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Does the non-farm sector affect production efficiency of the Vietnamese agricultural sector? A stochastic frontier production approach

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Abstract

This study examines the impact of the non-farm sector on farm value-added and production efficiency in the Vietnamese agricultural sector by using data from the Vietnam Household Living Standard Survey 2012. Production function and stochastic frontier production analysis is used to determine the impact, and the instrumental variables method is applied to address endogeneity. We find that the Vietnamese non-farm sector has a positive effect on both farm value-added and efficiency. This result indicates that income from non-farm activities relaxes liquidity constraints and farmers can reinvest this capital in agricultural production. Our result provides evidence of the important role played by the non-farm sector in relaxing credit constraints and enhancing agricultural production efficiency for developing countries.

Keywords: non-farm activities, endogeneity, instrumental variables, Vietnamese agriculture

1 Introduction

Rural household livelihoods have become diversified owing to multiple incomes from many different activities, and non-farm income sources are considered to play a progressively important role over time. Previous empirical evidence has indicated that the non-farm sector of developing countries has gradually been expanding in recent years to play an important role in household income (Haggblade *et al.*, 2010; Ferreira & Lanjouw, 2001). By the mid-2000s, 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).

Previous studies have asserted that there is a synergistic relationship between farm and non-farm sectors. Participation in the non-farm sector by farm households is a decision that influences not only farm income but also agricultural performance. Empirical studies on this issue indicate that the non-farm sector has positive, negative and nil impacts on agricultural production efficiency and output. The non-farm works of farm households could influence on household decision, especially the use of family labour and consumption decision of households. Hazell & Hojjati (1995) reported that in imperfect capital markets, farm households often use off-farm work to raise cash with a view to relaxing their cash flow and liquidity constraints.

Vietnam is an interesting place to study the effect of the non-farm sector on agricultural production for several reasons. Its agricultural sector has made enormous progress since the *Doi Moi* reform policy in 1986. Vietnam has achieved explosive growth in agricultural exports to become one of the biggest agricultural exporters in the world after this reform. The subsequent openness and liberalisation of Vietnamese markets has played a crucial role in the development of the non-farm sector too. In 1993, 16.5 % of the workforce of rural households were engaged in the non-farm economy (Hoang *et al.*, 2014). This proportion has risen to 34 % by 2008 (ibid) and 46.15 % by 2016 (GSO, 2018). The share of households' non-farm income was 29 % in 1998, 42 % by 2008 (Hoang *et al.*, 2014), and 51 % by 2016 (GSO, 2018). The growth of the Vietnamese agricultural sector has lagged the non-agricultural sector, and non-agricultural income has grown more rapidly than agricultural income (Stampini & Davis, 2009). The agricultural labour share decreased gradually after the reform till present, but still comprises the highest single proportion of the total la-

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bour force, falling from 65 % in 2000 to 47 % in 2012 (Group W. B., 2016). Farming activity primarily depends on household labour (De Brauw, 2010). The shift of household labour from farm activity to non-farm activities might affect agricultural outcome. Meanwhile, Vietnam's agricultural sector has notched impressive achievements in agricultural yield, output, and exports in the last decade. Thus, it leads to the following questions. How has Vietnamese agriculture maintained its competitive position in global agricultural production at the same time as its non-farm sector has expanded and developed in recent years? Is there a link between the farm and non-farm sectors in Vietnam's rural economy? Is the relationship competitive or complementary? In this study, we attempt to investigate how the non-farm sector affects production efficiency in the context of imperfect markets and the development of Vietnam's rural economy.

In Vietnam, little attention has been paid to analysis of the relationship between the non-farm sector and agricultural production efficiency. The objective of this study is to estimate the effect of the non-farm activities on production efficiency in Vietnam. Studies on non-farm employment in some Asia developing countries are mainly concerned with the impact of this sector on household welfare or poverty reduction. However, there has been less focus in the literature on how participation in non-farm activities affects the efficiency of agricultural production in Asian countries as well as Vietnam. Existing studies on this regard in Asian countries were done only in China (Zhang *et al.*, 2016) and Taiwan (Chang & Wen, 2011). This clearly shows that there is a knowledge gap in Vietnam and other developing Asian countries. Therefore, our study contributes to the existing literature by examining the relationship between Vietnam's non-farm participation and production efficiency. This study may to be considered a representative of sample of rural households for developing countries of Asia as well as the world. In addition, some studies on this topic have dealt with the endogeneity problem of non-farm participation (De Brauw, 2010; Pfeiffer *et al.*, 2009). In this study, we attempt to treat this problem through the instrumental variable approach to avoid biased estimates.

2 Literature review and theoretical framework

2.1 Literature review

Studies within a wide range of approaches examined issues relating to rural non-farm activities. The most common studies of non/off-farm employment indicated the important contribution of this income source to enhancing household's income (Ferreira & Lanjouw, 2001; Haggblade, 2010), smoothing consumption (Seng, 2015; Mishra *et al.*, 2015), reducing poverty (Lanjouw & Lanjouw, 2001; Haggblade, 2010, Hoang *et al.*, 2014), and manage risk (Chang & Mishra, 2008). Some of the empirical studies indicated an inextricable linkage between farm and non-farm sectors. Pfeiffer *et al.* (2009) suggested that the direct impact of non/off-farm income on agricultural production is through lost labour because family labour cannot substitute perfectly by hired labour in the context of imperfection market. Moreover, evidence in the literature suggested that earnings from non/off-farm activities could loosen liquidity constraints via providing cash for farm investment activity (Pfeiffer *et al.*, 2009; Oseni & Winter, 2009; Hertz, 2009, Stampini & Davis, 2009).

