ISSN 2414-584X

Agricultural and Resource Economics: International Scientific E-Journal

Volume 10
No 3
2024

ARE journal

are-journal.com

Vol 10 No 3 (2024): (In progress)

DOI: https://doi.org/10.51599/are.2024.10.03

Published: 2024-09-20

Time series forecasting of price of the agricultural products using data science

Tetiana Kmytiuk, Ginta Majore, Tetiana Bilyk

5-33

DOI: https://doi.org/10.51599/are.2024.10.03.01

PDF

Fisheries management for food security in the Maldives

Nadhiya Abdulla, Natalia Vasylieva, Iryna Volovyk

34-55

DOI: https://doi.org/10.51599/are.2024.10.03.02

PDF

Export of agricultural products as a determinant of currency security of Ukrainian economy

Victoria Kovalenko, Sergii Sheludko, Valentyna Aranchyi, Valentyna Chumak, Olga Doroshenko
56–79
DOI: https://doi.org/10.51599/are.2024.10.03.03

PDF

Benefits, barriers, and levels of e-commerce adoption: study of traditional beverage SMEs

Nuning Setyowati, Masyhuri, Jangkung Handoyo Mulyo, Irham
80–106
DOI: https://doi.org/10.51599/are.2024.10.03.04

PDF

Factors affecting households food security during pandemic Covid-19

Yeni Budiawati, Ronnie S. Natawidjaja, Tomy Perdana, Maman H. Karmana
107–132
DOI: https://doi.org/10.51599/are.2024.10.03.05

PDF

Regional development of wine tourism in the context of climate change: the experience of the Odesa region

Volodymyr Pechko, Iryna Kovalova, Nina Muliukina, Halyna Lyashenko, Iryna Belous
133–167
DOI: https://doi.org/10.51599/are.2024.10.03.06

PDF (Українська)

Impact of Covid-19 pandemic on Indonesia's agricultural subsectors: an ARDL approach

Surya Abadi Sembiring, Jongkers Tampubolon
168–191
DOI: https://doi.org/10.51599/are.2024.10.03.07

PDF

Production and management practices and technologies used for growing potatoes and tomatoes

Diriba Shiferaw Geleta, Sisay Yefru Derbe, Bezawit Seifu Woldegiorgis, Samuel Weldeyohanis Kifle, Bernd Müller
192–218
DOI: https://doi.org/10.51599/are.2024.10.03.08

PDF

Competition in the vegetable market and challenges for the industry: a bibliometric analysis of dominant publications

Eter Kharaishvili, Lela Aduashvili
219–247
DOI: https://doi.org/10.51599/are.2024.10.03.09

PDF

Rationality of soybean farmers: the findings from rainfed field agroecosystems

Dedi Djuliansah, Trisna Insan Noor, Zulfikar Noormansyah, Muhamad Nurdin Yusuf
248–269
DOI: https://doi.org/10.51599/are.2024.10.03.10

PDF

Does non-farm employment influence a farmer's decision to adopt hybrid rice seeds or improved variety?

Hang Thi Thuy Nguyen, Pham Xuan Hung, Phuong Nu Minh Le
270–302
DOI: https://doi.org/10.51599/are.2024.10.03.11

PDF

e-ISSN 2414-584X

Scopus

JEL: Q12, Q16, O13

Hang Thi Thuy Nguyen, Pham Xuan Hung, Phuong Nu Minh Le

University of Economics – Hue University
Vietnam

DOES NON-FARM EMPLOYMENT INFLUENCE A FARMER'S DECISION TO ADOPT HYBRID RICE SEEDS OR IMPROVED VARIETY?

Purpose. *The study aims to examine the effect of non-farm employment decisions on the adoption decision of rice hybrid seeds or improved variety in Vietnam.*

Methodology / approach. *This study uses panel data from the Vietnam Access to Resources Household Survey (VARHS) 2008–2016 dataset. The study uses the correlated random effect Probit model with the Mundlak approach to control unobserved heterogeneity of panel data and the endogenous switching Probit model (ESPM) to solve the endogeneity problem and self-selection of the non-farm participation variable.*

Results. *There has been increasing interest that the development of rural non-farm employment has effects on agricultural production as well as agricultural growth. However, still relatively poor understanding of how non-farm participation affects the farmers' decision to adopt modern technologies in the face of market failure. Our findings indicate that non-farm employment has a positive effect on the adoption of rice hybrid seeds or improved varieties in Vietnam. The value ATT is predicted from the endogenous switching Probit model, which implies that farm households who engage in non-farm employment had a 35.1 % of probability of modern varieties adoption, vs. 19.0 % in the sample overall.*

Originality / scientific novelty. *This study adds evidence from a developing country (using the example of Vietnam) to the broader literature on the role of non-farm employment participation on farmers' adoption behaviour under market imperfections. In addition, the research addresses the limitations of unobserved heterogeneity of an unbalanced panel by applying the Mundlak approach and contributes to the literature by controlling the endogenous problem and self-selection problem of non-farm participation by using the endogenous switching Probit model.*

Practical value / implications. *Based on the empirical results of this paper, some policy implications are provided to develop the rural non-farm sector and to diffuse modern technologies among rural farmers.*

Key words: *non-farm employment, technology adoption, hybrid seeds or improved variety, endogenous switching Probit model, Vietnam.*

1. INTRODUCTION

The use of modern technology in agriculture comes with a lot of benefits. It is essential for increasing productivity and farm output as well as improving household income and poverty reduction. Adoption of improved technologies is believed to be a major factor in the success of the Green revolution experienced by Asian countries. Agricultural technology adoption can be used in different aspects such as application of chemical inputs (such as herbicide, pesticide, fertiliser), adopting the improved varieties or hybrid seeds, applying the natural resource management practices (such as crop rotation, intercropping, water and soil management, organic farming), and mechanisation or invest in infrastructure in production (Ruzzante, 2021). However, farmers are constrained to adopt technologies by market imperfections (high transaction cost, credit access), various risks, poor access to information, and insufficient skills of farmers (Amare & Shiferaw, 2017; Pfeiffer et al., 2009; Shiferaw et al., 2015). Particularly in developing countries, where markets are imperfect and failing, farmers may or may not choose to accept these challenges and adopt new technology. A potential option for easing restrictions for these farmers could be their participation in non-agricultural sectors.

In recent years, the growth in the share of non-farm income in rural households confirms the increased importance of the rural non-farm economy. This non-farm income source comprised 34 % of total rural household income in Africa, 47 % in Latin America and the Caribbean, and 51 % in Asia (Haggblade et al., 2010) compared with a global average of approximately 58 % (Davis et al., 2010). The progressive transition of the rural economy from the agriculture sector to the non-farm sector is considered an essential feature of the rural economic growth of the developing world. It is obvious that non-farm income plays a critical role in the increase of welfare, the smoothing of consumption, and the reduction of poverty in rural households in developing countries (Bui & Hoang, 2021; Haggblade et al., 2010; Hoang et al., 2014; Mishra et al., 2015; Seng, 2015). Non-farm income derives primarily from members of the farm household working or doing business in non-farm sectors (i.e., providing labour to non-farming enterprises, henceforth simply “non-farm employment”).

Several studies have investigated the relationship between non-farm employment and agricultural productivity, and many of these studies have indicated a synergistic relationship between non-farm employment and farm production. Barrett et al. (2001), Ellis & Freeman (2004), Pfeiffer et al. (2009), and Hertz (2009) found that income from non-farm employment can help farm households cope with agricultural risk and ease liquidity constraints on productivity-enhancing investment. Oseni & Winters (2009) found that participating in non-farm employment complements agricultural endeavours by adding capital to farm production. On the other hand, engaging in non-farm employment may reduce agricultural productivity due to the lost labour effect, in which farm households supply labour to non-farm employment instead of devoting it to farming (Nguyen & Kondo, 2020; Pfeiffer et al., 2009). Meanwhile, Ellis & Allison (2004) found that non-farm employment can help low-income farmers overcome barriers to the adoption of new technology, thus improving agricultural productivity. Thus, it can be seen that in order to reduce the constraints or difficulties about the credit of households in applying technology to agricultural production, their participation in the rural non-agricultural sector might be a potential option.

Rice production in rural Viet Nam offers an interesting and important example of the farmer’s choice to adopt new technology. Rice production accounts for 60 % of sown areas in Vietnam and 50 % of total food harvest in Vietnam. Rice production is growing by 3.3 % per year and yields are increasing by 2.5 % per year during 1995–2022 period (General Statistics Office, 2022). The adoption of new technologies to rice production is still a great concern to scientists, economists, and the government in

Vietnam because it is a key to enhance output, yield, and the quality of rice product, as well as to reduce poverty in the country. The growth of rice yield over the past time in Vietnam clearly had a significant contribution of the adoption of modern technology into the production. In particular, the number of soil tillage implements (such as rotary tillers, power harrows, and disc harrows) in 2018 increased by 1.6 times and the number of modern harvesters increased by 25.6 times compared to 2006 (Hossen et al., 2020). Hang et al. (2024) indicated that adopting hybrid rice varieties increases rice yield and technical efficiency in Vietnam. Moreover, since the Doi Moi policy in 1986 in Vietnam, it has changed the rural economy and brought development to the rural non-farm sector. The early years of the 21st century so far have witnessed particularly strong development in the non-farm sector in rural areas of Vietnam (Nguyen, 2019). But even as rice production has grown, the proportion of rural households with non-farm employment has increased sharply, from 28.9 % in 2006 to 46.2 % in 2016 (Nguyen, 2019). This motivates our research question: does the growth in non-farm employment observed in rural Vietnam hinder or help farmers to adopt new technologies?

This paper investigates the effect of non-farm employment on the farmer's decision to adopt a new technology, focusing on the specific case of farm households in rural Vietnam, who decide whether to use improved rice seeds (new hybrid seeds or new varietal seeds) or not. Our study makes three key contributions to the literature. Firstly, we address the limitations of unobserved heterogeneity of an unbalanced panel by applying the Mundlak approach. Secondly, we contribute to the literature by controlling the endogenous problem and self-selection problem of non-farm participation into one model of technology adoption by using the endogenous switching Probit model. Thirdly, the study contributes data from Vietnam – a developing country – to the broader literature on the role of non-farm employment participation on farmers' behaviour in adopting modern technology in the case of the imperfection market.

2. LITERATURE REVIEW

2.1. Analysis of literature. Rural non-farm employment includes all economic activities, except for the production of primary agricultural commodities, which are wage-paying activities and self-employment in commerce, manufacturing, and other services (Reardon et al., 1998). The previous studies indicate that households are often motivated to participate in non-farm activities because of two main factors: the pull and push factors. The "pull factors" are incentives, that induce farm households to participate in the non-farm sector when non-farm activities offer higher returns than farm activities (Barrett et al., 2001). The "push factors" that drive households to undertake rural non-farm activities are: first, increasing household income to supply their livelihood (Minot et al., 2006); second, the risks of farming or limited risk-bearing capacity which induce households to diversify income sources and decrease the consumption uncertainties (Barrett et al., 2001; Reardon et al., 1998) and third, the imperfection or failure of farm inputs and credit markets that force farm households to pay for inputs with their own money (Reardon et al., 1998).

The framework for analysis of the rural non-farm employment by Buchenrieder & Möllers (2006) indicated a set of demand-pull and distress-push factors that affect the people's participation decisions in non-farm sectors. Particularly, the demand-pull factors describe agricultural labour force takes advantage of more employment opportunities in the rural non-farm economy, including education level, skills, knowledge, social networks facilitating non-farm activities, appropriate infrastructure (roads, schooling, and vocational training network), information availability, efficient land and credit markets (Buchenrieder & Möllers, 2006). While, the distress-push factors related to inadequate agricultural incomes and other negative factors push workers into non-farm jobs, consisting insufficient access to land and low land productivity, low labour productivity, lack of self-financing capability for farm investments, inefficient land and credit markets, large family size, natural disasters, lack of infrastructure, lack of livelihood capital assets (Buchenrieder & Möllers, 2006).

