Resource use efficiency with self-selectivity: an application of a switching regression framework to stochastic frontier models

Sanzidur Rahman[1]

Address for Correspondence:

Dr. Sanzidur Rahman

School of Economic Studies

The University of Manchester

Oxford Road

Manchester, M13 9PL

England, UK

Phone: (0161) 275 4865

Fax: (0161) 275 4812

E-mail: Sanzidur.Rahman@man.ac.uk

September 2002

---

[1] Hallsworth Fellow, School of Economic Studies, University of Manchester, Manchester, UK.

Resource use efficiency with self-selectivity: an application of a switching regression framework to stochastic frontier models

Abstract: *The use of switching regression framework on stochastic frontier models to analyse resource use efficiency while taking account of the self-selective nature of farmers' variety choice decisions were demonstrated and applied to a sample of Bangladeshi rice producers. Results show that serious selection bias exists in both traditional rice and modern rice stochastic profit functions, thereby establishing the need to take into account the self-selective variety choice decisions made by the farmers. Increases in land, modern irrigation, and lower seed prices increase the probability for choosing modern rice. Among the cited reasons for choice, getting higher yield and fodder and fewer concerns for associated increased water, labour and production costs as well as lower prices and shorter maturity period are the motives behind choosing modern varieties. High levels of inefficiency exist in both traditional and modern rice cultivation. The mean level of profit efficiency is 56% and 48% for modern rice and traditional rice varieties suggesting that an estimated 44% and 52% of the profit is lost due to a combination of both technical and allocative inefficiency. The efficiency differences are explained by infrastructure, extension services, tenancy* and *share of non-agricultural income.*

JEL Classification: O33, Q18, and C21.

Keywords: Self-selectivity, switching regression, stochastic frontiers, profit efficiency, Bangladesh

Running title: Resource use efficiency with self-selectivity

Resource use efficiency with self-selectivity: an application of a switching regression framework to stochastic frontier models

1. Introduction

Bangladesh agriculture, dominated by rice production, is already operating at its land frontier and has very little or no scope to increase the supply of land to meet the growing demand for food required for its ever-increasing population. The expansion in crop area, which was a major source of production growth till the 1980s, has been exhausted and the area under rice started to decline thereafter (Husain et al., 2001). The observed growth in rice production, at an annual rate of 2.34% for the period 1973 – 1999, has been largely attributed to conversion of traditional rice to modern varieties rather than to increases in yields of modern rice varieties (Baffes and Gautam, 2001). Currently, 61% of total rice area is allocated to modern varieties (BBS, 2001). However, this is true only when overall annual production area is considered. There is a seasonal dimension in area allocated to modern rice varieties and the resultant output. In general, rice occupies about 70% of the cultivated land and is grown in all three seasons – Aus (pre-monsoon), Aman (monsoon), and Boro (dry winter). Aman is the principal growing season, which accounts for 57% of annual gross rice area followed by Boro (27%) and Aus (16%), respectively (BBS, 2001). The composition of area allocated to traditional rice still revolves around 70% in Aus, 57% in Aman and only 8% in Boro season (BBS, 2001). Lack of access to irrigation has been traditionally considered as the binding constraint for continued widespread production of traditional rice in Aus and Aman seasons resulting in lower than potentially obtainable production provided all areas were allocated to modern rice as observed in the case of Boro season (e.g., 92% of rice area in this season in 1997 are modern varieties) since modern rice varieties are still capable of providing yield levels twice that of traditional varieties. Therefore, on one hand, there is an urgent need to increase food production by raising productivity of land presumably by increasing the adoption rate of modern rice varieties, which was claimed to have already reached its ceiling level (Bera and Kelly, 1990). At the other end of the spectrum, the United Nations projects that farmers will have to generate large marketable surplus to feed the growing urban population (estimated at 46% of total population of 173 million) by 2020 (Husain et al., 2001). This implies that Bangladeshi farmers not only need to speed up their adoption rate of modern varieties as well as become more efficient in their production activities, but also to be responsive to market indicators, so that the scarce resources are utilized efficiently to increase productivity as well as profitability, and ensure supply to the urban market.

Given this backdrop, the present study sets out to simultaneously analyse three key issues: (a) examination of decisions affecting modern variety adoption, (b) estimation of production efficiency (technical and allocative efficiency combined) of the rice farmers while taking into account the self-selective nature of the choice between traditional and modern rice varieties, and (c) socio-economic factors explaining variation in individual farmers' efficiency level. The importance arises because farmers facing same prices and having similar socio-economic circumstances still choose to grow either traditional varieties or modern varieties of rice in specific plots of land available to him/her in a given season, where presumably lack of irrigation may not be the only binding constraint. Ignoring this self-selective nature of variety choice decision while studying farming efficiency inherently leads to biased results, although this was the norm that abounds in the literature studying efficiency. The relationships between adoption decision, efficiency, market indicators and household characteristics as a whole have not been studied in Bangladesh although studies on selected aspects are available which inherently suffer from bias in results as noted above. An understanding of these relationships could provide the policymakers with information to design programmes that can contribute to measures needed to expand the food production potential of the nation.

The paper proceeds as follows. The next section outlines the modelling framework for the problem under study and its application to efficiency analysis. Section three describes the data. The fourth section reports and interprets the results. Section five begins with the farm level efficiency measures and identifies policy-relevant variables explaining variation in efficiency and the final section concludes.

2. Switching regression model for measuring production efficiency with self-selectivity: a three stage estimation procedure

Conventionally, a simple two-stage switching regression procedure for solving self-selectivity problem is available in the literature. Our desire to estimate production efficiency while taking into account decision to choose varieties requires an additional stage leading to call it a three-stage estimation procedure. The details are presented below.