Table 1 shows the relationship between the effect of the non-farm sector on production efficiency or output and GDP per capita. The data in the table depict both positive, negative and no effect of the non-farm sector on farm performance.

The studies have found a positive effect of off-farm income/employment on production efficiency in some countries, such as Nigeria, Slovenia, China, and Taiwan. Shittu (2014) suggested that the level of production efficiency is enhanced by diversification of income sources in rural Southwest Nigeria. Bojnec & Fertő (2011) explained that this positive effect between off-farm income and technical efficiency level in Slovenia might be due to non-farm cash investment in farming activity and improvement of farming technology. The study of Zhang *et al.*, (2016) concluded that households with off-farm participation are more likely to adopt new technologies and agricultural machinery in China. Chang & Wen (2011) indicated that off-farm work is associated with higher technical efficiency, farmers with off-farm work are more efficient than without off-farm work in Taiwan. The author supposed that off-farm work may provide a vehicle for family labour reallocation and hence improve efficiency.

In contrast to these studies, a negative effect was found in other countries, such as Uganda, Albania, Kosovo, Mexico, Nicaragua, and United States; however, no effect has been found for a study in Norway. The study of Diiro (2013) analysed the effect of off-farm earning on the level of technical efficiency of maize farming in Uganda. The author suggested that this outcome was negative because off-farm work opportunities compete with agricultural labour. Kilic *et al.* (2009) also found a negative sign and believed that when the agricultural investment is risky, the non-farm jobs and investment options may compete for the labour and capital of farm households in Albania. Sauer *et al.* (2015) assumed that the adverse effect of migration on farm technical efficiency comes from the 'lost labour effect' in Kosovo. Pfeiffer *et al.* (2009), studying the impact of off-farm income on agri-

Table 1: *Summary of literature showing relationship between the non-farm sector and production efficiency*

Authors	*Country*	*Year of data*	*Dependent variable*	*Non-farm variable*	*Impact*	*GDP per capita (PPP)*
Shittu (2014)	Nigeria	2005/2006	Inefficiency level	Off-farm income share	Positive	4,149
Bojnec & Fertő (2013)	Slovenia	2004–2008	Technical efficiency level	Off-farm income	Positive	25,963– 31,138
Zhang *et al.* (2016)	China	2002–2010	Technical efficiency level	Number of off-farm labourers	Positive	4,315–9,526
Diiro (2013)	Uganda	2005/2006 and 2009/2010	Technical efficiency level	Off-farm income	Negative	1,223–1,485
Kilic *et al.* (2009)	Albania	2005	Inefficiency level	Non-farm income	Negative	7,733
Sauer *et al.* (2015)	Kosovo	2005–2008	Inefficiency level	Migration intensity (% of total available work time per household)	Negative	6,698–7,525
Pfeiffer *et al.* (2009)	Mexico	2003	Inefficiency level Agricultural output	Off-farm income	Slightly positive Negative	15,251
Lien *et al.* (2010)	Norway	1991–2005	Inefficiency level	Off-farm work hours	No effect	43,925–62,865
Abdulai & Eberlin (2001)	Nicaragua	1994/ 1995	Inefficiency level	Non-farm work hours	Negative	2,840
Sabati *et al.* (2018)	U.S.	2010	Technical inefficiency level	Off-farm income	Negative	49,374
Chang & Wen (2011)	Taiwan (China)	2005/2006	Technical efficiency level	Off-farm work	Positive	6,411

GDP (gross domestic product) per capita (PPP; purchasing power parity) from World Bank database. Unit of GDP per capita is US Dollar. Base year is 2011. Source: Authors' synthesis.

cultural production in Mexico, supposed that off-farm activities compete with agricultural production for scarce family labour. Another research from Latin America also found a negatively significant relationship between the non-farm employment and the technical efficiency of rural households in Nicaragua (Abdulai & Eberlin, 2001). These latter authors suggested that an increase in the non-farm works is accompanied by a reallocation of time away from farm activities, thus leading to a decrease in the production efficiency. Table 1 also presents the GDP per capita of several countries. Based on the income classification by the World Bank, the world's economies are divided into four income groups such as low, lower-middle, upper-middle, and high-income countries[1]. The upper-middle income countries per capita (e.g. Nigeria, China and Taiwan) showed a positive effect (excluding Slovenia). Negative and no effect appeared in three income groups: lower-middle income (e.g. Uganda and Nicaragua), upper-middle income (e.g. Albania, Kosovo), and high income (e.g., Mexico, United States, and Norway). In summary, the existing literature provides some evidence on the effect of off-farm income on production efficiency. The negative impact is via lost family labour for off-farm works, because the high transaction cost induces the imperfect substitutability between family and hired labour, agricultural output must be sacrificed in order to obtain off-farm income (Pfeiffer *et al.*, 2009). On the other side, the positive effect is explained through the fact that non/off-farm income can provide cash to invest on production inputs or technologies.

