Labor Dependence, Income Diversification, Rural Credit, and Technical Efficiency of Small-Holder Coffee Farms: A Case Study of Cu M'gar District, Dak Lak Province, Vietnam

HO QUOC THONG

Tay Nguyen University – thongdhtn@gmail.com

TUYET HOA NIEKDAM

Tay Nguyen University – hoaniekdam@gmail.com

ARTICLE INFO

ABSTRACT

Vietnam coffee sector plays a crucial role not only in the country's economy but also in the global coffee market, and improving coffee production efficiency may benefit coffee producers. However, small-holder coffee farming households still encounter many difficulties regarding resources and socio-economic conditions affecting coffee production efficiency. This study examines relationships among income diversification, rural credit loan, labor dependence, and technical efficiency in coffee production through a face-to-face survey with participation of 143 coffee farming households conducted in Cu M'gar District, Dak Lak Province, Vietnam. The stochastic frontier model shows that the mean of technical efficiency scores is 0.64, and it also verifies the existence of inefficiency variation. Both Maximum Likelihood Estimate (MLE) and Feasible Generalized Least Square (FGLS) consistently indicate that a higher level of diversity in income sources negatively affects coffee production efficiency. Additionally, independence in labor resource for coffee farming may help farmers increase technical efficiency of coffee production. Credit loan has a positive and statistically significant relationship with technical efficiency of coffee production. These relationships hold especially true for smallholder coffee farms with ethnic minority household heads. The policy options of credit loan access, intensive investment in coffee production rather than diversification of coffee farmers' income sources, and independent management strategies for labor sources are suggested as an integrated approach to improve technical efficiency in coffee production of smallholder coffee farms.

1. Introduction

Enhancing agricultural production efficiency is not only to improve farmers' income but also to overcome many burdens on urban areas in developing world. It is nature of the economic theory that resources transit from inefficient sectors to more efficient areas. Reducing urban population and objectively limiting labor migrants to cities are particularly policy-makers' primary consideration to lessen serious problems for major cities. Creating more jobs available for rural labors at their community and making more efficient use of resources are known as an integrated strategy to sustainably improve household income, which is also an economic incentive to shorten living standard gaps between urban and rural areas.

There were several studies to examine how socio-economic factors contribute to levels of efficiency in agricultural production. For instance, agricultural labors are highly seasonal; thus, diversifying income sources was suggested to be better for farmers (Illukpitiya & Yanagida, 2010). Labor is one of the most important factors for any kind of agricultural production. Comparing the marginal physical product with respect to this factor and wage is unrealistic; this distortion, however, may occur when the family labor and the hired labor are not separately treated in production models. Kumbhakar (1996) found that wages for agricultural labors are relatively equal to the marginal product, and family labors were more technically efficient than hired labors in agricultural production. In addition, rural credit, income diversification, and education of household heads were taken into account in several previous studies (Ilslukpitiya & Yanagida, 2010; Kamil et al., 2009; Kehinde et al., 2010; Marsh, 2007; Obwona, 2002), yet very few studies examined inefficiency in coffee production, and none investigated socio-economic factors, such as labor dependence, income diversification, credit loan, education or ethnicity, and management of coffee production efficiency in Vietnam, the second largest coffee producer in the globe.

Coffee is the primary export crop for Vietnamese agriculture and takes a major part in the country's economy. This is particularly true for the Central Highlands of Vietnam and their role in the world coffee market. In these Central Highlands, farmers' incomes are mostly dependent on coffee production. Dak Lak province has been the largest coffee producer in terms of both coffee yield and land area in Vietnam. It is apparent that agricultural production in this area has been dominated by coffee production (Meyfroidt et al., 2013). To illustrate, land area, as it relates to coffee farming in the province,

represents approximately 190,200 hectares, and Cu M'gar, which is its largest coffee farming district, occupies around 40,000 hectares, accounting for roughly 20% (Dak Lak Statistical Office, 2011).

Moreover, the recorded price drop in 2001 is not a unique event. Historical data of coffee production in Vietnam have shown that when yield is high, the farm gate price of coffee decreases; this leaves farmers facing uncertainty in the total income generated from coffee growing business. Income diversification by engaging in non-farm activities (rather than crop diversification) is often thought to help small-sized farmers mitigate this risk by generating another source of income to stabilize the total income. However, it has been documented in several prior investigations that diversification through non-farm income activities does not always generate higher income (e.g., Coelli & Fleming 2004; Vedenov et al., 2007). The present paper also aims to provide further empirical evidence on this issue.

In Dak Lak province the population growth is a complex issue for local government and authorities. Many people have moved to cities from rural areas, some for schooling, and others for their living; on the other hand, due to favorable conditions for agricultural production, there have been a number of migrants from the country's Northern provinces transiting and settling in the province[1]. Notably, short-term migrants from other provinces having moved to Dak Lak during coffee harvesting season prove significant. Therefore, examining socio-economic factors that have effects on levels of efficiency in coffee production and assessing the current production situation through usage of econometric model of production should be beneficial to both policy makers and coffee growers.

In dealing with such problems and explaining the current state of local coffee production, we estimate a stochastic production function using a survey sample of 143 farms located in one of the largest coffee producing areas in the region. Our empirical results allow for several important contributions. Firstly, it would be meaningful to confirm the existence of inefficiency in coffee production. Secondly, policy interventions may take account of the role of labor dependence, credit for coffee production, and income diversification strategies. These are a few critical factors to the improved efficiency of coffee farming, thereby enhancing economic benefits not only for farmers but also for the coffee industry and the Central Highlands' economy. Further

analyses with larger datasets and more details of social economic characteristics would provide more constructive policy options.

