Article

Farm Mechanization and Non-farm Employment in Rural Central Vietnam: A Heterogeneous Analysis

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Abstract

Agricultural mechanization is crucial for enhancing agricultural production efficiency. Concurrently, rapid economic growth has generated more non-farm employment opportunities, especially in rural regions. However, rapid urbanization and industrialization have led to labor shortages in agriculture, threatening the sustainability of agricultural development. This study investigates the relationship between farm mechanization and non-farm employment using a panel dataset of 828 households from four survey waves (2010, 2013, 2016, 2017) in three rural provinces in Central Vietnam and a simultaneous equations model. Findings reveal a positive interdependence relationship exists between mechanization expenditure and the share of non-farm working members in households. Heterogeneity analysis suggests that the interactive relationship between non-farm employment and mechanization varies across household head genders. Furthermore, the participation of household non-farm employment in both types (wage employment and self-employment) is correlated with higher mechanization expenditure. These findings underscore the need for government policies that create more non-farm employment opportunities, especially for rural women, and increase investment in scale-appropriate and user-friendly machinery development to improve agricultural production and rural households' welfare.

Keywords: Agricultural mechanization; Non-farm employment; Rural Vietnam; Simultaneous equations model; Instrumental variable

JEL Codes: O13; O18; J21

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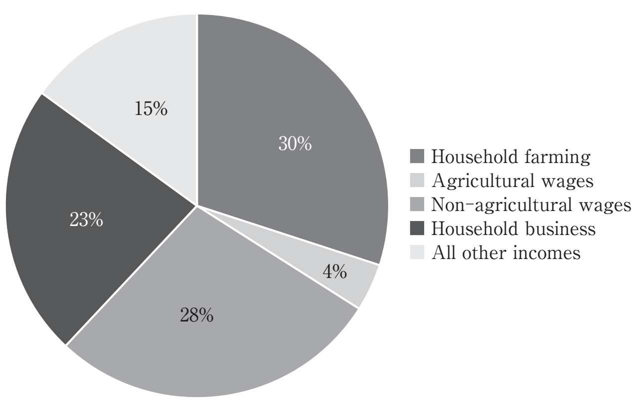
1. Introduction

Vietnam's rapid economic growth in recent decades has fundamentally changed economic activity patterns. While agriculture is still a key livelihood source, rural households have steadily diversified out of agriculture due to farm drudgery, low returns and high risks from climate change and market volatility. Meanwhile, the urbanization and industrialization have created many stable, better-paying job opportunities in manufacturing, trade, and services (Duong *et al.* 2021). Consequently, the agriculture workforce share has declined significantly from 50% in 2010 to 38% in 2018 (ADB 2022). This structural shift has contributed to rising agricultural real wages and a narrowing of the rural-urban wage gap between farm and non-farm sectors. In 2002, household income from agriculture accounted for 46.5% of total household income while wage job income only contributed 7.6% (Liu *et al.* 2020). However, by 2018, non-farm income from wages and household self-businesses had become the major income source, making up 59% of total household income, while agriculture's share had fallen to 34% (World Bank 2021) (Figure 1). These trends underscore the growing importance of non-farm employment in rural Vietnam and highlight the ongoing structural transformation of the economy.

However, Vietnams' rapid industrialization and urbanization have created agricultural labor shortages, increasing mechanization demand. The land consolidation policies and the promotion of large-field models have further enabled mechanization development (CSAM 2024). Vietnamese government also implemented various policies to promote agricultural mechanization, primarily by providing loans with preferential interest rates to farmers to buy machinery. For instance, Decision No. 48/NQ-CP (2009) provided full loan coverage for

Figure 1. Composition of rural household incomes by source (%) in 2018.



Source: (World Bank 2021)

domestically produced agricultural machinery (with at least 60% locally made components) at favorable interest rates. Later, Decision No. 68/2013/QD-TTg removed the local-content requirement but introduced a condition requiring farmers to secure machinery service contracts through the Vietnam Bank for Agriculture and Rural Development (Vietnam Government Portal n.d.). While these policies were not explicitly designed to promote mechanization, they have played a crucial role in expanding machinery investment. Between 2011 and 2016, the number of tractors in Vietnam surged by 82%, while the number of combine harvesters increased by 80% from 2011 to 2021 (Du and Onaka 2020; Sakata 2020; Takeshima *et al.* 2018).

In Vietnam, agricultural mechanization still concentrated in regions with larger, less fragmented farms, such as the Red River, Mekong, and Central Coast deltas. Moreover, its adoption is uneven across different stages of rice production. By 2020, mechanized plowing had reached 91% of rice land, and mechanical harvesting covered 85.3%. However, machine transplantation remained low at just 31.7% (GSO 2021).

