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Resource use efficiency under self-selectivity: the case of Bangladeshi rice producers

Sanzidur Rahman†

The paper jointly evaluates the determinants of switching to modern rice and its productivity while allowing for production inefficiency at the level of individual producers. Model diagnostics reveal that serious selection bias exists, justifying the use of a sample selection framework in stochastic frontier models. Results revealed that modern variety selection decisions are influenced positively by the availability of irrigation and gross return from rice and negatively by a rise in the relative wage of labour. Adoption of modern rice is higher in underdeveloped regions. Seasonality and geography/location does matter in adoption decisions. Stochastic production frontier results reveal that land, labour and irrigation are the significant determinants of modern rice productivity. Decreasing returns to scale prevail in modern rice production. The mean level of technical efficiency (MTE) is estimated at 0.82. Results also demonstrate that the conventional stochastic frontier model significantly overestimates inefficiency by three points (MTE = 0.79). Policy implications include measures to increase access to irrigation, tenurial reform and keeping rice prices high to boost farm returns and offset the impact of a rise in the labour wage which will synergistically increase the adoption of modern rice as well as farm productivity.

Key words: Bangladesh, modern rice producers, sample selection framework, stochastic production frontiers, technical efficiency.

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 rising population. The expansion in crop area, which was the 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 2.3 per cent for the period 1973–1999, has been largely attributed to conversion of traditional varieties to modern varieties rather than to increases in yield of the latter (Baffes and Gautam 2001). Currently, 70 per cent of total rice area is allocated to modern varieties (MoA 2007). However, this holds only when the overall annual production area is considered. There is a seasonal dimension in the area allocated to modern rice varieties. In general, rice occupies about 74 per cent of the cultivated land and is grown in all three seasons – Aus (premonsoon), Aman (monsoon) and

† Sanzidur Rahman (e-mail: srahman@plymouth.ac.uk) is Associate Professor in Rural Development, School of Geography, Earth and Environmental Sciences, University of Plymouth, Drake Circus, Plymouth, UK.

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Boro (dry winter). Aman is the principal growing season, which accounts for 51 per cent of annual gross rice area followed by Boro (39 per cent) and Aus (10 per cent), respectively (MoA 2007). The composition of area allocated to traditional rice still covers around 56 per cent in Aus, 45 per cent in Aman and only 5 per cent in Boro season, respectively (MoA 2007). Lack of access to irrigation has been traditionally considered as the binding constraint for continued widespread production of traditional rice in the Aus and Aman seasons, thereby resulting in lower productivity as compared with the Boro season (e.g., Hossain 1989; Hossain *et al.* 1990). This is because modern rice varieties are still capable of providing significantly higher yield levels as compared with traditional varieties. For example, the farm-level yield of modern rice varieties over all seasons is estimated at 4.2 mt/ha as compared with the traditional rice varieties of 2.3 mt/ha, implying a productivity gain of 80 per cent (Rahman 1998). Therefore, on the one hand, there is an urgent need to increase food production by raising land productivity, which is largely possible by increasing the adoption rate of modern rice varieties in all seasons possibly up to 85 per cent of total rice area (Baffes and Gautam 2001). On the other hand, the United Nations Organization projects that farmers will have to generate a large marketable surplus to feed the growing urban population (estimated at 46 per cent of the 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 rice, but also to become efficient and be responsive to market indicators, so that the scarce resources are utilised efficiently, thereby leading to an increase in productivity as well as to ensure supply to the urban market.

Against this background, important lessons can be learned from a joint evaluation of: (i) the determinants of switching to modern rice, (ii) the determinants of modern rice productivity, allowing for production inefficiency at the level of the individual producer and (iii) 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 to incorporate a sample selection procedure in stochastic frontier models. The utility of this framework is its ability to remove the bias of sample selection inherent in these types of studies. The bias arises because rational farmers choose between traditional or modern rice varieties depending on price and nonprice factors as well as their own socioeconomic circumstances. Therefore, in this model of rational variety choice, using observations from a single variety (be it traditional or modern rice) alone is likely to produce biased estimates of the production function which will be carried onto biased estimates of production efficiency. This happens because the omission of a particular variety from estimation leads to nonzero conditional expectations of the error terms of individual production functions of traditional and modern rice, respectively.

