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Productive Efficiency of Crop Farms in Viet Nam: A DEA with a Smooth Bootstrap Application

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Abstract

Rice and maize are the two most important annual crops in Viet Nam. Rice production is sufficient for self-consumption and exportation, whereas maize production is insufficient and must be imported because of the growing feed industry. In Son La, the largest area in the Northwest with the greatest production of maize, maize is cultivated continuously all year, whereas paddy rice is cultivated mostly in the spring. To our knowledge, this article is the first study to estimate farm-level technical and scale efficiencies and to identify the factors influencing them. This study first applied a standard and smooth bootstrap DEA method to estimate the technical and scale efficiencies, then used a Tobit regression method to identify factors influencing these efficiencies among farms. The results showed that the opportunity for both technical and scale inefficiencies of maize and rice crops is insignificant. Findings from the second stage indicated that the age of the head of household, the numbers of family, the national electricity source, the distance to the nearest market, and the access to credit, extension services and milling machines are the main factors affecting the technical and scale efficiencies of rice and maize crops. The findings suggest continuing improvement of management, co-operation in cultivation, crop diversity and optimal use rice plots. The results also recommend expanding the national electricity source, emphasizing policies for adjusting customs and knowledge, using credit in appropriate ways and continuing to enhance extension services.

Keywords: annual crops, rice crop, maize crop, DEA, smooth bootstrap, technical efficiency, scale efficiency, Vietnam

1. Introduction

Although the role of agriculture in the economy of Viet Nam has recently declined, it is still the most important economic sector. Agriculture contributed 20% of the GDP and comprised 47% of the total employment in Viet Nam in 2012 (World Bank, 2014). Decision No. 432/QD-TTg on approving the Viet Nam Sustainable Development Strategy for 2011-2020 emphasizes that "*To shift the structure of agriculture and rural areas towards industrialization, promote regional advantages; develop quality agricultural products; combine production with local and foreign market in order to lift the efficiency of using natural resources…*" (Prime Minister of Vietnam, 2012). This strategy extends the application of scientific and technological advances to increase the quantity and quality of agricultural production.

Rice and maize are the two most important annual crops. Their planted area and production are the highest compared with all types of annual crops, such as sugar cane, soya bean, and peanut. By 2012, the planted area of rice and maize was 7761.2 and 1172.5 thousand ha, respectively; production was 43737.8 and 5193.5 thousand tons, respectively (GSO, 2013). Rice is mostly used for food consumption and export, whereas maize production is insufficient and must be imported for the feed industry (USDA, 2014).

The Northwest is the poorest among the seven regions in Viet Nam. Because the topography is high and mountainous, paddy rice production is insufficient, and maize production has been increasing rapidly in recent years. Maize has become the main income source for farmers (Luckmann, Ihle, & Grethe, 2011). Maize is the top annual crop in the Northwest. The area and production in 2011 were 28.74% and 14.92%, respectively (GSO, 2012b).

Son La, one of the seven provinces in the Northwest, has the largest area and greatest production of maize. The planted area and production of maize in 2012 was 168.7 thousand ha and 667.4 thousand tons, respectively. However, the planted area and production of paddy rice had only 48.2 thousand ha and 162.9 thousand tons, respectively (GSO, 2013). Maize is cultivated continuously all year, whereas paddy rice is cultivated mostly in the spring.

Son La Province and the Northwest are also facing many problems. The transportation system is poorly developed. Many ethnic groups live together with low education and traditional customs. The ratio of poverty in the Northwest in 2013 was 58.7%, which is high compared with the ratio for the entire country: 17.2% (GSO, 2012a). The annual crop plots are highly fragmented and very small. Farmers work as individuals and do not want to join co-operatives. Therefore, applying scientific and advance technologies here is a significant challenge for farmers and the government.

Although rice and maize have an important role in the Northwest social-economic structure, there are few studies regarding the efficiency of rice and maize crop production. To our knowledge, this article is the first study to estimate farm-level technical and scale efficiencies and identify the factors influencing them. This study estimated farm efficiency using a nonparametric method with a smooth bootstrap procedure to avoid measurement errors and data noise. After obtaining the technical and scale efficiencies, a Tobit regression method was used to determine the factors influencing these efficiencies.

