The impact of corruption on farmers' efficiency in rice production: A natural experiment from Bangladesh

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Abstract

This article explores the impact of corruption on farm-level efficiency in two different rice cropping seasons in Bangladesh. The two different cropping seasons have different production and marketing conditions such that cost of corruption can be hypothesized being positively correlated with technical efficiency in one season while negatively in the other. A total of 210 rice farmer's data were analyzed through a stochastic frontier efficiency model. The results actually suggest that corruption costs might be efficiency enhancing or reducing, depending on the specific situation and context. If input markets are sufficiently well working, and farmers face liquidity constraints, corruption costs reduce efficiency. Under such settings, farmers have to bear extra cost imposed by corruption, and hence cannot purchase their required quantity of inputs. But, when famer's capital requirement is relatively less, and input markets are highly restricted; bribe helps to access to market. The bribe paying farmers can acquire more inputs, and hence will operate at higher level of efficiency. This finding underlines the advantages of open markets in Bangladesh and other developing countries, as restricting markets will encourage corruption.

INTRODUCTION

In the last decades agricultural economists learned much about productivity and efficiency of smallholder farmers in developing countries. Impacts of different technologies, the influence of farmers' personal characteristics or the relevance of functioning credit and land markets are well documented. Also the impact of policy variables such as subsidies, export tax, infrastructure, extension service, land redistribution and others are empirically analysed. However, governance aspects, such as corruption, which cannot be neglected in development strategies for smallholder farmers, are not analysed in the literature yet.

The impact of corruption on farm productivity is particularly relevant for a country such as Bangladesh, which is ranked 134 in the well-known Corruption Perceptions Index (Transparency International, 2010). In Bangladesh, farmers experience corruption particularly on the fertilizer market, the seed market, in the subsidised use of irrigation pumps, and within the extension service. Government pays subsidy on fertilizers prices, to ease fertilizer purchase for resource poor farmers. But these subsidies fail to reach their target beneficiary, as the wholesalers grab the benefits (Ministry of Agriculture, 2006). Islam (2004) found that a small amount of quality seed remains available in Bangladesh, but their distribution system to the end users was faulty, irregular and inefficient mainly because of high price of seeds, lack of proper monitoring and involvement of some corrupt dealers in the seed distribution system. Besides, irregularities, favoritism and nepotism seriously exist in extension services, and few farmers get benefit of these services (Ministry of Agriculture, 2006).

To our knowledge there is not any empirical study about corruption impacts on farm productivity and hence efficiency. We, thus, draw on studies from other sectors as a starting point. Fisman & Svensson (2007) estimated that cost of corruption reduces firm growth three times higher more than an equivalent tax. According to Mauro (1995), corruption cuts down investment, and hence capital accumulation might be at lower level. He estimated that by improving the integrity and efficiency of bureaucracy to the level of Uruguay, Bangladesh could have increased its investment rate by almost 5 per cent points and yearly GDP growth rate by over 0.5 per cent point.

Alternative roles of corruption are theoretically derived in literatures. Corruption greases the wheels where bureaucracy is sluggish and ineffective (Huntington, 1968). To dishonest bureaucrats and government officials, bribe is an incentive for faster work. Corruption is thought to be a second best option for efficiency and growth in developing countries, where the regulations are 'pervasive and cumbersome' (Leff, 1964; Huntington, 1968; Bardhan, 1997). Bribe can work as 'speed money' and can enhance technology transfer (Méon & Weill, 2005). According to Lui (1985) bribe may reduce inefficiencies caused by public administration by reducing waiting costs. He believed that a system built on bribery will lead to an efficient process for allocating licenses and government contracts, since the most efficient firms can afford the highest bribes.

The above literature implies that depending on the research perspective and the specific case, corruption may have different impacts in a specific situation. Thus, a reasonable development strategy for a specific region and economic sector cannot be formulated without understanding the corruption in that case. Moreover, no literature is available about impact of corruption on farm efficiency.

