Technical Efficiency of Thai Jasmine Rice Farmers: Comparing Price Support Program Participants and Non-Participants

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Abstract

The rice price support program (PSP) in Thailand is designed to support rice prices and raise incomes of rice farmers. However, it has been argued that the program only attracts participation from certain types of farmers, in particular larger and more efficient farmers with higher farm incomes. This raises the question of whether there is a difference in the technical efficiency of program participants and non-participants. This paper investigates two issues: (a) what are the key determinants of farmers' decision to participate in the PSP? and (b) do program participants and non-participants use different rice production technologies and have different levels of technical efficiency. We take a stochastic frontier approach to answering these questions but because farmers self-select into the PSP the standard stochastic frontier model may lead to biased estimation. In response we augment the standard stochastic frontier model with a participation equation explaining the decision to participate in the PSP, and then use Heckman's two-step estimation and Greene's sample selection stochastic production frontier model to explore levels of technical efficiency among participants and non-participants. Results indicate that the participation decision is governed by key factors that include land size and the financial position of the farm. Results also show there is no strong evidence to support the presence of selectivity bias in the stochastic frontier estimates. In addition, a likelihood-ratio test indicates that participants and non-participants use the same frontier production technology. The analysis of technical efficiency reveals that participants are more technically efficient than non-participants. The findings therefore suggest that larger farmers participate more in the PSP and that these program participants tend to be more technically efficient farmers.

KEYWORDS: Selectivity bias, technical efficiency, stochastic production frontier, jasmine rice, Thailand, price support program

INTRODUCTION

In Thailand, the rice price support program (PSP) continues to be used to support rice prices and raise farm incomes. Under the PSP, farmers are allowed to sell their paddy rice to the Government at the support price, which is administratively determined. Then farmers are given four months to redeem the pledged paddy (reject the Government offer and sell their rice on the open market), otherwise they will have to deliver the paddy to the Government and receive the support price. The primary objective of the program has turned from an initial focus on stabilizing rice prices to raising farm incomes as, over time, the support price has been raised more and more relative to the market price. As a result, Thailand has witnessed an enormous increase in rice production from 27.16 million tons in 2001 to 37.43 million tons in 2012.

Some policymakers have questioned the effectiveness of the PSP. In particular, it has been argued that large-scale commercialized farmers are the major recipients of the benefits while small-scale farm households tend to have been left out (Poapongsakorn and Charupong, 2010).This raises two important questions. First, what factors influence farmer decisions to participate in the PSP? Second, are there differences in the rice production technology being used and the level of technical efficiency among program participants and non-participants? The decision to participate will be governed by the size of the support price relative to the market prices but other individual farm characteristics such as size and financial position may also influence the costs of participation for individual farms. For example, farmers who deliver rice to the Government typically have to wait extra time to receive payment and the size, scope, and financial position of the farm may influence their ability to accept delayed payment. The PSP may also attract new farmers and marginal farmers who otherwise would not have brought land into rice production, and these new entrants may use different technologies and have different levels of technical efficiency. The determinants of the participation decision and the distribution of technical efficiency among participants and non-participants is important information for evaluating the full economic effects of the PSP. The stochastic frontier model (SFM) is a standard approach to evaluating the nature of production technologies and the distribution of technical efficiency among a sample of firms (Aigner, Lovell, and Schmidt (1977). Several studies have applied the SFM to samples of Thai rice farmers (Chaovanapoonphol, Battese, and Chang, 2009; Rahman, Wiboonpongse, Sriboonchitta, and Chaovanapoonphol, 2009; Srisompun and Isvilanonda, 2012). Yet, the issue of whether PSP participants and nonparticipants use the same production technologies and have the same levels of technical efficiency has not been investigated in the literature to date. One approach would be to estimate different SFMs for each subsample of data (participants and nonparticipants) and compare results. However, the fact that farmers choose to participate or not in a way that is likely non-random way may lead to sample selection bias in estimates from this naïve approach. Failure to account for such selectivity could bias the estimated parameters of both the stochastic frontier production technology and the distribution of technical efficiency.

In response we augment the standard stochastic frontier model with a participation equation explaining the decision to participate in the PSP, and then use Heckman's two-step estimation and Greene's sample selection stochastic production frontier model to explore levels of technical efficiency among participants and non-participants. The resulting model is used to investigate two important issues: (a) what are the key determinants of farmers' decision to participate in the PSP? and (b) do program participants and non-participants use different rice production technologies and have different levels of technical efficiency.