Most farmers still rely on renting machinery or hiring mechanization services, primarily due to small-scale and fragmented landholdings. Government loan programs, while available, remain inefficient, only 3.5% of mechanization service providers and 34.4% of farmers have successfully accessed financing (CSAM, 2024). These loans also fail to meet actual demand, as machine costs often exceed available financing options.

Existing studies in Vietnam have shown that mechanization significantly boosts farmers' incomes by 10–20% by increasing yields and reducing production costs (Nguyen and Warr 2020; Nguyen 2022). However, no research has examined the relationship between mechanization and non-farm employment, despite both playing a crucial role in rural development. Understanding this interaction is essential for shaping policies that promote sustainable economic growth in rural areas.

This study aims to investigate the interrelationship between mechanization adoption and non-farm employment participation in Vietnam. Using panel household survey data and a simultaneous equation model, it seeks to provide empirical insights into how mechanization influences labor allocation beyond agriculture. These findings can help design policies that enhance agricultural productivity while fostering broader economic opportunities for rural communities.

The remaining of this paper is structured as follows. Section 2 summarizes the literature review. Section 3 explains estimation strategy. Section 4 presents the data and descriptive statistics, while Section 5 discusses the empirical results. Section 6 concludes this paper.

2. Literature review

Given structural transformation, labor scarcity, aging agricultural population, rising labor costs, growing drudgery aversion, and farm intensification, farm labor replacement by machinery has become increasingly popular. The widespread adoption of agricultural mechanization has significantly contributed to agricultural production and rural development (Chaudhary *et al.* 2022; Hamilton *et al.* 2022). Many developing countries, such as China, Bangladesh and Vietnam (Qiao 2017; Rahman *et al.* 2021; Takeshima *et al.* 2018) have actively promoted mechanization as a strategy for agricultural growth.

Existing literature has focused mainly on the link between mechanization and agricultural production, showing that mechanization enhances agricultural sustainability by improving productivity, yields and farmers' incomes, reducing drudgery and minimizing harvest losses (Ma *et al.* 2024; Peng *et al.* 2022; Sims *et al.* 2016). Specifically, mechanization significantly lowers labor costs and addresses seasonal labor shortages (Rahman *et al.* 2021; Sarkar 2020), thus increasing labor productivity and ensuring food security (Paudel *et al.* 2019). Moreover, with the rise of multi-cropping systems to meet food demands, mechanization enables timely crop establishment and efficient farm operations (Belton *et al.* 2024). Additionally, the massive use of agricultural machinery facilitates rural land consolidation and farm expansion, further boosting agricultural production and household incomes (Qian *et al.* 2022; Van den Berg *et al.* 2007; Yang *et al.* 2013).

However, existing studies focus primarily on the direct effects of mechanization within the agricultural sector (Zhou *et al.* 2022; Zhou and Ma 2022). Yet, mechanization extends beyond agriculture through its broader impact on rural labor dynamics and structural (Li *et al.* 2021; Wang *et al.* 2016). As mechanization reduces on-farm labor demand, surplus labor may transition into the local non-farm sector or pursue migration opportunities. According to Lanjouw and Lanjouw (2001) and Haggblade et al. (2007), non-farm employment refers to all income-generating activities in rural areas except crop and livestock production and fishing and hunting. Specifically, non-farm employment includes wage employment outside their own household (with agricultural wage employment in other farms is also included) and household non-farm enterprises (i.e., self-employment). The labor shift from agriculture sector to non-farm sectors has broader implications for rural economic development as non-farm employment provides a crucial pathway for income diversification, poverty alleviation, and improved household welfare (Bui and Hoang 2021; Rahut *et al.* 2018; Sen *et al.* 2021). Structural transformation through promoting the non-farm rural economy is now an explicit priority for developing countries. Rural households' decision to engage in non-farm employment is driven by both "pull" factors (e.g., better job opportunities with lower risk and higher return) and "push" factors (e.g., agricultural land scarcity, insufficient income from agriculture) (Atamanov and Van Den Berg 2012; Barrett *et al.* 2001; Duong *et al.* 2021). Additionally, given the imperfect credit markets in developing countries, non-farm income provides an important financial buffer for households against borrowing constraints or income shocks (Mathenge *et al.* 2015).

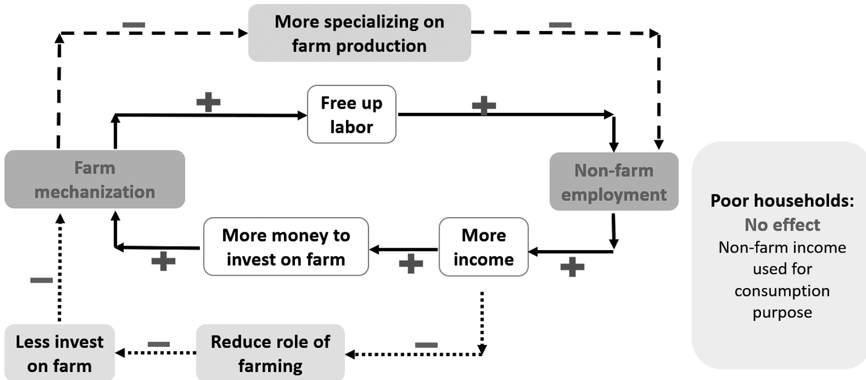
While mechanization and non-farm employment are both important to rural development, the literature contains conflicting arguments about the interaction between farm mechanization and farmers' choices to participate in non-farm sectors. Mechanization influences the supply side of the rural nonfarm economy, primarily through the labor channel (Haggblade and Hazell 1989).