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 analysing determinants of technology adoption

Several studies have analysed the determinants of modern technology adoption by farmers in developing countries using simple ad hoc models. These are typically ordinary least squares (OLS), probit or tobit regressions of technology adoption on variables representing: (i) socioeconomic circumstances of farmers – such as, farm size, tenurial status, farmers' education level, farming experience, family size and gender and (ii) institutional and bio-physical factors – such as irrigation, credit, extension contact, membership of organisations, and distance to market/bus stop/extension office (e.g., Hossain 1989; Nkamleu and Adesina 2000; Shiyani *et al*. 2002; 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 maximisation 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 an important bearing on productivity and resource allocation decisions, and hence provides an incomplete picture of farmers' decision-making processes.

The model of technology adoption developed by Pitt (1983) explicitly takes into account price and nonprice 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 *et al*. (1977), a large number of studies followed which typically place the farming efficiency of developing country farmers in a range of 60 per cent to 82 per cent (e.g., Ali and Flinn 1989; Wang *et al*. 1996; Coelli *et al*. 2002; Rahman 2003; Bravo-Ureta *et al*. 2007). 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 incorporating 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, 2008) proposed an internally consistent method of incorporating 'sample selection' in a stochastic frontier framework which was adopted in our study and is elaborated as follows.

Farmers are assumed to choose between modern and traditional rice varieties to maximise profits subject to a set of price and nonprice factors. The decision of the *i*th farmer to choose modern rice is described by an unobservable selection criterion function, I_i*, which 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 selection criterion function is not observed. Rather a dummy variable, I, is observed. The variable takes a value of 1 for modern rice farms and 0 otherwise. The model is specified as:

$$I_i^* = \alpha' \mathbf{z}_i + w_i, I_i = 1(I_i^* > 0) \tag{1}$$

where z is a vector of exogenous variables explaining the decision to grow modern or traditional rice, α is a vector of parameters and w is the error term distributed as $N(0, \sigma^2)$.

The production behaviour of the modern rice farmers is modelled by postulating a restricted translog stochastic production frontier function as follows:[1]

$$y_i = TL(\beta' \mathbf{x}_i + v_i - u_i) iff\, I = 1 \tag{2}$$

where $\mathbf{x}$ represent inputs, y represents modern rice output, β are the parameters and v is the two-sided random error, independent of the u, representing

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

random shocks, such as exogenous factors, measurement errors, omitted explanatory variables and statistical noise; u is a nonnegative random variable associated with inefficiency in production, assumed to be independently distributed as a zero-truncated normal distribution, $u = |U|\ with\ U \sim N[0, \sigma_u^2]$.

The 'sample selection bias' arises as a result of the correlation of the unobservables in the stochastic frontier function with those in the variety selection equation (Greene 2008). In this sample selection framework proposed by Greene (2006, 2008), it is assumed that the unobservables in the variety selection equation is correlated with the 'noise' in the stochastic frontier model. In other words, w in (1) is correlated with v in (2), and therefore, (v, w) are distributed as bivariate normal distribution with $[(0,0),(\sigma_v^2, \rho\sigma_v, 1)]$. The vectors (y, x) are observed when $I = 1$.

Development of the estimator for this model is detailed by Greene (2006, 2008). We only report the final log likelihood function to be estimated (Greene 2006):

$$\log L_s = \sum\nolimits_i \log \frac{1}{R}\sum_{r=1}^{R}\left\{ I_i \left[\frac{2}{\sigma_u}\phi\left(\frac{\beta'\mathbf{x} + \sigma_v v_{ir} - y}{\sigma_u}\right)\Phi\left(\frac{\alpha'\mathbf{z} + \rho\, v_{ir}}{\sqrt{1-\rho^2}}\right)\right]\right.$$
$$\left. + (1 - I_i)\left[\Phi\left(\frac{-\alpha'\mathbf{z} - \rho\, v_{ir}}{\sqrt{1-\rho^2}}\right)\right]\right\}. \tag{3}$$

As the integral of this function does not exist in a closed form, Greene (2006, 2008) proposes computation by simulation. When $\rho = 0$ (i.e., the parameter which measures the correlation between w in (1) and v in (2)), the model reduces to that of the conventional stochastic frontier model and thus provides us with a method of testing existence of sample selection bias or selectivity (Greene 2008). The model is estimated using NLOGIT Version 4 (ESI 2007).

4. Data and variables

4.1. Data

This study utilises cross-sectional primary data for the crop year 1996. The data were collected by a team of field researchers via an intensive farm survey coordinated by the author. Multistage random sampling techniques were used in selecting study locations as well as the sample farmers. Three agro-ecological regions of Bangladesh are represented in the dataset: the Old Brahmaputra Floodplain, the High Ganges River Floodplain and the Middle Meghna River Floodplain. Samples from 21 villages – eight villages of the Jamalpur Sadar subdistrict of Jamalpur, six villages of the Manirampur subdistrict of Jessore and seven villages of the Matlab subdistrict of Chandpur – were used to represent these regions.

