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Profit Efficiency of Rice Farmers in Cambodia

The Differences between Organic and Conventional Farming

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Abstract

This article highlights some important issues regarding the relative profit efficiency of organic and conventional farming in selected study areas of Cambodia, by estimating pool and separate profit frontiers of the two groups and accounting for the self-selection problem. We identify the relationship between the efficiency score from each frontier with farmers' characteristics. The results indicate that farmers cannot manage their rice farming effectively in larger fields and fail to optimize their labor input and costs owing to limited skills and knowledge in rice production. Organic fertilizers can help to increase farmers' rice income, while chemical fertilizers are less effective in doing so. Interestingly, being an organic farmer had no effect on farmers' income elasticity when we conducted pool frontier estimation. However, these results were rejected by an LR test that was favorable to the estimation of a separate frontier, which suggested a better efficiency score if farmers adopted organic farming. We found some significant factors influencing the efficiency score, including *education, own-tractor,* and *credit use* (negative correlation) and *selling, other farming,* and *number of poultry* (positive correlation). *Off farm* was negatively correlated with the efficiency score in organic farming, but positively correlated in matched conventional.

Keywords: profit efficiency, organic rice, conventional rice, stochastic production frontier, propensity score matching, Cambodia

1. Introduction

To help mitigate environmental problems, sustainable farming systems have existed for over half a century. Organic farming is regarded as one of the most environmentally friendly practices that can solve some environmental deterioration issues, leading many countries to adopt this farming practice. However, it is still questionable whether organic farming can be adopted on a global level, or can help to increase farmers' income. These questions remain the main concerns in the production of organic products in the developing world.

Able to produce organic rice and skeptical about the excessive use of farm chemicals, Cambodian farmers have adopted organic rice practices since 2003 (Cambodian Organic Agriculture Association [COrAA], 2011). During the first few years, Cambodian rice farmers produced organic rice with surprising success, and many organic rice cooperatives became established throughout the main rice production areas in Cambodia. However, not surprisingly, after the support from NGOs was terminated, organic rice farming diminished in scale, and many organic rice farmers reverted to conventional farming, although some studies, for example: Taing (2008), and Sa (2011), documented that organic farming could increase farmers' rice yield and profit.

Many studies about organic practice, for example: Cary and Wilkinson (1997), Musshoff and Hirschauer (2008), Sheeder and Lynne (2009) and Ponti, Rijk, and Ittersum (2012), have acknowledged that financial concerns are the main motivating factors behind the increased adoption of organic farming. Generally, organic products often obtain price premiums (Nieberg & Offermann, 2003). However, as argued by Imbens and Wooldridge (2009), the better performance of technology adopters might result from differences in their characteristics, rather than being adopters or non-adopters, implying that a selection bias exists among farmers. This could affect farmers' adoption decision and, hence, performance. To solve the selection bias problems of organic rice farming adoption in Cambodia, Khoy, Nanseki, and Chomei (2015, 2016) employed two approaches, propensity score matching and endogenous switching regression, to evaluate the impact of the adoption. Their studies suggested that Cambodian rice farmers could benefit from adopting organic rice farming in terms of rice yield and profit.

Even organic rice farming has been introduced for years; information regarding production practices is very limited. In particular, none of the studies focus on the respective efficiency of organic and conventional rice farming. Some studies, Taing (2008) and Sa (2011), have tried to directly compare the yield and profit differences between organic and conventional rice farmers, but didn't account for selection bias. Khoy et al. (2015, 2016) accounted for selection bias in their studies by applying propensity score matching and endogenous switching regression. However, their work did not describe the profit efficiency of organic and conventional farmers. Thath (2014) studied the cost efficiency of Cambodian rice farmers by comparing different rice production zones, but this study did not explicitly analyze organic rice farming. Self-selection remains the main issue although some articles have documented that the organic movement is the potential practice of profit gains compared to conventional rice production, especially for smaller farms. Some farmers could obtain higher profit when adopting organic rice farming, while many would not receive this benefit in terms of their conditional issues. Furthermore, many farmers are reluctant to begin this new practice because they believe their present farming has suited them, and they have become accustomed to it. As Khoy et al. (2016) demonstrated, Cambodian farmers adopted organic rice farming based on their comparative advantage, suggesting farmers who possessed relative advantage with organic farming adopted the new practice, and those who were suited to conventional stayed with the old practice. Hence, the detail about the relative profit efficiency between organic and conventional farmers needs to be examined.

This study aims to assess the profit efficiency of organic and conventional farmers and its' determinants by accounting for selection bias. The article highlights two important aspects of the profit efficiency of organic and conventional rice farming in Cambodia. First, pooled and separate profit frontiers between organic and conventional farmers that account for the self-selection problem were estimated. Second, the relationship between the efficiency score from each profit frontier and farmers' characteristics was identified.

