Joint determination of the choice of growing season and economic efficiency of maize in Bangladesh

Article

Accepted Version

REVISED VERSION
(incorporating all comments of the referee)

Joint determination of the choice of growing season and economic efficiency of maize in Bangladesh

Sanzidur Rahman

School of Geography, Earth and Environmental Sciences, University of Plymouth, Drake Circus, Plymouth, PL4 8AA, United Kingdom, E-mail: srahman@plymouth.ac.uk

Md. Sayedur Rahman

On-farm Research Division, Bangladesh Agricultural Research Institute (BARI), Kushtia, Bangladesh, E-mail: sayedecon@yahoo.com

Md. Habibur Rahman

Department of Agricultural Economics, Bangladesh Agricultural University, Mymensingh, Bangladesh, E-mail: habib_econ@yahoo.com

Address for correspondence

Dr. Sanzidur Rahman

Associate Professor in Rural Development

School of Geography, Earth and Environmental Sciences

University of Plymouth

Drake Circus

Plymouth, PL4 8AA

Phone: +44-1752-585911

Fax: +44-1752-585998

E-mail: srahman@plymouth.ac.uk

June 2011

Joint determination of the choice of growing season and economic efficiency of maize in Bangladesh

ABSTRACT

The paper jointly evaluates the determinants of the choice of maize growing season (winter vs. summer maize) and economic efficiency of individual producers in Bangladesh using a sample selection framework applied to stochastic frontier models. Model diagnostics reveal that sample selection bias is significant, thereby, justifying the use of this approach. Probit results reveal that the probability to choose winter maize are influenced positively by gross return, subsistence pressure, and soil suitability whereas extension contact influences choice negatively. Stochastic cost frontier results reveal that a rise in input prices and output level increase production cost as expected. Among the variables representing the production environment, soil suitability and stability of mean temperature reduces cost whereas precipitation increases cost. The mean level of economic efficiency is estimated at 0.91, implying that scope still exists to reduce cost further by jointly eliminating technical and allocative inefficiency. Policy implications include measures to improve soil suitability, development of temperature resistant varieties, and price policies to check input price rise while boosting maize price which will synergistically increase adoption rate as well as profitability of winter maize cultivation in Bangladesh.

JEL Classification: O33, Q18, and C21.

Keywords: Season selection decision, stochastic cost frontier, economic efficiency, sample selection framework, maize crop, Bangladesh

1. Introduction

Bangladesh economy is dominated by agriculture contributing 14.9% to the Gross Domestic Product (GDP). Of this, the crop sub-sector alone contributes 11.3% to the GDP (BBS, 2010). Agriculture sector generates about 35.0% of the total foreign exchange earnings (Husain, *et al.*, 2001 and Islam, *et al.*, 2004) and is the main source of employment absorbing

48.1% of the labour force (BBS, 2010). Land is the most important and scarce means of production resulting in intensive cropping on all available cultivable land. The current level of cropping intensity is estimated at 179.0% (BBS, 2010). It has been increasingly realized that economic development in Bangladesh can not be achieved without making a real breakthrough in the agricultural sector (Baksh, 2003).

Although rice is the main staple food grain, maize is gaining importance as a third crop after wheat covering 0.9% and 1.7% of the total and net cropped area, respectively (BBS, 2010). Also, the yield potential of the composite varieties of maize released from the Bangladesh Agricultural Research Institute are 5.5 - 7.0 t/ha and the hybrid varieties are 7.4 – 12.0 t/ha which are well above the world average of 5.2 t/ha (FAO, 2009). Furthermore, maize production and yield has experienced an explosive growth in Bangladesh in recent years. For example, the cropped area of maize increased from only 2,654 ha in 1971-72 to 128,285 ha in 2008-09; production from 2,249 t to 730,000 t; and yield from 0.9 t/ha to 5.7 t/ha during the same period. Maize has now positioned itself as the 1st among the cereals in terms of yield rate (5.7 t/ha) as compared to rice (2.8 t/ha) and wheat (2.2 t/ha) (BBS, 2010).

