https://doi.org/10.17221/68/2025-AGRICECON

Non-farm employment and agricultural mechanisation adoption: A reciprocal relationship

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Citation: Nguyen H.T.T., Le T.Q.A., Hung P.X., Phan N.T. (2026): Non-farm employment and agricultural mechanisation adoption: A reciprocal relationship. Agric. Econ. – Czech, 72: 37–55.

Abstract: This study investigates the reciprocal relationship between non-farm employment and mechanisation adoption of smallholders in Vietnam using the longitudinal Vietnam Access to Resources Household Survey (VARHS) 2008–2016 dataset. By employing the correlated random effects with the Mundlak approach to address the selection bias from the unobserved heterogeneity of panel data and the instrumental variables regressions to treat the endogeneity issue of non-farm participation and mechanisation adoption, the findings revealed that non-farm employment and mechanisation adoption have a positive interactive relationship. The mechanisation adoption in agricultural production could save farm labour and allow farmers to engage in non-farm activities. Conversely, non-farm earnings could relax financial constraints and provide opportunities for farmers to invest in mechanisation. The agricultural labour shifting to non-farm work was replaced by hiring machinery services rather than machinery investment when the service market was available and cost-effective. Our study implies practical policies and actionable plans to encourage non-farm employment and facilitate agricultural mechanisation toward sustainable agriculture and inclusive development in rural communities.

Keywords: instrumental variable approach; mechanisation adoption; Mundlak approach; non-farm working day; interactive relationship

Agricultural mechanisation strategy is considered as one of the fundamental pathways to achieving production efficiency, sustainable agriculture and inclusive development in rural regions (Wang et al. 2016; Daum 2023). Under the drivers of population growth, agricultural intensification, labour shortage and drudgery reduction, the transition from manual labour-based production to mechanisation-based production has been largely incentivised in smallholders in developing countries (Benin 2015; Ma et al. 2018). Technological advancements in mechanical applications have continuously facilitated considerable economic and social opportunities for farm households. Mechanised farming in sustainable production has not only provided positive impacts on land productivity (Mano et al. 2020; Zhou and Ma 2022), but also created yield increase and improved livelihoods for local farmers (Benin 2015). For instance, the use of tractors in soil conservation techniques has boosted productivity and intensified rice farming systems in Cote d'Ivoire (Mano et al. 2020). Mechanised processing improved income and production efficiency for small cassava farmers in Uganda (Abass et al. 2017). In China, mechanisation saved production costs, improved yields of grain and enhanced rural household income (Sang et al. 2023). Agricultural mechanisation also reduced social vulnerability

Partly funded by the University of Economics, Hue University under Grant No. NNC2023-01

https://doi.org/10.17221/68/2025-AGRICECON

by increasing work stability and mitigating gender bias (Zhou and Ma 2021). In particular, as rural-to-urban migration has usually left women primarily responsible for family agricultural tasks, mechanisation helped them maintain or enhanced their farm-based livelihoods (Ma et al. 2018). Additionally, the innovations in research and development of machinery and the socialisation of mechanical agricultural services have been increasingly promoted in agricultural operations in smallholders toward sustainable development (Mottaleb et al. 2016; Belton et al. 2021; Daum 2023).

Technological change has been associated with critical opportunities for farm households to diversify intra-household workforce participation (Afridi et al. 2023). Since mechanisation can address seasonal labour shortages, reduce the strenuous nature of power-intensive tasks, and streamline farming operations, it accumulates complementary advantages in increasing the involvement of farm households in off-farm jobs (Belton et al. 2021). Especially, integrating non-farm work with mechanised production serves as a risk-coping strategy to respond to weather-related risks and other unpredictable agricultural production challenges. Non-farm employment is essential for sustainable and inclusive rural development. For instance, engaging in off-farm jobs helps rural families grow their income (Anang et al. 2020; Bai et al. 2024), improves necessary expenditures (Hossain and Al-Amin 2019), strengthens food security (Kuwornu et al. 2018) and reduces poverty and social vulnerability (Zereyesus et al. 2017; Bui and Hoang 2021). Participating in off-cropping activities is recognised as a strategic approach to enhancing household capacity and resilience against climate change, boosting farm investment and increasing productivity (Danso-Abbeam et al. 2021). Non-farm involvement also has a positive effect on the adoption of green control techniques toward sustainable agricultural development (Yu et al. 2023). Moreover, the growth of the non-farm market has provided further opportunities for women to increase their decision-making power and operational capacities in the family (Majlesi 2016). Off-farm employment also fosters farmers in education and training programs, helps members have better control of household resources, enhances dietary diversity, reduces domestic violence, and ultimately enhances family living standards (Heath 2014; Bai et al. 2024).

Driven by sustainable agriculture and rural development, the interaction between agricultural mechanisation and non-farm employment has been extensively examined in previous studies. In China, joint decisions of adopting machinery and joining in off-farm work had significant impacts on farm performance, in which, machinery use increased maize yields and off-farm employment reduced input expenses (Ma et al. 2018). Mechanised farmers had higher possibilities to participate in off-farm work than non-mechanised farmers (Aryal et al. 2019). While a considerable amount of empirical literature has investigated the one-way causal relationship between the adoption of agricultural mechanisation and non-farm employment behaviour of smallholders, little attention has been paid to measuring their two-way reciprocal relationship. Although they both represent strategies of sustainable agriculture and inclusive rural development, and there is no typical constraint on the temporal sequence between them. In some cases, non-farm employment and agricultural mechanisation simultaneously promote local farm expansion (Li et al. 2021). Particularly, the adoption of agricultural mechanisation proved the positive impact on the participation in the rural non-farm sector in Bangladesh, establishing the link between labour-saving technology adoption and off-farm engagement (Ahmed and Goodwin 2016). Increasing off-farm work is associated with less time spent on the farm, hence, buying agricultural services becomes a critical demand for farmers in time allocation (Su et al. 2016). Therefore, engaging in off-farm work has positively influenced agricultural mechanisation services adoption, considered as a kind of substitution between labour and capital, especially in the context of aging populations, rising labour wages, and rural transformation (Wang et al. 2016; Yi 2018). Further exploration revealed that an increase in off-farm employment has led to reduced machinery ownership but increased market machinery services (Ji et al. 2012). Regarding two-way reciprocal relationship, the research by Zheng et al. (2022) indicates that non-farm employment and agricultural mechanisation have a jointly causal interaction. In particular, their study found that non-farm employment significantly promoted mechanisation service expenditure and the decision of mechanisation service usage, and *vice versa*. However, despite capturing endogeneity issues in empirical analysis, this study has not evaluated the interactive relationships of these two activities over a dynamic term, as it was based on cross-sectional data. Revisiting the reciprocal relationship between non-farm employment and agricultural mechanisation using longitudinal data would strengthen their causal evidence, and enable a more dynamic analysis of these activities over time.