2. Method

2.1 Study Site and Data Collection

This study was conducted in two provinces, Takeo and Kampot province. We purposely selected three targeted districts from two provinces, because there are organic rice cooperatives located in those districts, they border one other, and they possess similar social demographic and agro-ecosystems. The districts are Srer Cheng Organic Agriculture Development Cooperative, situated in Chum Kiri district, Kampot Province; Chhuk Organic Agriculture Development Cooperative, in Chhuk district, Kampot province; and Trapaing Sronger Agriculture Development Cooperative in Tram Kak District, Takeo Province. Random organic and conventional farmers were selected from each cooperative and district. Data was collected by face-to-face interviews for the 2013 wet season rice production. A total of 221 respondents were interviewed, of which 84 organic respondents were selected from organic cooperatives and 137 were randomly selected from conventional farmers in the same study areas. Among all respondents, 36, 21, and 27 organic farmers, and 64, 49, and 24 conventional farmers, were selected from Chum Kiri, Chhuk, and Tram Kak districts, respectively.

2.2 Analytical Framework

This article discusses some issues arising from a comparison of profit efficiency between organic and conventional rice farmers in Cambodia, by estimating both pool and separate profit frontiers using stochastic production frontiers, controlling for farmers' selection bias. We employed propensity score matching to control for farmers' observable characteristics. We then ran a regression of the efficiency score generated from each frontier with farmers' characteristics.

In microeconomic theory, the production or profit frontier explains the maximum output resulting from a set of production inputs and technology. While some inputs are decided by farmers, some are exogenously generated by fixed technology provided to farmers. This would add some constraints and/or advantages to the production performance of farmers (Mayen, Balagtas, & Alexander, 2010). In our study, organic farmers in particular adopted a set of technologies that would affect their performance. Thus, the production inputs of organic and conventional farmers may be different. To account for technology differences between organic and conventional farmers, Mayen et al. (2010) included a treatment variable (organic or conventional) to estimate the production frontier and discussed whether the correlation coefficient of the treatment variable had a positive or negative effect on farmers. We believe that estimating the production frontier separately would result in a better conclusion, as organic and conventional might be two completely different groups in terms of the allocation of production inputs. This simply means that the production inputs for the production frontiers of organic farmers may differ from those of conventional farmers (Bravo-Ureta, Greene, & Solís, 2012). We conduct a LR test proposed by Greene (2007), to confirm our assumption of a technology difference.

In addition to the technology difference issue, farmers themselves decided whether to adopt this technique or not, which resulted in selection bias among farmers. To accurately evaluate the impact of organic farming adoption and its correlated factors on profit efficiency levels, we applied a multi-step framework to account for potential selection problems in the estimation of the Stochastic Production Frontier (SPF) model. Monteiro (2010) demonstrated that in order to obtain an accurate estimation of adoption impact, we have to set a control group that has characteristics that are as similar as possible to those in the treated group. Propensity Score Matching (PSM) has become a common approach that can balance the observed characteristics of the control group to resemble those in the treated group. In other words, this approach can generate the counterfactual situation and mitigate potential selection bias associated with observable characteristics (Rosenbaum and Rubin 1983). PSM is used in some recent studies such as Bravo-Ureta, Almeida, Solís, and Inestroza (2011), Bravo-Ureta et al. (2012), Cerdán-Infantes, Maffioli, and Ubfal (2008) and Mayen et al. (2010) to access the impact of technology adoption.

For this paper, we estimated the pool and separate profit frontier by employing a SPF approach in unmatched and matched samples generated by PSM, to correct for biases from observed characteristics. We then measured and compared efficiency scores from each frontier between organic and conventional farmers, before and after matching. We firstly estimated the profit frontier of the pool unmatched sample by including an adopter variable (organic or conventional farmer) as an input variable, and we also estimated the separate profit frontiers of organic and conventional farmers. In the second step, the pool and separate profit frontiers were re-estimated by using a matched sample produced by PSM. After assessing the different profit efficiencies, we identified the relationship between the efficiency score of each frontier and farmers' social economic characteristics, by employing OLS regression.

2.3 Empirical Models

2.3.1 Stochastic Production Frontier (SPF)

The SPF framework was used to estimate profit frontiers and the profit efficiency score. This approach can deal with the stochastic nature of agricultural processes. The SPF model is written as:

$$ln y_i = \beta x_i + v_i - u_i \tag{1}$$

where y_i denotes the output (we used profit as the output), x_i (in logarithm) is a vector of the production inputs (described in table 1), β is a vector of parameters to be estimated, v_i is a two-sided stochastic term that accounts for statistical noise, and u_i is a non-negative stochastic term representing inefficiency.