2. Theoretical framework and methodology

2.1. Theoretical framework

Since Aigner et al. (1977) and Meeusen and van Den Broeck (1977) independently and simultaneously proposed the fundamental stochastic frontier model, various models have been recommended and applied. The efficient frontier is known as either the maximum level of output for a given set of inputs (an output orientation) or the minimum set of inputs required to produce a given set of outputs (an input orientation) (Tingley et al., 2005).
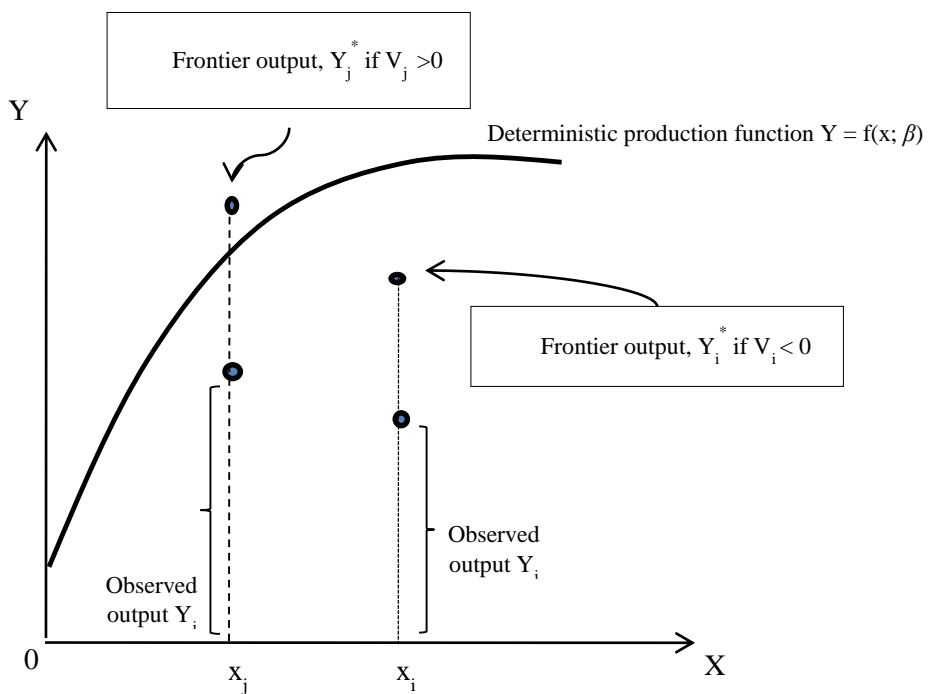

Figure with:
- Box: Frontier output, Y_j^* if $V_j > 0$
- Deterministic production function $Y = f(x; \beta)$
- Box: Frontier output, Y_i^* if $V_i < 0$
- Observed output Y_i
- Observed output Y_j
- Axes: Y, X, with x_j and x_i marked

Figure 1. Stochastic frontier production function (Battese, 1992)

The basic structure of the stochastic production frontier model is indicated in Figure 1, which describes the production activities of two firms as represented by *i* and *j*. Firm *j* uses inputs with values given by x_j (the vector x_j) and obtains the actual output, Y_j, but

the stochastic frontier output, Y_j^*, exceeds the value on the deterministic production frontier, $f(x_j;\beta)$, because its production activity is associated with "favorable" conditions for which the random error, V_i, is positive. On the other hand, firm i uses input with values given by x_i (the vector x_i) and obtains the output, Y_i, which has the corresponding frontier output, Y_i^*, which lies below the value on the deterministic frontier function, $f(x_j;\beta)$, because its production activity is associated with "unfavorable" conditions for which the random error, V_i, is negative. In both cases the observed outputs are less than the corresponding frontier values, but the stochastic frontier production values lie around the deterministic production function associated with the producers involved. It is also possible that a stochastic frontier value lies on the deterministic frontier if the random error, V, equals zero. This case may happen if the observed output, the stochastic production frontier value, and the deterministic production frontier are all equal besides the random error, V, and the technical inefficiency effects, U, both of which equal zero.

2.2. Methodology

There are two main approaches applied to analyze the determinants of technical efficiency with stochastic production framework. One is two-step procedure consisting of two independent stages. The first stage is to estimate the production function and efficiency scores, and in the second stage, estimated efficiencies are regressed against a vector of explanatory variables (see Pitt & Lee, 1981; Ben-Belhassen & Womack, 2000). However, for regression it is assumed that the residuals consisting of efficiency scores are identically and independently distributed. Also in the second step, the technical efficiency depends on explanatory variables as farm's specific characteristics. This suggests that this assumption is violated (Nchare, 2007). To deal with this problem, Battese and Coelli (1995) and Huang and Liu (1994) proposed a single-step approach in which explanatory variables are incorporated directly into the inefficiency error component. In this method the variance of the inefficiency error component is hypothesized to be a function of firm's specific characteristics. Afterward, there have been a number of studies that successfully applied this approach, including Alvarez and Arias (2004) and Illukpitiya and Yanagida (2010).