Farmers facing the same set of prices and socio-economic circumstances still make a choice between growing traditional varieties and modern varieties in a specific plot of land in a given season. This implies that the decision to grow one variety is not necessarily independent of that to grow the other and, therefore, selecting only traditional rice growers or modern rice growers separately introduces sample selection bias. The problem can be corrected by the application of a switching regression model with endogenous switching (Maddala, 1983). Empirical application of this model to input demand in agriculture include studies by Pitt (1983), Pitt and Sumodiningrat (1991), Freeman et al., (1998), and Feder et al., (1990). The three-stage switching regression model applied in this study uses a probit model in the first stage to determine price and non-price factors affecting the decision to adopt modern varieties of rice. In the second stage, separate regression equations are used to model the production behaviour of groups of farmers conditional on a specified criterion function of variety selection. In the third stage, separate stochastic profit functions with inefficiency effects models were postulated using transformed variables from the second stage that takes into account the self-selected variety selection decision as well.

Farmers are assumed to choose between modern and traditional rice varieties to maximize profits subject to a set of price and non-price factors. The decision of the *i*th farmer to choose modern varieties is described by an unobservable selection criterion function, I^*, that is postulated to be a function of a vector of exogenous input and output prices, fixed factor endowments, selected household socio-economic characteristics and explicitly revealed motivation for choosing the particular variety and is specified as:

$$I^* = \delta' K_i + u_i \qquad (1)$$

where K is a vector of exogenous variables explaining the decision to grow modern or traditional rice, δ is a vector of parameters and u 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 when a plot is planted with modern varieties and 0 otherwise: that is,

$$I = 1 \text{ iff } I^* = \delta' K_i + u_i \geq 0$$

$$I = 0, \text{ otherwise} \qquad (2)$$

The production behaviour of the two groups of farmers, the traditional rice and modern rice growers, is modelled by postulating two variable profit functions as follows:

$$\textit{Modern rice profit function}: \quad \pi_{1i} = \beta'_1 P_i + \gamma'_1 Z_i + u_{1i} \quad \textit{iff } I = 1 \qquad (3)$$

$$\textit{Traditional rice profit function}: \quad \pi_{2i} = \beta'_2 P_i + \gamma'_2 Z_i + u_{2i} \quad \textit{iff } I = 0 \qquad (4)$$

where P is a vector of variable input prices, Z is a vector of fixed factors; π_{1i} and π_{2i} represent variable profits of the *i*th farm under modern and traditional rice varieties; β's and γ's are vectors of parameters; and u_{1i} and u_{2i} are error terms distributed as $N(0,\sigma^2_1)$ and $N(0,\sigma^2_2)$, respectively. It is assumed that the u_i are correlated with u_{1i} and u_{2i} (Maddala, 1983). Parameters of the selection criterion function (equation 2) can be estimated by the probit maximum likelihood method. Applying OLS to estimate the parameters of the two profit functions (equations 3 and 4) will yield inconsistent estimates because the expected value of the error term conditional on the sample selection criterion (see equations 5 and 6) is non-zero (Maddala, 1983). Since, δ can be estimated only up to a scale factor, it is then assumed that u_{1i}, u_{2i}, and u_i have a trivariate normal distribution with zero mean and a non-singular covariance matrix. Although maximization of the bivariate probit likelihood function for this switching regression model is feasible (Maddala, 1983), a simple two-stage estimation method, proposed by Lee (1978), is applied to estimate the system of equations in 2, 3 and 4.

Since production decision depends on the variety selection criterion function, the expected value of the error terms, u_{1i} in (3) and u_{2i} in (4) can be expressed as:

$$E(u_{1i} \mid u_i \leq \delta' K_i) = E(\sigma_{1u} u_i \mid u_i \leq \delta' K_i) = -\sigma_{1u} \frac{\phi(\delta' K_i)}{\varphi(\delta' K_i)} \qquad (5)$$

$$E(u_{2i} \mid u_i \geq \delta' K_i) = E(\sigma_{2u} u_i \mid u_i \geq \delta' K_i) = \sigma_{2u} \frac{\phi(\delta' K_i)}{[1-\varphi(\delta' K_i)]} \qquad (6)$$

where ϕ and φ are the probability density function and cumulative distribution function of the standard normal distribution, respectively. The ratio ϕ/φ evaluated at $\delta' K_i$ for each I is known as the inverse Mills ratio (IMR). For convenience define these IMR as:

$$\lambda_{1i} = \phi(\delta' K_i) / \varphi(\delta' K_i)$$
$$and$$
$$\lambda_{2i} = \phi(\delta' K_i) / [1-\varphi(\delta' K_i)] \qquad (7)$$

These terms are then included in the specification of equations (3) and (4) to yield

$$\textit{Modern rice profit function}: \quad \pi_{1i} = \beta'_1 P_i + \gamma'_1 Z_i - \sigma_{1u}\lambda_{1i} + \varepsilon_{1i} \quad \textit{if } I = 1 \ (8)$$
$$\textit{Traditional rice profit function}: \quad \pi_{2i} = \beta'_2 P_i + \gamma'_2 Z_i + \sigma_{2u}\lambda_{2i} + \varepsilon_{2i} \quad \textit{if } I = 0 \ (9)$$

where, ε_{1i} and ε_{2i}, the new residuals have zero conditional means. These residuals are, however, heteroscedastic. Therefore, estimating equations (8) and (9) by weighted least squares, WLS, rather than ordinary least squares, OLS, would give efficient parameter estimates.

The three-stage estimation procedure is summarized as follows. In the first stage the probit maximum likelihood estimation procedure is used to obtain estimates of δ from equation (1). By substituting the estimated values of δ, estimates for λ_{1i} and λ_{2i} are obtained from (7). In the second stage, equations (8) and (9) are estimated by WLS using the estimated values of λ_{1i} and λ_{2i} as instruments to obtain computed values of variances of ε_{1i} and ε_{2i}, which are then use as weights in the final stage estimation of profit frontier functions to purge off the heteroscedasticity in residuals (for details of derivation, see Appendix).

