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Give a Fish or Teach to Fish? Poverty Alleviation Effect of Government Support Policies and Self-Help Commercial Activities

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ABSTRACT *This study explores the interactive effect of self-help efforts, specifically through household decisions to engage in commercialisation, and external supports provided via government antipoverty policies, on poverty reduction among poor households in northern Vietnam. With observational data from 1383 surveyed households, we use an estimation strategy combining inverse probability weighting, regression adjustment, and two-stage least squares to address selection bias and omitted variable bias in two variables of interest. We find that while these two interventions are individually effective in alleviating poverty, their combination is not necessarily as effective. Our results show that commercialisation only reduces poverty among non-supported households, while government supports are more effective among non-commercial households. This substitution of effects comes from the nature of support targeting and commercialisation. Households receiving supports often have lower capacity, making commercialisation ineffective or even impossible. Furthermore, current support policies are insufficient to enhance the impact of commercialisation. These results suggest that there could be more effective ways to combine external interventions and self-help efforts to better alleviate poverty.*

KEYWORDS: Commercialisation; anti-poverty policy; multidimensional poverty

> Give a man a fish, and you feed him for a day.
>
> Teach a man to fish, and you feed him for a lifetime. – Proverb

1. Introduction

Recent years have seen a halt in the decades-long decline in global poverty (World Bank, 2017, 2022), highlighting the need for a deeper understanding of how self-sustaining activities and

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governmental support can effectively work together to reduce poverty. Despite consensus on the effectiveness of these methods, their interplay remains unclear, underscoring the importance of further research to develop sustainable poverty-eradication strategies. When it comes to poverty eradication activities at the individual level, one of the self-reliant efforts to reduce poverty is commercialisation, marking the active progress of the poor from subsistence to market and profit orientation (Pingali & Rosegrant, 1995; von Braun, Kennedy, et al., 1994). Commercialisation is postulated to increase household productivity (Barrett, 2008; Tipraqsa & Schreinemachers, 2009), employment (von Braun, 1995), and asset accumulation rates (Poulton, 2017). Given this, the extant literature is well-established by empirical evidence proving the positive effects of commercialisation and market participation on farming households' welfare, measured either by income (Barrett et al., 2012; Bellemare, 2012; Muriithi & Matz, 2015; Rao & Qaim, 2011; Tipraqsa & Schreinemachers, 2009) or by multidimensional poverty and asset holdings (Birhanu, Tsehay, & Bimerew, 2021; Ogutu & Qaim, 2019; Tabe Ojong, Hauser, & Mausch, 2022).

However, as commercialisation requires a certain level of capacity, opting for commercialisation is not an arbitrary decision that every household can make (Poulton, 2017; Saha, Sabates-Wheeler, & Thompson, 2021). In hindsight, this forms a partial poverty trap, where households below a relative threshold do not have access to the market (Banerjee & Duflo, 2011;Barrett, 2008). Support policies, therefore, are introduced to help them escape this trap. In our study area of North Vietnam, the two most common anti-poverty policies are (1) human support regarding health, education, or production training, and (2) living support, including house construction, living expenses coverage, or productive in-kind transfers. The effectiveness of these policies has been widely discussed in previous papers using different methods and yielding various outcomes (Banerjee & Duflo, 2011; Hoang-Duc, Nguyen-Thu, Nguyen-Anh, et al., 2024; Imai, Arun, & Annim, 2010; King et al., 2009; Qin & Chong, 2018; Nguyen-Anh, Hoang-Duc, Le-Ngoc, & Nguyen, 2022). In interaction with commercialisation, it is postulated that certain policies can 'enhance the social welfare effect of commercialisation' (von Braun, 1995), while others can stimulate the transition process itself (Pingali, 1997;von Braun, 1995). This is also mentioned in more recent research by Tabe Ojong et al. (2022) and Saha et al. (2021). On the other hand, support policies are also required to address potential adverse effects of commercialisation, such as food security risks (von Braun, 1995) or increasing inequality (Ogutu & Qaim, 2019). Commercialisation can also affect the efficiency of these policies. Barrett (2008) suggested that in more market-integrated areas, policies may work better.

Despite the existence of the aforementioned arguments, there have been few empirical studies on this relationship. Therefore, this paper fills the gap by elucidating the link between governmental anti-poverty support and self-reliant commercialisation activities, as well as their joint effects on the welfare of the poor.

However, the inclusion of support policies or commercialisation in each other's nexus with households' welfare is not a simple addition of variables, as they may be subject to endogeneity and selection bias when households with certain characteristics are more likely to commercialise and have a higher chance of receiving support. This paper addresses the dual problem of commercialisation endogeneity and support policy selection bias using matching with inverse probability weighting (IPW) and instrumental variables (IVs). This approach allows us to more clearly identify the treatment effect of commercialisation and its synergy with that of support policies. We found that, overall, commercialisation helps reduce households' multidimensional poverty index (MP index). However, the strength of these effects is not enhanced by the introduction of support policies, including living support and human support. Yet, there are heterogeneous effects between these two support groups: while living support increases commercialisation participation, human support does not have the same effect. The effects of commercialisation and human support on the MP index are compatible, but the presence of both does not significantly reduce households' MP index. The results also indicate that commercialisation can be stimulated via living support, but for it to be efficient, households need support that improves human capacity.

Most empirical studies on the subject, particularly concerning the study approach, focus on income-based poverty analysis, which has been criticised for failing to offer a comprehensive picture of household well-being (Falkingham & Namazie, 2002). The monetary approach to poverty neglects fundamental aspects of individual welfare, such as education and infrastructure, as well as the complex linkage between income and the satisfaction of basic needs among the poor (Meemken, Spielman, & Qaim, 2017; Ogutu & Qaim, 2019). In the literature, the assumption that the latter is the objective of the former has led to the growing substitution of income-based poverty measures with the MP index. The MP index is considered a more accurate measure of poverty due to its capacity to measure both the incidence and intensity of deprivations experienced by the poor (UNICEF, 2021). This measurement identifies the root causes of poverty, enabling the poor to overcome it without outside assistance (Alkire & Foster, 2011; Alkire & Santos, 2014). This allows for sustainable poverty alleviation, as top-down initiatives may be ineffective due to location and other factors, making scaling up challenging (Banerjee & Duflo, 2011).

The rest of this paper is organised as follows. In Section 2, we discuss and propose a conceptual framework on households' commercialisation decisions and supports assigned based on their livelihood assets. Section 3 describes the study areas, contexts, and the measurement of the MP index and commercialisation. Matching techniques and treatment effect identification are discussed in Section 4. Section 5 reports and discusses the estimation results, and Section 6 concludes the paper.

2. Conceptual framework

2.1. Effects of commercialisation, government policies, and their combination

Commercialisation within agriculture serves as a potent mechanism for poverty reduction, operating through multifaceted pathways that encompass both exogenous and endogenous dynamics. Exogenously, the process of commercialisation is propelled by factors such as population shifts, technological advancements, and policy interventions, which stimulate farmers' integration into markets (Muriithi & Matz, 2015;von Braun, 1995). Enhanced access to new technologies and infrastructural investments amplifies agricultural productivity and market participation, thereby augmenting total factor productivity and fostering increased market transactions (Cazzuffi, McKay, & Perge, 2020;Ogutu & Qaim, 2019). Simultaneously, endogenous consequences manifest within households, shaping resource allocation, decision-making dynamics, and intra-household distribution patterns (Tabe Ojong et al., 2022;von Braun, 1995). As commercialisation unfolds, households reallocate income towards food and non-food consumption, thus addressing basic needs and improving living standards (Ogutu, Gödecke, & Qaim, 2020;von Braun, 1995). Moreover, the income gains derived from commercialisation contribute to human capital formation, particularly in terms of education and health investments, which fortify long-term welfare outcomes (Ogutu & Qaim, 2019; von Braun, 1995). While commercialisation predominantly influences income poverty, its effects extend to multidimensional poverty dimensions, albeit with varying magnitudes. Studies underscore the heterogeneous nature of these impacts, with nuanced results emerging from cross-sectional and panel data analyses. Particularly, cross-sectional analyses often reveal positive associations between commercialisation and household welfare indicators, indicating that increased participation in commercial agriculture is generally beneficial for poverty alleviation (Ogutu & Qaim, 2019). However, panel data uncover a spectrum of outcomes, showing that while some households experience significant improvements in welfare due to commercialisation, others may not reap the same benefits or may even face adverse consequences (Birhanu et al., 2021; Carletto, Corral, & Guelfi, 2017; Cazzuffi et al., 2020; Muriithi & Matz, 2015).