We contribute to the empirical literature by analysing data from a natural experiment in Bangladesh. The impact of farm-level corruption costs on farms' technical efficiency is analysed based on a sample of 210 farm households. For two consecutive rice growing seasons with different production and market conditions, we hypothesize an efficiency increasing impact of corruption costs in the first season, while we expect decreasing technical efficiency with higher corruption costs in the second season. We proceed with some background on rice production and related corruption in Bangladesh. Then, the research hypotheses are derived. The empirical model and the data are presented before results, and conclusions finish the paper.

BACKGROUND AND HYPOTHESES

There are three specific rice growing seasons in Bangladesh: *Aus, Aman* and *Boro*. As among these three seasons, *Aman* and *Boro* are dominant in terms of production and area cultivated. *Aman* is grown during the rainy season and natural rainfall is likely to be sufficient for the traditional rice varieties used. Farmers need to irrigate only when there is inadequate or irregular rainfall. On the other hand, *Boro* rice is cultivated during the winter, and more HYV seeds are used. Consequently, the (marginal) productivity of both irrigation and fertilizer in rice cultivation is much higher in *Boro* season compared to *Aman* season.

Rice farmers in Bangladesh face different kinds of corruption. For example, irrigating is subsidized for farmers. A certain portion of the electricity bill for operating irrigation equipments is refunded to the farmers. But in reality, while receiving the subsidy in form of refunded electricity bill, farmers have to pay bribe to 'motivate'the administrative persons working properly. Furthermore, different mineral fertilizers are subsidized and the market is highly regulated including government fixed prices and assignment of dealers and retailers. In addition, in the *Aman* season, farmers had to get slip from extension agents to collect fertilizers from the retailers. Collecting slip in many cases was not possible without paying bribe. Consequently, the market was far from competitive and subsidies were likely to be extracted to some extent by the dealers, retailers and extension agents as well as water pump owners.

How do these corruption phenomena influence technical efficiency of rice production? For our intuitive explanation we, first, account for the following deviation from common production theory: perfect adjustment of inputs is impossible in rice production after seeding when e.g. fertilizer availability – without paying bribe – turns out to be insufficient several weeks after seeding. Now imagine two identical farmers who choose the same input bundle in a corruption-free world. Then (imperfectly anticipated) corruption comes into play and a farmer who is not willing or not able to pay bribe cannot realize his optimal input bundle (taking into account marginal costs of corruption for some inputs). Consequently, he will be less technically efficient than the bribe paying farmer.

We now differentiate between a situation with several capital-constrained farmers (e.g. due to high input prices) and a situation without capital constraints. Even in a corruption-free world a capital-constraint farmer's input bundle will deviate more or less from optimal. Additional costs such as bribe will further reduce the overall productivity of his input bundle. Consequently, for highly capital-constrained farmers one can expect that higher bribe payments reduce efficiency. If – in contrast – most of the sample farmers are not capital-constrained high corruption costs maybe an indicator for being more efficient than other farmers, e.g. because the realized input bundle is closer to optimal than other farmers' bundles, the received input quality is higher than other farmers' input quality, or the farmer is simpler smarter in 'greasing the wheels' and therefore he may be also smarter in other management activities. Such high corruption costs are particularly necessary when market aggregated supply is limited.

Consequently, we expect a technical efficiency increasing effect of corruption costs if capital-constraints are not much relevant in the sample but input markets are quantity restricted. In contrast we expect that corruption costs decrease technical efficiency if many farmers in the sample are capital-constrained and input markets are not quantity restricted for the well capital-endowed farmers.

