et al. 2021).

3 Estimation method

The identification of effects in this study faces a classical selection bias problem. Which means the criteria and characteristics upon which the households are selected for supports are highly correlated to their outcomes measured as MPI, being multidimensionally poor or not, or income per capita. This confounds our point estimations of the policy impact, as the treatment assignment mechanism is not random. Also, since the two groups, control and treated, are too different, the results will also be biased by heterogeneous treatment effects. Given that, our main estimator is doubly robust using inverse probability weighting with regression adjustment (IPWRA) due to its perk of reducing estimation errors when estimating counterfactual causality effects. The main idea of this method lies in the combination of both propensity scores and the conditional mean of outcome models (Sloczyński & Wooldridge 2018). Wooldridge (2007) suggested that inverse probability weighting is beneficial when the outcome variable has a restricted range, which is highly applicable in this paper as our most focused outcome is MPI ranging from 0 to 1. Also, adding regression adjustment helps reduce the heterogeneous treatment effects, resulting in a less biased estimation (Wooldridge 2010). Our strategy for doing so is as follows:

First, we identify the two sets of variables that explain the assignment of treatments. In this case, these variables are criteria for a household to receive human support or living support that are discussed in subSect. 2.1. As these sets of variables can reflect the treatment assignment mechanism, using them to match or to weight (using propensity score) will create a conditional random treatment environment, making it possible to calculate the causal effect of these supports as long as the probability of receiving treatment is positive across dimensions in the control group. Second, we also use a set of variables that drive household poverty to include in regression adjustments to reduce heterogeneous treatment effect bias.

In a randomised control setting, the average treatment effect on the treated (ATET) is calculated as follows:

$$ATET = \frac{1}{N_T} \sum_{i=1}^{N_T} \left(E\left[Y_1 \mid T = 1\right] - E\left[Y_0 \mid T = 1\right] \right) \tag{1}$$

where Y_1 is the realised outcome and Y_0 is the potential outcome at the treatment group (in this case, the realised outcome at the control group); $T = 1$ denotes the presence of treatment; N_T is the number of treated units. Yet, since $E\left[Y_0 \mid T = 1\right]$ is unobservable, we must calculate the probability of treatment assignment via propensity score. It can be done simply by estimating a probit model with the treatment as a dependent variable and the observable confounders mentioned above as independent variables. The functional forms for these equations are described in Eq. 6 and Eq. 7 in the Appendix. The propensity score $P\left(T \mid x_i\right)$, with x_i is the matrix of observable covariates, is then used as the weight for the outcome models.

$$\text{Inverse probability} = \begin{cases} \frac{1}{P(T|x_i)} & \text{if } T = 1 \\ \frac{1}{1-P(T|x_i)} & \text{if } T = 0 \end{cases} \tag{2}$$

Given that, we can calculate the treatment effect for a unit as

$$\tau = E\left[Y_1 - Y_0\right] = \left[\frac{Y_{T=1}}{P\left(T \mid x_i\right)}\right] - \left[\frac{Y_{T=0}}{1 - P\left(T \mid x_i\right)}\right] \tag{3}$$

The ATET is then

$$\text{ATET} = \frac{1}{N_T}\sum\nolimits_{i=1}^{N_T}\left(\left[\frac{\widehat{Y}_{T=1}}{\widehat{P}\left(T \mid x_i\right)}\right] - \left[\frac{\widehat{Y}_{T=0}}{1 - \widehat{P}\left(T \mid x_i\right)}\right]\right) \tag{4}$$

with

$$\begin{cases} \widehat{Y}_{T=1} = \left(\widehat{\beta}_{00} + \widehat{\beta}_{01}x_i\right)_{T=1} \\ \widehat{Y}_{T=0} = \left(\widehat{\beta}_{10} + \widehat{\beta}_{11}x_i\right)_{T=0} \end{cases} \tag{5}$$

are the adjusted regression outcome models for the treated and untreated, respectively. Due to the nature of the data, we specify outcome models of MPI as fractional probit, being multidimensionally poor as probit, and income per capita as simple linear.

We also integrate a set of control variables into our analysis to account for the effects of household- and commune-level features. The list of household level control variables first accounts for household borrowing, the ratio of monthly household income from agricultural production to monthly total household income, the average educational level, gender ratio (female ratio), dependent member ratio of the household, and the health status of the household head. It also accounts for household cultivated land area and the household's lack of capital and production-related resources. At the commune level, the selected parameters include the perceived community spirit among the dwellers, regional natural conditions, and the distance from the household location to the centre, closest market, and road. The majority of home welfare studies in Vietnam and other nations, particularly those concerned with poverty elimination, include information on the socioeconomic characteristics of individual households and entire communes. In addition to having direct effects on household multidimensional poverty, it has been demonstrated that these characteristics are among the most important criteria for the assignment and stratification of support under support programmes (which in turn influence household multidimensional poverty).

Other than the IPWRA, we also use other estimators to calculate the ATET, including regression adjustment (RA), nearest-neighbour matching (NN Match), propensity score matching (PS Match), and fractional probit (probit, or linear OLS depending on the outcomes). For each estimator, we note the inclusion of treatment covariates or outcome covariates below the ATET results. Comparisons across these estimators will also provide a sense of the result's robustness, as the results will be more reliable if their signs and magnitudes are consistent across estimators. For IPWRA, NN Match, and PS Match, we can also view the balance of covariates between treatment groups after weighting and matching, adding another way to test the credibility of results.

