WOMEN'S LABOUR CONTRIBUTION TO PRODUCTIVITY AND EFFICIENCY IN AGRICULTURE: EMPIRICAL EVIDENCE FROM BANGLADESH

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ABSTRACT

This paper examines the contribution of women's labour input to productivity and efficiency in crop farming using a large survey dataset of 1,839 households from 16 villages in two agro-ecological regions of Bangladesh. Results reveal that female labour accounts for a substantial 28% of total labour use (mainly supplied from the family) and contributes significantly to productivity as well as technical efficiency. Contrary to expectation, the cost share of female labour input is significantly higher than the male share, and has a substitution relationship with all other inputs, including male labour. The estimated mean level of technical efficiency is 0.90, implying that crop output might be increased by 10% by eliminating technical inefficiency. Both male and female education have a significant impact on improving technical efficiency. Other significant technical efficiency shifters are farming experience, family size and crop diversification. Owner operators are found to be technically inefficient relative to the tenants. Policy implications include creation of a hired labour market for female labour so that more women can be involved in the production process, and can contribute to towards improving productivity and efficiency. Also, investment in education for both men and women, strategies to promote crop diversification, and effective regulation/modification of the tenancy market will significantly improve technical efficiency in this case.

JEL classification: O33; Q18; C21

Key words: Women's labour contribution, Multiple crop farming, Stochastic frontier, Input distance function, Technical efficiency, Bangladesh.

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1. Introduction

There is a widespread agreement that rural women in Asia play an important role in agriculture (Kaur and Sharma, 1991; Unnevehr and Stanford, 1985) though its reflection is yet to be seen in the formulation of agricultural development policies (Agarwal, 1998). For example, about 84% of all economically active women are involved in agriculture in India with a positive correlation between agricultural growth rates and employment of female agricultural labour (World Bank, 1991). A commonly held view on women's involvement in agricultural production in Bangladesh is that they are involved only in the post-harvest processing of crops, limiting their contribution to national economy (Rahman, 2000). In fact, a simple change in the definition of women's work increased the estimate of women in the labour force from 3.2 million in the Labour Force Survey (LFS) in 1985/86 to 21 million in the LFS in 1989 and the increase was largely in rural regions (Rahman and Routray, 1998). The recent estimate of women in the labour force stands at 12.2 million[2] in the LFS in 2005/06 (BBS, 2007). It is believed that women's labour accounts for at least 25% of the value added from sowing to post-harvest operation in rice production (Scott and Carr, 1985).

Women in Asian societies, particularly from poorer households, balance the multiplicity of demands on their labour time between economic (wage earning and income-replacing work like fuelwood and water collection, care of livestock) and domestic activities (cooking, cleaning and child care) by working longer hours (Kabeer, 1994). For example, the average working day for women is estimated at 13.2 hours in India (Kaur and Sharma, 1991) and 11.1 hours (domestic and agriculture work only) in Bangladesh (Zaman, 1995). Although it is widely held that the

[2] There has been an increase in the eligible age from population aged 10+ years to 15+ years to be included in the pool of "economically active population" from 1999/2000. Therefore, if we take into account the number of women aged between 10–14 years, the number of women in labour force will increase by another 3-4 million.

gender division of labour in Bangladesh is strictly demarcated, with women being responsible for agricultural work within the household and not allowed to undertake field work (Begum, 1985; Abdullah, 1985), contrasting evidence is also available (Zaman, 1995). Bangladeshi women spent an average of 3.1 hours per day on agricultural work (4.4 hours per day during busy season) while men spent 5.1 hours (Zaman, 1995) which is not substantially lower from an average of 4.4 hours for rural women in India (Kaur and Sharma, 1991). Actually, the share of women in labour use ranges between 11–18% in foodgrain (rice and wheat) production and 14–48% in non-cereal (highest for vegetables) production in Bangladesh (Rahman, 2000).

Given that Bangladeshi women do undertake field work in agriculture, a further question is whether they are as productive and efficient as men. An argument often used against women farmers is that they are less efficient when compared to their male counterparts (FAO, 1985). Whether women are more or less efficient than men in farming is a hotly debated issue and results vary among the few studies that were undertaken in Africa during the 1990s (Adesina and Djato, 1997), while none is yet available for Bangladesh. Also, there has been criticism of the methods employed to examine gender differences in productivity in the literature (see Quisumbing, 1996 for a review). The dominant use of a dummy variable approach for headship on the input side of the production function as the stratifying variable (as seen in the literature) disguises the nature of the household structure and the intra-household decision making process, as it does not provide information on the decisions taken by family members (Quisumbing, 1996; Aly and Shields, 2010). Also, most of these studies used deterministic models which assume farmers to be fully efficient in their production technologies. With the development of stochastic frontier analysis by Aigner, Lovell and Schmidt (1977), a large number of studies followed which typically place farming efficiency of developing country farmers in the range of 60% to

82% (e.g., Bravo-Ureta et al., 2007; Rahman, 2003; Coelli et al., 2002; Ali and Flinn, 1989; Wang et al., 1996). Failure to recognise that farmers are generally and inherently inefficient will bias estimates of gender differences in productivity. Furthermore, most of these studies do not take into account any relative disadvantage faced by women (e.g., educational opportunities) when examining gender differences in productivity (Quisumbing, 1996).

The aims of this study are: (i) to determine the level of women's labour contribution to productivity in multiple-crop farming in Bangladesh, while allowing for inefficiency amongst producers; (ii) to determine the influence of women's labour input on production efficiency, while simultaneously controlling for women's educational level as a technical efficiency shifter, thereby addressing both major shortcomings of the existing literature. We undertake this task by employing a stochastic input distance function approach.

The paper is organised as follows. Section 2 reviews relevant literature examining gender differences in agricultural productivity. Section 3 presents the analytical framework, the model, and various performance measures developed to address the research objectives. Section 4 presents the results. The final section concludes and draws policy implications.

2. Gender differences in agricultural productivity

Quisumbing (1996), based on a comprehensive review of a number of studies undertaken during the 1970s, 1980s and 1990s, noted that the data used to measure gender differences in agricultural productivity is flawed. Most studies applied pooled regression with dummy variables to account for male and female farm managers and found insignificant coefficients on the dummies, implying that both men and women are equally efficient. Quisumbing (1996) argued that using such dummies exclude information on decisions by family members who are not household heads, and recommended the use of a more disaggregated measure of gender difference. She also argued that in all these studies information did not exist to identify whether the processes of allocation of human and physical capital to men and women had a bearing on any observed gender differences in productivity. For example, underinvestment in girls' education by parents in their resource allocation decisions could lead to lower probabilities of female farmers adopting new technologies and, therefore, being less efficient (Quisumbing, 1996). Jacoby (1992) provided a very detailed analysis of productivity differences between men and women in peasant agriculture of the Peruvian Sierra and identified a gender division of labour, implying that male and female labour are not perfectly substitutable. He further concluded that the use of animal traction and land affect the marginal productivity of male and female labour differently and, therefore, these two types of labour cannot be aggregated. Adesina and Djato (1997), using a deterministic profit function analysis, concluded that the relative degree of efficiency of women is similar to that of men in Cote d'Ivoire, although their measure of gender difference using a dummy variable has been criticised by Quisumbing (1996). More recently, Aly and Shields (2010) examine productivity differences of female and male labourers in Nepalese agriculture using two approaches: a Cobb-Douglas production function and a ray-homothetic function. They conclude that, although there is a gender gap in productivity, once differences in irrigation and type of seeds used by male and female farmers are included in the model, the magnitude of the difference is reduced and the estimated coefficient becomes insignificant. However, their study, although an improvement over those available in the literature, still assumes farmers to be fully efficient in their production technologies, which may bias the results.