We measured the efficiency score suggested by Battese and Coelli (1988). Because the output is in natural logarithmic form, the efficiency score is specified as:

$$\mathrm{TE_i} = \mathrm{y_i}/\exp^{(\beta x_i + v_i)} = \exp^{(\beta x_i + v_i - u_i)}/\exp^{(\beta x_i + v_i)} = \exp^{(-u_i)} \tag{2}$$

2.3.2 Propensity Score Matching (PSM)

PSM is a two-step procedure (Becker & Ichino, 2002). Firstly, farmers' propensity scores were determined by estimating the probability model in probit or logit, specified as:

$$Y\,(1;0) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n \tag{3}$$

where Y is a binary dependent variable (1=Organic farmer; 0=Conventional farmer), β is the regression coefficient to be estimated, and X is an independent variable to be explained (described in table 1). The propensity score of each farmer is then estimated based on the following equation:

$$P_{score} = 1/[1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n)}] \tag{4}$$

Secondly, each farmer in the organic group is matched up to a conventional farmer with similar propensity score values, by using some comparison techniques, in order to estimate the average treatment effect (ATE). Here, we adopted single nearest neighbor matching (NNM) to measure average treatment effect on treated (ATT).

2.3.3 OLS Regression

We employed OLS regression to identify the relationship between farmers' efficiency score and their characteristics, before and after the matching procedure. The OLS model is written as:

$$y_i = \beta_0 + \beta_i x_i + \varepsilon_i \tag{5}$$

where y is the dependent variable (efficiency score), x is the independent variable to be explained (described in table 1), β is the regression coefficient to be estimated, and ε is an error term.

2.4 Description of Data Variables

Table 1 describes all the variables used in each model. It shows the variable name, definition, and unit of each variable. In SPF, *rice income* regarded as profit was used as the output variable. We have used *production land, labor input, organic fertilizer, chemical fertilizer, other cost,* and a dummy *adopter* variable as production inputs in pool frontier analysis. We excluded the *adopter* variable in the separate frontier estimation. After estimating SPF, an efficiency score was estimated and used as a dependent variable in the OLS regression. We included independent variables such as *age, gender,* and *education* for farmers' characteristics; *farming labor, rice plots, rice field, selling, other farming, number of cows, number of poultry,* and *membership* for farm characteristics; and *off farm, own-tractor,* and *credit-use* for economic characteristics.

Table 1. Definitions of variables to be used in each approach

Variable	Definition	Unit
	Stochastic production frontier model	
Rice income[a]	Total rice income per hectare (excluding family labor cost)	\$/ha
Production land	Organic rice production land (for conventional: rice field size produced Phka Rumduol Rice variety)	Ha
Labor input	Total labor employed in rice production per hectare	Man-day
Organic fertilizer	Total organic fertilizer applied in rice production per hectare	Kg
Che. fertilizer	Total chemical fertilizer applied in rice production per hectare	Kg
Other cost	Total production cost excluded labor and fertilizer cost	US\$
Adopter	= 1 if farmer produces organic rice	Dummy
	OLS regression	
TE score	TE score estimated from SPF	0-1
Age	Age of household head	Years
Gender	= 1 if household head is male	Dummy
Education	Years of schooling of household head	Year
Farming labor	Number of family labors available for rice farming	Person
Rice plots	Numbers of rice plots farmers owned	Number
Rice field	Total rice field size farmers owned	Ha
Selling	= 1 if farmers sell their rice	Dummy
Other farming	= 1 if farmers have other farm activities besides rice	Dummy
No. of cows	Numbers of cows they owned	Number
No. of poultry	Numbers of poultry they raised	Number
Membership	= 1 if farmers belong to any agricultural related group	Dummy
Off farm	= 1 if farmers have off-farm job	Dummy
Own-tractor	= 1 if farmers have two-wheel tractor	Dummy
Credit-use	= 1 if farmers loan credit	Dummy
	Propensity score matching	
Adopter	= 1 if farmer produces organic rice	Dummy
Age	Age of household head	Years
Gender	= 1 if household head is male	Dummy
Education	Years of schooling of household head	Year
Farming labor	Number of family labors available for rice farming	Person
House size	The square meter of house farmers owned	M^2
Rice plots	Numbers of rice plots farmers owned	Number
Rice field	Total rice field size farmers owned	Ha

Other farming	= 1 if farmers have other farm activities besides rice	Dummy
No. of cows	Numbers of cows they owned	Number
No. of poultry	Numbers of poultry they raised	Number
Off farm	= 1 if farmers have off-farm job	Dummy
Own-tractor	= 1 if farmers have two-wheel tractor	Dummy
Credit-use	= 1 if farmers loan credit	Dummy

Note. a: Rice income = (Yield * Price) – (Fixed cost + Variable cost); Family labor cost is not included in variable cost; It was regarded as profit.