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In developing countries with imperfect markets, the relationship between non-agricultural activities and mechanisation adoption in agriculture is often complicated, particularly in the presence of market services. Non-farm employment affects the demand for mechanisation in agricultural production (Ji et al. 2012). When a market of hiring agricultural machinery services is available, participation in non-farm works enables farmers to be more likely to hire mechanisation services. Income generated from non-agriculture activities can relax financial constraints and provide cash for farmers to invest in machinery (Pfeiffer et al. 2009; Nguyen and Kondo 2020). Furthermore, agricultural mechanisation adoption can also encourage households to join in off-farm jobs of farm households by increasing non-farm labour supply. While most previous studies have focused on mechanisation services, a lack of research simultaneously explores both options for mechanisation adoption in farm households, including purchasing agricultural machines and using mechanisation services, in addressing a two-way relationship.

Therefore, addressing the endogeneity issues of agricultural mechanisation and non-farm employment participation, our study adds three key contributions to previous studies. First, this study estimates a two-way reciprocal relationship between mechanisation adoption decision and non-farm employment participation in Vietnam using longitudinal data. Second, our study enhances the theoretical framework by consolidating the agricultural household model, providing evidence of the interactive and interdependent relationship between technology adoption decisions and labour allocation within farm households in market imperfection. Third, our paper investigates the reciprocal relationship between non-farm employment and two types of mechanisation, including owning machinery and using mechanisation services, which offers an overall view of mechanisation adoption in Vietnam. Finally, by exploring the underlying factors determining the decision of agricultural mechanisation and non-farm employment participation, this study provides a better understanding and further discussions on the contextual factors of both activities, considered as foundations to develop policy options for effectively facilitating non-farm work and sustainably promoting scale-appropriate agricultural mechanisation.

Overview of agricultural mechanisation and non-farm employment of farmers in Vietnam. Although Vietnam is one of the leading rice exporters, poverty among rice producers remains prevalent (World Bank Group 2016) and income diversification is one of the central priorities of rural farmers toward sustainable development. Due to low agricultural labour productivity, particularly in rice production, structural transformation through expanding agricultural mechanisation and encouraging a non-farm rural economy has been targeted strategy of the Vietnamese government (Newman et al. 2020). Historically, the growth of mechanisation in Vietnam has followed a non-linear pattern, characterised by an initial increase in tractor use before the 1975 reunification period, followed by a decline during the 1980s to 1990s due to reduced supplies and an increased agricultural workforce, prior to rapid growth after 2000 thanks to considerable economic reforms in land use and market (Takeshima et al. 2020). For instance, the number of tractors grew from nearly 400 000 units in 2006 to over 700 000 units in 2016, with the proportions of machines powered greater than 12HP increasing from 32% to 42% during that period (Sakata 2020). Land consolidation resulting from the amended Land Law of 2013 (No. 45/2013/QH13), supportive policies on the reduction of agricultural losses from Decision No. 68/2013/QD-TTg, along with technological innovations and market incentives have all promoted the adoption of mechanisation in farm households (Nguyen and Warr 2020; Tran et al. 2022; Do et al. 2023). Currently, rising real agricultural wages, rural labour shortages, and rural-urban migration are considered key drivers of the replacement of labour by machine (Liu et al. 2020; van Aalst et al. 2023). Rice cultivation is the most common farming system adopting machinery as labour-saving inputs in soil preparation, irrigation, sowing, threshing, harvesting, and post-harvesting (Le et al. 2024). Used machinery had been innovated and updated from two-wheel and four-wheel tractors to combine-harvesters and power tillers to increase productivity and reduce production losses. These advancements in labour-saving technology have demonstrated different features in facilitating sustainable farming practices and reducing environmental externalities of farm machinery (World Bank Group 2016). In Vietnam, in addition to ownership that accounts for substantial capital investment in farming operations, farmers can choose rental services for different stages in tillage, irrigation, and harvest via fee-for-service arrangements. Although machinery ownership and custom hiring services comprise two forms of agricultural mechanisation, the latter is more prevalent in rural regions. In the mechanisation process, increasing farmers' perception and education, linked with upgrading farming technological knowledge, play a vital role in sustainable livelihoods (Tran et al. 2023; Phung and Dao 2024).

https://doi.org/10.17221/68/2025-AGRICECON

In another strand, the historic transition from a centrally planned to a market-oriented economy in Vietnam has provided greater opportunities for labour to shift from agricultural to non-agricultural sectors. Farmers' livelihoods have diversified into non-farm employment in the context of the structural transformation of rural Vietnam (Liu et al. 2020). The share of non-farm sectors in rural Vietnam increased from 38.1% in 2010 to 47.4% in 2017, in which, the regions of Red River Delta, Southeast, and Mekong River Delta had the highest portions (Nguyen 2019). Nationwide off-farm household ratios continued to rise from 28.9% in 2006 to 46.2% in 2016 (Nguyen 2019). Not only effectively reallocating production time, non-farm involvement also increases agricultural efficiency (Hoang et al. 2014). Joining non-farm employment has positive effects on household welfare by improving income, reducing poverty and ensuring food security (Hoang et al. 2014; Duong et al. 2021). For instance, the study of Hoang et al. (2014) showed that an extra person working in the non-farm sector helped increase household expenditure by 14% and reduce poverty by 7–12%. Moreover, since Vietnam is one of the vulnerable countries suffering from natural disasters and climate change, participating in off-farm work has been a critical decision for rural farmers to enhance their resilience (Duong et al. 2021). Access to non-agricultural work significantly reduces economic vulnerability (Bui and Hoang 2021) and household income diversification effectively contributes to reducing poverty and mitigating production risks in Vietnam (Imai et al. 2015). In addition, increased access to non-farm employment opportunities contributes to lowering the vulnerability to unpredictable climate change impacts for limited-income households, especially poor women (Ngo and Tran 2024). As a result, enhancing the knowledge and skills of rural people plays an important role in equitable and inclusive development.

In summary, facilitating appropriate-scale machinery access, enabling custom hiring services, and broadening non-farm income-generated opportunities through improved access to knowledge, market and social support, are necessary tools for sustainable rural development in Vietnam. Agricultural mechanisation and non-farm employment can perform in a complementary mechanism to improve rural household well-being. Agricultural mechanisation can support the reallocation of intra-household labour, which motivates farmers to join off-farm labour markets. In turn, households can utilise their non-farm earnings to invest in time-saving and high-efficiency technologies to create high-value agricultural production. Addressing these potentials and barriers, creating a supportive environment for transformation to agricultural mechanisation, improving sustainable agri-food systems, and diversifying non-farm income-generating activities are central demands of development policies in rural Vietnam.

MATERIAL AND METHODS

Estimation model

To investigate the reciprocal relationship between mechanisation adoption decision and non-farm employment participation, we simultaneously estimated two equations. The first equation, defined as the non-farm employment equation, estimates the effect of adopting mechanisation on the working time in non-farm activities. The second equation, defined as the mechanisation adoption equation, estimates the effect of non-farm working time on the adoption mechanisation of farmers. Thus, non-farm employment and mechanisation adoption variables will change the roles respectively between dependent and independent variables.