However, the unconfoundedness assumption is not refutable, making it impossible to test post-estimation. Therefore, we also include a sensitivity analysis of our data to violations of unconfoundedness, developed by Masten et al. (2024). This analysis was based on "a class of assumptions called conditional c-dependence." This class measures relaxations of conditional independence by a single scalar parameter $c \in [0, 1]$. This

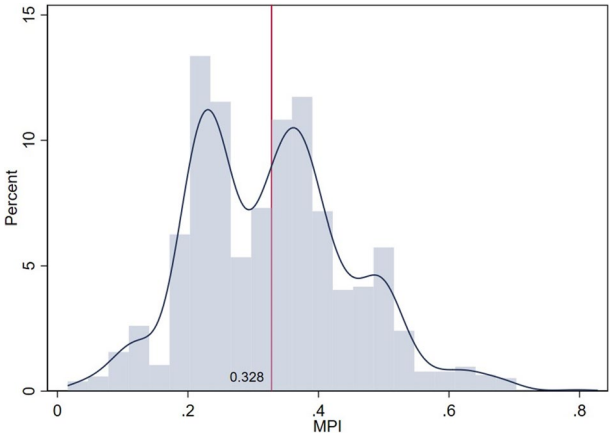

Fig. 1 MPI in the survey areas

parameter c is the "largest difference between the propensity score and the probability of treatment conditional on covariates and an unobserved potential outcome". This means that when $c = 0$, unconfoundedness holds perfectly, but when $c > 0$, the propensity score $P(T = 1 \mid X = x)$ is allowed to differ from the unknown conditional probability $P\left(T = 1 \middle| Y_x = y_x \middle| X = x\right)$ by at most c with Y_x denoting potential outcomes. Given that, we calculate the breakdown point c_{BP}, which is essentially the largest c value that, if we cross (more relaxation of unconfoundedness), the ATET parameter cannot be trusted. Thus, it can be interpreted that the larger the breakdown point, the more reliable an estimator is. Moreover, we can also calculate the variation in the leave-out-variable-k propensity score (denoted as Δk) with k being each covariate we used for weighting or matching (Table 10 and 13). This means that "c reflects the additional impact of an unobservable on treatment while Δk captures the additional impact of an observable on treatment" (Masten et al. 2024). Therefore, we can compare c_{BP} to Δk, if c_{BP} is larger than Δk at higher relaxation levels, our ATET estimates can be considered robust. If not, more analysis would be needed to conclude. We will present this more in our empirical results in subsection 4.3. For an in-depth theoretical explanation and empirical presentation, see Masten et al. (2024) and Masten and Poirier (2018).

4 Results

4.1 MPI in study areas

Among the 1,538 surveyed poor households, 49.9% are multidimensionally poor as per our MPI measurement. On average, households lack 32.8% of their non-income poverty indicators (Fig. 1) and earn around 10 million VND per annum, equivalent to about US$3.96 (2011 PPP) per day (Table 4).

Each year, households in poor districts would get reassessed for their poverty status. This is a six-step procedure that involves district and commune-level committees, village leaders, union representatives, and households. The households being reviewed in each annual period fall into two groups: (1) those who are within the poor or near-poor groups in the previous periods; or (2) those who file a request for review of poverty

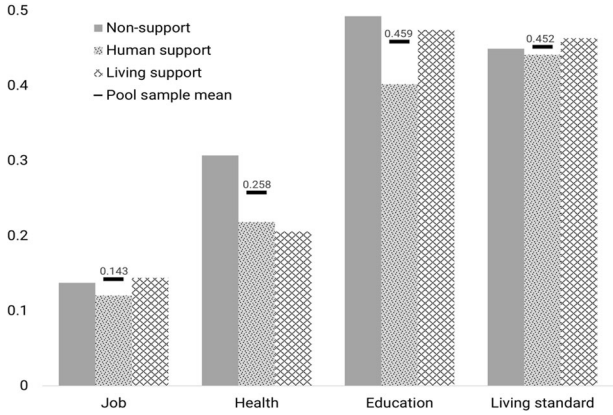

Fig. 2 Deprivation status by support group

in the current period. Either way, both groups must go through the same procedure, including being interviewed, scored, and voted to be recognised as poor or near-poor households. The status of "poor" and "near-poor" will be assigned to households based on their levels of income per capita and deprivations of social services as listed in Table 5. Currently, according to Decree 07/ND-CP, a "poor" household in rural areas is the one having 1.5 million VND/capita/month or less and being deprived of 3 or more social services; a "near-poor" household has 1.5 million VND or less and is deprived of less than 3 social services. A detailed process of review is presented in Appendix Fig. 11. Those who escape the poverty and near-poverty lines are called "escapee." For simplicity, in this paper, we label all other households that are not in the review process "escapee" as well. *De jure*, they are similar in terms of the score and rank that have been used to review the poverty status. The "poverty group" variable reported in Table 4 shows the current poverty status of households as assessed the year before the survey. In our study area, 54.8% of households are under the poverty line as per the national standard, 29.8% are near-poor, and the other 15.4% have just escaped poverty.

Regarding the components of MPI, households in the poor parts of Ha-Giang suffer from deprivations unequally. Living standard and education deprivations stand out as the preeminent kinds of deprivation experienced by households, while deprivations of employment and health are less widespread. In particular, 45.9% and 45.2% of households are deprived of education and normal living standards, respectively. 25.8% of households lack nutrition and health insurance. Only 14.3% of households have unemployed members, or more than half of members are dependents.

The contribution of each deprivation to the MPI also varies by the support that households receive. Figure 2 indicates that, in health and education dimensions, non-supported households are more deprived compared to the human-supported and living-supported groups. Meanwhile, in job and living standard dimensions, households with living support tend to be more deprived. It should be noted that these are simple descriptive statistics and are not controlled for selection bias. One could argue, for example, that because living supports aim to improve the living standards of the poor, they are typically assigned to those who lack this dimension. The next section would delve into the results on the effect of support policies and address these bias arguments.

Table 6 Effect of human support on multidimensional poverty

	(1) MPI	(2) Multidimensionally poor
ATET Human support	−0.039***	−0.093**
	(0.008)	(0.042)
POmean Human support (0)	0.333***	0.482***
	(0.008)	(0.039)
Outcome covariates	Yes	Yes
Treatment covariates	Yes	Yes
Observations	1197	1197
Outcome mean	0.328	0.496
Sesitivity breakdown	0.138	0.081

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Support effect on poverty

We examine the effect of governmental anti-poverty support via two data subsets. One includes 1,197 household observations, in which 410 households received human support and the remaining 787 households did not receive any support. The other subset includes 936 observations: 149 living-supported ones and 787 not-supported ones. We examine these support effects on MPI. We also look into the effect of support in reducing the probability of households falling under the multidimensional poverty threshold at 1/3 MPI. While the main part of the paper discusses results from IPWRA estimators, we will include the results from other estimators in the Appendix for robustness. These include the regression adjustment (RA), the nearest-neighbour matching (NN Match), the propensity score matching (PS Match), and the conventional linear fractional probit model.

