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Impacts of Off-Farm Income on Technical Efficiency of Rice Farming: Correction to Bias

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Abstract

Most of Indonesia's rice farming households are small-scale, with farming income equivalent to below the poverty line. Sources of income from outside the farm can be a complement to the low income obtained from farming. The purpose of the study was to analyze the effect of off-farm income on the technical efficiency of rice farming. This study employed secondary data and analyzed using the stochastic production frontier model, with corrections for the bias associated with the observed and unobserved variables first. This study showed that the education level of the head of the household had a significant positive effect on the opportunity to obtain off-farm income. Land area and fertilizer have a significant effect on increasing rice farming production. Rice farming in the household group without off-farm income has a relatively higher level of technical efficiency than the household group with off-farm income. Therefore, government policies regarding farmers' access to land and fertilizers are needed to increase rice production. Opportunities for farm households to obtain off-farm income will be even greater if policies enable them to obtain a better education.

Keywords: *Propensity Score Matching; Rice Farming; Selectivity-Corrected Stochastic Production Frontiers; Unobserved Variable.*
JEL Classification: O13; O47; Q12

INTRODUCTION

Based on the 2018 inter-census agricultural survey (Sutas) results, 48% of farming households cultivate rice as their main source of income. Most of the farming households in Indonesia can be categorized as a smallholder, with a farm area of fewer than 0.5 hectares. With paddy fields of less than 0.5 hectares, farmer households will only earn an on-farm income equivalent to below the World Bank poverty line, which is 1.9 USD per capita/day (Susilowati and Maulana, 2012).

Apart from limited on-farm income sources for small farmer households, their asset ownership is generally limited. With limited assets, working capital needs for farming are difficult to obtain from commercial bank sources, considering that commercial bank credit requires collateral. Pfeiffer, Alejandro, and Taylor (2009), as well as Nguyen and Kondo (2020), state that in situations where there are problems with access to credit in rural areas, part of off-farm income can be used to buy production inputs to improve farm productivity and efficiency.

There are many studies on the technical efficiency of small-scale farming in developing countries (Ainembabazi et al. 2017; Anang et al. 2016; Beyene et al. 2020; Hakim et al. 2020). However these various studies do not explicitly account for possible selectivity biases due to observed and unobserved variables in the model. The presence of selectivity bias in the analysis of technical efficiency cannot be ignored as it can lead to biases in the relative range of parameters of the stochastic model of the production frontier and the technical efficiencies obtained (Villano et al. 2015).

In natural sciences research, intervention effects can be obtained by controlling other variables in the laboratory setting. To estimate the impact of an intervention, such as technology or government policy on the farm's technical efficiency, there is a potential bias associated with the observed and unobserved variables (Bravo-Ureta et al., 2012). Correction of bias caused by observed variables is generally done by ensuring that the treated group or beneficiaries group has the same characteristics, in terms of observed variables, as the control group or non-beneficiaries group. After it is confirmed that the two groups to be compared have similar characteristics, a comparison of the level of technical efficiency between them is carried out. Comparing two groups of farmers who are similar in the observed variables will ensure that if there is a difference in the value of the two groups' technical efficiency, it is a result of the adoption of a technology or intervention and not because of differences in the observed variables. Comparing two groups of farmers who are not similar will potentially produce biased results. The propensity score matching (PSM) method is often used to consider the bias that comes from the observed variables (Zhang et al., 2020; Wossen et al., 2017).

Furthermore, biased results can also be caused by unobserved variables that arise from the relationship of unobserved characteristics in the two groups compared to noise in the stochastic production frontier equation. If this relationship is not taken into account, it can lead to bias, known as unobserved variables bias (Bravo-Ureta et al., 2012). The stochastic production frontier sample selection technique introduced by Greene (2010) is a technique to correct the bias associated with unobserved variables.