Maize possesses a wide genetic variability enabling it to grow successfully in any environment and in Bangladesh it is grown both in winter and summer time, although the former is the dominant pattern. However, it is not clear as to why farmers choose to grow either summer maize or winter maize but not both even though maize provides higher returns as compared to both rice (Baksh, 2003) and wheat (Hasan, 2006). We postulate that a host of socio-economic factors as well as the production environment within which the farmers operate may be responsible for making the choice of growing season and resulting outcome. It is known that the production environment significantly influence productivity and efficiency (Sherlund et al., 2002; Rahman and Hasan, 2008), but whether it also influences the choice of growing season of a crop is not very clear.

Given this backdrop, the present study is aimed at jointly evaluating the decision to choose maize growing season (i.e., winter vs. summer maize) and its economic efficiency at the individual producer level. We undertake such a task by using a model recently developed by Greene (2006, 2008) 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 summer and winter maize depending on socio-economic as well as the environmental factors within which they have to operate. Therefore, in this model of rational season selection decision, using observations from a single season (be it summer or winter maize) alone is likely to produce biased estimates of the production function which will be carried onto biased estimates of production efficiency.

The paper is organized as follows. Section 2 describes the methodology and the data. Section 3 presents the results. The final section concludes and draws policy implications.

2. Methodology

2.1. Theoretical Framework

Greene (2006) criticised the most common approach to remove sample selection bias, known as Heckman's approach (1976), because it is inappropriate in models that are not linear, such as probit, Tobit and so forth. This is because: (i) the impact on the conditional mean of the model of interest, if it is non-linear, will not necessarily take the form of an inverse Mills ratio, which is used to correct for the sample selection bias in Heckman's approach; (ii) 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; and finally (iii) 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 summer and winter maize to maximize profits subject to a set of socio-economic and environmental factors. The decision of the *i*th farmer to choose winter maize is described by an unobservable selection criterion function, I_i*, which is postulated to be a function of gross return, factors representing farmers' socio-economic circumstances, and a bio-physical factor within which farmers operate. The selection criterion function is not observed. Rather a dummy variable, I, is observed. The variable takes a value of 1 for winter maize farms and 0 otherwise. The model is specified as:

$$I_i* = \boldsymbol{\gamma}'\mathbf{z}_i + w_i, I_i = 1 \quad (I_i* > 0) \qquad (1)$$

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

The production performance of the winter maize farmers is modelled by postulating an extended Cobb-Douglas stochastic cost frontier function[1]. The advantages of choosing a cost frontier function are: (a) it is self-dual to an underlying production frontier, (2) since a cost frontier is specified as a function of input prices which are exogenous in nature and therefore, free from any potential endogeneity problem arising from specifying a production frontier; (3) it will allow us to determine the level of economic efficiency, also known as cost efficiency, which results from both technical efficiency and allocative efficiency. Technical efficiency refers to a producer's ability to obtain the highest possible output from a given quantity of inputs (Rahman, 2003). Allocative efficiency refers to a producer's ability to

[1] We did not use the translog model in order to avoid collinearity because we are using a large number of input prices. Moreover, Kopp and Smith (1980) suggest that the choice of functional form has a limited effect on efficiency. Consequently, the Cobb-Douglas specification is widely used in production or cost frontier studies (e.g., Hazarika and Alwang, 2003; Rahman and Hasan, 2008; Asadullah and Rahman, 2009).

maximise profit given technical efficiency. A producer may be technically efficient but allocatively inefficient (Hazarika and Alwang, 2003). Therefore, economic/cost efficiency refers to a producer's ability to produce the maximum possible output from a given quantity of inputs at the lowest possible cost and has direct implication for competitiveness of the Bangladeshi farmers in the international market.

The model is written as follows[2]:

$$C_i = CD(\alpha' q_i + \boldsymbol{\beta}' \mathbf{w}_i + \boldsymbol{\omega}' \mathbf{e}_i + v_i + u_i) \qquad \text{iff } I = 1 \qquad (2)$$

where **w** represent input prices (normalized with one of the input prices to impose homogeneity condition), **e** represent environmental factors, q represents output level, C represents cost of production, α, β and ω are the parameters; and v is the two sided random error, independent of the u, representing random shocks, such as exogenous factors, measurement errors, omitted explanatory variables, and statistical noise; and u is a non-negative random variable associated with inefficiency in production, assumed to be independently distributed as a zero-truncated normal distribution, $u = |U| \text{ with } U \sim N[0, \sigma_u^2]$.