According to the results reported in column (1) of Table 6, current human support is effective in lowering the MPI of poor households in Ha-Giang province. Being supported with human capacity development helps the poor households reduce 3.9% MPI, which is equivalent to an 11.7% reduction from the mean and an 11.9% reduction from the mean of the treated.[4] Since human support can reduce households' MPI, it can help lift those on the verge out of multidimensional poverty. Column (2) of Table 6 shows the effect of human support on households being multidimensionally poor. This type of governmental intervention can reduce the share of households under the multidimensional poverty line by 9.3%, which is equivalent to about 19.5% reduction from the mean of the treated.

Regarding living support, column (1) of Table 7 shows the treatment effects of a 3.2% reduction in households' MPI. This equals about 9.1% reduction from the mean of the treated. The lifting effect of living support (column (2) Table 7) is not as statistically significant as its effect on reducing MPI. Being assigned to living support tends to reduce the share of multidimensionally poor households by 11.4%, equivalent to a 20.3% reduction from the mean of the treated.

[4] These are calculated by taking the ratio of the "Human support" coefficients to the "Outcome mean" value and the "Potential outcome mean" value, respectively.

Table 7 Effect of living support on multidimensional poverty

	(1) MPI	(2) Multidimensionally poor
ATET Living support	−0.032**	−0.114**
	(0.013)	(0.053)
POmean Living support (0)	0.353***	0.562***
	(0.012)	(0.045)
Outcome covariates	Yes	Yes
Treatment covariates	Yes	Yes
Observations	936	936
Outcome mean	0.342	0.536
Sesitivity breakdown	0.046	0.015

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8 Effect of human support on MPI components

	(1) Job	(2) Education	(3) Living standard	(4) Health
ATET Human support	−0.014	−0.062***	−0.016	−0.054**
	(0.014)	(0.016)	(0.013)	(0.022)
POmean Human support (0)	0.132***	0.461***	0.454***	0.267***
	(0.014)	(0.014)	(0.012)	(0.020)
Outcome covariates	Yes	Yes	Yes	Yes
Treatment covariates	Yes	Yes	Yes	Yes
Observations	1197	1197	1197	1197
Outcome mean	0.132	0.459	0.447	0.274
Sensitivity breakdown	0.010	0.039	0.049	0.021

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9 Effect of living support on MPI components

	(1) Job	(2) Education	(3) Living standard	(4) Health
ATET Living support	−0.004	−0.016	0.028*	−0.143***
	(0.026)	(0.021)	(0.014)	(0.034)
POmean Living support (0)	0.154***	0.502***	0.431***	0.334***
	(0.028)	(0.015)	(0.013)	(0.027)
Outcome covariates	Yes	Yes	Yes	Yes
Treatment covariates	Yes	Yes	Yes	Yes
Observations	936	936	936	936
Outcome mean	0.139	0.489	0.452	0.288
Sensitivity breakdown	0.003	0.013	0.010	0.112

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10 Variation in leave-out-variable-k propensity score, human support sample

Quantile	0.500	0.750	0.900	Max
Education	0.013	0.027	0.045	0.153
Age	0.015	0.030	0.046	0.107
Age x Age	0.020	0.040	0.059	0.218
Health	0.036	0.064	0.089	0.282
Dependent ratio	0.018	0.036	0.056	0.125
No. of members	0.020	0.039	0.061	0.172
Near poor	0.041	0.076	0.098	0.148
Escapee	0.034	0.083	0.148	0.391
Participate in union(s)	0.030	0.100	0.223	0.313
Near poor x Participate in union(s)	0.015	0.027	0.033	0.048
Escapee x Participate in union(s)	0.015	0.034	0.057	0.102

We also delve further into the effects of support on each of the components of MPI, namely: job, health, education, and living standard. Tables 8 and 9 show that different anti-poverty policies have different effects on poverty alleviation. Regarding human supports, Table 8 shows that they are effective in reducing households' deprivations in health and education. For the health component, human support helps reduce the intensity of health deprivations by 5.4%, equivalent to a 20.2% reduction from the treated mean. For the education component, households with human support are 6.2% less deprived than those who do not, which is a 13.4% reduction from the treated mean.

Unlike human support having an effect on multiple deprivations, living support is shown to only ameliorate the health status of the poor (Table 9). However, this effect is of substantial magnitude, reducing 14.3% in the intensity of health deprivation, equivalent to a 42.8% reduction from the treated mean. We also witness a significant estimate of living support on households' living standards, but with a positive sign, which means households being supported with housing, electricity, agricultural land, and resources are worse off in terms of asset holdings and other living standard indicators. We will analyse this further in the robustness check and discussion sections.

4.3 Robustness checks

In this section, we will present the sensitivity analyses, the balance of covariates, and the overidentification tests related to the results. We also discuss some results from other estimators and compare them with our main IPWRA one.

Regarding the human support results, the sensitivity breakdown point for the MPI estimation is 0.138 (Table 6) signalling a good insensitivity to unobserved confoundedness.[5] To actually see the meaning of this value, we need to compare it to the propensity score of the observed covariates in Table 10. The quantiles in this table are the proxies used to calibrate the relaxation levels of the unconfoundedness assumption (Masten and Poirier 2018; Masten et al. 2024).

As the breakdown point for the ATET on MPI is at 0.138, we can see that it is larger than all propensity score values of covariates at the 90th percentile, except for *Escapee* and

[5] For reference, Masten et al. (2024) calculated the c_{BP} of both an experimental dataset and an observational dataset from LaLonde (1986). The former weighted at 0.082 and the latter at 0.037.

Table 11 Covariate-balance summary statistics of human support

	Raw		IP Weighted		NN Matched		PS Matched	
	Std. diff.	Var. ratio	Std. diff.	Var. ratio	Std. diff.	Var. ratio	Std. diff.	Var. ratio
Education	0.208	1.070	−0.013	0.862	0.064	1.403	−0.009	1.495
Age	−0.268	0.548	−0.015	0.999	0.031	1.177	−0.084	1.086
Age × Age	−0.301	0.386	−0.013	1.073	0.049	1.355	−0.063	1.095
Health	−0.222	1.404	0.005	1.184	−0.105	1.177	−0.056	1.111
Dependent ratio	0.175	0.761	0.050	0.866	0.054	1.182	0.070	1.000
No. of members	0.178	0.802	0.065	0.840	0.079	1.283	0.182	1.174
Poverty group								
Near poor	−0.169	0.903	−0.005	0.996	0.000	1.000	−0.103	0.932
Escapee	−0.369	0.494	−0.001	0.997	0.000	1.000	0.069	1.224
Union(s)	0.617	1.378	−0.036	1.005	0.000	1.000	−0.148	1.037
Near poor × Union(s)	0.158	1.345	−0.005	0.993	0.000	1.000	−0.192	0.780
Escapee × Union(s)	0.115	1.481	−0.001	0.997	0.000	1.000	0.064	1.227
No. of observations	1,197		1,197.0		820		820	
Treated observations	410		598.4		410		410	
Control observations	787		598.6		410		410	
Overidentification test								
Chi2(12)	12.810							
Prob > Chi2	0.383							
Overidentification test (base covariates)								
Chi2(9)	11.662							
Prob > Chi2	0.233							