Information was obtained on input and output quantities as well as prices, at the plot level. Additionally, socioeconomic characteristics of the farm families and village-level infrastructural development and soil fertility data were also recorded. The geographical dispersion of the sample plots and imperfections in input markets in Bangladesh ensure adequate variability in prices across the cross-section. A total of 946 observations (324 observations of traditional rice varieties and 622 observations of modern rice varieties) constitute the final sample.

4.2. The variables

Two sets of variables are needed for this study: One for the probit variety selection equation model and the other for the stochastic production frontier model, discussed below. The dependent variable in the probit equation is the farmers' variety selection criterion. This is a binary variable that takes the value of 1 if a plot is planted with modern rice varieties and 0 otherwise. The explanatory variables include relative prices of variable inputs (P'_i) of fertilizers, labour and pesticides normalised by the price of output (P_y: rice). The other variables included in the probit equation are gross returns from rice production per ha, access to irrigation, infrastructure index,[2] soil fertility index,[3] farmer's education, farming experience, dummy variables to account for seasonality (*Kharif* season – premonsoon/monsoon) and location (Jamalpur and Jessore regions).

All the input and output variables used in the stochastic production frontier were measured on a per farm basis. The five input variables used in the model include land, labour, chemical fertilizers, pesticides and irrigation, and all are expected to have a positive relationship with rice output. As 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 the variables are presented in Table 1. We see that modern rice provides significantly higher yields as well as returns. Among the

[2] The index of infrastructure was constructed using the 'cost of access' approach. A total of 13 elements were considered for its construction. These are (1) primary market, (2) secondary market, (3) storage facility, (4) rice mill, (5) paved road, (6) bus stop, (7) bank, (8) union office, (9) agricultural extension office, (10) high school, (11) college, (12) Thana (subdistrict) headquarters and (13) post office. The distance of these facilities from the village and the travel cost incurred to access these facilities was utilized to construct the index. A high index value refers to highly under developed infrastructure (for details of construction procedure, see Ahmed and Hossain 1990).

[3] The 'soil fertility index' was 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 of soil and electrical conductivity of soil (for details of sampling and tests, see Rahman and Parkinson 2007).

Table 1 Summary statistics of the variables

Variable name	Traditional varieties		Modern varieties		Mean difference (MV-TV)	*t*-ratio
	Mean	Standard deviation	Mean	Standard deviation		
Prices and profits						
Rice price (taka/kg)	5.61	0.52	5.62	0.50	0.01	0.16
Fertilizer price (taka/kg)	5.72	1.28	6.57	1.46	0.85	9.19***
Labour wage (taka/person-day)	46.19	7.13	44.98	9.33	−1.21	−2.23**
Pesticide price (taka/100 ml or gm)	83.40	15.55	84.32	14.71	0.91	0.87
Gross return per ha (taka/ha)	1911.77	737.61	2573.12	877.85	661.35	11.59***
Inputs and outputs						
Rice output (kg/ha)	3196.80	1197.57	4334.56	1316.27	1137.76	13.28***
Amount of land cultivated per farm (ha)	0.35	0.42	0.33	0.33	−0.02	−0.85
Fertilizers (kg/ha)	158.88	98.85	262.34	94.18	103.46	15.52***
Labour (person-days/ha)	81.59	37.96	110.41	50.27	28.82	9.88***
Pesticides (ml or gm/ha)	212.58	592.73	634.53	832.52	421.96	9.00***
Irrigation (taka/ha)	653.68	1384.13	2299.18	2145.62	1645.50	12.51***
Socioeconomic and environmental factors						
Index of underdevelopment of infrastructure (number)	31.48	13.09	36.93	15.27	5.45	5.73***
Index of soil fertility (number)	1.70	0.20	1.66	0.18	−0.04	−3.04***
Irrigation access (proportion of cultivated land under irrigation)	0.27	0.44	0.77	0.42	0.50	16.98***
Farming experience (years)	26.50	14.80	25.02	14.69	−1.47	−1.46
Farmer's education (completed year of schooling)	4.06	4.66	3.71	4.33	−0.35	1.14
Kharif season (dummy variable)	0.72	—	0.33	—	−0.39	−12.62***
Jamalpur region (dummy variable)	0.51	—	0.49	—	−0.02	0.50
Jessore region (dummy variable)	0.32	—	0.18	—	−0.16	−5.13***
Observations	324		622			