Several studies suggested that farm machinery reduces labor requirements for agricultural production, allowing households to reallocate more labor to non-farm sectors. For example, Goodwin and Ahmed (2016) found that rural farmers in Bangladesh who utilize mechanization such as tractors and power tillers are more likely to engage in non-farm work. Lu and Xie (2018) found that smaller and user-friendly machinery supports elderly farmers in substituting labor inputs in China. Daum et al. (2019) revealed that using tractors in farm production allows female farmers to have more time for non-farm work in Zambia. Nguyen and Warr (2020) showed that mechanization enables farmers to allocate more farm labor time to non-farm work in Vietnam.

Conversely, some scholars argue that agricultural machinery is often indivisible, meaning its efficiency is maximized when used on larger farms (Abeyratne and Takeshima 2020; Li *et al.* 2021). Foster and Rosenzweig (2011) and Prosterman et al. (1998) similarly suggest that mechanization reduces operational costs per unit of land only when applied at scale. As a result, mechanization may encourage farmers to expand their land holdings to optimize efficiency, leading to greater specialization in agriculture. This expansion could, in turn, reduce household labor availability for non-farm employment.

Another strand of literature has also explored how non-farm employment affects mechanization. Several studies support the income effects of non-farm employment, suggesting additional incomes from non-farm activities relax the budget constraints and enable farmers' investment in farm inputs or technology (Aryal *et al.* 2019; Deng *et al.* 2020; Ma *et al.* 2018a; Nguyen *et al.* 2019). These investments can be short-term (e.g., buying fertilizers and pesticides) or long-term (e.g., buying machinery or hiring machinery services) (Nguyen et al., 2019; Nguyen et al., 2021). Conversely, some scholars argue that higher income from non-farm employment compared to farming can reduce the importance of agricultural production in household livelihoods, leading to reduced investment in farming and mechanization (Barrett *et al.* 2001; Berhe 2024; Nasir and Bekele 2014). In the case of poor households, non-farm employment might not affect mechanization if households spend additional income on consumption rather than reinvesting in agriculture (Berhe 2024).

Figure 2. Relationship between farm mechanization and non-farm employment.



Source: Author's illustration

Based on evidence from existing literature, the study summarizes potential pathways through which agricultural mechanization and non-farm employment influence each other (Figure 2). However, previous research has largely examined only one direction of this relationship, either how mechanization affects non-farm employment or how non-farm employment impacts mechanization. Evidence shows that farmers usually make joint decisions on non-farm employment participation and mechanization investment, and common unobserved factors (e.g., individual abilities and motivations) can simultaneously influence these choices (Ji *et al.* 2012; Ma *et al.* 2018b; Paudel *et al.* 2020). Analyzing these relationships in isolation may overlook the complexities of rural labor and agricultural investment decisions. While mechanization improves agricultural efficiency, its broader implications for labor reallocation and rural economic diversification remain complex and context-specific. Further research is needed to explore how mechanization reshapes rural livelihoods, particularly in balancing agricultural intensification with non-farm employment opportunities.

Despite the importance of this interdependence, empirical evidence on the bidirectional relationship between non-farm employment and mechanization remains scarce. We found only one study that explores the interrelationship between these two issues, namely Zheng et al. (2021). Using cross-sectional data in China, this study concluded that non-farm employment significantly increases mechanization service expenditure, and vice versa. While this provides valuable insights, its reliance on cross-sectional data limits its explanatory power regarding causal relationships.

The objective of this paper is to address these research gaps by analyzing the interrelationship between mechanization and non-farm employment in rural Vietnam. The study contributes to literature threefold. First, using panel data from rural Vietnam, it simultaneously investigates the impact of non-farm employment on mechanization and vice versa, accounting for potential endogeneity from unobserved factors and reverse causality. Second, the study examines heterogeneous effects of non-farm employment on agricultural mechanization by household head gender, as differences in human capital and resource endowments between male and female-headed households might affect household labor allocation and mechanization investment（Afridi *et al.* 2023）. However, relevant studies in this field remain scarce. Third, it broadens the understanding of non-farm employment-mechanization dynamics using different proxies for non-farm employment, including the share of non-farm workers in household, and employment types（wage employment and self-employment）.

