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THE IMPACT OF NON-FARM EMPLOYMENT ON TECHNOLOGY ADOPTION IN RICE PRODUCTION: EVIDENCE IN VIETNAM

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ABSTRACT
Adoption of improved technologies in agriculture is believed to be a major factor in the success of the green revolution experienced by Asian countries. In Vietnam, rice is a dominant crop, and the yield has increased considerably during the period 2000-2020. Through using the data from the Vietnam Access to Resources Household Survey (VARHS) 2008-2016, the paper describes the overview of non-farm employment and technology adoption levels in rice production. The study used the cross-sectional data from VARHS 2016 to examine the relationship between non-farm employment and technology adoption in rice production. The Probit model is employed for binary response technology adoption decisions, and the instrumental variables method is applied to address endogeneity. The estimation results indicate that the earnings from non-farm employment can facilitate rice farmers in adopting modern technology as hybrid seeds or improved varieties, chemical inputs, and mechanization.

Keywords: Technology adoption; Non-farm employment; Credit constraints; Vietnam
JEL codes: Q12, Q16, O13

1. INTRODUCTION

Adoption of improved technologies in agriculture is believed to be a major factor in the success of the green revolution experienced by Asian countries. However, farmers are constrained from adopting technologies by market imperfections (high transaction costs, credit access), various risks, poor access to information, and insufficient skills of farmers (Amare & Shiferaw, 2017; Pfeiffer et al., 2009; Shiferaw, 2015). Particularly in developing countries, where markets are imperfect, farmers may or may not choose to adopt new technology because of credit constraints (Nguyen et al., 2024). To relax these constraints, farmers can borrow credit from formal and informal institutions, but they can also participate in rural or urban non-farm sectors.

The previous studies have indicated that there is a synergistic relationship between farm and rural non-farm activities. However, only a few studies have investigated the effect of non-farm employment on technology adoption in agricultural production. Almost all studies indicated that the income from non-farm activities could loosen the liquidity/credit constraints in the presence of market

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failure. As a developing country, Vietnam might be an interesting country to study the relationship between rural non-farm employment and technology adoption for the following reasons. In Vietnam, rice is a dominant crop, accounting for more than 60% of the total cropping area, and the country is the third-largest rice exporter in the world, after Thailand and India. According to the General Statistical Office of Vietnam, rice yield had increased considerably from 4,240 kg/ha in 2000 to 5,870 kg/ha in 2020, in which adopting modern technology may be the main factor. In addition, after the Doi Moi policy in 1986, the rural non-farm sector developed strongly in Vietnam, together with liberalization and globalization, and the non-farm income sources have increasingly played an important role in total household income. Thus, this paper aims to investigate whether participation in non-farm activities (including wage employment and non-farm self-employment) can help Vietnamese farmers to adopt modern technology in rice production.

In addition, the previous empirical studies of the relationship between non-farm employment and technology adoption were conducted for one type of technology. However, no study has investigated this relationship with the application of multiple technologies in agricultural production. Therefore, the purpose of our paper is to explore the effect of non-farm employment on the adoption of four types of agricultural technologies in Vietnamese rice production, including hybrid seed/improved variety, chemical fertilizer, herbicide/pesticide, and mechanization. Studying this relationship with different types of technology will contribute to the literature more comprehensively. Because of the different investment costs of the types of technology, the adoption decision of farmers might be different with the participation in non-farm activities.

2. LITERATURE REVIEW

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 summarizes 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.