Note: ***Significant at 1 per cent level ($P < 0.01$); **Significant at 5 per cent level ($P < 0.05$). — refers to not applicable. Exchange rate: 1 US dollar = 42.7 Taka (approximately) during 1996–97 (BBS 2001).

prices, the fertilizer price is significantly higher for modern rice producers, whereas the labour wage is significantly lower. Use of all inputs is significantly higher for modern rice farmers although there is no difference in the amount of land cultivated per farm. Furthermore, among the bio-physical and socioeconomic factors, significant differences exist between modern and traditional rice producers. For example, modern rice farmers have significantly greater access to irrigation. The proportion of farmers producing modern rice was significantly lower in the Jamalpur and Jessore regions. Also, modern rice farmers are located in underdeveloped regions as well as areas with poor soils. However, there is no difference in the average level of education and farming experience between producers of the different varieties.

The chi-squared test statistic in the probit variety selection equation is significant at the 1 per cent level, confirming the joint significance of the parameters (Table 2). The McFadden R-squared is estimated at 0.47. About 86 per cent of the observations were accurately predicted. Access to irrigation is the single most important determinant of the probability of choosing modern rice. The marginal effect of this variable is estimated at 0.21 implying that a one per cent increase in the proportion of area irrigated will increase the adoption probability of modern rice by 0.21 per cent. The gross return generated from rice production is also an important determinant of choosing modern rice. Among the prices, a rise in the relative wage of labour would decrease the probability of choosing modern rice significantly. This is because modern rice technology is a labour-intensive technology (Table 1) and transplanting, in particular, requires a large amount of labour in a short space of time, where use of only family labour may not be sufficient. Therefore, a rise in the labour cost will significantly depress the adoption of modern rice technology. Previous studies (e.g., Hossain 1989; Ahmed and Hossain 1990; and Hossain *et al.* 1990) also confirmed that modern rice technology uses a significantly higher share of hired labour.

Level of infrastructure development is also an important factor indicating that the probability of choosing modern rice decreases with infrastructure development.[4] This is because, in underdeveloped regions, adoption of modern rice technology provides the best possible option to improve farmers' income, as opportunities for producing high valued cash crops or seeking off-farm employment are highly limited (Rahman 2009). Therefore, given limited number of options to choose from, farmers in underdeveloped regions resort to producing modern rice provided that basic irrigation facilities exist. Ahmed and Hossain (1990) found a positive but nonsignificant influence of infrastructural development on modern rice adoption and concluded that 'the effects of infrastructure are primarily indirect, through prices and technology adoption (i.e., *irrigation*). The direct effect (*of infrastructure*), which is inde-

[4] The index reflects the underdevelopment of infrastructure, and therefore, a positive sign indicates a negative effect on the dependent variable (i.e., modern rice adoption) and vice versa.

Table 2 Parameter estimates of the probit variety selection equation

Variables	Probit coefficients		Marginal effects	
	Coefficient	*t*-ratio	Coefficient	*t*-ratio
Constant	1.5403*	1.86	0.4482*	1.86
Gross return per ha	0.0003***	4.00	0.0001***	4.08
Fertilizer price	0.0769	0.28	0.0223	0.27
Labour wage	−0.1258**	−2.50	−0.0366**	−2.51
Pesticide price	0.0326	1.55	0.0095	1.55
Index of underdevelopment of infrastructure	0.0284***	4.66	0.0083***	4.65
Soil fertility index	−0.6794	−1.57	−0.1977	−1.57
Irrigation access	0.7013***	5.35	0.2129***	5.23
Farming experience	−0.0048	−1.14	−0.0014	−1.14
Farmer's education	−0.0188	−1.35	−0.0055	−1.36
Kharif season	−1.7890***	−13.34	−0.5137***	−15.63
Jamalpur region	−0.4562**	−2.03	−0.1323**	−2.06
Jessore region	−0.6265**	−2.15	−0.2037**	−2.00
Model diagnostics				
Log likelihood	−323.60			
McFadden R^2	0.47			
Chi-squared	568.74***			
Degrees of freedom	12			
Accuracy of prediction (%)	86.16			
Number of total observations	946			

Note: ***Significant at 1 per cent level ($P < 0.01$); **Significant at 5 per cent level ($P < 0.05$); *Significant at 10 per cent level ($P < 0.10$); Marginal effects for dummy variables are computed at P|1 − P|0 (NLOGIT 2007).

pendent of prices and technology, is not significant' (p. 36). We also find a positive influence of irrigation on modern rice adoption. Developed infrastructure, on the other hand, opens up various opportunities, including scope for off-farm work and businesses, which presumably provide higher returns than modern rice farming, particularly for small and marginal farmers. Ahmed and Hossain (1990) concluded that infrastructure has profound impacts on the incomes of the poor in Bangladesh, thereby raising their income by 33 per cent, which includes a doubling of wages and an increase in income from business and industries by 17 per cent.