Governmental anti-poverty support programmes play a pivotal role in mitigating the poverty trap and uplifting the socio-economic status of the poor (Balboni, Bandiera, Burgess, Ghatak, & Heil, 2022; Ghatak, 2015; Hoang-Duc, Nguyen-Thu, Nguyen-Anh, et al., 2024). These programmes encompass targeted transfers, social work, and social protection initiatives aimed at redistributing resources to disadvantaged populations. Social protection programmes offer monetary aid or non-cash benefits to disadvantaged households, improving their ability to obtain necessary products and services. Unconditional transfer programmes enhance disposable income, resulting in increased spending, asset accumulation, and food security, while conditional transfer programmes, elicit favourable behavioural modifications and improve welfare indicators (Blattman, Fiala, & Martinez, 2014; Ghatak, 2015). These programmes help individuals shift from temporary jobs to more secure self-employment prospects in agriculture or small businesses (Balboni et al., 2022;Banerjee & Duflo, 2011). Additionally, social protection programmes act as a safety net for vulnerable populations, cushioning them from adverse shocks and providing vital support during times of need (Borga & D'Ambrosio, 2021). Consequently, individuals living in extreme poverty are the most affected by these programmes, as they derive the greatest benefit from them over a longer period (Banerjee, Duflo, & Sharma, 2021;Borga & D'Ambrosio, 2021). By enhancing household income, consumption, and access to essential services, these programmes contribute to multidimensional poverty alleviation, ultimately fostering sustainable pathways out of poverty for the most marginalised segments of society.

Regarding the interaction between commercialisation and anti-poverty support policies, the extant literature reveals a limited number of studies. Among these, researchers often posit a positive complementary effect of this combination on the outcomes for the poor. von Braun (1995) postulated that certain policies can enhance the social welfare effects of commercialisation or stimulate the transition process from subsistence farming households to commercial production ones. This implies that the right policies can improve the effects of commercialisation both through its intensive and extensive margins. Pingali (1997) further adds that, at the macro level, policies facilitating trade liberalisation can accelerate the commercialisation process. However, an important role of policies is to mitigate the problems that arise during the mass transition towards commercialisation, which can lead to unsustainable growth. On a smaller scale, Saha et al. (2021) emphasises the role of targeted supports for those with lower capacity to transition to commercialisation. This is because commercialisation is associated with higher risks, which can worsen the situation of poor households with lower capacity. (Ogutu & Qaim, 2019) and Tabe Ojong et al. (2022) also highlight the issue of increasing inequality among poor households due to potential unequal gains from commercialisation and indicate that policies need to address this among the poor. These studies provide conceptual arguments that policies can either promote commercialisation or mitigate its potential adverse social consequences. Conversely, commercialisation may also affect policy efficiency. Barrett (2008) suggested that in more market-integrated areas, anti-poverty policies can be more effective due to lower barriers to reach. However, this claim is limited to market policies related to price or trade regulation rather than to anti-poverty policies.

2.2. Confounders selection

We devote the remainder of this section to the conceptual framework for selecting confounders to addresstheendogeneityofcommercialisationandtheselectionbiasofsupportpolicies. Previous studies analysing the effects of commercialisation or support policies on household welfare have all had to address the issue of endogeneity or selection bias. In short, commercialisation is not a random decision, and support policies are not randomly assigned to households due to their differing characteristics and resources. These factors might also affect household welfare, thereby confounding the actual treatment effects on the outcomes of interest.

According to Poulton (2017), commercialisation occurs when production output exceeds expectations and resources are allocated for commercial operations. For this to happen, households must retain sufficient amounts of land, physical capital, and financial capital. Additionally, households' connectedness and the gender of heads may also influence the decision to commercialise. Research by Awotide, Karimov, and Diagne (2016) and Birhanu et al. (2021) found that market participation is influenced by factors beyond IVs, such as motorbike ownership, the presence of salespeople, and market distance. In their panel data study, Muriithi and Matz (2015) used a fixed-effects model to account for household heterogeneity and welfare differences. According to Saha et al. (2021) and Barrett et al. (2012), households with greater resources, skills, and motivation tend to self-select towards commercialisation and reap its benefits.

The same issue, often referred to as selection bias, can be observed when households are targeted to receive anti-poverty support policies. These supports are not assigned to households at random but based on a set of criteria and characteristics that reflect their welfare (Imai et al., 2010; Ravallion, 2007). This practice of targeting policies is a result of efforts to help the right people with the right amount. However, it is almost impossible to assess the effectiveness of policies by simply comparing the treated and untreated groups. Therefore, previous studies have adopted counterfactual causality estimation to address issues with observational data (Harding, 2003; Imai et al., 2010; Michler & Josephson, 2017; Qin & Chong, 2018). Yet, one of the biggest difficulties with this approach is selecting a set of observables that can conceptually explain which household receives which support.

Given this, we conceptualise a framework to guide our further analyses in this study. In this framework, the decision to commercialise is influenced by households' assets and capacity, which also affect their outcome, the MP index. To identify the effect of commercialisation on welfare, we need to block these backdoor paths. Based on these assets and capacities, local authorities also provide poor households with governmental supports, including human support and living support. Therefore, although not exhaustive, this framework provides a foundation for partially addressing reverse causality, where supports are targeted to households with lower MP indices. To achieve this, we select a set of variables as determinants of commercialisation and another set as eligibility criteria for receiving supports. Previous literature on commercialisation often uses household characteristics as proxies for household capacity, such as education, age, health, gender composition, number of members, cultivated and area, or the ratio of Agricultural income. However, since many of these characteristics are used by local authorities to target policies, they remain endogenous. Consequently, we follow previous studies that use instrumental variables to extract the exogenous variation in commercialisation (discussed in Section 4). For support eligibility, given that we have two main support policies, we use two sets of variables. Human support is determined by education, age, dependency ratio, health, number of members, poverty group status, and participation in unions. Living support is targeted based on housing conditions, borrowing status, dependency ratio, number of members, poverty group status, and participation in unions. A more detailed description and discussion of support targeting can be found in the first part of the Supplementary file.

3. Background, data collection, and key measurements

3.1. *Background and household survey*

Due to inclusive growth resulting from deliberate policies, Vietnam has been able to eradicate poverty across all demographic categories, both urban and rural, from 1980 to 2021. The poverty rate decreased from 14.5% in 2008 to 2.23% in 2021, with significant reductions in national, regional, and individual poverty levels (World Bank, 2022). However, these hard-won development achievements may be unsustainable. In mountainous areas with high ethnic minority populations, poverty rates remain high (Cuong, Tung, & Westbrook, 2015; Lanjouw, Marra, &

Nguyen, 2017), and the risk of non-poor households regressing into poverty is alarming (Le et al., 2015). Rural populations in informal sectors face poverty due to inadequate policies and assistance programmes (Nguyen, Vu, & Nguyen, 2012). This tendency may be attributed to income-based poverty metrics failing to accurately reflect the true poverty situation in Vietnam (Meemken et al., 2017; Ogutu & Qaim, 2019).

Given this background, multidimensional poverty has received considerable attention, with Decree No. 07/2021/ND-CP on multidimensional poverty standards for the 2021–2025 period serving as the benchmark. Initial outcomes include a low multidimensional poverty rate of 7.1% in 2021 compared to seven other Southeast Asian countries (Nguyen, 2022). However, multidimensional poverty persists in remote, mountainous areas such as Ha Giang province (Le et al., 2015).[1]

We collected data through random surveys among households listed in the communal poverty assessment lists across all 10 districts of Ha Giang province. Surveyors visited the households and interviewed household heads or members aged 18 years or older. The majority of people in Ha Giang work from home or on their own farms, ensuring that our survey was not biased by those who chose to stay at home or relocate for work. The final sample includes 1,383 households. Table 1 provides descriptive analyses of the dataset.