In this study we perform the stochastic frontier analysis along with the production model proposed by Battese and Coelli (1995):

$$y_i = f(x_{ij}; \beta_j).exp\{V_i - U_i\} \tag{1}$$

where y_i is the production of the ith firm, $i = 1,…$n; x_i is a vector of *m* inputs used by the ith firm; β_j is a vector of parameters to be estimated; the random error, V_i where $i = 1,…$n, captures the effects of statistical noise, which are assumed to be independently and identically distributed as N(0, σ_v^2); U_is where $i = 1,…$n are non-negative random variables associated with technical inefficiency in production, which are assumed to be independently and identically distributed exponential or half-normal variable [U_i ~ (|N(0, σ_u^2)|)]. The deterministic production function is written as: $f(x_i; \beta)$, while [$f(x_{ij}; \beta_j)$. exp $\{v_i\}$] is the stochastic production frontier.

Technical efficiency of the ith producer can be described as:

$$TE_i = \frac{y_i}{f(x_{ij};\beta_j).exp\{V_i\}} \tag{2}$$

This equation defines technical efficiency as the ratio of observed output to the maximum feasible output in an environment characterized by exp $\{V_i\}$. It implies that y_i can obtain its maximum feasible value of [$f(x_{ij}; \beta_j)$. exp $\{v_i\}$] if and only if $TE_i = 1$. Otherwise $TE_i < 1$ provides a measure of the shortfall of observed output from maximum feasible output in an environment characterized by exp $\{v_i\}$, which is allowed to vary across producers.

$$TE_i = exp(-u_i) \tag{3}$$

where u_i are non-negative random variables, called technical inefficiency effects. These u_i are assumed to be independently distributed and defined by the truncated normal distribution, with mean μ_i and variance σ_u^2, and are represented as:

$$u_i = Z_i\delta + W_i \tag{4}$$

where W_is for $i = 1,…$n are random errors, defined by the truncation of the normal distribution with mean zero and variance σ_u^2. The point of truncation is $-Z_i\delta$, i.e. $W_i \geq -Z_i\delta$. Z_is are the firm-specific variables which may also include input variables in the stochastic production frontier, provided that the technical inefficiency effects are stochastic.

3. Data sources

The survey was conducted in the Cu M'gar District, Dak Lak Province, located in the Central Highlands of Vietnam. In recent years the country has produced about 20% of global coffee production, and this region has contributed about 85% of the country's coffee output. Of the five coffee-growing provinces, Dak Lak is the largest in terms of

both cultivating area and production with about 50% of total national coffee production. The Cu M'gar District where the samples were obtained is known as a key coffee planting area in the region (see Dang & Shively, 2008).

The data collection procedure involves a two-stage random sampling technique. Initially, five out of 13 communes in the district were randomly identified. The regional distribution of coffee farmers in the five selected communes is relatively equal. Next, about 30 households in each commune were randomly selected. This procedure was used to ensure geographical representation of farmers with different production conditions across the district and to avoid the possibility of excessive number of farmers from any particular commune. In addition, this procedure also allows one to conduct a survey with limited cost and time. After the removal of missing data, the sample includes 143 farmers interviewed using the face-to-face technique with a developed questionnaire set. The questionnaire consists of demographic information about household characteristics, input and output data, and socio-economic and geographical information pertaining to agricultural production. Ahead of the main survey, a pre-test for the purpose of evaluation and refinement of the instrument was conducted. The data and variables are defined and summarized in following table:

Table 1

Summary statistics of coffee production and socio-economic variables

Variable		Obs.	Mean	Std. dev.	Min	Max
Yield	Coffee yield measured in kilogram per hectare	143	2,491.11	1,118.53	296.30	5,000.00
Production	Coffee production of the household measured in kilograms	143	1,533.08	1,361.86	50.00	8,000.00
Area	Cultivating area of the household measured in hectares	143	0.57	0.38	0.10	2.00
Inorgarnicf	Chemical fertilizers applied in kilograms	143	1,112.53	1,232.88	0.00	7,556.88
Organic	Organic fertilizers applied in kilograms	143	290.95	850.33	0.00	5,715.10

Variable		Obs.	Mean	Std. dev.	Min	Max
Pesticide	Pesticide applied in litters	143	52.89	80.37	0.00	630.00
Water	Irrigation water used in 1,000 cubic meters	143	20,749.37	19,310.64	1,200.00	120,000.00
Labor	Total labor used for coffee production in man-days	143	134.74	102.02	25.00	600.00
Ethnic	Ethnicity of the household head, 1 if Kinh majority, and 0 otherwise	143	0.44	0.50	0.00	1.00
Edu	Number of years that the household head completed for formal education	143	5.92	3.98	0.00	12.00
Credit	Amount of credit loan of the household in million VND	143	22.63	22.06	0.00	115.00
Simpson	Inverse of Simpson diversity index for the household's income[2]	143	1.82	0.71	1.00	3.93
Laborindex	Proportion of hired labor over total labor applied for coffee production	143	0.23	0.22	0.00	0.72
Exper	Coffee farming experience of the household head measured in years	143	9.25	5.04	2.00	27.00

4. Empirical models and estimation results

4.1. Empirical models

In this study the cross-sectional production frontier model has been chosen as an appropriate empirical one. For the research site it was observed that farmers do not

normally keep records on past farming activities; hence, data collection is dependent on the recall method. Farmers are highly knowledgeable about their levels of input application and the production on their coffee plantations during the current cropping year.