How can we test these hypotheses? We have a unique dataset which offers a natural experiment with the same farmers in two different production seasons. *Aman* season is characterized by less intensive production and, thus, be lower capital requirements. In addition in 2008 season farmers faced a specific 'corruption environment' in *Aman* season which led to quantity restricted fertilizer markets. In the subsequent *Boro* season fertilizer markets had not been restricted in their aggregate quantities anymore since marketing channels had been changed by the government, but many farmers had been capital-constrained since capital requirements are higher in this production season with high costs for irrigation and HYV seeds. Consequently, for *Aman* season we hypothesize that cost of corruption increase a farmer's technical efficiency while corruption costs are expected to reduce technical efficiency in *Boro* season. We now explain that the production and market conditions in both the seasons actually led to natural experiment we set out above.

In the *Aman* season, fertilizer dealers were assigned at union level (administrative unit over village level), and each dealer was allowed to appoint two representatives to sell fertilizers in the respective union's villages. As dealers had freedom to select representatives, in many cases they selected their relatives or friends, who had no or little experience in fertilizer marketing. Considering number of villages and farm households, two representatives for one union is hardly sufficient. Farmers also had very little idea and information about assigned representatives for their union. Furthermore, farmers had to get slip from extension agents to collect fertilizers. In the slip the maximum quantity of fertilizer that a farmer was allowed to purchase was mentioned. Many farmers reported not to have desirable quantity mentioned on the slip. Collecting appropriate slip in many cases was only possible with paying bribe. In addition, high world-market prices for fertilizer reduced imports. Consequently, 27.7% of our farmers reported to have been input restricted in *Aman* season though having enough money to buy more fertilizer (Table 1). Only 1% of the farmers reported that they had been capital-constrained.

For the following *Boro* season, the government modified the fertilizer marketing channel. Dealers were appointed at district level, and depending on the size of the union, maximum nine retailers were appointed for each union. The slip system was abolished. Moreover, imports had been easier in *Boro* season since world-market prices declined. Consequently, only 5.4% of the farmers reported to have been input restricted though having enough money to buy more inputs (Table 1). As explained above farmers have to bear costs for irrigation, HYV seeds, and 30% more fertilizer use (Table 1) in *Boro* season. Consequently, 19 of the 210 farmers reported that they had been capital-constrained in *Boro* season.

Summarizing, rice production in 2008-09, *Aman* and *Boro* season actually constitutes a natural experiment for analyzing the impact of corruption on technical efficiency.

EMPIRICAL MODEL AND DATA

The hypotheses are tested by means of a stochastic production frontier model. Such a model allows for estimating farmers' technical efficiency in rice production as well as estimating determinants for different efficiency levels. Among the determinants we test for any significant impacts of cost of corruption on technical efficiency. Formally, the translog stochastic production frontier for the *i*th farm is defined as:

$$\ln \mathbf{y}_{\mathbf{i}} = \alpha_0 + \sum_{\mathbf{j}=1}^{\mathbf{J}} \alpha_{\mathbf{j}} \ln \mathbf{x}_{\mathbf{ji}} + \frac{1}{2}\sum_{\mathbf{j}=1}^{\mathbf{J}} \left(\ln \mathbf{x}_{\mathbf{ji}}\right)^2 + \frac{1}{2}\sum_{\mathbf{j}=1}^{\mathbf{J}}\sum_{\mathbf{k}=1}^{\mathbf{K}} \beta_{\mathbf{jk}} \ln \mathbf{x}_{\mathbf{ji}} \ln \mathbf{x}_{\mathbf{ki}} + \sum_{\mathbf{m}=1}^{\mathbf{M}} \tau_{\mathbf{m}} \mathbf{D}_{\mathbf{mi}} + \mathbf{v}_{\mathbf{i}} - \mathbf{u}_{\mathbf{i}} \; \ldots \; .(1)$$

Where the dependent variable y_i is the quantity of total paddy production (kg) x_{ji} is quantity of input *j* for farmer *i*, and D_{di} is dummy m indicating shifting parameters in the production function; v_i is the common i.i.d error term while u_i is a one-sided half-normal error representing technical inefficiency.