In the third stage, two stochastic profit frontiers for traditional rice and modern rice producers are postulated using the transformed equations from (8) and (9) using WLS:

$$\textit{Modern rice stochastic profit frontier}: \quad \pi^*_{1i} = \beta'_1 P^*_i + \gamma'_1 Z^*_i - \sigma_{1u}\lambda^*_{1i} + v_{1i} - \theta_{1i} \quad (10)$$

$$\textit{Traditional rice stochastic profit frontier}: \quad \pi^*_{2i} = \beta'_2 P^*_i + \gamma'_2 Z^*_i + \sigma_{2u}\lambda^*_{2i} + v_{2i} - \theta_{2i} \quad (11)$$

where, v_{1i} is distributed as $N(0, \sigma^2_{v1})$ and v_{2i} is distributed as $N(0, \sigma^2_{v2})$ representing the random effects, measurement errors, omitted explanatory variables and statistical noise; and the component θ is a non-negative one-sided error term representing the inefficiency of the farm. In a stochastic production frontier model, this residual represents "technical efficiency". Under the assumption of profit maximization, in a stochastic profit frontier function, which is also assumed to behave in a manner consistent with stochastic production frontier function, this residual represents "profit efficiency" which is a direct measure of production efficiency that combines both technical and allocative inefficiency components (Ali and Flinn, 1989). This is an improvement from conventional estimation of technical efficiency only, which may not be appropriate when farmers face different prices and have different factor endowments. Profit efficiency, therefore, is defined as the ability of a farm to achieve highest possible profit given the prices and levels of fixed factors of that farm and profit inefficiency in this context is defined as loss of profit from not operating on the frontier (Ali and Flinn, 1989).

The transformed equations 10 and 11, wherein each variable is weighted by the computed variances of ε_{1i} and ε_{2i} from equations 8 and 9, respectively were estimated by applying the single-step stochastic frontier with inefficiency effects model proposed by Battesse and Coelli (1995) in the third stage to obtain firm-specific profit efficiency scores. The conventionally used two-step estimation procedure where firm-specific efficiencies were estimated using stochastic frontier technique in the first-step, and then the predicted efficiency indices were regressed against a number of household characteristics, in an attempt to explain the observed differences in efficiency among farms in the second step (e.g., Sharif and Dar, 1996; Wang et al., 1996), suffer from inconsistency in its assumptions regarding the independence of the inefficiency effects in the two estimation steps[1] (Coelli, 1996). Wang and Schmidt (2002) further demonstrated that this two-step procedure produces seriously biased results and strongly argues in favour of choosing only one-step estimation procedure.

In this one-step inefficiency effects model proposed by Battesse and Coelli (1995), the θ_{1i} and θ_{2i} terms in equation (10 and 11) are assumed to be a function of a set of non-negative random variables (W_i) that reflect the efficiency of the farm.

$$\textit{Inefficiency effect of modern rice}: \qquad \theta_{1i} = \tau'_1 W_i + \omega_{1i} \qquad (12)$$

$$\textit{Inefficiency effect of traditioanal rice}: \qquad \theta_{2i} = \tau'_2 W_i + \omega_{2i} \qquad (13)$$

They are assumed to be independently distributed, such that efficiency measures are obtained by truncation of the normal distribution with mean, $\mu_{1i} = \tau_{10} + \sum_d \tau_{1d} W_{di}$ and variance $\sigma_{\mu 1}{}^2$ for modern rice function and $\mu_{2i} = \tau_{20} + \sum_d \tau_{2d} W_{di}$ and variance $\sigma_{\mu 2}{}^2$ for traditional rice function, respectively; where W_{di} is the dth explanatory variable associated with inefficiencies on farm i and τ' s are the unknown parameters.

The production/profit efficiency of farm i in the context of the stochastic profit frontier function is defined as

$$Modern\,rice\,function: \qquad EFF_{1i} = E[\exp(-\theta_{1i})] = E[\exp(-\tau_{10} - \sum_{d=1}^{D} \tau_{1d} W_{di})] \qquad (14)$$

$$Traditional\,rice\,function: \qquad EFF_{2i} = E[\exp(-\theta_{2i})] = E[\exp(-\tau_{20} - \sum_{d=1}^{D} \tau_{2d} W_{di})] \qquad (15)$$

where E is the expectation operator. The method of maximum likelihood is used to estimate the unknown parameters, with the stochastic frontier and the inefficiency effects functions estimated simultaneously. The likelihood function is expressed in term of the variance parameters, $\sigma^2 = \sigma_v^2 + \sigma_\theta^2$ and $\gamma = \sigma_\theta^2 / \sigma^2$ (Battesse and Coelli, 1995).

3. Data and Variables

Data

Primary data for the study pertains to an intensive farm-survey of rice producers conducted during February to April 1997 in three agro-ecological regions of Bangladesh. Samples were collected from eight villages of the Jamalpur Sadar sub-district of Jamalpur, representing wet agro-ecology, six villages of the Manirampur sub-district of Jessore, representing dry agro-ecology, and seven villages of the Matlab sub-district of Chandpur, representing wet agro-ecology in an agriculturally advanced area. A total of 406 farm households from these 21 villages were selected following a multistage stratified random sampling procedure.

As mentioned earlier, the composition of area allocated to traditional rice still revolves around 70% in Aus, 57% in Aman and only 8% in Boro season. In our sampled farmers, the composition of traditional rice growers is 24% in Aman season and 65% in Aus season. And more than 90% of the farmers grew modern rice in the Boro season, similar to the trend observed at the national level. Therefore, in this study, samples were extracted for those who grew either traditional or modern varieties during Aus and Aman season, respectively. The total number of observations stands at 521 (117 observations [85 in Aman and 32 in Aus season] for traditional rice, and 404 observations [355 in Aman and 49 for Aus season] for modern rice, respectively). The observations for Boro seasons were discarded.

Variables

In analysing crop production, it is often the case that data is only available for the major inputs, such as land, labour, fertiliser, and animal power. However, crop production is affected by many other variables that play significant roles in explaining performance. In this study, an attempt was made to collect information on almost all the inputs used for rice production. Thus, information on the use of seeds, pesticides, farm capital assets, and irrigation was collected. This is expected to increase the explanatory power of the analysis significantly. Table 1 shows the description of the variables used in the analyses.