Our study analysed unbalanced panel data to capture all possible observations and expect precise estimations (Biørn 2004). To control the selection bias arising from unobserved heterogeneity in time-invariant characteristics of households, we applied the correlated random effects (CRE) in combination with the Mundlak approach. According to Wooldridge (2019) and the Mundlak device (1978), unobserved heterogeneity of household characteristics is controlled using the demeaning technique. We incorporated time averages of household-varying, farm-varying characteristics, and time dummies into our models as independent variables. In addition, our analysis faces another econometric issue: the endogeneity problem associated with non-farm employment and mechanisation adoption. The instrumental variables (IV) approach is employed to treat this issue. Therefore, our study attempts to address two distinct econometric problems, including selection bias resulting from unobserved heterogeneity and the endogeneity problem.

The correlated random effect with the Mundlak approach. To explore the impact of mechanisation adoption on non-farm employment, our study utilises the theoretical framework of non-farm employment decision proposed by Mollers and Buchenrieder (2005) and the agricultural household model with technology adoption developed by Fernandez-Cornezo et al. (2005). The framework of non-farm participation decision indicates that the determinants that affect

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non-farm participation are 'demand-pull' and 'distress-push' factors containing the institutional, individual, and household characteristics (Mollers and Buchenrieder 2005). According to the agricultural household model, the decisions of farm households in production (including technology adoption), consumption, and labour allocation are interdependent (Singh et al. 1986; Fernandez-Cornezo et al. 2005). In this analysis, the non-farm employment equation is a linear function of mechanisation adoption and other explanatory variables, including household characteristics, farmland attributes and social capital. The regression equation of the 'non-farm employment equation' of farm household *i* at time *t* with additive heterogeneity can be demonstrated as follows:

$$NF_{it} = \alpha_0 + \alpha_1 M_{it} + \alpha_2 Z_{ijt} + c_{1i} + u_{1it} \quad (1)$$

where: NF_{it} – the non-farm working time of i^{th} rice household at time t; α_0 – the constant parameter, α_1 – the parameters of the vector of explanatory variables; M_{it} – the binary variable of mechanisation adoption decision of i^{th} rice household at time t; Z_{ijt} – a vector of explanatory variables j^{th} presenting household's characteristics, farmland characteristics, social capital characteristics, time dummies of i^{th} rice household at time t; c_{1i} – the unobserved heterogeneity; u_{1it} – the idiosyncratic errors; t – 2008, 2010, 2012, 2014, 2016.

To explore the effect of non-farm participation on the mechanisation adoption decision of farm households, we utilise agricultural technology adoption theory to construct the model of adoption technology decision. Following this theory, the technology adoption decision of farm households is influenced by human capital factors, social capital factors, and institutional factors (Mwangi and Kariuki 2015; Varma 2019). Thus, we employ the Probit model in the mechanisation adoption equation. The regression model of the mechanisation adoption equation of farm household *i* at time *t* with additive heterogeneity can be specified as follows:

$$M_{it} = \beta_0 + \beta_1 NF_{it} + \beta_2 Z_{ijt} + c_{2i} + u_{2it} \quad (2)$$

where: β_0 – constant parameter; β_1, β_2 – the parameters of explanatory variables NF_{it} and Z_{ijt}; c_{2i} – the unobserved heterogeneity; u_{2it} – the idiosyncratic errors.

Alternatively, M_{it}^{*} is a latent variable which captures the household's mechanisation adoption decision and is modelled as follows:

$$M_{it} = \begin{cases} 1 & if\ M_{it}^{*} > 0 \\ 0 & if\ M_{it}^{*} \le 0 \end{cases} \quad (3)$$

Using fixed-effects estimator in the linear model may be inappropriate for unbalanced panels because the selection may be correlated with heterogeneity and cause inconsistency (Wooldridge 2019). On the other hand, random effects estimation allows the inclusion of time-invariant explanatory variables in the model. Thus, for this study, the correlated random-effects estimation with the Mundlak approach for the unbalanced panel is suitable to control for the unobserved heterogeneity of time-invariant variables. Under the Mundlak approach, the demeaning technique is employed by adding the time averages of the household-varying, farm-varying, and social capital-varying characteristics into the model. The time-invariant characteristics that will not be included in the model in this study are the gender and ethnicity of the household head.

Let

$$\overline{Z_{ij}} = T^{-1} \sum_{t=1}^{T_i} Z_{ijt} \quad (4)$$

where: $\overline{Z_i}$ – the time averages of household, social capital and farmland-varying characteristics variables; T – ; t – 2008, 2010, 2012, 2014, 2016.

According to the correlated random effects estimator, the unobserved heterogeneity c_{1i} and c_{2i} is a linear function of $\overline{Z_{ij}}$ (Wooldridge 2019):

$$c_{1i} = \gamma_1 \overline{Z_{ij}} + \nu_{1i} \quad (5)$$
$$c_{2i} = \gamma_2 \overline{Z_{ij}} + \nu_{2i} \quad (6)$$

where: ν_{1i}, ν_{2i} – the error terms from the equation of unobserved heterogeneity c_{1i}, c_{2i}; γ_1, γ_2 – the parameters of the unobserved heterogeneity c_{1i}, c_{2i} equation.

Thus, Equations (1 and 2) can be re-written as follows:

$$NF_{it} = \alpha_0 + \alpha_1 M_{it} + \alpha_2 Z_{ijt} + \gamma_1 \overline{Z_{ij}} + \varepsilon_{1it} \quad (7)$$
$$M_{it} = \beta_0 + \beta_1 NF_{it} + \beta_2 Z_{ijt} + \gamma_2 \overline{Z_{ij}} + \varepsilon_{2it} \quad (8)$$

where: $\varepsilon_{1it} = \nu_{1i} + u_{1it}$; $\varepsilon_{2it} = \nu_{2i} + u_{2it}$

The instrumental variable approach. As mentioned above, the IV approach will be applied to treat the endogeneity problem of mechanisation adoption and non-farm variables, ensuring unbiased estimations. According to Wooldridge (2013), the IV approach can solve the endogeneity problem by using a suitable proxy variable that does not directly affect the outcome variables (NF_{it} and M_{it}) and must correlate with the endogenous variables. Thus, the two-stage least squared (2SLS) method and IV-Probit analysis for pooled data are employed in the equations for non-farm employment and mechanisation adoption, respectively. The first-stage

https://doi.org/10.17221/68/2025-AGRICECON

endogenous equation shows the relationship between endogenous variables (mechanisation adoption and non-farm employment) and the instrumental variables which are demonstrated as follows:

$$M_{it} = \lambda_0 + \lambda_1 IV_{1it} + \lambda_2 Z_{ijt} + \mu_{1it} \quad (9)$$

$$NF_{it} = \eta_0 + \eta_1 IV_{2it} + \eta_2 Z_{ijt} + \mu_{2it} \quad (10)$$

where: IV_{1it} and IV_{2it} – the instrumental variables; μ_{1it} and μ_{2it} – the error terms. λ_0, η_0 – the constant parameters; λ_1, λ_2, η_1, η_2 – the parameters of explanation variables of the first-stage regressions of mechanisation adoption and non-farm employment.

In the first-stage regression of Equation (9), we estimate the Probit model with pooled data and random effects including time dummy variables in the estimation. The ordinary least squared (OLS) with pooled data and random-effects are also used in the first-stage regression of Equation (10).