THEORETICAL FRAMEWORK

The standard stochastic frontier model (SFM) proposed by Aigner, Lovell, and Schmidt (1977) (hereafter the ALS model)is specified as:

$$\text{(1)} \qquad y_i = \boldsymbol{\beta}'\boldsymbol{x_i} + v_i - u_i\ ,$$

$$u_i = \sigma_u |U_i|,\ \ U_i \sim N[0,1]$$

$$v_i = \sigma_v V_i,\ \ V_i \sim N[0,1]$$

where y_i,$\boldsymbol{x_i}$,v_i, and u_i represent output, input vector, idiosyncratic error in the production frontier, and technical inefficiency, respectively. Technical inefficiency $u_i$is assumed to be truncated normal and takes only non-negative values. The frontier is assumed linear in parameters but nonlinearity of the production frontier is allowed through transformations of the y_i, and $\boldsymbol{x_i}$values (e.g. log transformations and including higher order terms in $\boldsymbol{x_i}$).The standard model assumes that the mean level of technical inefficiency is invariant across observations. However, Kumbhakar et al. (1991) show how to relax this assumption by allowing the mean to be a function of exogenous variables (e.g. management skills). This specification allows a part of the technical inefficiency to be explained by farm-specific factors. Econometric estimation provides estimates of the frontier parameters together with an auxiliary model of technical inefficiency as a function of farm-specific factors.

One underlying assumption of SFMs is that all farmers in the sample have access to the same production technology. If some characteristics allow a sub-sample of farmers to have access to a different production technology, a separate estimation of the stochastic frontier production is needed. However, these subsample estimations may then provide biased estimation of population production functions if the farmers' decision on which technology to use is governed by farm and farmer characteristics. Treating the observed data as if they are randomly sampled from the population and estimating the SFM of each subsample separately potentially biases the estimated parameters.

There are two approaches to accounting for this selectivity bias in SFMs: (a) the Heckman's two-step procedure to correct for sample selection bias by appending the inverse Mill's ratio as a covariate in separate SFMs for each sub-sample (Heckman, 1979); (b) Greene's SFMs with correction for sample selection bias. Green's model jointly estimates the selection models and the SFMs allowing for correlated errors (Greene, 2010).

Estimation Using Heckman's Approach

Let d_i^* be a latent variable representing an unobservable selection criterion variable which is postulated to be a function of some exogenous variables ($\boldsymbol{z_i}$):

(2) $$d_i^* = \boldsymbol{\alpha}'\boldsymbol{z_i} + w_i$$

where $\boldsymbol{\alpha}$ is a vector of parameters and *w* is the error term distributed as $N(0, \sigma_w^2)$. The selection criterion variable is unobserved. Rather, a dummy variable, d_i, is observed and takes a value of 1 when $\boldsymbol{\alpha}'\boldsymbol{z_i} + w_i > 0$ and the decision is made to participate and zero otherwise:

(3) $$d_i = 1[\boldsymbol{\alpha}'\boldsymbol{z_i} + w_i > 0],\ w_i \sim N[0,1]$$

SFM estimation by Heckman's (1979) two-step procedure to correct for sample selection bias involves the following steps: (1) fit the probit model for the sample selection equation and (2) estimate a SFM for each subsample but including the inverse Mill ratio (IMR) from the first step as an independent variable to correct for selectivity bias and test its significance. The model can be specified as (3) plus:

(4) Regime 1: $$y_{i1} = \boldsymbol{\beta_1}'\boldsymbol{x_{1i}} + \rho_1 IMR_{1i} + v_{i1} - u_{i1} \qquad if \quad d_i = 0$$

(5) Regime 2: $$y_{i2} = \boldsymbol{\beta_2}'\boldsymbol{x_{2i}} + \rho_2 IMR_{2i} + v_{i2} - u_{i2} \qquad if \quad d_i = 1$$

where $u_{ji} = \sigma_{ju}|U_{ji}|,\ \ U_{ji} \sim N[0,1] \quad ;\ j = 1,2$

$v_{ji} = \sigma_{jv}V_{ji},\ \ V_{ji} \sim N[0,1] \quad ;\ j = 1,2$

ρ_j is the parameter that detects the presence of selectivity bias

Estimation Using Greene's Model

Greene (2010) argues that the Heckman's switching regression is inappropriate in models that are nonlinear because: (1)in nonlinear models like the SFM the impact on the conditional mean of the model of interest will not necessarily take the form of an inverse Mill ratio; (2) The bivariate normality assumption needed to justify the inclusion of the inverse Mills ratio in the second model does not generally appear anywhere in the SFM; and (3) the dependent variable, conditioned on the sample selection, is unlikely to have the distribution described by the model in the absence of selection.