We have specified some variables to be included in PSM for balancing the characteristics between organic and conventional farmers. The balanced variables are *age, gender, education, farming labor, rice plots, rice field, selling, other farming, number of cows, number of poultry, off farm, own-tractor,* and *credit-use*. We believe that these variables potentially influence farmers' propensity to adopt organic rice farming.

3. Results and Discussions

3.1 Descriptive Results Before and After Matching

Table 2 presents the descriptive statistics and statistical significance tests of two farmer groups, before and after matching.

Table 2. Descriptive results and statistical significant test between organic and conventional farmers

	Unmatched				Matched			
	Pool	Organic	Con.		Pool	Organic	Con.	
Variable	M (221)	M (84)	M (137)	Diff.	M (121)	M (84)	M (37)	Diff.
Age	46.15	47.35	45.42	1.92	46.69	47.35	45.19	2.16
Gender	0.90	0.94	0.88	0.06	0.94	0.94	0.95	-0.01
Education	5.90	7.11	5.17	1.94***	7.00	7.11	6.76	0.35
Farming labor	2.79	2.85	2.76	0.09	2.83	2.85	2.81	0.03
House size	38.21	39.35	37.51	1.84	39.13	39.35	38.63	0.73
Rice plots	2.57	2.82	2.42	0.41***	2.73	2.82	2.51	0.31
Rice field	1.02	1.17	0.94	0.23***	1.12	1.17	1.01	0.15
Selling	0.80	0.96	0.69	0.27***	0.93	0.96	0.86	0.10**
Other farming	0.29	0.44	0.19	0.25***	0.42	0.44	0.38	0.06
No. of cows	2.60	3.12	2.28	0.83***	3.02	3.12	2.81	0.31
No. of poultry	81.41	121.74	56.68	65.06	133.98	121.74	161.76	-40.02
Membership	0.52	0.98	0.25	0.73***	0.74	0.98	0.19	0.79***
Off farm	0.21	0.26	0.18	0.08	0.26	0.26	0.27	-0.01
Own-tractor	0.19	0.25	0.15	0.10*	0.21	0.25	0.14	0.11
Credit use	0.24	0.19	0.26	-0.07	0.17	0.19	0.11	0.08
Production land	0.59	0.47	0.66	-0.19***	0.52	0.47	0.63	-0.16**
Labor input	254.50	282.70	237.21	45.49**	274.55	282.70	256.03	26.67
Org. fertilizer	1586.87	2115.29	1262.88	852.42***	2016.54	2115.29	1792.34	322.95
Che. fertilizer	83.92	0.00	135.38	-135.38	34.12	0.00	111.59	-111.59
Other cost	172.78	168.65	175.31	-6.66	162.63	168.65	148.96	19.69
Yield	2.86	3.32	2.58	0.75***	3.12	3.32	2.68	0.65***
Rice income	603.13	973.77	375.88	597.90***	827.43	973.77	495.17	478.60***

Note. *, **, *** significant at 10%, 5%, and 1% respectively; Con. is conventional; Diff. is difference; M is mean; Values in parenthesis represent the numbers of sample in each group

Before matching, many variables were statistically different between organic and conventional farmers. It indicates that the education of organic farmers was 1.94 years higher than that of conventional farmers. Organic farmers also owned statistically more numbers of rice plots, and possessed larger rice field size vis-à-vis conventional farmers. We found that 96 percent of organic farmers had sold their products, which was 27 percent higher than conventional farmers. Organic farmers also had a higher percentage of other farming activity, and raised more cows. In addition, almost all organic farmers (98 percent) belonged to some agricultural groups (*membership*) compared to only 25 percent of conventional farmers. Organic farmers also had a bigger proportion of owning tractor versus conventional. Based on unmatched results, our testing implies that organic farmers possess better characteristics vis-à-vis conventional farmers. They have higher education that could aid the adoption of new technology because they can access much information through various sources. Organic farmers possess larger farms, greater farming skills, and more machinery, favorable conditions for them to adopt organic farming.