IP Weighted: Inverse probability weighted; NN Matched: Nearest neighbour matched; PS Matched: Propensity score matched

Std. diff.: Standardised difference; Var. ratio: Variance ratio

Participate in union(*s*). Thus, we looked closer to these two's kernel density estimate of the absolute difference between the propensity score and the leave-out-variable-*k* propensity score for *k* being *Escapee* and *Participate in union*(*s*). These density plots can be seen in Section 6 (Appendix Figs. 7 and 8). Looking at the plot of *Participate in union*(*s*), we can see that there is a small proportion of units who have values larger than the breakdown point of 0.138 while the distribution of propensity score difference for *Escapee* falls mostly below the breakdown. We analysed the effect of leaving out this variable from our estimators; this procedure is adopted from Masten et al. (2024). We calculate the ATET of human support using all the specified observed confounders and covariates except for *Participate in union*(*s*) and get the point estimate of $ATET_{-k} = -0.040$. Then we calculate the effect of omitting it on the ATET point estimand as $\left|\frac{ATET - ATET_{-k}}{ATET}\right|_{\%} = 1.17\%$. Since omitting *Participate in union*(*s*) only changes the ATET point estimate by around 1.17%, it is reasonable to disregard this one and conclude that our ATET estimation is robust for the effect of human support.

Similarly, for the poverty incident estimation with human support, we have a breakdown point c_{BP} of 0.081, higher than all propensity score values of covariates at the 75th percentile, except for *Escapee* and *Participate in union*(*s*). From the previous procedure, we can

Table 12 Covariate-balance summary statistics of living support

	Raw		IP Weighted		NN Matched		PS Matched	
	Std. diff.	Var. ratio	Std. diff.	Var. ratio	Std. diff.	Var. ratio	Std. diff.	Var. ratio
Borrowing	0.546	1.087	−0.031	1.013	0.095	0.972	−0.083	1.041
Unstable housing	−0.376	1.072	−0.068	0.991	0.013	1.003	−0.054	0.992
Dependent ratio	0.205	1.135	0.043	1.078	0.021	1.070	0.038	1.047
No. of members	−0.080	1.402	0.033	1.444	0.045	1.350	0.029	1.168
Dependent ratio × No. of member	0.076	1.163	0.056	1.358	0.055	1.270	0.030	1.232
Poverty group								
Near poor	−0.702	0.403	−0.019	0.953	0.000	1.000	0.068	1.204
Escapee	−0.528	0.286	0.022	1.093	0.000	1.000	−0.029	0.895
Union(s)	0.025	1.036	−0.050	0.947	0.000	1.000	0.031	1.039
Near poor × Union(s)	−0.363	0.284	−0.017	0.918	0.000	1.000	0.000	1.000
Escapee × Union(s)	−0.108	0.618	0.028	1.163	0.000	1.000	0.083	1.644
No. of observations	936		936.0		298		298	
Treated observations	149		469.9		149		149	
Control observations	787		466.1		149		149	
Overidentification test								
Chi2(11)	11.631							
Prob > Chi2	0.392							
Overidentification test (base covariates)								
Chi2(8)	11.044							
Prob > Chi2	0.199							

IP Weighted: Inverse probability weighted; NN Matched: Nearest neighbour matched; PS Matched: Propensity score matched

Std. diff.: Standardised difference; Var. ratio: Variance ratio

also claim that our ATET estimation for the effect of human support for being under the multidimensional poverty line is robust to unobserved unconfoundedness. For the component estimations (Table 8), the sensitivity breakdown points of two significant estimates are 0.039 for *Education* and 0.021 for *Health*. Compared with the values from Table 10, only the ATET estimations of human support on *Education* are robust with relaxation at the 50th percentile, while those for *Health* are not. Therefore, even though we found a causal effect of human support on households' health, the evidence from just the IPWRA estimator is not yet robust.

Because of that, we also used other estimators, including nearest-neighbour matching and propensity score matching, to see the consistency of the results. From columns (7) and (8) of Appendix Table 18, we can see that human support can significantly reduce the health deprivations of households by 7.7%–8.9%, which is quite different from the result from IPWRA. Moreover, from Table 11, we can see that inverse probability weight results in better covariates balance[6] than NN match and PS match; also, the overidentification tests of IP weight are valid ($p-value > 0.05$ implying that covariates are balanced for this estimator). Therefore, we can conclude that although there is evidence that human support can reduce households' health deprivations, this evidence is not strong in our study.

[6] As the standard difference between these two groups is closest to 0 and the variance ratio is closest to 1 compared with the NN match or PS match.

Table 13 Variation in leave-out-variable-k propensity score, living support sample

Quantile	0.500	0.750	0.900	Max
Near poor	0.047	0.111	0.152	0.360
Escapee	0.030	0.091	0.191	0.459
Participate in union(s)	0.001	0.013	0.019	0.080
Near poor x Participate in union(s)	0.003	0.008	0.016	0.045
Escapee x Participate in union(s)	0.004	0.016	0.039	0.175
Borrowing	0.049	0.099	0.129	0.187
Unstable housing	0.051	0.095	0.154	0.221
Dependent ratio	0.004	0.011	0.025	0.137
No. of member	0.001	0.002	0.006	0.021
Dependent ratio x No. of member	0.002	0.005	0.012	0.046

Regarding the effect of living support, from Table 7, we can see that the sensitivity breakdown points for both estimates are much lower than that from Table 6. With $c_{BP} = 0.046$, the estimator cannot be considered robust even at the 50th percentile of unconfoundedness assumption relaxation because c_{BP} is smaller than the leave-out-variable-k propensity score of multiple covariates, all of which cannot be left out of the estimator since that will make a huge difference to the ATET result. Similarly, with a sensitivity breakdown point of 0.015, the result on the effect of living support on multidimensional poverty incidents is also not robust for our IPWRA estimator. With the same approach as with human support results, we also estimated the living support effect with other techniques (Appendix Tables 16 and 17). Although all estimators resulted in negative coefficients, their magnitudes largely varied. Even when the balance and overidentification tests from Table 12 show that our specification is decent across estimators, there are still unobserved covariates that we cannot include. Therefore, although there are signs of living support's effect on multidimensional poverty, the results are not strongly convincing.