[1]The thresholds for classification by income in 2018 are: Low income : <996 US$, lower-middle income: 996 - 3,895 US$, upper-middle income: 3,896 - 12,055 US$, high income: > 12,055 US$. (Source: New country classifications by income level: 2018-2019, https://blogs.worldbank.org/opendata/new-country-classifications-income-level-2018-2019

2.2 Theoretical framework

This study employed the theoretical framework based on the agricultural household model, which was first proposed by Singh *et al.* (1986) and further developed by Chavas *et al.* (2005) and Pfeiffer *et al.* (2009). In this model, farm's household production, consumption and labour allocation decisions are interdependent or non-separate household model. The framework is a strong evidence about labour and credit market imperfections for farm and non-farm activities in developing countries.

In the context of labour market imperfection, it is less likely for family labour to be substituted by hired labour as such substitution tends to incur high transaction costs. Family labour as an input of agricultural production (L_f) cannot exceed total family members' time (L) minus off-farm work ($L_n f$) and leisure time (x_l) (Pfeiffer *et al.*, 2009).

$$L_f + L_{nf} + x_l = L \tag{1}$$

Equation (1) is called the labour constraint of households.

According to Pfeiffer *et al.* (2009), if credit is not available or the credit market is imperfect, expenditures on inputs for agricultural production (including hired labour) cannot exceed household's exogenous income and savings (S) plus income received from off-farm work, which is shown by equation 2:

$$p_x X \leq \omega L_{nf} + S \tag{2}$$

where p_x is the price for inputs X; ω is the non-farm wage rate. Equation 2 is the type of liquidity constraint.

Consumption decisions of households are subject to the budget constraint (Eq.3). The constraint requires that consumption expenditures (C) cannot exceed total household income which is computed by farm revenue ($P_y Y$), minus production cost ($p_x X$), plus the sum of non-farm income and other income or savings (S).

$$C \leq P_y Y - p_x X + \omega L_{nf} + S \tag{3}$$

where P_y is the output price, Y is farm output quantity.

The production activities of farm household can be written as a function $Y = f(X, L_f, K)$ of family labour (L_f), other inputs (X) such as fertilisers, hired machinery, hired labour, and fixed capital and land (K) .

The utility maximisation, $U = U(C, x_l)$, is maximised by choosing optimal consumption and leisure time subject to the credit constraint under the credit rationing.

$$MaxU(C, x_l) = U[P_y.f(X, L_f, K) - p_x X + \omega L_n f + S, x_l] \tag{4}$$

s.t. $p_x X \leq \omega L_{nf} + S$

The Lagrangian function is specified in the following.

$$\begin{aligned} L &= U(C, x_l) + \lambda(\omega L_{nf} + S - p_x X) \\ L &= U[P_y.f(X, L_f, K) - p_x X + \omega L_{nf} + S, x_l] \\ &\quad + \lambda(\omega L_n f + S - p_x X) \end{aligned} \tag{5}$$

Where λ is the Lagrange multiplier.

The first-order necessary Kuhn-Tucker condition for the credit constraint with respect to inputs used (X), is:

$$\frac{\partial L}{\partial X} \leq 0 \implies P_y.f'(X, L_f, K) - p_x - \lambda p_x \leq 0 \tag{6}$$

$$X\frac{\partial L}{\partial X} = 0 \implies X[P_y.f'(X, L_f, K) - p_x - \lambda p_x] = 0 \tag{7}$$

The constraint conditions are equation (2) and

$$\lambda(\omega L_n f + S - p_x X) = 0 \tag{8}$$

When the credit is binding ($\lambda > 0$), the equation (2) becomes: $(\omega L_n f + S - p_x X) = 0$. Because $X \geq 0$ and $\lambda \geq 0$, the equation (6) can be rewriten as:

$$P_y.f'(X, L_f, K) - p_x - \lambda p_x = 0$$

$$\implies P_y.f'(X, L_f, K) = (1 + \lambda)p_x$$

We can see that $(1 + \lambda)p_x > p_x$ ($due\,to\,\lambda > 0$). This indicates that in the presence of credit constraint or imperfect credit market, the shadow value of purchased inputs will be higher than the input price. It means that less of other inputs will be used. Therefore, the optimal production function is less efficient $f'(X, L_f, K)_0 > (X, L_f, K)_{optimal}$.

Building on this agricultural household model, the key purpose was to identify if non-farm participation can potentially influence production efficiency. In the case of imperfect credit market, the participation in non-farm activities may cause the changes in the use of agricultural inputs of farming households, leading to the change in efficiency. In short, the presence of credit constraints is the key factor determining the relationship between rural non-farm activities and agricultural production efficiency.

3 Methodology

3.1 Stochastic production frontier analysis (SFA)

Stochastic production frontier analysis is an appropriate method to estimate the efficiency of production for this study. This analysis approach consists of two stages of estimation that aid the analysis of the impact of non-farm activities on production efficiency. The method relies on estimating a production function with two error terms, one for noise and one for inefficiency. The stochastic production frontier model has an advantage that introduces a noise term that represents the measurement error and exogenous shocks beyond the control of production units. Thus, this approach seems consistent to measure inefficiency because of eliminating noise from the error term. While the non-parametric (data envelopment analysis) method assumes that all deviations from the efficient frontier are due to inefficiencies. The stochastic production frontier and technical efficiency can be estimated in two stages. The first-stage estimates the stochastic production frontier model. In the second stage, the effect of the non-farm sector on production efficiency can be identified by estimating the inefficiency model.