The 'sample selection bias' arises as a result of the correlation of the unobservables in the stochastic cost frontier function with those in the season selection equation (Greene, 2008). In this sample selection framework proposed by Greene (2006, 2008), it is assumed that the unobservables in the season selection equation is correlated with the 'noise' in the stochastic cost frontier model. In other words, w in (1) is correlated with v in (2), and

[2] Only winter maize cost frontier function is shown here. The counterpart is the summer maize cost frontier. The model selects the winter maize producers from the total sample (composed of both winter and summer maize producers) based on the information provided in the probit selection equation.

therefore, (v, w) are distributed as bivariate normal distribution with $[(0,0),(\sigma_v{}^2,\rho\sigma_v,1)]$. The vectors ($C$, q,$\boldsymbol{w}$,$\boldsymbol{e}$) are observed when I = 1.

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

$$\log L_s = \sum_i \log \frac{1}{R}\sum_{r=1}^{R}\left\{ I_i\left[\frac{2}{\sigma_u}\phi\left(\frac{\alpha q + \boldsymbol{\beta}'\mathbf{w} + \varpi'\mathbf{e} + \sigma_v v_{ir} - C)}{\sigma_u}\right)\Phi\left(\frac{\boldsymbol{\gamma}'\mathbf{z} + \rho v_{ir}}{\sqrt{1-\rho^2}}\right)\right] + (1-I_i)\left[\Phi\left(\frac{-\boldsymbol{\gamma}'\mathbf{z} - \rho v_{ir}}{\sqrt{1-\rho^2}}\right)\right]\right\} \quad (3)$$

Since the integral of this function does not exist in a closed form, Greene (2006; 2008) proposes computation by simulation. When ρ = 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).

2.2. Study areas and the sample farmers

Maize is cultivated almost all over the country, though the intensity of planted area and land suitability are not equal in all regions. Therefore, we computed a maize area index for each greater district[3]. The maize area index for the *j*th district is expressed as:

$$MAI_j = (Area_j / GCA_j) * 100, \quad (4)$$

where *MAI* is the maize area index, *Area* is the maize area and *GCA* is the gross cropped area. In other words, the index reflects the share of maize cropped area in GCA expressed in percentage. Based on this index, maize growing regions were classified into three levels of intensity: high intensity (MAI>1.0), medium intensity (0.50<MAI<1.0), and low intensity areas (MAI<0.5).

[3] Although there are 64 districts in Bangladesh, most secondary data are still reported at the level of these 21 former greater districts.

A multistage sampling procedure was adopted to select the sample farmers. First, for winter maize, three areas were selected according to the rank of *MAI* as well as percent of total winter maize area. The selected regions are Kushtia, Bogra and Dinajpur which covered 59% of total winter maize area of the country. Similar exercise was repeated for summer maize. The selected regions are Dhaka, Bogra and Dinajpur which covered 64% of total summer maize area of the country (Table 1). In the second stage, one new district was chosen from each aforesaid selected greater district according to higher percent of maize area and ease of communication. Then, one upazila (sub district) from each new district and one union from each upazila were selected purposively. Finally, six villages (one from each union) were selected randomly for collection of primary data. In the third stage, a number of steps were followed to select the households to ensure a high level of representation. At first, a list of all maize growing farmers was collected from the Department of Agricultural Extension (DAE). Then, these farm holdings were stratified into three standard farm-size categories commonly adopted in Bangladesh (e.g., Rahman and Hasan, 2008). Then, a total of 300 winter maize and 150 summer maize producing households were selected following a standard stratified random sampling procedure (Table 1). Two sets of structured questionnaires were administered: one for collecting preliminary information of the whole population (i.e., all the maize growers of the village), and another for in depth information from the sampled farmers. These questionnaires were pre-tested prior to finalization. Data on production technologies of maize were recorded seasonally by three visits covering each of the crop seasons. First visit was done just after sowing of seeds, second visit following completion of all intercultural operations and the last one after harvesting and threshing of the crop. The formal survey for data collection started from the maize growing seasons (winter and summer) during 2006-07. For winter season maize, data were collected from November 2006 to April 2007, while for summer season maize data were collected from February to July 2007.