Following the stochastic production frontier model developed by Aigner et al. (1977) and Meeusen and van Den Broeck (1977), the stochastic frontier coffee production function for this study is specified as:

$$Lny_i = \beta_0 + \sum_{j=1}^{6} \beta_j lnx_{ji} + V_i - U_i \tag{5}$$

where subscript i refers to the ith coffee farm in the sample, Ln denotes the natural logarithm, y is coffee output, x_js are input variables $(j = 1, 2 \dots 6)$, described in Table 1 and considered conventional production factors as widely indicated in literature, βs are parameters to be estimated, V_is are iid $N(0, \sigma_v^2)$ random variables, and U_is are independently distributed ($|N(Z_i\delta, \sigma_u^2 |)$ technical inefficiency effects, which are, according to Battese and Coelli (1995), further defined as follows:

$$(1 - TE_i) = U_i = \delta_0 + \sum_{m=1}^{7} \delta_m Z_{m_i} + W_i \tag{6}$$

where Zs represent farm-specific variables, as defined and summarized in Table 1, δs are unknown parameters to be estimated, and W_i is a random variable as defined in Equation (6). For these equations the dependent variable is defined in terms of technical inefficiency, and a farm-specific variable having an estimated negative (positive) coefficient will have a positive (negative) effect on technical efficiency. Technical efficiency of the ith sample farm, TE_i, is estimated as defined in Equation (2).

The parameters for the stochastic production frontier model in Equation (5) and those for the technical inefficiency model in Equation (6) are also simultaneously estimated by employing the maximum-likelihood estimation (MLE) program FRONTIER 4.1 (Coelli, 1994), which generates the variance parameters of the likelihood function in terms of $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/\sigma^2$. Due to its value and significance, γ is an important parameter in determining the nature of a stochastic frontier; rejection of the null hypothesis $H_0: \gamma = 0$ suggests the existence of a stochastic production frontier. Similarly, $\gamma = 1$ implies that all deviations from the stochastic frontier are completely efficient due to technical inefficiency effects (Coelli et al., 1998).

In addition, in terms of the choice of functional forms, there are several forms that are commonly used in the literature. One may use the Cobb-Douglas functional form, one

of the most well-known functional forms in the production theory. Another popular option is the translog function, which may explain some additional features of the dataset or production technology, i.e. non-linearity. However, there is lack of theoretical study indicating which functional form is superior to others. Furthermore, a limitation of the current study is that the sample size is small. Then, the translog function may reduce the degree of freedom that may affect the overall significance of the model. Therefore, the standard Cobb-Douglas functional form is employed for this study.

In Central Highlands of Vietnam there are representatives of almost all Vietnamese ethnic groups working in the agricultural production sector. Among these, Kinh group constitutes the majority, and others are known as local and migrated groups such as Ede, Mnong, and Tay. An earlier study having conducted in the region suggested that Kinh households have better economic conditions than the others (e.g., loan access and off-farm employment) (Dang & Shively, 2008). Moreover, Vietnam's ethnic minorities tend to have poorer living standards than the Kinh group (van de Walle & Gunewardena, 2001). This is considered as inequality or differences between this and others, which, therefore, needs contemplating as for further investigations.

Household characteristics are often included in the technical inefficiency model in empirical studies of smallholders farming. A few common independent variables comprise formal education level of household head (Picazo-Tadeo et al., 2011), credit loans (Binam et al., 2004), crop diversification (Illukpitiya & Yanagida, 2010), farming experience and age of household head (Ofori-Bah & Asafu-Adjaye, 2011), and the role of labor dependence (Rahman, 2009).

4.2. Estimation results

The results of MLE performed to estimate stochastic production frontier are shown in Table 2. Consistency in effects of input factors on coffee production as well as those of socio-economic factors on coffee production efficiency can be confirmed by performing OLS regression. However, OLS regression results clearly show the heteroskadesticity problem related to the dataset. Thus, Feasible Generalized Least Square (FGLS) is employed to solve this common problem (see Illukpitiya & Yanagida, 2010). The results of FGLS are also presented in Table 2. Additionally, the Variance Inflation Factor (VIF) is tested to check the problem of multicolinearity, which does not exist as demonstrated by the results for the dataset.

It is noted that the FGLS estimation is an alternative way of the OLS estimation, and it allows the presence of heteroskadesticity to be observed (Nowak-Lehmann et al., 2011). Although, the OLS is simple, and the technique is widely understood by large pools of audiences, appropriate use of the stochastic frontier approach implies that it may cause biases (Battese & Coelli, 1995). Hence, in addition to the stochastic frontier analysis, applying the FGLS in this paper is expected to provide another angle of empirical description of the production technology and inefficiency variation.

Furthermore, the FGLS serves two purposes in this paper. *First,* the production technology is examined as a production function. *Second,* inefficiency scores, bounded from zero to one, are regressed against social economic variables. The dependent variable is bounded, but the OLS can also be an option for examining factors affecting inefficiency variation. McDonald (2009) argued that the Ordinary Least Squared (OLS) used to estimate bound data (i.e. between zero and one) also produce similar inference, and it is easily understood by larger communities without requiring greater statistical expertise of researchers. Although McDonald (2009) utilized Data Envelopment Analysis (DEA) for technical efficiency as a dependent variable, this variable is also bounded between zero and one, and it has similar inference, i.e. relative measure among farms. Therefore, in the presence of estimation problems, the FGLS estimation is to examine inefficiency variation, which may provide robustness of the stochastic analysis.

