Production efficiency of Jasmine rice producers in northern and northeastern Thailand

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Abstract: *The paper jointly evaluates the determinants of switching to Jasmine rice and its productivity while allowing for production inefficiency at the level of individual producers. Model diagnostics reveal that serious selection bias exists, justifying use of a sample selection framework in stochastic frontier models. Results from the probit variety selection equation reveal that gross return (mainly powered by significantly higher Jasmine rice price), access to irrigation and education are the important determinants of choosing Jasmine rice. Results from the stochastic production frontier reveal that land, irrigation and fertilizers are the significant determinants of Jasmine rice productivity. Significantly lower productivity in Phitsanulok and Tung Gula Rong Hai provinces demonstrate the influence of biophysical and environmental factors on productivity performance. The mean level of technical efficiency is estimated at 0.63 suggesting that 59% [100-63/63] of the productivity is lost due to technical inefficiency. Policy implications include measures to keep Jasmine rice price high, increase access to irrigation and fertilizer availability, as well as investment in education targeted to farm households which will synergistically increase adoption of Jasmine rice as well as farm productivity.*

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Running title: Production efficiency of Jasmine rice producers

1. Introduction

Fierce competition in the already thin world rice market for low quality rice exports has raised concerns about the future of rice production in Thailand due to lower production cost of its exporting competitors, e.g., Vietnam, although history suggests that Thailand enjoys stable earnings and low competition in the high quality rice market. Jasmine rice (known as Khao Dawk Mali in Thai), a non-glutinous fragrant variety, is considered to be the top quality rice in Thailand and is thought of as an alternative crop to overcome the existing bottlenecks in the export market. Since the mid-1980s the government of Thailand has adopted a strategy to promote the production and export of Jasmine rice, which faces only two major rivals: fragrant Basmati rice from Pakistan and/or India and American Long Grain rice. As a result of policy support, the production share of Jasmine rice increased from 16.8% of total rice area in 1990 to 28.3% in 1998. In terms of absolute area expansion, Jasmine rice has increased from 9.9 million rai (1 ha = 6.25 rai) to 17.3 million rai during the same period, a 74% increase. Thailand also has enjoyed an anticipated fast growth in Jasmine rice exports increasing from 1,358 million Baht in 1988 to 40,358 million Baht in 2006 (OAE, 1998; 2007). The principal gain is in the value of exports rather than volume during this period. The export price of Jasmine rice has increased by 44.4% compared with non-Jasmine rice (14.9%), indicating positive impacts of the policy shift to promote high quality rice to boost export earnings as well as avoid competition in the thin world rice market. The increase in export price, as well as the doubling of farm prices of Jasmine rice between 1988 and 2007, was largely responsible for the increased volume of production, as it provided farmers with incentives to switch to Jasmine rice.

Over the past two decades, the overall growth rate of rice yield in Thailand is estimated at 2.5% per annum (OAE, 2007). In 2006, the average yield of all varieties of rice is estimated at 500 kg per rai, and the yield of Jasmine rice in the northeastern region of Thailand including the Tung Gula Rong Hai (TGR) province (the main Jasmine rice area) is estimated at 300-370 kg per rai. However, despite consistent growth in yields, the actual yield level of Thai rice is only 66% of the world average, indicating serious bottlenecks in the production process which are worth investigating. One of the obvious bottlenecks in boosting rice yield in Thailand is the neck blast disease which affects all types of rice. A single outbreak in 1992 affected 1.25 million rai incurring a loss in crop worth 1.00 billion Baht. However, neck blast disease may not be the only binding constraint. A host of price and non-price factors (e.g. high ratio of fertilizer price to rice price, unreliable irrigation, severe drought and other biophysical, environmental and socio-economic circumstances of farmers) could be responsible for stagnant rice yield levels in Thailand, despite the overall production boom in Jasmine rice.

Against this background, important lessons can be learned from a joint evaluation of: (a) the determinants of switching to Jasmine rice; (b) the determinants of Jasmine rice productivity, allowing for production inefficiency at the level of the individual producer; (c) the level of production performance (technical efficiency scores) of individual producers. We undertake such a task in this study using a model recently developed by Greene (2006), which provides a general framework of sample selection procedure in stochastic frontier models.