In terms of the living support effect on four MPI components, we see two significant ones: a large reduction in health deprivation and a slight increase in living standard deprivation. Regarding the former, this estimate has a sensitivity breakdown point of 0.112 (Table 7), indicating robustness to confoundedness. Indeed, combined with the propensity scores from Table 13, our estimate can satisfy the assumption at the 75th percentile. Other estimators for the health-living support nexus also show significance with approximately equal magnitudes (Appendix Table 19). On the other hand, the adverse effect seen from the IPWRA estimator between living standard and living support is not assisted by other estimators. Moreover, with $C_{BP} = 0.010$, this estimator is not robust to the violation of the unconfoundedness assumption.

5 Discussions

Under this study, it has been proved that beneficiaries of governmental human and living support enjoy a reduction in their multidimensional poverty, as measured by both MPI and the incidence of households falling under the multidimensional poverty line. This is made possible by its alleviation effect on their health and education deprivations, while that on job and living standard deprivations remains elusive. These findings are partially in line with the findings of Chowdhury and Mukhopadhaya (2012), Pan et al. (2021b), Borga and D'Ambrosio

(2021), Fiszbein and Schady (2009), and Giang and Nguyen (2017), who advocate for the positive impact of certain types of support on the multidimensional poverty status of the poor.

Aligning with the theoretical background, we find that human support can reduce households' deprivation in education. That effect on health is also found with weaker evidence. On the other hand, living support only appears to improve households' health conditions. These are channels through which current support policies can reduce multidimensional poverty in Vietnam. In terms of education improvement, within the data of this study, we show that government support can improve one of two items of this dimension: school attendance. As multiple policies in the human support category make cash transfers to households, they have more resources to invest in their children. Combined with a policy to waive tuition fees, the opportunity cost of not sending children to school increases, which leads to higher enrolment. Regarding health, insurance possession can improve directly from two of the listed policies, while improving nutrition might come indirectly via increasing income, as suggested by Borga and D'Ambrosio (2021).

One of our interesting results is the positive effect of living support, which include land allocation and production resources provision, on health. One possible channel might be increasing agricultural products from home-farming, which increases households' self-sufficient food consumption. This argument is supported by the background of our studied areas, where people often consume what they grow, and by the fact that there is not yet evidence of the poor benefiting job-wise from current supports. This means support policies are effective in increasing household agriculture production, but not yet enough to push them towards non-farm jobs or wage occupations, as observed by Balboni et al. (2021) and Banerjee et al. (2021).

Another interesting result comes from the living standard component. We found no effect of either human support or living support on the improvement of households' living standards. This is because the items making up the measurement of this component in MPI are not directly influenced by current support, or if indirectly, due to a lack of panel data, we are unable to explore yet. Indeed, there are policies that transfer production assets to households, but these are not counted towards the asset holdings of households, which include automobiles or electrical equipment. Other aspects, such as clean water, electricity, or the Internet, often depend on the public infrastructure, and the poor do not have the adequate resources to access them. There are also policies supporting poor households to build stable houses with basic access to water and electricity, but there might possibly be delays between being enlisted for support and actual implementation.

However, there are three points in our results that should be noted. First, based on the empirical evidence, households see a significantly large improvement in their poverty status, which is made possible by reductions in some of the deprivation components. However, it is impossible from these results to conclude that the poor can get out of poverty via these supports, as we have not further studied their persistent effects. As presented in subsection 2.4, increases in income, consumption, asset holdings, healthcare, and school enrolment can come early with the receipt of interventions. Yet, whether or not the poor can escape the poverty trap depends on their transitions towards better occupations, which often comes clear 3 years after interventions (Banerjee et al. 2021).

Second, it is unambiguous that the recipients of support will directly benefit from what was given to them. Households' income and consumption will increase upon receiving cash transfers; their food security will improve if they are beneficiaries of food safety net programmes; and their children's health and schooling will improve if those programmes focus on delivering these public services. Therefore, it is important to have a clear view of what has been delivered and what the objectives are. Mistaking this will lead to faulty assessments and implementations of support policies.

Third, this study seeks to determine whether households' multidimensional poverty situation is alleviated if they receive support, as opposed to focusing on the impact of how many benefits households have received or how long households have received those benefits. Likewise, the purpose of this research is not to conduct a detailed analysis of the effects of a single type of support or programme on poverty reduction but rather to gain a more holistic understanding of the interdependent effects of two categories of support, including human support and living support. The reason this issue is interesting is due to the complex context of development policy implementation in Vietnam, as presented in subsection 2.1. The setting of mistargeting and policy profiteering makes it difficult for effect evaluation. Therefore, this paper is not an endline assessment of the listed policies, but it attempts to suggest more systematic approaches to studying their effects.

6 Policy implications and conclusion

The analysis of data collected on the multidimensional poverty and deprivation status of 1,538 mountainous, ethnic households reveals that governmental support for human capital fosterage and production facilitation assists households in escaping multidimensional poverty. Nonetheless, it is noteworthy that governmental support does not mitigate all of the deprivations suffered by the poor. The alleviation impact of human assistance is observed in education and health deprivations, but the effect of living support is limited to health deprivation. Employment and living standard deprivations appear to be untapped by the influence of assistance initiatives. The results indicate that despite their coverage extension and initial success, the effect of governmental support is still limited, indicating shortcomings in the design of support policies and corresponding programmes.

Given the above context, this study offers policymakers some recommendations. First, poverty-supporting measures must be more precisely targeted at the poor to avoid leakage and under-coverage. Mis-targeting will reduce the efficiency of support and deter adjustment efforts for these policies. Second, in addition to general knowledge education and training, policymakers must pay more attention to the training of specialised knowledge and skills necessary for the development of production in their locality or for an occupation shift. In other words, education and training programmes must be more comprehensive in order to increase the employability of the poor. Last but not least, the findings of this study necessitate ongoing evaluation and enhancement of support policies and programs. Policymakers should regularly evaluate the efficacy of their initiatives and be willing to make adjustments based on new information and input.