Production inputs and outputs of organic and conventional farmers are also presented in table 2. The results from the unmatched sample show that organic farmers allocate statistically fewer hectares of their land (production land) to organic farming compared to conventional farmers for the phka rumduol rice variety. The results suggest that organic farming is more labor intensive, organic farmers employing 45.49 man-day/ha of labor input, which is significantly higher than conventional farming, because organic farmers need to employ more labor to meet organic farming requirements. Not surprisingly, organic farmers applied more organic fertilizer to their farm and obtained a significantly higher yield and income compared to conventional farmers. Nevertheless, as argued earlier, this improved performance in rice farming may be due to the better characteristics of organic farmers rather than being conducting organic farming per se. Hence, we used PSM to control for characteristic differences so as to obtain unbiased results.

After we conducted the matching approach, the difference between the two groups was minimized. For all the variables included in PSM, only the variable selling was still significant, while the other variables showed no significant difference. For variables excluded in PSM, membership, production land, yield, and rice income still showed significant differences. Surprisingly, there is no significance difference for application of organic fertilizer between the two groups, suggesting matched conventional farmers have knowledge about the advantages of organic fertilizer. The reduction in significant difference between the two groups could be because PSM minimizes the heterogeneity and the matched sample became more homogeneous in term of observed variables used in the analysis. As shown in figure 1, compared to all conventional farmers, the propensity score of matched conventional farmers is similar to that of organic farmers. This suggests that our proposed matching technique was fairly successful.

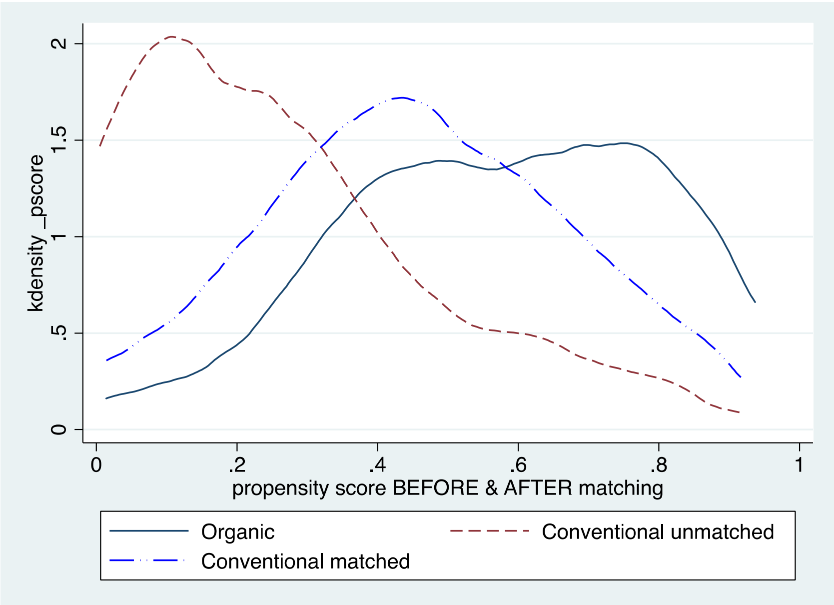

Figure 1. Kernel density of propensity score matching

3.2 Stochastic Production Frontier Results

Table 3 gives stochastic production frontier results of unmatched and matched sample. It also shows the pool and separate frontier results. For the unmatched pool sample, we found that production land, labor input, and other costs were negative and statistically significant with output, while organic fertilizer was positive and significant. A negative relationship between production land and output indicates that producing rice in a larger field size does not increase farmers' profit elasticity, as Cambodian farmers are not able to manage the large field effectively due to limited production techniques and skills. The result was consistent with Islam, Sipilainen, and Sumelius (2011) with respect to the profit efficiency of rice farmers in Bangladesh, but it was inconsistent with Kiatpathomchai (2008) who assessed the economic efficiency of rice production in Thailand, and Thath (2014) who focused on the cost efficiency of rice farming in Cambodia. Labor input and other costs were negative and significant suggesting that sample farmers failed to manage input effectively. The optimal use of labor input and cost are necessary to increase farmers' efficiency. Aung (2011) suggests a different result for rice farmers in Myanmar in the case of labor input. The results show that applying organic fertilizer helps to increase profit elasticity, as it helps to increase the yield and minimize the external input cost. Conversely, applying chemical fertilizer would decrease farmers' rice income even there was no significant correlation. This result was consistent with that of Aung (2011), but contrasted with that of Costantin, Martin, and Rivera (2009) in the case of the Brazilian grain crops. Asian Development Bank (2014) pointed out that applying both organic and inorganic fertilizer could increase rice farmers' production and value of production. As expected, compared to a conventional farmer, adopting organic practices (an adopter) could increase profit elasticity, the variable adopter having a positive and statistically significant correlation coefficient. However, this result might be due to farmers' particular characteristics rather than being organic or conventional. We will discuss this matter in more depth below in the matched results.