The stochastic production frontier approach was first proposed by Aigner *et al.* (1977) and Meeusen & Van den Broeck (1977). The stochastic frontier production function is defined as:

$$Y_i = f(X_i j; \beta) \exp(V_i - U_i) \tag{9}$$

where Y_i is the output of the i-th farm; $X_i j$ is input j used by farm i; beta s a vector of parameters to be estimated; and V_j is a disturbance associated with the stochastic effects outside the firm's control (for example, weather, natural disasters, luck, and measurement errors in production). The random error V_j is assumed to be independently and identically normal distributed as $N(0, \lambda v^2)$. σv^2 is the variance of V_i. U_i represents the technical inefficiency of agricultural production, which is assumed to be non-negative and independently distributed (Coelli *et al.*, 2005). The distribution of term U_i is half-normal or exponential or gamma (Aigne *et al.*,1977; Meeusen & Van den Broeck, 1977). We assume the term U_i follows a half-normal distribution, $N(0, \sigma v^2)$. V_i and U_i are assumed to be independent. Following Battese & Coelli (1995), the technical inefficiency term U_i is specified by:

$$U_i = \delta Z_i + \mu_i \tag{10}$$

where Z_i is a vector of explanatory variables of the i-th farm. δ is a vector of parameters to be estimated. μ_i is a disturbance term following identically distribution.

The parameters of β of the stochastic production frontier model (9) are estimated by maximum likelihood. The likelihood function consists of the joint density function of V_i and U_i. Aigner *et al.* (1977) suggested that the maximum-likelihood estimates of the parameters of the model can be obtained in terms of the parameterization, $\lambda = \sigma_u / \sigma_v$ and $\sigma^2 = \sigma_u^2 + \sigma_v^2$.

According to Battese & Corra (1977), the ratio of variance parametery, which represents the variability sensitivity of U_i to total variance σ^2, can be calculated as follows: $\gamma = \sigma_u^2 / \sigma^2$. The value of γ is bounded between 0 and 1 ($0 \leq \gamma \leq 1$). A value of γ to 0 indicates that the deviation from the frontier is entirely due to noise, and a value of 1 indicates that all deviations are due to technical inefficiency.

Following Jondrow *et al.* (1982), the value of technical inefficiency (Ui) for the half-normal model can be computed directly with the following equation:

$$E[U_i|\varepsilon_i] = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi(z_i)}{1-\Phi(z_i)} - z_i\right] \tag{11}$$

where, $Z_i = \frac{\varepsilon_i \lambda}{\sigma}$, "$\varepsilon_i = V_i - U_i$"

ϕ"(.)" represents the standard normal density, Φ"(.)" represents the cumulative normal distribution function.

3.2 Empirical model

The purpose of our empirical analysis is to answer whether the non-farm sector affects production efficiency. The utilisation of the stochastic frontier approach allows us to compute each agricultural household's degree of technical inefficiency. The stochastic frontier production function model is specified as follows.

$$InY_i = \alpha_0 + \sum_{j=1}^{5} a_{1j}\, lnX_{ij} + \sum_{j=1}^{5} \alpha_2 j D_{ij} + V_i - U_i \tag{12}$$

where, Y_i is value-added of agricultural (including crops, livestock, and agricultural services), forestry, and aquaculture production activities of household i. Value-added is defined as the total agricultural output revenue minus the cost of intermediate inputs, including seed breeds, fertiliser, pesticide, herbicide, energy, and other intermediate costs. Hence, the input variables of value-added estimation include land, labour, and capital. We estimate the value-added model to control the differences of technical efficiency resulting from the agricultural product mix. X_{ij} ($j = 1, ..., 5$) is input j used for the i-th farm household, in which, X_{i1} is family farm labour, measured by working days. Family farm labour is calculated by the total working days of members in a family who undertake all farming activities including agriculture, forestry, and aquaculture activities. X_{i2} is farmland, which is the total farmland area in hectares. X_{i3} is the fixed asset depreciation cost; X_{i4} is the hired machine cost; and X_{i5} is the hired labour cost.

D_{ij} are dummy variables that take the value one if the $i - th$ input quantity is zero, except family labour. A number of households have input values of zero. Because it is impossible to calculate the log of zero, we introduce dummy variables. The values of dummy and $log(X_{ij})$ variables of such inputs are redefined as follows:

$$D_{ij} = \begin{cases} 1 & if\ X_{ij} = 0 \\ 0 & if\ X_{ij} > 0 \end{cases}$$

Therefore, we set the value of $\log(X_{ij})$ as follows:

$$log(X_{ij}) = \begin{cases} log(X_{ij}) & if\ X_{ij} > 0 \\ 0 & if\ X_{ij} = 0 \end{cases}$$

V_i is disturbance. U_i is technical inefficiency.