There have been many studies on the linkages between the agriculture and non-farm sectors as well as the impact of non-farm participation on agricultural efficiency and performance in many countries; especially in developing countries where credit constraints are still a matter of great concern. The implementation of technology in the production process is also considered to be a decision of farmers to increase the efficiency of agricultural production. The agricultural technology types include adoption of chemical fertiliser (Ethiopia), improved variety of farm products (Uganda, Congo, the USA), soil and water conservation technology (China, Ghana), and mechanisation (China, Bangladesh). These types are consistent with the following categories given by Ruzzante et al. (2021): (1) natural resource management such as minimal or no tillage, organic farming, crop rotation, intercropping, water and soil management; (2) adopting improved varieties or hybrid seeds to increase yield; (3) applying chemical inputs such as chemical fertilisers, pesticides, herbicides; and (4) mechanisation and infrastructure investment. Studies on the relationship between non-farm employment and technology adoption in agriculture were carried out with different types of agricultural technology. Table 1 below summarises countries and years of the analysis, types of farm technology, empirical methodology, and the sign (+/–) of the effect of non-farm employment on technology adoption.

Two studies investigate the effect of non-farm employment on natural resource management technologies. Danso-Abbeam et al. (2020) study the effect of non-farm employment on the adoption of "Zai" technology (the use of traditional land-restoration techniques) in Ghana. Through using Propensity score matching method and Inverse-Probability weighted Regression Adjustment, the article indicated that diversification of non-farm income increases the likelihood of applying "Zai" technology to agricultural production in this country. Huang et al. (2019) study the impact of non-farm employment on the adoption of soil and water conservation technology in China. The results of the study indicate that participation in non-agricultural employment hindered the adoption of soil and water conservation practices by Chinese farmers.

Table 1

Summary of previous empirical studies on the relationship between technology adoption and non-farm employment

Authors	Country, year	Type of farm technology	Methodology	Sign
Beshir et al. (2012)	Ethiopia, 2009	Chemical fertiliser adoption	Double hurdle model	+
Zhang et al. (2020)	China/Sichuan, 1995–2017; Henan, 1998–2016	Chemical fertiliser intensity	The system generalised method of moments	+
Fernandez-Cornejo et al. (2005)	The USA, 2000	Adoption of herbicide-tolerant soybeans	Probit, IV	+
Diiro & Sam (2015)	Uganda, 2009–2010	Adopting improved maize seed technologies	Two stage Probit, semiparametric estimates	+
Danso-Abbeam et al. (2020)	Ghana, 2018	Zai-technology in maize production	Propensity score matching, inverse-probability weighted regression adjustment	+
Yi (2018)	China, 2016	Adoption of agricultural mechanisation services	Seemingly unrelated regression, multivariate Probit	+
Huang et al. (2019)	China, 2016	Adoption of soil and water conservation technology	Ordinary least squared	–
Ahmed & Goodwin (2016)	Bangladesh, 2000–2008	Agricultural mechanisation adoption	Bivariate Probit, endogenous switching Probit	+
Zheng et al. (2021)	China, 2019	Mechanisation service expenditure	Conditional mixed process (CMP), 2-stage Probit least squares	+
Dontsop-Nguezet et al. (2016)	DR Congo, 2006–2007	Adoption of improved cassava and beans varieties	Binary Probit, semi-parametric estimation	+

Source: authors' synthesis.

Regarding the technology type of applying improved varieties or hybrid seeds, the study by Fernandez-Cornejo et al. (2005) estimated the model for the adoption of herbicide-tolerant soybean varieties using the nationwide survey of soybean farms in the United States. They find a positive relationship between non-farm income and the adoption of herbicide-resistant soybeans, possibly because the adoption of herbicide-tolerant soybean may help farmers to save management time in the weed-control and allow them to engage in non-farm employment. Diiro & Sam (2015) investigated the effect of non-farm income on the adoption of improved maize varieties in Uganda. They find that non-farm income has a positive effect on the adoption of improved maize varieties, possibly because non-farm income relieves credit constraints. Dontsop-Nguezet et al. (2016) also find a positive relationship between non-farm employment and the adoption of improved cassava and bean varieties in the Republic of Congo. The study also confirms that this link can occur through the return investment of non-farm income in agricultural innovation.

Related studies investigate the effect of non-farm employment on the use of chemical inputs. The study by Beshir et al. (2012) assess the determinants of chemical fertiliser adoption in Ethiopia by using survey data. They find that the income from non-farm employment positively affected the adoption of chemical fertiliser by Ethiopian farmers. They also indicate that off/non-farm income sources may solve the financial constraints of technology adoption in agricultural production via providing cash to purchase chemical fertiliser. Zhang et al. (2020) also studied the relationship between non-farm employment and the use of chemical fertiliser intensity in the mountainous and plain areas of China. They find that the effect of non-farm employment on the adoption of chemical fertiliser is different in the two regions; there is an inverted U-shaped relationship in the mountainous region, but there is a positive linear relationship in the plains region.

As for the technology of applying mechanisation to agricultural production, there are also a few studies that were conducted to investigate the relationship between mechanisation in agricultural production and non-farm employment. Specifically, Ahmed & Goodwin (2016) focused on studying the role of agricultural mechanisation on non-farm labour supply behaviour in Bangladesh. They find that the application of labour-saving technology (mechanisation) increases the probability of participation in the rural non-farm sector and the non-farm labour supply of farm household. The study by Yi (2018) has shown that participation in non-farm employment has a positive effect on the adoption of agricultural mechanisation services among maize farm households in China. The article also indicated that the increased income might foster the demand for using of agricultural mechanisation services in China. In another study in China, Zheng et al. (2021) examined the interaction relationship between non-farm employment and the expenditure on agricultural mechanisation services in rural areas. They find that non-farm employment significantly increases mechanisation services expenditure; and conversely, the adoption of agricultural mechanisation has facilitated farmers to participate more in non-farm employment.

Regarding the methodology, most empirical studies above regress a dummy variable related to technology adoption onto a dummy variable of non-farm employment (or non-farm income). These studies also use the instrumental variables (IV) Probit method to deal with the endogeneity of non-farm employment variables.

Indeed, most of these studies found a positive effect of non-farm employment on technology adoption, regardless of the type of farm technology, implying that farmers have the incentive to adopt better or modern technology if they have household members who work in the non-farm sectors. The direction of causality is not always clear, however, non-farm employment may provide income that finances the household's adoption of new technology, or, alternatively, new technology may be labour-saving, which enables the household to engage in more non-farm employment. Further, it is theoretically possible that non-farm employment could be negatively associated with the adoption of new technology if farmer households choose to divert labour to non-farm employment at the expense of on-farm employment, including efforts to adopt new technology. We develop a theoretical model of the farm household's decision problem in the section below.

2.2. Theoretical framework. In this section, we discuss the theoretical framework related to the relationship between non-farm employment and agricultural technology adoption in farm households. Firstly, our study is based on the agricultural technology adoption theory with the economic constraints paradigm to identify and classify the set of influence factors that will be used in the estimation model. In agricultural production, the decision to adopt new agricultural technology is not a simple decision with yes or no; but this is a decision that is influenced by the interaction of many factors in the presence of various constraints such as budget constraint, lack of information, and the availability of the technology (Feder et al., 1985; Foster & Rosenzweig, 2010; Ghimire et al., 2015; Loevinsohn et al., 2012; Mwangi & Kariuki, 2015). According to the theory, the technology adoption decision of farmers aims to maximise utility, subject to these constraints (Varma, 2019). The literatures showed that the agricultural adoption technology decision is affected by economics factors, human capital, social factors, and institutional factors (Fernandez-Cornejo et al., 2005; Foster & Rosenzweig, 2010; Mwangi & Kariuki, 2015; Varma, 2019). The adoption decision model can be presented in a random utility framework (Asfaw, 2012; De Janvry et al., 2011; Ghimire, 2015):

$$U_i^* = X_i\beta + u_i \,, \tag{1}$$

$$\text{with } U_i = \begin{cases} 1 \; if \; U_i^* > 0 \\ 0 \; otherwise \end{cases},$$

where U_i^* is expected utility, which describes the choice of agricultural technology adoption of farmers;

X_i is a vector of explanatory variables that determine the decision to adopt technology;

β is a vector of parameters of the explanatory variables;

u_i is the random error term.

To establish the relationship between non-farm employment and agricultural technology adoption, we based on the agricultural household model of Singh et al. (1986). This model thereafter developed by Fernandez-Cornezo et al. (2005) with the introduction of the agricultural technology adoption decision and non-farm labour. According to the agricultural household model, the decisions of farm households in production, consumption, and labour allocation are interdependent and must obtain the utility maximisation. The study of Fernandez-Cornezo et al. (2005) indicated that farm household maximise their utility subject to three constraints, that is, income constraints, technological constraints of agricultural production, and time constraints. The utility of households is maximised by choosing the optimal consumption of goods purchased (q), leisure time (x_l), and other exogenous factors to household decisions (H). Thus, farm household maximise utility function (U) subject to income, technology, and time constraints can be modelled as below:

$$Max\, U = U(q,\, x_l,\, H), \tag{2}$$

subject to the constraints:

$p_c q = p_f Q - p_X X + wL_{nf} + S$ (income constraint); (3)

$Q = Q[X(T), L_f(T), D]$ (technology constraint); (4)

$L = L_f(T) + L_{nf} + x_l$ (time constraint). (5)

Equation (3) is the household's income constraint where p_c and q denote the price and quantity of goods for consumption;

p_f and Q are the price and quantity of farm output, respectively;

p_x and X represent the price and quantity vectors of farm inputs such as land, capital, fertiliser, etc.;

w is the non-farm wage and L_{nf} denote the amount of time working in the non-farm jobs by household's member;

S is the other income sources. The income constraint of farm households implies that if credit is not available or the credit market is imperfect, the consumption of purchased goods and expenditures in farm inputs cannot exceed total household income including farm income, non-farm income, and other income.

Equation (4) represents the farm household's technology constraint where L_f is the amount of time working in the farm production;

T is the technology adoption decision;

D is a vector of exogenous factors that shift the production function.

The adoption of some agricultural technology may reduce the working time in farm production and possibly change the use of other farm inputs X. Hence, the farm working time and the vectors of farm inputs are the functions of T, technology adoption.

Equation (5) is the time constraint of the farm households, where, the total time of farm households (L) is a fixed number that is allocated among farm production (L_f), non-farm jobs (L_{nf}), and leisure time (x_l). In the context of labour market imperfection, it is less likely for family labour to be substituted by hired labour because of the high transaction costs for that substitution. Thus, farm labour (L_f) should be less than the total time of farm households (L) minus non-farm jobs (L_{nf}) and leisure time (x_l), thereby, equation (5) is also called labour constraint (Nguyen & Kondo, 2020; Pfeiffer et al., 2009).

Then, substituting the technological constraint (equation (4)) into the household income constraint (equation (3)), we obtain the measure of household income with technological constraints, as shown below:

$$p_c q = p_f Q\big(X(T), L_f(T), D\big) - p_X X(T) + wL_{nf} + S. \qquad (6)$$

The Lagrangian function allows differentiation of the farm household utility function which is shown as follows:

$$\mathcal{L} = U(q,\, x_l,\, H) + \lambda\big[p_f Q\big(X(T), L_f(T), D\big) - p_X X(T) + wL_{nf} + S - p_c q\big] + \\ + \mu[L - L_f(T) - L_{nf} - x_l], \qquad (7)$$

where λ and μ are the Lagrange multipliers of the income and the time constraints, respectively.