Table 3. Pool and separate stochastic production frontier analysis of unmatched and matched sample

Variable	Unmatched pool sample		Organic		Conventional		Matched pool sample		Matched conventional	
Log (Rice Income)	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Production land	-0.269***	0.063	-0.279***	0.098	-0.258***	0.086	-0.347***	0.077	-0.315**	0.149
Labor input	-0.368***	0.089	-0.314**	0.136	-0.449***	0.119	-0.475***	0.108	-0.711***	0.174
Organic fertilizer	0.029*	0.016	0.123**	0.060	0.025	0.018	0.099***	0.036	0.076	0.050
Chemical fertilizer	-0.009	0.045			-0.022	0.061	-0.220***	0.076	-0.174	0.162
Other cost	-0.157***	0.041	-0.076	0.051	-0.217***	0.060	-0.126***	0.050	-0.356**	0.140
Adopter	0.270***	0.086					-0.175	0.144		
Constant	3.895***	0.250	3.527***	0.329	4.246***	0.347	4.228***	0.292	5.164***	0.851
Variance of u	0.141***	0.019	0.092***	0.026	0.154***	0.027	0.078*	0.040	0.007	0.593
Variance of v	0.133***	0.012	0.104***	0.017	0.154***	0.017	0.133***	0.021	0.168***	0.032
Lambda	1.061***	0.028	0.885***	0.039	0.997***	0.038	0.583***	0.059	0.043	0.619
	N = 221		N = 84		N = 137		N = 121		N = 37	
	Chi^2 = 190.440***		Chi^2 = 21.170***		Chi^2 = 28.840***		Chi^2 = 137.730***		Chi^2 = 52.680***	
	Log like. = 56.859		Log like. = 48.299		Log like. = 18.532		Log like. = 55.298		Log like. = 13.383	

Note. *, **, *** significant at 10%, 5%, and 1% respectively; Coef. is coefficient; Std. Err. is standard error

In the separate frontier result for the unmatched sample, production land, and labor input were negative and significantly associated with rice income for both organic and conventional groups. As stated earlier in the pool analysis, this suggests that both groups of farmers cannot manage their larger sized rice farms properly and fail to allocate labor to their farms efficiently. Our results show that organic fertilizer is positively and significantly correlated with output suggesting organic substance could increase income elasticity for organic farmers. For conventional farmers, results also suggest a positive correlation between organic fertilizer and rice income and a negative relationship between chemical fertilizer and rice income, but in both cases, the correlation is not statistically significant. Hence, organic fertilizer can increase rice income for both organic and conventional farmers, while chemical fertilizer lowered conventional farmers' rice income. Other costs were negatively related with output for both groups, but it was only statistically significant for conventional farmers.

Following the matching process, we also estimated SPF in pool and separate frontiers. In pool estimation, there were surprising changes of statistical significance. Production land, labor input, and other costs showed no difference to the unmatched pool estimation in terms of sign and statistical significance of its correlation coefficient. However, organic fertilizer, and chemical fertilizer became highly significant with the same sign. This strongly suggests that organic fertilizer can help to increase farmers' rice income, while chemical fertilizer lowers their income. Interestingly, the variable adopter was negative and has no statistical significance, which suggests that organic farming had no effect on farmers' rice income. This result is consistent with (Mayen et al., 2010) who conducted tests on dairy farms in the United States. Therefore, the greater efficiency of organic farmers was most likely due to their characteristics, rather than due to conducting organic or conventional farming, when estimated in the pool frontier. These results were rejected by a LR test suggested by Greene (2007), which produced better results for the separate frontier estimation for organic and conventional farmers. We estimated a LR test based on the following equation:

$$LR = 2*[\ln L_P - (\ln L_O + \ln L_C)] \tag{6}$$

where $\ln L_P$, $\ln L_O$, and $\ln L_C$ denote the log-likelihood values obtained from the pool frontier, organic frontier, and conventional frontier, respectively, in both unmatched and matched sample. The estimated LR tests were -19.944 in the unmatched sample and -12.768 in the matched sample. This rejected the null hypothesis for the equality of the pool and separate frontier model, with 0.01 significance in both cases (unmatched and matched sample). This confirms that the production inputs included in the estimation varied across the two groups of farmers, and the negative sign of the LR test offered the indicator favorable to the separate frontier estimation. Hence, we can infer that using pool estimation for the profit frontier of organic and conventional farmers leads to overstatement of the efficiency of conventional farmers. By allowing the variable adopter in pool estimation before and after matching, we cannot accurately confirm the efficiency of both organic and conventional farmers. We will compare and discuss the farmers' level of efficiency in the next section. For the result in the matched conventional frontier, we find similar results to those in the unmatched conventional, in terms of both sign and significance of correlation coefficient.