3. Estimation strategies

Following Zheng et al.（2021）, the empirical model starts with estimating the impact of farm mechanization on non-farm employment, and models farmers' non-farm employment decisions within the random utility maximization framework. A farmer will engage in non-farm employment when the utility derived from that employment is higher than the utility obtained from not participating in non-farm activities. The decision-making process of joining non-farm employment can be modeled as follows:

$$O_{ijt}=\alpha_1+\alpha_2 M_{it}+\alpha_3 X_{it}+\varepsilon_{ijt} \tag{1}$$

In equation (1), O_{ijt} refers to the share of household members in household i from village j in year t engaging in non-farm employment; M_{it} refers to mechanization expenditure of household i from in year t; X_{it} is vector of household and village characteristics affecting non-farm employment and ε_{ijt} is the error term.

Regarding the impact of non-farm employment on farm machinery, the study assumes that mechanization expenditure M_{ijt} is a linear function of non-farm employment O_{it}, a vector of explanatory variables X_{it} and error term u_{ijt}. The specification can be shown as follows:

$$M_{ijt}=\beta_1+\beta_2 O_{it}+\beta_3 X_{it}+u_{ijt} \tag{2}$$

Since the non-farm employment and farm machinery usage decisions are interrelated rather than independent, they can affect each other. Thus, the study employs a simultaneous equation model to capture this interrelation. This simultaneous equation model is specified as follows:

$$O_{ijt}=\theta_1+\theta_2 M_{it}+\theta_3 X_{it}+\theta_4 D_{jt}+\mu_{ijt} \tag{3}$$

$$M_{ijt}=\delta_1+\delta_2 O_{it}+\delta_3 X_{it}+\delta_4 Z_{jt}+\vartheta_{ijt} \tag{4}$$

where O_{ijt} and M_{it} refers to the share of non-farm working members and mechanization expenditure of household *i* from village j in year t, respectively. X_{it} is vector of household and village characteristics that affect non-farm employment and mechanization. μ_{ijt} and ϑ_{ijt}

are the error terms of non-farm employment and mechanization estimation, respectively.

The study uses an instrumental variable (IV) approach to address endogeneity between two dependent variables, by including D_{jt} as IV for non-farm employment equation (Eq. 3) and Z_{jt} as IV for mechanization equation (Eq. 4). In principle, D_{jt} should affect non-farm employment, but not farm mechanization. Similarly, Z_{jt} should influence farm mechanization, but not non-farm employment. The study uses the average non-farm income per capita at village level as IV in non-farm employment estimation (as D_{jt} in Eq. 3). This IV reflects the opportunity cost of farm labor in the local economy (Drall and Mandal 2024) and is expected to positively affect households' decision to join non-farm work. The study selects the average mechanization expenditure of other households (except for the household itself) in the same village as IV in mechanization estimation (as Z_{jt} in Eq. 4). Neighbors' machinery usage behaviors might influence farmers' decisions to use mechanization but not directly affect non-farm employment decisions (Zheng *et al.* 2021).

The inclusion of farm mechanization (M_{ijt}) in the estimation of non-farm employment and vice versa leads to an endogeneity issue. The study addresses this issue by using the three-stage least squares (3SLS) model proposed by Zellner and Theil (1992). The 3SLS model accounts for the correlation of endogenous dependent variables and error terms in Eq. (1) and Eq. (2). This model generates more efficient parameter estimates than two-stage least squares or seemingly unrelated regression, which ignores the potential correlation across equation disturbances (Zellner and Theil 1992). In the first stage, all endogenous variables are regressed on instrumental variables to obtain their predicted values. In the second stage, consistent covariance matrix of the equation disturbances is obtained by analyzing the residuals of the estimations from the estimation of each structure equation in the first stage). In the last stage, a generalized least squares estimation is performed using the instrumented values from the first stage and the covariance matrix from the second stage.

The study conducts several quality tests to check the robustness, including exclusion restriction test, instrument validity test, and Breusch-Pagan Lagrange Multiplier Test for independent equations. The Likelihood Ratio (LR) Test and Wald Test are used to check for overall system heteroscedasticity to confirm the appropriateness of simultaneous equations model (Appendix Table A2 to Table A4). To account for common unobserved characteristics among households in the same village, standard errors are clustered at the village level (Abadie *et al.* 2023).