Differentiating, the non-farm participation and technology adoption decisions may be obtained from the Kuhn-Tucker first-order conditions:

$$\frac{\partial \mathcal{L}}{\partial X} = \lambda \left[p_f \left(\frac{\partial Q}{\partial X} \right) - p_X \right] = 0; \tag{8}$$

$$\frac{\partial \mathcal{L}}{\partial L_f} = \lambda p_f \left(\frac{\partial Q}{\partial L_f} \right) - \mu = 0; \tag{9}$$

$$\frac{\partial \mathcal{L}}{\partial T} = \lambda \left\{ p_f \left[\left(\frac{\partial Q}{\partial X} \right) * \left(\frac{\partial X}{\partial T} \right) + \left(\frac{\partial Q}{\partial L_f} \right) * \left(\frac{\partial L_f}{\partial T} \right) \right] \right\} - p_X \left(\frac{\partial X}{\partial T} \right) - \mu \left(\frac{\partial L_f}{\partial T} \right) = 0; \tag{10}$$

$$\frac{\partial \mathcal{L}}{\partial L_{nf}} = \lambda w - \mu \le 0, \;\; L_{nf}(\lambda w - \mu) = 0; \tag{11}$$

$$\frac{\partial \mathcal{L}}{\partial q} = U_q - \lambda p_f = 0; \tag{12}$$

$$\frac{\partial \mathcal{L}}{\partial x_l} = U_{x_l} - \mu = 0; \tag{13}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = p_f Q\big(X(T), L_f(T), D\big) - \; p_X X(T) + wL_{nf} + S - p_c q = 0; \tag{14}$$

$$\frac{\partial \mathcal{L}}{\partial \mu} = L - L_f(T) - L_{nf} - x_l. \tag{15}$$

The optimality conditions for non-farm employment can be found by combining equation (11) with equations (9) and (13), yielding:

$$w = p_f \left(\frac{\partial Q}{\partial L_f} \right) = \frac{\mu}{\lambda}. \tag{16}$$

Equation (16) shows the marginal value of farm labour, $p_f \left(\frac{\partial Q}{\partial L_f} \right)$, must be equal to the non-farm wage rate, w. In addition, the non-farm wage rate should be equal to the marginal rate of substitution between leisure and consumption goods ($w=\mu/\lambda$) (Ahmed & Goodwin, 2016; Fernandez-Cornejo et al., 2005).

When the interior solution for non-farm labour (L_{nf}) occurs, the equation (8) and (9) can be solve independently to obtain the demand functions for on-farm labour (L_f): $L_f^* = L_f(p_X, w, p_f, T, D)$; and the demand functions for purchased farm inputs: $X^* = X(p_X, w, p_f, T, D)$. These optimal input demand functions are substituted into technology constraint (4), giving the optimal farm output as follows:

$$Q^* = Q(p_X, w, p_f, T, D). \tag{17}$$

Solving jointly equations (11), (12), (13), (14), and (17), we obtain the household's optimal amount of leisure demand and consumption good, as follow:

$$x_l^* = x_l(p_X, w, p_c, p_f, T, D);$$

$$q^* = q(p_X, w, p_c, p_f, T, D).$$

As Huffman (1991) notes, the supply function for non-farm time is obtained from the optimal levels of leisure time and on-farm labour demand:

$$L_{nf}^* = L - L_f^* - x_l^* = L_{nf}(p_X, w, p_c, p_f, T, D, H). \tag{18}$$

The equation (18) implies that the technology adoption decision in agricultural production is expected to increase the supply of household labour into the non-farm activities. Based on the theoretical discussion above, all exogenous variables that affect the productive capacity should be included in the estimation models used to assess the relationship between non-farm employment and the adoption of new technology.

3. METHODOLOGY

3.1. Data. This study uses the dataset from Vietnam Access to Resources Household Survey (VARHS) which is collected from the United Nations University World Institute for Development Economics (UNU_WIDER) website. This survey is considered to be a comprehensive survey of the development and changes in Vietnamese agriculture, which was conducted by the Central Institute of Economic Management (CIEM), the Institute of Labour Science and Social Affairs (ILSSA), and the Institute of Policy and Strategy for Agriculture and Rural Development (CAP-IPSARD). The VARHS survey has been conducted once every two years. This dataset provides the information about social and economic characteristics of households in the rural areas of twelve provinces located across the five main regions of Vietnam[1].

This paper uses the panel dataset VARHS from 2008 to 2016[2]. Our study only focuses on rice farm households with unbalanced panel data. We also use the data from the commune survey of VARHS for the instrumental variables (IVs). The commune dataset provides the socio-economic information of the communes including non-farm employment characteristics, thus, it is appropriate for the choice of instrumental variables. After dropping missing values, the total observations of 2008–2016 consist of 8,012 which is used in this study[3].

3.2. Methods. Our study focuses on analysing the impact of non-farm employment on the adoption decision of hybrid seed or improved variety in rice production using different approaches. We decide to analyse the unbalanced panel data because the random individual heterogeneity is far more important than random time specific heterogeneity (Biørn, 1999). Thus, the correlated random effects approaches for unbalanced panel and nonlinear model are used in this analysis which is proposed by Wooldridge (Wooldridge, 2019). To address the selection bias from the unobserved heterogeneity of time-invariant farm household characteristics, social capital and farmland characteristics, we use a correlated random-effects Probit model with the Mundlak approach to conduct this analysis. Following the Mundlak (1978) approach, we control the unobserved heterogeneities by using the time demeaning technique and dummy time period, that is, adding time averaged of household and farm-varying characteristics variables and dummy time variables into the list of independent variables. In addition, other econometric problems in our analysis are the endogeneity problem and self-selection problem of dummy non-farm variable. To address both problems, more complex regressions are used in this analysis, including the instrumental variables (IV) approach and the endogenous switching Probit model (ESPM).

3.2.1. Correlated random-effects Probit model with the Mundlak approach. In this study, we use the agricultural technology adoption theory to build a model of a

---

[1] The dataset includes Ha Tay (Red River Delta), Lao Cai, Phu Tho, 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), and Long An (Mekong River Delta).
[2] VARHS 2008, 2010, 2012, 2014 and 2016.
[3] The total rice households of 2008 is 1,564; 2010 consists 1,498 households; 2012 consists 1,749 households; 2014 consists 1,670 households; and 2016 consists 1,531 households.

farmer's decision to adopt a new technology to maximise utility. To estimate the impact of the non-farm activities on the agricultural technology adoption decision, we apply the Probit model for binary response because the outcome variable is a dummy variable that indicates the technology adoption decision. The adoption technology decision of farm household *i* at time *t* with additive heterogeneity can be presented as follow:

$$y_{it} = \beta X_{it} + c_i + u_{it}, \tag{19}$$

where y_{it} denotes the binary response variable of the decision of technology adoption of i^{th} rice farmer at time t;

t = 2008, 2010, 2012, 2014, 2016;

X_{it} is a vector of explanatory variables presenting household's characteristics (including non-farm variable); c_i is the unobserved heterogeneity;

u_{it} is idiosyncratic the errors;

y^* is a latent variable that we can observe this binary variable as below:

$$y_{it}^* = \begin{cases} 1 & if\ y_{it}^* > 0 \\ 0 & if\ y_{it}^* \leq 0 \end{cases}. \tag{20}$$

The binary Probit model with heterogeneity and strictly exogenous covariates can be written in the probability of household *i* at time *t* as below:

$$P(y_{it} = 1|X_i, c_i) = P(y_{it} = 1|X_{it}, c_i) = \Phi(\beta X_{it} + c_i), \tag{21}$$

where $\Phi(.)$ represents the standard normal cumulative distribution function.

The fixed-effect estimators for non-linear models usually obtain the incidental parameters problem when the unobserved effect is controlled through estimating separate parameters for each population unit. In addition, the fixed-effects model can control the time-invariant variables, however, it can not estimate them directly. While the advantage of random effects model is allowing the time-invariant explanatory variables in the model.

Following the Mundlak approach, we use the demeaning technique to control the unobserved effects or sample selection problem. We define $\overline{X_\iota}$ as the time averages of household, social capital and farmland-varying characteristics variables, whereas $\overline{X_\iota} = T^{-1}\sum_{t=1}^{T_i} X_{it}$ (t = 2008, …, 2016). Along with the Mundlak assumption, the unobserved heterogeneity is linearly related to $\overline{X_\iota}$: $c_i = \gamma\overline{X_\iota} + \nu_i$. Finally, the equation (22) can be re-written as below:

$$y_{it} = \alpha + \beta X_{it} + \gamma\overline{X_\iota} + \varepsilon_{it}, \tag{22}$$

where $\varepsilon_{it} = \nu_i + u_{it}$.

Thus, the correlated random effects Probit model with the Mundlak device is consistent in our analysis because the analysis is able to control the incidental parameters problem and the unobserved heterogeneity of time-invariant farm household, social capital and farmland characteristics through allowing the demeaning technique; thereby addressing the selection biases.

3.2.2. Instrumental variables (IV) approach and endogenous switching Probit model. An additional consideration in estimating the relationship between non-farm participation and technology adoption decision is the endogeneity problem of the non-farm variable. In particular, the non-farm variable is not only correlated with the outcome variable (y_{it}) but also with the other explanatory variables. On the other hand, the unobserved households' characteristics variables (ε_{it}) are correlated with the adoption decision of hybrid seeds or improved variety (y_{it}) and non-farm participation, thus it may give biased estimates in our analysis. We use the instrumental variables (IV) approach to estimate the appropriate models to solve the problem of endogeneity of non-farm variable. The IV approach attempts to solve the problem by replacing unobservable with a suitable proxy variable that correlated with non-farm variable and uncorrelated with the outcome variable (y_{it}) or the error term (ε_{it}) (Wooldridge, 2019). The Probit model is applied for first stage endogenous regression, which shows the relation between the endogenous non-farm variable and the instrumental variables. The estimation equation is specified as follows:

$$NF_{it} = \lambda_0 + \lambda_1 X_{it1} + \lambda_2 I_{it} + \mu_{it}, \tag{23}$$

where NF_{it} the non-farm participation of i^{th} rice household at time t;

X_{it1} is a vector of explanatory variables presenting household's characteristics (excluding non-farm variable);

I_i is instrumental variables; and μ_i is the errors term.

In this first stage regression, we estimate both pooled and random effects models and add the year dummy variables in both estimation models for controlling heterogeneity of panel data. We also use the F-test of the joint significance of instrumental variables in this regression to test whether the instruments are weak or not. We can indicate that the instruments are strong instrumental variables if the F-test results are greater than 10.

The initial model that we use to investigate the relationship between the adoption decision of hybrid seed or improved variety and non-farm participation is the Probit model. When applying the IV approach to the non-linear regression Probit model, the endogenous non-farm variable must be continuous. However, in this study, we use the binary variable non-farm participation, thus the IV approach with binary dependent variable or IV-Probit is not make sense. On the other hand, the IV approach, particularly two-stage least squared estimates (2SLS), facilitates several tests to examine the validity of the instrumental variables. Although the use of the IV method in this situation for linear and nonlinear models are inefficient, we aim to apply this approach to check the validity of instruments and also check the sign of the relationship between non-farm employment and technology adoption decisions after using IV to solve the endogeneity problem. Furthermore, this analysis not only encounters the endogeneity problem but also the self-selection of the non-farm participation variable. Therefore, we use the endogenous switching Probit model (ESPM) with pooled data for dealing with a binary dependent variable and the endogenous dummy treatment variable. This model performs the maximum likelihood method to fit the model of binary choice and with binary endogenous regressor by simultaneously estimating the binary selection and the binary outcome parts of the model to bring consistent estimation (Lokshin & Sajaia, 2011). The ESPM is considered more efficient because it could relax the assumption of equality of coefficients of the adoption equation in two regimes (Ahmed & Goodwin, 2016). However, this method has a limitation that cannot solve completely the selection bias from the unobserved heterogeneity of panel data, we therefore apply the ESPM with pooled data and also use time dummies in the estimates. The binary outcomes conditional on technology adoption decision are specified as an endogenous switching regime model as follow:

Regime 1: $y_{1it} = \alpha_1 + \beta_1 X_{1it} + \varepsilon_{1it}$ if $NF_{it} = 1$;

Regime 2: $P_{0it} = \alpha_0 + \beta_0 X_{0it} + \varepsilon_{0it}$ if $NF_{it} = 0$,

where y_{1it} and y_{0it} are the latent variables that determine the observed binary outcomes.