The study has inescapable drawbacks, the first of which is the absence of longitudinal data. This prevents the study's findings from studying the longer-term effects of these two types of support. This necessitates future research utilising panel data to explain this problem. In addition, classifying different kinds of support into two big groups is both a boon and a bane. Although this study gives a general overview of the effectiveness of human support and living support in decreasing multidimensional poverty, it does not delve into each support type or programme to determine which support types or programmes are efficient and which need to be modified or abolished. The subsequent studies may develop upon our study designs, but they should go further into the effect analysis of each type or programme of support in order to provide more in-depth insights.

Appendix 1

Table 14 Effect of human support on MPI, other estimators

	(1) RA	(2) NN-Match	(3) PS-Match	(4) Fractional probit
ATET Human support	−0.038***	−0.044***	−0.049***	−0.046***
	(0.007)	(0.011)	(0.011)	(0.007)
Potential outcome mean				
Human support (0)	0.332*** (0.007)			
Outcome covariates	Yes	No	No	Yes
Treatment covariates	No	Yes	Yes	Yes
Observations	1197	1197	1197	1197
Outcome mean	0.328	0.328	0.328	0.328
Sensitivity breakdown	0.138	0.138	0.138	0.138

Robust standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 15 Effect of human support on being multidimensionally poor, other estimators

	(1) RA	(2) NN-Match	(3) PS-Match	(4) Probit
ATET Human support	−0.085**	−0.122**	−0.134***	−0.174***
	(0.034)	(0.052)	(0.049)	(0.040)
Potential outcome mean				
Human support (0)	0.474*** (0.029)			
Outcome covariates	Yes	No	No	Yes
Treatment covariates	No	Yes	Yes	Yes
Observations	1197	1197	1197	1197
Outcome mean	0.496	0.496	0.496	0.496
Sensitivity breakdown	0.081	0.081	0.081	0.081

Robust standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 16 Effect of living support on MPI, other estimators

	(1) RA	(2) NN-Match	(3) PS-Match	(4) Fractional probit
ATET Living support	−0.045***	−0.045***	−0.047***	−0.079***
	(0.011)	(0.016)	(0.018)	(0.029)
Potential outcome mean				
Living support (0)	0.367*** (0.010)			
Outcome covariates	Yes	No	No	Yes
Treatment covariates	No	Yes	Yes	Yes
Observations	936	936	936	936
Outcome mean	0.342	0.342	0.342	0.342
Sensitivity breakdown	0.046	0.046	0.046	0.046

Robust standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 17 Effect of living support on being multidimensionally poor, other estimators

	(1) RA	(2) NN-Match	(3) PS-Match	(4) Probit
ATET Living support	−0.169***	−0.124*	−0.124*	−0.355**
	(0.046)	(0.064)	(0.064)	(0.151)
Potential outcome mean				
Living support (0)	0.618*** (0.034)			
Outcome covariates	Yes	No	No	Yes
Treatment covariates	No	Yes	Yes	Yes
Observations	936	936	936	936
Outcome mean	0.536	0.536	0.536	0.536
Sensitivity breakdown	0.015	0.015	0.015	0.015

Robust standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 18 Effect of human support on MPI components, other estimators

	(1) Job	(2) Job	(3) Education	(4) Education	(5) Living standard	(6) Living standard	(7) Health	(8) Health
ATET Human support	0.021	−0.013	−0.050**	−0.034*	−0.058***	−0.073***	−0.089***	−0.077***
	(0.015)	(0.021)	(0.021)	(0.020)	(0.016)	(0.015)	(0.030)	(0.029)
Outcome covariates	No	No	No	No	No	No	No	No
Treatment covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1197	1197	1197	1197	1197	1197	1197	1197
Outcome mean	0.132	0.132	0.459	0.459	0.447	0.447	0.274	0.274
Sensitivity breakdown	0.010	0.010	0.039	0.039	0.049	0.049	0.021	0.021

(1), (3), (5), and (7) are from NN Match. (2), (4), (6), and (8) are from PS Match

Robust standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 19 Effect of living support on MPI components, other estimators

	(1) Job	(2) Job	(3) Education	(4) Education	(5) Living standard	(6) Living standard	(7) Health	(8) Health
ATET Living support	0.001	0.004	0.005	0.000	0.008	0.005	−0.195***	−0.196***
	(0.020)	(0.025)	(0.022)	(0.024)	(0.019)	(0.017)	(0.044)	(0.044)
Outcome covariates	No	No	No	No	No	No	No	No
Treatment covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	936	936	936	936	936	936	936	936
Outcome mean	0.139	0.139	0.489	0.489	0.452	0.452	0.288	0.288
Sensitivity breakdown	0.003	0.003	0.013	0.013	0.010	0.010	0.112	0.112

(1), (3), (5), and (7) are from NN Match. (2), (4), (6), and (8) are from PS Match