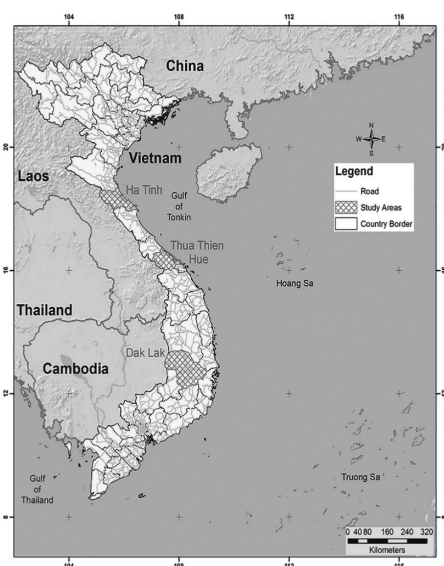
4. Data and descriptive statistics

4.1 Research sites and data

The study uses the data for Vietnam from "Thailand-Vietnam Socioeconomic Panel" (TVSEP) project. While long-term socioeconomic panel data are available in developed countries, such datasets remain scarce in developing countries like Vietnam (Klasen and Povel 2016). The TVSEP data collect information about 2,200 households from 220 villages in three rural provinces in Vietnam (Ha Tinh, Thua Thien Hue, and Dak Lak) (Figure 3). Using a systematic sampling procedure, this sample is representative of the rural population in these poor provinces (Hardeweg *et al.* 2016). TVSEP followed a three-stage random sampling method from commune, village, and household levels. First, these provinces were purposely selected for their low income per capita, high agricultural dependence, and poor infrastructure. Second, two villages from each sub-district were then sampled based on population size, then ten households per village were randomly chosen. Because rice is the dominant crop for most farmers surveyed and rice cultivation is also labor-intensive, engaging in non-farm employment might affect rice production via labor channels. The study keeps only those households (i) cultivating rice, (ii) participating in all four waves (2010, 2013, 2016, 2017), and (iii) not having missing data. The final sample for analysis consists of 828 rice households across four waves, totaling 3312 observations.

The data covers a wide range of information on the socio-economic characteristics of

Figure 3. Study sites of the TVSEP project in Vietnam.



Source: Nguyen et al. (2021)

households and village-level data needed to calculate the two dependent variables: information on individual household members (e.g., age, education, health, and employment status), information on crop production (production costs, productivity, and output values), households' livelihood strategies and income (agricultural production, non-farm employment, and natural resource extraction), household expenditure, remittances and village infrastructures. All monetary values are converted to 2005 PPP US$. The data collected refers to the last 12 months before the survey. Table A1 in the Appendix presents detailed variable definitions.

4.2 Measurements of key variables

Non-farm employment variable

Non-farm employment is measured as the share of non-farm working members over the total household members. To enrich the understanding of the interrelationship between non-farm employment and mechanization, the study conducts further analyses using non-farm employment types (i.e., wage employment and self-employment) as non-farm employment indicators.

Mechanization variable

In the study areas, farmers may own, borrow, or rent machinery for farming activities. To assess the level of mechanization in rice production, the paper uses the logarithm of total mechanization expenditure per hectare as the dependent variable. This expenditure encompasses all costs associated with machinery use, including rental fees, maintenance expenses, and operational costs. Unlike previous studies that have measured mechanization using dummy variables (Aryal *et al.* 2019), count data (Ma *et al.* 2018b), or machine horsepower (Zhou *et al.* 2018), this measurement allows us to further contribute to existing literature on mechanization in Vietnam.

4.3 Descriptive statistics

Table 1 shows descriptive summaries of all variables in the analysis. The share of non-farm working members slightly increases over time. Mechanization expenditure has increased substantially from PPP$ 283 in 2010 to PPP$ 382 in 2017.

On average, household heads are about 52 years old with secondary education, and over 78% report good health. More than 80% of households are male-headed, but this proportion has been declining. Household size averages four members with about 27% being dependent members. The average farm size is 0.6 ha, showing that most surveyed farms are small-scale. Household phone and motorcycle ownership have increased significantly, highlighting the importance of these devices (Bierkamp *et al.* 2024; Hübler and Hartje 2016).

Table 1. Descriptive statistics of sampled households by year

	Pool sample (n = 3312)	2010 (n = 828)	2013 (n = 828)	2016 (n = 828)	2017 (n = 828)
Mechanization expenditure	320.244 (233.534)	283.059 (264.125)	228.045 (195.411)	387.228 (221.584)	382.642 (207.405)
Share of non-farm working members in household	0.330 (0.235)	0.281 (0.206)	0.318 (0.224)	0.356 (0.250)	0.367 (0.247)
Age	52.035 (11.413)	48.438 (11.359)	51.409 (11.284)	53.697 (10.983)	54.597 (11.04)
Gender	0.838 (0.369)	0.866 (0.341)	0.847 (0.361)	0.822 (0.382)	0.816 (0.387)
Education	1.759 (0.972)	1.764 (0.968)	1.784 (0.982)	1.74 (0.963)	1.749 (0.973)
Health	0.781 (0.414)	0.774 (0.418)	0.673 (0.47)	0.861 (0.346)	0.816 (0.387)
Household size	4.952 (1.744)	5.522 (1.794)	4.938 (1.689)	4.664 (1.647)	4.684 (1.707)
Dependency ratio	0.273 (0.249)	0.292 (0.226)	0.27 (0.244)	0.264 (0.26)	0.264 (0.262)
Farm size	0.647 (0.715)	0.568 (0.531)	0.854 (0.903)	0.575 (0.674)	0.589 (0.661)
Phone	0.87 (0.336)	0.737 (0.441)	0.919 (0.273)	0.914 (0.28)	0.911 (0.285)
Motorcycle	0.814 (0.389)	0.726 (0.446)	0.808 (0.394)	0.854 (0.353)	0.867 (0.34)
Asset	640.025 (956.398)	369.557 (352.894)	572.442 (774.667)	661.432 (970.981)	956.671 (1347.59)
Made roads	0.7841 (0.4115)	0.7138 (0.452)	0.6546 (0.476)	0.8841 (0.320)	0.8841 (0.323)
Further analysis					
Non-farm self-employment	0.249 (0.432)	0.244 (0.430)	0.238 (0.426)	0.255 (0.436)	0.258 (0.438)
Non-farm wage employment	0.751 (0.432)	0.723 (0.448)	0.738 (0.440)	0.766 (0.424)	0.778 (0.416)