Many studies have been carried out on the impact of technology adoption or intervention on technical efficiency by correcting the bias associated with observed variables (for example, by Oduol et al., 2011; Asante, Villano, and Battese, 2014; Abdulai, Zakariah, and Donkoh, 2018; Priscilla and Chauhan, 2019). However, studies of the adoption impact of a technology or intervention on the technical efficiency of farming by correcting the bias of observed and unobserved variables simultaneously have not been done. There are different studies between Bravo-Ureta et al. (2012) the impact of the MARENA program on Honduran technical competence González-Flores et al. (2014) examining the impact of high-value technology markets in the Ecuadorian Sierra; Lowe and Tamini (2019) examine tenure security and farm efficiency in Benin; Oragonju et al. (2021) who investigated the effect of cooperative cultivation on the technical efficiency of maize production in Nigeria; and the study of Azumah et al. (2019) on sample selection correction realized from a stochastic analysis of a frontier rice farmer in northern Ghana.

Both observed and unobserved variables may also bias the effect of non-farm income on agricultural technology efficiency. Ahmed and Malesi (2018) examined the impact of non-farm income on the efficiency of agricultural technology by correcting for biases associated with observed and unobserved variables. Efficiency of Maize Producers in Eastern Ethiopia. However as far as the authors know this has not been found in the case of Indonesia. Based on the above explanation the purpose of this study is to analyze the effect of non-farm income on the technical efficiency of rice cultivation in Indonesia and to correct the bias associated with observed and unobserved variables.

Ahmed and Melesse (2018) research used primary data with a sampling design formulated specifically to answer the research problems. Of course, in formulating the sampling design and data collection methods, they had planned to minimize the possible bias, as suggested by Duflo, Glennerster, and Kremer (2007). Meanwhile, this research used secondary data whose research design and sampling design were not intended to answer specific research problems. The possibility of the presence of selection bias problems is getting bigger with the use of secondary data, so the results of this study are expected to have an important contribution to research on the stochastic production frontier model in Indonesia. Policies to increase agricultural production need to be strengthened by empirical evidence, generally, the policies made have the potential to cause bias. Because efforts to increase production and productivity generally pay less attention to technical efficiency, especially in rice plants (Rada et al, 2011). This potential bias occurs, especially in policies to provide input subsidies that will be used by farmers (Minviel and Latruffe, 2017; Mango, 2015), thus information and knowledge about technical efficiency are very useful for policymakers in increasing agricultural production in aggregate and useful for public policy to improve income distribution.

METHOD

Estimation Strategy and Econometric Models

Analysis of the impact of the program on technical efficiency (TE), by directly comparing the TE score between the program participants (treatment) and non-participants (control) groups, there is a potential for biased observed variables and biased unobserved variables (Bravo-Ureta et al., 2012; Greene, 2010). To measure the effect of off-farm income on the technical efficiency of rice farming in this research, we corrected the bias of observed variables and the bias of unobserved variables. Following Bravo-Ureta et al. (2012) and Chen et al. (2022), we use a propensity score matching (PSM) approach to correct for biases from observed variables. Furthermore, we use selectivity-corrected stochastic production frontier (SC-SPF) models to correct bias for unobserved variables.

Propensity score matching

The effect of off-farm income on the TE in this study is non-experimental, so there is the potential for confounding problems. Where TE is not only influenced by off-farm income but also influenced by other explanatory variables (observed variables). PSM can solve the confounding problem. PSM is a method to form a control group (without off-farm income) that has a distribution of observed variables as close as possible to the distribution in the treatment group (with off-farm income). So that each farmer in the treatment group has the best comparison in the control group, based on the similarity in the observed variables (Khandker et al., 2010). The similarity is shown by the smallest difference in propensity score (PS), where PS describes the probability of farmers having off-farm income sources based on the observed variables (Grotta and Bellocco, 2014; Khandker et al., 2010; Sianesi, 2001). To generate the propensity score (PS) for each farmer through PSM, we used a probit binary choice model. Where, the PS value describes the probability that farmers have off-farm income sources, based on observed variables (Khandker et al., 2010). Furthermore, to obtain a control group whose characteristics are as similar as possible to the treatment group, we followed Baglan et al. (2020a), which use the "one-to-one nearest neighbor matching without replacement" technique, which is estimated through the PSMATCH2-STATA Package (Leuven and Sianesi, 2003). This technique is used because it is relatively easy to apply and has an intuitive interpretation (Rosenbaum and Rubin, 1983; Baglan et al., 2020a). Through this technique, each farmer in the treatment group will have a matched partner with a farmer in the control group, and farmers who do not meet the common support conditions are discarded and not used in the analysis. The final result of the process is a matched sample.