[Insert Table 1 here]

The dependent variable in the first stage probit equation is the farmers' variety selection criterion. This is a binary variable takes the value of 1 if a plot is planted with modern rice varieties and 0 otherwise. The explanatory variables comprised of both the continuous and binary variables. The explanatory variable includes, prices of variables inputs (P'_i) of fertilizers, labour, animal power services, seeds, and pesticides normalized by the price of output (P_y: rice) so that the function is homogenous of degree one in prices consistent with the requirement for a well-behaved profit function specification in the second stage. The money prices of all five inputs were normalized by the price of rice[2]. The fixed factor endowment includes, area planted to rice by the farmer, irrigation cost and stock of farm capital equipment measured in thousands of taka. Subsistence pressure, measured by family size, is also included to examine its influence in variety selection decision. Next, seven decision-making factors in the form of dummy variables were incorporated. These were constructed based on farmers' responses to specific questions related to motivations behind growing modern rice and traditional rice varieties. The concerned variable (D_i) takes a value of 1 if the farmer agrees to the question and 0 otherwise. The first three variables (D_1, D_2 and D_3) correspond to motivation behind growing modern rice varieties and the latter four variables (D_4, D_5, D_6, and D_7) correspond to motivation behind growing traditional rice varieties. Except subsistence pressure, all other continuous variables were logged.

In the second stage, deterministic Cobb-Douglas restricted profit functions were postulated. The dependent variable in the second stage regression is the log of restricted profit (π') defined as the total revenue less total variable costs of labour, animal power services, seeds, fertilizers and pesticides normalized by the price of rice. Except the subsistence pressure variable, all other variables used in the first stage probit equation were included in the respective second stage WLS regression of the profit functions. The maintained hypothesis is that this variable is not likely to directly influence farm level efficiency. Thus, the model is identified as at least one explanatory variable from the first stage probit regression is not included in the second stage WLS regression (Maddala, 1983).

In the third stage, the transformed Cobb-Douglas stochastic profit frontier functions (wherein all variables were weighted by the estimates of variances of ε_{1i} and ε_{2i} obtained from the second stage regressions) were estimated to obtain farm-specific profit efficiency scores for growing modern rice and traditional rice varieties adjusted for self-selective variety choice decisions simultaneously with socio-economic factors explaining variation in efficiency levels. Nine variables representing socio-economic characteristics of the farm households and farmers' production circumstances were chosen as regressors for explaining inefficiency. The list included –tenancy (dummy variable for tenurial status. The value is 1 if the farmer is an owner operator, and 0 otherwise), experience (number of years producing rice), age (years), education (completed years of schooling), number of working persons in the family (used to pick up possible disguised unemployment), extension contact (dummy variable to measure the influence of agricultural extension on efficiency. Value is 1 if the farmer has had contact with an Agricultural Extension Officer in the past year, 0 otherwise), non-agricultural income share (proportion of total household income obtained from non-agricultural sources), index of underdevelopment of infrastructure[3], and index of soil fertility[4].

4. Empirical results

The summary statistics of the variables used appears in Table 2. A number of points can be noted from Table 2. First, we note that these farms are quite small, with average sizes of only one third of a hectare. We also observe that the mean profit is much higher for modern varieties of rice owing to higher yield. We see that the average level of education is four years; the average age of the farmer is 47 years; the average duration of involvement in farming is 25 years, average number of working persons is two, family size is 6 persons per household; 18% of income is derived from off-farm; approximately 56% of farms are owner-operated; and only 12% of farmers have had contact with extension officers during the past year.

[Insert Table 2 here]

Table 3 shows the maximum-likelihood estimates of the probit variety selection criterion model. The choice of explanatory variables correctly predicted farmers' variety selection decision for 83% of the observations. The Likelihood Ratio test results, presented at the bottom of Table 3, further statistically validates that these variables contribute significantly as a group to the explanation of the variety selection decision of the farmers. The value of the McFadden R^2 also confirms that these variables largely explain farmers' decision to choose modern varieties[5]. Among the price variables, lowering of seed prices increases the probability of choosing modern rice. This is expected since the number of observations used in the study is heavily weighed towards production in the Aman season. The most popular seed sowing practice for this season is the transplantation technique, which is heavier on seed cost in the form of seedlings that are either grown in a separate seedbed or purchased directly from the market. Thus the relative cost incurred for seed is higher as compared to broadcasting technique normally applied during Aus season for growing traditional rice varieties.

[Insert Table 3 here]

Availability of land as well as modern irrigation facilities significantly increases the probability of choosing modern varieties whereas other forms of farm wealth affects negatively.

All the decision-making variables significantly influence variety choice decisions, mostly with correct expected sign. Among the revealed decision-making variables, desire to get high yield as well as fodder for livestock and/or fuel use significantly increases the probability of choosing modern rice. Also, those farmers who are not concerned with higher labour, water and overall production cost, choose modern varieties. The desire to get high price and to grow within a short maturity period, however, has inconsistent signs than expected for unknown reasons. Subsistence pressure does not influence significantly in variety choice decisions.

The WLS coefficient estimates of the second stage switching regression models of modern rice and traditional rice profit functions were suppressed and not shown here. The results of the third stage estimation of the transformed stochastic profit frontiers with inefficiency effects for modern and traditional rice adjusted for self-selective variety choice decision was reported in Table 4.

The lower section of Table 4 reports the results of hypothesis test that the efficiency effects are not simply random errors. The key parameter is $\gamma = \sigma_\theta^2/(\sigma_\theta^2 + \sigma_v^2)$, which is the ratio of the errors in equation (1) and is bounded between zero and one, where if $\gamma = 0$, inefficiency is not present, and if $\gamma = 1$, there is no random noise[6]. For all the functions, γ is very close to 1 and is significantly different from zero, thereby, establishing the fact that high level of inefficiencies exist in both types of rice farming. Moreover, the corresponding variance-ratio parameter[7] γ^* implies that 85.1% and 97.3% of the differences between observed and the maximum frontier profits for modern rice and traditional rice farming is due to the existing differences in efficiency levels among farmers.