Production related data on all inputs e.g. seed, manures, fertilizers, pesticides, irrigation, mechanical power, animal power, human labour etc. and all management operations like ploughing, seeding, fertilizing, irrigation, weeding, harvesting, threshing, winnowing, and bagging, time and methods of maize cultivation and socio-economics data such as age, education, farming experience, farm size, and household size of the farmers were recorded. Market prices of maize and its by-product as well as input prices were also recorded.

[Insert Table 1 here]

2.3. The variables

Two sets of variables are needed for this study: One for the probit season selection model; the other for the stochastic production frontier model, discussed below. The dependent variable in the probit equation is the farmers' season selection criterion. This is a binary variable that takes the value of 1 if a plot is planted with winter maize and 0 otherwise. The explanatory variables include, gross return from maize (Tk/ha), farm operation size (ha), irrigation intensity (Tk/ha), farmer's education (completed years of schooling), farmer's age (years), farming experience (years), subsistence pressure (persons per household), and extension contact (1 = if had extension or training, 0 otherwise). Also an environmental variable, the soil suitability index (number) is included.

Apart from the maize output level, the six normalized input prices (actually seven, since seed price is used to normalize these six input prices) used in the model include, land rent (Tk/ha), labour wage (Tk/person-day), mechanical power price (Tk/ha), chemical fertilizer price (Tk/kg), irrigation price (Tk/ha) and organic manure price (Tk/kg), and all are expected to have a positive relationship with the cost of maize production (Tk). The four environmental variables included in the model are land suitability index (number), soil suitability index (number), total rainfall during the growing season[4] (mm), and temperature stability (i.e., mean temperature range calculated as maximum – minimum temperature) during the season[5] (^{0}C). We expect negative relationship of cost with land and soil quality variables but the influence of other two variables (rainfall and temperature) are unknown. Since the variables in the probit season selection equation and the stochastic cost frontier differ substantially, the structural model satisfies the identification criterion (Maddala 1983).

3. Results

3.1. Socio-economics, production environment and resource use patterns

Table 2 presents the comparison of socio-economic circumstances, production environment and resource use patterns among winter and summer maize farmers. Some interesting observations can be made from the results of this exercise. We see that although there are no significant differences in farmers' socio-economic circumstances (i.e., age, education, and farming experiences except subsistence pressure), the winter maize growers tend to be large farmers as evident from their overall farm operation size. The summer maize growers received significantly higher level of extension and/or training support which is surprising. One reason may be the proximity of one summer maize sampled region to capital Dhaka where agricultural support services might be better as compared to remote regions. Significant differences exist with respect to all the environmental variables. Rainfall is

[4] Data on total rainfall is also collected from the Bangladesh Meteorological Department (BMD). Time-series data on monthly rainfall collected at selected measurement stations that correspond closely to each greater district (sometimes two stations fall within one district) is available from BMD. We have used data for corresponding months of the maize growing season (November – April for winter maize and February – July for summer maize) of the sampled regions.

[5] BMD also collects mean monthly maximum and minimum temperature disaggregated at regional level. We have used data for corresponding months of the maize growing season (November – April for winter maize and February – July for summer maize).

significantly higher during the summer period as expected. Variability in temperature is, however, significantly higher in the winter season. Winter maize is grown on significantly better land types and soils than summer maize. In terms of resource use and outputs, winter maize generates significantly higher yield and returns. Use of inorganic fertilizers, organic manure, irrigation and mechanical power are also significantly higher in winter maize production although there is no difference in the cultivated area and labour use rates between the seasons, which is again surprising. One reason forwarded by the farmers for significantly lower use of inorganic fertilizers and not using organic manure during summer maize is that they planted this crop immediately after harvesting potatoes, which initially had received high doses of organic and inorganic fertilizers. Therefore, the inherent fertility of the soils is assumed to be high and carried through to summer maize crop, which apparently does not seem to be a valid assumption, as the yields are significantly lower for summer maize.