Note: Standard deviation in parentheses.
Source: Author's calculations

Household asset values per capita surged from PPP$ 369 in 2010 to PPP$ 956 in 2017. Village characteristics have also improved over time. The proportion of villages with high-quality roads increased from 71% in 2010 to 88% in 2017, enhancing connectivity and accessibility.

The study further examines employment types as non-farm employment indicators. On average, households show a stronger preference for non-farm wage employment (75%) over self-employment (24.9%).

5. Results and discussion

5.1 Interrelationship between farm mechanization and non-farm employment

Table 2 presents the results of simultaneous equations model with farm mechanization

Table 2. Interrelationship between mechanization and non-farm employment

	Share of non-farm working members		Mechanization expenditure	
Mechanization expenditure	0.007***	(0.002)		
Share of non-farm working members			4.466**	(1.740)
Average village mechanization expenditure			0.681***	(0.058)
Average village non-farm income per capita	0.024***	(0.004)		
Age	0.000	(0.001)	0.027**	(0.011)
Gender	0.018	(0.015)	−0.764***	(0.264)
Education	−0.011*	(0.006)	0.263***	(0.088)
Health	−0.232***	(0.023)	1.495***	(0.539)
Household size	−0.020***	(0.006)	0.680***	(0.151)
Dependency ratio	0.045***	(0.011)	−0.057	(0.223)
Farm size	0.002	(0.003)	−0.131***	(0.046)
Hue	−0.019**	(0.008)	0.007	(0.258)
Dak Lak	−0.057***	(0.017)	1.374***	(0.404)
Made roads	−0.003	(0.014)	0.161	(0.347)
Phone	0.006	(0.013)	0.585**	(0.256)
Motor	0.033**	(0.016)	0.143	(0.304)
Asset	0.017***	(0.006)	0.138	(0.105)
Constant	0.031	(0.055)	−3.128***	(1.194)
N	3,312		3,312	

Note: Robust standard errors clustered at village level in parentheses. Control for province and time fixed effects. ***$p<0.01$, **$p<0.05$, *$p<0.10$.
Source: Author's calculations.

and non-farm employment as dependent variables. It appears that farm mechanization and non-farm employment have a significant and positive interrelationship.

Specifically, when the share of non-farm working members in the household increases by 1%, the mechanization expenditure increases by 446.6%. This finding further confirms the income effect of non-farm employment: households with more members participating in the non-farm achieve higher household income, allowing them to invest more in farm mechanization to address labor shortages and enhance production efficiency (Yi *et al.* 2019; Zheng *et al.* 2021). This result aligns with previous studies, which concluded that the income from non-farm activities can help alleviate credit constraints for farmers, enabling them to pay more for inputs in agricultural production, including farm machinery (Anríquez and Daidone 2010; Hertz 2009; Mondal *et al.* 2021; Takahashi and Otsuka 2009). This also implies that promoting the rural non-farm sector will enhance growth of the farm sector also (Pfeiffer *et al.* 2009).

Similarly, a 1% increase in mechanization expenditure increased the share of non-farm working members by 0.00007. Mechanization replaces farm labor input and frees up household members to pursue non-farm opportunities (Adu-Baffour *et al.* 2019; Goodwin and Ahmed 2016; Nguyen and Warr 2020; Zheng *et al.* 2021). This helps households diversify their livelihoods, reduce income risks, and maximize income by allocating labor to more

Table 3. Heterogeneous analysis by gender of household head

	Impact of mechanization expenditure on share of non-farm working members	Impact of share of non-farm working members on mechanization expenditure
Male	0.008*** (0.003)	5.146*** (1.945)
Female	0.000 (0.003)	0.325 (3.402)

Note: Robust standard errors clustered at village level in parentheses. Control for province and time fixed effects. ***p<0.01, **p<0.05, *p<0.10.
Source: Author's calculations

stable and higher-return activities.