Profitability of rice farming increases with decline in input prices, fertilizers, seeds and labour wages (only in traditional rice farming), as expected. Also, profitability increases with increase in land under cultivation. Profitability of modern rice farming increases with irrigation as expected. On the other hand, since traditional rice varieties are not quite responsive to supplementary water control, lower use of irrigation raises its profitability.

The coefficient on the selectivity variable is significantly different from zero in both profit functions with opposite signs, thereby, establishing that serious selection bias exists in estimating equations from a sub-sample of farmers who produce either modern rice and/or traditional rice (Pitt, 1983) and the decision to choose the switching regression model in this study was appropriate.

[Insert Table 4 here]

The summary statistics for the measures of profit efficiency of modern rice and traditional rice farming are listed in Table 5. Both farming practices suffer from high level of profit inefficiency and the average profit efficiency scores are 0.56 in modern rice and 0.48 in traditional rice farming. This indicates, for example, that the average farm producing modern rice could increase profits up to 34% and traditional rice up to 48% by improving their technical and allocative efficiency. Farmers exhibit wide range of profit inefficiency in both farming practices, ranging from 97% to 8% less than maximum profit in modern rice farming and 97% to 1% less than maximum profit in traditional rice farming, respectively. Observation of wide variation in profit efficiency is not surprising and similar to the results of Ali and Flinn, (1989), Ali et al., (1994), and Wang et al., (1996) for Pakistan Punjab, North-west Pakistan, and China, respectively[8]. Only 37% of modern rice and 27% of traditional rice farmers seem to be operating at a profit efficiency level of 70% and above. These results imply that a considerable amount of profit can be obtained by improving technical and allocative efficiency in Bangladeshi rice production.

[Insert Table 5]

5. Factors explaining inefficiency

The lower section of Table 4 provides the socio-economic variables that are assumed to explain the observed wide variation in efficiency amongst both categories of farmers. Before discussing the results, we should first clearly state our prior expectations regarding the signs on these variables. We expected that *tenancy, education, age, experience, soil fertility,* and *extension* would all be positively related to efficiency, while *infrastructure* (lack of)*, working adults,* and *percentage of non-farm income* would be associated with lower efficiency levels.

Results show that *owner operators* perform better than the *tenants* in modern rice farming. This is perhaps due to relatively higher input intensive nature of modern rice farming where owner-operators have incentives to invest more in terms of irrigation and other capital equipment compared to tenants. The input sensitivity of modern rice production, therefore, may result in lower efficiency when less than optimal level of investment is made as with the case of tenants.

Education is negatively associated with efficiency for both types of rice production. Similar results have been reported in past analyses of technical efficiency in Bangladeshi agriculture (for example see Wadud and White, 2000). Education pulls away households from farming as it opens up opportunities to engage in off-farm work that are often more rewarding than farming on small pieces of land. The age and experience results are poor and most likely a consequence of older farmers although have more knowledge of their land are also being less willing to adopt new ideas. The *working adults* variable did not pick up the disguised unemployment effect.

The variables that have worked well in explaining inefficiency in modern rice farming are *infrastructure, extension contact* and *non-farm income*. Modern rice producers benefit significantly from better *infrastructure*[9]. It is evident that badly developed infrastructure has negative effects on both technical and allocative inefficiency. Technical efficiency would be adversely affected by not having inputs to use at the correct time, or not at all, and allocative efficiency would be affected by these constraints as well. On the other hand, those who are located in remote regions perform better in traditional rice production as it relies on less of modern inputs.

The *percentage of income earned off-farm* was included to reflect the relative importance of non-agricultural work in the household. The positive sign on the estimated coefficient points towards a situation where those households who have higher opportunity to engage in off-farm work fail to pay much attention to their crops relative to other farmers.

The *extension service*, which is particularly aimed at diffusing modern rice technology to the farmers, seemed to play its part in increasing efficiency in modern rice production although it reached only a fraction of the total farming population (see Table 2).

The *soil fertility* variable with consistent sign in the modern rice function indicates that this variable has little influence upon the observed efficiency differentials. This lends support to the assertion that much of the efficiency differences between these farms may be put down to management issues.

6. Conclusions and policy implications

The study demonstrated the use of switching regression framework on stochastic frontier models to analyse resource use efficiency while taking account of the self-selective nature of farmers' variety choice decisions and applied to a sample of Bangladesh rice producers. Using detailed survey data obtained from 406 rice farms spread over 21 villages in 1997 we obtain factors determining choice of rice varieties as well as measures of profit inefficiency with wide variation among both traditional and modern rice farmers. Results show that serious selection bias exists in both traditional rice and modern rice profit functions, thereby establishing the need to take into account the self-selective variety choice decisions made by the farmers. Increases in land, modern irrigation, and lower seed prices increase the probability for choosing modern rice. Among the cited reasons for choice, getting higher yield and fodder and fewer concerns for associated increased water, labour and production costs as well as lower prices and maturity period are important motives behind choosing modern varieties.

The mean level of efficiency is 0.56 in modern rice farming and 0.48 in traditional rice farming indicating that there remains considerable scope to increase profits by improving technical and allocative efficiency. The relatively lower level of efficiency during the season under consideration is perhaps due to the variation in irrigation support as access to irrigation significantly increases decision to choose modern varieties. Farmers tend to rely on monsoon rain to a large extent for irrigation in order to save large expenses incurred for mechanical irrigation, which runs up to 9.4% of gross value of output during the Aman season.

The farm-specific variables used to explain inefficiencies indicate that those farmers who have better access to input markets, and those who do less off-farm work tend to be more efficient. Owner operators are relatively more efficient than the tenants. Extension services have a positive influence in increasing efficiency in modern rice farming. The policy implications are clear. Adoption of modern rice varieties in Aman and Aus seasons can be increased by expanding irrigation facilities and lowering input prices, particularly seeds, fertilizers, and labour wages. Inefficiency in farming can be reduced significantly by improving the infrastructure and strengthening extension services. Also, land reform measures aimed at promoting land ownership will have a positive role in increasing efficiency of these modern rice producers who will ultimately be put under pressure to provide food for the rapidly growing urban population in the coming years in Bangladesh.