Recently, two studies analyse the influence of women's input on technical efficiency with mixed results. Bozoglu and Ceyhan (2007) use a stochastic production frontier to analyze the technical efficiency of vegetables production in Samsun province, Turkey with a small sample of 75 farmers. They conclude that women's participation in farm decision-making significantly improves technical efficiency. However, Hasnah et al., (2004) do not find any significant influence of the share of female labour input as a technical efficiency shifter in the oil palm sector in West Sumatra, Indonesia.

The contribution of our study to the existing literature is two fold: (a) we provide an explicit examination of women's labour contribution to agricultural productivity while recognising that farmers may not be perfectly efficient in their production process (i.e., an improvement over Jacoby's (1992) and Aly and Shield's (2010) work); (b) we provide a simultaneous examination of women's labour contribution to production efficiency, while explicitly controlling for women's educational achievement as a technical efficiency shifter (i.e., addressing Quisumbing's (1996) major criticism of ignoring women's relative disadvantage with respect to human and physical capital). In addition, our analysis is conducted on a large dataset of 1,839 households (details in Section 3.2).

3. Research Methodology

3.1 *Analytical framework*

In order to examine women's labour contribution in the farming sector characterised by multiple crop production, a multi-output, multi-input production technology specification is required. A distance function approach (either output-orientated or input-orientated) is appropriate here, and can be analyzed using either parametric or non-parametric methods. In addition, the distance function approach allows the production frontier to be estimated without assuming separability of inputs and outputs (Kumbhakar, et al., 2007). An output oriented approach to measure technical efficiency is appropriate when output is endogenous (e.g., revenue maximization case) and inputs are exogenous, whereas an input oriented approach is appropriate when inputs are endogenous (e.g., cost minimization case) and output is exogenous (Kumbhakar et al., 2007). There is a criticism that parameter estimates of the distance functions may be affected by simultaneous equations bias (e.g., Sickles et al., 1996; Atkinson et al., 1999; and Alvarez, 2000). These authors went to correct this criticism by use of instrumental variables, although they did not clearly specify the source of suspected simultaneous equations bias (Coelli, 2000). Some also simply argue that because the ratios of inputs appear on the right-hand-side of the estimating equation (in the case of an input distance function) there must be a simultaneous feedback problem because these input variables are assumed to be "endogenous" variables. However, Coelli (2000) clearly demonstrated that OLS (Ordinary Least Squares) provides consistent estimates of the parameters of the input distance function under an assumption of cost minimizing behaviour. We assume that this conclusion can be generalized to MLE (Maximum Likelihood Estimation) procedure as well. In fact as Coelli (2000) concludes, "distance functions are no more subject to possible endogeneity criticisms than production functions … when cost minimising behaviour is a reasonable assumption, the input distance function has a clear advantage over the production function, because the distance function has an endogenous dependent variable and exogenous regressors, while the production function has the converse …. (and) distance functions release us from the shackles of the single-output assumption, (making) the case for the use of distance functions further strengthened" (p.20-21). We use an input-orientated stochastic distance function to address our research questions. This is because, in an economy like Bangladesh, on the one hand, inputs are scarce, particularly the land input, and on the other hand, farmers are often constrained by cash/credit (Rahman, 2009). Therefore, it is logical to assume that cost minimization is the prime concern. Also, the choice of a stochastic distance function approach instead of a deterministic approach (i.e., Data Envelopment Analysis) has been adopted because of its ability to separate the random noise (e.g., weather variation, measurement errors, etc.) from technical inefficiency effects. For example, weather variation could be a major issue when examining farming performance over a crop year cycle, particularly, in a country like Bangladesh, implying that choice of a stochastic approach is more appropriate.

Specifically, the following series of questions is addressed: (a) whether female labour input affects productivity; (b) whether the productivity of male and female labour differs; (c) what is the relationship between female and male labour inputs (d) whether female labour input affects technical efficiency; (e) whether women's educational achievement affects technical efficiency. We specify the actual amount of female labour used in farming as an independent variable in the stochastic input distance function and the share of female labour to total labour as one of the technical efficiency shifters. Also, the highest educational level of male and female members in the household, as well as other indicators representing farm characteristics, are included in the inefficiency effects model to explain the underlying causes of deviation from the frontier.

We begin by defining the production technology of the farm using the input set, L(y), which represents the set of all input vectors, $x \in R_+^K$, which can produce the output vector $y \in R_+^M$. That is,

$$L(y) = \{x \in R_+^K : x\, can\ produce\ y\} \qquad (1)$$

The input-distance function is then defined on the input set, L(y), as

$$D_I(x, y) = \max\{\rho : (x/\rho) \in L(y)\} \qquad (2)$$

$D_I(x,y)$ is non-decreasing, positively linearly homogenous and concave in x, and increasing in y. The distance function, $D_I(x,y)$, takes a value which is greater than or equal to one if the input vector, x, is an element of the feasible input set, $L(y)$ [$D_I(x,y) \geq 1$ if $x \in L(y)$]. Furthermore, the distance function is unity if x is located on the inner boundary of the input set. Thus, the input distance function can be interpreted as the multi-input input-requirement function allowing for deviations (distance) from the frontier, which are interpreted in terms of technical efficiency (Morrison-Paul and Nehring, 2005).

3.2 The model

For empirical implementation of the distance function, a functional form must be specified. Also, it is particularly important in a multi-output and multi-input context to minimize *a priori* restrictions on the relationships among inputs and outputs, and, therefore, a flexible technological representation, allowing for substitution effects within the function, is desirable for the empirical implementation of the model (Morrison-Paul et al., 2000). We select the translog (TL) functional form used by many (e.g., Rahman, 2009, Morrison-Paul and Nehring, 2005; Irz and Thirtle, 2004; Morrison-Paul et al., 2000; Coelli and Perelman, 1999).

The translog input distance function with M outputs and K inputs for the I farms (denoted i) is given as:

$$\ln D_i = \alpha_0 + \sum_k \alpha_k \ln X_{ki} + \frac{1}{2}\sum_k \sum_l \alpha_{kl} \ln X_{ki} \ln X_{li} +$$
$$\sum_m \beta_m \ln Y_{mi} + \frac{1}{2}\sum_m \sum_n \beta_{mn} \ln Y_{mi} \ln Y_{ni} + \sum_k \sum_m \tau_{km} \ln X_k \ln Y_m \qquad (1)$$

The summation sign over k, l implies summation over all K inputs X_k, and similarly over m, n for the M outputs Y_m.