Furthermore, the results reveal that non-farm employment has a stronger impact on mechanization. This may be due to the synchronized mechanization in the study area, which primarily focused on land preparation and harvesting. Farmers still need to allocate labor to specific production tasks that have not yet been mechanized, limiting the overall labor-saving effect of mechanization. This aligns with previous research suggesting that higher levels of mechanization lead to greater reductions in farm labor demand (Amoozad-Khalili *et al.* 2020) and increased participation in non-farm employment (Ma *et al.* 2024).

5.2 Heterogeneous analysis

5.2.1 Heterogeneity analysis by gender of household head

Table 3 examines heterogeneity by household head gender. The findings show that in male-headed households, mechanization significantly increases the share of household members working non-farm, and vice versa.

However, no significant relationship is observed in female-headed households, probably due to gender-based differences in rice production. In Vietnam, men typically handle labor-intensive tasks like land preparation and harvesting, while women focus on seed preparation, weeding, and post-harvest processing (Tran *et al.* 2020). Consequently, when men shift to non-farm employment, households increase mechanization investment to compensate labor shortages in mechanized production stages (Paudel *et al.* 2020). This underscores the need to promote full mechanization in rice production, which could provide greater benefits for women. Expanding mechanization would not only facilitate timely crop cultivation and enhance productivity but also improve the well-being of female-headed households by increasing their access to machinery, reducing costs, and alleviating the physical burden of agricultural work (Ma *et al.* 2024).

Moreover, female-headed households in the study area tend to be more vulnerable. Most of female household heads are divorced or widows. Their education level and income are significantly lower than male-headed households, while bearing greater childcare and elder-care responsibilities, limiting their non-farm employment participation (Table 4). Moreover, financial constraints restrict their access to farm machinery, given the substantial capital

Table 4. Difference between male-headed households and female-headed households.

	Male-headed households	Female-headed households	Difference t-test
Total annual income per capita (PPP USD)	1610.954	1418.065	−192.889***
Education	1.305	1.847	−0.541***
Number of children under 6 years old	0.264	0.314	0.050**
Marital status of household head (1=married, 0 otherwise)	0.981	0.217	−0.763***

Note: ***p<0.01, **p<0.05, *p<0.10.
Source: Survey data

investment required (Murray *et al.* 2016). Limited education and technical skills further prevent them from using machinery (Fischer *et al.* 2018). This finding aligns with Zheng et al. (2021) in China and (Paudel *et al.* 2020) in Nepal, which report lower mechanization adoption rates among female-headed households compared to their male-headed counterparts. Addressing these gender disparities through improved access to education, training, and financial resources is essential for increasing mechanization adoption among women. Enhancing their participation in mechanized farming can, in turn, improve their opportunities for non-farm employment and contribute to broader rural development.

5.2.2 Heterogeneity analysis by type of non-farm employment

In this section, the study conducts further analyses using employment types (wage employment and self-employment) as non-farm employment indicators.

Given the binary nature of employment type variables, the paper follows Adeline and Moussa (2020) and employs a conditional mixed process model for analysis. Table 5 shows that mechanization does not significantly affect wage employment. This is probably because mechanization is not fully integrated in poor rural areas but concentrated on specific production stages (e.g., land preparation and harvesting). This reduces households' likelihood of securing wage employment, particularly permanent positions with specific working time requirements.

However, mechanization significantly increases self-employment participation. This contrasts with Ma et al. (2024), who found no impact of mechanization adoption on self-employment in China. They argue that starting a business requires an initial capital investment, which poses a barrier for farmers entering that sector. However, self-employment in rural Vietnam often involves selling household agricultural products at local markets, opening small retail stores, or engaging in food processing. These activities do not require official registration, are tax-exempt, demand low capital investment, and offer flexible working hours. This flexibility enables farmers to continue farming while generating additional income from their own businesses.

Table 5 also examines the influence of different non-farm employment types on farm

Table 5. Relationship between different non-farm employment types and mechanization

	Mechanization expenditure	Non-farm self-employment	Non-farm wage employment
Mechanization expenditure		0.061** (0.031)	−0.018 (0.016)
Non-farm self-employment	0.294** (0.145)		
Non-farm wage employment	1.017** (0.449)		

Note: Robust standard errors clustered at village level in parentheses. Control for province and time fixed effects. ***$p<0.01$, **$p<0.05$, *$p<0.10$.
Source: Author's calculations

mechanization. The results show that engagement in both employment types is significantly correlated with higher mechanization investment, highlighting the importance of non-farm employment in improving mechanization. However, wage employment has a more substantial impact on mechanization, compared to self-employment. This is probably because wage employment provides a more stable and reliable income flow than small self-business (Chawanote 2014). Moreover, for permanent wage jobs, laborers may find it difficult to return home during peak seasons. Therefore, households may increase reliance on mechanization to compensate for labor shortages during critical production stages.