In the second stage, we estimate the inefficiency model in order to measure the impact of non-farm income and non-farm participation on production efficiency. The effect is computed by the following regression equation:

$$U_i = \delta_0 + \sum_{k=1}^{13} \delta_{1k} Z_{ik} + \delta_2 N_i + \mu_i \tag{13}$$

where, Z_{ik} are variables representing the socio-economic characteristics of $i-th$ farm households, extension services, supporting policy, credit and regional dummy variables. The extension services is a binary variable that takes one if farmers perceived a benefit from extension services in agriculture, forestry, and fisheries and zero for farmers that did not perceive a benefit or did not know. Supporting policy variable represents policy support in agricultural production for farm households, such as support in machine, production inputs (fertiliser, breed animals, and seedlings). It equals one if farmers benefitted from the policy and zero for farmers that did not benefit or did not know about the policy. Credit variable representing the total farm household credit borrowed from banks and other financial institutions for agriculture, forestry, and fisheries production during the year. For the regional dummy variables, we choose Midland and Northern Mountainous Areas as the base region.

N_i represents the non-farm variables, including non-farm income and non-farm participation of the household head and/or spouse. Non-farm income is the total earnings from non-farm jobs of all members of a household. The dummy variable non-farm participation of the household head or spouse takes the value of one if the household head or spouse participates in non-farm work, and otherwise zero.

3.3 *Estimation strategy*

The estimation of equations (13) is challenging because the participation in non-farm activities is not a random process and non-farm variables are not exogenous but endogenous. The main econometric issue that we need to take care of is the endogenous nature of participation in the non-farm sector. To deal with this problem, we deploy the Instrumental Variables (IV) method as the estimation strategy. The endogeneity problem is that non-farm variables (N_i) are correlated with the error term (μ_i). The IV framework attempts to find suitable proxy variables that are uncorrelated with μ_i and correlated with non-farm variables but have no direct effect on the outcome. This in turn enables consistent estimation. A single endogenous regression equation is expressed as follows:

$$N_i = \lambda_0 + \lambda\, E_i + \lambda_1\, I_i + \varepsilon_i \tag{14}$$

where, E_i is a vector of exogenous variables that include household characteristic variables and regional dummy variables. I_i is a vector of IVs.

We choose three IVs to treat the endogeneity problem of non-farm variables. The first instrument, Time_Town, is the commuting time from the commune to the nearest town. The second instrument, Time_City, is the commuting time from the commune to the nearest city or provincial capital. The unit of both instruments is minutes, and both assume that the mode of commute is private or public transport. We propose that the time taken for a household member to travel from the village to the nearest town or city could be good instruments for non-farm activities. These variables could explain the potential opportunities for participation in non-farm employment of households if they live near a town or city and the convenience of travel time. To obtain these data, we use the commune survey of Vietnam Household Living Standard Surveys (VHLSS) 2012, conducted in 2,218 communes. However, there are a number of missing values, reducing the sample size of both communes and households. The last instrument is the education of the household head. The purpose of using education as an IV is to justify the model. Education is considered important for non-farm participation in theory. Potential participation in non-farm works and the magnitude of non-farm income depend greatly on the level of the household's education. Hence, the education variable also correlates to non-farm variables. However, the education level seems to correlate with both non-farm participation and agricultural outcome. This might not satisfy the relevance condition of the instrument. According to the statistics, the education level of households that participate in non-farm activities is higher than those that do not participate, by 7.03 and 5.74 grades respectively. This finding implies that a higher education level is necessary to participate in non-farm activities, while a high education level is not required for agricultural production. Thus, the correlation between the education variable and non-farm variables

Table 2: *Descriptive statistics of variables*

Variables	*Explanation*	*Mean*	*S.D.*
Value-added	Million VND	36.776	62.17
Production input variables			
Family farm labour	Day per year	743	330.88
Farmland	Hectare (for example, crop land, forest-land, water surface, garden, and shifting cultivation farm land)	0.86	1.21
Fixed asset depreciation	Million VND	1,072	3.14
Hired machinery	Million VND	1,650	4.37
Hired labour	Million VND	2,416	11.44
Household socio-economic characteristic variables			
Head's gender	Male=1, female=0	0.83	0.38
Head's age	Years	49	13.66
Education	Schooling completed years	6.68	3.55
Household size	Number of members per household	4.04	1.56
Ethnicity	Kinh=1, other ethnicity=0	0.74	0.44
Extension services	Yes=1, no or does not know=0	0.13	0.34
Supporting policy	Yes=1, no or does not know=0	0.09	0.29
Credit	Million VND	2.85	9.53
Regional dummy variables			
RRD	Red River Delta	0.22	0.41
MNM	Midland and Northern Mountainous (base region)	0.24	
NCC	Northern and Central Coast	0.24	0.43
CHL	Central Highland	0.07	0.26
SEA	South-eastern Area	0.05	0.21
MRD	Mekong River Delta	0.18	0.38
Non-farm variables			
Non-farm income	Million VND	40.94	46.24
Non-farm participation	Participate in non-farm work by head or spouse=1, no=0	0.73	0.45
Instrumental variables			
Time_Town	The time from the commune to the nearest town (minute)	31.79	33.87
Time_City	The time from the commune to the nearest city (minute)	86.58	74.50

Source: VHLSS 2012. Number of observations = 4,823.
VND is Vietnam's currency (Vietnamese Dong) and one million VND = 47.62 US$ in 2012 (calculated based on *tradingeconomics.com*

may be stronger than the correlation between education and efficiency. To adjust the models, we use education as an IV.