Certain regularity conditions must hold for this function. These are: homogeneity of degree one in inputs and symmetry of the cross effects. Therefore, the following constraints are required:

$$\sum_k \alpha = 1,\ \sum_{kl} \alpha_{kl} = 0, \sum_{km} \tau_{km} = 0 (k = 1,....K), and$$

$$\alpha_{kl} = \alpha_{lk} (k, l, = 1,....K),\ and \qquad (2a)$$

$$\beta_{mn} = \beta_{nm} (m, m = 1,.....M),\ respectively. \qquad (2b)$$

Following Lovell et al., (1994), we impose these constraints by normalizing the function by one of the inputs. In this case, equation (1) becomes

$$\ln D_i / X_{1i} = \alpha_0 + \sum_k \alpha_k \ln X^*_{ki} + \frac{1}{2} \sum_k \sum_l \alpha_{kl} \ln X^*_{ki} \ln X^*_{li} +$$
$$\sum_m \beta_m \ln Y_{mi} + \frac{1}{2} \sum_m \sum_n \beta_{mn} \ln Y_{mi} \ln Y_{ni} + \sum_k \sum_m \tau_{km} \ln X^*_k \ln Y_m$$
$$= TL(\mathbf{X}^*, \mathbf{Y}) \qquad (3)$$

Rewriting this function with $-\ln D_i = -u_i$ as a one sided error term, and including “white noise” error terms v_i representing random factors such as measurement error or unobserved inputs, provides the following estimating equation:

$$-\ln X_{1,i} = TL(\mathbf{X}^*, \mathbf{Y}) - u_i + v_i \qquad (4)$$

Coefficient estimates for this equation have the opposite signs from those of a standard input requirement function (Morrison-Paul and Nehring, 2005). However, to interpret various performance measures derivable from equation (4) more similarly to those from more familiar functions, we reverse their signs following Morrison-Paul et al., (2000) and Morrison-Paul and Nehring, (2005):

$$\ln X_{1,i} = -TL(\mathbf{X}^*, \mathbf{Y}) - u_i + v_i \qquad (5)$$

This equation is now written as a standard stochastic production frontier form (with a two-part error term representing deviations from the frontier and random error). This model can be estimated econometrically using the maximum likelihood method, assuming that v_i are independently and identically distributed with mean zero and variance, σ_v^2 ; and the u_i are non-negative random variables independently distributed as truncations at zero of the normal distribution with unknown variance, σ_u^2, and unknown mean, μ, defined by:

$$\mu = \delta_0 + \sum_{d1} \delta_d Z_{di} \qquad (6)$$

Estimates of the parameters of the equations (5) and (6) were obtained using maximum likelihood procedures in a single stage as detailed by Coelli and Perelman (1999). STATA Software Version 8 was used for the analyses (Stata Corp, 2003).

3.3 The performance measures

Various performance measures of the production process can be derived as elasticities from this estimated model. The combined first-order input elasticities represent scale economies showing the extent to which productivity increases with input growth. The second-order elasticities reflect production complementarities that reflect economic impacts from output jointness (Morrison-Paul and Nehring, 2005). Specifically, for the input distance function, the **X-Y** scale economy relationship is represented by the sum of individual input elasticities and reflects how much overall input use must increase to support a 1% increase in all outputs. Formally, the individual input elasticity summarizing the input expansion required for a 1% increase in Y_m is $-\varepsilon_{D,Ym} = -\partial \ln D / \partial \ln Y_m = \partial \ln X_1 / \partial \ln Y_m = \varepsilon_{Ym}$. Such a measure can be thought of as an "input share" of Y_m (relative to X_I). In combination, these elasticties represent scale economies: $-\varepsilon_{D,Y} = -\sum_m \partial \ln D / \partial \ln Y_m = \sum_m \partial \ln X_1 / \partial \ln Y_m = \sum_m \varepsilon_{Y_m} = \varepsilon_Y$. The extent of scale economies (for proportional changes in all inputs) is implied by the short-fall of ε_Y from 1 (Morrison-Paul and Nehring, 2005).

The first-order elasticities ε_{Ym} *and* ε_{Y} can also be decomposed into second-order effects reflecting output compositions as scale expands. This information is implied by technological bias measures indicating how the Y_m input elasticity or share (ε_{Ym}) reflects a change in another output. Such measures provide insights about the output jointness of the production system. Specifically, $\varepsilon_{Ym,Yn} = \partial\varepsilon_{Ym} / \partial \ln Y_n$ represents the increase in the Y_m input share as Y_n increases. If $\varepsilon_{Ym,Yn} < 0$, output jointness or complementarity is implied; that is - input use does not have to increase as much to expand Y_m if the Y_n level is greater. This elasticity is represented by the cross-output coefficient estimate $\beta_{mn} : \varepsilon_{Ym,Yn} = \beta_{mn} = \varepsilon_{Yn,Ym}$ (Morrison-Paul and Nehring, 2005).

In addition to information about output patterns, some insight into input contributions can be obtained from the input distance function using the duality between the input distance function and the cost function. Since the input distance function completely describes the production technology, one may use it to describe the characteristics of the frontier or surface technology, including curvature, i.e., the degree of substitutability along the surface technology, (Grosskopf et al., 1995). Therefore, the indirect Morishima elasticity of substitution (MES) from an input distance function can be computed as (Blackorby and Russell, 1989):

$$MES_{X,kl} = -\frac{d\ln[D_k / D_l]}{d\ln[X_k / X_l]} = X_k \frac{D_{kl}}{D_l} - X_k \frac{D_{kk}}{D_k} \qquad (7)$$

where the subscripts on the distance functions refer to partial derivatives with respect to inputs. Because of the duality between the input distance function and the cost function, the first derivatives of the distance function with respect to inputs yield the normalized shadow price of that input, and therefore, the first component of the definition may be thought of as the ratio of the percentage change in the shadow prices brought about by a 1% change in the ratio of inputs (Kumar, 2006). This represents the change in relative marginal products and input prices required to affect substitution under cost minimisation. High values reflect low substitutability and low values reflect relative ease of substitution between the inputs (Kumar, 2006; Morrison-Paul et al., 2000). The MES can be simplified as follows (Kumar, 2006):

$$MES_{X,kl} = \varepsilon_{X,kl} - \varepsilon_{X,kk} \qquad (8)$$

where $\varepsilon_{X,kl}$ and $\varepsilon_{X,kk}$ are the constant output cross and own elasticity of shadow prices with respect to input quantities. The first term provides information on whether pairs of inputs are net substitutes or net complements, and the second term is the own price elasticity of demand for the inputs (Kumar, 2006). It should be noted that these elasticities are indirect elasticities. Therefore, for $\varepsilon_{X,kl}>0$ net complements are indicated, and for $\varepsilon_{X,kl}<0$ net substitutes are indicated (Kumar, 2006). Also, the MES may not be symmetric, i.e., $MES_{X,kl} \neq MES_{X,lk}$.

The Allen elasticity of substitution (AES) may also be derived from the input distance function as follows (Kumar, 2006):

$$AES_{X,kl} = \frac{D * D_{kl}}{D_k * D_l} = \varepsilon_{X,kl} / S_k \qquad (9)$$

where S_k is the first order derivative of the translog input distance function with respect to input X_k, i.e., $S_k = \partial \ln D / \partial \ln X_k = -\partial \ln X_1 / \partial \ln X_k^*$ (10)

The shadow price elasticities with respect to input quantities (to compute MES and AES presented above) are given by (Kumar, 2006):

$$\begin{aligned} &\varepsilon_{X,kl} = [\alpha_{kl} + S_k S_l] / S_k \quad if \;\; k \neq l; \;\; and \\ &\varepsilon_{X,kk} = [\alpha_{kk} + S_k (S_k - 1)] / S_k \quad if \; k = k \end{aligned} \qquad (11)$$

Stern (2008) developed a new derivation of the Hicks elasticity of substitution (HES) from an input distance function. The HES is defined for movement along a constant distance line similar to shadow elasticity of substitution derived from the cost function that is defined for movement along an isocost line (Stern, 2008). The HES (also known as the direct elasticity of substitution) is defined as:

$$HES_{X,kl} = \frac{-\frac{D_{kk}}{D_k D_k} + 2\frac{D_{kl}}{D_k D_l} - \frac{D_{ll}}{D_l D_l}}{\frac{1}{D_k X_k} + \frac{1}{D_l X_l}} \qquad (10)$$

where D is the input distance function. The elasticity is symmetric and as this elasticity is the inverse of the traditional Hick's elasticity of substitution, greater values indicate less substitutability (Stern, 2008). Also, for HES>0 net substitutes are indicated.