There have been several studies regarding the efficiency of agriculture in Viet Nam. Khai and Yabe (2011) used stochastic production frontier analysis (SFA) with the Cobb-Douglas production function to measure the technical efficiency (TE) of rice production. Rios and Shively (2005) used a standard DEA method to first estimate technical and cost efficiencies and then a standard Tobit regression to identify the factor effect on these efficiencies of coffee farms in Dak Lak Province, Viet Nam. Linh (2012) is the first author to use a smooth bootstrapped DEA method to estimate technical and scale efficiencies of rice farms in the first step. Linh (2012) then used a standard and weight Tobit to determine the factors influencing technical efficiency. However, Linh (2012) used the Vietnam Household Living Standard Survey 2003-2004 (VHLSS 2004) for 8,813 households in all of Vietnam and only for rice farms. Dao and Lewis (2013) estimated the technical and scale efficiencies of annual crop farms in northern Vietnam using a DEA smooth bootstrap approach. However, Dao and Lewis (2013) have only used a DEA smooth bootstrap approach in the first step because the second step to identify factors was not completed. Dao and Lewis (2013) also did not focus on analyzing maize and rice farms in the Northwest.

This paper has two objectives. First, we estimate the technical and scale efficiencies of both rice and maize crops in Son La Province, Vietnam using a standard and smooth bootstrap DEA method. Second, we use a Tobit regression method to identify the factors influencing these efficiencies among farms.

The next section describes a short review of the methodology. Section 3 describes the main characteristics of the data. The results and discussion are presented in section 4. Finally, conclusions and several recommendations are provided.

2. Methodology

Efficiency can be estimated by two methods, namely, parametric and non-parametric. In the literature, most parametric approaches use the Stochastic Frontier Analysis (SFA) method, whereas the non-parametric approach uses Data Envelopment Analysis (DEA). The main difference between these two methods is based on the way that the production possibility frontier can be estimated. An advantage of the DEA method is that it does not require a functional form, whereas SFA requires a functional form.

DEA requires detailed information regarding all inputs and output data. Following the work of Coelli, Rahman, and Thirtle (2002); Farell (1957) and others, the four efficiencies often measured are technical, scale, allocative and cost. However, the allocative and cost efficiencies are strengthened by the availability of all inputs and output prices, which were difficult to collect when we conducted the field survey. Because the survey was conducted based on farmers' memories, sometimes they could not remember details. Therefore, this article focuses on measuring technical efficiency (TE) and scale efficiency (SE).

DEA has input orientations and output orientations. This study employed DEA to measure farm efficiency using an input orientation. We first used the smooth bootstrap procedure proposed by Simar and Wilson (2000) to estimate bias and the confident interval for technical efficiency (TE). We then used Tobit analysis to identify the exogenous factors affecting the estimated efficiency. We used the package FEAR developed by Wilson (2008) in the R platform and Stata software in the process.

2.1 Technical and Scale Efficiencies

The DEA production frontier is constructed and solved using linear programing techniques. Considering an i^{th} farm out of a total of *n* farms, the input-based technical efficiency (TE) under variable return to scale (VRS) is calculated as:

$$TE_i = min_{\theta,\lambda}\theta_i, \text{ Subject to } Y_i \leq Y\lambda;\ \theta_i X_i \geq X_i;\ \lambda \geq 0;\ \sum_{i=1}^{n}\lambda_i = 1 \quad (1)$$

Where,

Y and X are the output and input vectors, respectively. The value of θ_i is the technical efficiency score for the *i = th* farm under VRS. In general, $0 \leq \theta_i \leq 1$, when $\theta_i = 1$, indicating that the farm is producing on the production frontier and is therefore technically efficient, whereas $\theta_i < 1$ shows that the farm is technically inefficient.