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 fertilizer adoption	Double hurdle model	+
Fernandez-Cornejo et al. (2005)	US/ 2000	Adoption of Herbicide-tolerant soybeans	Probit, IV	+
Diiro & Sam (2015)	Uganda/ 2009-10	Adopting improved maize seed technologies	Two stage Probit, Semiparametric estimates	+
Danso-Abbeam et al. (2020)	Ghana/2012	Zai-technology in maize production	Propensity score matching	+
Q. Yi (2018)	China/ 2016	Adoption of agricultural mechanization services	Seemingly unrelated regression, Multivariate Probit	+

Huang et al. (2019)	China/ 2016	Adoption of soil and water conservation technology	Mediation effect test method	–
Ahmed & Goodwin (2016)	Bangladesh/ 2000-2008	Agricultural mechanization adoption	Bivariate Probit, Endogenous switching probit	+
Zheng et al. (2021)	China/	Mechanization service expenditure.	Conditional mixed process (CMP), 2-stage probit least squares	+
Dontsop-Nguezet et al. (2016)	DR Congo/ 2006-07	Adoption of improved cassava and beans varieties.	Binary Probit, Semi-parametric estimation	+
Nguyen et al. (2024)	Vietnam/2008-2016	Adoption of hybrid rice seeds or improved varieties	The correlated random effect Probit model with the Mundlak approach, endogenous switching Probit model	+

(Source: Authors' synthesis)

Technology types include adoption of chemical fertilizer (Ethiopia), improved variety of farm products (Uganda, Congo, US), soil and water conservation technology (China, Ghana), and mechanization (China, Bangladesh). These types are consistent with the following categories given by Ruzzante et al. (2021): (1) natural resource management (such as crop rotation, intercropping, water and soil management, organic farming), (2) applying improved varieties or hybrid seed, (3) applying chemical inputs (such as chemical fertilizer, herbicide and pesticide), and (4) mechanization and infrastructure.

Regarding the methodology, typical empirical studies on the relationship between technology adoption and non-farm employment regress a dummy variable related to technology adoption on a dummy variable on non-farm employment (or non-farm income). For estimation, most of them use the instrumental variables (IV) probit method to deal with the endogeneity issue of non-farm employment variables.

Most of these studies found a positive effect of non-farm employment on technology adoption, regardless of the types of farm technology, implying that farmers have an incentive to adopt better or modern technology if they have household members who work in the non-farm sectors. This result might be convincing because participation in non-farm work relaxes the budget constraint of farm households to help them purchase better or modern inputs (including chemical fertilizer and farm machinery) or adopt improved varieties. On the other hand, we still might expect a negative effect of participation in non-farm work on technology adoption because this participation can reduce farmers' incentive to invest in agricultural production, and it can induce them to exit from farming in the future.

Most previous studies concentrated on the relationship between non-farm employment and the adoption of one type of technology. In Vietnam, the recent research of Nguyen et al. (2024) also investigated the impact of non-farm employment participation on adopting hybrid seeds or improved varieties in rice production. Therefore, our study can fill the research gap by examining the impact of non-farm employment on multiple agricultural technologies at once, rather than just one technology as in previous studies.

3. DATA AND METHODS

3.1. Data

We use data from the Vietnam Access to Resources Household Survey (VARHS), which is collected from the website of the United Nations University World Institute for Development Economics (UNU_WIDER). The survey has been conducted once every two years. VARHS is conducted in 12 provinces located across the five main regions of Vietnam. Our study only focuses on rice farm households.[1]

Our paper uses the VARHS dataset 2008-2016 to calculate some indices with the aim of seeing the overview of the rural non-farm sector and technology adoption in rice production in Vietnam. To investigate the impact of non-farm employment on technology adoption in rice production, we only use the VARHS 2016 dataset. The total observations in this estimation is 1,531.

3.2. Methods

To investigate the impact of non-farm employment on technology adoption, we applied the Probit model for binary response because the outcome variable (technology adoption decision) is a binary variable. The regression equation of the technology adoption decision is presented as follows:

$$\boldsymbol{TA_i = \alpha + \beta NF_i + \delta Z_i + \varepsilon_i}$$

where TA_i denotes the decision of technology adoption of i-th rice farmer; $\boldsymbol{Z_i}$ denotes other exogenous variables for farmer $\boldsymbol{i}$ to explain technology adoption, and $\varepsilon_i \sim$ N(0, 1) is the error term. TA^* is a latent variable that is observed:

$$\boldsymbol{TA_i^* = \begin{cases} 1 & if\ TA_i^* > 0 \\ 0 & if\ TA_i^* \leq 0 \end{cases}}$$