4.2.1. Stochastic production model

Overall, both MLE and FGLS results indicate similar inference identifying factors contributing to coffee production. The estimated results show that coffee cultivating area, amount of inorganic fertilizers, and labor use have positive and statistically significant relationships with the coffee output. On the other hand, irrigation water is insignificant for both production models. In fact, coffee plants are intensively water-consuming, whereas local coffee farmers do not have to pay any fee when extracting surface or ground water for coffee production. This leads to a consequence that the amount of water irrigation for coffee farming dramatically varies among farmers due to geographical difference. The reason is also that water sources may be favorable for some coffee farms, while some others may have a lot of difficulties to obtain irrigation water. In addition, rainfall is very important for coffee farming as this water source may replace a certain amount of irrigation water, which this study fails to control. This result, especially for the FGLS model, is consistent with the one suggested by a previous study that in Central

Highlands of Vietnam, coffee farmers are likely to overuse irrigation water for coffee farming (D'haeze et al., 2003). Regarding the organic fertilizer, the results verify that within a crop year the relationship between coffee output and organic fertilizer application is not significant. In reality farmers may not apply organic fertilizers every crop year but every two years instead. Technically, it may take more than a year for coffee plants to get changed by organic fertilizer use.

Table 2

MLE model vs. FGLS model[3]

		MLE model				FGLS model				
Parameter	Variable	Coef.	Std.	t-ratio		Coef.	Std.	t-ratio	p>|t|	
	Production frontier model					Production model: $R^2 = 0.77$				
β_0	Constant	6.3004	0.7752	8.1278	***	5.8070	0.9977	5.8200	0.0000	***
β_1	Lnarea	0.7362	0.0971	7.5804	***	0.7787	0.1304	5.9700	0.0000	***
β_2	Lninorganic	0.0341	0.0211	1.6176	*	0.0506	0.0160	3.1600	0.0020	***
β_3	Lnorganic	0.0007	0.0019	0.3909		-0.0004	0.0027	-0.1300	0.8940	
β_4	Lnpesticide	0.0029	0.0033	0.8915		0.0095	0.0041	2.3500	0.0200	**
β_5	Lnwater	0.0246	0.0384	0.6417		-0.0278	0.0498	-0.5600	0.5780	
β_6	Lnlabor	0.2560	0.0763	3.3561	***	0.3864	0.1040	3.7200	0.0000	***
	Inefficiency model					Inefficiency model: $R^2 = 0.44$				
δ_0	Constant	-0.1354	0.5028	-0.2692		0.2917	0.0665	4.3800	0.0000	***
δ_1	Ethnic	-0.6745	0.3094	-2.1799	***	-0.1293	0.0331	-3.9000	0.0000	***
δ_2	Edu	-0.0339	0.0260	-1.3066		-0.0075	0.0043	-1.7600	0.0810	*
δ_3	Credit	-0.0149	0.0091	-1.6257	*	-0.0018	0.0007	-2.7300	0.0070	***
δ_4	Simpson	0.4273	0.1449	2.9490	***	0.1062	0.0218	4.8800	0.0000	***
δ_5	Laborindex	1.0005	0.4650	2.1515	**	0.2085	0.0673	3.1000	0.0020	***
δ_6	Exper	-0.0126	0.0198	-0.6377		-0.0029	0.0030	-0.9800	0.3300	
σ^2		0.3931	0.1314	2.9915	***					
γ		0.9368	0.0304	30.8304	***					

*** significant at 1%

** significant at 5%

* significant at 10%

4.2.2. Coffee production efficiency

The common tests for stochastic frontier analysis are performed, and the results of these tests imply the appropriate use of this approach. As presented in Table 2, the γ-parameter associated with the variances in the stochastic production frontiers for the model is estimated to be 0.93 and is statistically significant with the t-value of 30.83. Although the γ-parameter cannot be exactly interpreted as the proportion of the total variance explained by technical inefficiency effects, the relative contribution of the inefficiency effects to the total variance term (γ^*) are calculated based on the γ-parameter[4]. The relative contributions are 82.90%, which means that about 83% of the variance of the total residual is explained by the inefficiency effects. In addition, the σ^2 parameter is calculated to be 0.3931 with t-statistic of 2.99. This confirms the existence of inefficiency variation in the stochastic model.

It is noteworthy that there are two common types of technical efficiency orientation. Input-oriented efficiency explains that given an amount of output, the efficiency implies how much firms or farms could reduce their input levels proportionally. On the other hand, output-oriented technical efficiency indicates that given a level of the input factor, the efficiency refers to how much firms or farms could increase their output level. In the context of agricultural production, households usually have more control over inputs than outputs (Illukpitiya & Yanagida, 2010). That is, this study uses the input-oriented technical efficiency assumption for the empirical analysis. Figure 2 plots the distribution of technical efficiency scores among 143 observed coffee households. The average efficiency score is 0.64 and statistically significant (the t-ratio associated with γ-parameter is equal to 30.83). This means that coffee farmers may have a potential improvement of coffee production of about 36% without increasing input production factors.

The bar chart shows that there are clearly two categories of farmers regarding technical efficiency scores. One group achieves the score range from 0.7 to 1, and the other, from 0.1 to 0.7, forms the majority of farmers. Furthermore, a pair-wise test performed reveals that Kinh households, known as the majority group, are more technically efficient than the category of other ethnic groups (t = 5.88; p = 0.0000).
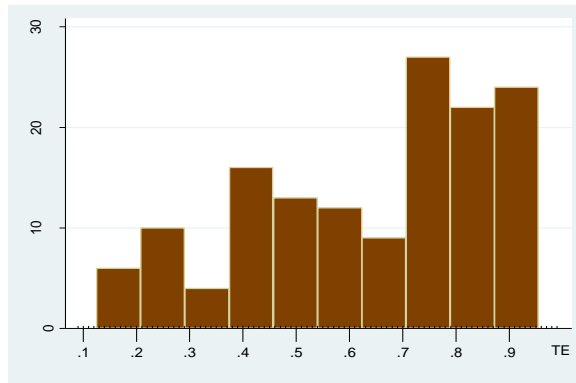
Figure 2. Technical efficiency distribution