3.2. Commercialisation definition and measurement

Commercialisation of farming households, specifically agricultural commercialisation, can be defined as the participation of farmers in output markets (Barrett, 2008; Ogutu & Qaim, 2019; von Braun, Kennedy, et al., 1994). Previous studies usually quantify commercialisation in two ways: either as a binary treatment indicating whether the household participates in output markets or as a continuous 'treatment' showing the share of farm products sold out of total agricultural production (Birhanu et al., 2021; Muriithi & Matz, 2015; von Braun, Kennedy, et al., 1994). The inclusion of both dummy and continuous measures of commercialisation allows researchers to examine its causal effects even in areas where semi-subsistence agriculture is common (Ogutu & Qaim, 2019).

However, in this paper, we propose a different measurement of commercialisation for the following reasons. Firstly, our household survey experiences reveal that it is not an easy task to fully capture households' inflow and outflow of cash and production. As a result, the data collected about the share of commercialised production, as suggested above, may not be accurate or reliable. In fact, when asked, household heads often showed confusion in differentiating the income or share of sold output from the total income or production. This task became even more difficult when we attempted to collect information about the past, usually the last 12 or 24 months, as suggested in previous studies (Carletto et al., 2017; Ogutu & Qaim, 2019; von Braun, Kennedy, et al., 1994). This is due to the following reasons: (1) households in the studied areas mostly do not keep any records of their finances or production, and (2) household members participate in various types of jobs, making it hard to track their income. Thus, it might be more reliable to collect information about the present rather than the past[2] as the primary source of data, especially from household surveys in underdeveloped areas. Additionally, for small farming households that face constraints related to monoculture, commercialisation is also a way to increase and diversify their nutritional intake (Bonuedi, Kornher, & Gerber, 2021; Carletto et al., 2017; Ogutu et al., 2020). Therefore, selling one type of product and buying another is a common practice among these households to satisfy their basic needs. This flow of goods might even occur without the medium function of cash; thus, households are very unlikely to remember and accurately report it to researchers.

Secondly, agricultural commercialisation differs from rural commercialisation in general (von Braun, 1995). This is evident in our study areas, where, in addition to agricultural products, households also commercialise non-agricultural items such as handcrafts, home-made food, or

Table 1. Variable description

		Pool		Human-support – subset		Living-support-subset	
		($N = 1{,}383$)		($N = 930$)		($N = 770$)	
		Mean (Std.dev.)	Min Max	Mean (Std.dev.)	Min Max	Mean (Std.dev.)	Min Max
MPI		0.257	0.000	0.250	0.000	0.258	0.000
		(0.136)	0.688	(0.137)	0.688	(0.137)	0.688
Deprived components							
	Job	0.140	0.000	0.126	0.000	0.129	0.000
		(0.227)	1.000	(0.22)	1.000	(0.221)	1.000
	Heath	0.215	0.000	0.219	0.000	0.223	0.000
		(0.265)	1.000	(0.268)	1.000	(0.271)	1.000
	Education	0.239	0.000	0.233	0.000	0.249	0.000
		(0.284)	1.000	(0.289)	1.000	(0.292)	1.000
Poverty group							
	Poor	0.730	0	0.658	0	0.674	0
		(0.444)	1	(0.475)	1	(0.469)	1
	Near-poor	0.162	0	0.194	0	0.179	0
		(0.369)	1	(0.395)	1	(0.384)	1
	Non-poor	0.108	0	0.148	0	0.147	0
		(0.311)	1	(0.356)	1	(0.354)	1
Human support		0.443	0	0.337	0	–	0
		(0.497)	1	(0.473)	1	–	0
Living support		0.328	0	–	0	0.199	0
		(0.469)	1	–	0	(0.399)	1
Commercialisation index		0.112	0	0.099	0.000	0.124	0.000
		(0.212)	1	(0.192)	1.000	(0.216)	1.000
Commercialisation dummy		0.265	0	0.251	0	0.294	0
		(0.442)	1	(0.434)	1	(0.456)	1
Education (household average)		2.941	1	2.552	1	2.472	1
		(0.844)	7	(0.85)	7	(0.842)	7
Female ratio		0.482	0	0.447	0	0.471	0
		(0.192)	1	(0.191)	1	(0.199)	1
Age (household average)		28.531	8.333	28.634	8.333	30.034	8.333
		(11.117)	82	(10.754)	81	(11.826)	82
No. of member		4.563	1	4.553	1	4.384	1

(*continued*)

Table 1. (*Continued*)

	Pool		Human-support – subset		Living-support-subset	
	($N = 1,383$)		($N = 930$)		($N = 770$)	
	Mean (Std.dev.)	Min Max	Mean (Std.dev.)	Min Max	Mean (Std.dev.)	Min Max
	(1.235)	9	(1.609)	9	(1.66)	9
No. of labour	2.591	0	2.642	0	2.609	0
	(1.235)	8	(1.188)	7	(1.206)	7
Dependant ratio	0.405	0.000	0.389	0.000	0.376	0.000
	(0.231)	1000	(0.23)	1000	(0.245)	1000
Perceived health (household head)	4114	1	4168	1	4184	1
	(0.987)	5	(0.999)	5	(0.995)	5
Perceived connectedness (household head)	3.360	1	3.305	1	3.275	1
	(1.389)	5	(1.438)	5	(1.458)	5
Participation in union	0.322	0	0.302	0	0.245	0
	(0.467)	1	(0.459)	1	(0.431)	1
Cultivated land area (m^2)	3829.220	0	4032.190	0	3206.434	0
	(4551.537)	40300	(4665.629)	40300	(3675.664)	33378.4
Agricultural share of income	0.354	0.000	0.386	0.000	0.363	0.000
	(0.36)	1.000	(0.349)	1.000	(0.361)	1.000
Borrow dummy	0.426	0	0.398	0	0.434	0
	(0.495)	1	(0.49)	1	(0.496)	1
Borrow amount (million VND)	16.537	0	15.201	0	16.671	0
	(23.556)	200	(22.781)	200	(23.31)	150
Unstable house dummy	0.735	0	0.738	0	0.671	0
	(0.441)	1	(0.44)	1	(0.47)	1
Distance to center (km)	4.008	0	4.030	0	3.768	0
	(2.982)	18	(3.003)	18	(3.071)	18
Distance to market (km)	10.172	0.3	8.232	0.3	8.658	0.3
	(10.632)	50	(6.612)	45	(6.747)	45

imported groceries. Therefore, in these areas, the classical concept of agricultural commercialisation, as discussed in Binswanger and von Braun (1991); Pingali (1997); Poulton (2017), which posits a shift in farmers' objectives from food self-sufficiency to profit maximisation, may not fully reflect households' motivations. Since non-agricultural products are also present, commercialisation is no longer simply the result of households meeting their subsistence needs and generating surplus (Pingali & Rosegrant, 1995). Consequently, calculating the commercialisation index (Birhanu et al., 2021;von Braun, Kennedy, et al., 1994) may not capture households' rational decisions to participate in output markets.

Pingali and Rosegrant (1995) stated that agricultural commercialisation is not only a shift in the use of agricultural production output away from subsistence but is also 'accompanied by [. . .] withdrawal of labour from the agricultural sector'. (Pingali & Rosegrant, 1995, p. 183) As discussed above, since the current measurement of agricultural commercialisation cannot be reliably conducted and cannot fully reflect the rational choice of households to participate in markets in our study areas, we propose an alternative measurement based on household members' jobs. We capture the voluntary commercialisation of households using two terms: (1) a binary term that equals 1 if any household members report their jobs as selling and equals 0 otherwise; and (2) a continuous term showing the ratio of household members engaged in commerce versus the total number of household workers.