The ESPM also can calculate the average treatment effects (ATE) and the average effects of treatment on the treated (ATT) after estimating the model's parameters (Lokshin & Sajaia, 2011). The average treatment effect (ATE), which is the mean expected effect of the treatment for all households with observed characteristics *x* can be presented as follow:

$$TE(x) = Pr(NF = 1, X = x) - Pr(NF = 0, X = x) = F(X_1\beta_1) - F(X_0\beta_0),$$

$$ATE = \frac{1}{N}\sum_{i=1}^{N} TE(x_i), \tag{24}$$

where N is the number of all households including non-farm participants and non-participants.

The average effect of the treatment on the treated (ATT), or the expected effect of the treatment on individuals with observed characteristics *x* who participated in non-farm employment, can be presented as follow:

$$TT(x) = Pr(y_1 = 1|NF = 1, X = x) - Pr(y_0 = 1|NF = 1, X = x),$$

$$ATT = \frac{1}{N}\sum_{i=1}^{N_{NF}} TT(x_i), \tag{25}$$

where N_{NF} is the number of households who participate in non-farm employment.

The effect of the treatment on the untreated (TU), or the expected effect of the treatment on individuals with observed characteristics *x* who did not participate in non-farm employment, can be presented as follow:

$$TU(x) = Pr(y_1 = 1|NF = 0, X = x) - Pr(y_0 = 1|NF = 0, X = x),$$

$$ATU = \frac{1}{N_{NNF}}\sum_{i=1}^{N_{NNF}} TU(x_i). \tag{26}$$

where N_{NNF} is the number of households who did not participate in non-farm employment.

Identification strategy. In this analysis, we identified three instruments to control the endogeneity problem of non-farm employment participation that must satisfy the two conditions: instrumental relevance and instrumental exogeneity. The relevance condition means that the instruments are correlated with the endogenous non-farm variable. The exogeneity condition indicates that the instruments must be uncorrelated with the error term (ε_{it}). Our first instrument is Non-farm employment opportunity, which is a dummy variable for the enterprises/firms/factories located in the commune. We suppose that the enterprises/firms/factories located in the commune will bring the opportunity for household members to engage in non-farm employment. Next, we choose dummy variable Traditional occupation villages as an instrument. As in many developing countries, in rural areas, there are usually villages with traditional occupations that encourage farm households to participate in production and diversify their incomes. The last instrumental variable is Distance to the nearest daily permanent market, which is measured in kilometres. The reason to choose this variable as an instrument, that is, it is not a choice variable, and it is related to the appearance of the infrastructure that impacts the chances of non-farm jobs. To obtain these variables, we use the commune survey of the VARHS dataset from each year. Then, we conduct to merge the data of these variables with household data, the observations with missing values will elicit out of the final dataset.

The definition of variables used in this study is presented in the Table 2.

Table 2

Definition of used variables

Variables	Definition
Dependent variables	
Adopt hybrid seed or improved variety	Adopt hybrid seed or improved variety (binary, adopt = 1, non-adopt = 0)
Non-farm employment variables	
Non-farm participation	Binary, if at least one household member engages into non-farm activities = 1, otherwise 0
Household characteristics	
Head's gender	Male = 1, female = 0
Head's age	Years
Head's education	Schooling completed years
Ethnicity	The major ethnicity (*Kinh*) = 1, minorities = 0
Household labour	The number of family labour
Farm land characteristics	
Riceland cultivation	The total of riceland cultivation area in 3 most recent seasons in this year (hectare)
Number plot	Number of plot
Irrigation condition	The proportion of farm land irrigated, %
Social capital	
Credit	The amount of credit that borrowed for rice production (1000 VND)
Extension services	Binary, if household obtain assistance or information from extension services (such as new seed, fertiliser, irrigation, …) = 1, otherwise 0
FBO-member	Binary, membership of farmer-based organisation (such as women's union, farmer's union, farmer interest group, and cooperative) = 1, otherwise 0
Distance seed supplier	Distance from household to the nearest seed supplier (km)
Time dummy variables	
Year dummy	Binary, dummy variables of years: 2008, 2010, 2012, 2014, 2016
Instrumental variables	
Non-farm employment opportunity	Binary, the enterprises/firms/factories located in the commune (Yes = 1, no = 0)
Traditional occupation villages	Binary, the traditional occupation villages located in the commune (Yes = 1, no = 0)
Distance to the nearest daily permanent market	The distance from the commune headquarter to the nearest daily market with permanent location, km

Source: formed by the authors.

To examine the impact of non-farm employment on the decision of technology adoption, we only focus on the adoption of rice hybrid seed or improved variety of rice farmers to be the dependent variable. Non-farm employment variable is defined as at least one member of farm households participating in two activities including non-farm wage employment and non-farm self-employment. The other independent variables used include household characteristics, farmland characteristics, social capital, time dummy variables, and non-farm participation variable. The instrumental variables, which are used in this study consist three variables: (1) the dummy non-farm employment opportunity variable, which is defined as the enterprises/firms/factories located in the commune; (2) the dummy variable of the traditional occupation villages located in the commune; and (3) the distance from the commune headquarter to the nearest daily market with permanent location.

4. RESULTS

4.1. Overview of non-farm sector and the adoption of rice hybrid seed or improved variety in Vietnam. Since the Doi Moi policy in 1986, the Vietnamese rural economy's structure has changed with the expansion of the non-farm sector. The openness and liberalisation of the market together with the diversification of the rural household income policy of the government facilitated rural households to participate in other activities outside of farm activities easily.

With VARHS, we first examine working days and incomes from farm and non-farm activities during the period 2008–2016 in order to see the development of the rural non-farm sector (Table 3). Table 3 shows that the average farm work days per household decreased from 303 in 2008 to 170 in 2016, whereas non-farm work days increased from 246 in 2008 to 289 in 2016. The share of non-farm work days in the total household working days increased from 44.8 % in 2008 to 63.0 % in 2016. These results indicated that Vietnamese farm households increasingly participated into non-farm activities to diversify their income sources in this period. The agricultural income increased from VND 14 million in 2008 to VND 26 million in 2016, whereas non-farm income rapidly increased from VND 17 million in 2008 to 57 million VND in 2016. Indeed, non-farm income continued to exceed farm income after 2008 and the former was more than twice the latter in 2016. However, the share of agricultural income tended to decrease in the total household income, while this figure of non-farm income increased from 42.9 % to 58.1 % in the period 2008–2016. In non-farm activities, wage employment is the main activity with the majority of working time and the main source of income of household non-farm income.

In addition, the non-farm employment participation rate witnessed a considerable increase from 71.3 to 82.8 % in the 2008–2016 period. Adoption rates for hybrid seeds or improved variety do not show a clear tendency over the observed period. However, this rate was around more than 80 % during the period implying the increasing of farmers' awareness about the adoption of modern technology in order to improve agricultural performance.

Table 3

Non-farm employment, household income, and adoption of hybrid seeds or improved variety of Vietnamese rice farm households

Indicators	2008	2010	2012	2014	2016
1. Total household work days	549.8	494.3	481.5	437.3	458.7
Farm work days	303.4 (55.2%)	256.0 (51.8%)	230.1 (47.8%)	169.6 (38.8%)	169.7 (37.0%)
Non-farm work days	246.4 (44.8%)	238.3 (48.2%)	251.4 (52.2%)	267.7 (61.2%)	289.0 (63.0%)
Wage employment, days	180.3	184.0	193.0	215.7	237.2
Self-employment, days	66.2	54.3	58.4	52.0	51.8
2. Total household income	39.1	55.2	72.5	86.1	97.7
Agricultural income	14.1 (36.2%)	20.4 (37.0%)	20.8 (28.7%)	24.1 (28.0%)	26.1 (26.7%)
Non-farm income	16.8 (42.9%)	23.0 (41.6%)	36.5 (50.3%)	45.2 (52.5%)	56.8 (58.1%)
Wage income	10.1	15.9	24.3	34.7	43.3
Self-employment income	6.7	7.1	12.2	10.5	13.5
Other income	8.2 (20.9%)	11.8 (21.4%)	15.2 (21.0%)	16.8 (19.5%)	14.8 (15.2%)
3. Non-farm employment participation rate, %	71.3	75.7	78.7	81.2	82.8
4. Adoption rates of hybrid seeds or improved variety, %	85.0	77.7	81.2	84.6	82.4

Note. Unit for incomes is million Vietnam dong (VND).
Source: authors' calculation from VARHS 2008–2016.

To focus on the relationship between the adoption of hybrid seeds or improved variety and non-farm employment, Figure 1 shows adoption rates hybrid seeds or improved variety for households with and without non-farm workers (including both wage workers and self-employed workers), and the non-farm participation rate between adopters and non-adopter of hybrid seeds or improved variety. Overall, households with non-farm workers have higher (or at least similar) adoption rates of hybrid seeds or improved variety compared with households without non-farm workers. Similarly, the non-farm participation rate of rice farmers who adopt hybrid seeds or improved variety was higher than the non-adopters ones. Although our sample cannot clearly show the tendency of adoption hybrid seeds or improved variety during 8 years, but we might see the reciprocal relationship between the non-farm employment and the adoption of hybrid seeds or improved variety.

4.2. Descriptive statistics of variables used. Our study used the unbalanced panel data of VARHS 2008–2016 for the five rounds of data with a total sample of 8,012 observations. Of which, 6,584 observations adopted rice hybrid seeds or improved variety and 1,428 for non-adopters; 6,247 observations engaged in non-farm employment, and 1,765 for non-participants in the 2008–2016 period. Table 4 provides the descriptive statistics of the total sample size and is also divided into two groups: participants and non-participants non-farm employment, two groups adopters and non-adopters hybrid seeds or improved variety. The t-test statistic is used to observe the differences between the two groups. From the table, the proportion of rice hybrid seeds or improved variety was 0.822 whereas this proportion of the non-farm participant group was higher than the non-participant ones (0.832 and 0.786 respectively). The average participation rate of non-farm households was 0.780, whereas there was a difference between adopters and non-adopters groups. Households adopting rice hybrid seeds or improved variety tended to engage in non-farm employment more than non-adopters.

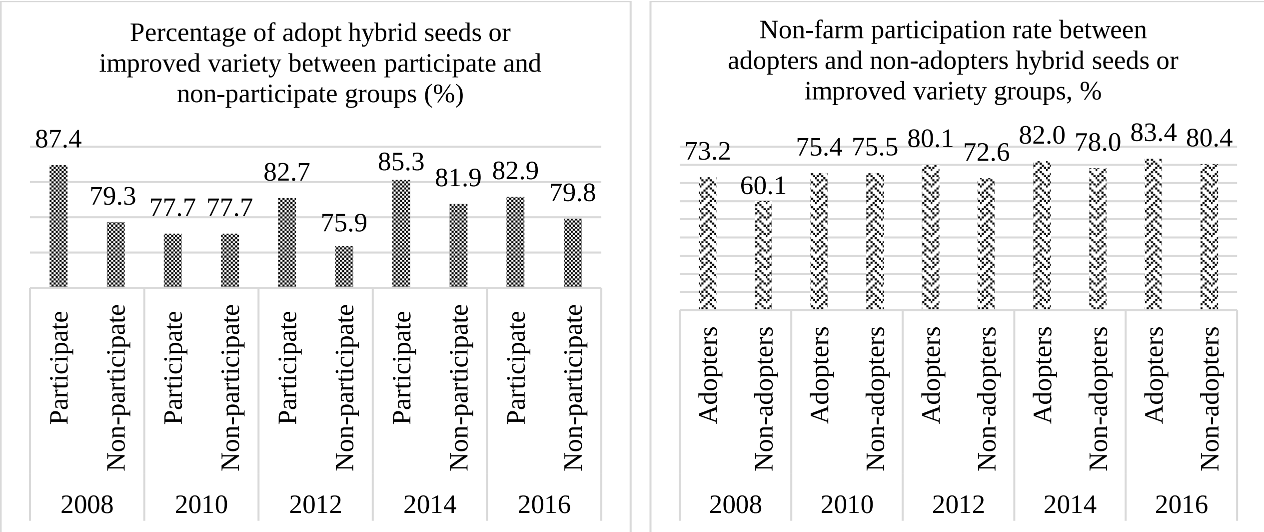

Figure 1. Adoption rate of hybrid seeds or improved variety and non-farm participation rate between two groups of Vietnamese rice farmers

Source: calculated by authors.