4.2.3. Income diversification

As shown by the estimated results, the inverse Simpson index of income diversification has a negative and statistically significant relationship with the technical efficiency of coffee production, which is also presented in Figure 3. This implies that income diversification does not help improve the efficiency of coffee production which is the largest income source of most observed farmers. Furthermore, the farmers who have more diverse income sources are likely to be less efficient in coffee production. Table 2 indicates that the similar inference can also be generated by the FGLS model. Both estimation models confirm a negative and significant effect of income diversification on coffee production efficiency.
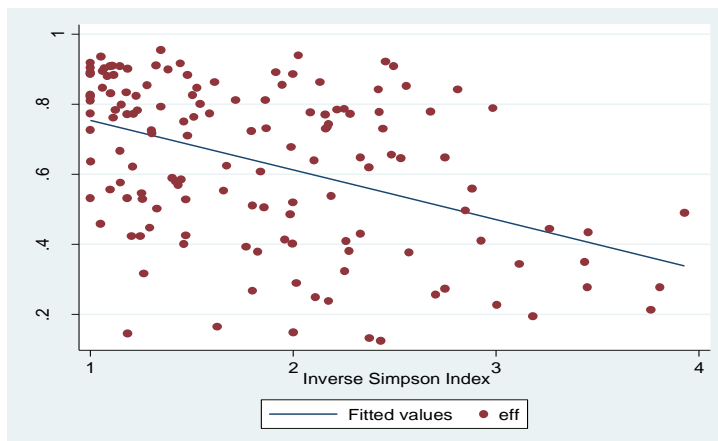

Figure 3. Inverse Simpson index vs. efficiency score

It is consistent with differences in coffee production efficiency between the Kinh group and minority household group. The pair-wise t-test[5] results show that income sources of the minority group are more likely to be diverse than those of Kinh households (t = 1.94; p = 0.03). This may explain that the industrial crop as coffee tends to be intensively invested and the diverse income sources may lead to lack of farmers' intensive attention to coffee production exclusively for minority households.

4.2.4. Credit loan

Table 2 demonstrates that the amount of credit loan plays a vital role in farmers' success in coffee production. As shown by the MLE result, credit loan negatively and significantly affects technical inefficiency, which holds consistent with the FGLS estimation and clarifies why farmers who are likely to be more technically efficient receive larger amounts of loan. There are, nevertheless, still farmers with small amounts of credit despite their high efficiency in coffee production. These ones may have a strong financial condition, so a small amount of credit could also be enough for investing in their farming activities. In addition, the Kinh households might also receive statistically larger amounts of loan than their ethnic minority counterparts (t = 3.90; corresponding p = 0.0001).
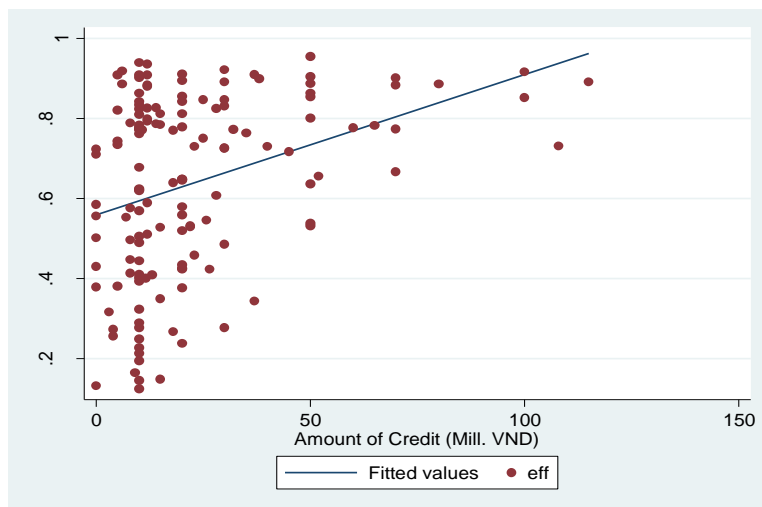

Figure 4. Credit loan vs. efficiency score

4.2.5. Labor dependence

Also in Table 2 there is a negative and statistically significant relationship between the technical efficiency of smallholder coffee farms and labor dependence index. This index ranges from 0 to 1, representing the degree of hired labor independence. It is equal to 0, meaning that the household is fully independent on hired labor, and to 1, explaining full dependence on hired labor. On average a coffee farm has to hire 23% of labor force, and the corresponding MLE coefficient is estimated to be 1. This implies that the technical efficiency of coffee farming households may increase by some 20% if they have enough labor sources for their farming activities. Figure 5 depicts an inverse relationship between the index and efficiency score, which is also similar to the results of both MLE and FGLS shown in Table 2.
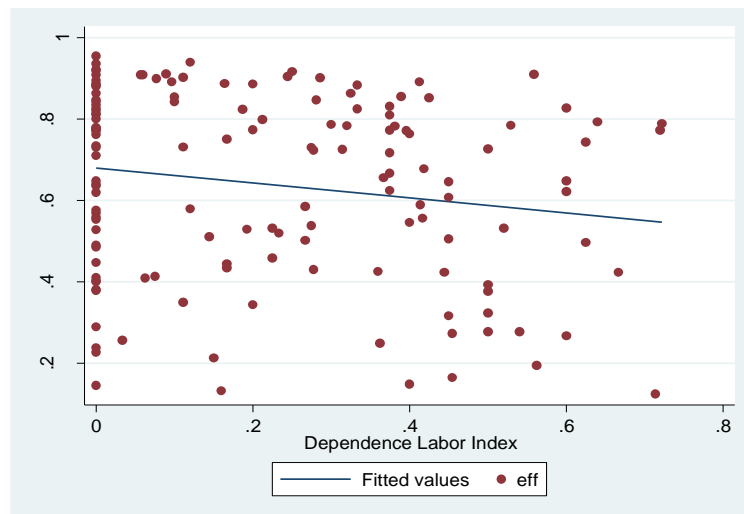