Identification strategy. In this study, we employ two sets of instrumental variables to address the endogeneity problem: one for mechanisation adoption [IV_{1it} in Equation (9)] and another for non-farm employment [IV_{2it} in Equation (10)]. The validity conditions of instrumental variables require that they must satisfy two conditions: relevance and exogeneity. Regarding the endogenous mechanisation adoption variable, we choose two instrumental variables: the 'distance to the extension centre' variable and the 'distance to the extension shop' variable. The 'distance to the extension centre' variable is defined as the nearest distance from the commune centre to the extension centre, measured in kilometres. In Vietnam, extension centres are typically located in the centre of districts or provinces. The 'distance to the extension shop' variable is the nearest distance from the commune centre to the extension shop, which is also measured in kilometres. Extension service shops usually sell agricultural inputs to farmers, including agricultural machineries, and are often situated near markets or on main roads/highways. Therefore, we suppose that the distances to the extension centre and extension shop will influence the decision of mechanisation adoption of farm households when they can access information and support about new technology, agricultural machinery, and mechanisation services for their farming activities.

Regarding the endogenous non-farm employment variable, we use two instrumental variables: The 'non-farm employment opportunity' variable and the 'distance to the nearest daily market' variable. The instrument 'non-farm employment opportunity' is a binary variable that expresses the availability of enterprises, firms, factories or traditional occupation villages located within the commune or neighbouring communes. The presence of these enterprises, firms, factories or traditional occupation villages will create opportunities for family members to participate in non-farm employment. The second instrumental variable 'distance to the nearest daily market' is measured in kilometres. This variable was chosen as an instrument because it indicates farm households' access to the infrastructure and services that can influence their likelihood of joining in non-farm jobs. All the instrumental variables used in this analysis are derived from the commune survey of the Vietnam Access to Resources Household Survey (VARHS) dataset.

Data and descriptive statistics

Data source. This study employs the VARHS dataset from 2008 to 2016. We collected this dataset from the United Nations University World Institute for Development Economics (UNU-WIDER) website. The newest dataset of 2018 and 2020 has not been published on the UNU-WIDER website yet. The large-scale surveys were conducted in collaboration with the Central Institute for Economic Management (CIEM), the Institute of Labour Science and Social Affairs (ILSSA), the Centre for Agricultural Policy (CAP), and the Development Economics Research Group (DERG) of the University of Copenhagen.

First conducted in 2002, the VARHS surveys have been carried out every two years. The surveys capture the representatives of rural households in 12 provinces located in the five regions of Vietnam [Ha Tay, Phu Tho (Red River Delta), Lao Cai, Lai Chau, Dien Bien (Midland and Northern Mountainous Areas), Nghe An, Quang Nam, Khanh Hoa (Northern and Central Coast), Dak Lak, Dak Nong, Lam Dong (Central Highland), Long An (Mekong River Delta)], covering the diversity of geographic, topographic, climatic, socio-economic, and cultural features. This dataset includes both commune and household data, providing detailed information about the demographic, social, and economic characteristics of rural communes and households. Our paper used the unbalanced panel data from 2008 to 2016 and concentrated on rice farmers. We also utilised commune data to construct instrumental variables for our analysis and subsequently merged these with the household data. After removing missing observations, our final dataset comprises 8 012 (1 564 observations from 2008, 1 498 from 2010, 1 749 from 2012, 1 670 from 2014 and 1 531 from 2016).

Descriptive statistics of used variables. Table 1 shows the definition of variables used in this study.

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Table 1. The definition of variables

Variables	Definition
Dependent variables	
Non-farm employment time	the total of non-farm working days of family members
Mechanisation adoption	binary, 1 if farm household uses the mechanisation services or owns the agricultural machinery, 0 otherwise
Using mechanisation services	binary, 1 if farm household uses the mechanisation services, 0 otherwise
Owning machinery	binary, 1 if farm household owns the agricultural machinery (such as rice milling machinery, grain harvesting machinery, pesticide sprayers, tractor, plough etc.), 0 otherwise
Household characteristics	
Gender	gender of head's household (male = 1, female = 0)
Age	age of head's households (years)
Education	completed schooling years of head's households
Ethnicity	the major ethnicity (Kinh) = 1, minorities = 0
Household labour	the number of family labour
Farmland characteristics	
Farmland	the total of farm land area of household (hectare)
Number_plot	number of plots
Irrigation_condition	the proportion of farm irrigated land (%)
Social capital	
Credit	the amount of credit that was borrowed for rice production (0.038 USD)
Extension services	binary, 1 if household obtains assistance or information from extension services (such as new seeds, fertiliser, irrigation, etc.), 0 otherwise
FRO-member	binary, 1 if family member is a membership of farmer related organisations, 0 otherwise
Time dummy variables	
Year dummy	binary, dummy variables of years: 2008, 2010, 2012, 2014, 2016
Instrumental variables for mechanisation equation	
Distance to the extension centre	the distance from the commune centre to the nearest extension centre (km)
Distance to the extension shop	the distance from the commune centre to the nearest extension shop (km)
Instrumental variables for non-farm equation	
Non-farm employment opportunity	binary, 1 if the enterprises/firms/factories or traditional occupation villages are located in the commune or neighbouring communes where people can work and come back within the day, 0 otherwise
Distance to the nearest daily market	the distance from the commune headquarter to the nearest daily market with location (km)

FRO-member – farmer related organisations
Source: Authors' computation

https://doi.org/10.17221/68/2025-AGRICECON

The non-farm employment working time variable is defined as the sum of working days of all household members engaged in two non-farm activities: non-farm wage jobs and non-farm self-employment. One of the objectives of this paper is to investigate which specific type of mechanisation adoption (using mechanisation services or owning agricultural machines) has a relationship with non-farm employment. Thus, our study uses three dummy variables denoting mechanisation adoption: adopting mechanisation (either using mechanisation services or owning agricultural machinery), using mechanisation services, and owning machinery. The explanatory independent variables include household characteristics, farmland characteristics, and social capital characteristics.

Table 2 displays the descriptive statistics of all variables used in this study. We divided the total sample size into participants and non-participants in non-farm

Table 2. Descriptive statistics of variables used

Variable	Non-farm participation		Mechanisation adoption		Total
	participants (n = 6 248)	non-participants (n = 1 765)	adopters (n = 5 667)	non-adopters (n = 2 345)	(n = 8 012)
Dependent variables					
Non-farm employment time	–	–	285.470	196.001	259.284
Mechanisation adoption	0.731	0.624	–	–	0.707
Using mechanisation services	0.681	0.546	–	–	0.651
Owning machinery	0.119	0.151	–	–	0.126
Household characteristics					
Gender	0.818	0.823	0.811	0.838	0.819
Age	50.538	53.605	51.882	49.6	51.213
Education	7.156	5.920	7.319	5.831	6.884
Ethnicity	0.769	0.621	0.844	0.478	0.737
Household labour	3.222	2.580	3.039	3.179	3.080
Farm land characteristics					
Farmland	0.676	1.183	0.761	0.852	0.788
Number_plot	5.005	5.457	5.197	4.884	5.105
Irrigation_condition	77.319	64.750	79.952	61.487	74.551
Social capital					
Credit	1 531.31	3 190.24	2 511.124	412.736	1 896.718
Extension services	0.923	0.838	0.924	0.856	0.904
FRO-member	0.777	0.669	0.765	0.726	0.753
Instrumental variables for mechanisation equation					
Distance to the extension centre	–	–	11.082	16.281	12.604
Distance to the extension shop	–	–	4.477	9.889	6.061
Instrumental variables for non-farm equation					
Non-farm employment opportunity	0.858	0.763	–	–	0.837
Distance to the nearest daily market	1.457	3.050	–	–	1.807