4 Data

For statistical purposes, this study refers to the Vietnam Household Living Standard Surveys 2012 (VHLSS 2012). This survey of household living standards was conducted by the General Statistics Office of Vietnam within the framework of the World Bank's Living Standard Measurement Surveys (LSMS). This dataset was first implemented in 1992-1993 and 1997-1998, which form part of the Rural Income Generating Activities (RIGA) dataset. From 2002 up to now, this data is collected every 2 years in even years by the General Statistics Office covering all provinces of the country. Data is collected on household composition, education, health, employment, migration, housing, fertility, agricultural and non-agricultural businesses, consumption, income, and access to credit. In the VHLSS 2012, 9,399 households were interviewed, comprising 2,703 urban households and 6,696 rural households.

In this research, we choose households that were engaged in agricultural, forestry, and aquaculture activities. We aggregate the output of the three primary sectors – agriculture, forestry, and aquaculture – because we want to evaluate the impact of the non-farm sector on the output and production efficiency of farm activities. Households with missing values for family labour were eliminated. There are missing values for family labour in the dataset, because in some households, agricultural activity is not the main or even second main job, thus, agricultural family labour of those households was not investigated. We also used the commune survey of the VHLSS 2012 for instrumental variables (IVs). This survey investigated the socio-economic characteristics of the communes to facilitate the choice of IVs. However, some communes have missing values. Therefore, the number of households in our analysis is reduced to 4,823.

Table 2 presents the descriptive statistics of the dependent variables, independent variables, and IVs used in estimating the production function, stochastic frontier, and inefficiency models.

Table 3: *Stochastic frontier production function model*

	Value added (log)	
Dependent variable	*Coefficient*	*S.E.*
Production inputs		
Family farm labour (log)	0.326***	[0.01]
Farm land (log)	0.255***	[0.01]
Fixed asset depreciation (log)	0.241***	[0.01]
Hired machinery (log)	0.198***	[0.01]
Hired labour (log)	0.259***	[0.01]
Dummy variables		
Farmland	-0.700***	[0.06]
Fixed asset depreciation	-0.644***	[0.02]
Hired machinery	-0.253***	[0.02]
Hired labour	-0.264***	[0.02]
Constant	2.255***	[0.09]
Log-likelihood	4,914.992	
Number of obs.	4,823	
σ_v	0.523	
σ_u	0.708	
σ^2	0.774	
Γ	1.353	

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

5 Results

5.1 Stochastic frontier production function

The maximum likelihood estimates of the parameters of the stochastic production frontier are presented in Table 3. All coefficients of inputs in the stochastic frontier production model have positive signs and are significant at the 1 % significance level. The result indicates that family labour has the highest production elasticity among all of the inputs with a coefficient of 0.326. The estimation also shows a higher elasticity for family labour than for hired labour and the total sum of labour elasticity is 0.585. This result may reflect the relative importance of family labourers over hired labourers, because the former usually pay more attention to their own production and are characterised by higher labour quality. The sum of elasticity of all inputs is 1.279. This result indicates that on average, the agricultural output value of farm households has increasing returns to scale.

5.2 Inefficiency model

Based on the estimation from the stochastic frontier production function, we obtain the predicted inefficiency level of each household. The inefficiency model gives some insights into the factors affecting the technical efficiency of Vietnamese farm households, in which negative signs means that the variables reduce technical efficiency and positive signs mean that the variables increase technical efficiency. We also use both OLS (Ordinary Least Squares) and IV approaches in the inefficiency model. Table 5 represents the regression results of the OLS and IV inefficiency models with robust standard error.

In IV inefficiency models, our analysis shows a positive effect of the non-farm sector on farm production efficiency. The coefficients of the two non-farm variables (non-farm income and non-farm participation) are both statistically significant at the 1 % significance level (-0.0013 and -0.189, respectively). This means that if households earn or obtain more than 1 million VND from non-farm work, the inefficiency level would decrease 0.13 %. Participation of the head or spouse in non-farm employment would lead to a reduction in the inefficiency level by 18.9 %. Thus, our results reveal that farm households that participate in non-farm work have higher technical efficiency. This effect can be interpreted as a significant positive effect of relaxing liquidity constraints. Labour supply to the non-farm sector has a positive effect on the production efficiency of the farming sector.