The next section briefly reviews relevant literature on technology adoption in developing countries. Section 3 describes the theoretical framework of the model. Section 4 describes the data. Section 5 presents the results. The final section concludes and draws policy implications.

2. Studies analyzing determinants of technology adoption

Several studies have analyzed the determinants of modern technology adoption by farmers in developing countries using simple ad-hoc models. These are typically OLS, probit or tobit regressions of technology adoption on variables representing: (a) socio-economic circumstances of farmers – such as, farm size, tenurial status, farmers' education level, farming experience, family size, and gender; and (b) institutional and bio-physical factors – such as, irrigation, credit, extension contact, membership in organizations, and distance to market/bus stop/extension office (e.g., Hossain, 1989; Nkamleu and Adesina, 2000; Shiyani, et al., 2002; Floyd et al., 2003; Ransom, et al., 2003; Asfaw and Admassie, 2004). Few of these studies outline the implicit theoretical underpinning of such ad-hoc modelling (e.g., Nkamleu and Adesina, 2000), which is the assumption of utility maximization by rational farmers. Furthermore, all of these studies ignored or omitted price factors (both input and output prices) as determinants of technology adoption, which has important bearing on productivity and resource allocation decisions, and hence provide an incomplete picture of farmers' decision-making processes.

The model of technology adoption developed by Pitt (1983) explicitly takes into account price and non-price factors in determining adoption while allowing for switching between varieties, but assumes farmers to be fully efficient in their production technologies. With the development of stochastic frontier analysis by Aigner, Lovell and Schmidt (1977), a large number of studies followed which typically place the farming efficiency of developing country farmers in a range of 60% to 82% (e.g., Rahman, 2003; Coelli et al., 2002; Ali and Flinn, 1989; Wang et al., 1996). As a result, analysis of factors determining technology adoption under the assumption of the farmer being fully efficient inherently incorporates bias into the results. The contribution of this study to the existing literature on the economics of technology adoption, as well as efficiency analyses, is the extension of the model of technology adoption developed by Pitt (1983) to relax the restrictive assumption of fully efficient farmers. This approach is used to jointly address our three key research questions.

3. Theoretical Framework

The conventional approach to incorporate selectivity is the estimation procedure proposed by Heckman (1976) which involves the following two steps:

- Step 1: Fit the probit model for the sample selection equation.
- Step 2: Using the selected sample, fit the second step model (Ordinary Least Squares or Weighted Least Squares) by adding the inverse Mills ratio from the first step as an independent variable to correct for selectivity bias and test its significance.

However, Greene (2006) claims that such an approach is inappropriate for several reasons in models that are not linear, such as probit, tobit and so forth. This is because:

- The impact on the conditional mean of the model of interest will not necessarily take the form of an inverse Mills ratio. Such an adjustment is appropriate and is specific to linear models only.
- 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 model.
- The dependent variable, conditioned on the sample selection, is unlikely to have the distribution described by the model in the absence of selection (Greene, 2006).

Hence, Greene (2006) proposed an internally consistent method of incorporating 'sample selection' into a model. Specifically, to incorporate selectivity in a stochastic frontier framework, Greene (2006) proposed the following analytical approach.

$$d^* = \alpha' z + w, d = 1 \quad (d^* > 0) \qquad (1)$$

$$y = \beta' x + v - u \qquad (2)$$

$$u = |U| \ with \ U \sim N[0, \sigma_u{}^2]$$

$$(v, w) \sim bivariate \ normal \ with \ [(0,0), (\sigma_v{}^2, \rho\sigma_v, 1)]$$

$$(y, x) \quad only \ observed \ when \ d = 1$$

where d is a probit selection equation (with adoption depending on a host of price and non-price factors) and y is the stochastic frontier function, specified only for the adopting farms.

The estimator is developed as follows (Greene, 2006): w is conditional on v as:

$w|v = \rho v + h \; where \; h \sim N[0,(1-\rho^2)]$, and h is independent of v.