In case of a constant return to scale (CRS), we can easily impose it by deleting the convexity constraint $\sum_{i=1}^{n}\lambda_i = 1$ in Equation (1). Therefore, we can easily calculate scale efficiency (SE) by Coelli et al. (2002):

$$SE = TE_{CRS}/TE_{VRS} \quad (2)$$

We can also calculate the non-increasing to scale (NIRS) by replacing the convexity restriction $\sum_{i=1}^{n}\lambda_i = 1$ in Equation (1) to $\sum_{i=1}^{n}\lambda_i \leq 1$. In general, $0 \leq \theta_i \leq 1$ if SE = 1, and farms are considered to be scale efficient. If $TE_{VRS} = TE_{NIRS}$ and SE < 1, the farm is operating under a decreasing return to scale (DRS), or is "too large". If $TE_{VRS} \neq TE_{NIRS}$ and SE < 1, the farm is operating under an increasing return to scale (IRS) or is "too small". Finally, if $TE_{VRS} = TE_{CRS}$, the farm is operating under a CRS (Coelli et al., 2002).

2.2 Bootstrapping in DEA

DEA is a deterministic method, and one of its disadvantages is that no statistical noise is assumed in the analysis. Although DEA methods have been widely applied to date, many researchers have completely ignored the statistical noise in the estimators. This oversight can cause bias in the DEA estimates and mistaken results (Dao & Lewis, 2013). Simar and Wilson (1998, 2000) proved that bootstrapping is the best method to construct the statistical properties of DEA. In the bootstrap method, the data are simulated by resampling. Therefore, the data generating process (DGP) can be mimicked to the correct data generation. In the literature, several studies have applied the bootstrap method of Simar and Wilson (2000), such as Brummer (2001); Dao and Lewis (2013); Gocht and Balcombe (2006); Latruffe, Balcombe, Davidova, and Zawalinska (2005).

After using a smooth bootstrap procedure, we can check the biased DEA estimators and locate their confidence interval. The confidence interval is an important index to determine the exact results. The larger the variance, the more incorrect the efficiency results may be. Efron and Tibshinari (1993) have suggested that the number of iterations should be less than 1000 if researchers only want to estimate bias and standard deviation. Because we are more interested in confidence interval estimation, in our study, 2,000 bootstrap iterations were performed.

2.3 Variables Explaining the Efficiency Estimates

This article used Tobit analysis in the second stage to evaluate the factors influencing efficiency similar to most authors. Crop production is affected by many exogenous factors, such as household characteristics, household assets, extensions, and weather. Moreover, farms operating at optimal scale are assumed in constant return to scale (CRS) technical efficiency (Karimov, 2013). Therefore, this study selected the technical efficiency under variable return to scale (VRS) to become dependent variables in the Tobit model.

However, which index is suitable to use for analysis: the bias-corrected estimator or original technical efficiency? Simar & Wilson (2000) have suggested that using only bias-corrected estimates in the second step when,

$$\hat{\sigma}^2 < \frac{1}{3}(bias[\hat{\theta}])^2 \quad (3)$$

Where $\hat{\sigma}^2$ is the sample variance of the bootstrap values, and $\hat{\theta}$ is the uncorrected estimated score. In our study, using only bias-corrected estimates could not occur. Thus, we used the original technical efficiency score (TE_{VRS}) in the second stage.

The estimated coefficients in the Tobit regression models can not directly be used to interpret the results as the true marginal effect. This coefficient will affect the mean value of the dependent variable (Yi), given that it is observed and also affects the probability of the dependent variable being observed (Y^*_i) (Gujarati, 2011).

Therefore, similar to other studies, this study uses the marginal effects of all independent variables that are reported and calculated at the sample mean.

3. Data and Variables Used

The data used for this study originate from a survey conducted in six communes located in three districts of Son La Province, in northwest Vietnam. The survey was conducted from February to March 2014. The respondents were selected through a multi-stage sampling procedure. Three districts in the survey were based on three types of altitude: Mai Son < 1,000 m, Moc Chau 1,000 − 2,000 m and Phu Yen > 2,000 m. A total of 360 farm households from 12 villages were interviewed. Of this total, 292 households cultivate both rice and maize, 60 households cultivate only maize, six households cultivate only rice, and four conduct business. Therefore, we used the data of 292 household farms to compare the efficiency between the two main crops.