Notes

1. In this commonly used two-step approach, the first stage involves the specification and estimation of the stochastic frontier function and the prediction of inefficiency effects, under the assumption that these inefficiency effects are identically distributed with one-sided error terms. The second step involves the specification of a regression model for predicted inefficiency effects, which contradicts the assumption of an identically distributed one-sided error term in the stochastic frontier (Kumbhakar et al., 1991; Battesse and Coelli, 1995).
2. The prices are computed by dividing the total expenditure by total quantities of relevant inputs. The cost of home supplied inputs was imputed by market prices.
3. A composite index of underdevelopment of infrastructure was constructed using the cost of access approach. A total of 13 elements are considered for its construction. These are, primary market, secondary market, storage facility, rice mill, paved road, bus stop, bank, union office, agricultural extension office, high school, college, thana (sub-district) headquarter, and post office. Note that a high index value indicates a highly underdeveloped infrastructure.
4. The soil fertility index is constructed from test results of soil samples collected from the study villages during the field survey. Ten soil fertility parameters were tested. These are: soil pH, available nitrogen, available potassium, available phosphorus, available sulphur, available zinc, soil texture, soil organic matter content, cation exchange capacity (CEC) of soil, and electrical conductivity of soil. A high index value refers to better soil fertility.
5. McFadden R^2 is not comparable to the Adjusted R^2 in the OLS regression. The value of McFadden R^2 lies in the range of 0.20 – 0.40 in this type of model (Sonka, et al., 1989). Our result shows a value of 0.39, which is at the upper end of the range.

6. If γ is not significantly different from zero, the variance of the inefficiency effects, i.e., ω_{1i} and ω_{2i} in equations 14 and 15 is zero, and the model reduces to a mean response function in which the inefficiency variables enter directly (Battese and Coelli, 1995).
7. The parameter γ is not equal to the ratio of the variance of the efficiency effects to the total residual variance because the variance of θ_i is equal to $[(\pi-2)/\pi]\sigma^2$ not σ^2. The relative contribution of the inefficiency effect to the total variance term (γ^*) is equal to $\gamma^* = \gamma/[\gamma+(1-\gamma)\pi/(\pi-2)]$ (Coelli et al., 1998).
8. Ali and Flinn (1989) reported mean profit efficiency level of 0.69 (range 13 to 95%) for Basmati rice producers of Pakistan Punjab. Ali et al., (1994) reported mean profit efficiency level of 0.75 (range 4 to 90%) for rice producers in North-West Frontier province of Pakistan. Wang et al., (1996) reported mean profit efficiency level of 0.62 (range 6 to 93%) for rural farm households in China.
9. The constructed index represents level of underdevelopment of infrastructure. Therefore, a positive coefficient indicates positive effect on efficiency or negative effect on inefficiency.

References

Ali, F., Parikh, A., Shah, M.K., 1994. "Measurement of profit efficiency using behavioural and stochastic frontier approaches". *Applied Economics*, **26**, 181 – 188.

Ali, M., Flinn, J.C., 1989. "Profit efficiency among Basmati rice producers in Pakistan Punjab". *American Journal of Agricultural Economics*, **71**, 303 – 310.

Baffes, J., Gautam, M., 2001. "Assessing the sustainability of rice production growth in Bangladesh". *Food Policy,* **26**, 515 – 542.

BBS, 2001. *Statistical Yearbook of Bangladesh, 1999*. Bangladesh Bureau of Statistics, Dhaka

Bera, A.K., Kelly, T.G., 1990. "Adoption of high yielding rice varieties in Bangladesh: an econometric analysis. *Journal of Development Economics*, **33**, 263 – 285.

Feder, G., Lau, L.J., Lin, J.Y., Luo, X., 1990. "The relationship between credit and productivity in Chinese agriculture: a micro-economic model of disequilibrium". *American Journal of Agricultural Economics*, **72**: 1151 – 1157.

Freeman, H.A., Ehui, S.K., Jabbar, M.A., 1998. "Credit constraints and smallholder dairy production in the East African highlands: application of a switching regression model". *Agricultural Economics*, **19**: 33 – 44.

Green, W.,1997. LIMDEP Computer Program Version 7.0. Econometric Software, Inc. New York.

Husain, A.M.M., Hossain, M., Janaiah, A., 2001. "Hybrid rice adoption in Bangladesh: socio-economic assessment of farmers' experiences". BRAC Research Monograph Series No. 18. Dhaka: BRAC, Bangladesh.

Lee, L.F., 1978. "Unionism and wage rates: a simultaneous equation model with qualitative and limited dependent variables". *International Economic Review*, **19**: 415 – 433.

Maddalla, G.S., 1983. *Limited Dependent and Qualitative Variables in Econometrics*. Cambridge, Cambridge University Press.

Pitt, M., 1983. “Farm level fertilizer demand in Java: a meta-production function approach”. American Journal of Agricultural Economics, **65**: 502 – 208.

Pitt, M., Sumodiningrat, G., 1991. “Risk, schooling and the choice of seed technology in developing countries: a meta-profit function approach”. *International Economic Review*, **32**: 457 – 473.

Sonka, S.T., Hornbaker, R.H., Hudson, M.A., 1989. “Managerial performance and income variability for a sample of Illinois cash grain producers”. *North Central Journal of Agricultural Economics*, **11**: 101 – 118.

Wadud, A., White, B., 2000. “Farm household efficiency in Bangladesh: a comparison of stochastic frontier and DEA methods”. *Applied* Economics, **32**, 1665 – 1673.

Wang, J., Cramer, G.L., Wailes, E.J., 1996. “Production efficiency of Chinese agriculture: evidence from rural household survey data”. *Agricultural Economics*, **15**, 17 – 28.

Wang, H-J., Schmidt, P., 2002. “One-Step and Two-step estimation of the effects of exogenous variables on technical efficiency levels”. *Journal of Productivity Analysis*, **18**: 129 – 144.

Table 1. Description of explanatory variables.