FRO-member – farmer related organisations
Source: Authors' computation based on VARHS 2008–2016 dataset

https://doi.org/10.17221/68/2025-AGRICECON

activities (6 248 and 1 765 observations, respectively), and adopters and non-adopters of mechanisation (5 667 and 2 345 observations, respectively). The average working days on non-farm employment was 259 days per household, in which, the non-farm working time of the mechanisation adopters (285 days) was higher than that (196 days) of non-adopters. On average, 70.7% of farm households adopted mechanisation in rice production, in which, 65.1% used mechanisation services or hired machinery, and only 12.6% owned agricultural machinery. In addition, the proportions of adopting mechanisation and using mechanisation services of non-farm participants were higher than those of non-participants.

Table 2 also reports the differences in household characteristics between non-farm participants and non-participants, as well as mechanisation adopters and non-adopters. Compared with non-participants, household heads of non-farm participants were generally younger, better educated, had more family labour, smaller farm sizes, fewer plots, a higher percentage of irrigated farmland, and were less likely to require credit. They also obtained more assistance from extension services. Compared with non-adopters, mechanisation adopters tended to be older, better educated, predominately Kinh people, had a smaller number of family labourers, more farm plots, higher percentages of irrigated farmland, and a greater likelihood of borrowing credit and receiving assistance from extension services.

RESULTS AND DISCUSSION

Before exploring the estimation results on the reciprocal relationship between non-farm employment and mechanisation adoption, we present the results of the first stage regressions of non-farm working time and mechanisation adoption decision [Equations (7 and 8)] in Supplementary Table S1. In the first stage of analysing non-farm employment, our study employs both pooled OLS and random effect OLS, and all instruments used are statistically significant in both models. The positive coefficient of non-farm employment opportunity indicates that the availability of firms, factories or traditional occupation villages located in the commune or neighbouring communes increases the number of non-farm working days of farm households. A longer distance to the nearest daily market decreases non-farm working time. Results of the *F*-test for instruments of non-farm employment in the first-stage model also satisfy the relevant condition [greater than 10 (Stock and Yogo 2005)]. Consequently, we use Probit model with pooled data and random effects in the first stage of analysing mechanisation adoption. The estimation results show that all instruments are negatively significant in both models, implying that longer distances to the extension centre and the extension shop restrict the mechanisation adoption in farm activities of households. The *F*-test results for all instruments of mechanisation adoption variables in both models are greater than 10, confirming that the instruments are valid and significantly relevant.

Table 3 presents the estimation results on the reciprocal relationship between non-farm employment and mechanisation adoption decisions in the control of unobserved heterogeneity and endogeneity problems. In the non-farm employment equation, our study estimates the effect of adopting mechanisation decisions on non-farm working time by applying three different models: OLS random effects, CRE with the Mundlak approach, and 2SLS (pooled) models. Results show that the parameters of the mechanisation adoption variable are positively significant in all three models. By addressing of unobserved heterogeneity and endogenous problems in this analysis, we discover a positive effect of adopting mechanisation on non-farm working time. The finding indicates that an increase in the probability of adopting mechanisation decisions leads to an increase in non-farm working days of farm households. Adopting mechanisation in agricultural production can substitute or save family labour time and allow farmers to join other non-farm job opportunities. Our study is consistent with other studies emphasising the crucial role of agricultural mechanisation in enabling household members to participate in other activities beyond farm production (Ahmed and Goodwin 2016; Ma et al. 2018; Aryal et al. 2019; Nguyen and Warr 2020; Zheng et al. 2022). In addition, Table 3 demonstrates the impact of non-farm working time on the adopting mechanisation decision. This analysis employs four models, including the random effects probit, the CRE probit model with the Mundlak approach, 2SLS (pooled), and IV probit models. The coefficients of the non-farm employment time variable are all positively significant in four models, indicating that non-farm employment has a favourable impact on the decision of mechanisation adoption of farm households. This finding implies that income generated from non-farm work can provide cashable earnings to help farmers adopt mechanisation in agricultural production by investing in agricultural machinery or using mechanisation services. Our result aligns with the results of Ji

https://doi.org/10.17221/68/2025-AGRICECON

Table 3. The reciprocal relationship between non-farm employment and mechanisation adoption

Variables	Non-farm employment (NFE)			Mechanisation adoption			
	random effects	CRE Mundlak	2SLS – pooled	RE Probit	CRE Probit – Mundlak	2SLS – pooled	IV Probit – pooled
Mechanisation adoption	0.347***	0.339***	8.983***	–	–	–	–
	[0.10]	[0.10]	[1.81]				
Non-farm employment time (log)	–	–	–	0.017***	0.016***	0.074***	0.176***
				[0.00]	[0.00]	[0.01]	[0.02]
Household characteristics							
Gender	−0.608***	−0.579***	−0.707***	0.053	0.039	0.054***	0.140***
	[0.15]	[0.15]	[0.17]	[0.05]	[0.05]	[0.02]	[0.04]
Age	−0.035***	−0.020*	−0.040***	0.003**	0.003	0.003***	0.008***
	[0.00]	[0.01]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]
Education	0.073***	0.066***	0.024	0.021***	0.020***	0.001	0.001
	[0.02]	[0.02]	[0.02]	[0.01]	[0.01]	[0.00]	[0.01]
Ethnicity	1.667***	1.281***	−1.200**	0.936***	0.883***	0.194***	0.412***
	[0.16]	[0.17]	[0.59]	[0.05]	[0.05]	[0.03]	[0.10]
Household labour	0.927***	0.913***	0.941***	−0.021	−0.047**	−0.079***	−0.166***
	[0.04]	[0.06]	[0.05]	[0.01]	[0.02]	[0.01]	[0.02]
Farm land characteristics							
Farmland	−0.357***	−0.115*	−0.519***	0.054***	−0.033	0.042***	0.111***
	[0.06]	[0.07]	[0.06]	[0.02]	[0.03]	[0.01]	[0.02]
Number_plot	−0.099***	−0.035	−0.231***	0.048***	0.046***	0.021***	0.055***
	[0.02]	[0.03]	[0.03]	[0.01]	[0.01]	[0.00]	[0.01]
Irrigation_condition	0.005***	−0.0009	−0.004	0.005***	0.002***	0.001***	0.002***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Social capital							
Credit (log)	−0.006	0.011	−0.084***	0.037***	0.027***	0.009***	0.029***
	[0.02]	[0.02]	[0.02]	[0.01]	[0.01]	[0.00]	[0.01]
Extension services	0.956***	0.895***	0.285	0.240***	0.172**	0.007	0.020
	[0.17]	[0.19]	[0.28]	[0.07]	[0.08]	[0.03]	[0.07]
FRO-member	0.171	0.013	0.059	0.081*	0.121**	0.004	0.009
	[0.11]	[0.14]	[0.15]	[0.04]	[0.06]	[0.01]	[0.04]
Year dummy variables	yes	yes	yes	yes	yes	yes	yes
Time averages of household and farm-varying characteristics		yes			yes		
Constant	−0.121	−1.278**	−1.690***	−1.119***	−1.399***	0.171***	−0.769***
	[0.37]	[0.56]	[0.49]	[0.13]	[0.18]	[0.04]	[0.13]
Number of observations	8 012	8 012	8 012	8 012	8 012	8 012	8 012
LR test of rho = 0: chi^2, χ^2 (1)				54.59***	53.33***		