Greene proposed an internally consistent method of incorporating the sample selection problem in a SFM. The error term in the selection model (w_i) is assumed to be correlated with the noise in the SFM (v_i). The correlation between (v_i) and (w_i) is denoted by ρ. Greene's model is then written as:

(6) $d_i = 1[\boldsymbol{\alpha}'\boldsymbol{z_i} + w_i > 0],\ w_i \sim N[0,1]$

$y_i = \boldsymbol{\beta}'\boldsymbol{x_i} + \varepsilon_i\ ,\ \ \varepsilon_i \sim N[0, \sigma_\varepsilon^2]$

where $(y_i, \boldsymbol{x_i})$ observed only when $d_i = 1$,

$\varepsilon_i = v_i - u_i, \quad u_i = \sigma_u|U_i|,\ \ U_i \sim N[0,1], \quad v_i = \sigma_v V_i,\ \ V_i \sim N[0,1],$

$(w_i, v_i) \sim bivariatenormalwith\ correlation\ \Delta$

The conditional density for an observation in Green's model is

(7) $f(y_i | x_i, |U_i|, \boldsymbol{z}_i, d_i)$

$$= \left[d_i \left\{ \begin{array}{c} \left(\dfrac{exp\left(\dfrac{\frac{1}{2}(y_i - \beta' x_i + \sigma_u |U_i|)^2}{\sigma_v^2}\right)}{\sigma_v \sqrt{2\Pi}} \right) \\ \times \Phi\left(\dfrac{\rho(y_i - \beta' x_i + \sigma_u |U_i| / \sigma_\varepsilon) + \boldsymbol{\alpha}' \boldsymbol{z_i}}{\sqrt{1 - \rho^2}}\right) \end{array} \right\} + (1 - d_i)\Phi(-\boldsymbol{\alpha}' \boldsymbol{z_i}) \right]$$

The unconditional log likelihood for the model in (6)is formed by integrating out the unobserved $|U_i|$then maximizing with respect to the unknown parameters.

(8) $logL(\beta, \sigma_u, \sigma_{v,} \alpha, \rho) = \sum_{i=1}^{N} \log \int_{|U_i|} f(y_i | x_i, |U_i|, \boldsymbol{z}_i, d_i)\, p(|U_i|) d(|U_i|)$

where $p(|U_i|) = \frac{\phi(|U_i|)}{\Phi(0)} = exp\left(-\frac{1}{2}|U_i|^2\right)\sqrt{\frac{2}{\Pi}}\ ,\ |U_i| \geq 0$

Since the integral of this function does not exist in a closed form, Greene (2010) proposes computation by simulation. The simulated log likelihood function is

(9) $$logL_s(\beta,\sigma_u,\sigma_{v,}\alpha,\rho)$$

$$= \sum_{i=1}^{N} log\frac{1}{R}\sum_{r=1}^{R}\left[d_i \left\{ \begin{array}{c} \left(\dfrac{exp\left(\dfrac{\frac{1}{2}(y_i-\beta'x_i+\sigma_u|U_{ir}|)^2}{\sigma_v^2}\right)}{\sigma_v\sqrt{2\Pi}} \right) \\ \times\,\Phi\left(\dfrac{\rho(y_i-\beta'x_i+\sigma_u|U_{ir}|/\sigma_\varepsilon)+\boldsymbol{\alpha}'\boldsymbol{z_i}}{\sqrt{1-\rho^2}}\right) \end{array} \right\} + (1-d_i)\Phi(-\boldsymbol{\alpha}'\boldsymbol{z_i}) \right]$$

The single equation MLE of $\boldsymbol{\alpha}$ in the probit equation in (6) is consistent, albeit inefficient. For purposes of estimation of the parameters of the SFM, the estimates of $\boldsymbol{\alpha}$ is taken as given in the simulate log likelihood in (9), then use the Murphy and Topel (2002) correction to adjust for the standard errors in the same fashion as Heckman's correction of the canonical selection model in (4) and (5).