Regarding household characteristics, the proportion of male-headed households in non-farm participants and non-participants groups are 0.818 and 0.823, respectively; and in adopters and non-adopters groups are 0.817 and 0.828, respectively. The t-test statistic results indicate that there are no differences between those groups. The average age of head households was 51.214, whereas farmers who participate in non-farm employment are younger that non-participants, while the mean age of adopters group is higher than non-adopters ones. The average schooling completed years of households in the non-farm participant group was higher than the non-participant one (7.156 and 5.920 respectively). Similarly, the rice farmers who adopted technology had higher education levels than the non-adopters (7.122 and 5.785 respectively). The descriptive statistics further indicate that the minor ethnicities households participated in non-farm activities and adopted hybrid seeds or improved variety less than the Kinh households. The mean number of household labour of the non-farm participation group were significantly higher than the non-participation group, but the figures for the technology adoption group were significantly less than the non-adopters.

For farmland characteristics, farm households engaged in non-agricultural activities and adopting modern technologies had significantly smaller areas under rice than households that were not engaged in such activities and did not adopt modern technologies. However, there are also differences between those groups regarding the fragmentation of farmland. Rice households of the non-farm participation group had a number of plots less than the non-participation households (5.006 and 5.457 respectively). Farm households might save a lot of working time in farm production if the fragmentation level of farmland is low; thus, they could engage in other activities outside of farm activities. While farm household who adopted hybrid seeds or improved variety had the fragmentation level significantly higher than the non-adopters (5.201 and 4.663 respectively). The ownership of many plots of farmland has facilitated rice farmers to apply new modern varieties to different plots. The proportion of irrigated land in the non-farm participation households group was higher than the non-participation ones; similarly, this rate was higher among the adopters of modern varieties than among the non-adopters.

Table 4

Descriptive statistics of variables used

Variable	Non-farm employment participation			Adopt hybrid seeds or improved variety			Pooled (N = 8,012)
	Participants (N = 6,247)	Non-participants (N = 1,765)	Mean difference	Adopters (N = 6,584)	Non-adopters (N = 1,428)	Mean difference	
Dependent variables							
Adopt hybrid seed or improved variety	0.832	0.786	-0.045***	-	-	-	0.822
Non-farm employment variables							
Non-farm participation	-	-	-	0.789	0.736	-0.053***	0.780
Household characteristics							
Head's gender	0.818	0.823	0.005	0.817	0.828	0.011	0.819
Head's age	50.539	53.605	3.067***	51.397	50.375	-1.022***	51.214
Head's education	7.156	5.920	-1.237***	7.122	5.785	-1.337***	6.884
Ethnicity	0.769	0.621	-0.148***	0.773	0.569	-0.203***	0.737
Household labour	3.222	2.580	-0.642***	3.045	3.244	0.199***	3.080
Farm land characteristics							
Riceland cultivation	0.636	0.987	0.351***	0.652	0.998	0.346***	0.713
Number plot	5.006	5.457	0.452***	5.201	4.663	-0.538***	5.105
Irrigation condition	77.319	64.750	-12.569***	76.686	64.690	-11.995***	74.551
Social capital							
Credit	1,531.556	3,190.241	1,658.93***	1,541.741	3,534.723	1,992.983***	1,896.955
Extension services	0.923	0.838	-0.085***	0.906	0.898	-0.007	0.904
FBO-member	0.777	0.669	-0.108***	0.767	0.690	-0.077***	0.753
Distance seed supplier	7.979	18.735	10.757***	10.801	8.260	-2.541	10.348
Instrumental variables							
Non-farm employment opportunity	0.744	0.584	-0.161***	-	-	-	0.709
Traditional occupation villages	0.331	0.256	-0.075***	-	-	-	0.314
Distance to the nearest daily permanent market	1.457	3.050	1.593***	-	-	-	1.807

Notes. 1. Sample t test for differences between participants and non-participants in non-farm employment, adopters and non-adopters.

2. ***, **, * indicate statistical significant at 1 %, 5, 10 % level, respectively.

Source: authors' estimation based on VARHS 2008–2016.

The descriptive statistics of social capital characteristics indicate that farm households that did not participate in non-farm employment tended to borrow credit more than the participation households, and the adopting technology rice households borrowed credit less than the non-adopters. In addition, the proportion of non-farm participation rice farmers who obtained assistance from extension services was more than the non-participation ones; but this criterion was not different between adopters and non-adopters of modern variety groups. The average estimated proportion of farmer-based organisation membership was 0.753, whereas the figures in non-farm participation and non-participation groups were 0.777 and 0.669 respectively, and adopters and non-adopters groups were 0.767 and 0.690 respectively. There was a significant difference in distance from households to the nearest seed supplier between two groups non-farm participants and non-participants, of which this distance of non-farm participants was shorter than the non-participants.

4.3. Binary Probit and IV models estimates. Firstly, we present the estimation results of the first stage regression of non-farm employment participation (Table 5).

Table 5

First stage regression of non-farm employment participation

Probit model		Pooled		Random effects	
		Coef.	S.E.	Coef.	S.E.
Household characteristics	Head's gender	-0.235***	[0.05]	-0.268***	[0.07]
	Head's age	-0.013***	[0.00]	-0.018***	[0.00]
	Head's education	0.014***	[0.01]	0.014**	[0.01]
	Ethnicity	0.378***	[0.05]	0.582***	[0.08]
	Household labour	0.302***	[0.04]	0.377***	[0.02]
Farmland characteristics	Riceland cultivation	-0.113***	[0.01]	-0.144***	[0.02]
	Number plot	-0.044***	[0.01]	-0.051***	[0.01]
	Irrigation condition	0.003***	[0.00]	0.003***	[0.00]
Social capital	Credit (log)	0.011*	[0.01]	0.013*	[0.01]
	Extension services	0.323***	[0.06]	0.402***	[0.08]
	FBO-member	0.085*	[0.04]	0.082	[0.05]
	Distance seed supplier	-0.0004**	[0.00]	-0.0005*	[0.00]
Instrumental variables	Non-farm employment opportunity	0.245***	[0.04]	0.279***	[0.05]
	Traditional occupation villages	0.126***	[0.04]	0.124***	[0.05]
	Distance to the nearest daily permanent market	-0.013***	[0.00]	-0.015***	[0.00]
Year dummy variables	Year dummy (based 2008)	Yes		Yes	
Constant		-0.112***	[0.12]	-0.004**	[0.17]
Number of observations		8,012		8,012	
F-test for instruments		76.52		52.78	
sigma_u		-	-	0.821	[0.04]
rho		-	-	0.407	[0.02]
Wald test of rho = 0: chi^2 (1)		-	-	393.20 (p-value=0.000)	

Notes. 1. ***, **, * indicate statistical significant at 1 %, 5, 10 % level, respectively.
2. Robust standard errors for all regressions.
Source: authors' estimation based on VARHS 2008–2016.

We use two models the pooled Probit and Probit random effects in this estimation and apply F-test in both models to identify whether the instruments are weak or not. The estimation shows that the coefficient of almost the independent variables including household characteristics, farmland characteristics, social capital are statistically significant at 1 %, 5, and 10 % level in both pooled and random effects models. The results of three instrumental variables (Non-farm employment opportunity, Traditional occupation villages, Distance to the nearest daily permanent market) are highly significant at 1 % level. The coefficient of IVs non-farm employment opportunity is positively significant implies that the presence of the manufactories or companies at the commune will create the chances for farm households engage into non-farm activities. Similarly, variables of traditional occupation villages have a positive sign with non-farm participation in both models. While the distance to the nearest daily permanent market variable negatively impacts on the participation of non-farm employment, indicating that the presence and distance of the permanent market will influence the chance of the development of non-farm sectors in rural areas. The F-test is used in both models, which demonstrates the relevance condition of the instrumental variables. The F-test results for all instrumental variables in the pooled Probit and Probit random effects models are 76.52 and 52.78 respectively (greater than 10), thus, we can conclude that these instruments are strong and satisfy the relevance condition.

Table 6 presents the estimation results on the impact of non-farm employment participation on adopting of hybrid seeds or improved variety of rice farmers in Vietnam in both binary Probit models and the IV methods. In the Probit models analysis with the unbalanced data, we estimate three models, that is, the pooled, correlated random effects, and the correlated random effects with the Mundlak approach with the aim to check the different results of those models. The pooled and correlated random effects Probit models use the year dummies, while the correlated random effects with the Mundlak approach add both the year dummies and the time average of explanatory variables. From Table 6, the coefficients of the non-farm variable are not statistically significant in all three Probit models. This result indicates that the participation of non-farm employment has no impact on the decision of the adoption of hybrid seeds or improved variety of farmers even when our analysis controlled the unobserved heterogeneity of unbalanced panel data. The estimation results of Probit models also present similar results of the remaining explanatory variables of the two models the pooled and correlated random effects, while the estimate of the correlated random effects of the Probit model with the Mundlak approach differs significantly from the other two models.

For the endogeneity problem of non-farm participation, our study conducts the IV approach to avoid the bias estimation. Although this approach has limitation with the use of binary outcome variable, the applying this method could help to examine the validity of the instruments through the Two stage least squared model (2SLS). As mentioned in the methodology section, the IV Probit is not made sense and is inefficient because of the binary of endogenous variable, but this model can be used to check the sign of the relationship between non-farm participation and the technology adoption decision before the next estimation – the endogenous switching Probit model. Our study conducts to estimate the pooled 2SLS, fixed effects 2SLS, and pooled IV Probit whose results along with some test statistics are reported in Table 6.

Table 6

Impact of non-farm employment participation on the adoption of hybrid seeds or improved variety: Binary Probit and IV models estimates

Variable	Probit			2SLS		IV Probit (Pooled)
	Pooled	Random effects	CRE Mundlak	Pooled	Fixed effects	
Non-farm participation	0.054	0.048	-0.003	0.703***	0.365*	1.809***
	[0.04]	[0.05]	[0.06]	[0.14]	[0.25]	[0.19]
Household characteristics						
Head's gender	0.033	0.047	0.054	0.049***	0.043	0.135***
	[0.05]	[0.06]	[0.06]	[0.02]	[0.03]	[0.04]
Head's age	0.001	0.001	-0.003	0.003***	0.001	0.007***
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]
Head's education	0.024***	0.029***	0.008	0.004*	0.003	0.009*
	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.01]
Ethnicity	0.380***	0.421***	-0.314***	0.014	-0.028	0.051
	[0.04]	[0.06]	[0.07]	[0.02]	[0.05]	[0.06]
Household labour	-0.054***	-0.054***	-0.005	-0.067***	-0.029	-0.176***
	[0.01]	[0.02]	[0.03]	[0.01]	[0.02]	[0.02]
Farm land characteristics						
Riceland cultivation	-0.055***	-0.060***	0.030	0.007	0.019	0.017
	[0.01]	[0.01]	[0.03]	[0.01]	[0.01]	[0.01]
Number plot	0.058***	0.063***	0.012	0.020***	0.003	0.061***
	[0.01]	[0.01]	[0.02]	[0.00]	[0.00]	[0.01]
Irrigation condition	0.004***	0.004***	0.001	0.0002	0.0003	0.001
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Social capital						
Credit (log)	-0.020***	-0.018***	-0.006	-0.007***	-0.003	-0.019***
	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.01]
Extension services	-0.071	-0.129*	-0.218**	-0.096***	-0.092***	-0.270***
	[0.07]	[0.08]	[0.09]	[0.03]	[0.03]	[0.06]
FBO-member	0.159***	0.146***	0.012	0.021	-0.002	0.053
	[0.04]	[0.05]	[0.06]	[0.01]	[0.02]	[0.04]
Distance seed supplier	0.0003	0.0003	-0.0003	0.0001***	0.00004	0.0004
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Time averages of household and farm-varying characteristics		-	Yes	-	-	-
Constant	0.030	0.120	-0.599***	0.215***	-	-0.844***
	[0.12]	[0.14]	[0.23]	[0.08]	-	[0.14]
Number of observations	8,012	8,012	8,012	8,012	7,790	8,012
LR test of rho=0: chi^2 (1)		110.36***	101.68***	-	-	-
Wald test of exogeneity $\chi2$		-	-	-	-	36.20***
Underidentification test (Kleibergen-Paap LM statistic)				74.220	17.523	-
Weak identification test (Cragg-Donald Wald F-statistic)				29.527	17.983	-
Overidentification test (Hansen J statistic $\chi2$)	-	-	-	3.929 (p-value=0.140)	3.183 (p-value=0.204)	

Notes. 1. ***, **, * indicate statistical significant at 1 %, 5, 10 % level, respectively.