In addition, other econometric problems in our analysis are the endogeneity problem of the non-farm variable. Thus, to deal with the endogeneity of the non-farm participation variable, we employ the instrumental variables approach by using the IV-Probit model. The first stage endogenous regression, which shows the relation between the endogenous non-farm variable and the instrumental variables, is specified as follows:

$$\boldsymbol{NF_i = \theta_1 + \theta_2 Z_i + \theta_3 I_i} + \mu_i$$

where $\boldsymbol{I_i}$ are the instrumental variables.

In our empirical analysis, the dependent variable TA includes adoption of 1) hybrid seed or improved variety, 2) chemical fertilizer, 3) pesticide and herbicide, and 4) mechanization. Independent variables include non-farm income variable, household characteristics, farm land characteristics, and social capital variables. A detailed definition of these variables is shown in Table 2.

[1] See Newman, Singhal, and Tarp (2020) for more details about VARHS.

Table 2. Definition of Variables Used in the Empirical Analysis

Variables	Definition
Dependent variables	
Hybrid seed or improved variety	Dummy variable taking on 1 if the households adopt hybrid seed or improved variety
Chemical fertilizer	Dummy variable taking on 1 if the households adopt chemical fertilizer
Pesticide/herbicide	Dummy variable taking on 1 if the households adopt pesticide or herbicide
Mechanization	Dummy variable taking on 1 if the households adopt mechanization (including owning agricultural machine or hiring machine services
Non-farm employment variable	
Non-farm income	The total income from non-farm activities of all households members (including wage employment and self-employment)
Household characteristics	
Gender	Dummy variable taking on 1 if the head is male
Age	Age of the head
Education	Schooling completed years of the head
Vocational training	Dummy variable taking on 1 if the head got the vocational training diploma
High school	Dummy variable taking on 1 if the head got the high school diploma
Junior college	Dummy variable taking on 1 if the head got the junior college diploma
Ethnicity	Dummy variable taking on 1 if the head is Kinh (major ethnicity)
Household size	Number of household members
Farm land characteristics	
Farm land	Total farm land area of the household (hectare)
Rice land cultivation	Total of land cultivated area for rice production in 3 most recent seasons (hectare)
Number of plots	Number of plots managed by the household
Social capital	
Extension services	Dummy variable taking on 1 if the household has assistance or information from extension services on new seed, fertilizer, irrigation etc.
FBO-member	Dummy variable taking on 1 if the household is a member of farmer-based organization.
Instrumental variables	
Non-farm employment opportunity	Dummy variable taking on 1 if the enterprises/firms/ factories are located in the commune or neighboring communes where people can work and come back within the day.
Share of non-farm workers in the commune	Share of non-farm workers in total labor force in the commune (%)

(Source: Authors' synthesis)

In this study, we choose two instrumental variables (IVs) to treat the endogeneity problem of the non-farm employment variable from the commune data of VARHS. Following the IV method, the IVs must satisfy two conditions, that is instrumental relevance condition and the instrumental exogeneity condition. The instrumental relevance condition means that the instruments are correlated with the endogenous non-farm variable. The instrumental exogeneity condition indicates that the instruments must be uncorrelated with the error term (ε_i). Following this, two selected IVs include non-farm employment opportunity and the share of non-farm labor 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. The share of non-farm labor in the commune is chosen as an IV because it represents the overall prevalence of non-farm work in the commune. To check the validity of IVs, the Cragg-Donald Wald F statistic for the weak identification test and the Hansen J statistic for the overidentification test of all instruments are employed through estimation of the 2SLS model.