As production practices and technologies are different in *Aman* and *Boro* season, we estimate separate models for each and two input variables differ. The input factor variables for *Aman* season are: quantity of seed (kg), quantity of chemical fertilizers (kg), quantity of labour (man-days), cost of land preparation and equipments (BDT[1]), and quantity of land (hectare). The dummy variables for the same season are: organic manure (1 = used), irrigation (1 = irrigated), and pesticides (1 = used). For *Boro* season, measurement of the variables is identical to *Aman* season except for seed and irrigation. For seed costs are used instead of quantity to capture the quality differences of seeds due to widespread use of HYV seeds. In addition, a dummy variable reflects HYV of a farmer in *Boro* season. Irrigation is indicated by a dummy in *Aman* season since natural rainfall is sufficient in general. Only one fourth of the farmers irrigate. On the other hand, *Boro* rice is cultivated during the dry season. Moreover, due to widespread use of HYV seeds, water requirement in *Boro* season is high. We, thus, decided to use cost of irrigation to reflect farmers' input choice on irrigation in *Boro* season.

The model for the technical inefficiency for both the seasons is defined as:

$$\mathbf{u_i} = \delta_0 + \sum_{\mathbf{d}=1}^{8} \delta_{\mathbf{d}} \mathbf{z_{di}} + \omega_{\mathbf{i}} \quad \text{(2)}$$

Here, the socio-economic characteristics of the farm to explain inefficiency are presented by z_i. These variables are: dummy of extension service received (1=received); household head's years of experience in rice farming; dummy for infrastructure (1=improved peri-urban infrastructure, 0=less developed rural infrastructure); education of household head (0=Illiterate, 1=Primary education, 2=Secondary, 3=Higher secondary, 4= Above higher secondary) off farm income share (share of off farm income to household's total income) own land share (share of own land to total land under rice cultivation); dummy for input restricted farmer (1=input restricted farmers, i.e. farmers who failed to collect required quantity of inputs due to unavailability in the market though having enough money to pay bribe or to buy more inputs), and cost of corruption for availing inputs and getting services (BDT); and ω_i is random error, which is assumed to follow a positive half normal distribution.

Technical efficiency (TE_i) of the *i*th farm is the ratio of the observed output for the *i*th farm, relative to the potential output defined by the frontier function, where the input vector $\mathbf{x_i}$ for the farm is given. Thus, the technical efficiency of farmer *i* is equal to

$$\mathrm{TE_i} = \frac{\mathrm{y_i}}{\exp(\mathrm{x_i}\beta)} = \frac{\exp(\mathrm{x_i}\beta - \mathrm{u_i})}{\exp(\mathrm{x_i}\beta)} = \exp(-\mathrm{u_i}) \quad \text{(3)}$$

The technical efficiency of a farmer is between zero and one. The maximum-likelihood estimates for all parameter of the stochastic frontier and inefficiency model, is obtained by using the computer program STATA 10.

Survey and Data

The survey data are collected through a multi-stage random sampling, 210 rice growers belonging to six villages of six different districts of Bangladesh had been interviewed.

[1] Exchange rate: 1 Euro = 97.5 BDT.

The districts had above-median rice production in 2008/09. Thus we have 32 districts selected. From these districts the top three and bottom three districts had been chosen according to the proportion of households experienced corruption in service sectors.[2] From each district the sub-districts with highest rice production had been chosen and among the sub-districts the villages with highest rice production. In the final stage, 35 farm households from each village were selected randomly from list of farmers available with the local office of Department of Agricultural Extension. Despite the variables used in the analysis at hand data had been collected about agricultural production in general, household characteristics, nutritional status, and corruption experience.