Variables	Type	Description
Input prices		
Fertilizer price	Continuous	Price of fertilizers normalized by price of rice (taka[a]/kg)
Labour wage	Continuous	Wage of labour normalized by price of rice (taka/person day)
Seed price	Continuous	Price of seed normalized by price of rice (taka/kg)
Animal power price	Continuous	Price of animal power services normalized by price of rice (taka/animal-pair day)
Pesticide price	Continuous	Price of pesticides normalized by price of rice (taka/100 gm or ml of active ingredients)
Fixed factors		
Land	Continuous	Area planted to rice by the farmer (ha)
Farm capital	Continuous	Stock of farm capital equipment ('000 taka)
Irrigation	Continuous	Cost of irrigation (taka)
Decision-making variables: motivation behind growing modern rice varieties		
D_1	Binary	Value is 1 if the motivation is to get high yield, 0 otherwise
D_2	Binary	Value is 1 if the motivation is to get high price, 0 otherwise
D_3	Binary	Value is 1 if the motivation is that modern rice have short maturity period, 0 otherwise
Decision-making variables: motivation behind growing traditional rice varieties		
D_4	Binary	Value is 1 if the motivation is that traditional rice requires less labour, 0 otherwise
D_5	Binary	Value is 1 if the motivation is that traditional rice requires less water, 0 otherwise
D_6	Binary	Value is 1 if the motivation is that traditional rice have lower production cost, 0 otherwise
D_7	Binary	Value is 1 if the motivation is to get high fodder yield, 0 otherwise
Farm-specific variables		
Subsistence	Continuous	Subsistence pressure measured by family size (number)
Infrastructure	Continuous	Index of underdevelopment of infrastructure (number)
Soil fertility	Continuous	Index of soil fertility (number)
Tenancy	Binary	Value is 1 if owner operator, 0 otherwise
Age	Continuous	Years
Experience	Continuous	Number of years in farming
Education	Continuous	Completed years of schooling
Working	Continuous	Number of working members per household
Extension	Binary	Value is 1 if the farmer has had contact with an Agricultural Extension Officer in the past year, 0 otherwise
Non-farm income	Continuous	Proportion of total household income obtained from non-agricultural sources

Note: [a] Exchange rate: 1 US dollar = 42.7 Taka (approximately) during 1996-97 (BBS, 2001).

Table 2. Summary statistics

Variables	Mean	Standard deviation
Output, profits and prices		
Rice output (kg)	1082.24	1272.13
Rice output of modern rice farmers (kg)	1186.41	1297.56
Rice output of traditional rice farmers (kg)	722.51	1112.17
Profit (taka)	3599.70	5120.26
Profit from modern rice (taka)	3968.84	5146.44
Profit from traditional rice (taka)	2325.06	4836.93
Rice price (taka/kg)	5.58	0.55
Fertilizer price (taka/kg)	6.81	1.26
Labour wage (taka/day)	43.88	8.23
Animal power (taka/pair-day)	81.75	18.69
Seed price (taka/kg)	10.11	2.44
Pesticide price (taka/100 gm or ml)	83.88	14.92
Land cultivated (ha)	0.33	0.38
Farm capital ('000 taka)	13.28	18.89
Irrigation (taka)	223.51	676.00
Motivation behind decision to grow modern varieties		
To get high yield (D_1) (%)	0.98	0.16
To get high price (D_2) (%)	0.48	0.50
Shorter maturity period (D_3) (%)	0.49	0.50
Motivation behind decision to grow traditional varieties		
Requires less labour (D_4) (%)	0.27	0.45
Requires less water (D_5) (%)	0.21	0.41
Lower cost of production (D_6) (%)	0.07	0.26
To get more fodder (D_7) (%)	0.22	0.42
Farm-specific variables		
Subsistence pressure (number)	6.14	2.50
Tenancy (%)	0.56	0.50
Education of the farmer (years)	4.02	4.52
Age (years)	46.83	15.33
Experience (years)	24.63	14.83
Working member (number)	2.10	1.30
Extension contact (%)	0.12	0.32
Infrastructure index (number)	35.69	15.24
Soil fertility index (number)	1.66	0.18
Non-agricultural income share (%)	0.18	0.28

Note: Exchange rate: 1 US dollar = 42.7 Taka (approximately) during 1996-97 (BBS, 2001).

Table 3. Probit model for variety selection criterion

Variables	Coefficients	t-ratio
Prices		
ln Fertilizer price	-0.1483	-0.397
ln Labour wage	0.7319	1.608
ln Seed price	-1.2933	-3.555***
ln Animal power price	0.2786	0.821
ln Pesticide price	-0.3013	-0.881
Fixed factor endowments		
ln Land cultivated	0.2013	2.395**
ln Farm capital	-0.1425	-3.215***
ln Irrigation	0.1783	5.187***
Decision making variables		
To get high yield (D_1)	0.8603	2.003**
To get high price (D_2)	-0.7655	-4.248***
Shorter maturity period (D_3)	-0.3293	-1.846*
Requires less labour (D_4)	-0.7058	-2.564**
Requires less water (D_5)	-0.4737	-1.691*
Lower cost of production (D_6)	-0.7458	-2.774***
To get more fodder (D_7)	0.7629	3.264***
Farm-specific characteristics		
Subsistence pressure	-0.0460	-1.508
Constant	1.7332	1.262
Log-likelihood	-200.325	
Likelihood ratio (LR) test ($\chi^2_{16,0.95}$)	154.349***	
Percentage of correct predictions	0.83	
McFadden R^2 ($1 - Log_{max}/Log_0$)	38.52	

Note: *** significant at 1 percent level ($p<0.01$);
** significant at 5 percent level ($p<0.05$);
* significant at 10 percent level ($p<0.10$)

Table 4. Third stage estimation of the transformed stochastic profit frontiers with inefficiency effects for modern rice and traditional rice farmers adjusted for self-selective variety choice decisions