3.3 Efficiency Score of Farmers

We present and compare the average efficiency scores of organic and conventional farmers in table 4. In pool estimation, farmers had an average efficiency score of 0.877 for the unmatched sample, and this increased to 0.928 after we matched the sample and estimated the production frontier. The increase in average score after matching suggests that the extent of poor farmers' characteristics had been reduced. The matched sample was also more homogenous. There was significant difference between organic and conventional farmers for the unmatched sample, but no significant difference in the matched sample, and matched PSM (ATT) resulted from single nearest neighbor matching. Again, this suggests that organic farming had no effect on farmers' efficiency when we estimated it in a pooled frontier.

Table 4. The estimation and comparison of efficiency score between organic and conventional farmers

Variable	Pool estimation				Separate estimation			
	All	Organic	Conventional	Diff.	All	Organic	Conventional	Diff.
Unmatched	0.877	0.891	0.869	0.022*	0.832	0.915	0.780	0.135***
Matched	0.928	0.929	0.925	0.005	0.878	0.915	0.792	0.123***
Matched PSM[a]	ATT	0.891	0.894	-0.003	ATT	0.915	0.799	0.116***

Note. *, **, *** significant at 10%, 5%, and 1% respectively; Diff. is difference; a: we estimate average treatment effect on treated (ATT) by employing single nearest neighbor matching

However, when we estimated the profit frontier differently, results indicate that, on average, farmers had a 0.832 efficiency score in the unmatched sample, lower than those in the pool estimation. In the matched sample, the average score was 0.878, which is also lower than the pool estimation. The lower average efficiency score in the separate estimation is due to the decrease in efficiency score for conventional farmers. In Contrast to pool frontier estimation, there is a highly significant difference between organic and conventional farmers in the unmatched sample, matched sample, and matched PSM. The highly significant difference even in the matched sample and matched PSM suggest that organic farming would help to increase farmers' profit efficiency when we estimate in a separate frontier. When two groups were estimating in the pool frontier, the efficiency score of conventional farmers increased, leading to no significant difference between the two groups. This was because organic farmers allocated higher production inputs to their smaller production land, while conventional farmers allocated lower inputs to their larger field. On the other hand, estimating the separate frontier allowed us to calculate efficiency scores for conventional farmers accurately, because the score of all conventional farmers was estimated for their most efficient farm. Eventually, after conducting a LR test, we could obtain better results in the separate frontier.

3.4 Determinants of Profit Efficiency Score

In this section, we will explain how farmers' characteristic affects their efficiency score. The relationship between efficiency score and farmers' characteristics was shown in table 5. All the results of efficiency score estimated from the unmatched pool sample, unmatched separate frontier (organic and unmatched conventional), matched pool sample, and matched conventional, were used as the dependent variable regressed with some independent variables.

Table 5. Relationships between efficiency score and farmers' characteristics by OLS regression estimation

	Unmatched pool sample		Organic		Conventional		Matched pool sample		Matched conventional	
Variable	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Age	0.001	0.001	0.000	0.001	0.000	0.001	0.000	0.000	-0.001	0.003
Gender	0.024	0.020	0.010	0.028	0.006	0.036	0.004	0.015	-0.152	0.108
Education	-0.004**	0.002	-0.001	0.002	-0.009**	0.004	-0.002	0.001	-0.016**	0.007
Farming labor	0.004	0.006	0.005	0.006	0.017	0.014	0.003	0.003	0.020	0.029
Rice plots	0.009	0.007	-0.007	0.007	0.016	0.015	-0.004	0.004	0.003	0.031
Rice field	0.003	0.013	0.011	0.014	0.002	0.027	0.009	0.007	0.013	0.043
Selling	0.060***	0.016	0.056	0.038	0.095***	0.029	0.026*	0.014	0.028	0.064
Other farming	0.026*	0.014	0.019	0.016	0.037	0.031	0.018**	0.008	-0.006	0.050
No. of cows	0.000	0.005	-0.002	0.005	-0.011	0.011	0.000	0.003	-0.017	0.019
No. of poultry	0.000	0.000	0.000	0.000	0.000**	0.000	0.000	0.000	0.000**	0.000
Membership	0.010	0.013	0.017	0.045	0.024	0.034	0.007	0.008	0.074	0.069
Off farm	-0.022	0.014	-0.030*	0.016	0.012	0.030	-0.009	0.008	0.173***	0.052
Own-tractor	0.000	0.016	-0.035**	0.016	0.032	0.038	-0.016*	0.009	0.037	0.067
Credit use	-0.026*	0.015	-0.032*	0.018	-0.034	0.034	-0.011	0.010	0.037	0.087
Constant	0.766***	0.036	0.842***	0.061	0.697***	0.069	0.890***	0.024	0.987***	0.163