Table 1: Summary statistics of the variables used in the stochastic frontier model

Variables		*Aman*	*Boro*
Variables in the production function			
Quantity of paddy produced (kg/farm)		2449.6	4079.6
Quantity of seed (kg/farm)		33.2	
Cost of seed (BDT/farm)			1177.2
Quantity of fertilizer (kg/farm)		183.1	237.9
Quantity of labour (man-days/farm)		70.5	77.3
Quantity of land (hectare/farm)		0.7	0.6
Cost of land preparation & equipments (BDT/farm)		3307.3	4958.2
Cost of irrigation (BDT/farm)			5573.5
% of farmers implying irrigation		26.4	
% of farmers implying organic manure		7.2	8.0
% of farmers using HYV seeds			20.3
Variables used in the inefficiency model			
% of farmers received extension services		41.6	44.4
Household head's year of experiences		22.1	22.0
Mean of share of off farm income to total income		0.3	0.3
Mean of share of own land to total land		0.8	0.8
Cost of corruption (BDT)		1843.2	983.4
% of farmers being input restricted		27.7	5.4
Infrastructure	Peri-urban	34.2	36.9
	Rural	65.8	63.1
Education	Illiterate	43.1	42.3
	Primary	10.9	11.2
	Secondary	36.6	38.0
	Higher secondary	6.4	5.4
	Above higher secondary	3.0	3.2

Source: Field survey 2009.

The summary statistics of the variables used in the model are presented in Table 1. Farmers use around one half hectare for rice cultivation, around 70 to 80 man-days are needed for one growing period on a farm. In general, per-farm production and requirement of inputs is higher in *Boro* season than in *Aman* season. The only exception is with quantity of land cultivated. Probably, irrigation requirement limited availability of appropriate rice land in *Boro* season. Due to irrigation and HYV seed, costs in *Boro*

[2] The proportion was estimated from the database of 'National Household Survey 2007 on Corruption in Bangladesh'. The survey was conducted by Transparency International Bangladesh. The survey covered 62 districts of the country. The two districts not covered by the survey, did not appear in our first ranking.

season sum up to 61,674 BDT/hectare, including e.g. hired labour, fertilizer, land rent. This is substantially higher than in *Aman* season with roughly 35,798 BDT/hectare.

The summary statistics of the variables used in the technical inefficiency model are presented in the lower portion of Table 1. Majority of farmers in both seasons do not receive any services from the government extension office. Agriculture is the major source of farm household's income in both the seasons. Around two-third of household's income is coming from different agricultural activities. Farm households mostly cultivate own land. Rented in land contributes less than one-third of the total land under rice production. All the variables except cost of corruption and the number of input restricted do not vary much between the two seasons. Compared to *Boro* season, cost of corruption in *Aman* season is almost double. Proportion of farmers being input restricted is more than five times higher in *Aman* season than *Boro* season. Restricted fertilizer marketing channel and unexpected higher fertilizer price in *Aman* season, created uncertainty and volatility in the input market. Corrupt dealers utilized these market situations and created artificial crisis. Ultimately higher proportion of farmers became input restricted, and had to bear higher cost of corruption.

The following three components are incorporated in the cost of corruption:

i) Excess payment in the input market (BDT): Excess payment in the input market is the difference between government fixed retailer price and the actual price paid by the farmers. Only the subsidized inputs are considered here. In addition, bribe paid by irrigation pump owners to collect irrigation subsidy, is also included.

ii) Monetary value of time wasted and excess transportation cost (BDT): A farmer may experience time wastage due to repeated visits to dealers and for waiting in queue. Moreover, a farmer may have to bear excess transportation cost for repeated visits, and separate transportation of small quantities instead of a common large one. These two cost components are incorporated in cost of corruption only when there was no supply shortage; and if farmers had enough capital, and willingness to purchase input. To ensure that there was no supply shortage, secondary data about fertilizer and seed supply in the local market was checked. Time wasted is measured in man-days and then multiplied with the wage rate. Here we have used farm specific wage rate that were available at the time of collecting that specific input. Excess transportation cost includes cost of vehicles, which was obtained in the questionnaire.

iii) Cost of corruption in government extension services (BDT): Some of the demonstration plot organizers reported not to receive proper quantity of inputs from the extension office while organizing demonstration plots. The monetary value of these inputs that the extension office was supposed to but did not supply, constitute the final part of cost of corruption.