4. RESULTS AND DISCUSSION

4.1. Overview of non-farm sector and technology adoption in Vietnamese rice production

By using VARHS 2008-2016, we first examine working days and incomes from farm and non-farm activities in the period 2008-2016 (Table 3). Table 3 shows that farm work days decreased from 303 in 2008 to 170 in 2016, whereas non-farm work days increased from 246 in 2008 to 289 in 2016. In non-farm activities, wage employment rapidly increased from 180 in 2008 to 237 in 2016, whereas self-employment decreased from 66 in 2008 to 52 in 2016. In relation to these working days, agricultural income increased from 14 million VND in 208 to 26 million VND in 2016, whereas non-farm income rapidly increased from 17 million VND in 2008 to 57 million VND in 2016. Therefore, non-farm income continued to exceed farm income after 2008, and the former was more than twice the latter in 2016.

Table 3. Non-Farm Employment and Income of Vietnamese Farm Households for 2008-2016

	2008	2010	2012	2014	2016
Farm work days	303.4	256.0	230.4	169.6	169.7
Non-farm work days	246.4	238.3	249.8	267.7	289.0
Wage employment (days)	180.3	184.0	192.4	215.7	237.2
Self-employment (days)	66.2	54.3	57.4	52.0	51.8
Agricultural income	14.1	20.4	20.6	24.14	26.15
Non-farm income	16.8	23.0	36.3	45.2	56.8
Wage income	10.1	15.9	20.6	34.7	43.3
Self-employment income	6.7	7.0	12.1	10.5	13.5

Note: Unit for incomes is million Vietnam dong (VND)

(Source: Author's calculation from VARHS 2008-2016)

Next, Table 4 shows adoption rates of various types of farm technology. Adoption rates of chemical fertilizer, pesticide, and herbicide exceed 90%, implying that most farmers apply these modern inputs. Adoption rates for hybrid seed or improved variety are slightly lower than those for chemical fertilizer and pesticide, 78%-85%, and they do not show a clear tendency over the observed period. Furthermore, the mechanization rate is a little lower, and it is between 78% and 84%. Although we cannot find a clear tendency in technology adoption rates, expenditures for chemical fertilizer, pesticide, and hired machinery services increased during the observed period.

Table 4. Technology Adoption Rates (%) in Vietnamese Rice Production for 2008-2016

	2008	2010	2012	2014	2016
Hybrid seed or improved variety	85	77.7	81	84.6	82.4
Chemical fertilizer	93.7	95.5	95.1	96	95.9
Pesticide and herbicide	96.1	95.3	93.3	92.5	94.1
Mechanization	78.9	81.3	80.3	83.8	77.7

Note: Adoption of mechanization means owning farm machinery or hiring machine services

(Source: Authors' calculation from VARHS 2008-2016)

To focus on the relationship between technology adoption and non-farm employment, Table 5 shows technology adoption rates for households with and without non-farm workers (including both wage workers and self-employed workers). Overall, households with non-farm workers have higher (or at least similar) adoption rates of better technology compared with households without non-farm workers. More specifically, households with non-farm workers had a much higher adoption rate of chemical fertilizer up to 2012, but this relation weakened after that. A similar relation was observed for the adoption of hybrid seed or improved variety, although the adoption rate was the same in 2010 between the two household groups. Higher adoption rate for households with non-farm workers was weakly observed for the adoption of pesticide and herbicide between 2008-2016. Finally, the mechanization rate for households with non-farm workers was much higher in 2008 and 2014, but this relation was weak for the other years. In sum, households with non-farm workers tend to have higher technology adoption rates in earlier years of our sample, but this tendency is weakened in later years of our sample.