DATA

The empirical analysis is based on a sample of 387 jasmine-rice farm households chosen from 21 villages located across Buriram province. The province is one of the largest producers of jasmine rice in Thailand whose shares represent approximately 15% of total area and production of jasmine rice in 2011[1]. Six districts from 23 districts located across the province were randomly selected. Then, two villages located in irrigated areas and two villages located in areas with no irrigation system in place are randomly chosen from each selected districts, constituting a total sample of 24 villages. Finally, 20 jasmine-rice farm

[1] Thailand Office of Agricultural Economics

households from each village were scheduled for an interview. Due to some technical problems, however, the survey only took place in 21 villages from which data from 387 rice farm households were collected. The data include inputs used, geographical location of plots, and socio-economic characteristics of farm household members. The information collected covers the major (1^{st}) rice season in 2012/13. The sample contains 130 farmers, who have participated in the PSP during the2012/13 major cropping season, and 257 non-participants.

MODEL SPECIFICATION

This study uses both the Heckman and Greene methods to estimate stochastic production frontier models of PSP participants and non-participants while controlling for selectivity bias. Both methods require two sets of variables; one for the production frontier and the other for the probit model which models a farmer's decision to participate in the PSP. The functional form used for the frontier is extended Cobb-Douglas so that for j = 1, 2 sub - samples (participants and nonparticipants) the model is:

$$(10)\quad LNPROD_{ji} = \beta_{j0} + \beta_{j1}LNFERT_{ji} + \beta_{j2}LNSEED_{ji} + \beta_{j3}LNLAND_{ji} + \beta_{j4}LNLANDSQ_{ji} + \beta_{j5}IRR_{ji} + \beta_{j6}TECH_{ji} + v_{ji} - u_{ji}$$

where $u_i = \sigma_u|U_i|,\ \ U_i \sim N[0,1]$;

$$v_i = \sigma_v V_i,\ \ V_i \sim N[0,1];$$

with *i* indexing farms. The dependent variable *LNPROD* is log of total production of jasmine rice. The explanatory variables include a set of log inputs; land (*LNLAND*), land squared (*LNLDSQ*), fertilizer (*LNFERT*), seeds (*LNSEED*),a dummy variable indicating whether land is irrigated (IRR), and a dummy variable taking a value of one if a farmer uses transplanting and zero if they seed (*TECH*). Labor is not included because high collinearity between labor and land size will result in imprecise estimates of these variables. To evaluate sensitivity to exclusion of a labor variable we also estimated models with a labor variable (*LNLAB)*, measured as a sum of family and hired labors used in rice production.

The probit participation-decision equation is specified as

$$(11)\quad PSP_i = 1[\alpha_0 + \alpha_1 EDU_i + \alpha_2 EXP_i + \alpha_3 LAND_i + \alpha_4 TRANSPOR_i + \alpha_5 STORAGE_i + \alpha_6 BORROW_i + \alpha_7 BAAC_i + \alpha_8 DIST_i + \alpha_9 CROP2_i + \alpha_k \sum_k^5 REGION_{ik} + w_i > 0]$$

$$where \quad w_i \sim N[0,1]$$

As the distance from plots to the nearest depot (*DIST*) increases, farmers may have less incentive to sell to the government because they have to bear higher costs of transporting rice, especially if several trips are needed. By the same token, lack of transportation (*TRANSPOR*) may cause farmers to sell their harvest to other buyers located nearby instead. Farmers are expected to be more likely to participate in the program if they own a storage facility (*STORAGE*) because it gives farmers more flexible time to sell.