https://doi.org/10.17221/68/2025-AGRICECON

Table 3 to be continued

Variables	Non-farm employment (NFE)			Mechanisation adoption			
	random effects	CRE Mundlak	2SLS – pooled	RE Probit	CRE Probit – Mundlak	2SLS – pooled	IV Probit – pooled
Wald test of exogeneity χ^2							29.70***
Underidentification test			41.822			71.891	
Weak identification test (Cragg-Donald Wald F statistic)			26.771			43.196	
Overidentification test (Hansen J statistic χ^2)			1.034 (P-value = 0.309)			0.018 (P-value = 0.893)	

***, ** and *significance at 1%, 5% and 10% levels, respectively; values in parentheses are standard errors, the standard error is robust in the random effects, CRE with Mundlak of NFE equation, IV Probit, and 2SLS of both NFE and adopt mechanisation equations

2SLS – two-stage least squared; CRE – correlated random effects; FRO – farmer related organisations; IV – instrumental variable; LR – Likelihood ratio

Source: Authors' estimation from VARHS 2008–2016 dataset

et al. (2012), Wang et al. (2016), and Yi (2018) in China, and Takahashi and Otsuka (2009) in the Philippines. Therefore, the agricultural mechanisation adoption and participation in non-farm employment of farm households exhibit a positively reciprocal relationship or a dynamic, often complementary, relationship. While adopting mechanisation can save and displace labour in agricultural cultivation, driving them towards non-farm sectors. Conversely, the earnings from non-farm work can provide the financial source for farmers to invest in mechanisation.

The estimation results from the 2SLS model further aim to test the validity of instrumental variables for non-farm employment (NFE) and mechanisation adoption equations. In the NFE equation, the value of the Cragg-Donald Wald F statistic is 26.771, indicating that the instrumental variables pass the weak instruments test. An over-identification test (Hansen J statistic) is also implemented to evaluate the exogeneity condition of the instruments. The value of the over-identification test of IVs for NFE equation is 1.034, with a P-value of 0.309. This implies that the instruments are exogenous variables. Thus, the instrumental variables used to treat the endogenous mechanisation adoption variable satisfy the requirements for both instrumental relevance and exogeneity. In the mechanisation adoption equation, the value of the weak identification test is 43.196 and the value of the over-identification test is 0.018 with a P-value of 0.893. Therefore, the instrumental variables for the mechanisation equation are also valid and satisfy two conditions.

Regarding the determinants of non-farm working time, the results present that non-farm employment time is also determined by other control variables such as household characteristics, farmland characteristics, and social capital factors. The coefficients of the head's gender are negative and significant in all models, indicating that if head's household is female, the household will participate in non-farm work more than the male head. This result implies that the work management in the family by a female head may facilitate their spouses participation in non-farm employment. Younger age and better education are strong motivators for farm households to pursue non-farm jobs. The Kinh ethnic group works in the non-farm sector more than minority groups, likely thanks to advantages and opportunities such as language skills and proximity to urban centres. The number of household labour is an important factor for determining non-farm employment participation, as it positively affects the supply of family labour for such activities. The negatively significant coefficients associated with farmland size and the number of plots indicate that larger and more fragmented farms reduce the likelihood of participating in non-farm work. This finding indicates that larger farms also be more likely to increase labour requirements in agriculture, which

https://doi.org/10.17221/68/2025-AGRICECON

could lead to potentially limiting the time available for non-farm work. The variable related to extension services shows a positive and significant relationship, implying that assistance from these services could encourage farm households to engage more in non-farm jobs.

In examining the factors that influence mechanisation adoption decision, our estimation results also reveal several key determinants, including gender, age, ethnicity, farmland size, number of plots, irrigation condition, access to credit, extension services, and membership of farmer-related organisations. Specifically, male heads tend to adopt mechanisation in agricultural production more than female heads. This result reveals that male heads are usually more proactive in making decisions regarding the farming process, particularly in the adoption of mechanisation. Older farmers are generally more biased toward mechanisation adoption than younger farmers due to aging issues. Interestingly, the positively significant coefficient of ethnicity indicates that minority ethnic groups are less likely to adopt mechanisation than the Kinh people. In 2SLS and IV probit models, the coefficient of the number of household labour variable is negatively significant. This finding implies that households with a larger labour force have a lower probability of mechanisation adoption because they can rely on their sufficient supply of labour in agricultural activities. The farmland area and the number of plots also have a positive impact on the mechanisation adoption of households. Large farms often require higher labour source or labour cost. Mechanisation in agriculture can help reduce their dependence on manual labour, lowering production costs or cost-effective and mitigating labour constraints. In addition, mechanisation allows larger farms to cultivate and harvest crops faster and with less labour, leading to increased overall productivity and potentially higher yields. The positively significant parameter of the irrigation condition variable shows that a higher proportion of irrigated farmland likely facilitates farmers to adopt mechanisation. The result also indicates that access to credit has a positive influence on mechanisation adoption, suggesting that mechanisation adopters tend to borrow more credit for farm production than non-adopters. Lastly, the coefficients associated with extension services and FRO membership demonstrate positive significance in random effect probit and CRE Probit with Mundlak models. These results refer that the assistance of extension services and membership in farmer-related organisations would support farmers in adopting mechanisation.

To identify which type of mechanisation correlated to non-farm employment, our study estimated the two-way reciprocal relationship between non-farm participation and two types of mechanisation adoption: using mechanisation services and owning agricultural machinery. Similarly, we employed the OLS random effects, CRE combined with Mundlak approach, and 2SLS (pooled data) in the NFE equation; the RE probit, CRE Probit with Mundlak approach, 2SLS (pooled data), and IV probit (pooled data) in using mechanisation services and owning machinery equations, as shown in Table 4 and Table 5. The results in Table 4 indicate a two-way reciprocal relationship between non-farm employment and the use of mechanisation services. In a one-way relationship, using mechanisation services positively affects non-farm employment in all three models. Conversely, non-farm working time also positively influences the use of mechanisation services decisions in all four models. Furthermore, results of the weak identification test and overidentification test in the 2SLS model in both equations report that the instruments of two endogenous variables (non-farm employment and using mechanisation services) are valid and satisfy the instrumental relevance and exogeneity conditions.