Finally, from the one-sided error term, u_i, we can quantify the level of technical efficiency, TE = exp(u_i) (for details, see Coelli et al., 1998).

3.4 Data and the study area

Primary data for the study pertains to an intensive farm-survey from two agro-ecological regions[3] conducted during 1990. A complete household census of eight villages from the *Jamalpur Sadar Thana* (central sub-district) of the Jamalpur region representing wet agroecology and six villages from the *Manirampur Thana* (sub-district) of the Jessore region representing dry agroecology were conducted. The survey/census covered a total of 1,839 households (923 in Jamalpur and 916 in Jessore, respectively). Selection of these villages was conducted by BRAC. A multistage random sampling technique was employed to locate the districts, the *thana* (sub-district), and then the villages in each of the two sub-districts. Finally, all households from these

[3] These data were collected by BRAC (one of the largest national non-governmental organisations in the world) to serve as a baseline information for a longitudinal study project, called the Village Study Project (VSP). The baseline data collection took about 6 months engaging 16 field researchers who were stationed in the core village of each thana. The author of this paper was a member of the core research team and contributed significantly in the design of the baseline survey and was responsible for co-ordinating the data collection team from the head office at that time.

16 villages were surveyed. Details of labour input data classified by gender[4] for each individual crop[5] produced over a one year crop-cycle were collected in addition to information on other inputs and the socio-economic circumstances of the surveyed households.

Although the data collected for this study are 20 years old, little has changed with regard to the farming practices, operating institutions and the relationship between male and female labour use in Bangladesh over this period, except for an increase in the level of modern rice technology adoption from 30% of gross cropped area in 1990 to 51% in 2005 (MoA, 2008). For example, a recent farm survey in 2006 of the Gher farming system (shrimp-prawn-modern rice joint culture) from the Southwest region of Bangladesh showed that the female labour ratio is only 11% and most of this is supplied from the family. Therefore, we argue that our results are capable of providing valuable information of relevance to policy makers and development practitioners alike.

3.5 The empirical model

The production structure of crop farming in Bangladesh is specified using a multi-output multi-input stochastic input distance function. The general form of the flexible translog stochastic input distance function for the i^{th} farm is defined as:

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[4] Male and female labour input was measured separately by the amount of labour used for each of the seven specific agricultural operations (e.g., seedbed and/or land preparation, sowing and/or transplanting, weeding, irrigation, fertiliser and pesticide application, harvesting, and threshing and/or winnowing operations) for each of the crops produced.

[5] The crop groups are: 1) traditional rice varieties (Aus – pre-monsoon, Aman – monsoon, and Boro – dry seasons); 2) modern/high yielding rice varieties (Aus, Aman, and Boro seasons); 3) wheats; 4) jutes; 5) potatoes; 6) pulses (include lentil, mungbean, and gram); 7) spices (include onion, garlic, chilly, ginger, and turmeric); 8) oilseeds (include sesame, mustard, and groundnut); 9) vegetables (eggplant, cauliflower, cabbage, arum, beans, gourds, radish, and leafy vegetables); and 10) cotton.

$$\ln X_{1i} = \alpha_0 + \sum_{k=2}^{7} \alpha_k \ln X^*_{ki} + \frac{1}{2}\sum_{k=2}^{7}\sum_{l=2}^{7} \alpha_{kl} \ln X^*_{ki} \ln X^*_{li} + \sum_{m=1}^{4} \beta_m \ln Y_{mi} + \frac{1}{2}\sum_{m=1}^{4}\sum_{n=1}^{4} \beta_{mn} \ln Y_{mi} \ln Y_{ni} + \sum_{k=2}^{7}\sum_{m=1}^{4} \tau_{km} \ln X^*_k \ln Y_m - u_i + v_i \qquad (8)$$

and

$$u_i = \delta_0 + \sum_{d=1}^{9} \delta_d Z_{id} + \zeta^*_i \qquad (8a)$$

where the dependent variable X_1 is the land cultivated per farm in one crop year; X^* are the other inputs normalized by the land variable (X_1); v is the two sided random error and u is the one sided error in eq. (8); ln is the natural logarithm; Z in eq. (8a) are the variables representing farm specific characteristics to explain inefficiency; ζ is the truncated random variable[6]; $\alpha_{0},$ $\alpha_{k},$, $\alpha_{kl},$ $\beta_m,$ $\beta_{mn},$ $\tau_{km},$ $\delta_0,$ and δ_d are the parameters to be estimated.

The model consists of seven production inputs (X); four outputs (Y); and nine variables representing socio-economic characteristics of the farm (Z) included in the inefficiency effects model as predictors of technical inefficiency. The seven inputs used in the analyses are: X_1 = land under all crops (ha), X_2 = total female (family supplied + hired) labour (woman-days), X_3 = total male (family supplied + hired) labour (man-days), X_4 = fertilizers (kg); X_5 = animal power services (animal-pair days); X_6 = irrigation (taka); X_7 = pesticides (taka). The four outputs are: Y_1 = traditional rice (kg); Y_2 = modern rice (kg); Y_3 = wheat (kg); Y_4 = cash crops[7] (including jute, cotton, oilseeds, spices, pulses, potatoes, and vegetables) (Bangladeshi taka). The nine variables

[6] We actually conducted a Likelihood Ratio test regarding the choice of the distribution of the inefficiency term: half-normal versus truncated normal and the result is presented in Table 2.

[7] The gross value of each output is used to construct this compound (aggregate) variable, and is expressed as Bangladeshi Taka per farm.

representing socio-economic characteristics of the farm are: Z_1 = female headed household dummy; Z_2 = age of the farmer; Z_3 = family size; Z_4 = highest educational level of the male member in the household; Z_5 = highest educational level of the female member in the household; Z_6 = share of female labour in total labour; Z_7 = tenurial status dummy; Z_8 = regional dummy for farmers located in Jessore region; Z_9 = Herfindahl index of crop diversification (*HI*)[8]. Table 1 presents the definitions, units of measurement, and summary statistics for all variables.

Table 1. Summary statistics of the variables per farm.

Name	Description	Measurement	Mean	Standard deviation
Output variables				
Y_1	Traditional rice	kg	357.5	890.9
Y_2	Modern rice	kg	1212.9	2106.0
Y_3	Wheat	kg	38.2	200.7
Y_4	Cash crops[a]	taka	10824.9	16956.2
Input variables				
X_1	Land area cultivated	ha	0.8	1.1
X_2	Female labour	woman-days	12.1	16.2
X_3	Male labour	man-days	94.9	127.7
X_4	Fertilizer	kg	148.8	283.0
X_5	Irrigation	taka	665.9	1502.9
X_6	Pesticides	taka	99.1	258.9
X_7	Animal power services	animal pair-days	20.1	28.8
Farm-specific variables				
Z_1	Female headed households	1 if head, 0 otherwise	0.1	--
Z_2	Age of the farmer	years	42.0	13.3
Z_3	Family size	persons per household	5.4	2.5
Z_4	Highest level of male education	completed years of schooling	4.0	4.5
Z_5	Highest level of female education	completed years of schooling	2.2	3.2
Z_6	Share of female labour	proportion of total labour	0.3	0.3
Z_7	Tenurial status	1 if owner-operator 0 otherwise	0.2	--

[8] The Herfindahl index (*HI*) is represented as $HI = \sum a_i^2$, $0 \leq HI \leq 1$, where a_i represents the area share occupied by the *i*th crop in total area *A*. A zero value denotes perfect diversification and a value of 1 denotes perfect specialization.