RESULTS

The results are organised in three subsections. First, we test whether the model specification is appropriate, followed by results on the production frontier function before the determinants of inefficiency – including costs of corruption are reported.

Specification tests

Specification tests show that the model specification outlined above is appropriate for our data. First, the translog specification is to be preferred over Cobb-Douglas in both seasons (Table 2). Furthermore, there are inefficiency effects in the model. The variance-ratio parameter γ^* implies that 91.4 per cent of the differences between observed and the maximum frontier production for *Aman* rice farming is due to differences in efficiency levels among farmers. This difference is 82.6 per cent in *Boro* season (Table 4).

Table 2: Specification Tests

Null Hypothesis	*Aman*	*Boro*
Functional form test: Cobb-Douglas versus translog model $(H_0 : \beta_{jk} = 0)$		
Likelihood test statistics (χ^2)	87.59***	52.58***
No inefficiency effects $(H_0 : \delta_0 = \delta_1 = ... = \delta_8 = 0)$		
Likelihood test statistics (χ^2)	36.88***	25.17***
No inefficiency present in the model $(H_0 : \mu = \gamma = 0)^a$		
Likelihood test statistics (χ^2)	87.68***	133.80***

Note: [a] Since the test involves testing of γ parameter, it has a mixed χ^2 distribution. The value of χ^2 is taken from Kodde & Palm (1986). *** indicate significance at 1% level.
Source: Own estimation.

We further found that monotonicity, i.e. positive marginal products for all inputs, and diminishing marginal productivities are fulfilled for all the inputs. By using the *predictnl* command in STATA 10, both these tests are conducted at the sample mean.

Parameter Estimates of Stochastic Production Frontier

The MLE estimates of the translog stochastic production frontier function are presented in Table 4. The estimated output elasticity of land is 0.702 and 0.826 in *Aman* and *Boro* season, respectively; implying that a 1 per cent increase in land area will result in 0.702 and 0.826 per cent increase in rice production in *Aman* and *Boro* season, respectively. Asadullah & Rahman (2009) estimated output elasticity of land for Bangladeshi rice producers, varies from 0.65 to 0.71. Using panel data across 23 major rice producing districts of Bangladesh over the period 1994-1999, Selim (2010) estimated land elasticity of output is almost near to one. High land elasticity for Bangladeshi rice growers is also estimated by Wadud & White (2000) and Rahman (2003).

Table 4: MLE estimates of the translog stochastic production frontier function

	Aman		*Boro*	
Variables	Coeffi.	SE	Coeffi.	SE
Constant	7.826***	0.011	8.287***	0.049
Seed	0.097	0.059	0.012	0.026
Fertilizer	0.035	0.031	0.119***	0.040
Labour	0.136**	0.060	0.137***	0.059
Land preparation & equipments	0.032	0.071	0.106	0.138
Irrigation	-0.060	0.040	0.179***	0.068
Land	0.702***	0.066	0.826***	0.085
Seed ^{2}	0.064	0.143	-0.023	0.046
Seed × Fertilizer	0.172**	0.076	0.022	0.093
Seed × Labour	0.401**	0.172	0.106	0.086
Seed × Land preparation & equipments	-0.132	0.087	-0.018	0.130