Note. *, **, *** significant at 10%, 5%, and 1% respectively; Coef. is coefficient; Std. Err. is standard error

Our results showed that education was negatively correlated with efficiency score in the unmatched pool sample, with the conventional and matched conventional indicating that farmers with higher educational levels obtain a lower efficiency score. Generally, more educated farmers often had other jobs, in addition to their farming activity, that could result in a lower efficiency score. This was consistent with Thath (2014), but inconsistent with Aung (2011).

The category of selling was positively associated with the efficiency score in the unmatched pool sample, organic unmatched conventional, and matched pool sample. This suggests business oriented farmers may increase efficiency due to their motivation in gaining profit from rice production. Other farming was positively associated with the efficiency score in the unmatched and matched pool sample, indicating that farmers with other farming activity may be more accessible to organic resources, and have higher skill and knowledge levels in farming activities. Number of poultry was positively correlated with efficiency score in organic, conventional and matched conventional. This was because farmers who raised more poultry may have an additional organic resource to their farm, and had greater knowledge of farming.

Off farm is negatively correlated with efficiency score in organic, but positively associated with efficiency score in matched conventional. Organic farmers with off farm jobs may focus more on their off farm job rather than rice farming, which would result in poor management in farming practice. However, matched conventional was found to be more efficient when they have an off farm job. This suggests that, in the matched conventional sample, those farmers with an off farm job were able to manage their business activities more effectively. Own-tractor is negatively associated with efficiency score in the organic and matched pool sample. With a tractor, farmers may increase their production cost if it helped to increase productivity and intensity of adoption of organic farming. Credit use is negatively associated with efficiency score in the unmatched pool sample and the organic sample. It is often associated with poorer farmers who have easy access to credit funding, and as a result, would get lower performance in farming.

4. Conclusions and Implication

This study contributes some important findings regarding the relative profit efficiency of organic and conventional farming, by highlighting pool and separate profit frontiers between organic and conventional farmers, accounting for the self-selection problem, and identifying the relationship between efficiency score from each profit frontier and farmers' characteristics.

Our results show that organic farmers possess better characteristics versus conventional farmers. This necessitated we control for those differences to access an accurate estimate for the profit efficiency of both groups. After we conducted the matching approach, the difference between the two groups was minimized, indicating that our proposed matching technique was fairly successful.

The tests of the stochastic production frontier indicate that farmers cannot manage their rice farming effectively if they produce in a larger field owing to their limited skills and knowledge in rice production. In addition, with higher labor input and other input costs, farmers have lower income elasticity, suggesting farmers have little knowledge in the optimization of their farm inputs. Organic fertilizer helps to increase farmers' rice income for both groups, while chemical fertilizer was found to be less effective in doing so. Furthermore, being an organic farmer would result in higher rice income in the unmatched pool sample, but it had no effect after matching. However, these results were rejected by a LR test that was favorable to the separate frontier estimation.

In comparing efficiency scores of pool estimation, average efficiency score had increased from 0.877 for the unmatched sample to 0.928 for the matched sample. There was significant difference between organic and conventional farmers for the unmatched sample, but no significant difference in the matched sample and matched PSM (ATT), suggesting that organic farming had no effect on farmers' efficiency. In contrast, the organic group had a higher efficiency score compared to those in conventional, for both unmatched sample, matched sample and matched PSM, suggesting that organic farming helps to increase farmers' profit efficiency when we estimate the profit frontier separately. We believe that estimating a separate frontier allowed us to calculate the efficiency score for conventional farmers accurately, as the production practice was different across the two groups, this being confirmed by the LR test.

We found some factors significantly influence farmers' efficiency score. Education, own-tractor, and credit use are negatively correlated with efficiency score. While selling, other farming, and number of poultry are positively correlated with efficiency score. Off farm is negatively correlated with efficiency score in organic, but positively correlated with efficiency score in matched conventional.

From this study we would suggest all relevant organizations should introduce an effective technique that would help farmers to manage their rice farming on a larger scale, and allocate their labor input and cost more efficiently, by encouraging farmers to further apply organic fertilizer, raise more livestock, and engage with other cropping systems. Farmers should be supported to commercialize themselves to get benefit from rice production, by encouraging them to grow either market demand variety or organic rice, together with mixed farming systems, which is more sustainable to increase their profit efficiency.

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