Robust standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

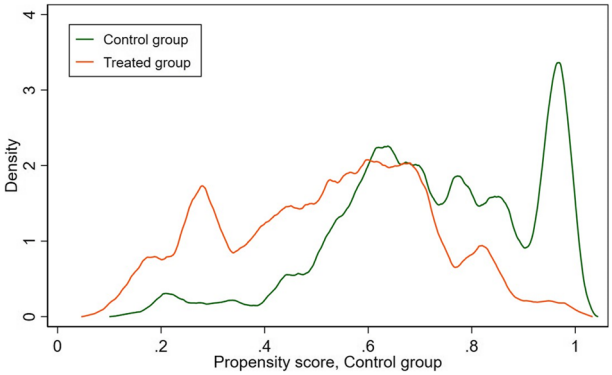

Fig. 3 Human support inverse probability weighting overlap plot

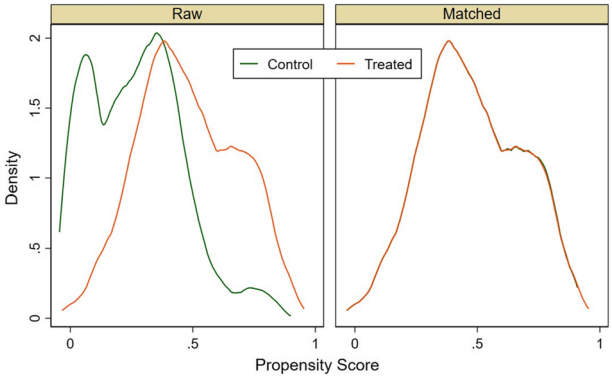

Fig. 4 Human support propensity score matching balance plot

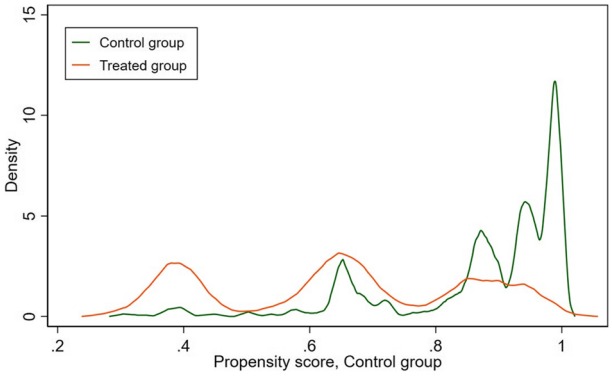

Fig. 5 Living support inverse probability weighting overlap plot

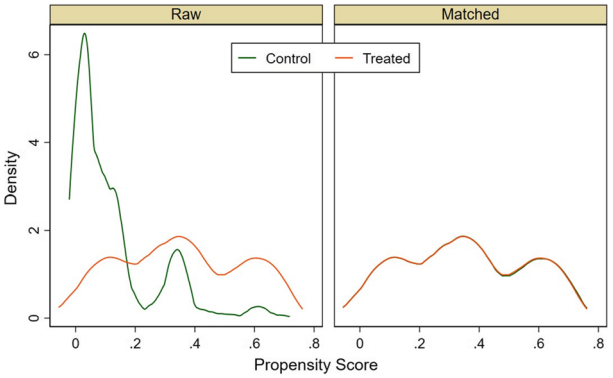

Fig. 6 Living support propensity score matching balance plot

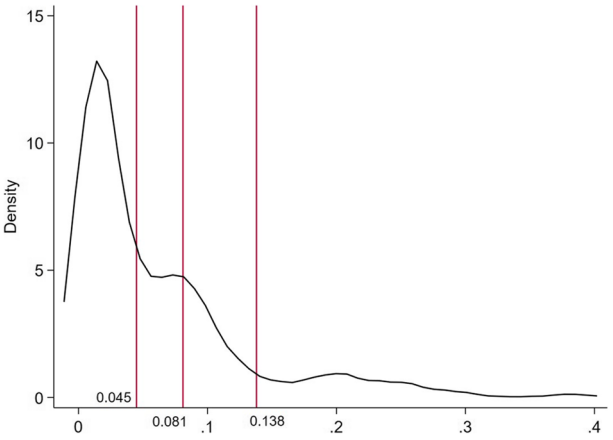

Fig. 7 Kernel density estimate of the absolute difference between propensity score and leave-out-variable-k propensity score for $k = Escapee$, Human support dataset

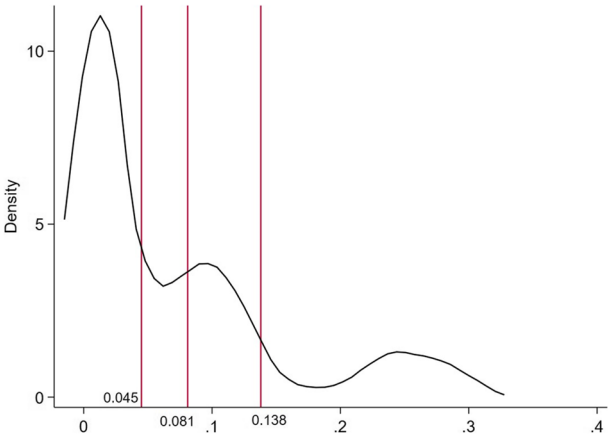

Fig. 8 Kernel density estimate of the absolute difference between propensity score and leave-out-variable-k propensity score for $k = Participate\ in\ union(s)$, Human support dataset

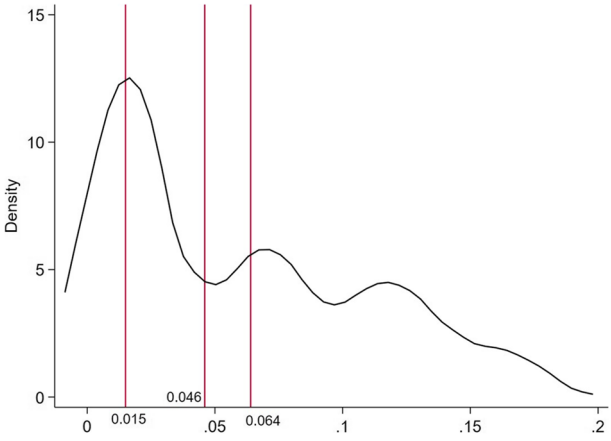

Fig. 9 Kernel density estimate of the absolute difference between propensity score and leave-out-variable-k propensity score for *k* = *Borrowing*, Living support dataset

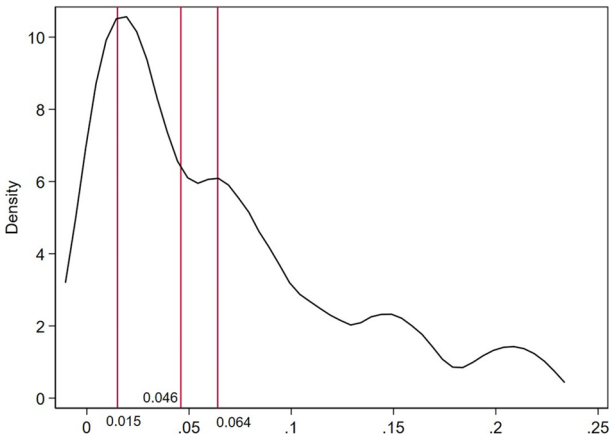

Fig. 10 Kernel density estimate of the absolute difference between propensity score and leave-out-variable-k propensity score for *k* = *Unstable housing*, Human support dataset