Seasonality has an important influence on modern rice technology adoption, as expected. The probability of modern rice adoption is significantly lower in the *Kharif* season (the premonsoon and monsoon season). One of the main reasons is the cost of supplementary irrigation, which is estimated at 12.8 per cent of the gross value of output for modern rice and only 2.6 per cent for traditional rice (Rahman 1998). Hence, farmers rely on monsoon rain for crop production in the Aus and Aman seasons, and therefore, planting a traditional variety is a preferred option. This perhaps explains why after four decades of thrust in the diffusion of the 'Green Revolution' technology the composition of the area allocated to traditional rice still accounts for 56 per cent in the Aus and 45 per cent in the Aman season, respectively (MoA 2007). Also, the probability of choosing modern rice is significantly lower in the Jamalpur and Jessore regions compared with the Comilla region. This is because the Jamalpur and Jessore study regions fall under *Agro-ecological Region 9* (defined as *Old Brahmaputra Floodplain*) and *Agro-ecological Region 11* (defined as *High Ganges River Floodplain*), respectively where the agricultural system is mainly rainfed (UNDP/FAO 1988). On the other hand, the Comilla study region falls under *Agro-ecological Region 16* (defined as *Middle Meghna River Floodplain*), wherein a Flood Control, Drainage and Irrigation (FCD/I) project was constructed with an embankment on only one side of the Matlab Thana in 1987, thereby leading to an increase in cropping intensity inside the embankment with two or three modern rice crops grown in a year (Rahman 1998).

Prior to discussing the results of the stochastic production frontier, we report the series of hypothesis tests conducted. The first test was to select the functional form. The second test was to decide whether the frontier model is an appropriate choice rather than a standard average production function. Third is the model specification test, i.e., testing whether sample selection bias is present or not. All tests were conducted at the sample means, which is also the point of approximation in this study. 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. The first test was conducted to determine the appropriate functional form, i.e., the choice between Cobb–Douglas and a translog functional form (H_0: $\beta_{jk} = 0$ for all jk). A generalised likelihood ratio (LR) test confirmed that the choice of translog production function is a better representation of the production structure.

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, which if negative implies that inefficiency is present, thereby justifying use of the stochastic frontier framework. 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, implying that the use of the stochastic frontier framework is justified.

Third, we conduct the model specification test. This was done by fitting the sample selection model while constraining ρ to equal zero (Greene 2008). The log likelihood functions were then compared using the chi-squared statistic. The null hypothesis of 'no sample selection bias' has been strongly rejected, implying that the use of sample selection framework is valid and justified. The coefficient on the ρ variable reported at the bottom of Table 4 also confirms that sample selection bias is present ($P < 0.01$).

Finally, in the lower panel in Table 3, we have provided checks for the regularity conditions of the translog production frontier. The two checks are (i) monotonicity, i.e., positive marginal products, with respect to all inputs

Table 3 Hypothesis tests

Name of the test	Parameter restrictions	Test statistic	Degrees of freedom	χ^2 critical value at 5%	Outcome
Functional from test	H_0: all $\beta_{jk} = 0$	Likelihood ratio (LR) = 59.55	15	25.00	Reject H_0. CD is inadequate
Frontier test	H_0: M3T = 0 (i.e., no inefficiency component)	z-statistic = −1.67	—	P-value = 0.048	Reject H_0. Frontier not OLS
Model specification test	H_0: $\rho = 0$ (i.e., sample selection bias is not present)	LR = 243.60	23	35.17	Reject H_0. Sample selection bias is present in the model
Regularity conditions check	Monotonicity ($dy/dx_i > 0$) for every input			Diminishing marginal productivity ($d^2y/dx^2_i < 0$) for every input)	
	Value	Outcome		Value	Outcome
Land	4195.33	Fulfilled		−1083.64	Fulfilled
Fertilizer	0.04	Fulfilled		−0.02	Fulfilled
Labour	4.21	Fulfilled		−0.09	Fulfilled
Pesticides	1.93	Fulfilled		−0.64	Fulfilled
Irrigation	0.02	Fulfilled		−0.06	Fulfilled

Note: — refers to not applicable.