Z_8	Jessore region	1 if Jessore 0 otherwise	0.5	--
Z_9	Herfindahl index of crop diversification	number	0.7	0.3
	Number of observations		1839	

Note: [a] = Exchange rate of USD 1.00 = Taka 32.9 in 1990 (BBS, 1992)

The justification for inclusion of these variables is as follows. We have specified a dummy for female headed households to test whether women as farm managers have any influence on technical efficiency, as the literature suggests that women as farm managers are equally productive with men (Quisumbing, 1996).

Farmers' age is used to account for his/her experience in farming and its consequent influence on technical efficiency, where the results in the literature are mixed. Although Rahman (2003) and Asadullah and Rahman (2009) conclude that older farmers tend to be technically inefficient compared with their younger peers in Bangladesh, Llewelyn and Williams (1996) and Battese et al., (1996) conclude otherwise for Indonesian and Pakistani farmers, respectively.

Use of the education level of the farmer as a technical efficiency shifter is fairly common (e.g., Asadullah and Rahman, 2009; Wang et al., 1996; Wadud and White, 2000). The education variable is also used as a surrogate for a number of factors. At the technical level, access to information as well as the capacity to understand the technical aspects related to crop production is expected to improve with education, thereby, influencing technical efficiency. Surprisingly, the majority of studies on to the effects of education on farm production in Bangladesh fail to find any significant impact. For instance Deb (1995), Wadud and White (2000), Coelli et al. (2002), and Rahman and Rahman (2009) did not find any significant effect of education on production efficiency. However, Asadullah and Rahman (2009), using a large dataset of 2,357 households from 141 villages in the *Matlab* district in Bangladesh, conclude that education of the household matters in raising productivity, boosting potential output and improving efficiency. In this study, we move a step further and aim to determine whether womens' education has an independent influence on technical efficiency, while controlling for the influence of mens' education in the household, addressing the criticism of Quisumbing (1996).

In this study, we are specifically interested in determining whether women's labour input has an influence on technical efficiency. Therefore, the share of female labour in total labour used in farming is included to account for its influence in the model, as in Hasnah et al., (2004).

Tenurial status is also seen as an important technical efficiency shifter in Bangladesh agriculture. For example, Rahman (2003), Asadulah and Rahman (2009), and Rahman and Rahman (2009) all note that owner operators are relatively more technically efficient than tenants.

Another key question of interest is whether farming inefficiencies are related to the degree of diversification (or specialization), since the literature on this issue is mixed (e.g., Coelli and Fleming, 2004; Llewelyn and Williams, 1996; Haji, 2007 and Rahman, 2009). Specialization of farming activity may lead to greater efficiency or *vice versa*. The expectation is that specialization in production leads to efficiency gains in the division of labour and management of resources (Coelli and Fleming, 2004). A Herfindahl index is used to represent the specialization variable. Although, this index is mainly used in the marketing industry to analyze market concentration, it has also been used to represent crop diversification and/or concentration (e.g., Llewelyn and Williams, 1996; Rahman, 2009). Finally, a regional dummy for Jessore is included in order to examine whether geography matters for production performance.

4. Results

From the information provided in Table 1, we see that the average farm size is small (0.81 ha). Share of female labour input in total labour is 28%. Average highest educational level of both male and female members is low. The level of female education is about half of the level of male education. The family size is 5.4 persons per household, which is very close to the national average of 5.6 according to the 1991 population census (BBS, 2000). Dominant crops are modern varieties of rice and cash crops.

Maximum Likelihood Estimation (MLE) is used to estimate the parameters of the stochastic input distance function and the inefficiency effects model jointly in a single stage using STATA Version 8 (Stata Corp, 2003). Prior to discussing the results of the input distance function and the inefficiency effects model, we report the series of hypothesis tests conducted to select the functional form and to decide whether the frontier model is an appropriate choice rather than a standard mean-response or average production function. We also test regarding the choice of the distribution of the inefficiency term: truncated normal versus half-normal distribution.

We also test for the monotonicity condition requiring that the distance function be non-decreasing in inputs (i.e., $\{i.e., (\partial \ln D / \partial X_k) \geq 0\}$ and non-increasing in outputs $\{i.e., (\partial \ln D / \partial Y_m) \leq 0\}$ (Hailu and Veeman, 2000). We then check the curvature conditions of the input distance function. The input distance function should be concave in inputs and quasi-concave in outputs (Hailu and Veeman, 2000). Also tests were conducted to check input-output separability, the presence of inefficiency and returns to scale in crop farming. The results are reported in Table 2.

The first test was conducted to determine the appropriate functional form, i.e., the choice between a Cobb-Douglas or a translog functional form (H_0: $\alpha_{kl} = 0$ for all kl). A generalised Likelihood Ratio (LR) test confirms that the choice of a translog production function is a better representation of the production structure.

Given the functional form, we next check the sign of the third moment and the skewness of the OLS residuals of the data in order to justify the use of the stochastic frontier framework (and hence the Maximum Likelihood Estimation procedure)[9]. The computed value of Coelli's (1995) standard normal skewness statistic (M3T) based on the third moment of the OLS residuals is estimated at 12.49 (Table 2) which is tested against H_0: M3T = 0. The null hypothesis of 'no inefficiency component' is strongly rejected in all cases and, therefore, the use of the stochastic frontier framework is justified. The coefficient of γ reported at the mid-panel of Appendix Table A1 also confirms the strong presence of technical inefficiency. The value of γ ranges between 0 to 1, with 0 denoting no inefficiency and 1 being perfectly inefficient.

Next, we test for the preferred distribution of the inefficiency term. The generalized LR test result presented in Table 2 confirms that the truncated normal distribution of the inefficiency term is a preferred choice.

Next, we check the monotonicity condition of the input distance function. The results presented in the mid-panel of Table 2 clearly demonstrate that the required conditions hold for all inputs and outputs. Next, we conduct the curvature conditions check by examining the Hessian matrix of the second order partial differentials of the input distance function with respect to inputs and outputs as described by Chiang (1984), The checks reveal that the estimated distance function was found to be concave in inputs and quasi-concave in outputs at all data points.

Next, we test for the separability of the inputs and outputs in the input distance function. This hypothesis is defined mathematically by equating all cross-terms between inputs and

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

outputs (τ_{km}) to zero (Irz and Thirtle, 2004). These restrictions are strongly rejected, which implies that it is not possible to aggregate consistently all the outputs into a single index. This is why the distance function is more appropriate in our context, compared with a stochastic frontier production function, which requires output aggregation prior to estimation.

Next we determine whether the variables introduced as inefficiency effects improve the explanatory power of the model. The null hypothesis is rejected at the 1% level, implying that the distributions of inefficiencies are not identical across individual observations (Irz and Thirtle, 2004).