Assuming that the bias associated with unobserved variables has been corrected, the effect of off-farm income on the TE can be calculated directly through the average treatment effect on the treated (Bravo-Ureta et al., 2020; Vilano et al., 2015) as:

$$ATET = E(Y_1|D = 1) - E(Y_0|D = 0). \quad [1]$$

Where, Y_1 and Y_0 respectively are the average TE values for the treated and control groups, while D is the dummy variable equal to 1 for treated units (Khandker et al. 2010).

Selectivity-Corrected Stochastic Production Frontier Models

The technical efficiency score (TE score) of a farm can be calculated through a stochastic production frontier (SPF) approach, as introduced by Aigner et al. (1977). The TE score is calculated by separating the error term into the inefficiency term and statistical noise. However, the conventional prediction of the treatment effect on the TE score through SPF models has the potential to bias unobserved variables (Bravo-Ureta et al., 2012; Lawin and Tamini, 2018). The selectivity-corrected stochastic production frontier (SC-SPF) models introduced by Greene (2010) are aimed at reducing the bias associated with these unobserved variables. SC-SPF models are expressed in the following two equations (Greene, 2010):

bracketselection models: $d_i = 1[\alpha' z_i + w_i > 0], \quad w_i \sim N[0,1]$ [2]

SPF models: $y_i = \beta' x_i + \varepsilon_i$ [3]

Error structure:

$$\varepsilon_i = v_i + u_i$$
$$u_i = \sigma_u |U_i| \text{ with } U_i \sim N[0,1]$$
$$v_i = \sigma_v V_i \text{ with } V_i \sim N[0,1]$$
$$(v_i, w_i) \sim \text{ normal bivariate } [(0,1), (1, \rho\sigma_v, \sigma_v^2)].$$

There is a potential relationship between the unobserved characteristics (error term,w_i) in equation (2), and noise (v_i) in equation (3). Ignoring the relationship w_i

and v_i in the prediction of the TE score of the treatment group and the control group will lead to bias unobserved variables (Greene, 2010). The structure and estimation of the SPF sample selection model in detail can be seen in Greene (2010).

Following Greene (2010), for equation (1) we use the probit binary choice model. Where, d is equal to 1 for farmers with off-farm income (treatment group) and 0 if without off-farm income (control group), notation α is the parameters to be estimated, and z is the vector of explanatory variables.

Meanwhile, for equation (2) we use the Cobb-Douglas production function approach. Based on a survey of the production function used in various major research studies in agriculture, the Cobb-Douglas production function was generally chosen (Ahmad and Bravo-Ureta, 1996; Coelli and Battese, 1996; Meeusen and van Den Broeck, 1977; Mwangi, Ndirangu, and Isaboke, 2020; Tabe-Ojong Jr and Molua, 2017). Various properties that are considered superior in the Cobb-Douglas model are why this model is widely employed as a model of the production function used. The Cobb-Douglas model is especially advantageous compared to the Translog model when some observations are dropped according to the PSM procedure because they belong to the off-support category. The Cobb-Douglas model does require relatively few degrees of freedom compared to the requirement of the Translog model. The Cobb-Douglas model is also relatively free from the phenomena of multicollinearity and heteroscedasticity. The only drawback of Cobb-Douglas is that it is more restrictive than the flexible Translog model. For example, the Cobb-Douglas model requires all regression coefficients to be positive because the Cobb Douglas function cannot be maximized. Whereas an input variable may have been saturated, it must be reduced to increase production. In addition, another requirement is that the sum of all that e powers of the variables must be equal to one to meet the requirements of constant return to scale. The Cobb-Douglas SPF models are formulated as:

$$ln\, Y_i = \beta_0 + \sum \beta_j \, ln\, X_{ij} + v_i - u_i \qquad [4]$$

Where, β_0 and β_j are parameters to be estimated, ln is the natural logarithm, y is the output, x is a vector of inputs in the production frontier. The definition of output and input variables of pthe roduction function, as well as vthe ector z can be seen in Table 1. To estimate the coefficients of SC-SPF models, we used LIMDEP 11 (Greene, 2016). The coefficients of the SC-SPF models were estimated based on the matched sample so that the TE score obtained was corrected for biased observed and unobserved variables. Furthermore, as a comparison, we used conventional-SPF separated models based on unmatched samples.