The results in all inefficiency models show that the coefficients of gender of the household head, household size, and ethnicity have positive signs. The positive sign of the household head's gender indicates that male household heads are more efficient than female household heads. The household size variable has a positive impact on farm technical effi-

Table 4: *The impact of the non-farm (NF) sector on farm efficiency level by inefficiency models.*

	OLS		*IV*	
Dependent variable†	*NF income*	*NF participation*	*NF income*	*NF participation*
Non-farm variables				
Non-farm income	0.0004***		-0.0013***	
	[0.00]		[0.00]	
Non-farm participation		0.001		-0.189**
		[0.01]		[0.07]
Household socio-economic characteristic variables				
Head's gender	-0.056***	-0.057***	-0.061***	0.060***
	[0.01]	[0.01]	[0.01]	[0.01]
Head's age	0.003***	0.003***	0.003***	0.003***
	[0.00]	[0.00]	[0.00]	[0.00]
Education	-0.004***	-0.003***		
	[0.00]	[0.00]		
Household size	-0.023***	-0.020***	-0.008	-0.019***
	[0.00]	[0.00]	[0.00]	[0.00]
Ethnicity	-0.096***	-0.087***	-0.059***	-0.051**
	[0.01]	[0.01]	[0.02]	[0.02]
Extension services	-0.011	-0.013	-0.017	-0.016
	[0.01]	[0.01]	[0.01]	[0.01]
Supporting policy	-0.013	-0.013	-0.015	-0.025*
	[0.02]	[0.02]	[0.01]	[0.01]
Credit	0.00003	-0.0001	-0.0004	-0.0002
	[0.00]	[0.00]	[0.00]	[0.00]
Regional dummy variables (base region = MNM)				
RRD	-0.021	-0.016	0.001	-0.006
	[0.01]	[0.01]	[0.02]	[0.01]
NCC	0.084***	0.082***	0.078***	0.069***
	[0.01]	[0.01]	[0.01]	[0.01]
CHL	0.073***	0.067***	0.048***	0.075***
	[0.02]	[0.02]	[0.02]	[0.02]
SEA	-0.001	0.003	0.013	0.016
	[0.02]	[0.02]	[0.03]	[0.03]
MRD	0.064***	0.063***	0.060***	0.056***
	[0.01]	[0.02]	[0.02]	[0.02]
Constant	0.623***	0.607***	0.558***	0.702***
	[0.03]	[0.03]	[0.03]	[0.05]
Number of obs	4,823	4,823	4,823	4,823
R-squared	0.07	0.07		
Center R_squared			0.01	-0.01
Uncenter R_squared			0.79	0.78
Weak identification test			73.863	29.917
Overidentification test (Hansen J statistic χ^2)			0.380	1.292
p_value			0.827	0.524

† inefficiency level ($U_j = -log(TE_j)$)
1) ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
2) OLS: Ordinary Least Squares, IV: Instrumental Variables, RRD: Red River Delta, MNM: Midland and Northern Mountainous, NCC: Northern and Central Coast, CHL: Central Highland, SEA: South-eastern Area, MRD: Mekong River Delta.
3) Values in parentheses indicate robust standard errors. In the IV models, the standard error is clustered at the commune level.
4) Instrumental variables: Time_Town, Time_City, Education.

ciency, which means that large farm households will increase efficiency. The coefficient of the binary ethnicity variable is significant and shows a positive relationship with efficiency level, which indicates that textitKinh households could produce their agricultural output with higher technical efficiency than other minorities could. The reason could be that the farming practices of minority ethnicities are shifting cultivation, with less use of inputs that increase productivity, such as fertilisers and machinery; hence, this reduces the production efficiency of minorities relative to *Kinh* households. By contrast, the coefficient of the household head's age shows a negative impact on technical efficiency, which indicates that households with younger heads are more technically efficient than those with older heads.

In addition, the estimation shows that the variables of extension services, supporting policy, and credit are not significant. The insignificance of extension services and supporting policy variables implies that those extension services and policies for farm households are not strong enough to help farmers improve their efficiency.

Table 5: *Non-farm income with non-credit and credit households.*

	non-credit households		*credit households*		
	Mean	*S.D.*	*Mean*	*S.D.*	*T-test*‡
non-farm income§	43.95	48.48	25.96	28.49	0.000***

‡ mean difference>0; § Unit: million VND (Vietnamese Dong).
Source: VHLSS 2012.

The credit variable is not significant in the inefficiency model. Theoretically, providing credit for farming can relax liquidity constraints and improve technical efficiency. If farmers are capital constrained, then credit can contribute to improving agricultural production. However, our result shows no impact of credit on technical efficiency, which is contrary to the above-mentioned theory. First, we consider the relationship between non-farm income and credit, which is shown in Table 6. The result indicates that households with credit have lower non-farm income than do those with no credit. A t-test is used to examine the mean difference in non-farm income between non-credit and credit households. The probability of the case mean difference being greater than zero is 0.000, which implies that the mean values of non-farm income are different in the two groups and the non-farm income of non-credit households is greater than that of credit households. This finding implies that non-farm income sources are quite important for households and can substitute for credit. Moreover, households might not use this loan for investment or purchasing inputs in agricultural production and may use it for consumption or education. For these reasons, the credit variable is not significant in these models.

Table 6: *Frequency distribution of technical efficiency of households.*

TE level*	*Number*	*Percentage*
-50	1037	21.50
50-60	1284	26.62
60-70	1502	31.14
70-80	837	17.36
80-90	162	3.36
90-100	1	0.02
Mean TE	59.2	
Minimum TE	5.1	
Maximum TE	92.2	

* TE: technical efficiency in percent (%) and calculated based on Table 3.