For this measurement to be valid, the number of workers in each household must be sufficiently large for the ratio to vary enough to be considered a continuous censored distribution rather than a discrete one. In our study areas, the average household size is 4.6, and the average number of available workers is 2.6, with a maximum of 7. Thus, the mean values and standard errors of commercialisation indices calculated (Table 1) are quite close to those from Ghana, Tanzania, Nigeria, and Zimbabwe (Saha et al., 2021), Kenya (Muriithi & Matz, 2015; Ogutu & Qaim, 2019), Pakistan (Rabbi et al., 2019), and Sierra Leone (Bonuedi et al., 2021).

3.3. Multidimensional poverty measurement

Our MP index is based on the framework developed by Alkire and Foster (2011); Alkire et al. (2015) and UNDP and OPHI (2021), with modifications in line with Decree No.07[3] from the Vietnamese government for the multidimensional poverty assessment framework for 20212025. This adaptation enables a more thorough assessment of the MP index within Vietnam's specific circumstances. The original MP index measuring framework, developed by Alkire and Foster (2011) and further refined by Alkire et al. (2015), assesses the weighted deprivation of families based on 10 variables across three dimensions: education, health, and standard of living. However, this list of indicators and dimensions can be adjusted to incorporate additional aspects such as quality of work, empowerment, physical safety, social connection, and psychological wellness and happiness Alkire et al. (2015). The Vietnamese government's Decree No. 07 introduces the 'Job' dimension, which includes two metrics concerning unemployment and the ratio of household dependents. Besides this addition, we made several modifications to the original MP index structure, primarily due to data availability. This leads to a collection of four dimensions and 14 indicators that contribute to the MP index, as displayed in Table 2.

The distribution of MP indices in the studied areas follows a bell-shaped curve with a mean of 0.257 and is truncated at 0 (Figure 1). The distributions for households receiving human support and those receiving living support also follow the same shape (Figures S3 and S4). Moreover, as illustrated by Figure 2, non-commercial households are significantly more deprived than commercial households in terms of the MP index and all four components. Local households predominantly suffer from severe asset deprivation, with the corresponding figures for non-commercial households and commercial households being 0.437 and 0.421, respectively. Deprivation in health and education also contributes significantly to the MP index, although the extent varies between the two groups of households. The job dimension is the least-deprived

Table 2. MPI measuring structure

Dimension	Indicator	Weight (w)	Deprivation cut-off (z)
Job	Joblessness	1/8	Any household member is of working age and able to work but has not job
	Dependant ratio	1/8	The household has more than 50% total member as dependent (children under 16 years old, elderly, disabled member)
Health	Nutrition	1/8	The household's total nutrition input is less than 50% of its demand
	Insurance	1/8	Any 6 years old and above 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 years 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, 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

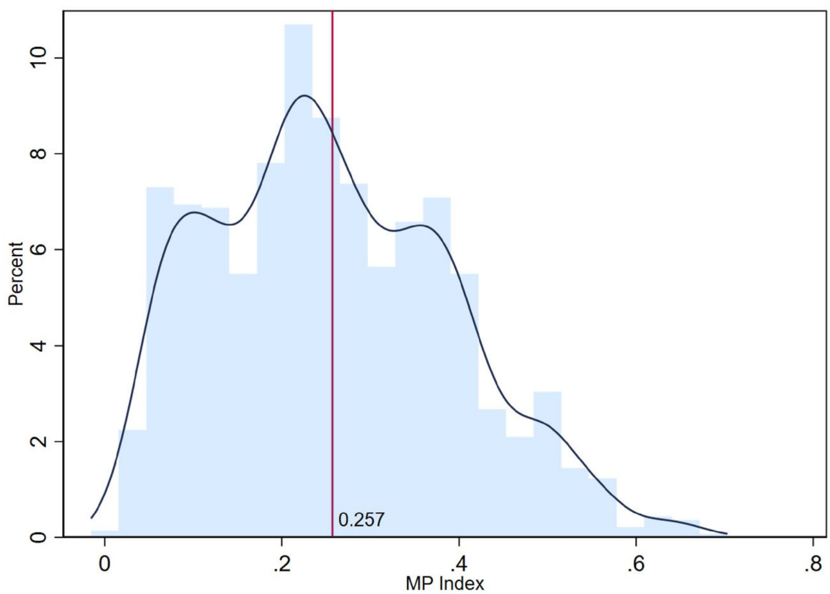

Figure 1. Distribution of MP Index among studied households.

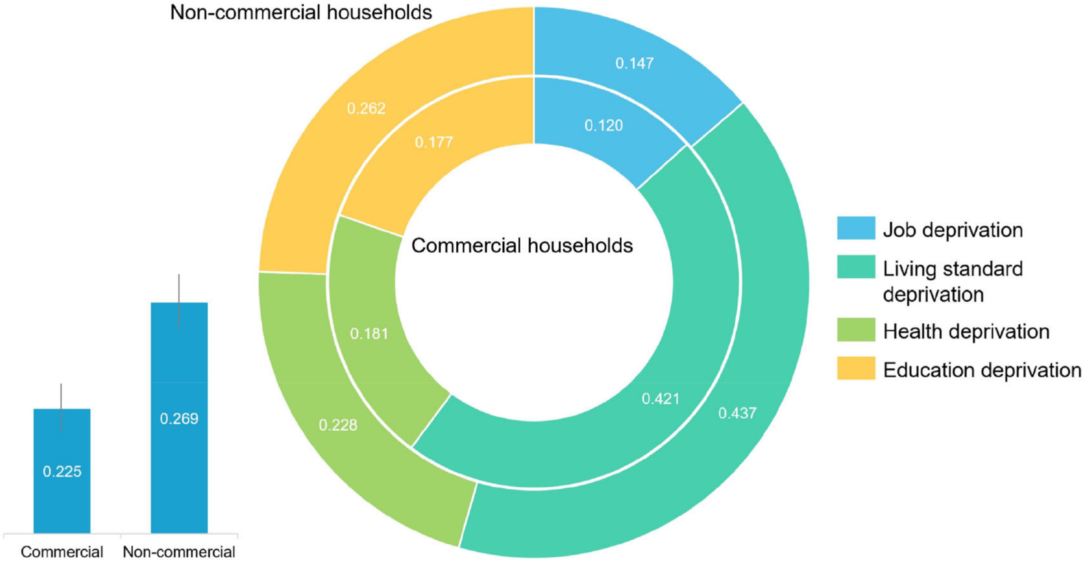

Figure 2. MPI and deprivation status by commercialisation group.

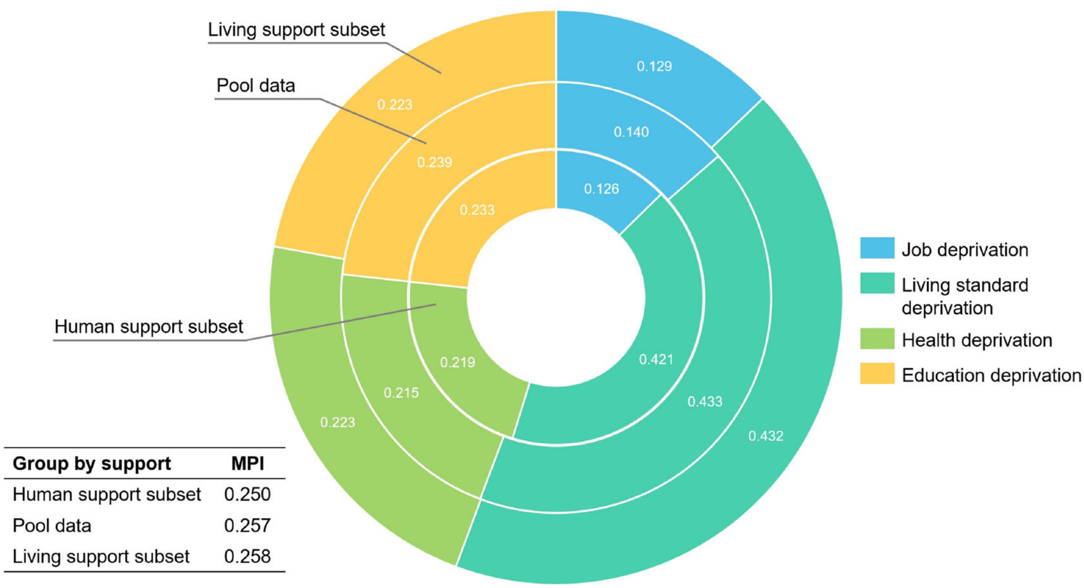

Figure 3. MPI and deprivation status by support group.

for these households. On the other hand, Figure 3 provides insights into the MP index and the deprivation status of local households based on support provision.