Table 4 Parameter estimates of the stochastic production frontier model for modern rice corrected for sample selection bias

Variables	Stochastic production frontier model (jointly estimated with the probit seed selection equation)		Conventional estimation of the stochastic production frontier with inefficiency effects model	
	Coefficient	*t*-ratio	Coefficient	*t*-ratio
Production frontier function				
Constant	6.6970***	59.45	6.7335	58.50
ln Land	0.8684***	21.80	0.8061***	20.12
ln Fertilizer	0.0011	0.04	0.0289	1.10
ln Labour	0.0514*	1.64	0.0929***	2.83
ln Pesticides	0.0023	0.70	0.0036	1.08
ln Irrigation	0.0201***	9.07	0.0149***	5.82
0.5*(ln Land)^2	0.1120**	2.52	0.1167***	2.58
0.5*(ln Fertilizer)^2	−0.0223*	−1.69	−0.0147	−1.46
0.5*(ln Labour)^2	0.0422	0.87	0.0648	1.61
0.5*(ln Pesticides)^2	0.0099***	3.87	0.0091***	4.46
0.5*(ln Irrigation)^2	0.0017	1.33	0.0013	1.14
ln Land*ln Fertilizer	−0.0342	−0.91	−0.0379	−1.18
ln Land*ln Labour	−0.2378***	−2.82	−0.2502***	−3.15
ln Land*ln Pesticides	0.0141**	2.00	0.0119*	1.89
ln Land*ln Irrigation	0.0068*	1.70	0.0074*	1.84
ln Fertilizer*ln Labour	0.1115**	2.19	0.0994**	2.32
ln Fertilizer*ln Pesticides	−0.0063	−1.01	−0.0040	−0.97
ln Fertilizer*ln Irrigation	−0.0028	−1.09	−0.0029	−1.19
ln Labour*ln Pesticides	−0.0190***	−2.68	−0.0182***	−3.14
ln Labour*ln Irrigation	−0.0050	−1.31	−0.0044	−1.15
ln Pesticides*ln Irrigation	−0.0002	−0.05	0.0000	−0.01
Model diagnostics				
Log likelihood	−201.799		−24.4316	
σ_u	0.2589***	5.83	0.6875**	2.45
σ_v	0.2170***	12.31	0.0388***	4.41
ρ (sample selection bias, $\rho_{w,v}$)	−0.4638***	−2.99	—	—
γ	—	—	0.546***	3.89
Wald ($\chi^2_{20,95}$)	—	—	6894.86***	
Inefficiency effects model				
Constant	—	—	0.7489***	3.19
Farmer's education	—	—	0.0061	1.14
Farming experience	—	—	0.0027*	1.85
Index of underdevelopment of infrastructure	—	—	0.0044***	3.49
Soil fertility index	—	—	−0.3502**	−2.23
Irrigation access	—	—	−0.2397***	−2.64
Jamalpur region	—	—	−0.1828***	−3.24
Number of selected observations	622		622	

Note: ***Significant at 1 per cent level ($P < 0.01$); **Significant at 5 per cent level ($P < 0.05$); *Significant at 10 per cent level ($P < 0.10$). — refers to not applicable.

$\left(\frac{\partial y}{\partial x_i} > 0\right)$ 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 at the sample means, which is also the point of approximation.

Table 4 presents the results of the stochastic production frontier model corrected for sample selection bias. A total of 11 coefficients of a total of 20 are significantly different from zero at the 10 per cent 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 per cent level. The coefficient on the ρ variable is significantly different from zero at the 1 per cent level, which confirms that serious sample selection bias exists, thereby justifying the use of the sample selection framework. In other words, this finding confirms that estimation using observations from only single variety producers (either modern or traditional rice producer) will provide biased estimates of productivity, which will then be carried on to the biased estimates of efficiency scores as well (discussed below).