Therefore, $d^*|v = \alpha' z + \rho v + h,\; d = 1(d^* > 0|v)$

Then, $prob[d = 1 \; or \; 0 \,|\, z, v] = \Phi\left[(2d-1)\left(\frac{\alpha' z + \rho v}{\sqrt{1-\rho^2}}\right)\right]$ (3)

The sample is considered into two parts. For the selected observations, *d* = 1, conditioned on *v*, the joint density for *y* and *d* is the product of the marginals since conditioned on *v*, *y* and *d* are independent

$$f(y, d = 1|x, z, v) = f(y\,|\,x, v)\; prob(d = 1\,|\,z, v) \quad (4)$$

This is the second part. For the first part,

$$y\,|\,x, v = (\beta' x + \sigma_v v) - \sigma_u u$$

where *u* is the truncation at zero of a standard normal variable. The conditional density is given by:

$$f(y\,|\,x, v) = \frac{2}{\sigma_u}\phi\left(\frac{(\beta' x + \sigma_v v) - y}{\sigma_u}\right), (\beta' x + \sigma_v v) - y \geq 0 \quad (5)$$

Therefore, the joint conditional density is given by:

$$f(y, d = 1\,|\,x, z, v) = \frac{2}{\sigma_u}\phi\left(\frac{(\beta' x + \sigma_v v) - y}{\sigma_u}\right)\Phi\left(\frac{\alpha' z + \rho v}{\sqrt{1-\rho^2}}\right) \quad (6)$$

The unconditional density is obtained by integrating *v* out of (6). Since the integral does not exist in a closed form, Greene (2006) proposes computation by simulation. The final simulated log likelihood is given by (for details see Greene, 2006)

$$\log L_s = \sum_i \log \frac{1}{R}\sum_{r=1}^{R}\left\{d_i\left[\frac{2}{\sigma_u}\phi\left(\frac{\beta' x + \sigma_v v_{ir} - y)}{\sigma_u}\right)\Phi\left(\frac{\alpha' z + \rho v_{ir}}{\sqrt{1-\rho^2}}\right)\right] + (1-d_i)\left[\Phi\left(\frac{-\alpha' z - \rho v_{ir}}{\sqrt{1-\rho^2}}\right)\right]\right\}$$

(7).

The model is estimated using NLOGIT Version 4 (ESI, 2007).

4. Data and the variables

Data

The data used in this study were collected in the crop year 1999/2000 by interviewing farmers in three provinces: Chiang Mai; Phitsanulok; TGR. Chiang Mai province is located in the north of Thailand where farmers have greater access to irrigation, and is one of the few provinces in the north where Jasmine rice production for export was extensively promoted. Phitsanulok province is located at the lower north where a large proportion of farmers grow three rice crops a year of high yielding but poor quality rice varieties. TGR province is located in northeastern Thailand, and is the major Jasmine rice producing area of the country, but is endowed with poor irrigation facilities. A total of 348 farmers were interviewed of which 141 farmers were purely Jasmine rice producers while the remaining 207 farmers were mainly non-Jasmine rice producers[2].

The variables

Two sets of variables are needed for this study: One for the probit variety selection equation model; the other for the stochastic production frontier model. Some of the variables appear in more than one model based on our *a priori* expectation.

Empirical model

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[2] Farmers in these three provinces of Thailand usually grow non-Jasmine rice mainly for consumption whereas Jasmine rice is grown for sale only. Therefore, farmers fulfilling their own consumption needs will allocate most of their land for non-Jasmine rice and a small portion for Jasmine rice. In our sample, out of the 207 non-Jasmine rice farmers, 53 grew purely non-Jasmine rice while the remaining 154 farmers allocated small parts (less than a third) of their cultivated land for Jasmine rice, which we ignored, treating these farmers are primarily non-Jasmine rice producers.

Farmers are assumed to choose between Jasmine and non-Jasmine rice varieties to maximize return subject to a set of price and non-price factors. The decision of the *i*th farmer to choose Jasmine rice is described by an unobservable selection criterion function, I^*, that is postulated to be a function of a vector of exogenous output prices, and factors representing farmers' socio-economic circumstances, as well as bio-physical and environmental factors. The model is specified as:

$$I^* = \alpha' Z_i + w_i \qquad (7)$$

where Z is a vector of exogenous variables explaining the decision to grow Jasmine or non-Jasmine rice, α is a vector of parameters and w is the error term distributed as $N(0,\sigma^2)$. The selection criterion function is not observed. Rather a dummy variable, I, is observed. The variable takes a value of 1 for Jasmine rice farms and 0 otherwise:

$$I = 1 \text{ iff } I^* = \alpha' Z_i + w_i \geq 0$$

$$I = 0, \text{ otherwise} \qquad (8)$$

The production behaviour of the Jasmine rice farmers is modelled by postulating a restricted translog stochastic production frontier function as follows[3]:

$$\ln(Y_i) = \beta_0 + \sum_{k=1}^{4} \beta_k \ln(X_{ik}) + \frac{1}{2}\sum_{k=1}^{4}\sum_{j=1}^{4} \beta_{jk} \ln(X_{ik})\ln(X_{ij}) + \sum_{d=1}^{2} \delta_d D_d + v_i - u_i \qquad \text{iff } I = 1 \qquad (9)$$

where X represent inputs, Y represents Jasmine rice output, D stands for regional dummy variables accounting for differences in bio-physical and environmental factors; β *and* δ are the parameters; and v is the two sided random error, independent of the u, representing random shocks, such as exogenous factors, measurement errors, omitted explanatory

[3] Only the Jasmine rice production frontier function is shown here. The counterpart is the non-Jasmine rice production frontier. The model selects the Jasmine rice producers from the total sample (composed of both Jasmine and non-Jasmine rice producers) based on the information provided in the probit variety selection equation.

variables, and statistical noise. It is assumed that the w in (8) is correlated with v in (9), and therefore, (w,v) are distributed as bivariate normal with $[(0,0),(\sigma_v{}^2, \rho\sigma_v, 1)]$. The u is a non-negative random variable associated with inefficiency in production, assumed to be independently distributed as according to a zero-truncated normal distribution, $u = |U| \ with \ U \sim N[0, \sigma_u{}^2]$.

The explanatory variables for the selection of Jasmine rice include the gross return from growing rice (i.e., rice price x yield of rice per rai) and variables representing farmers' socio-economic circumstances as well as biophysical and environmental factors.

Gross return per rai (Baht/rai) is measured in nominal terms and is expected to have a positive relationship with the adoption of Jasmine rice. Environmental variables included in the model are: the amount of total rainfall in one year; the mean annual temperature. Dummy variables for the Phitsanulok and TGR provinces were incorporated because the physical and biological environments differ in these provinces as compared to Chiang Mai province. These provincial dummy variables not only reflect differences in the bio-physical environment, but also the marketing environment and are, therefore, expected to affect the decision regarding variety choice[4]. Variables representing farmers' socio-economic circumstances include a measure of access to irrigation (defined as the ratio of irrigated land to cultivated land), a dummy variable to account for farmers who transplanted their rice, the highest level of education in the household, and the farmers' attitude towards commercialization (ATC). The ATC variable is constructed as an index by assigning scores based on the degree of commercialization[5]. This variable is expected to be positively related to the choice of

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[4] We did not include a dummy variable to account for 'neck blast disease' because this has affected all types of rice and is, therefore, considered redundant.

[5] These scores were evaluated from the responses received to five questions: (1) Do you aim to sell your produce before consumption? (2) Do you always think of how to maximize profit when you produce? (3) Do you

Jasmine rice.

All the input and output variables used in the stochastic production frontier were measured on a per farm basis. The four input variables used in the model include land, labour, chemical fertilizers, and irrigation, and all are expected to have a positive relationship with rice output. Also, two regional dummy variables were included to account for differences with respect to bio-physical and environmental factors. One important input variable, tractor time spent on land preparation, was not included in the production model, because most farmers pay for hired tractor services at approximately the same rate per unit of land irrespective of the type of rice grown. The working time per unit of land in terms of the equivalent standard horse power tractor would then be approximately equal for all observations. This is because the contract is based on the same amount of service, i.e., finished ploughing.

Since the variables in the probit variety selection equation and the stochastic production frontier differ, the structural model satisfies the identification criterion (Maddala, 1983).