Also, the government also pays farmers storage fees if rice is kept with farmers after pledging. The variables *EDU* and *EXP* respectively denote head of household's years of education and years of rice-farming experience. These variables are expected to positively affect farmers' farm management skills. The notion of large farms having lower fixed costs associated with transporting rice to PSP depots implies that the probability of participation would increase as land size (*LAND*) increases. The variable *BORROW* indicates whether a farmer has borrowed money to finance his/her rice production. Farmers are expected to sell rice to non-government buyers to receive cash on spot so that they can repay loans immediately. The high level of the support price relative to market price is likely to induce farmers to sell to the government. As the distance from home to the nearest Bank of Agriculture and Agricultural Cooperatives (*BAAC)* increases, an incentive to participate may decrease because information about the PSP is less frequently communicated to farmers. The variable *CROP2* indicates whether a farmer produces second-season rice. The dummy variable *REGION* representing six different districts in which the survey took place is included to account for other regional-specific factors that possibly influence the participation but are not mentioned in the survey. For instance, farmers in certain districts are discouraged to participate due to a lengthy processing-time for transferring money to farmer's banking account the BAAC which tends to vary by branches. Sometimes, farmers have to sell to other buyers because a depot has exceeded its daily storage capacity.

Recall that the Heckman's method requires an inclusion of the inverse Mill's ratio (*IMR*). In the first step, the inverse Mill's ratio is obtained from a pooled - probit estimation as shown in (11). In the second step, separate production frontier models are estimated by appending the inverse Mill's ratio obtained from the first step as one of the independent variables. The selectivity bias is present if the estimated coefficient of *IMR* (ρ) is statistically difference from zero at least in one of the subsamples. In contrast, the Greene's method internally estimate (10) and (11) in one step by NLOGIT (version 4) for which the distributional assumptions of the error terms are as stated in (6).

RESULTS

Differences in Input Allocation and Farmers' Characteristics

Table 1 presents summary statistics for output, inputs, and characteristics of farmers classified by their PSP participation status. Note that log of total inputs and outputs are used independent and dependent variables, respectively. Yields and rates of input application are reported to show the difference in per-rai basis. Land size and rate of fertilizer use are significantly different between PSP participants and non-participants despite similar average yields. The difference in land size is quite large which indicates that the scale of production is much larger for participants. However, non-participants apply more fertilizer per rai. This may be because high market prices induce some farmers to apply more fertilizers and hope for higher yields. On average, participants have more years of education but less farming experience. The proportion of farmers lacking transportation and storage infrastructure is higher among non-participants. The proportion of participants who borrow money is higher than among participants. In fact, total household debts are statistically higher for those who participate in PSP (not shown). The distances to nearest PSP depot and BAAC are higher for non-participants. Yet, only the former is statistically significant. Lastly, a higher proportion of the participants reported that they also produce rice in the second season. This perhaps indicates that the participants are more commercialized.

Table 1. Average input used and farmers' characteristic variables

Variable	Non PSP (N=257)	PSP (N=130)	Mean Difference (Non PSP-PSP)	
Production[1]				
Yield (kg/rai[2])	348.80	345.15	3.65	
Fertilizer (kg/rai)	35.69	33.85	1.84	*
Seed (kg/rai)	26.42	25.93	0.49	
Labor (man-day/rai)	6.72	7.11	-0.39	
Land (rai)	13.42	30.29	-16.87	***
Irrigation (irrigated=1, zero otherwise)	0.33	0.39	-0.06	
Technique (transplanting=1,seeding=0)	0.13	0.15	-0.03	
Characteristics				
Education (years)	5.11	5.52	-0.41	*
Farming experience (years)	35.64	33.39	2.25	*
Land (rai)	13.42	30.29	-16.87	***
Transportation (own=1,none=0)	0.38	0.50	-0.12	***
Storage (own=1,none=0)	0.80	0.92	-0.12	***
Borrow (yes=1,no=0)	0.37	0.57	-0.20	***
Distance to nearest BAAC (km.)	8.31	7.75	0.56	
Distance to nearest PSP depot (km.)	17.06	14.64	2.85	***
2nd-season crop grower (yes=1,no=0)	0.17	0.23	-0.06	*

*** and ** denote 1% and 5% significant levels, respectively

[1] Note that logarithm of total production and inputs are used in regression analysis