[Insert Table 2 here]

3.2. Determinants of the choice of maize growing season

The Chi-squared test statistic in the probit season selection equation is significant at the 1% level, confirming joint significance of the parameters (Table 3). The McFadden R-squared is estimated at 0.54. About 88% of the observations were accurately predicted which is very satisfactory. Gross return from maize production and subsistence pressures are the important determinants of choosing winter maize. However, extension contact depresses choice of winter maize reason for which is not clear. The soil suitability significantly influence choice of winter maize cultivation, thereby, establishing our a priori expectation that environmental factors within which the farmers operate do play an important role in their decision making processes (Table 3).

[Insert Table 3 here]

3.3. Factors influencing cost of winter maize production

Prior to discussing the results of the stochastic cost frontier, we report two sets of hypothesis tests conducted. The first test was conducted to determine the appropriate functional form, i.e., the choice between Cobb-Douglas (using only standard input prices and output level) and an extended Cobb-Douglas functional form (adding environmental variables as well) (H_0: $\omega_k = 0$ for all k). A generalised Likelihood Ratio (LR) test confirmed that the choice of extended cost function is a better representation of the production structure ($\chi^2_{(4,0.95)}$= 8.57, p<0.05).

Second, we conduct the model specification test i.e., testing whether sample selection bias is present or not. 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 at 1 percent level, implying that the use of sample selection framework is valid and justified ($\chi^2_{(1,0.99)}$= 26.36, p<0.01). The coefficient on the ρ variable reported at the bottom of Table 4 also confirms that sample selection bias is present (p<0.01).

Table 4 presents the results of the stochastic cost frontier model corrected for sample selection bias. Nine coefficients out of a total of 11 are significantly different from zero at the 10% level at least, implying a good fit. Both the estimates of σ_u and σ_v are significantly different from zero at the 1% level. The coefficient on the ρ variable is significantly different from zero at the 1% 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 season of maize producers (either winter or summer maize producer) will provide biased estimates of cost, which will then be carried on to the biased estimates of economic efficiency scores as well.

[Insert Table 4 here]

Cost of maize production increases with an increase in output level as expected. Also, cost is influenced by a rise in input prices, consistent with theory. Since Cobb-Douglas model is used, the coefficients can be read directly as cost elasticities. Fertilizer price has the highest elasticity value of 0.29 implying that a one percent increase in fertilizer price will increase production cost by 0.29%. Similarly, labour wage and mechanical power prices exert similar upward pressure on production cost of maize. It is surprising to see that land rent has no significant influence.

As expected, the production environment within which the farmers operate significantly influence cost of maize production although incorporation of these variables are largely ignored in the literature analyzing productivity of agricultural crops with few exceptions (e.g., Sherlund et al., 2002; Rahman and Hasan, 2008; and Barrios et al., 2008). Cost of production is significantly lower when the soils are of good quality (i.e., silt or silt loam). The land type variable also has the correct sign but the coefficient is not significantly different from zero. Stability in mean temperature significantly reduces cost of maize production. However, high rainfall during the winter months increases cost.

3.4. Economic efficiency of winter maize farmers

The summary statistics of economic efficiency scores for winter maize farmers, corrected for sample selection bias, are presented in Table 5. The mean economic efficiency is estimated at 91% implying that 10% [(100-91)/91] of the profitability is lost due to a combination of technical and allocative inefficiency. This implies that the average farm producing winter maize could reduce cost by 10% by improving economic efficiency. Our estimate is at the higher end of the range seen in the literature (e.g., Hazarika and Alwang, 2003; Rahman and Hasan, 2008; Coelli et al., 2002; Bravo-Ureta et al., 2007) implying that maize performs relatively better than rice and wheat, particularly in Bangladesh (e.g., Rahman, 2003; Rahman and Hasan, 2008; Coelli et al., 2002). Farmers exhibit a wide range of economic inefficiency ranging from 1% to 26% in winter maize farming. Observation of wide variation in production efficiency is not surprising and is similar to the results of Rahman (2003); Ali and Flinn (1989), Wang et al. (1996), and Bravo et al. (2007) for Bangladesh, Pakistan Punjab, China, and a total of 167 case studies from developing countries, respectively.