Data and Descriptive Statistics

In general, exogenous variables that affect with/without off-farm income in the sample selection equation (2) employed are the socio-economic characteristics of farmers' households and the frequency of planting rice in a year (Ahmed and Melesse, 2018; Edet, Efiong and Okeke, 2021; Bhatta and Årethun, 2013). Meanwhile, the independent variable in the SPF equation (3) is the use of production inputs (Ahmed and Melesse, 2018; Olagunju et al., 2021). The definitions of the variables in this study, both used in PSM (Probit models) and SC-SPF models, are presented in Table 1.

Table 1. Definition of research variables used in the PSM and SC-SPF models

Variables	**Definition**
Output and input production $\{y, x\}$:	
y	Paddy production (Ton)
x (vector of production input):	
X1	Planted area (Hectare)
X2	Cost of labor (IDR. 000)
X3	Cost of seed (IDR. 000)
X4	Cost of fertilizer (IDR. 000)
X5	Cost of pesticides (IDR. 000)
Probit models $\{d, z\}$:	
d	An off-farm income dummy variable (1 if with off-farm income, 0 if without off-farm income). Off-farm income comes from the income of household members who work as agricultural laborers, non-agricultural workers, and entrepreneurs.
z (vector of explanatory variables):	
Z1	Non-labor income (such as, from leasing assets, government/other transfers, apart from income as foreign worker TKI/TKW) (IDR.000)
Z2	Age of household head (year)
Z3	Formal education of household head (year),
Z4	Gender of household head (1 if male, 0 if female)
Z5	Number of household members aged < 15 years (person)
Z6	The existence of household members as members of farmer groups (1 if existence, 0 if in existence)
Z7	The existence of migrating household members (1 if existence, 0 if in existence)
Z8	Planting intensity of rice plants in a year (1 if 3 times in a year, 0 if less than 3 times in a year)

The data used in this study are from a survey of farming households conducted in 2016 by the Research and Development Directorate of the Center for Social Economic and Agricultural Policies (PSE-KP) of the Indonesian Ministry of Agriculture. The sample size of the survey was 408. Farmers' families consider rice their main commodity. The sample data is a random sample from 14 rice-irrigated villages in 14 local rice production centers in Indonesia. The total sample consists of 246 households and 162 households with non-agricultural (off-farm) income.

Table 2 shows that farm households with off-farm income cultivate land with a smaller area than households without off-farm income, characterized by lower production volumes and less use of production inputs. This study found no significant difference in non-labor income between the two households, which also means that the income from off-farm was used to cover the lack of income derived from the rice farm. This result was reinforced because households with farm income tend to have a female head of household. Households with off-farm income also have more family members who migrate. In other words, off-farm income was obtained from household members who work outside their area.

Table 2. Descriptive statistics of research variables based on the unmatched sample

Variables	With off-farm income		Without off-farm income		P-value [a)]
	Mean	StDev	Mean	StDev	
Output and input production:					
Paddy production	5.949	4.950	7.184	6.276	0.028**
Planted area	0.439	0.363	0.532	0.487	0.028**
Cost of labor	4,969.238	4,201.349	5,696.264	5,644.975	0.137
Cost of seeds	369.037	316.495	367.049	403.140	0.956
Cost of fertilizer	1,504.529	1,243.566	1,790.316	1,749.223	0.055*
Cost of pesticides	1,079.693	1,230.082	1,467.985	1,883.294	0.012**
Explanatory variables:					
Non-labor income	1,253.770	5,766.054	986.136	4,168.697	0.611
Age of household head	53.000	9.252	54.827	9.912	0.058**
Education of household head	8.301	4.185	6.358	4.073	0.000***
Gender household head	0.951	0.216	0.975	0.156	0.221
Number of household members aged <15 years	0.980	0.910	0.728	0.856	0.006**
Existence of household members as members of farmer groups	0.565	0.497	0.494	0.502	0.159
Existence of migrating household members	0.492	0.501	0.142	0.350	0.000***
Planting intensity	0.325	0.469	0.302	0.461	0.630
Number of observations	**246**		**162**		

Note: [a)] Probability two-sample t-test of the means
*** Significant at 1%, ** Significant at 5%, * Significant at 10%.