Table 2. Hypothesis tests

Name of test	**Parameter restrictions**	**LR test statistic**	**Degrees of freedom**	**χ^2 Critical value 5%**	**Outcome**
Functional form test (Translog vs. Cobb-Douglas)	H_0: $\alpha_{kl} = \beta_{mn} = \tau_{km} = 0$ for all *k, l ,m,* and *n*	3155.62	55	73.31	Cobb-Douglas model is inadequate
Frontier vs. OLS[a]	H_0: M3T = 0 (i.e., no inefficiency component)	12.49 (z-statistic)	--	0.000 (p value of z)	Frontier not OLS
Distribution of the inefficiency term	H_0: No difference between truncated normal versus half-normal distribution of the inefficiency term	162.75	10	18.31	Truncated normal distribution is a preferred choice
Monotonicity condition check	$\{i.e., (\partial \ln D / \partial X_k) \geq 0\}$ for every input			$\{i.e., (\partial \ln D / \partial Y_m) \leq 0\}$ for every output	
Inputs	Value	Outcome	Outputs	Value	Outcome
Female labour	0.016	Fulfilled	Traditional rice	-0.002	Fulfilled
Male labour	0.002	Fulfilled	Modern rice	-0.006	Fulfilled
Fertilizer	0.002	Fulfilled	Wheat	-0.002	Fulfilled
Irrigation	0.003	Fulfilled	Cash crops	-0.011	Fulfilled
Pesticides	0.006	Fulfilled			
Animal power	0.012	Fulfilled			
Input-	H_0: all $\tau_{km} = 0$ for all *k*	424.38	24	36.42	Aggregating

output separability	and m				output into a single index will provide inconsistent result
Returns to scale (Scale economy if ε_Y<1)	H_0: $(\Sigma\beta_m) = 1$ for all m	553.50	1	2.71	Considerable scale economy exists
No inefficiency effects	H_0: $\delta_d = 0$ for all d	97.67	9	16.92	Inefficiencies are jointly explained by these variables

Note: [a] = The test is the Coelli's (1995) standard normal skewness statistic (*M3T*) based on the third moment of the residual.

Measures of economic performance

The parameter estimates of the stochastic input distance function and the inefficiency effects model for crop farming estimated jointly in a single stage is presented in Appendix Table A1. Three quarters of the coefficients in the input distance function are significantly different from zero at the 10% level at least. All the variables are mean-differenced prior to estimation so that the elasticities of the distance function with respect to input quantities and output quantities at the sample mean correspond simply to the first order coefficients. All the signs on the first order coefficients of inputs and outputs are consistent with *a priori* expectations.

The primary overall measure, representing output/input patterns and performance incentive to increase the scale and diversity of farm operations, is the scale elasticity ε_Y (Table 3) The presented measure suggests significant scale economies, (ε_Y<1 indicate scale economies). The result of the formal test for constant returns to scale (i.e., ε_Y=1) is presented in Table 2, which is strongly rejected in favour of increasing returns to scale. This finding is interesting because other studies tend to report decreasing returns to scale, particularly in cereal production, in developing economies. For example, Appleton and Balihuta (1996), Weir and Knight (2004), and Asadullah and Rahman (2009) report decreasing returns to scale in cereal/rice production for Ugandan, Ethiopian and Bangladeshi farmers, respectively.

Table 3. Output jointness, input, output, and efficiency elasticities

Variables	Symbol	Value	t-ratio
Output elasticities			
Scale economy	ε_{Y}	0.45	
Traditional rice	ε_{Y1}	0.06***	10.11
Modern rice	ε_{Y2}	0.32***	48.81
Wheat	ε_{Y3}	0.020	0.97
Cash crops	ε_{Y4}	0.05***	15.26
Input elasticities			
Female labour	ε_{X2}	-0.19***	-10.85
Male labour	ε_{X3}	-0.04	-1.38
Fertilizer	ε_{X4}	-0.05***	-3.36
Irrigation	ε_{X5}	-0.02**	-2.49
Pesticides	ε_{X6}	-0.02***	-3.16
Animal power	ε_{X7}	-0.28***	-10.31
Land	ε_{X1}	-0.41	--
Output jointness or complementarity			
Traditional rice and Modern rice	ε_{Y12}	-0.02***	-14.35
Traditional rice and Wheat	ε_{Y13}	-0.00**	-1.96
Traditional rice and Cash crops	ε_{Y14}	-0.00***	-2.74
Modern rice and Wheat	ε_{Y23}	-0.01***	-5.91
Modern rice and Cash crops	ε_{Y24}	-0.01***	-5.16
Wheat and Cash crops	ε_{Y34}	0.00	0.89
Efficiency elasticities			
Female headed households	ε_{Z1}	0.00	0.01
Age of the farmer	ε_{Z2}	0.07***	3.40
Family size	ε_{Z3}	0.08***	4.03
Highest level of male education	ε_{Z4}	0.03***	3.75
Highest level of female education	ε_{Z5}	0.01*	1.90
Share of women labour	ε_{Z6}	0.07***	3.37
Tenurial status	ε_{Z7}	-0.02***	-5.87
Jessore region	ε_{Z8}	0.01	0.87
Herfindahl index of crop diversification	ε_{Z9}	-0.04**	-2.31

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

The individual output contribution underlying the scale elasticity is also presented in Table 3. These elasticities with respect to output in a distance function also represent the cost elasticity of that particular output (Irz and Thirtle, 2004). Table 3 shows that (except wheat) all output elasticities are significantly different from zero, implying that increasing the production of any of these inputs will increase costs substantially. The estimate also shows that the cost elasticity of modern rice is 0.32 whereas the estimates for cash crops as well as traditional rice are only 0.05 and 0.06, respectively. This means that a 1% increase in modern rice output will increase cost by 0.32%, while the corresponding figure for traditional rice is only 0.06%.

Similarly, the elasticities of the distance function with respect to input quantities are equal to the cost shares and, therefore, reflect the relative importance of inputs in the production process. Table 3 reveals that all seven elasticities are negative, as expected, with only one input (male labour) being not significantly different from zero. The elasticity with respect to land is the largest with a value of -0.41, implying that the cost of land represents 41% of total cost at the sample mean[10]. This is not an unexpected result in a land scarce economy like Bangladesh. The next highest cost input is animal power services (-0.28) which is also expected because land preparation is dominated by the use of animal power services, particularly for rice cultivation. It is somewhat surprising to see that the input elasticity of female labour is almost four times greater than that of male labour. A test of the equality of these two production elasticities failed to reject the null hypothesis (H_0: $\alpha_2 - \alpha_3 = 0$) at 1% level of significance ($\chi^2 = 16.40$, $p<0.01$). The implication is that the female labour input plays a significant role in the production process and the contribution is significantly higher than that of male labour.

[10] Elasticity of the land variable is computed using the restrictions in equation (2a), and therefore, its significance cannot be determined

To further evaluate the implications of our estimates of output complementarities and their contribution to scale economies, we focus on the (second order) cross-effects. These estimates are represented by the cross-parameters of the estimated functions (β_{mn}), reproduced in the mid-panel of Table 3. Except for wheat and cash crops, all crop combinations are negative and significantly different from zero at 5% level at least, implying complementarities and/or output jointness (Morrison-Paul and Nehring, 2005). As expected, the complementarities are highest for the traditional and modern rice combination followed by the modern rice and wheat combinations. Overall, these results suggest that significant scope economies exist in Bangladeshi farming, consistent with the results found by Rahman (2009).