Figure 5. Labor dependence vs. efficiency score

5. Conclusion and policy options

Coffee farming is a key income-generating source of many farmers in the Central Highlands of Vietnam; therefore, increasing efficiency in coffee production of smallholders should be essential to the rural development in the region. The results confirm that the effect of inefficiency in coffee production is statistically significant. Evidently, the mean of technical efficiency scores is 0.64, indicating that there exists a potential in increasing coffee output with the given availability of input production

factors among smallholder coffee farms. Regarding socio-economic factors contributing to technical inefficiency in coffee production, statistical evidence demonstrates four significant factors. There are differences in the efficiency levels between different ethnic groups. Kinh households are likely to be more technically efficient than the minority group. Furthermore, diversification in household income sources does not appear to be a desired strategy to increase the efficiency in coffee production. It may, however, lead to reduction in technical efficiency in coffee production of smallholder coffee farms in the event of diversification of their income sources. In addition, rural credit loan is one of the keys to increased coffee production efficiency, and this nexus is positive and statistically significant. Another problem is that if farmers are dependent on hired labor sources for their coffee farming activities, it may lower their technical efficiency in this crop cultivation. Increasing the proportion of family labor man-days for coffee farming can help enhance the efficiency levels of smallholder coffee farms.

Based on the empirical results, policy options are suggested as to: (i) examining income sources of coffee farmers and allocating more resources (e.g., labor and capital) for coffee production rather than extensive investment in too many crops and activities; (ii) promoting rural credit programs so that coffee farmers can have access to finance and increase the amount of loan for coffee production; and (iii) improving availability of family labor sources and management of hired labors for coffee farming activities∎

Notes

[1] This piece of information with some statistics revealed by the Committee for Ethnic Minorities of Vietnam was retrieved on 12 April, 2012 from http://cema.gov.vn/modules.php?name=Content&op=details&mid=7786.

[2] $\text{Simpson} = 1/\sum_{i=1}^{6} P_i^2$ and $\sum_{i=1}^{6} P_i^2 = \left(\frac{I_1}{T}\right)^2 + \left(\frac{I_2}{T}\right)^2 + \left(\frac{I_3}{T}\right)^2 + \left(\frac{I_4}{T}\right)^2 + \left(\frac{I_5}{T}\right)^2 + \left(\frac{I_6}{T}\right)^2$

where T is total income of the household; Income from coffee production (I1); Income from rice production (I2); Income from other crops (I3); Income from livestock (I4); Income from agricultural services (I5); Income from non-agriculture activities (I6). The use of this inverse diversification index can be referred to in Illukpitiya and Yanagida (2010).

[3] It is important to note that the use of two techniques, MLE and FGLS, is to describe the production technology. First, MLE approach is a standard technique to estimate stochastic production frontiers in the efficiency literature. The parameters σ2 and γ are statistically significant at the 99%

confidence interval. This explains appropriateness of employing the stochastic frontier approach for this study and its stochastic nature in coffee production (see Iliyasu et al., 2014). Second, it is common that a production technology can be defined using a standard OLS estimator. Indeed, FGLS is a technique for estimating the unknown parameters in a linear regression model where OLS can be statistically inefficient (Nowak-Lehmann et al., 2011). There also exists heteroskedasticity in the dataset. That is, FGLS estimation can be used to illustrate the relationship between dependent and independent variables. In fact, the results of these two techniques are not comparable since assumptions of the error term are different.

[4] The parameter γ is not equal to the ratio of variance of technical inefficiency effects to the total residual variance because the variance of ui is equal to $[(\pi-2)/\pi]*\sigma2$ instead of $\sigma2$. The relative contribution of the inefficiency effect to the total variance, $\gamma*$, is equal to $\gamma/[(\gamma + (1-\gamma)\pi/(\pi-2)]$ (Coelli, 1998).

[5] The use of t-test makes ease for broader community of readers. In addition, the result of t-test provides robustness of the estimated result of the stochastic frontier analysis.

References

Aigner, D. J., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, *6*(1), 21–37.

Alvarez, A., & Arias, C. (2004). Technical efficiency and farm size: A conditional analysis. *Agricultural Economics*, *30*(3), 241–250. http://doi.org/10.1111/j.1574-0862.2004.tb00192.x

Battese, G. E. (1992). Frontier production functions and technical efficiency: A survey of empirical applications in agricultural economics. *Agricultural Economics*, *7*(3–4), 185–208.

Battese, G. E., & Coelli, T. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, *20*(2), 325–332. http://doi.org/10.1007/BF01205442

Binam, J. N., Tonyè, J., Wandji, N., Nyambi, G., & Akoa, M. (2004). Factors affecting the technical efficiency among smallholder farmers in the slash and burn agriculture zone of Cameroon. *Food Policy*, *29*(5), 531–545. http://doi.org/10.1016/j.foodpol.2004.07.013

Coelli, T. (1998). A multi-stage methodology for the solution of orientated DEA models. *Operations Research Letters*, *23*(3–5), 143–149. http://doi.org/10.1016/S0167-6377(98)00036-4

Coelli, T., & Fleming, E. (2004). Diversification economies and specialisation efficiencies in a mixed food and coffee smallholder farming system in Papua New Guinea. *Agricultural Economics*, *31*(2–3), 229–239. http://doi.org/10.1016/j.agecon.2004.09.010

Dak Lak Statistical Office. (2011). *Dak Lak Statistical Yearbook 2011*. Dak Lak Province, Vietnam: Dak Lak Statistical Office.