Output is measured as the gross income of rice and maize. Rice product is mostly used for self-consumption; maize product is used for both selling and self-consumption. Therefore, using profit or income from the rice and maize product index does not precisely show the technical and scale efficiencies. The inputs are planted land, family and hired labor, seed, fertilizer (including organic, NPK, nitrogenous and phosphate fertilizer), chemicals (including herbicide and pesticide) and other expenses (such as irrigation and transportation fees, etc.).

We also explain efficiency differences among farms using farm-specific variables. The selected variables are those most often used in the literature, such as the age and education of the household head, distance to the nearest market, access to credit, extension services, off-farm income and household assets (Binam, Tonyè, Wandji, Nyambi, & Akoa, 2004; Coelli et al., 2002; Linh, 2012).

Table 1 presents summary information regarding the variables used for rice and maize crops separately. The table shows that gross income from maize production is higher than rice production by 46,000 thousand vnd. The simple reason for this result is that all of the inputs of maize except other expenses are higher than rice. The planted rice crops are small by 0.32 ha, similar to the rice farm size in Bangladesh (Coelli et al., 2002), with an average size of only one-third of a hectare. The average size of a rice crop is equal to one-fifth the size of a maize crop. Most rice farms have only one or two plots. Because maize is cultivated on sloping land, it requires much more labor, seed, and fertilizer.

The farm-specific variables provide an overview of the farms' characteristics. The average age of the head of household is 44; the average education of the head of household is at the secondary level. The average family size is 5. Nearly 90% of farms use a national electricity source, and approximately 67% of farms have access to credit. The average distance to the nearest market is 9 km. Farmers have had contact with maize extensions more than rice. Few households have tractors and milling machines, and off-farm income is small: approximately 2 million Vietnamese dong per year.

Table 1. Descriptive variable used

Variable	Definition	Rice		Maize	
		Mean	SD	Mean	SD
Output and Inputs					
Output	Gross income (1,000vnd)	13,072.21	11,915.02	58,934.96	44,17566
Land	Cultivated land (ha)	0.32	0.44	1.48	1.10
Labor	Including family labor and hired labor (Man-days)	18.32	25.99	126.65	96.16
Seed	Total amount of seed (1,000vnd)	2,604.42	2,110.01	4,474.06	3,265.96
Fertilize	Total amount of fertilizer (1,000vnd)	2,638.31	2,356.90	9,146.38	6,485.98
Chemical	Total amount of chemicals (1,000vnd)	927.08	965.46	1,276.69	927.32
Others	Other expenses (1,000vnd)	190.34	819.79	117.89	766.24
Farm specific variables					
Age	Age of household head (years)	44.32	11.59	44.32	11.59
Edu	Schooling of household head (years)	6.62	3.22	6.62	3.22
Hhsize	Household members (person)	4.92	1.59	4.92	1.59
Sourele	Source of electricity of household, which takes 1 = use national source, 0 = otherwise	0.88	0.33	0.88	0.33
Dismark	Distance from household to nearest market (km)	9.20	7.11	9.20	7.11
Credit	Takes 1 if farmer has access to credit, 0 = not	0.67	0.47	0.67	0.47
Extent	Takes 1 if farmers received the information from extension services, 0 = none	0.41	0.49	0.94	0.24
Motor	Motorcycle of household, which takes 1 = have milling, 0 = otherwise	0.30	0.46	0.30	0.46
Tractor	Tractor machine of household, which takes 1 = have tractor, 0 = otherwise	0.22	0.41	0.22	0.41
Milling	Milling machine of household, which takes 1 = have milling, 0 = otherwise	0.28	0.48	0.28	0.48
Offic	Off-farm income of household (Million vnd)	1.99	10.39	1.99	10.39

Source: Own survey, 2014.

4. Results and Discussion

4.1 Technical and Scale Efficiencies

The standard DEA technical estimates under VRS and CRS are reported in Table 2. The results show that the majority of farms are inefficient in both the technical and scale efficiencies of rice and maize production.

The average technical efficiency score under VRS is 0.63 for rice crops and 0.54 for maize, with 34 rice and 19 maize crops fully efficient. These results suggest that, on average, farms can still maintain the same output performance with a decrease in the inputs by 37% for rice crops and 46% for maize crops. The results also indicate that technical efficiency under CRS and VRS in rice production is higher than in maize production, which may be partly because of the insufficiency and sloping of maize crop lands.