[2] 2.5 rai= 1 acre

Source: author's survey

Determinants of PSP Participation

The results from the probit model of PSP participation are shown in Table 2. Neither education nor farming experience has a statistically significant impact on the likelihood of program participation. Similarly, owning a vehicle that can be used for transporting rice increases the probability of program participation but its effect is statistically insignificant. Owning a storage facility increases the probability of participation and this effect is statistically significant at the 10% level. The ability to store facilitates program participation because the government's PSP depots are often overwhelmed at the beginning of harvest season and participants have to delay delivery. Without storage farmers would have to sell immediately on the market. However, the distance to nearest government's PSP depot does not have a statistically significant impact on the likelihood of program participation, once regional differences are accounted for. Distance to nearest BAAC has a statistically significant (10% level) negative effect on the probability of program participation. The BAAC is a source of PSP program information and close proximity may also increase the ability of farmers to borrow money from the bank to finance the delayed payment that usually accompanies program participation. Similarly, farm borrowing has a positive relationship with program participation. Finally, higher land area increases the probability of program participation, as does the farmer's cultivation of rice during the second growing season. These factors indicate that there is a positive relationship between the degree of commercialization of the farm and the likelihood of participating in the PSP. However, a direction of causality cannot be determined; e.g. one may ask if large farms participate or participating farms get large.

Table 2. The estimated parameters of the probit model for participation decision

Variable	Coefficient	
Constant	-1.66	***
Education	-0.02	
Farming experience	-0.01	
Land	0.05	***
Transportation	0.16	
Storage	0.34	*
Borrow	0.41	***
Distance to nearest BAAC	-0.03	*
Distance to nearest PSP depot	0.01	
2nd-season crop grower	0.41	*
Region 1	0.34	
Region 2	-0.53	*
Region 3	0.85	***
Region 4	0.18	
Region 6	-0.15	
Model diagnostics		
Log likelihood	-180.62	
Chi squared	130.61	
P-value	0.00	
McFadden pseudo R-squared	0.27	

***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Frontier Production Technologies

Table 3 and Table 4 report the parameter estimates of stochastic production frontier of the participants and non-participants, respectively. The results in column 2 are from Greene's method while those in column 3 and 4 are from Heckman's method. In the table GRN and HECK-N denote results from the functional form for production technology described in (10) and (11) with an inclusion of the inverse Mill's ratio in the latter. The HECK-F results use alternative specification in which labor is additionally added. We evaluate this alternative specification because labor is considered a typical input used in rice production[2]. Note that HECK-N is nested in HECK-F. Results show that estimates from the two Heckman specifications are very similar but results from Green's model are quite different. This is possibly because Greene's model is over-parameterized. This divergence in parameter estimates using Greene's and Heckman's method has been noted in other studies as well (e.g., Wiboonponse et al., 2012).

Table3. Estimated parameters of stochastic production frontier for PSP participants

Variable	GRN coefficient		HECK-N coefficient		HECK-F coefficient	
Production function						
Constant	22.272		6.745	***	6.539	***
Fertilizer	0.1036		0.072		0.069	
Seed	0.0722		0.124	**	0.111	**
Labor					0.068	**
Land	1.4271	*	0.246		0.282	
Land squared	0.3576		0.062	*	0.050	
Irrigation	-0.0002		0.116	*	0.100	
Technique	0.1873		0.135	*	0.096	
Variance parameters						
Log likelihood	-1920.66		-42.47		-40.67	
σ_v	1.02		0.18		0.06	
σ_u	23.81		0.49		0.08	
$\rho_{(v,w),\text{Heckman}}$			-0.20	*	-0.17	
$\rho_{(v,w),\text{Greene}}$	0.33					

***, **, * denote 1%, 5%, and 10% significant levels, respectively.

[2] The alternative specification did not converge using Green's model and so results for that case are not shown. So, Greene's model can only be compared to Heckman's model using the nested specification (i.e. a specification in which labor is excluded)

Table4. Estimated parameters of stochastic production frontier for non-participants

Variable	GRN coefficient		HECK-N coefficient		HECK-F coefficient	
Production function						
Constant	12.374		5.617	***	5.395	***
Fertilizer	0.005		0.185	***	0.175	**
Seed	0.191	***	0.159	***	0.158	***
Labor					0.115	***
Land	0.012	**	0.569		0.512	***
Land squared	1.256		-0.008		-0.017	
Irrigation	0.426	***	0.115	**	0.181	***
Technique	0.264		0.036		0.006	
Variance parameters						
Log likelihood	-2015.97		-196.87		-189.63	
σ_v	0.98		0.16		0.15	
σ_u	5.97		0.91		0.90	
$\rho_{(v,w),\text{Heckman}}$			-0.11		-0.11	
$\rho_{(v,w),\text{Greene}}$	-0.0018					