[Insert Table 5 here]

4. Conclusions and policy implications

The present study jointly evaluates factors affecting Bangladeshi farmers' decision to choose the maize growing season and its economic efficiency at the individual producer level. The model diagnostics reveal that serious sample selection bias exists, thereby, justifying use of the sample selection framework in stochastic frontier models. The implication is that estimation from only single season of maize producers (i.e., either winter or summer maize producers) will provide biased results of the determinants of seasonal choice and profitability, as well as farm-specific economic efficiency scores.

The results confirm that both socio-economic and environmental factors significantly determine the probability of choosing winter maize. Rise in input prices significantly increase production cost of maize whereas good quality soils and stability in mean temperature reduce cost. Economic inefficiency still exists in winter maize production which arises due to a combination of both technical and allocative inefficiencies. The mean level of economic efficiency of these self-selected winter maize farmers is estimated at 91% implying that although the maize farmers in Bangladesh are doing very well, there is scope to reduce inefficiency.

The policy implications are clear. Investment in improving soil suitability and the development of temperature resistant varieties will significantly induce farmers to adopt winter maize technology as well as reduce cost of production. Similarly, price policies to curb rising input prices on one hand and keeping maize prices high on the other will boost farm returns and reduce production cost. In fact, high price of good quality seed, fertilizers and low price of maize were ranked as the 1^{st}, 4^{th} and 6^{th} major constraints by these maize growers. One important option to reduce high price of good quality maize seed will be to increase production and distribution of maize seeds by Bangladesh Agricultural Development Corporation (BADC) which is in charge of distributing high quality seeds of cereals and vegetables to farmers. BADC estimates that the sowing area of maize is 180,000 ha in 2011 which requires 6,250 t of maize seeds. However, the existing production of maize seed at BADC is 500 t (i.e., only 8 percent of the requirement) in 2011 which they project to raise to 2,200 t by 2015, which is still only 35% of existing requirement (BADC, online). Therefore, the other option is to encourage private sectors to enter the maize seed market through incentives as open competition will drive price downward, but care must be given to avoid collusion by a handful of big seed companies. Similarly, private sector should be encouraged to fill the gap in the fertilizer market as well which has been liberated from government control since 1992. In order to improve market price of maize crop, government may intervene in the market by restricting imports of maize and maize products (e.g., maize starch). At the same time government can promote vertical integration of value added products derived from maize (e.g., maize starch) which will drive demand for maize upward leading to a rise in its price. Also, awareness campaign to promote and/or include consumption of maize and maize products in Bangladeshi diets will boost demand for maize leading to a rise in its price. Although realization of these policy measures is formidable, a boost in maize production could significantly curb dependence on rice as the main staple in Bangladeshi diet, which is a goal worth pursuing.

References

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

Asadullah, N., Rahman, S. 2009. Farm productivity and efficiency in rural Bangladesh: the role of education revisited. *Applied Economics*, 41: 17-33.

Baksh, M. E. 2003. Economic efficiency and sustainability of wheat production in wheat-based cropping systems in north-west Bangladesh. Ph.D. dissertation. Department of Agricultural Economics, Bangladesh Agricultural University, Mymensingh-2202, Bangladesh.

BADC, online. Bangladesh Agricultural Development Corporation website. http://www.badc.gov.bd/index.php?option=com_content&view=article&id=4&Itemid=18 (accessed June 15, 2011).

BBS, 2010. *Statistical Yearbook of Bangladesh 2009.* Bangladesh Bureau of Statistics, Dhaka, Bangladesh.

BBS, 2007. *Statistical Yearbook of Bangladesh 2006.* Bangladesh Bureau of Statistics, Dhaka, Bangladesh.

Barrios, S., Ouattara, B., Strobl, E. 2008. The impact of climatic change on agricultural production: is it different for Africa? *Food Policy*, **33**: 287-298.

Bravo-Ureta, B.E., Solis, D., Lopez, V.H.M., Maripani, J.F., Thiam, A. and Rivas, T. 2007. Technical efficiency in farming: a meta regression analysis. *Journal of Productivity Analysis*, **27**:57-72.