6. Conclusions and policy implications

Using the simultaneous equations model to address potential endogeneity, the paper confirms a positive interrelationship between non-farm employment and farm mechanization in Vietnam. The analysis is based on a four-wave panel survey from the TVEP dataset. The findings indicate that a 1% increase in mechanization expenditure leads to a modest but statistically significant rise of 0.00007% in the share of household members engaged in non-farm employment. Conversely, a 1% increase in the proportion of household members working in non-farm sectors corresponds to a substantial 446.6% increase in mechanization expenditure.

Heterogeneous analysis reveals that mechanization has a significant positive impact on the share of household members engaging in non-farm employment only for male-headed households, and vice versa. However, no significant relationship is found for female-headed households. Additionally, the study finds that both wage employment and self-employment contribute positively to mechanization investment.

The findings of this study have significant policy implications.

Firstly, given the critical role of mechanized farming in enhancing farmers' livelihoods and promoting sustainable agriculture, government initiatives should prioritize the development and distribution of user-friendly machinery tailored for small-scale farms. Ensuring affordability and ease of use can drive widespread adoption.

Secondly, implementing more intensive land consolidation policies is crucial to reducing the fragmentation of farming plots. While existing policies may expand landholding sizes per household, fragmented plots continue to hinder efficiency. Policymakers should adopt context-specific strategies to address this challenge effectively.

Thirdly, promoting integrated mechanization systems for crop production and improving accessibility can further accelerate adoption and efficiency. Special attention should be given to designing technology that is accessible to less-educated farmers, ensuring broader participation in mechanized farming.

Fourthly, the strong interconnection between non-farm employment and mechanization underscores the need for policies that diversify farmers' income sources. Expanding local non-farm job opportunities through improved infrastructure and an investment-friendly business environment can enhance rural livelihoods while mitigating labor shortages caused by rural-to-urban migration.

Finally, addressing gender disparities in non-farm employment and mechanization is crucial. Women's access to agricultural technology and employment opportunities should be improved through targeted interventions such as financial support, skill development programs, and enhanced access to mechanization. Supporting female-headed households in this way can strengthen agricultural productivity, improve household welfare, and promote inclusive rural development.

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Appendix

Table A1. Definition and measurement of household and village characteristics

Variables	Definition
Dependent variables	
Share of non-farm working members in household	The share of household members employed in the non-farm sector (percentage)
Mechanization expenditure	Expenditure on mechanization (PPP USD/ha/year)
Independent variables	
Age	Age of household head (year)
Gender	1 if household head is male, 0 otherwise
Education	Education of household head (0-No education, 1-Primary, 2-Secondary, 3-High school, 4-vocational training, 5-University)
Health	1 if health condition of household head is good, 0 otherwise
Household size	Number of members in household (persons)
Dependency ratio	Number of members aged 0-14 and over 65/number of members aged 15-64
Farm size	Total cultivated rice land (ha)
Dak Lak	1 if households reside in Dak Lak, 0 otherwise, Ha Tinh as basis
Hue	1 if households reside in Hue, 0 otherwise, Ha Tinh as basis
Phone	1 if households have phones, 0 otherwise
Motorcycle	1 if households have motorcycles, 0 otherwise
Made roads	1 if village has paved road, 0 otherwise
Asset	Total asset value per capita (PPP USD)
Average village mechanization expenditure	Average expenditure on mechanization of other households within the same village (PPP USD/ha/year)
Average village non-farm income per capita	Average annual non-farm income per capita of the village (PPP USD/year)
Further analysis	
Household non-farm self-employment	1 if household participated in any type of non-farm self-employment, 0 otherwise
Household non-farm wage employment	1 if household participated in any type of non-farm wage employment, 0 otherwise

Table A2. Testing the exclusion restriction of instrumental variables

	Share of non-farm working members in household		Mechanization expenditure	
Instrumental variables				
Average village mechanization expenditure	−0.001	(0.002)	0.234***	(0.063)
Average village non-farm income	0.018***	(0.004)	0.010	(0.068)

Note: Standard deviations in parentheses. ***p<0.01, **p<0.05, *p<0.10.

Table A3. Instrumental variable validity test: IV-2SLS model

Treatment variable	First stage		Weak identification test (Cragg-Donald Wald F statistic)	Underidentification test (Kleibergen-Paap rk LM statistic)
	Coef.	se	F test	p_value
Share of non-farm working members in household	0.018***	0.004	41.582	0.000
Mechanization expenditure	0.234***	0.063	41.503	0.000

Table A4. Quality tests of the simultaneous estimation model

	chi2	Prob.>chi2
Tests of independent equations (Breusch-Pagan Lagrange Multiplier Test)	296.213	0.000
Tests of Overall System Heteroscedasticity (Likelihood Ratio LR Test)	310.306	0.000
Tests of Overall System Heteroscedasticity (Wald Test)	3491.947	0.000