The mean scores of scale efficiency for rice and maize production are the same: 0.89. This conclusion indicates that farm size is much less important in changing technical efficiency. The last three rows of Table 2 show the percentages of farms that have constant return to scale (CRS), decreasing return to scale (DRS) and increasing return to scale (IRS). Overall, farms are mostly under increasing return to scale in both rice and maize crops, with scores of 84.25% and 77.40%, respectively. These results mean that farms are “too small” and may need to increase their scales. Only 11 rice crops and 10 maize crops are producing at optimal scale.

The technical efficiency score for both crops under VRS is lower than the scale efficiency score. This conclusion indicates that the technical inefficiency of maize and rice farms is mainly affected by management rather than the operating scale. This finding is similar to the result of Karimov (2013), which estimated the efficiency of potato and H-W melon crops on Uzbekistan farms. This result implies that farmers must focus more on improving the management of crop production, and rice farms must also increase their scale efficiency.

Table 2. Frequency distribution of technical and scale efficiency estimates in a pooled sample

	Rice crop			Maize crop		
	TE_{CRS}	TE_{VRS}	SE	TE_{CRS}	TE_{VRS}	SE
Mean	0.56	0.63	0.89	0.48	0.54	0.89
Std.dev	0.20	0.22	0.14	0.21	0.21	0.15
Minimum	0.15	0.16	0.21	0.07	0.14	0.28
Maximum	1.00	1.00	1.00	1.00	1.00	1.00
<60 %	60.96	51.72	4.45	73.97	67.10	6.85
60-69 %	12.67	9.93	6.51	11.30	12.00	4.79
70-79 %	13.01	12.33	6.51	6.51	8.20	6.16
80-89 %	7.19	8.90	17.81	2.40	3.80	14.05
90-100 %	6.17	17.12	64.73	5.82	8.90	68.15
IRS %			84.25			77.40
DRS %			11.99			19.18
CRS %			3.76			3.42

Source: Own survey, 2014.

4.2 Smooth Bootstrap Results

To improve the robustness of the results and realizing that the standard DEA method may have biases in estimating efficiency scores, we used a smooth bootstrapping method. The results of bias-corrected TE_{VRS} are reported in the sixth column of Table 3. The confidence intervals (CIs) of bias-corrected TE_{VRS} are also shown in the seventh and eighth columns.

Table 3. Technical efficiency estimates using smooth bootstrap method

Variables	Sample	Initial TE_{CRS}	Initial TE_{VRS}	% of farm with $TE_{VRS} = 1$	Bias-Corrected TE_{VRS}	Lower bound	Upper bound
Rice crop							
Pooled sample	292	0.56	0.63	11.64	0.55	0.50	0.62
Mai Son	93	0.61	0.68	16.10	0.58	0.52	0.66
Moc Chau	87	0.69	0.76	26.40	0.66	0.59	0.75
Phu Yen	112	0.62	0.69	19.60	0.59	0.53	0.68
Maize crop							
Pooled sample	292	0.48	0.54	6.50	0.46	0.42	0.52
Mai Son	93	0.65	0.75	26.90	0.66	0.59	0.74
Moc Chau	87	0.50	0.60	9.20	0.51	0.45	0.58
Phu Yen	112	0.51	0.58	8.04	0.49	0.44	0.56

Source: Own survey, 2014.

The results show that the mean of bias-corrected TE results are lower than the initial scores, and no farms have a full technical efficiency score. Similar results are found in Linh (2012) for a single bootstrap and Olson and Vu (2009) for a double bootstrap. Comparing efficiency scores in the location category of rice crops, farmers in the Moc Chau district have a higher TE score (0.66 compared with 0.58 and 0.59). The difference between the initial and bias-corrected efficiency scores is also highest in this group (0.76 compared with 0.66). However, with maize crops, farmers in the Mai Son district have the highest initial and bias-corrected TE scores compared with the Moc Chau and Phu Yen districts. These results indicate that rice crops in Moc Chau and maize crops in Mai Son have much more efficient farmers in the sample.