Coelli, T.J. 1995. Estimators and hypothesis tests for a stochastic frontier function: a Monte-Carlo analysis. *Journal of Productivity Analysis*, **6**, 247 – 268.

ESI, 2007. NLOGIT-4, Econometric Software, Inc. New York.

FAO, 2009. FAOSTAT 2009 http://faostat.fao.org/site/567/DesktopDefault.aspx?PageID=567#ancor

Geene, W.H. 2008. A stochastic frontier model with correction for sample selection. Stern School of Business, New York University. NYU Working paper # 2451/26017.

Greene, W.H. 2006. A general approach to incorporating selectivity in a model. Stern School of Business, New York University.

Hazarika, G., Alwang, J. 2003. Access to credit, plot size, and cost inefficiency among smallholder tobacco cultivators in Malawi. *Agricultural Economics*, 29: 99-109.

Heckman, J. 1976. The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. *Annals of Economic and Social Measurement*, **5,** 475-92.

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

Islam, M. R., Hossain, M., Jaim, W.M.H. 2004. Technical efficiency of farm producing transplanted aman rice in Bangladesh. A comparative study of aromatic, fine and coarse variety. *Bangladesh Journal of Agricultural Economics*, 27: 1-24.

Kopp, R.J. and Smith, V.K. 1980, Frontier production function estimates for steam electric generation: a competitive analysis. *Southern Economic Journal*, 47, 1049-1059.

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

Rahman, S. 2003. Profit efficiency among Bangladeshi rice farmers. *Food Policy*, **28**, 487-503.

Rahman, S., Hasan, M.K. 2008. Impact of environmental production conditions on productivity and efficiency: the case of wheat producers in Bangladesh. *Journal of Environmental Management*, 88: 1495-1504.

Sherlund, S.M., Barrett, C.B., Adesina, A.A. 2002. Smallholder technical efficiency controlling for environmental production conditions. *Journal of Development Economics*, 69: 85 – 101.

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

Table 1. Selection of the study area and sample size

Greater district	New district	Area selection criteria			Farm size categories			
		Maize area index (MAI)	Intensity Rank (Out of 21 greater districts)	% of total maize area	Large farms (2.0 ha and above)	Medium farms (1.01 to <2.0 ha)	Small farms (up to 1.0 ha)	All categories
Winter Maize								
Kushtia	Chuadanga	2.31	1	31	27	39	34	100
Bogra	Bogra	0.92	3	17	18	34	48	100
Dinajpur	Dinajpur	0.45	5	11	27	37	36	100
All winter area		-	-	59	72	110	118	300
Summer maize								
Bogra	Bogra	0.58	2	25	4	11	35	50
Dinajpur	Thakurgaon	0.49	3	21	16	18	16	50
Dhaka	Manikganj	0.43	4	18	2	15	33	50

All summer area	-	-	64	22	44	84	150
Total sample	-	-	-	94	154	202	450

Source: BBS (2007), and field survey, 2007.

Table 2. Comparison of socio-economic factors, production environment and resource use patterns among winter and summer maize farmers.

Variable name	Winter maize		Summer maize		Mean difference (WM-SM)	t-ratio
	Mean	Standard deviation	Mean	Standard deviation		
Socio-economic factors						
Gross return per ha (Tk/ha)	72406.75	10010.11	57167.52	9057.50	15239.22***	16.07
Farm operation size (ha)	1.67	1.48	1.36	1.74	0.31*	1.84
Farmer's age (years)	40.94	11.07	42.82	13.35	-1.88	-1.47
Farmer's education (completed year of schooling)	5.44	4.35	5.12	4.23	0.32	0.75
Farming experience (years)	21.41	11.00	22.66	12.61	-1.25	-1.02
Subsistence pressure (persons per household)	5.43	2.28	4.81	1.69	0.63***	3.25
Extension contact (1 = if had training or extension contact, 0 otherwise)	0.48	--	0.57	--	-0.86*	1.70
Production environment						
Land suitability index (3 = highland/medium highland – most	1.97	0.23	1.84	0.39	0.13***	4.51