Variables	*Aman* Coeffi.	SE	*Boro* Coeffi.	SE
Seed × Land	-0.446***	0.217	-0.105	0.154
Seed × Irrigation			0.032	0.106
Fertilizer ^{2}	0.044	0.079	-0.469***	0.192
Fertilizer × Labour	0.246*	0.133	-0.261***	0.101
Fertilizer × Land preparation & equipments	-0.062	0.060	-0.833***	0.280
Fertilizer × Land	-0.388*	0.199	0.471	0.304
Fertilizer × Irrigation			0.697***	0.212
Labour ^{2}	-2.019***	0.480	-0.698	0.475
Labour × Land preparation & equipments	0.0002	0.145	-0.121	0.387
Labour × Land	1.295***	0.462	0.525	0.458
Labour × Irrigation			0.107	0.319
Land preparation & equipments ^{2}	-0.074***	0.028	1.320	0.862
Land preparation & equipments × Land	0.155	0.189	0.996**	0.450
Land preparation & equipments × Irrigation			-1.565**	0.704
Land ^{2}	-0.519*	0.312	-1.455***	0.546
Land × Irrigation			-0.318	0.389
Irrigation × Irrigation			1.168**	0.540
Organic manure	0.155**	0.071	0.017	0.025
HYV seed			0.062***	0.023
Pesticides	0.002	0.029	-0.020	0.034
Technical inefficiency model				
Constant	0.528***	0.117	0.142**	0.075
Extension Service	-0.041	0.069	0.002	0.027
Experience	-0.005*	0.003	0.001	0.001
Peri-urban infrastructure	0.095	0.074	0.164***	0.043
Education	-0.015	0.030	-0.002	0.012
Own land share	-0.308***	0.091	-0.071*	0.043
Off farm income share	0.068	0.052	0.038	0.025
Cost of corruption (100 BDT)	-0. 01***	0.000	0.002**	0.000
Input restricted farmers	0.095	0.073	0.012	0.059
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	0.082***	0.004	0.020***	0.004
$\gamma = \sigma_u^2 / \sigma^2$	0.967***	0.040	0.929***	0.108
γ^*	0.914		0.826	
Log likelihood function	87.68		133.80	
Technical efficiency	78.6		80.5	
Number of observations	202		187	

Note: $\gamma*$ is equal to $\gamma / \left[\gamma + (1-\gamma)\pi / (\pi - 2)\right]$ (Coelli et al., 1998). *, ** and *** indicate significance at 10%, 5%, and 1% level, respectively. Some variables are dropped due to high multicollinearity.

All the resource input variables were mean-differenced $\left(\mathbf{x}_{\mathbf{ik}} - \overline{\mathbf{x}}_{\mathbf{k}}\right)$prior to estimation.

Source: Own estimation.

The estimated elasticity of labour is almost equal and significantly positive in both the seasons. The estimated elasticities of labour indicate that, 1 per cent increase in quantity of labour used will result in 0.136 per cent and 0.137 per cent increase in *Aman* and *Boro* production, respectively. Irrigation and fertilizer also have significant impact on *Boro* rice production. One per cent increase in quantity of fertilizer and cost of irrigation will result in 0.119 per cent and 0.179 per cent increase in *Boro* rice production, respectively. Among the dummy variables organic manure in *Aman* season and HYV seed in *Boro* season have significant impact on production (Table 4). The sum of mean output elasticities for all the inputs are 1.002 and 1.378 for *Aman* and *Boro* season respectively. Using translog production function for *Aman* rice growers in Bangladesh, Rahman & Rahman (2008) estimated increasing returns to scale, too.

Technical efficiency in rice production

The mean technical efficiency is estimated at 78.6 per cent and 80.5 per cent for *Aman* and *Boro* growers, respectively (Table 4). Coelli et al. (2002) and Balcombe et al. (2007) also estimated higher technical efficiency for the modern variety growers (*Boro* growers) over the traditional variety growers (*Aman* growers). The estimated efficiency scores are in line with Wadud & White (2000); Rahman (2003); Asadullah & Rahman, (2009); and Selim (2010). Farmers exhibit a wide range of variation in technical efficiency, particularly in *Aman* season. In *Aman* season farmer's efficiency ranges from 0.280 to 0.999; whereas the range is 0.540 to 0.985 in *Boro* season. Efficiency is more homogenous in *Boro* season since irrigation prevents drought-caused extreme yield shortfalls.