4.1 Substitutability of female labour with other inputs

Table 4 presents the results of the three types of indirect substitution elasticities, namely, Morishima (MES), Allen (AES), and Hick's (HES) elasticity of substitution. Approximately 60% of the estimated substitution elasticities are significantly different from zero at the 10% level at least. With respect to MES and HES, we see that most of the inputs are substitutes although the degree of substitutability varies amongst inputs. We focus here on the substitutability between female labour and all other inputs. The MES results show that female labour is a substitute for male labour, fertilizers, irrigation and pesticides when row variables were considered and for irrigation and pesticides when column variables are considered. The AES results show that female labour is a substitute for male labour but a complement for animal power services. The HES results show that the female labour input is a substitute for all other inputs except male labour (not significant). The substitutability between female labour and other inputs implies that as the shadow price (or cost share) of female labour increases, the farmer employs more of other inputs. Overall, the estimated elasticity values show that male labour can be relatively easily substituted for female labour compared to all other inputs. This may partly explain lower use of female labour in farm production activities, particularly when hiring-in labour input.

Table 4. Indirect substitution elasticities

Variables	Female labour	Male labour	Fertilizer	Irrigation	Pesticides	Animal power
Morishima elasticitiy of substitution (*$MES_{X,kl}$*)						
Female labour	--	-0.76***	-0.89***	-0.99***	-1.01***	-0.18
Male labour	6.38	--	4.74	4.98	3.47	-0.93
Fertilizer	-0.41	-1.23**	--	-0.85***	-0.58**	-0.18
Irrigation	-0.81**	-1.49**	-0.89**	--	-0.58**	1.11
Pesticides	-3.04***	-5.63***	-2.38***	-2.72***	--	-0.54
Animal power	0.22	-1.15***	-0.21	-0.21	-0.11	-
Allen elasticity of substitution (*$AES_{X,kl}$*)						
Female labour	--					
Male labour	-0.04**	--				
Fertilizer	0.02	-0.02	--			
Irrigation	-0.00	-0.01	-0.00	--		
Pesticides	-0.01	-0.07***	0.01*	0.00	--	
Animal power	0.15***	-0.24***	0.03	0.03***	0.06***	--
Hick's elasticity of substitution (*$HES_{X,kl}$*)						
Female labour	--					
Male labour	-3.89	--				
Fertilizer	0.98***	-3.14	--			
Irrigation	0.70***	-1.54	0.63**	--		
Pesticides	2.52***	-2.63	2.39***	1.60***	--	
Animal power	1.35***	-6.13	0.89***	0.87***	2.95***	--

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

4.2 Efficiency effects of female labour input

Prior to the discussion of the determinants of technical inefficiency, we report summary statistics of technical efficiency scores. The mean technical efficiency is estimated at 0.90 implying that the average farm could increase production by 11% by optimising technical efficiency. Farmers exhibit a wide range of production inefficiency ranging from 53% to 99% in multiple crop farming. Observation of wide variation in production efficiency is not surprising and is similar to the results of Rahman, (2003), Ali and Flinn, (1989), and Wang et al., (1996) for Bangladesh, Pakistan, and China, respectively.

The lower panel of Appendix Table A1 provides the results of the inefficiency effects model. As mentioned above, the null hypothesis of 'no efficiency effects' (i.e., H_0: $\delta_d = 0$ for all d) is rejected at the 1% level of significance (Table 2), implying that all these variables jointly have an influence on the technical efficiency scores of individual farmers. The coefficients on these inefficiency predictors show only the direction of influence and do not provide information on the magnitude of influence. Therefore, we compute technical efficiency elasticities for these predictors using the Frame and Coelli (2001) framework. Table 3 presents the specific measure of responsiveness of each predictor on technical efficiency, not commonly reported in the existing literature.

Table 5. Technical efficiency in farming

Variables	**Efficiency scores**
Efficiency levels	
Upto 60%	0.9
61 – 70%	3.8
71 – 80%	13.9
81 – 90%	22.1
90 and above	59.3
Mean efficiency level	0.9
Standard deviation	0.1
Minimum	0.5
Maximum	1.0
Number of observations	1839

Older or experienced farmers are relatively technically more efficient compared with their younger peers, consistent with the findings of Llewelyn and Williams, (1996) and Battese et al., (1996) but not with Asadullah and Rahman, (2009). The elasticity estimate suggests that a 1% increase in the age of the farmer improves technical efficiency by 0.07%. Family size also significantly improves technical efficiency, perhaps through more timely supply of family labour. Tenants are relatively technically more efficient than the owner operators, which contradicts with the findings of other studies on Bangladesh (e.g., Rahman, 2003; Asadullah and Rahman, 2009). The contribution of female labour input significantly improves technical efficiency. The elasticity estimate indicates that a 1% increase in the share of female labour in total labour improves technical efficiency by 0.07%. Both male and female education have a significant influence on improving technical efficiency, although the level of influence of male education is three times that of female education. The significant role of education in improving technical efficiency in Bangladesh is also reported by Asadullah and Rahman (2009) and Sharif and Dar (1996). Crop diversification significantly improves technical efficiency, albeit with a relatively small effect. The elasticity estimate shows that a 1% increase in the Herfindahl index of crop diversification improves technical efficiency by 0.04%. The direction of the association is consistent with the findings of Rahman (2009) and Coelli and Fleming (2004) but not with Haji (2007) or Llewelyn and Williams (1996).

5. Discussion and policy implications

Rural women in Bangladesh, as elsewhere in Asia, play an important role in agriculture. The results of the present study confirm that female labour contributes significantly to productivity as well as technical efficiency. However, the remunerative employment of labour remains skewed in favour of men as they are mostly hired to meet the demand. The estimated 28% of female labour used in crop farming in our study is mainly supplied from the family, although 12% of all households reported hiring-in female labour in addition to male labour. The surveyed farmers are operating at a high level of technical efficiency of 90% implying that about

11% of the loss in potential output might be recovered if technical inefficiency could be completely eliminated.

The deprivation of women in gainful employment, reflected by weaker participation in the hired agricultural labour market, is largely due to cultural constructs in farming societies in Bangladesh. For example, Kabeer (1994) noted that though men can use their labour in a variety of ways with more ability to orient it towards income earning activities, women's ability to dispose their labour power is constrained by imposition of purdah as well as domestic obligations. Furthermore, Zaman (1995) claimed the existence of male preference in the agricultural labour market where females are hired for field agriculture only when the male labour supply is exhausted. Our results clearly show that female labour inputs can be substituted for male labour relative easily as compared to all other inputs. Our results also clearly demonstrate that female education has a significant influence on improving technical efficiency, as with the case of male education. Rahman (2000) notes that one of the major vehicles for creating awareness of gender discrimination is investment in human capital through gender sensitive literacy programs, as there is a positive relationship between the highest level of education of the household members and the demand for hired labour (both male and female). Balanced development implies that both men and women are provided with equal opportunities in all spheres of life. The dominance of the agricultural sector in the Bangladesh economy indicates that attempts to bridge the gap in employment opportunities between men and women has to be sought in the agricultural sector itself, since it engages the majority of the rural population, half of which are women (Rahman, 2000).

Apart from the information on the contribution of the female labour input, the results of our study also reveal that considerable scale economies exist in Bangladeshi farming systems.

The implication is that Bangladeshi farmers could gain by increasing their farm sizes. Conventionally, either constant or decreasing returns to scale in Bangladesh are usually reported in the literature (e.g., Wadud and White, 2000; Coelli et al., 2002; Rahman, 2003; Asadullah and Rahman, 2008). In addition, our results also suggest considerable scope economies in farming as a consequence of diversification of the cropping system, which also has a significant impact on technical efficiency.