suitable; 2 = medium land – suitable; 3 = low land – not suitable).						
Soil suitability index (4 = silt – most suitable; 3 = silt loam – highly suitable; 2 = clay loam – suitable; 1 = sandy – unsuitable)	3.31	0.57	3.04	0.26	0.27***	6.80
Temperature stability (mean temperature range, i.e., maximum – minimum temperature) during the growing season (^{0}C)	9.58	0.50	9.15	0.15	0.43***	13.86
Total rainfall during the growing season (mm)	200.33	63.54	1385.34	314.43	-1186.01***	-44.98
Production Inputs and outputs						
Maize output (kg/ha)	7988.70	561.34	5290.90	1720.9	2697.08***	18.41
Land (ha of maize area cultivated)	0.78	0.80	0.86	1.39	-0.08	-0.59
Labour (person days/ha)	148.67	28.84	146.04	37.80	2.63	0.74
Fertilizers (kg of nutrients/ha)	325.75	57.23	99.23	39.55	226.52***	48.62
Mechanical power (Tk/ha)	4146.16	676.47	2771.01	920.43	1375.15***	16.02
Irrigation (Tk/ha)	3210.22	852.42	2975.79	778.42	234.43***	2.89
Organic manure (kg/ha)	4324.28	4506.16	00.00	00.00	4324.28***	16.62
Observations	300		150			

Note: Exchange rate of USD 1.00 = Taka 68.80 in 2006-07 (BB, 2010)

*** Significant at 1 percent level ($p<0.01$)

** Significant at 5 percent level ($p<0.05$)

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

Source: Field survey 2007.

Table 3. Parameter estimates of the probit season selection equation

Variables	Probit coefficients	
	Coefficient	t-ratio
Constant	-13.7272***	-8.56
Socio-economic factors		
Gross return per ha	0.0002***	9.78
Irrigation cost	0.0016	1.24
Farm operation size	-0.0769	-1.16
Farmer’s age	0.0081	0.52
Farmer’s education	-0.0813	-1.05
Farmer’s education squared	0.0161*	1.71
Farming experience	0.0069	0.21
Farming experience squared	-0.0005	-0.91
Subsistence pressure	0.3649**	1.97
Subsistence pressure squared	-0.0127	-0.92
Extension contact	-1.9190***	-7.20
Production environment		

Soil suitability index	0.4289**	2.15
Model diagnostics		
Log likelihood	-126.84	
McFadden R-squared	0.55	
Chi-squared	308.08***	
Degrees of freedom	12	
Accuracy of prediction (%)	87.86	
Number of total observations	450	

Note: Marginal effects of the dummy variables are computed as P|1 - P|0 (ESI, 2007).

*** 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. Parameter estimates of the stochastic production frontier model for winter maize corrected for sample selection bias.

Variables	Parameters	Stochastic cost frontier model (jointly estimated with the probit seed selection equation)	
		Coefficient	t-ratio
Constant	α_0	7.385	13.10
Output level and normalized input prices			
ln Maize output	α_1	0.0112**	2.01
ln Mechanical power price	β_1	0.2255***	6.39
ln Labour wage	β_2	0.2087***	4.42
ln Irrigation price	β_3	0.0811***	4.81
ln Fertilizer price	β_4	0.2916***	6.08
ln Organic manure price	β_5	0.0779**	2.24
ln Land rent	β_6	-0.0044	-0.11
Production environment			
ln Land suitability index	ω_1	-0.0669	-0.72
ln Soil suitability index	ω_2	-0.0411**	-2.46
ln Total rainfall during the season	ω_3	01828***	5.40

ln Temperature stability (i.e., mean temperature range) during the season	ω_4	-1.0854***	-7.15
Model diagnostics			
Log likelihood		66.05	
σ_u		0.1224***	14.15
σ_v		0.0494***	8.12
ρ (Sample selection bias, $\rho_{w,v}$)		1.00***	435.25
Number of selected observations		300	

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. Distribution of economic efficiency scores of winter maize farmers.

	Stochastic cost frontier (corrected for sample selection bias)
Efficiency levels	
Upto 80%	2.30
81 – 90%	37.30
91% and above	60.40
Efficiency scores	
Minimum	0.74
Maximum	0.99
Mean	0.91
Number of observations	300