Table 5. Technology Adoption Rates (%) for Households with and without Non-Farm Workers

	2008		2010		2012		2014		2016	
Have non-farm workers?	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Hybrid seed or improved variety	97.2	84.8	97.1	90.7	96.5	89.8	96.3	94.7	96.4	93.3
Chemical fertilizer	96.8	94.2	96.2	92.3	93.9	90.9	92.4	92.8	95	89.6
Pesticide and herbicide	87.4	79.3	77.7	77.7	82.5	75.5	85.3	81.9	82.9	79.8
Mechanization	84.3	65.6	82.6	85	81.2	77	84.8	79.4	78.1	75.7

(Source: Authors' calculation from VARHS 2008-2016)

4.2. Empirical analysis of VARHS 2016

Table 6 presents the results of the first-stage regression of the endogenous non-farm variable. This indicates that the coefficients of the instrumental variables, non-farm employment opportunity and share of non-farm workers in the commune, are statistically significant, implying that they are relevant instruments. The F-statistic for testing the joint significance of these coefficients is greater than 10, which means that the IVs are strong instruments. The positive coefficients of these variables seem plausible because the non-farm income is expected to increase in regions with more non-farm employment opportunity and a higher share of non-farm workers. In addition, as other studies also explain, these regional-level variables are not likely to correlate with the error term in the technology adoption equation, implying that those two variables are valid instruments. Consequently, we use non-farm employment opportunity and the share of non-farm workers in the commune as instruments for non-farm employment in the second-stage regression.

Table 6. First-stage regression

Dependent variable: Non-farm income (log)		Coeficient	S.E.
Household characteristics	Gender	-0.570***	[0.21]
	Age	-0.033***	[0.01]
	Education	0.051*	[0.03]
	Vocational Training	0.648***	[0.22]
	High school	0.914*	[0.49]
	Junior college	1.110	[0.91]
	Ethnicity	1.192***	[0.23]
	Household size	0.680***	[0.05]
Farm land characteristics	Farm land	-0.256***	[0.08]
	Rice land cultivation	-0.011	[0.06]
	Number of plots	-0.029	[0.03]
Social capital	Extension services	0.569	[0.46]
	FBO-member	0.006	[0.19]
Instrumental variables	Non-farm employment opportunity	1.061***	[0.23]
	Share of non-farm workers in the commune	0.014***	[0.00]
	Constant	-1.412***	[0.69]
	F-test for instrument	18.43	
	Number of observations	1,531	

*Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.*

(Source: Authors' estimation from VARHS 2016)

Next, the estimation results of the impact of non-farm income on technology adoption are presented in Table 7. We estimate both the Probit model and the second-stage regression (IV-Probit) for four types of technology adoption (adoption of hybrid seed/improved variety, chemical fertilizer, pesticide/herbicide, and mechanization). In all cases, the estimated coefficients are positive. In the Probit model, the estimated coefficients are positive and statistically significant in adopting hybrid seed/improved variety, chemical fertilizer, and pesticide/herbicide. In the IV-Probit model, we found a statistically significant positive coefficient of non-farm income when farmers adopt hybrid seed/improved variety, pesticide/herbicide, and agricultural mechanization. Those results imply that the increase in non-farm income tends to increase the probability of adopting better technology. These results are consistent with the results in other previous studies, as shown in Table 1.

Table 7. Impact of non-farm employment on technology adoption: estimates of Probit and IV-Probit