5. Results

Summary statistics for all variables are presented in Table 1, showing that non-Jasmine rice provides significantly higher yield. However, Table 1 also shows that the price of Jasmine rice is significantly higher than non-Jasmine rice, with the return from Jasmine rice being significantly higher than from non-Jasmine rice. Furthermore, there seem to be no significant differences in the level of input use between Jasmine and non-Jasmine rice

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always think of the return on borrowed money and whether it is worth doing? (4) Do you always set a target of yield per unit of land regardless of production cost? (5) Do you use your borrowed money (planned for production) for social purposes when necessary? Each question is given a score of 1 for least agreed and a score of 5 for most agreed response, except for the answers to questions (4) and (5), where the scores run in the reverse order. The index was then constructed by summing up all the scores received from these five questions.

production, implying that the net return is higher for Jasmine rice producers. However, among the bio-physical, socio-economic and environmental factors, significant differences exist between Jasmine and non-Jasmine rice producers. For example, Jasmine rice farmers have significantly higher access to irrigation. The proportion of farmers producing Jasmine rice was significantly higher in TGR province, and significantly lower in Phitsanulok province. Jasmine rice producers received significantly less annual rainfall and experienced a lower mean annual temperature. We also see that the average level of education in the household for Jasmine rice producer is significantly higher, although the attitude towards commercialization did not differ significantly between producers of the different varieties.

[Insert Table 1 here]

The Chi-squared test statistic in the probit variety selection equation is significant at the 1% level, confirming the joint significance of the parameters (Table 2). The McFadden R-squared is estimated at 0.16. 71% of the observations were accurately predicted. Gross return is one of the important determinants of choosing Jasmine rice, as expected. Location also matters in choosing Jasmine rice. For example, the probability of choosing Jasmine rice is significantly higher in TGR as well as Phitsanulok provinces. Among the environmental factors, higher temperature significantly depresses the probability to choose Jasmine rice. Farmers' socio-economic circumstances also significantly affect probability of choosing Jasmine rice. Specifically, access to irrigation and educational level in the household significantly influence the probability of choosing Jasmine rice. However, there is no influence of farmers' attitude towards commercialization in choosing Jasmine rice, since both types of growers exhibit almost the same scores for this constructed index.

[Insert Table 2 here]

Prior to discussing the results of the production frontier, we report the series of hypothesis tests conducted to select the level of aggregation, the functional form and to decide whether the frontier model is an appropriate choice rather than a standard mean-response or average production function. The results are reported in Table 3. Sauer et al., (2006) raise the importance of checking theoretical consistency, flexibility and choice of the appropriate functional form when estimating stochastic production frontiers. However, given the complexity of our model and the focus on the empirical significance of the framework applied, we concentrate on the choice of an appropriate functional form that is also flexible. The first set of tests was conducted to determine the appropriate functional form, i.e., the choice between Cobb-Douglas vs. translog functional form (H_0: β_{jk} = 0 for all jk) for each province as well as for the total sample. Generalised Likelihood Ratio (LR) tests confirmed that the choice of translog production function is a better representation of the production structure in all cases.

Once the functional form is chosen, next we checked the sign of the third moment and the skewness of the OLS residuals of the data in order to justify the use of the stochastic frontier framework (and hence the Maximum Likelihood Estimation procedure)[6]. The computed value of Coelli's (1995) standard normal skewness statistic (M3T) based on the third moment of the OLS residuals is presented in the mid-panel of Table 3 which is tested against H_0: M3T = 0. The null hypothesis of 'no inefficiency component' is strongly rejected in all cases and, therefore, the use of the stochastic frontier framework is justified. The coefficient of γ reported at the bottom of Table 4 also strongly suggests the presence of technical inefficiency.

In the lower panel of Table 3, LR tests were conducted to determine whether the data from the three provinces can be pooled. The test suggested by Battese and Coelli (1988)

[6] In the stochastic frontier framework, the third moment is also the third sample moment of the u_i. Therefore, if it is negative, it implies that the OLS residuals are negatively skewed and technical inefficiency is present (Omer et al., 2007; Rahman and Hasan, 2008).

compares the value of log-likelihood for the pooled model (H_0) with the sum of log-likelihood for the sub-samples estimated separately (H_1). The degrees of freedom in this case is the number of parameters estimated (which is 19, see Table 4, column 3) multiplied by the difference in the number of estimating equations, which is two minus one (e.g., when pooling Chiang Mai and Phitsanulok). The test results consistently showed that all combinations can be pooled. We are mainly interested in whether the full sample can be estimated with certainty, which is validated from the test results.