***, **, * denote 1%, 5%, and 10% significant levels, respectively.

For the participants (Table 3), only land size is statistically significant using Greene's method. Under the HECK-N specification, all inputs except fertilizer are statistically significant. The HECK-F specification indicates that only seed and labor are statistically significant. However, log-likelihood-ratio test (LR-test) strongly rejects joint exclusion restrictions for land and land squared (not shown here). Hence, land is still a key factor of production. In case of the non-participants (Table 4), more parameters are statistically significance under Greene's model, seed, land, and irrigation. Yet, their estimates are very different from those estimated by the Heckman's method. Under the HECK-F specification, all variables except planting technique are statistically different from zero. Like the participants, the estimates of land and land squared are not individually significant but are jointly significant under HECK-N specification.

The estimates for the selectivity bias parameter (ρ) are reported at the bottom of Table 3 and 4.For the participants, we cannot reject the null hypothesis of no selectivity bias using Green's model of HECK-F. Selectivity bias is somewhat significant under the HECK-N specification as the null hypothesis is rejected but only at the 10% level (p-value = 0.095). For the non-participants, all three models reject the existence of selectivity bias. Therefore, the conclusion is that there is no strong evidence suggesting the presence of selectivity bias. This means the stochastic production frontier for the participants and non-participants can be estimated separately using the standard SFM if their production technologies indeed differ, or by pooling the data if their production frontiers are the same.

Table 5 and 6 report the parameter estimates of stochastic production frontier estimated by the standard SFM (ALS model) of the nested and full specification, respectively. In the tables ALS-N and ALS-F denote results from the functional form for production technology that are respectively identical to HECK-N and HECK-F except that now the inverse Mill's ratio is excluded. These two models are estimated using pooled/full sample. ALS-N1&2 and ALS-F1&2 denote sample-separated models in which all coefficients except variance parameters are constrained to have the same values as those of their full-sample models (ALS-N and ALS-F, respectively). ALS-N3&4 and ALS-F3&4 denote unconstrained sample-separated models in which no constraint is imposed on production technology and variance parameters. A LR-test for different production frontiers in these two subsamples strongly supports the null hypothesis of homogeneous production frontiers; i.e. testing full-sample model against (unconstrained) sample-separated models. This means the PSP does not cause participants to gain a better access to inputs or to use different production technology. A mean-difference test of equal variance parameters is strongly rejected; testing equal mean of the parameters σ_u and σ_v of the full-sample model against (constrained) sample-separated model (results are not reported). Therefore, technical efficiency for each sub-sample is estimated separately by constraining frontier parameters to be the same for participants and non-participants but allowing standard deviations of the errors (σ_u and σ_v) to differ across the sub-samples.

Table 5. Estimated parameters of the nested-model stochastic production frontier

Variable	ALS-N (Pooled) coefficient		ALS-N1 (Non PSP) coefficient	ALS-N2 (PSP) coefficient	ALS-N3 (Non PSP) coefficient		ALS-N4 (PSP) coefficient	
Production function								
Constant	5.645	***	constrained	constrained	5.409	***	6.189	***
Fertilizer	0.145	***	constrained	constrained	0.190	***	0.103	*
Seed	0.157	***	constrained	constrained	0.150	***	0.117	*
Land	0.475	***	constrained	constrained	0.562	***	0.267	
Land squared	0.027		constrained	constrained	0.005		0.069	*
Irrigation	0.150	***	constrained	constrained	0.135	**	0.141	**
Technique	0.103	*	constrained	constrained	0.052		0.122	*
Variance parameters								
Log likelihood	-258.23		-223.02	-48.02	-197.55		-43.70	
σ_v	0.18		0.20	0.14	0.17		0.25	
σ_u	0.78		0.86	0.60	0.90		0.38	
σ_ε^2	0.64		0.78	0.39	0.84		0.21	

***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Table 6. Estimated parameters of the full-model stochastic production frontier