Dependent variables	**Probit model**				**IV-Probit**			
	Hybrid seed or improved variety	Chemical fertilizer	Pesticide/ herbicide	Mechaniza-tion	Hybrid seed or improved variety	Chemical fertilizer	Pesticide/ herbicide	Mechaniza-tion
Non-farm employment variable								
Non-farm income (log)	0.047***	0.052***	0.046***	0.002	0.284***	0.119	0.198***	0.113*
	[0.01]	[0.02]	[0.02]	[0.01]	[0.02]	[0.13]	[0.07]	[0.07]
Household characteristics								
Gender	0.408	-0.064	-0.218	0.101	0.161*	-0.034	-0.077	0.181*
	[0.11]	[0.20]	[0.17]	[0.10]	[0.09]	[0.22]	[0.18]	[0.11]
Age	0.0004	0.012**	0.005	0.003	0.008***	0.014**	0.008*	0.006
	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]
Education	0.03**	0.039*	0.007	0.013	0.002	0.034	-0.004	0.005
	[0.01]	[0.02]	[0.02]	[0.01]	[0.01]	[0.02]	[0.02]	[0.01]
Vocational training	-0.136	-0.191	-0.25	0.004	-0.269***	-0.237	-0.344**	-0.084
	[0.12]	[0.20]	[0.15]	[0.11]	[0.09]	[0.21]	[0.14]	[0.12]
High school	-0.076	-0.293	-0.757***	-0.498**	-0.262	-0.34	-0.855***	-0.596***
	[0.28]	[0.45]	[0.27]	[0.22]	[0.22]	[0.45]	[0.25]	[0.22]
Junior college	-0.179	-0.743	-0.391	0.186	-0.49	-0.864	-0.52	0.056
	[0.48]	[0.61]	[0.57]	[0.47]	[0.38]	[0.60]	[0.52]	[0.46]
Ethnicity	0.564***	0.714***	0.295**	0.532***	-0.115	0.57	-0.016	0.306*
	[0.11]	[0.17]	[0.15]	[0.10]	[0.14]	[0.35]	[0.22]	[0.18]

Household size	-0.115***	-0.065	-0.024	-0.004	-0.232***	-0.098	-0.136**	-0.086
	[0.03]	[0.04]	[0.04]	[0.03]	[0.02]	[0.09]	[0.06]	[0.05]
Farm land characteristics								
Farm land	0.059	0.044	-0.069	0.057	0.105***	0.059	-0.017	0.086**
	[0.04]	[0.08]	[0.04]	[0.04]	[0.03]	[0.08]	[0.05]	[0.04]
Rice land cultivation	0.07	0.059	0.241*	0.28***	0.053	0.057	0.236*	0.277***
	[0.05]	[0.10]	[0.13]	[0.08]	[0.04]	[0.10]	[0.12]	[0.08]
Number of plots	0.036**	0.08**	0.057**	0.009	0.025*	0.076**	0.058**	0.013
	[0.02]	[0.03]	[0.03]	[0.02]	[0.01]	[0.03]	[0.02]	[0.02]
Social capital								
Extension services	0.221	0.219	-0.506	0.113	-0.035	0.167	-0.547	0.035
	[0.22]	[0.33]	[0.45]	[0.21]	[0.19]	[0.34]	[0.40]	[0.21]
FBO-member	0.041	0.216	0.137	0.259***	0.003	0.194	0.128	0.255***
	[0.10]	[0.15]	[0.13]	[0.09]	[0.08]	[0.15]	[0.12]	[0.09]
Constant	0.131	-0.059	1.466	-0.401	0.366	0.083	1.354**	-0.346
	[0.34]	[0.52]	[0.57]	[0.32]	[0.28]	[0.51]	[0.53]	[0.31]
Number of observations	1,531							

*Note: 1) ***,**,* denote the statistical significant at 1%, 5%, 10% level, respectively.*

2) Values in parentheses are standard errors.

(Source: Authors' estimation from VARHS 2016)

To check the validity of instrumental variables, we estimate the 2SLS model for all four types of technologies to obtain the results of the Cragg-Donald Wald F-statistic and the Hansen J statistic, which are presented in Table 8. The values of weak identification test statistic (Cragg-Donald Wald F statistic) are 18.429 and 18.71,2, which are greater than 10 in four models. Thus, the null hypothesis of the weak identification test is rejected, and all instrumental variables satisfy the relevance condition. The values over-identification test (Hansen J statistic) and p-value in four models show that all instruments are valid and satisfy the instrumental exogeneity condition in the three models: hybrid seed or improved variety, pesticide/ herbicide, and mechanization. The over-identification test result of chemical fertilizer is almost satisfactory, with a p-value of 0.086. Therefore, we can conclude that the two IVs are valid instruments.