4. Estimation method

This study aims to answer questions related to the interactive effects of external interventions, such as government support programmes, and self-help efforts, such as household participation in commercial activities, on poverty alleviation. The primary identification challenge is the endogenous nature of these two variables: households are targeted to receive policies based on their poverty status, they also choose to commercialise based on their resources. These endogenous problems have been discussed in many studies, such as Ogutu and Qaim (2019); Pingali and Rosegrant (1995); Poulton (2017); Rao and Qaim (2011); Tabe Ojong et al. (2022). These studies often use instrumental variables to address the endogeneity of commercialisation and quasi-experimental or counterfactual approaches to handle targeted policies. To address the research questions posed, we attempt to combine both approaches in this study.

To examine and compare the effect of commercialisation on household poverty, conditioned on the provision of support policies, a common practice is to include an interaction term of these two variables in a linear regression model[4]. This approach is equivalent to sub-setting the dataset into two groups (households receiving and not receiving support) and comparing the effect of commercialization between these two subsets. However, since support assignment is not random, indicating that these subsets have different distributions, this method is not viable. Moreover, households' decisions to commercialise also depend on their socio-economic resources, which biases the ordinary linear regression coefficients. To address this *dual endogeneity* problem, our strategy is to create two identical data subsets, differing only in the presence of government support. We then use the IV estimator within these subsets to obtain an unbiased estimate of the commercialisation effect. As the two subsets are identical, we can compare the IV estimators to observe how the commercialisation effect changes with the presence of support.

To perform the first step (creating identical subsets), we adopt the IPW technique. The first task is to calculate the propensity of receiving support based on a set of determinants using a binary response model. This set of determinants includes the *de jure* eligibility criteria used by the government to select targeted households. However, due to the presence of mis-targeting, we follow Cheng, Wang, and Chen (2022); Hoang-Duc, Nguyen-Thu, Nguyen-Anh, et al. (2024); Panda (2015); Rao and Qaim (2011) and include a *de facto* variable to capture household participation in unions, which can alter targeting results[5]. Consequently, our final set of determinants for support targeting is presented in Tables S4 and S5. By using the propensity score as inverse probability weights, we can construct a quasi-experimental dataset in which the *treated* (receiving support) and *control* (not receiving support) groups are identical. Thus, these two groups can be analysed as identical subsets from the same distribution.

We can present this step via the following equations:

$$\Pr(T = 1|\boldsymbol{X_T}) = \boldsymbol{\Phi}(\boldsymbol{X_T} \times \beta + \varepsilon_1), \tag{1}$$

in which T is the treatment: being targeted for supports; $\boldsymbol{X}_T$ is a set of policy eligibility; Φ is the cumulative distribution function of the standard normal distribution; and ε_1 is the error term. From that, we can predict the propensity score: $\widehat{\Pr}(T = 1|X_T) = \Phi\big(X_T \times \hat{\beta}\big)$ and calculate the inverse probability weight:

$$IPW = \begin{cases} \dfrac{1}{\Pr(T = 1|X_T)} & \text{if } \ T = 1 \\[2ex] \dfrac{\Pr(T = 1|X_T)}{1 - \Pr(T = 1|X_T)} & \text{if } \ T = 0 \end{cases} \tag{2}$$

This weight will then be used for weighted least square regression in the second step. It can be noticed that in Equation (2), we do not use the simple inverse probability weight normally used to calculate average treatment effect (ATE)[6] but we use the weights for average treatment effect for the treated (ATET). This is to facilitate later calculation of ATET of support policy and to relax the requirement for common support assumption (Wooldridge, 2010).

In step two, we use two-stage least squares (2SLS) to estimate the effect of commercialisation in these two groups. As a brief review, Ogutu and Qaim (2019) used the average number of motorcycles and the average number of main market sellers in each ward as instrumental variables for the level of commercialisation among households in Kenya. The former was argued to be a good proxy for market access, as bike owners, the haves, tend to provide transport services for the have-nots. The latter represents what is known as peer learning[7], showing the tendency of households to adopt beneficial practices. This IV was also used by Tabe Ojong et al. (2022) with a similar motivation for farmers in Ethiopia. Tipraqsa and Schreinemachers (2009) used a set of variables as instruments for the level of commercialisation in Thailand, including distance to output markets, connection to roads, number of city visits per year, existence of rice banks, and level of crop diversification. Following these previous studies, we use distance to market, average number of commercial labourers, and average number of motorbikes in a village (excluding the household of interest) as IVs for the commercialisation ratio[8]. Table S7 provides the first-stage regression results for these IVs, and Table S8 compares the naive OLS and 2SLS regressions. The IVs satisfy the relevance conditions, with first-stage F-statistics of approximately 20. Additionally, the second-stage Wald statistics satisfy the Stock-Yogo test for weak identification. We present the regression models as follows:

$$CI = \boldsymbol{X_Y} \times \alpha + \varepsilon_2, \tag{3}$$

$$\begin{cases} \dfrac{1}{1-\widehat{\Pr(T=1|X_T)}} \times Y_0 = \dfrac{1}{1-\widehat{\Pr(T=1|X_T)}} \left[\widehat{CI} \times \gamma_{0,0} + \boldsymbol{X_Y} \times \gamma_{1,0} + \varepsilon_3\right] \text{ if } T=0 \\ \dfrac{1}{\widehat{\Pr(T=1|X_T)}} \times Y_1 = \dfrac{1}{\widehat{\Pr(T=1|X_T)}} \left[\widehat{CI} \times \gamma_{0,1} + \boldsymbol{X_Y} \times \gamma_{1,1} + \varepsilon_4\right] \text{ if } T=1, \end{cases} \tag{4}$$

in which, CI is short for commercialisation index introduced in Subsection 3.2; X_Y is the set of households characteristics such as age, health, education, number of member, cultivated land area, or on-farm income ratio; Y is the outcome, which represents the MP index or the incidence of the households being below MP index $= \frac{1}{3}$. Equation (3) is the first-stage regression and Equation (4) is analogous to the second-stage. Note that $\left.\frac{1}{\widehat{\Pr(T=1|X_T)}}\right|_{T=1} = 1$ and $\left.\frac{1}{1-\widehat{Pr(T=1|X_T)}}\right|_{T=0} = \frac{\widehat{Pr(T=1|X_T)}}{1-\widehat{\Pr(T=1|X_T)}}$. After re-weighting, we can compare $\gamma_{0,0}$ and $\gamma_{0,1}$ to see the change in effect of commercialisation on outcome with or without the presence of supports. Two main conditions or assumptions for this method are common support and unconfoundedness. The former requires the overlap in propensity score distributions between the treated and control group, in this case, between the supported and non-supported. The latter assumes that after controlling for the set of variables $\boldsymbol{X_T}$, treatment is independent on potential outcomes. We will check if these assumptions hold in Subsection 5.3.

Additionally, the predicted $\hat{Y}_0$ estimated from Equation (4) is the potential outcome of the treated households if they had not been targeted for supports. From this strategy, we can also calculate the ATET of support via the IPW - regression adjustment (IPWRA) estimator. It is the difference between the predicted value of the two potential outcomes $\left(\hat{Y}_1 - \hat{Y}_0\right)$. Even though treatment effect of support is not the focus of this study, understanding this will help us with better reasoning the interaction between supports and commercialisation discussed in the subsequent sections. The ATET estimator is:

$$ATET = E\left[\hat{Y}\left(T=1|X'_Y\right) - \frac{\widehat{\Pr}(T=1|X_T) \times \hat{Y}\left(T=0|X'_Y\right)}{1-\widehat{\Pr}(T=1|X_T)}\right] \tag{5}$$

Here, $\boldsymbol{X'_Y}$ is the vector of $\boldsymbol{X_Y}$ and CI. $Y(T=1)$ and $Y(T=0)$ are equivalent to Y_1 and Y_0 in Equation (4). This ATET estimator is 'doubly robust', which accounts for both the covariates of the treatment model (determinants of receiving treatment, $\boldsymbol{X_T}$) and the covariates of the outcome models (explaining factors of the outcome, $\boldsymbol{X'_Y}$). The main idea of this method lies in the combination of both propensity score and the conditional mean of outcome models (Słoczyński

& Wooldridge, 2018). Wooldridge (2007) suggested this method would be beneficial when the outcome variable has a restricted range, which is highly applicable in this paper for both MP index and incidence of being below MP threshold.