Appendix 2

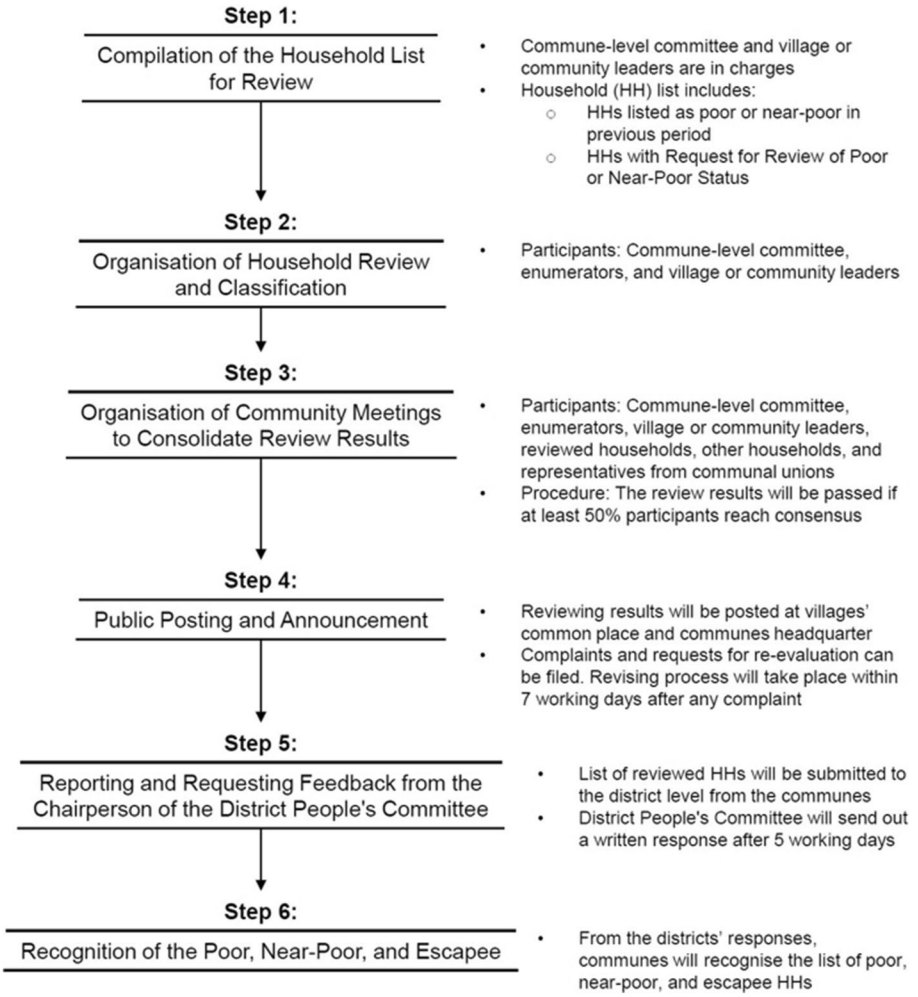

Fig. 11 Process of Periodic Review of Poor and Near-Poor Households

Table 20 Number of households receiving support

		Human support		Total
		Yes	No	
Living support	Yes	192	149	341
	No	410	787	1197
Total		602	936	1538

Determinants of receiving human support

$$\begin{aligned} Pr(Humansupport = 1|X) = \Phi(&\beta_{H0} + \beta_{H1}Education + \beta_{H2}Age + \beta_{H3}Perceveivedhealth \\ &+ \beta_{H4}Dependantratio + \beta_{H5}No.ofmember + \beta_{H6}Povertygroup \\ &+ \beta_{H7}Participateinunion(s) + \beta_{H8}Age^2 + \beta_{H9}Povertygroup \\ &\times Participateinunion(s)) \end{aligned} \tag{6}$$

Determinants of receiving living support

$$\begin{aligned} Pr(Livingsupport = 1|X) = \Phi(&\beta_{L0} + \beta_{L1}Borrow + \beta_{L2}Unstablehousing + \beta_{L3}Dependantratio \\ &+ \beta_{L4}No.ofmember + \beta_{L5}Povertygroup + \beta_{L6}Participateinunion(s) \\ &+ \beta_{L7}Povertygroup \times Participateinunion(s)) \end{aligned} \tag{7}$$

Simple differences in mean outcomes and heterogeneous treatment effect bias

Let's first look at the decomposition of the simple difference in mean outcomes (SDO) when we estimate the average treatment effect:

$$SDO = E\left[Y^1|D = 1\right] - E\left[Y^0|D = 0\right]$$

in which $Y^1|D = 1$ is the observed outcome of the treated group and $Y^0|D = 0$ is that for the control group.

Including the unobserved potential outcomes $Y^1|D = 0$ and $Y^0|D = 1$, we have the average treatment effect:

$$ATE = \left\{\pi Y^1\middle|D = 1 + (1-\pi)Y^1\middle|D = 0\right\} - \left\{\pi Y^0\middle|D = 1 + (1-\pi)Y^0\middle|D = 0\right\}$$

in which π is the share of treated group over the sample.

With some simple manipulations of the above identities, we have:

$$SDO = ATE + E[Y^0|D = 1] - E[Y^0|D = 0] + (1-\pi)(ATET - ATEU)$$

with $ATET = E[Y^1|D = 1] - E[Y^1|D = 0]$ and $ATEU = E[Y^0|D = 1] - E[Y^0|D = 0]$ are, respectively, average treatment effect on the treated and average treatment effect on the untreated.

Thus, we can see that SDO is a biased estimator of the ATE since it contains $E[Y^0|D = 1] - E[Y^0|D = 0]$ which is referred to as selection bias, and (ATET – ATEU) which is heterogeneous treatment effect bias.

Similarly, in our case of estimating the treatment effect on the treated, the estimate will be biased by the $ATEU - \frac{ATE}{(1-\pi)}$ which is the difference between the average treatment effect on the untreated and the average treatment effect of the whole sample. Basically, since this difference occurs due to the different nature of treatment groups, we can still call it heterogeneous treatment effect bias.

Empirically, this means that the coefficients we get from regressing the outcome on the treatment variable and other covariates will be biased since they do not reflect the difference among the means of the treated, untreated, and whole sample. This comes from the fact that treatments are not assigned randomly. The adjustment for this will be

to interact the treatment variable with every covariate included and regress the outcome on these interactions. This practice is called regression adjustment. It will account for the fact that the contribution of each covariate to the variance of the outcome differs among treated groups.

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All errors remain our own.

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Declarations

Competing interests The authors declare no competing interests.

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