Results from the stochastic production frontier for modern rice, corrected for sample selection bias, reveal that the productivity of rice farming increases with land area, labour and irrigation inputs. All the input variables were mean corrected ($X_{ik} - \bar{X}_k$) so that the coefficients on the first-order terms can be read directly as production elasticities. Land has the highest elasticity value of 0.87, implying that a one per cent increase in land area allocated to modern rice will increase production by 0.87 per cent. The production elasticity of labour has been estimated at 0.05 and irrigation at 0.02. Decreasing returns to scale exist in modern rice production, and the null hypothesis of 'constant returns to scale' (i.e., H_0: $\sum\beta_k = 1$ for all k; the sum is estimated at 0.94) is strongly rejected at the 1 per cent level of significance. We have also provided an estimate of a conventional stochastic production frontier with inefficiency effects model for comparison (see last two columns of Table 4). As can be seen from the parameter estimates, the coefficient on the land variable is underestimated by six points in the conventional model, and the coefficient on the labour variable is overestimated by four points. The overall returns to scale estimate in the conventional model is 0.95 and is also strongly rejected at the 5 per cent level of significance. Asadullah and Rahman (2009), Appleton and Balihuta (1996) and Weir and Knight (2004) also reported decreasing returns to scale in cereal production for Bangladeshi, Ugandan and Ethiopian farmers, respectively. Given widespread reporting of scale inefficiency among farmers in developing countries, estimates of 'decreasing returns to scale' seem consistent with expectation.

Results from the inefficiency effects model reveal that technical efficiency is significantly positively influenced by irrigation access, developed infrastructure and soil fertility. Farmers located in the Jamalpur region are technically efficient, and older farmers are relatively inefficient (see last two columns of Table 4).

The summary statistics of technical efficiency scores for modern rice farmers, corrected for sample selection bias, are presented in Table 5. The mean technical efficiency is estimated at 82 per cent, implying that 22 per cent

Table 5 Distribution of technical efficiency scores and 95 per cent confidence limits of modern rice farmers

	Stochastic production frontier (corrected for sample selection bias)	Conventional stochastic frontier with inefficiency effects model
Efficiency levels		
Up to 60%	0.96	6.30
61–70%	6.43	10.90
71–80%	22.99	27.70
81–90%	60.93	45.30
91% and above	8.68	9.80
Efficiency scores		
Minimum	0.48	0.43
Maximum	0.95	0.95
Mean	0.82 (0.07)	0.79 (0.10)
t-ratio of mean efficiency difference (sample selection corrected – conventional)	—	12.55*
Upper bound 95% confidence limit	0.98 (0.04)	0.97 (0.04)
Lower bound 95% confidence limit	0.62 (0.08)	0.61 (0.08)
Confidence interval (CI = Upper − Lower limits)	0.36 (0.05)	0.35 (0.06)
t-ratio of CI difference CI (sample selection corrected – conventional)	—	11.67*
Number of observations	622	622

Note: *Significant at 1 per cent level ($P < 0.01$). — refers to not applicable. Figures in parentheses are standard deviations.

[(100−82)/82] of the production is lost because of technical inefficiency. This implies that the average farm producing modern rice could increase production by 22 per cent by improving technical efficiency, which is substantial. Farmers exhibit a wide range of production inefficiency ranging from 48 per cent to 95 per cent in modern rice farming. Observation of wide variation in production efficiency is not surprising and is similar to the results of Ali and Flinn (1989), Wang *et al*. (1996) and Bravo-Ureta *et al*. (2007) for Pakistan Punjab, China and a total of 167 case studies from developing countries, respectively.

Overall, the efficiency scores for modern rice farmers, corrected for sample selection bias, are significantly higher by three points ($P < 0.01$) as compared with the conventional stochastic frontier model, thereby providing further justification for the use of a sample selection framework (see last column of Table 5). The direct estimation of the single equation stochastic production frontier model seems to have overstated the level of inefficiency both at the lower end and the upper end of the distribution. For example, only <1 per cent of modern rice farmers were operating at an efficiency level of below 60 per cent in our selection bias corrected model, whereas in the conventional model, the figure is 10.6 per cent. Also 70 per cent of modern rice farmers were operating at efficiency level of above 80 per cent in our selectivity model, whereas the figure is only 55 per cent in the conventional model. Figures 1–3

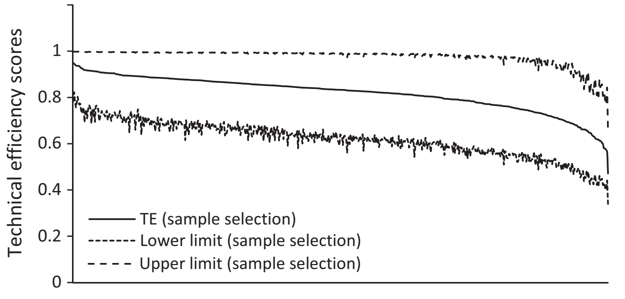

Figure 1 Confidence limits for technical efficiency (sample selection model).