Variable	ALS-F (Pooled) coefficient	ALS-F1 (Non PSP) coefficient	ALS-F2 (PSP) coefficient	ALS-F3 (Non PSP) coefficient	ALS-F4 (PSP) coefficient
Production function					
Constant	5.414 ***	constrained	constrained	5.178 ***	6.064 ***
Fertilizer	0.146 ***	constrained	constrained	0.179 ***	0.097 *
Seed	0.146 ***	constrained	constrained	0.146 ***	0.105 *
Labor	0.108 ***	constrained	constrained	0.120 ***	0.078 **
Land	0.443 ***	constrained	constrained	0.504 ***	0.299
Land squared	0.015	constrained	constrained	-0.005	0.054
Irrigation	0.180 ***	constrained	constrained	0.203 ***	0.113 *
Technique	0.044	constrained	constrained	0.022	0.092
Variance parameters					
Log likelihood	-251.05	-191.83	-47.16	-193.50	-41.79
σ_v	0.17	0.19	0.12	0.18	0.20
σ_u	0.78	0.85	0.61	0.88	0.46
σ_ε^2	0.64	0.75	0.38	0.80	0.25

***, **, * denote 1%, 5%, and 10% significant levels, respectively.

Technical Efficiency of PSP Participants and Non-Participants

Summary statistics of the technical efficiency scores for PSP participants and non-participants under ALS-N and ALS-F are presented in Table 7. On average, the participants are more technically efficient than the non-participants as indicated by the fact that mean technical efficiency is higher while having lower standard deviation. The distribution of technical efficiency scores for the participants displays leftward skew while that of the non-participants displays rightward skew (positively skewed). Under the ALS-N specification 23.08% of participants have technical efficiency scores above 0.8 compared to 16.74% for non-participants. Moreover, a higher proportion of non-participants technical efficiency scores are located in the lower tail of the distribution;

35.41% of the sample are located below 0.5 compared to 26.15% of participants. The ALS-F specification also produces similar observations. The distribution of technical efficiency scores are not much different from those reported in Table 6 when estimated from the unconstrained model using pooled sample (not shown here).

Table 7. Distribution of technical efficiencies

Interval	Nested Model		Full Model	
	NON-PSP (ALS-N1)	PSP (ALS-N2)	NON-PSP (ALS-F1)	PSP (ALS-F2)
0.91-1.00	1.95%	3.85%	2.33%	6.15%
0.81-0.90	14.79%	19.23%	15.56%	18.46%
0.71-0.80	19.84%	13.85%	16.73%	13.85%
0.61-0.70	13.23%	18.46%	16.34%	16.15%
0.51-0.60	14.79%	18.46%	12.84%	16.15%
under 0.51	35.41%	26.15%	36.19%	29.23%
Mean TE	0.58	0.63	0.58	0.63
Standard Deviation	0.22	0.17	0.22	0.18
Minimum	0.02	0.20	0.02	0.18
Maximum	0.93	0.94	0.93	0.95

CONCLUSION

The objective of this study was to identify the factors that determine Thai jasmine-rice farmers' decision to participate in the PSP and estimate the frontier production technology and technical efficiency of participants and non-participants. Two approaches to dealing with the selection bias problem were applied—Greene's model and Heckman's two-step adjustment approach. The result indicates that education and farming experience does not play an important role in determining farmer's participation decision. Households using loans are more likely to participate in the program than those who do not. Other barriers include distance to the nearest Bank of Agriculture and Agricultural Cooperatives (BAAC), which is a government-affiliated agency responsible for issuing loans to farmers.

The difference between parameter estimates obtained from the Heckman's and Greene's methods are large. The models estimated by the Greene's method clearly indicates that there is no statistical evidence of selection bias while only weak evidence was found under the Heckman's method. Therefore, the conclusion is that there is no selectivity bias and the production model can be estimated using the standard frontier model. However, the result from log-likelihood-ratio test indicates that both participants and non-participants share the same production technology but different distribution of inefficiency. So, technical efficiency scores for each group are computed separately assuming homogeneous production function. The analysis of technical efficiency reveals that the participants are more efficient because the mean of technical efficiency scores are relatively higher while their smaller variance are smaller. The distribution of their technical efficiency scores also displays leftward skew compared to the rightward skew in case of the participants. In other words, higher proportion the participants are located in the high-efficiency range and less in the low-efficiency range.

The findings from this study have some important policy implications. First, land size greatly influences the probability of participating in the program. This is consistent with the observation that most PSP participants produce rice on a large scale. Therefore, a significant portion of program benefits are captured by large farms. Since the participants are more technically efficient in production, one can also argue that the program tends to attract efficient farmers. Lastly, policymakers may as well need to investigate factors that significantly deter the farmers' participation decision if they want to distribute program benefits more evenly to all farmers.

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