Turning to the determinants of efficiency, the most interesting findings are the signs associated with cost of corruption. In both the seasons, cost of corruption is significant, though it is negative in *Aman* and positive in *Boro* (Table 4). Consequently, the hypothesized impacts of corruption can be empirically confirmed. The estimated elasticity for cost of corruption imply that, 1% higher cost of corruption increase technical efficiency in *Aman* season by around 1.5%-point while it decreases technical efficiency in *Boro* season by around 0.5%-points (Table 5).

Table 5: Elasticities of the efficiency variables

Variables	*Aman*	*Boro*
Experience	0.0063*	-0.0048
Education	0.0015	0.0006
Own land share	0.0217***	0.0127*
Off farm income share	-0.0021	-0.0029
Cost of corruption (100 BDT)	0.0145***	-0.0047**

Note: Following Rahman & Rahman (2008), the elasticity of technical efficiency for farmer *i* with respect to *j*th *z* vector was computed as: $\eta_{ij} = \frac{\partial \mathbf{TE}_i}{\partial \mathbf{z}_{ij}} \frac{\mathbf{z}_{ij}}{\mathbf{TE}_i}$; where, $\frac{\partial \mathbf{TE}_i}{\partial \mathbf{z}_{ij}} = \frac{\mathbf{A}}{\mathbf{C}^2}(\mathbf{CB}' - \mathbf{BC}' - \mathbf{CB})(1-\gamma)\delta_j$. *, ** and *** indicate significance at 10%, 5%, and 1% level, respectively.

Due to space constraints we only turn to the impact of own land share and the peri-urban infrastructural dummy. Farmers with a higher own land share are more efficient as in Coelli et al. (2003) and Rahman (2003). This might be explained through relatively lower quality of land, which is generally rented out to the tenants. The peri-urban infrastructure indicates that farmers with peri-urban infrastructure have relatively lower level of technical efficiency than their counterparts who live in rural areas. This contradicts with earlier findings of Ali & Flinn (1989), Ahmed & Hossain (1990), Coelli et al. (2002) and Rahman (2003). Since none of our rural areas has typical remote settings, i.e. no access through road, non-availability of transportation vehicles etcwe do not expect substantial differences in cost, effort and time of marketing between peri-urban and rural areas.

CONCLUSIONS

The impact of farm-level corruption costs on farms' technical efficiency was analysed based on a sample of 210 Bangladeshi rice growing farm households. For two consecutive rice growing seasons with different production and market conditions, we hypothesized an efficiency increasing impact of corruption costs in the first – *Aman* – season while we expected decreasing technical efficiency with higher corruption costs in the second – *Boro* – season. This natural experiment is possible since in *Aman* season 2008 the fertilizer market which is highly regulated by the government was quantity restricted for several reasons. Corruption allowed bribe payers to enter the input market and to acquire adequate fertilizer complementary to other inputs. Hence bribe payers are assumed to be more efficient. In contrast, fertilizer market was less restricted in *Boro* season but many farmers had been capital-constrained since production is more intensive in this season. In this case, additional corruption costs exacerbate the financing gap for some farmers and, thus, we expected that technical efficiency decreases with corruption costs in *Boro* season.

Our stochastic production frontier analysis actually finds that the cost of corruption in both seasons impacts technical efficiency in rice production in different directions like we hypothesized.

We conclude that bribe payments may be positive if they substitute (partially) for an insufficiently working price mechanism. This may happen on quantity-restricted input markets where prices can not affect the quantities traded. Policy interventions, thus, should not restrict quantities, since either corruptions or rent seeking will be the outcome. If, however, prices allocate an input bribe payments (for other goods and service) may still indirectly reduce the productivity of capital-constrained farmers. Consequently, bad governance can have severe side-effects on production of capital-constrained smallholders irrespective which services are corrupt.

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