RESULTS AND DISCUSSION

Determinants Affecting Off-Farm Income

Table 3 presents the estimation results of the probit models, namely the determinants that affect farmers working in off-farm activities, using unmatched data of households with and without off-farm income. The independent variables used in the determinant model of off-farm income together significantly affected off-farm income. This is indicated by the chi-square value, which is statistically significant at the 1% level.

Table 3. Determinant of off-farm income through probit models based on unmatched data

Variables	Coefficient	Std Dev	P-value
Constant	-0.277	0.629	0.660
Non-labor income	0.000	0.000	0.918
Age of household head	-0.002	0.008	0.833
Education of household head	0.669***	0.018	0.000
Gender of household head	-0.461	0.389	0.237
Number of a household member aged <15 years	0.181**	0.084	0.032
Existence of household members as members of farmer group	0.142	0.139	0.307
Existence of migrating household members	1.078***	0.152	0.000
Planting intensity	0.036	0.150	0.811
McFadden Pseudo R-square	0.156		
Log-likelihood function	-231.346		
Chi-square test statistic (degree of freedom=8)	85.497***		
Number of Observation	408		

Note: *** significant at 1 % level, ** significant at 5 % level, * significant at 10 % level.

The education level of the head of the household had a positive and significant effect on the household's opportunity to earn off-farm income. A study by Anang and Yeboah (2019) found that education is an important variable in determining non-agricultural employment in smallholder rice farming in northern Ghana. Households have more access to information and off-site employment opportunities as more educated household heads. Off-farm jobs generally require different skills than farm jobs. Higher education creates opportunities for farmers to earn off-time income.

The number of household members aged below 15 years had a positive effect on off-farm income. In rural and agricultural areas, household members under the age of 15 can generally do certain jobs in farming. This assistance for workers under 15 years is probably to help free up some workers over 15 years old to work in the off-farm sector. This was also reinforced by the variable number of household members who migrate, which positively and significantly affects the household's off-farm income. Referring to the small farmland area in Table 2, it seems that excess labor in the household, which cannot be absorbed by work in farming, is one of the reasons for family members to migrate and look for work in the off-farm sector.

Parameter Estimates for SC-SPF

To obtain a control group whose characteristics are as similar as possible to the treated group, we used the PSMATCH2-STATA Package (Leuven and Sianesi, 2003) with a probit binary choice model to generate the propensity score (PS), and "one-to-one nearest neighbor. matching without replacement" to get a control group that is matched with the treated group. From this process, 84 farmers in the treated group had to be dropped from the analysis because their PS values were outside the common support range. Thus, the treated group and control group each amounted to 162 farmer households, bringing a total of 324 farmer households as the matched data sample.

Table 4 presents the balance of matching covariates for farmer households for the matched sample, from PSTEST results after PSMATCH2 via probit and "one-to-one nearest neighbor matching without replacement". Table 4 shows the mean difference between farm groups with and without non-farm income for each explanatory variable in the matched sample except for two variables (i.e. primary household education and mobile household members) indicating that they are generally not significant. This shows that the quality of matching is good enough.

Table 4. Balance of matching covariates for farmer households for the matched sample

Matching covariates	Mean		Bias (%)	t-test	
	With off-farm income	Without off-farm income		t-statistics	P-value
Non-labor income	1531.5	986.14	9.5	0.86	0.393
Age of household head	53.142	54.827	-17.2	-1.55	0.123
Education of household head	7.673	6.358	31.7	2.85	0.005***
Gender household head	0.981	0.975	4.2	0.38	0.703
Number of a household member aged <15 years	0.889	0.728	18.2	1.64	0.102
Existence of household members as members of farmer groups	0.537	0.494	8.6	0.78	0.438
Existence of migrating household members	0.235	0.142	23.8	2.14	0.033**
Planting intensity	0.278	0.302	-5.4	-0.49	0.626
Number of observations		**162**		**162**	

Note: *** Significant at 1%, ** Significant at 5%, * Significant at 10%.