2. Values in parentheses are standard errors. The standard error is robust in the Pooled Probit, Pooled 2SLS, FE-2SLS, and IV Probit models.

3. In FE-2SLS model, the single groups were detected.

Source: authors' estimation based on VARHS 2008–2016.

The endogeneity of non-farm participation needs to be checked via the Wald test statistic in the IV Probit regression. The null hypothesis is the absence of endogeneity in the estimation. The Wald test is significant at the 1 % level, which rejects the null hypothesis. Indeed, non-farm participation variable is an endogenous variable, the analysis should be based on the IV approach to control the endogeneity problem. The values of weak identification test statistic (Cragg-Donald Wald F statistic) are 29.527 and 17.983 (greater than 10) in the pooled and fixed effects 2SLS models, respectively. The null hypothesis of the weak identification test is rejected and all instrumental variables satisfy the relevance condition. Another important test of instruments is the overidentification test, which presents the validity of IVs and must be uncorrelated with the error term. The values over-identification test (Hansen J statistic) are 3.929 with p-value 0.140 in the pooled model and 3.183 with p-value 0.204. Thus, the joint null hypothesis is not rejected and all three instruments are valid and satisfy the instrumental exogeneity condition.

Moreover, from the estimation results of the IV approach, the coefficient of the non-farm variable is positive and statistically significant in all three models (Table 6). We can see that when the endogeneity problem is controlled, the results of the non-farm variable totally changed and differed from the Probit models. In a comparison of estimation from the Probit model with the treatment of unobserved heterogeneity of panel data, the control of the endogeneity problem is more efficient. The finding indicates that the participation of non-farm employment has a positive effect on the adoption decision of hybrid seeds or improved variety of rice farmers in Vietnam. This result is confirmed by our next analysis – the endogenous switching Probit model.

4.4. Endogenous switching Probit model estimates. As the IV estimation of the Probit model is not a suitable approach with a dummy endogenous non-farm variable, the endogenous switching Probit model is used to estimate the effect of non-farm participation on the adoption decision of hybrid seeds or improved variety. The result of ESPM is presented in Table 7. The negative value of rho1 (-0.628) means that the unobservable that affects the household's participation in non-farm employment is negatively correlated to the unobservable that impacts on household's technology adoption decision. The likelihood-ratio test for joint independence of the equations is 20.34 with a p-value of 0.000 which the null hypothesis is rejected, thus, the maximum likelihood estimation of the technology adoption equation and the non-farm participation equation is valid. Therefore, this result indicates that estimating the binary Probit model would lead to bias and inconsistent results, and ESPM is an appropriate method.

In the selection non-farm employment equation, all three instrumental variables are statistically significant, and the results of coefficients of explanatory variables are similar to the first stage regression of the pooled model. Overall, the hybrid seeds or improved variety adoption decision effects of the household observable characteristics (including household characteristics, farmland characteristics, and social capital characteristics) differ considerably between the two regimes. The household with the older head is more likely to adopt a new modern variety among households not engaged in non-agricultural activities than among group households engaged in agricultural activities. The higher level of education of household heads could boost the adoption of new technology for households in the non-farm participation group more than in those that did not participate in the programme.

Table 7

Endogenous switching Probit estimates

Variable	Participants		Non-participants		Non-farm employment equation	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Household characteristics						
Head's gender	0.076	[0.05]	0.118	[0.10]	-0.233***	[0.05]
Head's age	0.002	[0.00]	0.008***	[0.00]	-0.013***	[0.00]
Head's education	0.016***	[0.01]	0.015	[0.01]	0.015***	[0.01]
Ethnicity	0.214***	[0.06]	0.335**	[0.14]	0.365***	[0.05]
Household labour	-0.096***	[0.02]	-0.154***	[0.04]	0.302***	[0.01]
Farm land characteristics						
Riceland cultivation	-0.045***	[0.02]	-0.00005	[0.02]	-0.107***	[0.01]
Number plot	0.068***	[0.01]	0.047***	[0.01]	-0.044***	[0.01]
Irrigation condition	0.002***	[0.00]	0.003**	[0.00]	0.003***	[0.00]
Social capital						
Credit (log)	-0.025***	[0.01]	-0.010	[0.01]	0.010	[0.01]
Extension services	-0.199**	[0.08]	-0.261**	[0.12]	0.318***	[0.06]
FBO-member	0.037	[0.05]	0.304***	[0.09]	0.082**	[0.04]
Distance seed supplier	0.002***	[0.00]	0.0002	[0.00]	-0.0004*	[0.00]
Year dummy	Yes		Yes		Yes	
Instrumental variable						
Non-farm employment opportunity		-	-	-	0.278***	[0.04]
Traditional occupation villages		-	-	-	0.114***	[0.04]
Distance to the nearest daily permanent market		-	-	-	-0.013***	[0.00]
Constant	0.717***	[0.14]	-0.557	[0.22]	-0.139	[0.12]
Number of observations	8,012					
athrho1	-0.737	0.215	-	-	-	-
athrho0	-0.614	0.227	-	-	-	-
rho1	-0.628	0.131	-	-	-	-
rho0	-0.547	0.159	-	-	-	-
Wald chi2 (22)	1,099.50***					
LR test of independent equation (rho1=rho0=0): chi2(2)	20.34 (p-value=0.000)					
Average treatment effect (ATE)	0.315					
Average treatment effect on the treated (ATT)	0.351					
Average treatment effect on the untreated (ATU)	0.190					

Notes. 1. ***, **, * indicate statistical significant at 1 %, 5, 10 % level, respectively.
2. Values in parentheses are standard errors.
Source: authors' estimation based on VARHS 2008–2016.

On the other hand, for the non-farm participation group, households with large rice land cultivation areas are less invested in new technology than the non-participant group. Rice farmers in the non-farm participant group who borrow credit for rice production will limit the adoption of hybrid seeds or improved variety. This is reasonable because if farmers join the non-farm sector, these earnings will help them to invest in new modern technology in rice production instead of borrowing other sources. In addition, farm households who is the member of farmer-based organisations tend to apply the modern variety more for the non-farm non-participants.

Meanwhile, some characteristics are statistically significant in both regimes (participants and non-participants). Farm households that are Kinh ethnicity (occupies the main population) are more likely to adopt technology than those of minorities ones. Having a large household labour prevents the adoption decisions of technology of rice farmers who engage and do not engage in non-farm employment. In addition, if rice farmers have many plots, they tend to adopt new varieties in rice production. Next, the good irrigation condition for farmland can boost the adoption of hybrid seeds or improved variety in rice production regardless of participation or not in non-farm employment. However, the assistance or information from extension services does not support for rice farmers to adopt technology in rice production.

Table 7 also shows the average treatment effect (ATE), the average treatment effect on the treated (ATT), and the average treatment effect on the untreated (ATU) non-farm participation in the adoption of hybrid seeds or improved variety decision. The ATE means that the probability of all households' adoption of modern variety is 31.5 %. The ATT value indicates that households who engage in non-farm employment had a 35.1 % of probability of technology adoption. Meanwhile, the average probability of adopting hybrid seeds or improved variety of households who did not participate in non-farm employment (ATU) is lower by 19.0 %.

4.5. Robustness check. In our analysis of section 4.3, non-farm employment is measured as a dichotomous variable with disadvantages. To enrich and ensure our estimation results on the impact of non-farm employment on the adoption decision of rice hybrid seeds or improved variety, we conduct additional analyses by using the non-farm working days variable. The non-farm working days variable is defined as total working days from non-farm employment of all members household.

Our additional analyses also estimated this relationship in Probit models (with the pooled, correlated random effects, and the correlated random effects with the Mundlak approach) and IV estimates (2SLS pooled, fixed effects 2SLS, and IV Probit), which are presented in Table 8. The estimation results show that the coefficients of non-farm working days are not statistically significant in the three Probit models. In IV estimations, the non-farm working days have positive effects on the adoption decision of rice hybrid seeds or improved variety in 2SLS pooled and IV Probit models. These results indicated that non-farm employment has no effect on adoption decisions when we control the unobserved heterogeneity of the panel data, and non-farm employment has a positive effect when we solve the endogeneity problem. The results in Table 8 are in line with the findings in Table 6, which confirm the robustness of our findings regarding the influence of non-farm employment participation on the decision of rice hybrid seeds or improved variety adoption.

Table 8

Impact of non-farm working time on the adoption of hybrid seeds or improved variety: Binary Probit and IV model estimates

Variable	Probit			2SLS		IV Probit (Pooled)
	Pooled	Random effects	CRE Mundlak	Pooled	Fixed effects	
Non-farm working days	0.0001	0.0001	0.00003	0.001***	0.001	0.002***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Household characteristics						
Head's gender	0.321	0.046	0.054	0.023*	0.021	0.094**
	[0.05]	[0.06]	[0.06]	[0.01]	[0.03]	[0.05]
Head's age	0.001	0.001	-0.003	0.0004	-0.0002	0.001
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]
Head's education	0.023***	0.028***	0.009	0.002	0.002	0.002
	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.01]
Ethnicity	0.374***	0.418***	0.317***	0.021	-0.045	0.039
	[0.05]	[0.06]	[0.07]	[0.02]	[0.05]	[0.09]
Household labour	-0.057***	-0.055***	-0.003	-0.057***	-0.011	-0.211***
	[0.01]	[0.02]	[0.03]	[0.01]	[0.07]	[0.03]
Farm land characteristics						
Riceland cultivation	-0.056***	-0.061***	0.030	-0.009**	0.010	-0.023*
	[0.01]	[0.01]	[0.03]	[0.00]	[0.01]	[0.01]
Number plot	0.059***	0.063***	0.011	0.019***	0.003	0.074***
	[0.01]	[0.01]	[0.02]	[0.00]	[0.01]	[0.01]
Irrigation condition	0.004***	0.004***	0.001	0.001***	0.0003	0.002***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Social capital						
Credit (log)	-0.019***	-0.018***	-0.006	-0.004**	-0.002	-0.012**
	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.01]
Extension services	-0.064	-0.123	-0.218**	-0.016	-0.053***	-0.074
	[0.07]	[0.08]	[0.09]	[0.02]	[0.02]	[0.06]
FBO-member	0.163***	0.15***	0.011	0.056***	0.006	0.187***
	[0.04]	[0.05]	[0.06]	[0.01]	[0.02]	[0.04]
Distance seed supplier	0.0003	0.0003	-0.0003	0.0001**	7.33E-06	0.0004
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Time averages of household and farm-varying characteristics	-	-	Yes	-	-	-
Constant	0.066	0.15	-0.607	0.641***	-	0.34
	[0.12]	[0.14]	[0.21]	[0.04]	-	[0.12]
Number of observations	8,012	8,012	8,012	8,012	7,790	8,012

Notes. 1. ***, **, * indicate statistical significant at 1 %, 5, 10 % level, respectively.