While the results from Equation (4) is adequate to make conclusion about how support provision affect the effect of commercialisation, we can go further and test statistically that difference. Following Wooldridge (2010), we also use a regression form of IPWRA estimation to see the difference between the effect of commercialisation in the supported group and the unsupported group more clearly.

$$IPW \times Y = IPW \times \left[T \times \delta_1 + \widehat{CI} \times \delta_2 + X_Y \times \delta_3 + T \times \left(\widehat{CI} - \overline{\widehat{CI}}\right) \times \delta_4 + T \times \left(X_Y - \overleftarrow{X}_Y\right) \times \delta_5 + \epsilon\right] \tag{6}$$

in which $\overline{\widehat{CI}}$ and $\overleftarrow{X}_Y$ are the sample mean of $\widehat{CI}$ and vector $\boldsymbol{X}_Y$. In Equation (6), δ_1 is the ATET estimator of supports, δ_2 is the effect of commercialisation on potential outcome if households receive no support ($T = 0$), and δ_4 is the difference between the effect of commercialisation conditioning on support presence. Noting that Equations (4)–(6) use the predicted value of the commercialisation index in our estimation, the standard errors of coefficients in these models are subject to biases. To correct these standard errors, we use bootstrapping throughout the entire process with 2000 replications. The use of bootstrapping to correct the standard errors of 2SLS and IPWRA estimators has been discussed and widely adopted in previous studies (Wooldridge, 2010).

5. Results and discussions

Before discussing our results, it is necessary to outline the structure of this section. Our analysis primarily subsets the data to adjust for undesirable variance in the two endogenous variables. Out of 1,383 households, 617 received no support, 613 received human support, 453 received living support, and 300 received both types of support in the original dataset. This means that some households received only living support, while others received only human support. By subsetting our data to include only one support group, we aim to create quasi-experimental data based on these supports and provide causal evidence about the effects of support and commercial activity. For instance, if we focus on the impact of human support, we will exclude all households receiving living support, leaving 617 households without any support and 313 households receiving solely human support (the human-support subset). We repeat this process for living support, resulting in a living-support subset with 617 households without any support and 153 households receiving solely living support. In the end, our comparisons are valid because we base the analysis of *treated* groups on a single *control* group consisting of 617 households receiving no support. Figure S5 provides a visual representation of our data subsets.

Our main results come from the 2SLS-IPWRA estimation presented in Section 4, which corrects for selection bias in treatment targeting and the endogeneity of commercialisation. The results indicate a substitution effect between supports and commercialisation, showing that households *not* receiving supports benefit more from self-help commercial activities. We will then offer more detailed explanations for these observations by examining the mechanisms of both supports and commercialisation and their interactions. We conclude by presenting multiple robustness checks and sensitivity analyses to confirm the credibility of our findings.

Table 3. Effects of commercialisation, conditioning on receiving supports

	MP index			Under MP line		
	(1) Not supported	(2) Supported	(3) Difference	(4) Not supported	(5) Supported	(6) = (5) – (4) Difference
Panel A: Human support						
Commercialisation index	−0.112*	0.008	0.120	−0.747***	−0.192	0.555
	(0.067)	(0.068)	(0.098)	(0.258)	(0.282)	(0.368)
Potential outcome mean	0.269***		−0.040***	0.320***		−0.087***
	(0.008)		(0.009)	(0.028)		(0.032)
Observed outcome mean	0.260	0.229		0.314	0.233	
Sensitivity breakdown	0.084	0.084	0.084	0.084	0.084	0.084
Obs.	617	317	930	617	317	930
Panel B: Living support						
Commercialisation index	−0.158**	−0.132	0.026	−0.885**	−0.155	0.730*
	(0.074)	(0.078)	(0.015)	(0.296)	(0.294)	(0.416)
Potential outcome mean	0.254***		−0.003	0.256***		0.012
	(0.019)		(0.019)	(0.060)		(0.065)
Observed outcome mean	0.260	0.251		0.314	0.268	
Sensitivity breakdown	0.013	0.013	0.013	0.013	0.013	0.013
Obs.	617	153	770	617	153	770

Notes: Results in columns (1) and (4) are from the re-weighted subsets showing the potential outcome and characteristics of supported households if they didn't receive supports. Columns (2) and (5) are from the subset of supported households. Results in (3) and (6) are from a regression form of IPWRA which shows the difference between effect of commercialisation between treated and control groups and the ATET of corresponding supports. Standard errors are in parentheses. All estimations are bootstrapped with 2000 replications.
$*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

5.1. *Main results*

Table 3 shows the effect of commercialisation on the outcomes for the poor: the MP index and the incidence of households being below the MP line ($MP\ index = \frac{1}{3}$). The results reveal two distinct patterns. First, the effect of commercialisation is prominent among non-supported households, while it is less pronounced or even insignificant among supported households.

Panel A of Table 3 reports that for both outcomes (the MP index and the incidence of households being below the MP threshold), commercialisation is only effective in reducing poverty among non-human-supported households. For households in this subset, the average number of workers is 2.64 (Table 1), which means that if one more household member joins commercialisation activities, the mean MP index will be reduced by approximately $\frac{1\times 0.112}{2.64}\% \approx 4.24\%$, and this reduction is significant at the 90% level (column 1). However, for supported households, commercialisation does not have a significant effect (column 2). This pattern persists for the other outcome: among non-supported households, an additional member participating in commercial activities reduces the probability of being below the MP line by 16.4%, significant at the 99% level (column 3), while this effect is not observed for supported households (column 4). On the other hand, human support is reported to reduce the MP index by 4% and the probability of being below the MP line by 8.7%[9]. Even though the direct difference between the coefficients of commercialisation is not statistically significant (columns 3 and 6), the difference in the actual effects is sufficient to conclude that human support policies counteract the poverty-alleviation effect of commercialisation (Table 4).

A similar pattern can be observed among households receiving living support (Panel B Table 3). From columns (1) and (2) of Panel B, despite both significantly reducing the MP index, the magnitude of the effect of commercialisation among non-supported households is larger than that among supported households. For the other outcome, the difference in the

Table 4. Effects of commercialisation, conditioning on receiving support

	MP index			Under MP line		
	(1) Not supported	(2) Supported	(3)=(2) – (1) Difference	(4) Not supported	(5) Supported	(6)=(5)–(4) Difference
Panel A: Human support						
Commercialisation index	−0.112*	0.008	0.120	−0.747***	−0.192	0.555
	(0.067)	(0.068)	(0.098)	(0.258)	(0.282)	(0.368)
Potential outcome mean	0.269***		−0.040***	0.320***		−0.087
	(0.008)		(0.009)	(0.028)		(0.032)
Observed outcome mean	0.260	0.229		0.314	0.233	
Sensitivity breakdown	0.084	0.084	0.084	0.084	0.084	0.084
Obs.	617	317	930	617	317	930
Panel B: Living support						
Commercialisation index	−0.158***	−0.132*	0.026	−0.885***	−0.155	0.730*
	(0.074)	(0.078)	(0.105)	(0.296)	(0.294)	(0.416)
Potential outcome mean	0.254***		−0.003	0.256***		0.012
	(0.019)		(0.019)	(0.060)		(0.065)
Observed outcome mean	0.260	0.251		0.314	0.268	
Sensitivity breakdown	0.013	0.013	0.013	0.013	0.013	0.013
Obs.	617	153	770	617	153	770

Notes: Results in columns (1) and (4) are from the re-weighted subsets showing the potential outcome and characteristics of supported households if they didn't receive supports. Columns (2) and (5) are from the subset of supported households. Results in (3) and (6) are from a regression form of IPWRA which shows the difference between effect of commercialisation between treated and control groups and the ATET of corresponding supports. Standard errors are in parentheses. All estimations are bootstrapped with 2000 replications.
$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.\ 01$.

effects of commercialisation between these two groups is significant at the 90% level (column 6). If one more person joins commercial activities, the chance of a household being below the MP threshold drops by $\frac{1\times0.885}{2.61}\% \approx 33.9\%$[10], while there is no significant effect among supported households. However, in this subset, unlike human support, living support is not effective in reducing poverty (columns 3 and 6).[11] This leads to our second observation from these results: the significance of these effects varies between data subsets based on support provision and also between outcomes. This variation could potentially be attributed to the distinct characteristics of human support and living support policies.