Table 5 presents the estimation results of the conventional SPF model for separate two group of data with unmatched data or without bias correction, and the SC-SPF models with matched data or corrected for bias observed and unobserved variables. The Gamma value (γ) estimated by the two SPF models, both for the group with off-farm income and the group without off-farm income, was not statistically significant. Gamma values (γ) for the group with off-farm income and the group without off-farm income in the conventional SPF model are 0.799 and 0.606, respectively, which means that 79.9 and 60.6 percent of the variability of rice farming output was related to the technical efficiency of agricultural production technology, while the rest is due to random noise. This Gamma (γ) value in the conventional-SPF model was slightly higher than the value obtained from the SC-SPF model based on matched data. The estimated values of log likelihood show that the SC-SPF model has a goodness of fit better than conventional-SPF models.

Table 5. Estimated parameters of conventional-SPF separated models and SC-SPF models

Variables	Conventional-SPF based on an unmatched sample		SC-SPF based on a matched sample	
	With off-farm income	Without off-farm income	With off-farm income	Without off-farm income
Constant	-0.920***	-1.645***	-0.066	-1.635***
	(0.354)	(0.506)	(0.469)	(0.632)
Planted area	0.569***	0.534***	0.678***	0.540***
	(0.045)	(0.060)	(0.057)	(0.075)
Cost of labor	0.035	0.240***	-0.004	0.233***
	(0.037)	(0.047)	(0.052)	(0.055)
Cost of seeds	0.005	0.065*	0.0003	0.061
	(0.008)	(0.038)	(0.015)	(0.040)
Cost of fertilizer	0.422***	0.202***	0.385***	0.209***
	(0.038)	(0.053)	(0.053)	(0.058)
Cost of pesticides	0.003	0.031	-0.030	0.029
	(0.013)	(0.033)	(0.041)	(0.038)
Log Likelihood	-24.547	-26.149	-111.455	-134.798
Gamma	0.799	0.606	0.817	0.594
Lambda (λ)	1.993	1.242	2.115	1.210
σ	0.389	0.364	0.399	0.368
σ_u	0.348	0.284	0.361	0.284
σ_v	0.174	0.229	0.171	0.234
Selectivity bias	-	-	0.550	0.205
(Rho(w, v))			(0.614)	(0.478)
Observations	246	162	162	162

Notes: Parentheses are the standard errors.
*** Significant at 1%, ** significant at 5%, * significant at 10%.

The results showed that all the various household rice farming inputs without off-farm income significantly affected the amount of output produced compared to households with off-farm income. Planted areas and fertilizer inputs have an important role in increasing production in both household groups. These two inputs significantly affect the level of rice production, both in the conventional-SPF model and in the SC-SPF model. The significance of the planted area in determining the increase in rice farming production was also obtained in the research of Azumah et al. (2019) in Northern Ghana and Rahman (2011) in Bangladesh. In the group of household rice farming without off-farm income in the SPF sample selection model, labor also has a positive and significant impact on increasing rice production, but not in households with off-farm income. This reinforces why households with off-farm income tend to have more migrating household members. The opportunity cost of migrating household members become lower in term of its impact on rice farming productivity. In other words, all of the input variables for rice farming without off-farm income in the conventional-SPF model based on unmatched data have a positive and significant impact on increasing rice production, except the cost of pesticides variable. Meanwhile, for rice farming with off-farm income, there are two input variables, namely labor and seed, that do not have a significant impact on increasing rice production.

Impacts of Off-farm Income on Technical Efficiency

The results of calculating the TE score using the conventional SPF discrete technology model are presented in Table 6. Table 6 shows a comparison of the frequency distribution of TE as well as a comparison of the average TE between groups of households with non-agricultural income. and the group of households with no non-agricultural income either through the traditional SPF model with mismatched data or through the SC-SPF model based on matched data. The results of this study show that the average difference in technical efficiency of rice farming in the SC-SPF model is greater than that using the conventional SPF based on inconsistent data but the difference is not significant.