2. Values in parentheses are standard errors. The standard error is robust in the Pooled Probit, Pooled 2SLS, FE-2SLS, and IV Probit models.

3. In FE-2SLS model, the single groups were detected.

Source: authors' estimation based on VARHS 2008–2016.

5. DISCUSSION

The central theme of the article is to examine the effect of non-farm employment on the decisions of technology adoption of farm households in Vietnam, in the case of the adoption of rice hybrid seeds or improved variety in rice production. Our estimation results show that participation in non-farm employment has a positive effect on the adoption of improved varieties. Our finding is rational and consistent with the studies of Fernandez-Cornejo et al. (2005), Diiro & Sam (2015), and Dontsop-Nguezet et al. (2016) who found a positive relationship between non-farm participation and the adoption of improved varieties. Regarding the relationship between non-farm employment and technology adoption in general, the finding is in line with the previous studies as Beshir et al. (2012), Zhang et al. (2020), Danso-Abbeam et al. (2020), Yi (2018), Huang et al. (2019), Ahmed & Goodwin (2016), and Zheng et al. (2021) who indicated that non-farm employment has positive impact of the technology adoption decision. They suppose that the income source from non-farm employment can provide credit source to adopt new technology. In the presence of market imperfection, the earning from non-farm jobs can loosen the liquidity constraint, hence, farmers could invest in agricultural innovation. On the other hand, the adoption of hybrid seeds or improved variety not only bring benefit to rice farmers that increase yield but also have a short growing period and resistance to pests. Hence, this can permit farmers to save management time in the production process, then allow them to engage in non-farm employment outside of farm activities.

Regarding the determinants of technology adoption, the discussion of results about the significant factors is presented as follows. From the results of Table 6 and Table 7, our estimates show that age had a positive effect on the adoption of hybrid seeds or improved variety. The reason might be the older farmers might have gained knowledge and experience in agricultural production, thereby they refer to adopt new technology in agriculture. However, this impact may decrease when the household head gets older. This result is consistent with the findings of Langyintuo & Mungoma (2008), Meshram et al. (2016) and Beshir et al. (2012). It was found that education also has a positive impact on the decision of farm households to adopt technologies. This finding implies education level could help to raise the capacity of farmers to access and get information or knowledge about new technologies. Our finding is in line with studies of Langyintuo & Mungoma (2008), Beshir et al. (2012) and Ruzzante et al. (2021). Household labour is found to be negatively influencing the adoption of hybrid seeds or improved variety in rice production. This finding is consistent with the study of Beshir et al. (2012), while in contrast to the results of Teklewold et al. (2013) and Nguyen & Hung (2022). This result can explain that the hybrid seeds or improved varieties might be the short-term varieties, which are considered as the saving-labour technology; therefore, they require less labour than the traditional varieties.

Farmland characteristics are factors directly influencing the decision to adopt the technology. In this study, the number of plots has a significantly positive impact on adopting new varieties. The result is consistent with the result of Nguyen & Hung (2022). The reason for this may be related to the reduction of farm risk, i.e. farm households with a large number of plots can try out new technologies by applying them to only a few plots (Nguyen & Hung, 2022). The proportion of irrigated land is found positive effect on the adoption of hybrid seeds or improved variety which is in line with the study of Zhang et al. (2020). This implies that the good condition of the irrigation system can facilitate farm households to adopt new technology in agriculture.

Access to advisory services is expected to have a positive impact on technology adoption. However, our result found a reverse causation (negative effect) between extension services and the adoption decision of hybrid seeds or improved variety. This study is in line with the result of Di Falco et al. (2018), which indicated farmers receiving improved seeds interact less with their social network. This finding implies the role of agricultural extension services in the adoption of improved varieties was still inefficient in Vietnam. While FBO-member (farm-based organisation member) has a positive effect on the adoption of improved varieties. This may be reasonable that organisation membership can encourage the adoption of new technologies. In addition, our study found that the non-farm group who borrows credit for rice production will limit the adoption of new varieties. This result is consistent with the findings of Diiro & Sam (2015), who found a negative relationship between technology adoption and access to credit. It may be reasonable because non-farm income might provide a cash source and replace borrowing credit.

6. CONCLUSIONS

Our study contributes to the literature by examining the influence of the decision to participate in non-farm employment on the adoption decision of rice hybrid seeds or improved variety using panel data from Vietnam. By using the correlated random effects Probit model with the Mundlak approach, we control the estimation bias from the unobserved heterogeneity of the panel data. The estimation results on the relationship between non-farm participation and the adoption decision of modern variety from the Probit model without and with the Mundlak approach do not show any impact. Furthermore, our analysis uses the endogenous switching Probit model to solve both the endogeneity problem and self-selection problem of non-farm employment participation variable. From the results of the IV approach, we found that non-farm participation has a positive effect on the technology adoption of Vietnamese rice farmers. The value ATT is predicted from the endogenous switching Probit model, which implies that farm households who engage in non-farm employment had a 35.1 % of probability of rice hybrid seeds or improved variety adoption; and is higher than households who did not participate in non-farm employment by 19.0 (ATU). Thus, our study provides valuable insight that the participation decision in non-farm employment induces a change in farmers' behaviour in adopting modern agricultural technologies. In particular, farmers tend to adopt modern technologies when they engage in non-farm activities.

Our findings offer several policy implications concerning the factors affecting technology adoption. Firstly, a strategy for promoting rural development to diversify farm households' income via non-farm employment should be considered, especially focusing on activities during the off-season, which in turn farmers could enhance investment in farm inputs and adopt new technology in agriculture. Policies targeting to encourage non-farm employment in rural areas include providing information about non-farm recruitment via information and communication technologies such as televisions, radios, mobile phones, and social media. Second, the study recommends that the technological adoption of farmers can be further improved by implementing policy interventions by raising their education, investing and enhancing the irrigation system to facilitate the adoption, improving the implementation efficiency of agricultural extension services, strengthening the establishment and promotion of farm-based organisations (FBOs) via government and development partners.

7. LIMITATIONS AND FUTURE RESEARCH

Our research is only focused on one type of technology adoption: hybrid seeds or improved variety. There are many types of technology adoption (Ruzzante et al., 2021), thus this phenomenon can be further studied on the relationship between non-farm employment and other type of technology adoption. Due to the availability of the VARHS dataset, the potential for future research could be related to mechanisation or chemical fertiliser adoption in agricultural production.

Besides, there probably exists a reciprocal relationship between non-farm employment and technology adoption. To some extent, the adoption of modern technology in agriculture can support farmers to save farm labour, and then they can participate in non-farm activities to diversify their income. Thus, further research could be developed on the investigation of this reciprocal causation.

Funding: this study partly funded by Hue University under research project DHH2023-06-132 of Dr. Hang Thi Thuy Nguyen.

Acknowledgments: we are grateful to the Economics Research Centre, Economics School, Nagoya University, Japan, which provided the two months visiting fellowship for the research collaboration of this project.

Conflicts of interest: the authors declare no conflict of interest.

REFERENCES

1. Ahmed, M., & Goodwin, B. (2016). Agricultural mechanization and non-farm labor supply of farm households: evidence from Bangladesh. *2016 Annual Meeting*, July 31 – August 2, Boston, Massachusetts. Agricultural and Applied Economics Association. https://doi.org/10.22004/ag.econ.236131.

2. Amare, M., & Shiferaw, B. (2017). Nonfarm employment, agricultural intensification, and productivity change: empirical findings from Uganda. *Agricultural Economics*, 48(S1), 59–72. https://doi.org/10.1111/agec.12386.

3. Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: evidence from Tanzania and Ethiopia. *Food Policy*, 37(3), 283–295. https://doi.org/10.1016/j.foodpol.2012.02.013.

4. Barrett, C. B., Reardon, T., & Webb, P. (2001). Nonfarm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications. *Food Policy*, 26(4), 315–331. https://doi.org/10.1016/S0306-9192(01)00014-8.

5. Beshir, H., Emana, B., Kassa, B., & Haji, J. (2012). Determinants of chemical fertilizer technology adoption in North eastern highlands of Ethiopia: the double hurdle approach. *Journal of Research in Economics and International Finance*, 1(2), 39–49.

https://www.interesjournals.org/archive/jreif-volume-1-issue-2-year-2012.html.

6. Biørn, E. (1999). Estimating regression systems from unbalanced panel data: A stepwise maximum likelihood procedure. *Working Paper No. 1999, 20*. Available at: http://hdl.handle.net/10419/63162.

7. Buchenrieder, G., & Möllers, J. (2006). A synthesis of theoretical concepts for analysing non-farm rural employment. *Quarterly Journal of International Agriculture*, 44(1). Available at: https://www.researchgate.net/publication/23511552.

8. Bui, L. K., & Hoang, H. (2021). Non-farm employment, food poverty and vulnerability in rural Vietnam. *Environment, Development and Sustainability*, 23(5), 7326–7357. https://doi.org/10.1007/s10668-020-00919-3.

9. Danso-Abbeam, G., Dagunga, G., & Ehiakpor, D. S. (2020). Rural non-farm income diversification: implications on smallholder farmers' welfare and agricultural technology adoption in Ghana. *Heliyon*, 6(11), e05393. https://doi.org/10.1016/j.heliyon.2020.e05393.

10. Davis, B., Winters, P., Carletto, G., Covarrubias, K., Quiñones, E. J., Zezza, A., ... & DiGiuseppe, S. (2010). A cross-country comparison of rural income generating activities. *World Development*, 38(1), 48–63. https://doi.org/10.1016/j.worlddev.2009.01.003.

11. De Janvry, A., Dustan, A., & Sadoulet, E. (2011). Recent advances in impact analysis methods for ex-post impact assessments of agricultural technology: options for the CGIAR. Consultative Group on International Agricultural Research. Independent Science and Partnership Council. Available at: https://cgspace.cgiar.org/server/api/core/bitstreams/87ca07e6-0a02-48d9-b8a2-f26d7bd2666a/content.

12. Di Falco, S., Feri, F., Pin, P., & Vollenweider, X. (2018). Ties that bind: network redistributive pressure and economic decisions in village economies. *Journal of Development Economics*, 131, 123–131. https://doi.org/10.1016/j.jdeveco.2017.12.001.

13. Diiro, G. M., & Sam, A. G. (2015). Agricultural technology adoption and nonfarm earnings in Uganda: a semiparametric analysis. *The Journal of Developing Areas*, 49(2), 145–162. https://doi.org/10.1353/jda.2015.0013.

14. Dontsop Nguezet, P. M., Manyong, V. M., Abdoulaye, T., Alene, A., Amato, M. S., Ainembabazi, J. H., ... & Okafor, C. (2016). Non-farm activities and adoption of improved cassava and beans varieties in South-Kivu, DR Congo. *Tropicultura*, 34(3), 262–275. https://hdl.handle.net/10568/77858.

15. Ellis, F., & Allison, E. (2004). Livelihood diversification and natural resource access. *LSP Working Paper 9*. Overseas Development Group, University of East Anglia. Available at: https://openknowledge.fao.org/server/api/core/bitstreams/3ed4fec9-5dee-4d7c-b497-ad441a2c89f8/content.

16. Ellis, F., & Freeman, H. A. (2004). Rural livelihoods and poverty reduction strategies in four African countries. *Journal of Development Studies*, 40(4), 1–30. https://doi.org/10.1080/00220380410001673175.

17. Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: a survey. *Economic Development and Cultural Change*, 33(2), 255–298. https://doi.org/10.1086/451461.

18. Fernandez-Cornejo, J., Hendricks, C., & Mishra, A. (2005). Technology adoption and off-farm household income: the case of herbicide-tolerant soybeans. *Journal of Agricultural and Applied Economics*, 37(3), 549–563. https://doi.org/10.1017/S1074070800027073.