To explain these results, we need to analyse the mechanisms through which support and commercialisation may complement or substitute each other's effects. It could be that different support groups have distinct channels of effect on households' outcomes, which may conflict with those of commercialisation. Alternatively, support groups might have varying degrees of direct synergy with commercialisation. We will explore this in Subsection 5.2. Moreover, the results show differences in effect between outcomes, which could be due to heterogeneous treatment effects between households near the MP index threshold and those further from it. We will examine this by focusing on households with an MP index value within two standard deviations on either side of the $\frac{1}{3}$ threshold in Subsection 5.3.

5.2. Mechanisms

Before discussing the evidence, it is worth noting that, in alignment with many previous studies in the literature, our data show that commercialisation reduces the MP index overall. This effect occurs at both the extensive and intensive margins, meaning that to reduce poverty, we can either increase the number of households participating in commercial activities or increase the intensity of participation among households. With that background knowledge, we identified two main explanations for the substitutive, rather than complementary, effects of commercialisation and government support.

First, by their nature, commercial activities and human support policies are determined based on the level of household human capacity, but in opposite directions. This means that both interventions cannot effectively coexist in our observed sample, resulting partly in the substitutive effects. Consistent with the theoretical background, it is evident that participating in commercial activities requires households to have a higher level of capacity, such as higher education, better health, a lower dependent ratio, a smaller household size, and a lower ratio of agricultural income (Table S6) (Barrett et al., 2012; Poulton, 2017; Saha et al., 2021; von Braun, 1995). This also means that commercialisation would be more effective among households with higher capacity. In contrast, human support policies target lower-capacity households with poorer health, a higher dependent ratio, and a larger family size (Table S4). Therefore, among households targeted by human support policies, we found no effect of commercialisation (Panel A Table 3). Similar results are reported in Table 5, where in our human-support subset (PanelA2), commercialisation does not have any effect on any components of the MP index. Furthermore, from Table 6, human support is not effective among households already participating in commercial activities.

These results show that, currently in rural Vietnam, there is no evidence that supports enhance the effect of commercialisation as postulated by von Braun (1995), Tabe Ojong et al. (2022), or Saha et al. (2021). Additionally, our data do not provide support for Barrett (2008)'s claim that policies can work better in market-integrated areas. While these findings do not disprove any of these claims, they do suggest that the effectiveness of such policies is highly contextual and dependent on the specific content of the policies. In the areas we studied, human support policies are more akin to social protection measures, providing safety nets to poor households to ensure they have the minimum means to sustain themselves. As such, they do not act as a catalyst to facilitate households' transition to a higher economic position, enabling them to escape poverty through self-help efforts such as commercialisation. This is why human support is effective for lower-capacity households (non-commercial ones) but not for higher-capacity households (commercial ones) (Table 6).

The same argument can be applied to those receiving living support: since these households have higher capacity and are not targeted for human support, commercialisation is more effective in reducing poverty among them (Panel B, Table 3). However, there is a slight decrease in effect among supported households compared to non-supported ones. This is because commercialisation affects poverty through the same channels as living support. From Panels B1 and B2 in Table 5, we can see that commercialisation reduces the MP index by decreasing health and living standard deprivations, which is similar to the effect of living support[12]. As the channels overlap, the combination of these two interventions does not further enhance the effect on poverty outcomes. However, unlike the human-support subset, we still observe a significant effect of commercialisation among supported households in the living-support subset. This leads us to the second explanation.

Second, living support encourages households to engage in commercial activities, whereas human support does not. Table 7 reports the causal effects of support on commercialisation participation. Overall, living support increases the household commercialisation index (column 3), while human support does not (column 5). The effect of living support comes from the extensive margin, which increases the number of households with members participating in commercial activities (column 1), rather than the intensive margin, which refers to the number of members participating among those already involved (column 2). These results reinforce our first explanation: support does not actually enhance the effectiveness of commercialisation but merely increases household participation.

Table 5. Effects of supports and commercialisation on MPI components

	MPI	Job	Health	Education	Living standard
Panel A1:					
Human support	−0.040***	−0.030*	−0.061***	−0.044**	−0.038***
	(0.009)	(0.016)	(0.021)	(0.020)	(0.014)
Estimator	IPWRA	IPW	IPW	IPW	IPW
Treatment covariates	Yes	Yes	Yes	Yes	Yes
Outcome covariates	Yes	No	No	No	No
Sensitivity breakpoint	0.084	0.016	0.014	0.023	0.052
No. of obs.	930	930	930	930	930
Panel A2:					
Commercialisation index	−0.037	0.024	−0.019	−0.063	−0.091
	(0.041)	(0.064)	(0.108)	(0.089)	(0.063)
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS
Control	Yes	Yes	Yes	Yes	Yes
No. of obs.	930	930	930	930	930
Panel B1:					
Living support	−0.018	−0.006	−0.081***	−0.021	0.035**
	(0.016)	(0.020)	(0.029)	(0.029)	(0.015)
Estimator	IPWRA	IPW	IPW	IPW	IPW
Treatment covariates	Yes	Yes	Yes	Yes	Yes
Outcome covariates	Yes	No	No	No	No
Sensitivity breakpoint	0.013	0.004	0.076	0.007	0.043
No. of obs.	770	770	770	770	770
Panel B2:					
Commercialisation index	−0.119***	0.058	−0.356***	−0.005	−0.173***
	(0.038)	(0.064)	(0.097)	(0.074)	(0.062)
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS
Control	Yes	Yes	Yes	Yes	Yes
No. of obs.	770	770	770	770	770

Notes: The table shows the effects of supports and commercialisation, individually, on MP index and its four components. Data used in Panel A1 and A2 are similar. Data used in Panel B1 and B2 are similar. Estimations in Panel A1 and B1 are without the inclusion of *Commercialisation index*. Estimations in Panel A2 and B2 are without the inclusion of *Human support* and *Living support*, respectively. Standard errors are in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

5.3. Robustness checks

In this subsection, we briefly present three exercises to corroborate the results. Detailed discussions can be found in the second part of the Supplementary file.

First, we take the opposite approach to Table 3 and examine the differences in the effect of support groups conditioned on commercialisation participation. As presented in Table 6, in our human support subset, support is only effective among non-commercial households. Conversely, living support seems to be more effective among commercial households (column 4). This is because living support can encourage commercialisation participation, which benefits households in the living-support sample. Our results remain consistent when we estimate the effects and interactions between support and commercialisation from the other direction.

Second, we account for the heterogeneous treatment effects between households near the MP index threshold and those further from it by repeating our analyses on trimmed subsets that are within two standard deviations of the threshold. The results shown in Table S1 indicate that the differences in commercialisation effects between supported and non-supported groups become more prominent: participating in commercial activities only helps reduce poverty among non-supported households, and this is consistent across both outcomes.