However, we observed contrasting results regarding the two-way relationship between non-farm employment and owning machinery of households (Table 5). In the non-farm employment equation, the estimation results show that owning machinery does not affect non-farm employment in OLS random effects and CRE with Mundlak approach models. However, a negative relationship was found in the 2SLS model. In the owning machinery equation, the non-farm employment time variable also shows no impact on owning machinery of farm households in the RE probit and CRE probit with Mundlak models. Negative effects were noted in the 2SLS and IV probit models. The absence of an effect or the negative relationship between non-farm working time and owning machinery is explained by the presence of a mechanisation services market. As the market for hiring machinery services develops, farmers tend to use these services instead of investing in purchasing machinery when participating in non-farm activities. In other words, when household labour from agriculture activity shifting to non-farm work is substituted by using mechanisation services rather than by owning machinery. This result is considered suitable because the average use of mechanisation services was 65.1%, while the proportion of ownership of agricultural machinery in farm households was only 12.6% (Table 2). This finding is consistent with the study by Ji et al. (2012), which demonstrated an inverse

https://doi.org/10.17221/68/2025-AGRICECON

Table 4. The reciprocal relationship between non-farm employment and using mechanisation services

Variables	Non-farm employment (NFE)			Using mechanisation services			
	random effects	CRE with Mundlak	2SLS – pooled	RE Probit	CRE Probit – Mundlak	2SLS – pooled	IV Probit – pooled
Using mechanisation services	0.399***	0.380***	7.197***	–	–	–	–
	[0.10]	[0.10]	[1.31]				
Non-farm employment time (log)	–	–	–	0.023***	0.023***	0.096***	0.213***
				[0.00]	[0.00]	[0.02]	[0.01]
Household characteristics							
Gender	–0.602***	–0.573**	–0.541***	–0.021	–0.032	0.047**	0.109***
	[0.15]	[0.15]	[0.15]	[0.05]	[0.05]	[0.02]	[0.04]
Age	–0.035***	–0.020*	–0.038***	0.004***	0.004	0.004***	0.009***
	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Education	0.073***	0.066***	0.047**	0.017***	0.017***	–0.003	–0.007
	[0.02]	[0.02]	[0.02]	[0.01]	[0.01]	[0.00]	[0.00]
Ethnicity	1.628***	1.252***	–0.975**	1.026***	0.948***	0.205***	0.302***
	[0.16]	[0.17]	[0.50]	[0.05]	[0.05]	[0.03]	[0.09]
Household labour	0.928***	0.914***	0.964***	–0.038***	–0.055**	–0.094***	–0.207***
	[0.04]	[0.06]	[0.04]	[0.01]	[0.02]	[0.02]	[0.02]
Farm land characteristics							
Farmland	–0.355***	–0.114*	–0.422***	0.008	-0.038	0.040***	0.091***
	[0.06]	[0.07]	[0.06]	[0.01]	[0.03]	[0.01]	[0.01]
Number_plot	–0.098***	–0.034	–0.165***	0.025***	0.024*	0.018***	0.039***
	[0.02]	[0.03]	[0.02]	[0.01]	[0.01]	[0.00]	[0.00]
Irrigation_condition	0.005***	–0.001	–0.002	0.005***	0.002**	0.001***	0.001**
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Social capital							
Credit (log)	–0.007	0.011	–0.077***	0.034***	0.023***	0.010***	0.024***
	[0.02]	[0.02]	[0.02]	[0.01]	[0.01]	[0.00]	[0.01]
Extension services	0.960***	0.901***	0.508**	0.202***	0.112	–0.026	–0.053
	[0.17]	[0.19]	[0.24]	[0.07]	[0.08]	[0.03]	[0.06]
FRO-member	0.176	0.013	0.246*	0.022	0.108*	–0.022	–0.047
	[0.11]	[0.14]	[0.13]	[0.04]	[0.06]	[0.02]	[0.03]
Year dummy variables	yes	yes	yes	yes	yes	yes	yes
Time averages of household and farm-varying characteristics		yes			yes		
Constant	–0.124	–1.280**	–1.349***	–1.142***	–1.438***	0.169***	–0.639***
	[0.37]	[0.56]	[0.42]	[0.13]	[0.18]	[0.04]	[0.12]
Number of observations	8 012	8 012	8 012	8 012	8 012	8 012	8 012
LR test of rho = 0: chi^2, χ^2 (1)				59.56***	56.12***		

https://doi.org/10.17221/68/2025-AGRICECON

Table 4 to be continued

Variables	Non-farm employment (NFE)			Using mechanisation services			
	random effects	CRE with Mundlak	2SLS – pooled	RE Probit	CRE Probit – Mundlak	2SLS – pooled	IV Probit – pooled
Wald test of exogeneity χ^2							57.95***
Underidentification test			73.264***			71.891***	
Weak identification test (Cragg-Donald Wald *F* statistic)			38.964			43.196	
Overidentification test (Hansen J statistic χ^2)			1.375 (*P*-value = 0.241)			0.137 (*P*-value = 0.712)	

***, ** and *significance at 1%, 5% and 10% levels, respectively; values in parentheses are standard errors, the standard error is robust in the random effects, CRE with Mundlak of NFE equation, IV Probit, and 2SLS of both NFE and adopt mechanisation equations

2SLS – two-stage least squared; CRE – correlated random effects; FRO – farmer related organisations; IV – instrumental variable; LR – likelihood ratio; Source: Authors' estimation from VARHS 2008–2016 dataset

relationship between off-farm employment and ownership of farm machinery.

In summary, participating in non-farm activities can provide cash for farmers, enabling them to hire agricultural machinery services; on the contrary, adopting mechanisation through hired services can help farmers save time on agricultural tasks, and allow them to engage more in non-farm jobs. Despite being

Table 5. The reciprocal relationship between non-farm employment and owning machinery

Variables	Non-farm employment (NFE)			Owning machinery			
	random effects	CRE with Mundlak	2SLS – pooled	RE Probit	CRE Probit – Mundlak	2SLS – pooled	IV Probit – pooled
Owning machinery	–0.088	–0.043	–20.867**	–	–	–	–
	[0.14]	[0.14]	[10.36]				
Non-farm employment time (log)	–	–	–	–0.004	–0.001	–0.023**	–0.133***
				[0.00]	[0.01]	[0.01]	[0.03]
Household characteristics							
Gender	–0.601***	–0.575***	0.354	0.485***	0.467***	0.033***	0.221***
	[0.15]	[0.15]	[0.54]	[0.11]	[0.11]	[0.01]	[0.07]
Age	–0.034***	–0.020*	–0.039***	–0.002	0.004	–0.001***	–0.006***
	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]
Education	0.076***	0.068***	0.150***	0.013	0.014	0.005***	0.025***
	[0.02]	[0.02]	[0.04]	[0.01]	[0.01]	[0.00]	[0.01]
Ethnicity	1.772***	1.378***	0.935**	–0.321***	–0.281***	0.004	0.053
	[0.15]	[0.17]	[0.43]	[0.09]	[0.10]	[0.02]	[0.08]
Household labour	0.926***	0.910***	1.034***	0.047**	0.015	0.026***	0.153***
	[0.04]	[0.06]	[0.09]	[0.02]	[0.03]	[0.01]	[0.03]

https://doi.org/10.17221/68/2025-AGRICECON

Table 5 to be continued.