Table 8. Test for validity of instrumental variables

Tests	Hybrid seed or improved variety	Chemical fertilizer	Pesticide/ herbicide	Mechanization
Weak identification test (Cragg-Donald Wald F-statistic)	18.429	18.429	18.712	18.712
Overidentification test (Hansen J statistic χ2)	3.219 (p-value=0.123)	5.343 (p-value=0.086)	2.735 (p-value=0.149)	1.452 (p-value= 0.2282)

(Source: Authors' estimation of 2SLS model from VARHS 2016)

Our results also found the influence of other determinants on technology adoption decisions. Although there are differences in the values of the estimated coefficients, the estimated coefficient results are similar in terms of the impact correlation between models (Probit and IV-Probit). In particular, the male-headed household tends to adopt hybrid seed/improved variety and agricultural mechanization than the female ones in the IV-Probit model. The older the head of household, the higher the probability of three types of technology adoption, including hybrid seed/improved variety, chemical fertilizer, and herbicide/pesticide (IV-Probit). Farmers who have completed higher school have a higher probability of adopting hybrid seed/improved variety and chemical fertilizer in the estimates of the Probit model. However, our results found that if the head has a vocational training diploma or a high school diploma, they tend not to adopt agricultural technologies. The Kinh households adopt modern agricultural technologies more than the minorities. Moreover, the estimation results indicate that the larger the household size, the less they apply technology as hybrid seed/improved variety and herbicide/pesticide, to agricultural production.

Regarding farm land characteristics, we found that the farm households that have larger farm land have a higher probability of adopting hybrid seed/improved variety and mechanization in the IV-Probit model. Meanwhile, rice farmers who have larger areas of rice cultivation tend to adopt herbicides/pesticides and mechanization in both the Probit and IV-Probit models. Our findings also show that if farm households have many farm plots, they will tend to adopt hybrid seed/improved variety, chemical fertilizer, and herbicide/pesticide in farming activity, except for mechanization. This could be explained by the adoption of mechanization for farms who has high fragmentation is more difficult. Finally, our results indicate that if rice farmers become members of the farm-based organizations, they have a higher probability of adopting mechanization (in both Probit and IV-Probit models).

5. CONCLUSION

This study uses the Vietnam Access to Resources Household Survey (VARHS) 2008-2016 to examine the impacts of participation in non-farm employment on farm technology adoption for rice farmers in Vietnam. By comparing technology adoption rates (chemical fertilizer, pesticide or herbicide, hybrid seeds or improved variety, and mechanization) between households with and without non-farm workers, we find that households with non-farm workers tend to have higher adoption rates of these technologies, as indicated by empirical studies for other countries. We also find that the higher adoption rates for these households tend to be weaker in later years of the sample period (2008-2016).

To check the statistical significance of this relation, we use VARHS 2016 to estimate the influence of non-farm income on four types of technologies. By using Probit and IV-Probit models, we found that non-farm income has a positive effect on adopting four types of technologies: hybrid seeds or improved variety, chemical fertilizer, herbicide/pesticide, and mechanization. These results imply that the non-farm income source could relax the credit constraints, providing the financial source for farmers to invest the modern technology. In addition, our findings reaffirm the role of non-farm income as an alternative financial channel that could facilitate farmers to overcome the credit constraints during the agricultural production process.

Our findings contribute several policy implications concerning the positive effect of non-farm employment on technology adoption. First, our study suggests policies targeting to encourage non-farm employment in rural areas, such as diversifying non-farm jobs policy in rural areas, and focusing on activities during the off-season aim to use the free time from agricultural activity. Second, providing information about non-farm recruitment via information and communication technologies such as televisions, radios, mobile phones, and social media; simultaneously, cooperating with farmers' based organizations and local authorities to provide information on non-farm jobs to farm households. Third, the study recommend that there should be policies to encourage and increase investment in research and development of technologies such as new improved varieties with high yield - high value - adapting to climate change; the chemical imputs; the modern cultivation practices to reduce production costs, reduce water use, increase productivity, and increase resistance to pests and climate change. Last, continue to implement land consolidation to facilitate the application of mechanization in agricultural production.

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