Finally, in the last panel we have provided checks for regularity conditions of the translog production frontier. The two checks are: (i) monotonicity, i.e., positive marginal products, with respect to all inputs $\left(\frac{\partial y}{\partial x_i} > 0\right)$ and thus non-negative production elasticities; and (ii) diminishing marginal productivity $\left(\frac{\partial^2 y}{\partial x_i^2} < 0\right)$ with respect to all inputs (i.e., the marginal products, apart from being positive should be decreasing in inputs) (Sauer et al., 2006). Results clearly demonstrate that both these restrictions hold for all the inputs[7].

[Insert Table 3 here]

Table 4 presents the results of the stochastic production frontier model corrected for selectivity bias (columns 2 and 3). Table 4 also presents the results for Jasmine rice producers using the conventional direct estimation of the stochastic production frontier with technical inefficiency effects (columns 4 and 5) for comparative purposes. A total of 11 coefficients out of a total of 16 are significantly different from zero at the 10% level at least, implying a good fit of the stochastic production frontier model corrected for selectivity bias. Both the estimates of σ_u and σ_v are significantly different from zero at the 1% level. The coefficient on the selectivity variable ($\rho_{w,v}$) is significantly different from zero at 1% level, which confirms

[7] Both these restrictions should hold at least at the point of approximation (for details, see Sauer et al., 2006)

that serious selection bias exists, thereby, justifying the use of a sample-selection framework in the stochastic frontier model. In other words, this finding confirms that estimation using observations from only single variety producers (either Jasmine or non-Jasmine rice producer) will provide biased estimates of productivity, which will then be carried on to the biased estimates of efficiency scores as well.

Results from the stochastic production frontier for Jasmine rice, controlling for selectivity bias, reveal that productivity of rice farming increases with land area, fertilizer and irrigation input as expected. All the input variables were mean corrected ($X_{ik} - \overline{X}_k$) so that the coefficients on the first order terms can be read directly as production elasticities. Land has the highest elasticity value of 0.56 implying that a one percent increase in land area allocated to Jasmine rice will increase production by 0.56%. The production elasticity of irrigation has been estimated at 0.35 and fertilizer at 0.24. In the conventional model only land seems to be the significant input in raising productivity with an elasticity value of 0.96, which probably overestimates the true effect. The contribution of labour input seems to be very low in both models. This may be due to the fact that all farmers were using labour input in same proportions. Productivity is significantly lower in Phitsanulok and TGR provinces as compared to Chiang Mai, which reinforces our *a priori* assumption that bio-physical as well as market environment factors significantly affect productivity. Increasing returns to scale exists in Jasmine rice production and the null hypothesis of 'constant returns to scale' (i.e., H_0: $\sum\beta_k = 1$ for all k) is strongly rejected in both models at the 1% level of significance. The implication is that farmers could achieve proportionately higher production by increasing their production scale.

[Insert Table 4 here]

The summary statistics of technical efficiency scores for Jasmine rice farmers, corrected for selectivity bias, are presented in Table 5. Table 5 also reports efficiency scores obtained from the conventional estimation of the stochastic production frontier with technical inefficiency effects for comparison. The mean technical efficiency, corrected for selectivity bias, is estimated at 63% implying that a substantial 59% [(100-63)/63] of the production is lost due to technical inefficiency alone. This implies that the average farm producing Jasmine rice could increase production by 59% by improving its technical efficiency, which is substantial. Farmers exhibit a wide range of production inefficiency ranging from 3% to 84% in Jasmine rice farming. Observation of wide variation in production efficiency is not surprising and is similar to the results of Rahman, (2003), Ali and Flinn, (1989), Ali et al., (1994), and Wang et al., (1996) for Pakistan Punjab, North-west Pakistan, and China, respectively.

[Insert Table 5 here]

Overall, the efficiency scores for Jasmine rice farmers, corrected for selectivity bias, are lower by three points ($p<0.05$) as compared to the conventional model (Table 5). The direct estimation of the single equation stochastic production frontier models for only Jasmine rice producers seems to have understated the level of inefficiency. For example, only 2.8% of Jasmine rice farmers were operating at efficiency level of 91% or above in our selectivity model, whereas in the conventional model, the figure is 18.4%.

The bottom panel of Table 4 presents the determinants of inefficiency jointly estimated with the stochastic production frontier using the conventional method. The null hypothesis of 'no efficiency effects' (i.e., H_0: $\tau_m = 0$ for all m) is rejected at the 1% level of significance, implying that all these variables jointly have an influence on the technical efficiency scores of individual farmers. Large farms seem to be relatively technically inefficient, as indicated by the significantly positive coefficient on the farm size variable, which is consistent with the existing literature (e.g., Ali et al., 1994). The coefficients on the irrigation and education variables have the right expected sign but are not significantly different from zero.