Variables	Traditional rice stochastic profit frontier		Modern rice stochastic profit frontier	
	Coefficient	t-ratio	Coefficient	t-ratio
Stochastic Profit Frontier Function				
Constant	7.4397	53.759***	7.4642	15.406***
Prices				
ln Fertilizer price	-0.6472	-3.424***	-0.6109	-1.823*
ln Labour wage	-0.4366	-1.699*	0.3834	0.930
ln Seed price	-0.6369	-4.226***	-1.2565	-3.065***
ln Animal power price	0.0574	1.033	0.2866	0.962
ln Pesticide price	0.3108	1.338	-0.2108	-0.629
Fixed factor endowments				
ln Land cultivated	2.1646	79.278***	2.3261	25.939***
ln Farm capital	0.0096	0.489	0.0019	0.044
ln Irrigation	-0.1735	-6.050***	0.0990	3.527***
Decision making variables				
To get high yield (D_1)	1.7836	4.597***	1.2231	2.458***
To get high price (D_2)	-0.1225	-0.902	-0.2685	-1.289
Shorter maturity period (D_3)	-0.4439	-4.923***	-0.2675	-1.483
Requires less labour (D_4)	0.2271	0.902	-0.7827	-2.501***
Requires less water (D_5)	-0.3576	-1.592	0.1127	0.369
Lower cost of production (D_6)	-0.0129	-0.066	0.0463	0.126
To get more fodder (D_7)	-0.0893	-0.243	0.3618	1.424
Selectivity variables				
λ_1 and λ_2	-0.2262	-1.990**	0.9348	2.115**
Variance parameters				
Sigma-squared ($\sigma^2 = \sigma_v^2 + \sigma_\theta^2$)	1.1967	7.381***	1.4586	3.088***
Gamma ($\sigma_\theta^2 / \sigma^2$)	0.99	107.403***	0.94	45.291***
Log likelihood	-100.8528		-376.453	
LR test	44.605***		86.775***	
Inefficiency effects function				
Constant	-1.0776	-1.214	-0.0209	-0.014
Tenancy	0.1542	0.523	-0.5894	-2.094**
Education	0.0966	2.259**	0.0699	2.083**
Age	0.0186	1.206	-0.0079	-0.576
Experience	0.0062	0.338	0.0108	0.707
Working member	-0.1850	-1.475	0.0634	0.728
Extension contact	0.1394	0.374	-0.9350	-1.815*
Infrastructure	-0.0263	-2.733***	0.0315	2.724***
Soil fertility	0.6246	1.103	-1.1794	-1.475
Non-farm income	-0.1691	-0.511	1.2507	2.308**

Note: *** significant at 1 percent level ($p<0.01$);
** significant at 5 percent level ($p<0.05$);

* significant at 10 percent level ($p<0.10$)

Table 5. Farm specific profit efficiency estimates

Efficiency levels	Traditional rice	Modern rice
Mean	0.48	0.56
Standard deviation	0.30	0.23
Maximum	0.99	0.92
Minimum	0.03	0.03
<40%	0.49	0.26
40 – 49%	0.11	0.12
50 – 59%	0.06	0.11
60 – 69%	0.07	0.14
70 – 79%	0.08	0.20
80 – 89%	0.03	0.16
90 – 100%	0.16	0.01
Number of observations	117	404

Appendix

Obtaining estimates of error variances $Var(\varepsilon_{1i})$ and $Var(\varepsilon_{2i})$

To obtain $Var(\varepsilon_{1i})$ and $Var(\varepsilon_{2i})$ the following relationships for the moments of the truncated bivariate normal distribution is used (Maddala, 1983: 225):

$E(u_{1i}/ I_i = 1) = -\sigma_{1u}\lambda_{1i}$

$E(u^2_{1i}/ I_i = 1) = \sigma^2_1 - \sigma^2_{1u}(\gamma' Z_i)\lambda_{1i}$

$E(u_{2i}/ I_i = 0) = \sigma_{2u}\lambda_{2i}$

$E(u^2_{2i}/ I_i = 0) = \sigma^2_2 - \sigma^2_{2u}(\gamma' Z_i)\lambda_{2i}$ (A1)

Hence,

$E(\varepsilon_{1i}/ I_i = 1) = E(\varepsilon_{2i}/ I_i = 0) = 0,$

and

$Var(\varepsilon_{1i}/ I_i = 1) = \sigma^2_1 - \lambda_{1i}(\gamma' Z_i + \lambda_{1i})$ (A2)

$Var(\varepsilon_{2i}/ I_i = 0) = \sigma^2_2 - \lambda_{2i}(\gamma' Z_i + \lambda_{2i})$ (A3)

From the first stage regression, we get estimates of λ_{1i} and λ_{2i}. In the second stage, se get estimates of only β_1, β_2, σ_{1u}, and σ_{2u}. To get the estimates of σ^2_1 and σ^2_2 we can proceed as follows.

After obtaining the estimates of β_1 and β_2, compute the residuals:

$$\hat{u}_{1i} = \pi_{1i} - \hat{\beta}'_1 P_i + \hat{\gamma}'_1 Z_i \qquad for\ I_i = 1$$

$$\hat{u}_{2i} = \pi_{2i} - \hat{\beta}'_2 P_i + \hat{\gamma}'_2 Z_i \qquad for\ I_i = 0$$

Then equations A1, A2 and A3 suggest that we estimate σ^2_1 and σ^2_2 by

$$\hat{\sigma}^2_1 = \frac{1}{N_1}\sum_{i=1}^{N_1}[\hat{u}_{1i} + \hat{\sigma}^2_{1u}(\hat{\gamma}' Z_i)\hat{\lambda}_{1i}] \qquad (A4)$$

$$\hat{\sigma}^2_2 = \frac{1}{N_2}\sum_{i=1}^{N_2}[\hat{u}_{2i} + \hat{\sigma}^2_{2u}(\hat{\gamma}' Z_i)\hat{\lambda}_{2i}] \qquad (A5)$$

where N_1 is the number of observations for which $I_i = 1$ and N_2 is the number of observations for which $I_i = 0$. To take care of the heteroscedasticity problem, we can use the estimated parameters to compute the error variances in A2 and A3 and then use them as weights in equations 10 and 11.