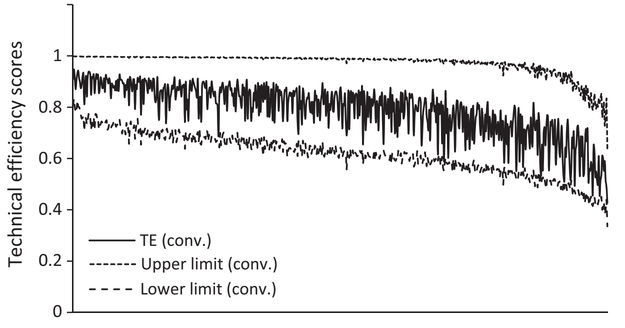

Figure 2 Confidence limits for technical efficiency (conventional model).

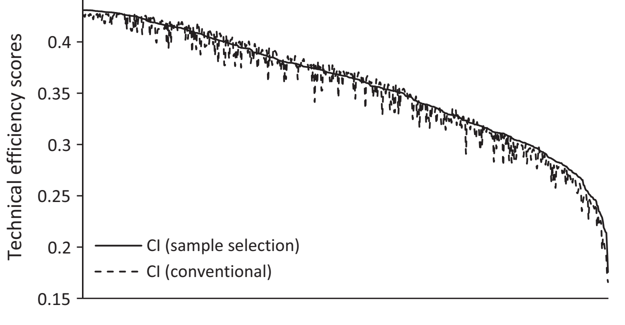

Figure 3 Confidence intervals for technical efficiency of sample selection model and conventional model.

and Table 5 also present distribution of the 95 per cent confidence limits for technical efficiency of individual farms for both models. Results reveal that the confidence limits show higher variability in the conventional model for the same farms and that the confidence intervals are significantly different between the two models.

6. Conclusions and policy implications

The study jointly evaluates the determinants of switching to modern rice as well as the determinants of modern rice productivity, while allowing for production inefficiency at the level of individual producers, in Bangladesh by applying a sample selection framework in stochastic frontier models. The model diagnostics reveal that serious sample selection bias exists, thereby justifying use of this framework. In other words, estimation from only single variety producers (i.e., either modern or traditional rice producers) will provide biased results of the determinants of technology adoption and productivity, as well as farm-specific technical efficiency scores, which are clearly demonstrated in this study.

The results confirm that both price and nonprice factors determine the probability of choosing modern rice technology. Specifically, access to irrigation and gross returns generated from production are the important determinants in choosing modern rice, although the labour wage, location and seasonality also matter in the selection decision as well. As shown in Table 1, the return from modern rice is significantly higher when compared with traditional rice, which is the main staple of Bangladeshi farmers. Therefore, the higher return of modern rice provides a good incentive to switch, which is further complemented by the availability of irrigation facilities. Results from the stochastic production frontier reveal that land, labour and irrigation inputs are the main determinants of modern rice productivity. A high level of inefficiency still exists in modern rice production. The mean level of technical efficiency of these self-selected modern rice farmers is estimated at 82 per cent, implying that there remains substantial scope to increase production by improving technical efficiency alone. Decreasing returns to scale also exist in modern rice production, implying that farmers are scale inefficient as well.

The policy implications of this study are clear. Investment in irrigation will boost the adoption of modern rice technology as well as its productivity, consistent with conventional wisdom. Furthermore, the results of this study also reveal that the adoption of modern rice technology is vulnerable to changes in the relative price of labour, whereas labour input is a significant determinant of modern rice productivity. Therefore, a policy response aimed at increasing the price of rice would be beneficial from the farmers/producers' perspective, as it would potentially offset any rise in the relative price of labour as well as keep modern rice production profitable. Another area of intervention is to increase the availability of land for modern rice cultivation, as it is one of the most important determinants of productivity. As tenurial arrangements in Bangladesh is exclusively geared towards facilitating rice farming, tenancy reform aimed at improving incentives for tenants would enable landless and marginal farmers to increase their farm size and/or enter into modern rice farming and contribute positively towards food production growth, which is an essential requirement for a food insecure country like Bangladesh.

The complex interplay of these factors on adoption rate and productivity perhaps explain the observed stagnancy in switching to modern rice in Bangladesh, despite four decades of a serious policy drive, aimed at increasing the diffusion of this technology throughout the country. Although responsiveness to returns exemplifies the commercial behaviour of farmers, it seems that return alone does not fully determine the decision to choose modern rice because other price and nonprice factors play an important role in determining variety selection decisions as well as productivity performance. Nevertheless, given the evidence of this study, policies aimed at raising the modern rice price, increasing access to irrigation and tenurial reform can be safely suggested as the way forward to promote adoption of modern rice technology as well as increase productivity of the Bangladeshi rice farmers.

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