Table 6. Effect of supports, conditioning on commercialization

	MP index				Under MP line			
	Human support		Living support		Human support		Living support	
	Non-commercial (1)	Commercial (2)	Non-commercial (3)	Commercial (4)	Non-commercial (5)	Commercial (6)	Non-commercial (7)	Commercial (8)
Support ATET	−0.046***	0.000	−0.013	−0.116***	−0.084**	−0.000	−0.069	−0.034
	(0.010)	(0.017)	(0.015)	(0.028)	(0.037)'	(0.053)	(0.056)	(0.078)
Mean outcome	0.262	0.214	0.276	0.217	0.33	0.159	0.362	0.168
No. of obs.	697	233	544	226	697	233	544	226

Notes: The estimator for these results is IPWRA with the corresponding supports being the treatment and MP index or Under MP line being the outcomes. Treatment and outcome model controls are $\boldsymbol{X_T}$ and $\boldsymbol{X}'_{\boldsymbol{Y}}$ in equation (5). Standard errors are in parentheses.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Lastly, we consider the two assumptions related to our main estimator: common support and unconfoundedness. Regarding the former, Figures S1 and S2 show the propensity score distributions for the supported and non-supported groups with a large degree of overlap. This means that for almost all our treated units, there exists a corresponding control unit with a positive probability of receiving treatment. Moreover, the weighted covariates show to be reasonably balanced, meaning common support holds (Tables S2 and S3). Regarding the latter, we follow Masten, Poirier, and Zhang (2023)'s sensitivity analysis to test the violation of unconfoundedness. The results suggest that our analyses on the human-support subset are robust to unobserved confounders, while, for the living-support subset, only the results related to health outcome are robust.

6. Policy implications and conclusion

In the context of increasing concern about poverty and alleviation efforts, this paper examines a composite welfare indicator, the MP index, to capture the essential attributes of the poor in Ha Giang – a northern province in Vietnam with the highest poverty rate. We use this indicator as an outcome to analyse the interactive effects of commercialisation and support policies on reducing poverty. With data from 1,383 households, we adopt a counterfactual causality approach using IPW combined with IPWRA and IVs to investigate the treatment effects of commercialisation and support policies across different data subsets. This strategy has several limitations. The first limitation relates to the cross-sectional nature of our dataset, which prevents us from analysing the dynamic mechanisms of commercialisation and support policies on reducing the MP index. The second limitation arises from identifying the true underlying drivers of commercialisation and eligibility for support due to household heterogeneity and mistargeting.

Despite these constraints, we can derive crucial insights. First, commercialisation can increase household welfare, and existing external measures may alleviate non-income poverty. However, the efficacy of human and living support differs greatly. Second, commercialisation is more effective among unsupported households and ineffective among supported ones. This is because commercialisation requires higher capacity, and there are currently no complementary synergies between commercialisation and support policies. Commercialisation and human support are, to a certain extent, compatible and interchangeable in improving welfare. On the other hand, the combination of living support and commercialisation can still weakly reduce poverty, but only by an extensive margin. This suggests that living support has the potential to motivate households to engage in commercial activities.

Table 7. Effects of supports on commercialisation

	(1) Commercialisation Dummy	(2) Commercialisation Index	(3) Commercialisation Index	(4) Commercialisation Dummy	(5) Commercialisation Index
Living support	0.250***	0.077	0.134***		
	(0.000)	(0.050)	(0.000)		
Human support				0.026	0.014
				(0.390)	(0.311)
Treatment model controls	Yes	Yes	Yes	Yes	Yes
Outcome model controls	Yes	Yes	Yes	Yes	Yes
No. of obs.	770	226	770	930	930

Notes: The estimator for these results is IPWRA with the corresponding supports being the treatment and commercialisation index or commercialisation dummy being the outcomes. Treatment and outcome model controls are $\boldsymbol{X_T}$ and $\boldsymbol{X'_Y}$ in equation (5). Results in column (2) are from the subset of those currently joining commercial activities. Standard errors are in parentheses.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Our results propose two main implications for current policies. First, anti-poverty policies should be more tailored to better support households, given the heterogeneity beyond the current eligibility criteria. Support policies in Vietnam currently target households based on a specific set of capacities and characteristics, such as age, health, education, or housing and production conditions. However, as demonstrated throughout this study, whether or not households participate in commercial activities also affects the effectiveness of these support policies, due to the existence of nearly two distinct groups of households in terms of capacity. This argument can be extended to other occupational trajectories, which are likely to be less homogeneous even with the same overall level of poverty. Unobservable factors, such as aspiration or capacity, which are difficult to accurately assess during policy targeting, may contribute to these differences.

Second, our current support policies do not have strong complementary synergies with commercialisation because they primarily act as a safety net for the extreme poor rather than as a *push* to lift households out of poverty through occupational transition or the accumulation of productive assets. Many previous studies have shown that policies providing social protection support, even over extended periods, are not as effective as a one-time substantial transfer of productive assets in altering poverty dynamics (Balboni et al., 2022; Banerjee et al., 2021). In the case of Vietnam, our results suggest that while commercialisation can help reduce poverty, there is room for improvement in policies to encourage commercial participation, as current living support is doing. More importantly, we need support policies that can enhance the effectiveness of commercialisation by focusing on its intensive margin. Such policies could aim to increase human capacity through training or provide an adequate amount of working assets to help households kick-start their commercialisation efforts. To achieve this effectively, more detailed studies are needed to understand the production processes of poor households and their product and income flows.

So, to conclude, what is the answer to the question in the title: give the fish or teach to fish? Perhaps we should do both if our goal is for households to escape the poverty trap. Social protection support policies, akin to ‘giving the fish’, are crucial for ultra-poor households as they enable these households to sustain the most basic living conditions. However, these policies alone cannot lift them out of poverty on a sustainable basis because they cannot provide substantial transfers to households. Due to their limited capacity and low risk tolerance, participating in commercial activities would be challenging. This means that they cannot initiate an occupational transition themselves or adopt a more market-driven production approach. Therefore, policies should also focus on ‘teaching to fish’, which involves providing an adequate amount of productive assets along with skills and market knowledge to facilitate a smooth transition. With appropriate policies, governments can not only stimulate commercialisation among households but also enhance its effectiveness in reducing poverty.

Notes

1. More details about Ha Giang province can be found in the first part of the Supplementary file.
2. Fortunately, this issue can be resolved through the inclusion of panel data from back-to-back surveys of the same household.
3. Decree No. 07, issued on January 27th, 2021, stipulates the criteria for measuring multidimensional poverty standards of poor households, near-poor households, and households with average living standards, as well as the responsibilities for implementing poverty reduction during the 2021-2025 period.
4. Such as: Outcome $= \beta_0 + \beta_1 \times$ Support $+\beta_2 \times$ Commercialisation $+\beta_3 \times$ Support $\times$ Commercialisation $+ \beta_4 \times \mathbf{X} + \epsilon$, with $\mathbf{X}$ being a vector of household control variables. β_3 will show the difference between the effect of commercialisation in supported and non-supported groups.
5. A detailed discussion on this matter can be found in the first part Supplementary file.
6. That is: $IPW = \begin{cases} \dfrac{1}{\widehat{\Pr}(T = 1|X_T)} & \text{if } T = 1 \\ \dfrac{1}{1 - \widehat{\Pr}(T = 1|X_T)} & \text{if } T = 0. \end{cases}$
7. More on this can be found in Krishnan and Patnam (2014) and Magnan, Spielman, Lybbert, and Gulati (2015), as suggested by Ogutu and Qaim (2019).
8. See Ogutu and Qaim (2019); Tabe Ojong et al. (2022); Tipraqsa and Schreinemachers (2009) for validation of the IVs.
9. Columns (3) and (6) show the difference between the potential outcomes of the supported and non-supported groups. In this case, it represents the ATET of human support. An analogous explanation applies to the effect of living support reported in Panel B.
10. This effect appears substantial, but it should be noted that the average number of workers in this group is only 2.61, so a one-unit increase is nearly equivalent to one standard deviation from this mean. Furthermore, this is not the actual effect of commercialisation; we are translating the results to interpret the effect of a one-unit increase in commercial labour. In practice, an increase of one unit of labour across the sample is unlikely, and the effect would be lower.
11. This does not mean that living support has no effect overall. Due to differences in the deprivation components of this subset compared to the total dataset, the ATET of living support is not significant. This result further supports our claim that these two types of support have complex and differing effects.
12. Subsection 5.3 will analyse the positive effect of living support on living standard deprivation.

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Data availability statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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