Dang, H., & Shively, G. (2008). Coffee boom, coffee bust, and smallholder response in Vietnam's Central Highlands. *Review of Development Economics*, *12*(2), 312–326. http://doi.org/10.1111/j.1467-9361.2007.00391.x

D'haeze, D., Deckers, J., Raes, D., Tran, A. P., & Nguyen, D. M. C. (2003). Over-irrigation of Coffea canephora in the Central Highlands of Vietnam revisited: Simulation of soil moisture dynamics in Rhodic Ferralsols. *Agricultural Water Management*, *63*(3), 185–202. http://doi.org/10.1016/S0378-3774(03)00181-1

Iliyasu, A., Mohamed, Z. A., Ismail, M. M., Abdullah, A. M., Kamarudin, S. M., & Mazuki, H. (2014). A review of production frontier research in aquaculture (2001–2011). *Aquaculture Economics & Management*, *18*(3), 221–247. http://doi.org/10.1080/13657305.2014.926464

Illukpitiya, P., & Yanagida, J. F. (2010). Farming vs forests: Trade-off between agriculture and the extraction of non-timber forest products. *Ecological Economics*, *69*(10), 1952–1963. http://doi.org/10.1016/j.ecolecon.2010.05.007

Kamil, A. A., Fatama, K., Pinang, P., & Society, M. H. (2009). Technical efficiency in stochastic frontier production model: An application to the manufacturing industry in Bangladesh. *Translog*, *3*(2), 1160–1169.

Kehinde, A. L., Awoyemi, T. T., Omonona, B. T., & Akande, J. A. (2010). Technical efficiency of sawnwood production in Ondo and Osun states, Nigeria. *Journal of Forest Economics*, *16*(1), 11–18. http://doi.org/10.1016/j.jfe.2009.04.001

Kumbhakar, S. C. (1996). A farm-level study of labor use and efficiency wages in Indian agriculture. *Journal of Econometrics*, *72*(1–2), 177–195. http://doi.org/10.1016/0304-4076(94)01719-0

Marsh, A. (2007). *Diversification by smallholder farmers: Vietnam Robusta Coffee*. Agricultural Management, Marketing, and Finance Working Document No. 19. Rome, Italy: Food and Agriculture Organisation of the United Nations.

McDonald, J. (2009). Using least squares and tobit in second stage DEA efficiency analyses. *European Journal of Operational Research*, *197*(2), 792–798. http://doi.org/10.1016/j.ejor.2008.07.039

Meeusen, W., & van Den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review*, *18*(2), 435–444.

Meyfroidt, P., Vu, T. P., & Hoang, V. A. (2013). Trajectories of deforestation, coffee expansion and displacement of shifting cultivation in the Central Highlands of Vietnam. *Global Environmental Change*, *23*(5), 1187–1198. http://doi.org/10.1016/j.gloenvcha.2013.04.005

Nchare, A. (2007). *Analysis of factors affecting technical efficiency of Arabica coffee producers in* Cameroon. AERC Research Paper No. 163. Nairobi: African Economic Research Consortium.

Nowak-Lehmann, D. F., Herzer, D., Vollmer, S., & Martínez-Zarzoso, I. (2011). Modelling the dynamics of market shares in a pooled data setting: Econometric and empirical issues. *Applied Economics*, *43*(7), 823–835. http://doi.org/10.1080/00036840802599925

Obwona, M. (2002). *Determinants of technical efficiency differentials among small- and medium-scale farmers in Uganda : A case of tobacco growers*. Kampala, Uganda: Economic Policy Research Center.

Ofori-Bah, A., & Asafu-Adjaye, J. (2011). Scope economies and technical efficiency of cocoa agroforesty systems in Ghana. *Ecological Economics*, *70*(8), 1508–1518. http://doi.org/10.1016/j.ecolecon.2011.03.013

Picazo-Tadeo, A. J., Gómez-Limón, J. A., & Reig-Martínez, E. (2011). Assessing farming eco-efficiency: A data envelopment analysis approach. *Journal of Environmental Management*, *92*(4), 1154–1164. http://doi.org/10.1016/j.jenvman.2010.11.025

Pitt, M. M., & Lee, L. F. (1981). The measurement and sources of technical inefficiency in the Indonesian weaving industry. *Journal of Development Economics*, *9*(1), 43–64.

Rahman, S. (2009). Whether crop diversification is a desired strategy for agricultural growth in Bangladesh? *Food Policy*, *34*(4), 340–349. http://doi.org/10.1016/j.foodpol.2009.02.004

Tingley, D., Pascoe, S., & Coglan, L. (2005). Factors affecting technical efficiency in fisheries: Stochastic production frontier versus data envelopment analysis approaches. *Fisheries Research*, *73*(3), 363–376. http://doi.org/10.1016/j.fishres.2005.01.008

Vedenov, D., Houston, J., & Cardenas, G. (2007). Production efficiency and diversification in Mexican coffee-producing districts. *Journal of Agricultural and Applied Economics*, *39*(3), 749–763.