Variables	Non-farm employment (NFE)			Owning machinery			
	random effects	CRE with Mundlak	2SLS – pooled	RE Probit	CRE Probit – Mundlak	2SLS – pooled	IV Probit – pooled
Farm land characteristics							
Farmland	–0.353***	–0.118*	0.274	0.142***	0.019	0.024***	0.052**
	[0.06]	[0.07]	[0.36]	[0.02]	[0.03]	[0.01]	[0.02]
Number_plot	–0.094***	–0.031	0.155	0.090***	0.072***	0.010***	0.040***
	[0.02]	[0.03]	[0.14]	[0.01]	[0.02]	[0.00]	[0.01]
Irrigation_condition	0.006***	–0.0007	0.014***	0.002*	0.002*	0.0004***	0.002***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Social capital							
Credit (log)	–0.004	0.013	0.031	0.011	0.002	0.002	0.008
	[0.02]	[0.02]	[0.04]	[0.01]	[0.01]	[0.00]	[0.01]
Extension services	0.982***	0.915***	1.529***	0.254**	0.234**	0.047***	0.263***
	[0.17]	[0.19]	[0.44]	[0.10]	[0.11]	[0.02]	[0.07]
FRO-member	0.183	0.024	0.748**	0.133*	0.026	0.029***	0.157***
	[0.11]	[0.14]	[0.30]	[0.07]	[0.08]	[0.01]	[0.04]
Year dummy variables	yes	yes	yes	yes	yes	yes	yes
Time averages of household and farm-varying characteristics		yes			yes		
Constant	–0.064	–1.266**	–1.168*	–2.973***	–3.246***	–0.045*	–1.900***
	[0.37]	[0.59]	[0.69]	[0.24]	[0.37]	[0.03]	[0.17]
Number of observations	8 012	8 012	8 012	8 012	8 012	8 012	8 012
LR test of rho = 0: chi^2, χ^2 (1)				537.4***	543.1***		
Wald test of exogeneity χ^2							10.53***
Underidentification test			5.760**			84.828***	
Weak identification test (Cragg-Donald Wald *F* statistic)			3.146			43.765	
Overidentification test (Hansen J statistic χ^2)			6.062 (*P*-value = 0.013)			1.961 (*P*-value = 0.161)	

***,** and *significance at 1%, 5% and 10% levels, respectively; values in parentheses are standard errors, the standard error is robust in the random effects, CRE with Mundlak of NFE equation, IV Probit, and 2SLS of both NFE and adopt mechanisation equations

2SLS – two-stage least squared; CRE – correlated random effects; FRO – farmer related organisations; IV – instrumental variable; LR – likelihood ratio

Source: Authors' estimation from VARHS 2008–2016 dataset

https://doi.org/10.17221/68/2025-AGRICECON

consistent with the findings of the study of Zheng et al. (2022), our research expands upon previous studies by verifying the reciprocal two-way relationship between non-farm employment and mechanisation adoption over a more dynamic timeframe. Additionally, we highlight the preference for using hired mechanisation services rather than by owning machinery in mechanisation adoption. This result may be derived from the time lags between farmers' decisions to pursue non-farm employment and their investment in agricultural machinery. Because buying agricultural machinery requires a large investment, farm households need to accumulate savings from non-farm work before they can invest in agricultural machinery. This process can take time, especially for those who have low non-farm income. Thus, due to this time lag issue, farm households choose to use the mechanisation services with lower investment than purchasing machinery. Our findings provide both theoretical and empirical insights into the household agricultural model.

CONCLUSION

This study concentrated on investigating the reciprocal relationship between non-farm employment participation and mechanisation adoption among farm households in Vietnam using longitudinal data from the VARHS 2008–2016 dataset. This study employs the correlated random effect with Mundlak approach to solve the selection bias arising from unobserved heterogeneity of longitudinal data and the IV approach to treat the endogeneity issues.

The findings show a positive reciprocal relationship between non-farm employment and mechanisation adoption. This implies that the increased participation in non-farm work can lead to greater investment in farm mechanisation, and conversely, the adoption of farm mechanisation – a labour-saving technology – can free up labour, allowing farmers to join in non-farm activities, creating a mutually beneficial relationship. Moreover, the results indicate that the labour shifting from farm to non-farm activities could be replaced by using mechanisation services rather than investing in machinery. This result reveals that Vietnamese farmers prefer to purchase mechanisation services when the service markets are available, as hiring these services represents a lower financial investment compared to buying agricultural machinery.

This reciprocal relationship has significant practical implications and broader social implications for rural development and the farm household economy. First, the shift towards non-farm employment is a key aspect of structural transformation from the agriculture sector to the non-farm sector in the rural economy, especially in developing economies as Vietnam. Mechanisation can facilitate this transformation by reducing labour needs in agriculture, allowing more farmers to participate in other sectors. Second, in many developing countries, access to credit and information about new technologies can be limited. The linkages between non-farm employment and mechanisation can help overcome these imperfections. The earnings from non-farm work could relax credit constraints and provide cash for farm households to invest in mechanisation for their farming operations. On the other hand, the experience gained from participation in non-farm employment can help farmers improve access to information and markets for farm inputs, such as hiring machinery markets.

Our findings have significant implications for developing practical policies and actionable plans to promote sustainable agriculture and inclusive rural development in developing countries. First, supportive activities for income diversification among farm households should be increasingly encouraged and expanded in rural areas. In particular, education and training programs relevant to non-farm employment opportunities should be largely organised to enhance the knowledge, practical skills and operational capacity of farmers in off-farm jobs. Second, related stakeholders should provide incentives for agricultural mechanisation by facilitating access to appropriate-scale machinery access for new users, broadening custom hiring services, and advancing research, development and applications of innovative technologies. These efforts can lead to the creation of a variety of cost-effective, time-saving, and efficiency-increasing machinery and equipment for local farmers. Third, the reciprocal relationship between non-farm employment and the use of mechanisation services highlights their complementary roles in improving the livelihoods of rural households. Therefore, fostering a favourable and flexible environment for the development of both non-farm employment and agricultural mechanisation is a vital strategy in rural development. In this regard, the cooperative efforts and actionable plans of local government, agricultural extensions, agricultural cooperatives, and farmer-related organisations to improve non-farm employment and agricultural mechanisation need to be actively engaged and expanded in rural localities. Fourth, a policy implication derived from findings of farm

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size's effect is that necessary to scientifically plan agricultural land and implement land consolidation to improve the efficiency of mechanisation in agricultural cultivation.

Our findings and policy implications can potentially be applied internationally in developing countries with similar agrarian structures, where there is an increasing need to diversify and transform rural economies, improve livelihoods, and modernise agricultural production. However, the limitation of our research is that we could not conduct in-depth analyses across regions. Because in Vietnam, there are differences in non-farm employment opportunities across regions, as well as the technology adoption behaviour of farmers across regions. Thus, further research could be conducted on the investigation of this relationship across regions in Vietnam. In addition, the environmental aspects of mechanisation adoption cannot be mentioned in this study with the limited dataset.

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Received: February 14, 2025
Accepted: October 8, 2025
Published online: January 16, 2026