Karimov (2013) has suggested that authors must use bias-corrected efficiency scores to recommend policy. This suggestion is based on the distance between the initial and bias-corrected TE. For detail, the initial TE_{VRS} for the pooled sample suggests that rice and maize farms could decrease their inputs by 37% and 46%, respectively. If full efficiency was achieved, the bias-corrected TE_{VRS} suggests decreasing inputs for rice and maize production approximately 45% and 54%, respectively.

Using the smooth bootstrap method, the width of the 95% confidence intervals is 0.12 for rice production and 0.10 for maize production. This finding is similar to Karimov (2013) and Latruffe et al. (2005) for the single bootstrap procedure. This result indicates that farms could be more inefficient if we used a confidence interval index rather than the single estimated point. For example, in the location category, the mean TE_{VRS} of maize crops in the Moc Chau district shows that, on average, farms could obtain the same level of output by reducing 40% of their inputs. However, the confidence interval explains that inputs could be reduced from 42% to 55%. If we do not use the DEA bootstrap method, farms that were originally identified as lying on the production frontier may, in fact, lie below it.

4.3 Factors Explaining Efficiencies

Table 4. Results of Tobit regression

Variable	Rice		Maize	
	TE_{VRS}	SE	TE_{VRS}	SE
Constant	0.6507***	0.8009***	0.4402***	1.1088 ***
	(0.0951)	(0.0520)	(0.0861)	(0.0581)
Age	-0.0022*	0.0009	-0.0020*	-0.0015*
	(0.0013)	(0.0007)	(0.0012)	(0.0008)
Edu	0.0029	-0.0002	-0.0029	-0.0032
	(0.0049)	(0.0027)	(0.0045)	(0.0029)
Hhsize	0.0029	-0.0051	0.0215**	-0.0088
	(0.0096)	(0.0052)	(0.0088)	(0.0059)
Sourele	0.1146**	0.0444	0.0764	-0.0137
	(0.0507)	(0.0277)	(0.0463)	(0.0311)
Dismark	-0.0013	-0.0039***	0.0018	-0.0028**
	(0.0021)	(0.0011)	(0.0019)	(0.0013)
Credit	-0.0245	0.0106	-0.0647**	-0.0048
	(0.0314)	(0.0171)	(0.0281)	(0.0189)
Extent	0.0158	0.0330**	0.1018 *	-0.0480
	(0.0293)	(0.0160)	(0.0565)	(0.0381)
Motor	-0.0111	0.0469	-0.0474	0.0144
	(0.0628)	(0.0349)	(0.0307)	(0.0206)
Tractor	-0.0062	0.0055	-0.0152	0.0072
	(0.0344)	(0.0187)	(0.0343)	(0.0230)
Milling	-0.0391	0.0512**	-0.0356	-0.0020
	(0.0379)	(0.0207)	(0.0286)	(0.0192)
Offic	0.0006	0.0003	0.0005	-0.0005
	(0.0014)	(0.0008)	(0.0013)	(0.0009)
Log likelihood	-39.42	161.33	4.01	134.68

Note. ***, **, *: Significance at the 1%, 5%, and 10% level, respectively.

Source: Own survey, 2014.

To explain the variation of technical and scale efficiencies, these scores were regressed concerning the farm characteristics using a Tobit regression model. The results of the Tobit model are presented in Table 4, and the partial effect of each factor is listed in Table 5.

The age of the household head has a significant and negative effect on the technical efficiency of rice crops and the technical and scale efficiencies of maize crops. If household heads are older, they do not want to change their cultivation methods, apply new technologies or expand scales of production. Younger heads of household are considered to be more flexible by adopting new knowledge and technology and increasing investment.

Source electricity has positive effects on the technical efficiency of both rice and maize crops. The results indicate that farms using a national electricity source have a higher technical efficiency than those that do not. Because a national electricity source is stable and powerful, farms can use it for crop activities, such as using pumps for irrigation.

Unexpectedly, the distance to market has a significant and negative impact on the scale efficiency of rice and maize crops. This finding shows that if the distance to market is nearer, the scale inefficiency of rice and maize crops will increase. Arable land for rice and maize crops is small and limited. Although natural conditions allow cultivation in two seasons per year, most farmers cultivate rice in one season. In addition, the custom of people upland is to relax after the harvest. Therefore, these farms will consume more if they are near the market and if they do not keep money to invest in increasing the scale of rice and maize production.