The weak identification test and overidentification test of the validity of the instruments are performed on IV regression. The values of Stock-Yogo (2002) weak identification test statistics of non-farm income and non-farm participation models are 73.863 and 29.917, respectively. From this result we consider the null hypothesis of weak identification is almost rejected. The overidentification test Hansen J statistic are 0.38 with p-value 0.827 in non-farm income model; 1.292 with p-value 0.524 in non-farm participation model. The joint null hypothesis of the validity of the instruments is not rejected for both models.

5.3 *Technical efficiency level*

Table 6 presents the distribution of technical efficiency of farm households based on the stochastic production frontier estimation. In this study, the technical efficiency level of households had a big gap, ranging from around 5.1 % to 92.2 %. The mean technical efficiency level was only 59.2 %. The technical efficiency distribution shows that about 79 % of all farm households had a technical efficiency level lower than 70 %. This result implies that the production efficiency of Vietnamese agriculture is still low, which could yield big opportunities for farmers to improve technical efficiency.

6 Discussion

The central theme of this study is the effects of the non-farm sector on production efficiency of rural farm households in Vietnam. Our estimation shows that non-farm variables have a positive impact on technical efficiency of farm households. This finding is consistent with the results of Bojnec & Fertő (2011), Shittu (2014), Zhang *et al.* (2016) and Chang & Wen (2011), who found a positive relationship between off/non-farm work/income and technical efficiency. These authors assumed that the liquidity-relaxing effect of non-farm income induces a positive effect on efficiency. While our estimation result is in contrast to the findings of Diiro (2013), Abdulai & Eberlin (2001), Kilic *et al.* (2009), Sauer *et al.* (2015), and Sabati *et al.* (2018) who found a negative impact on technical efficiency. These studies indicated that participation in off/non-farm employment compete with family agricultural labour in the context of imperfection markets.

The participation in non-farm activities is directly aimed at contributing to farm household income generation and may relax credit constraints, because there is a positive relationship between credit constraints and supply of non-agricultural labour (Stampini & Davis, 2009). The positive effect of non-farm activities on farm production efficiency in Vietnam seems to be through providing capital or credit for farmers to purchase quality inputs or machinery for agricultural production. In other words, in the presence of liquidity constraints, access to credit or other sources of income might allow farmers to invest in inputs, adopt new technologies or apply mechanisation in order to approach the production frontier. Because differences in the quality and quantity of applied production inputs influence overall technical efficiency level; increasing purchases of quality and high-yielding inputs could shift the entire input–output relationship and lead to higher technical efficiency.

However, under the constraint of family labour in an imperfect labour market, the participation of household members in non-farm work influences the decisions of household labour allocation, which induces increasing non-farm household labour use and decreasing on-farm labour supply. This outcome is called the lost-labour effect. In the presence of labour market failure, the lost labour may reduce efficiency and output, because it cannot be perfectly substituted by hired labour. However, the impact of this sector on technical efficiency is positive, and hence, the liquidity-relaxing effect seems to outweigh the decrease in efficiency induced by the lost-labour effect. This is because, first, the income from non-farm activities could allow households to hire labour to substitute family members in non-farm labour. Second, this type of earnings may be a credit source for households to buy or hire agricultural machinery in order to replace family labour.

In summary, diversifying income sources in the non-farm sector seems to enhance the production efficiency of Vietnamese agriculture.

7 Conclusion

Given the scarce literature on the relationship between farm and non-farm sectors in Vietnam, this study has attempted to discover the impact of the household non-farm sector on production efficiency using an IV estimation strategy. The empirical results indicate that there is a positive impact of the non-farm sector on farm efficiency in Vietnam. This positive effect may derive from the liquidity-relaxing effect of non-farm income because this earning could help farmers to invest backward into agriculture through purchasing quality inputs or machinery for agricultural production.

First, the study contributes to the literature on the relationship between rural non-farm employment and efficiency by providing an in-depth analysis of the case of Vietnam. These findings emphasize the importance of participation in non-farm activities as a strategy to raise farm income and enhance production efficiency. Second, this study provides support for the perspective on the importance of the non-farm sector to the development of the rural economy to helping ease credit constraints. Third, for the lower-middle income developing countries, our study contributes positive evidence that the non-farm sector can support agricultural production and enhance production efficiency by loosening credit constraints and providing capital for agricultural investment. We suggest that there is quite high applicability of our results to other developing countries, whose rural households, like those in Vietnam, are credit constrained and whose labour markets are also imperfect.

Our findings could help policy-makers to introduce the optimal policies for developing the Vietnamese rural economy and agricultural sector. Our findings suggest that policies focusing on the rural sector should encourage sustainable non-farm employment opportunities for surplus and seasonal labour of farm households, e.g. developing handicraft in the villages, creating small-industry jobs, trading services, and other services in the rural areas. Furthermore, these policies should create synergy between farm and non-farm sectors, for example, supporting the construction of infrastructures, communication, market, and transport network in the rural areas in order to facilitate trading of agricultural commodities between regions. In addition, for developing countries like Vietnam, where credit market is less developed and less liquid, our study suggests that policy-makers should more focus on developing non-farm employment than on credit markets to help farmers obtain sufficient means for investment in agricultural production. As non-farm income source could share and reduce the risk of farm production, borrowing money from credit institutions may bring the debt burden to farm households.

Supplement

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Conflict of interest

Authors state they have no conflict of interest.

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