Table 6. Frequency distribution of technical efficiency score of rice farming based on conventional-SPF model

Technical efficiency score	Conventional-SPF based on unmatched data			
	With off-farm income		Without off-farm income	
	Frequency	%	Frequency	%
0 - <0.50	7	2.8	1	0.6
0.50 - <0.60	11	4.5	0	0.0
0.60 - <0.70	37	15.0	16	9.9
0.70 - <0.80	80	32.5	48	29.6
0.80 - <0.90	90	36.6	89	54.9
0.90 – 1	21	8.5	8	4.9
Total	246	100	162	100
Min TE score	0.392		0.421	
Max TE score	0.943		0.930	
StDev TE score	0.111		0.080	
Mean TE score	0.771		0.803	
Difference (mean TE score)	0.032*** [a]			

Note: *** Significant at 1%, ** significant at 5%, * significant at 10%.
[a] Difference of two-sample t-test of the means

If we compare the average cost of technical efficiency of rice cultivation between groups of households with and without agricultural (off farm) income. The efficiency level of rice cultivation is relatively high in the group of households with no external income and is consistent with the individual data or the traditional data-based models with SPF and equalized or the SC-SPF models in Table 7. The findings of this study are in line with the research results of Chang and Wen (2011). However, the findings of this study differ from the initial thought and previous studies in other countries (Ahmed and Malesse, 2018) that households with off-farm income are estimated to have a higher level of rice farming efficiency than households without off-farm income.

The income from off-farm was not necessarily able to ease the budget constraint for rice farming, in the sense that additional income from off-farm income was allocated for household consumption needs that were not met entirely by income from rice farming. Moreover, his rice farming is not necessarily fully dedicated to the market but partly to the subsistence needs of his household. The research on farming in 9 developing countries published by FAO shows that there is still a subsistence nature of farming, both in terms of the aspect of the production output produced and the subsistence of the input aspect used (Rapsomanikis, 2015).

Table 7. Frequency distribution of technical efficiency score of rice farming based on SC-SPF model.

Technical efficiency score	Conventional-SPF based on unmatched data			
	With off-farm income		Without off-farm income	
	Frequency	%	Frequency	%
0 - <0.50	7	4.3	1	0.6
0.50 - <0.60	7	4.3	2	1.2
0.60 - <0.70	22	13.6	14	8.6
0.70 - <0.80	49	30.2	48	29.6
0.80 - <0.90	59	36.4	89	54.9
0.90 – 1	18	11.1	8	4.9
Total	162	100	162	100
Min TE score	0.344		0.481	
Max TE score	0.944		0.929	
StDev TE score	0.118		0.077	
Mean TE score	0.770		0.803	
Difference (mean TE score)	0.033*** [b)]			

Note: *** Significant at 1%, ** significant at 5%, * significant at 10%.
[b)] Difference of average treatment effect on the treated as stated in equation (1).

The average technical efficiency score difference between households with off-farm income and households without income is not much difference between the two SPF models used. The difference in technical efficiency scores between household groups using the conventional-SPF model and the SC-SPF model are 0.032 and 0.033, respectively. In other words, the conventional-SPF model that uses unmatched data tends to produce an underestimate. However, there is a very small difference in scores between those two household groups compared to the SC-SPF model based on matched data. Likewise, when using 70% as an efficiency score benchmark, it appears from this study that 17.6% of farm households are based on the conventional-SPF model and 14.95% when based on the SC-SPF model below the benchmark efficiency score.

CONCLUSION

The results of this study indicate that land area and fertilizer have an important role in increasing rice farming production in Indonesia. The smallness of the cultivated land area has made income from off-farm employment the mainstay of households to cover the lack of income obtained from rice farming. The education level of the head of the household has a significant positive effect on the opportunity of the household to obtain off-farm income. Based on the comparison of technical efficiency using the SC-SPF model with matched data, between households with off-farm income compared to households without off-farm income, it can be seen that households without off-farm income have a relatively higher level of technical efficiency.

Policy recommendations that can be proposed from this research include encouraging policies that can increase farmers' access to agricultural land and agricultural inputs, especially access to fertilizers. The availability of fertilizers during the growing season is very much needed by farmers, thus one form of increasing farmers' access to inputs is to supervise the distribution of fertilizers.

Besides that, it encourages farmers to be able to increase their land tenure, whether by utilizing agrarian policy programs or land consolidation among the farmers' land. Policies that can improve access to better education, whether in formal or informal forms, need to be implemented by the government. Non-formal education can be done by providing training related to cultivation and product processing activities (increasing added value) while increasing access to formal education, encouraging children of farmers to be able to attend formal education up to a secondary or undergraduate level so that it will improve the quality of life. opportunities for small land rice farmer households to earn income from the off-farm sector.

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