6. Conclusions and policy implications

The study jointly evaluates the determinants of switching to Jasmine rice as well as the determinants of Jasmine rice productivity, while allowing for production inefficiency at the level of individual producers, in northern and northeastern Thailand by applying a sample selection framework in stochastic frontier models. The model diagnostics reveal that serious selection bias exists, thereby justifying use of this framework. In other words, estimation from only single variety producers (i.e., either Jasmine or non-Jasmine rice producers) will provide biased results of the determinants of technology adoption and productivity, as well as farm-specific technical efficiency scores, as demonstrated in this study. Intuitively, the negative sign of the coefficient on the selectivity variable indicates that the bias is towards lower productivity, implying that the level of technology adoption may have a negative impact on productivity. This finding, therefore, has profound implications regarding the analysis of productivity impacts of new technologies. Our results indicate that, since technology adoption decisions and productivity performances are related, one should ideally consider the effect of the degree of adoption when evaluating the impacts of new technologies on productivity.

The results of this study confirm that gross return, access to irrigation and educational level in the household are the important determinants in choosing Jasmine rice, although location and environmental factors do matter in the selection decision as well. As shown in Table 1, the Jasmine rice price is significantly higher than the non-Jasmine rice price (particularly glutinous rice) which is the main staple of Thai farmers. Therefore, the significantly higher price of Jasmine rice provides a good incentive to switch, because it provides significantly higher return although at face value the yield of Jasmine rice is lower than non-Jasmine rice, which is further complemented by the availability of irrigation infrastructure.

Results from the stochastic production frontier reveal that, in addition to land, irrigation and fertilizer inputs, bio-physical and environmental factors (represented by regional dummies) also affect the productivity of Jasmine rice. A very high level of inefficiency exists in Jasmine rice production. The mean level of technical efficiency of these self-selected Jasmine rice farmers is estimated at 63%, implying that there remains substantial scope to increase production by improving technical efficiency alone. Increased returns to scale also exist in Jasmine rice production, implying that farmers could achieve higher production, and hence returns, by increasing their production scale.

The policy implications of this study are clear. Price policies to uphold the high Jasmine rice price seems to be an effective measure to increase its adoption rate because it leads to significantly higher return. Increasing access to irrigation will also boost the adoption of Jasmine rice technology. In addition, promotion of education (particularly secondary level education) targeted to farm households will synergistically increase the adoption rate of Jasmine rice. The mean level of highest education in the farm households is only 4.88 years (for Jasmine rice producers) which is less than a year above the compulsory primary level education of 4 years prescribed by law in Thailand. An increase in access to irrigation and fertilizer availability will have a substantial impact on productivity improvement in addition to land allocated to Jasmine rice. Thai farmers in general form groups and buy fertilizers in bulk in order to reduce the transportation and/or per unit cost of procuring fertilizers. The government should provide support for such activities as well as find ways to increase availability of fertilizers in remote areas of these provinces. The significantly lower productivity of Jasmine rice in Phitsanulok and TGR provinces point towards the importance of bio-physical and market environment factors, which need attention as well.

The complex interplay of these factors on adoption rate and productivity perhaps explains the observed stagnancy in switching to Jasmine rice in northern and northeastern Thailand, despite two decades of a serious policy drive aimed at increasing the diffusion of this technology to farmers in these regions. Although responsiveness to return (mainly influenced by significantly higher prices of Jasmine rice) exemplifies the commercial behaviour of the farmers in this transition economy, it seems that price alone does not fully determine the decision to choose Jasmine rice because bio-physical and other factors play an important role in determining variety selection decisions as well as productivity performance, and consequently the net returns derived from rice production. Nevertheless, given the evidence of this study, policies aimed at raising the Jasmine rice price, increasing access to irrigation and availability of fertilizers, investment in education targeted at farm households and research to combat lower productivity in unfavourable areas (e.g., in Phitsanulok and TGR provinces) through improvements in biotechnology, can be safely suggested as the way forward to promote Jasmine rice adoption as well as increase the productivity of Thai rice farmers.

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