Table 5. Partial effects of the Tobit regression

Variable	Rice		Maize	
	TE_{VRS}	SE	TE_{VRS}	SE
Age	-0.0022*	0.0009	-0.0020*	-0.0015*
Edu	0.0029	-0.0002	-0.0029	-0.0032
Hhsize	0.0030	-0.0051	0.0215**	-0.0088
Sourele	0.1146**	0.0444	0.0764*	-0.0137
Dismark	-0.0013	-0.0039***	0.0018	-0.0028**
Credit	-0.0245	0.01062	-0.0647**	-0.0048
Extent	0.0158	0.0330**	0.1018*	-0.0480
Motor	-0.0111	0.0469	-0.0474	0.0144
Tractor	-0.0062	0.0055	-0.0152	0.0072
Milling	-0.0391	0.0512**	-0.0356	-0.0020
Offic	0.0006	0.0003	0.0005	-0.0005

Note. ***, **, *: Significance at the 1%, 5%, and 10% levels, respectively.

Source: Own survey, 2014.

Family members have a positive effect on the technical efficiency of maize crops. This effect can come from the fact that maize plots are mainly located on upland, with a slope more than 15^{o}; thus, it costs time and money to use modern technology, such as a tractor for land preparation and a motor for transportation. In fact, farmers prepare land with animals or their hands. Thus, maize crops require more labor than rice crops. Family laborers will help farms save money and initiate production. This finding is inconsistent with Coelli et al. (2002) who found that larger families have a negative effect on the technical, allocative and cost efficiencies of modern Boro rice.

The insignificant effects of education, motors, tractors and off-farm income indicate that these factors have a low impact on different efficiencies. Experience may be a more important factor than the education of the household head, especially with the people in the highlands. Moreover, the average education of the household head is at the secondary level. Motors are mostly used for daily life rather than for cultivating activities. Rice plots are also small and fragmented; maize plots are located on sloping lands. Thus, tractors have no effect on either rice or maize efficiencies.

Finally, milling machines have a positive effect on the scale efficiency of rice crops. Farmers who have their own milling machine could improve the scale of their rice crop. Using milling machines should save time and costs for farmers and allow them to be proactive in their farm activities.

5. Conclusion

This study uses a smooth bootstrapping method to analyze the variability of DEA technical efficiency estimates and to correct for the inherent bias in the DEA method. This study use detailed survey data for 292 farms that cultivate both rice and maize crops in 12 villages in three districts in Son La Province, Vietnam. The study shows that the opportunity for both technical and scale inefficiencies of maize and rice crops is significant. The results indicate that the TE_{VRS} among farmers differs across districts. The bias-corrected point estimate of TE_{VRS} in rice and maize crops is 0.55 and 0.46, respectively. These numbers indicate that input levels could decrease 45% for rice and 54% for maize with the present levels of output. This result suggests continuing to improve the management of annual crop production and cultivation methods for farmers. In terms of the scale efficiency score, most rice and maize crops are producing under increasing return to scale. This score indicates that farm scales are mostly “too small”. Therefore, co-operation in cultivation, crop diversity and the optimal use of rice plots are several suggestions for optimal farm production.

In the second step, a Tobit regression is used to explain variations in efficiencies among farms. The results indicate that a national electricity source is an important factor to improve the technical efficiency of both rice and maize farms. Thus, expanding a national electricity source is an important strategy for the government in the near future to increase social welfare.

Large families are likely to be more technically efficient on maize farms. Because maize farms are mostly cultivated through human power, more people will be helpful. Therefore, motors and tractors are insignificant in both efficiencies of both types of farms. An undesirable credit factor is found to have a negative impact on the technical efficiency of maize farms; the distance to the nearest market has a negative effect on the scale efficiency of both rice and maize crops. These factors may come from outdated customs, low education and farmers’ life behavior. Therefore, policies for adjusting customs, knowledge and credit in appropriate ways should be emphasized. Extension services are considered to continue enhancement because they have a positive effect on the scale efficiency of rice crops and the technical efficiency of maize crops.

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