19. Foster, A. D., & Rosenzweig, M. R. (2010). Microeconomics of technology adoption. *Annual Review of Economics.*, 2(1), 395–424. https://doi.org/10.1146/annurev.economics.102308.124433.

20. General Statistics Office (2022). Statistical database of the General Statistics Office of Vietnam. Available at: https://www.gso.gov.vn/en/statistical-data.

21. Ghimire, R., Wen-Chi, H., & Shrestha, R. B. (2015). Factors affecting adoption of improved rice varieties among rural farm households in Central Nepal. *Rice Science*, 22(1), 35–43. https://doi.org/10.1016/j.rsci.2015.05.006.

22. Haggblade, S., Hazell, P., & Reardon, T. (2010). The rural non-farm economy: prospects for growth and poverty reduction. *World Development*, 38(10), 1429–1441. https://doi.org/10.1016/j.worlddev.2009.06.008.

23. Hang, N. T. T., Phuong, L. N. M., Hung, P. X., & Long, H. T. (2024). The effect of hybrid rice seeds adoption on the technical efficiency of rice farmers in Vietnam. *Hue University Journal of Science: Economics and Developmen*t, 133(5A), 33–52. https://doi.org/10.26459/hueunijed.v133i5A.7273.

24. Hertz, T. (2009). The effect of nonfarm income on investment in Bulgarian family farming. *Agricultural Economics*, 40(2), 161–176. https://doi.org/10.1111/j.1574-0862.2009.00367.x.

25. Hoang, T. X., Pham, C. S., & Ulubaşoğlu, M. A. (2014). Non-farm activity, household expenditure, and poverty reduction in rural Vietnam: 2002–2008. *World Development*, 64, 554–568. https://doi.org/10.1016/j.worlddev.2014.06.027.

26. Hossen, M. A., Talukder, M. R. A., Al Mamun, M. R., Rahaman, H., Paul, S., Rahman, M. M., ... & Islam, M. N. (2020). Mechanization status, promotional activities and government strategies of Thailand and Vietnam in comparison to Bangladesh. *AgriEngineering*, 2(4), 489–510. https://doi.org/10.3390/agriengineering2040033.

27. Huang, X., Lu, Q., Wang, L., Cui, M., & Yang, F. (2019). Does aging and off-farm employment hinder farmers' adoption behavior of soil and water conservation technology in the Loess Plateau? *International Journal of Climate Change Strategies and Management*, 12(1), 92–107. https://doi.org/10.1108/IJCCSM-04-2019-0021.

28. Huffman, W. (1991). *Agricultural household models: survey and critique*. Iowa State University, Department of Economics.

29. Loevinsohn, M., Sumberg, J., & Diagne, A. (2012). *Under what circumstances and conditions does adoption of technology result in increased agricultural productivity?* Protocol. London EPPI Centre, Social Science Research Unit. Available at:

https://eppi.ioe.ac.uk/cms/Portals/0/PDF%20reviews%20and%20summaries/Agricultural%20technology%202012Loevinsohn%20protocol.pdf?ver=2012-12-12-104836-213.

30. Langyintuo, A. S., & Mungoma, C. (2008). The effect of household wealth on the adoption of improved maize varieties in Zambia. *Food Policy*, 33(6), 550–559. https://doi.org/10.1016/j.foodpol.2008.04.002.

31. Lokshin, M., & Sajaia, Z. (2011). Impact of interventions on discrete outcomes: maximum likelihood estimation of the binary choice models with binary endogenous regressors. *The Stata Journal*, 11(3), 368–385. https://doi.org/10.1177/1536867X1101100303.

32. Meshram, V., Chobitkar, N., Paigwar, V., & Dhuware, S. (2016). Factors affecting on SRI system of paddy cultivation in Balaghat district of Madhya Pradesh. *Indian Research Journal of Extension Education*, 1, 202–204. Available at: https://api.seea.org.in/uploads/pdf/v12440.pdf.

33. Minot, N. Epprecht, M., Tran, T. T. A., & Le, Q. T. (2006). Income diversification and poverty in the Northern upland of Vietnam. *Research Report No. 145*. International Food Policy Research Institute, Washington, D. https://doi.org/10.2499/0896291480.

34. Mishra, A. K., Mottaleb, K. A., & Mohanty, S. (2015). Impact of off-farm income on food expenditures in rural Bangladesh: an unconditional quantile regression approach. *Agricultural Economics*, 46(2), 139–148. https://doi.org/10.1111/agec.12146.

35. Mundlak, Y. (1978). Models with variable coefficients: integration and extension in the econometrics of panel data L'Econométrie des données individuelles temporelles. *Annales de l'INSEE Paris*, 30–31, 483–510. https://doi.org/10.2307/20075301.

36. Mwangi, M., & Kariuki, S. (2015). Factors determining adoption of new agricultural technology by smallholder farmers in developing countries. *Journal of Economics and Sustainable Development*, 6(5), 208–216. Available at: https://core.ac.uk/download/pdf/234646919.pdf.

37. Nguyen, T. T. H. (2019). Linkage between farm and non-farm sectors and its impact on agricultural production: evidence from Vietnam *(DrS dissertation)*. Hokkaido University. https://doi.org/10.14943/doctoral.k13757.

38. Nguyen, H. T. T., & Kondo, T. (2020). Does the non-farm sector affect production efficiency of the Vietnamese agricultural sector? A stochastic frontier production approach. *Journal of Agriculture and Rural Development in the Tropics and Subtropics*, 121(2), 289–301. https://doi.org/10.17170/kobra-202011262277.

39. Nguyen, H. T. T., & Hung, P. X. (2022). Determinants of system of rice intensification adoption and its impacts on rice yield in the upland region of Central Vietnam. *Asian Journal of Agriculture and Rural Development*, 12(4), 306–315. https://doi.org/10.55493/5005.v12i4.4677.

40. Oseni, G., & Winters, P. (2009). Rural nonfarm activities and agricultural crop production in Nigeria. *Agricultural Economics*, 40(2), 189–201.

https://doi.org/10.1111/j.1574-0862.2009.00369.x.

41. Pfeiffer, L., López-Feldman, A., & Taylor, J. E. (2009). Is off-farm income reforming the farm? Evidence from Mexico. *Agricultural Economics*, 40(2), 125–138. https://doi.org/10.1111/j.1574-0862.2009.00365.x

42. Reardon, T., Stamoulis, K., Balisacan, A., Cruz, M., Berdegué, J., & Banks, B. (1998). Rural non-farm income in developing countries. In *The State of Food and Agriculture 1998* (pp. 283–356). Rome, FAO. Available at: https://www.fao.org/4/w9500e/w9500e.pdf.

43. Ruzzante, S., Labarta, R., & Bilton, A. (2021). Adoption of agricultural technology in the developing world: a meta-analysis of the empirical literature. *World Development*, 146, 105599. https://doi.org/10.1016/j.worlddev.2021.105599.

44. Seng, K. (2015). The effects of nonfarm activities on farm households' food consumption in rural Cambodia. *Development Studies Research*, 2(1), 77–89. https://doi.org/10.1080/21665095.2015.1098554.

45. Shiferaw, B., Kebede, T., Kassie, M., & Fisher, M. (2015). Market imperfections, access to information and technology adoption in Uganda: challenges of overcoming multiple constraints. *Agricultural Economics*, 46(4), 475–488. https://doi.org/10.1111/agec.12175.

46. Singh, I., Squire, L., & Strauss, J. (1986). *Agricultural household models: extensions, applications, and policy*. Washington, D.C., World Bank Group. Available at: http://documents.worldbank.org/curated/en/621291468739297175/Agricultural-household-models-extensions-applications-and-policy.

47. Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural Ethiopia. *Journal of Agricultural Economics*, 64(3), 597–623. https://doi.org/10.1111/1477-9552.12011.

48. Varma, P. (2019). Adoption and the impact of system of rice intensification on rice yields and household income: an analysis for India. *Applied Economics*, 51(45), 4956–4972. https://doi.org/10.1080/00036846.2019.1606408.

49. Wooldridge, J. M. (2019). Correlated random effects models with unbalanced panels. *Journal of Econometrics*, 211(1), 137–150. https://doi.org/10.1016/j.jeconom.2018.12.010.

50. Yi, Q. (2018). Adoption of agricultural mechanization services among maize farmers in China: impacts of population aging and off-farm employment. *2018 Conference*, July 28 – August 2, 2018, International Association of Agricultural Economists. Vancouver, British Columbia. https://doi.org/10.22004/ag.econ.277541.

51. Zhang, Y., Long, H., Li, Y., Ge, D., & Tu, S. (2020). How does off-farm work affect chemical fertilizer application? Evidence from China's mountainous and plain areas. *Land Use Policy*, 99, 104848. https://doi.org/10.1016/j.landusepol.2020.104848.

52. Zheng, H., Ma, W., Guo, Y., & Zhou, X. (2021). Interactive relationship between non-farm employment and mechanization service expenditure in rural China. *China Agricultural Economic Review*, 14(1), 84–105. https://doi.org/10.1108/CAER-10-2020-0251.

Citation:

Стиль – ДСТУ:

Nguyen H. T. T., Hung P. X., Le P. N. M. Does non-farm employment influence a farmer's decision to adopt hybrid rice seeds or improved variety? *Agricultural and Resource Economics*. 2024. Vol. 10. No. 3. Pp. 270–302. https://doi.org/10.51599/are.2024.10.03.11.

Style – APA:

Nguyen, H. T. T., Hung, P. X., & Le, P. N. M. (2024). Does non-farm employment influence a farmer's decision to adopt hybrid rice seeds or improved variety? *Agricultural and Resource Economics*, 10(3), 270–302. https://doi.org/10.51599/are.2024.10.03.11.

Scopus Preview

Source details

Agricultural and Resource Economics

Open Access

Years currently covered by Scopus: from 2019 to 2024

Publisher: Institute of Eastern European Research and Consulting

E-ISSN: 2414-584X

Subject area: Agricultural and Biological Sciences: Agricultural and Biological Sciences (miscellaneous)

Business, Management and Accounting: Business, Management and Accounting (miscellaneous)

Business, Management and Accounting: Marketing

Source type: Journal

View all documents > Set document alert Save to source list

CiteScore 2023
2.8

SJR 2023
0.305

SNIP 2023
0.583

CiteScore CiteScore rank & trend Scopus content coverage

CiteScore 2023

2.8 = 521 Citations 2020 - 2023 / 188 Documents 2020 - 2023

Calculated on 05 May, 2024

CiteScoreTracker 2024

2.9 = 485 Citations to date / 165 Documents to date

Last updated on 05 September, 2024 • Updated monthly

CiteScore rank 2023

Category	Rank	Percentile
Agricultural and Biological Sciences — Agricultural and Biological Sciences (miscellaneous)	#65/193	66th
Business, ...		

View CiteScore methodology > CiteScore FAQ > Add CiteScore to your site

Agricultural and Resource Economics

COUNTRY

Ukraine

Universities and research institutions in Ukraine

Media Ranking in Ukraine

SUBJECT AREA AND CATEGORY

Agricultural and Biological Sciences
- Agricultural and Biological Sciences (miscellaneous)

Business, Management and Accounting
- Business, Management and Accounting (miscellaneous)
- Marketing

PUBLISHER

Institute of Eastern European Research and Consulting

H-INDEX

9

PUBLICATION TYPE

Journals

ISSN

2414584X

COVERAGE

2019-2023

INFORMATION

Homepage

How to publish in this journal

editor@are-journal.com

Metrics based on Scopus® data as of March 2024

Leave a comment

Name

Email

(will not be published)

Tôi không phải là người máy

reCAPTCHA

Bảo mật - Điều khoản

Submit

The users of Scimago Journal & Country Rank have the possibility to dialogue through comments linked to a specific journal. The purpose is to have a forum in which general doubts about the processes of publication in the journal, experiences and other issues derived from the publication of papers are resolved. For topics on particular articles, maintain the dialogue through the usual channels with your editor.