It is encouraging to note that tenants are relatively technically more efficient than the owner operators. Tenancy (both crop-share and/or cash-rent tenancy) is a common feature of the agricultural sector in Bangladesh. The latest available Agricultural Census of 1996 reported that 37.5% of the farmers operated as tenants (either part or pure tenants) and 10.2% of farm holdings were landless (BBS, 2000) and that rice is the main crop grown by tenants (Akanda et al., 2008). In our sample, 32.5% of the farmers were part-tenants and 19.6% were pure tenants. Although a legal system of input and output sharing exists in the tenancy market, Akanda et al., (2008) argue that the existing economic structure does not fairly balance the returns from production between tenants and landowners (who gain relatively more). Therefore, proper regulation and/or modification of this important market is essential to safeguard the interests of the tenants, who would in turn boost potential output, at least according to these results.

The policy implications of this study are clear. Creation of a hired labour market for female labour is desirable so that more women can be involved in the production process and contribute positively towards improving productivity and efficiency and be remunerated for their contribution. Also, policies to promote crop diversification will improve overall productivity through scope economies and technical efficiency. The recent thrust at the planning level to promote crop diversification and allocating 8.9% of the total agricultural budget to this during the

Fifth Five Year Plan (1997–2002) appears to be a step in the right direction (PC, 1998). Furthermore, investment in education for both male and female members of the household and effective regulation/modification of the existing tenancy markets could significantly improve technical efficiency of the Bangladeshi farming system.

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Appendix

Appendix Table A1. Parameter estimates of the stochastic input distance function including inefficiency effects.

Variables	Parameters	Coefficients	t-ratio
Production Variables			
Constant	α_0	-2.00***	-34.76
ln(Female labour/Land)	α_2	-0.19***	-10.85
ln(Male labour/Land)	α_3	-0.04	-1.38
ln(Fertilizer/Land)	α_4	-0.05***	-3.36
ln(Irrigation/Land)	α_5	-0.02**	-2.49
ln(Pesticides/Land)	α_6	-0.02***	-3.16
ln(Animal power/Land)	α_7	-0.28***	-10.31
½ ln(Female labour/Land)^2	α_{22}	0.03**	0.15
½ ln(Male labour/Land)^2	α_{33}	-0.24***	-6.90
½ ln(Fertilizer/Land)^2	α_{44}	-0.01	-0.61
½ ln(Irrigation/Land)^2	α_{55}	-0.00	-1.03
½ ln(Pesticides/Land)^2	α_{66}	0.04***	7.86
½ ln(Animal power/Land)^2	α_{77}	-0.12**	-2.23
ln(Female labour/Land) x ln(Male labour/Land)	α_{23}	-0.03*	-1.69
ln(Female labour/Land) x ln(Fertilizer/Land)	α_{24}	-0.01	-0.76
ln(Female labour/Land) x ln(Irrigation/Land)	α_{25}	0.01	1.05
ln(Female labour/Land) x ln(Pesticides/Land)	α_{26}	0.01**	1.97
ln(Female labour/Land) x ln(Animal power/Land)	α_{27}	-0.10***	-4.87
ln(Male labour/Land) x ln(Fertilizer/Land)	α_{34}	0.02	1.18
ln(Male labour/Land) x ln(Irrigation/Land)	α_{35}	0.00	0.75
ln(Male labour/Land) x ln(Pesticides/Land)	α_{36}	-0.01	-1.52
ln(Male labour/Land) x ln(Animal power/Land)	α_{37}	-0.02	-0.74
ln(Fertilizer/Land) x ln(Irrigation/Land)	α_{45}	0.01	1.15
ln(Fertilizer/Land) x ln(Pesticides/Land)	α_{46}	0.07***	4.75
ln(Fertilizer/Land) x ln(Animal power/Land)	α_{47}	0.25***	7.07
ln(Irrigation/Land) x ln(Pesticides/Land)	α_{56}	-0.00	-0.79
ln(Irrigation/Land) x ln(Animal power/Land)	α_{57}	-0.02**	-2.31
ln(Pesticides/Land) x ln(Animal power/Land)	α_{67}	-0.05***	-3.82
ln(Traditional rice)	β_1	0.06***	10.11
ln(Modern rice)	β_2	0.32***	48.81
ln(Modern wheat)	β_3	0.02	0.97
ln(Cash crops)	β_4	0.05***	15.26
½ ln(Traditional rice)^2	β_{11}	0.07***	16.62
½ ln(Modern rice)^2	β_{22}	0.10***	28.49
½ ln(Wheat)^2	β_{33}	0.03***	3.15
½ ln(Cash crops)^2	β_{44}	0.02***	10.02
ln(Traditional rice) x ln(Modern rice)	β_{12}	-0.02***	-14.35
ln(Traditional rice) x ln(Wheat)	β_{13}	-0.01**	-1.96
ln(Traditional rice) x ln(Cash crops)	β_{14}	-0.00***	-2.74

Variables	Parameters	Coefficients	t-ratio
ln(Modern rice) x ln(Wheat)	β_{23}	-0.01***	-5.91
ln(Modern rice) x ln(Cash crops)	β_{24}	-0.01***	-5.16
ln(Wheat) x ln(Cash crops)	β_{34}	0.00	0.89
ln(Female labour/Land) x ln(Traditional rice)	τ_{21}	0.01***	3.91
ln(Female labour/Land) x ln(Modern rice)	τ_{22}	0.03***	7.39
ln(Female labour/Land) x ln(Wheat)	τ_{23}	0.02***	2.86
ln(Female labour/Land) x ln(Cash crops)	τ_{24}	-0.00	-1.20
ln(Male labour/Land) x ln(Traditional rice)	τ_{31}	0.03***	3.28
ln(Male labour/Land) x ln(Modern rice)	τ_{32}	-0.06***	-5.80
ln(Male labour/Land) x ln(Wheat)	τ_{33}	-0.03*	-1.93
ln(Male labour/Land) x ln(Cash crops)	τ_{34}	0.05***	9.07
ln(Fertilizers/Land) x ln(Traditional rice)	τ_{41}	-0.01*	-1.91
ln(Fertilizers/Land) x ln(Modern rice)	τ_{42}	-0.00	-1.14
ln(Fertilizers/Land) x ln(Wheat)	τ_{43}	0.00	0.19
ln(Fertilizers/Land) x ln(Cash crops)	τ_{44}	-0.01**	-2.27
ln(Irrigation/Land) x ln(Traditional rice)	τ_{51}	-0.00***	-2.73
ln(Irrigation/Land) x ln(Modern rice)	τ_{52}	0.00**	1.98
ln(Irrigation/Land) x ln(Wheat)	τ_{53}	0.001**	2.22
ln(Irrigation/Land) x ln(Cash crops)	τ_{54}	-0.00***	-2.75
ln(Pesticides/Land) x ln(Traditional rice)	τ_{61}	0.00***	2.64
ln(Pesticides/Land) x ln(Modern rice)	τ_{62}	0.01***	2.97
ln(Pesticides/Land) x ln(Wheat)	τ_{63}	0.01**	2.46
ln(Pesticides/Land) x ln(Cash crops)	τ_{64}	0.01***	4.30
ln(Animal power/Land) x ln(Traditional rice)	τ_{71}	0.01	1.06
ln(Animal power/Land) x ln(Modern rice)	τ_{72}	0.06***	7.03
ln(Animal power/Land) x ln(Wheat)	τ_{73}	-0.02	-0.97
ln(Animal power/Land) x ln(Cash crops)	τ_{74}	-0.00	-0.57
Model diagnostics			
Gamma	γ	0.79***	12.31
Sigma-squared	σ_s^2	0.09***	3.10
Log likelihood		-416.06	
$\chi^2_{(65,0.99)}$		1672.70***	
Inefficiency effects function			
Constant	δ_0	0.46***	4.80
Female headed households	δ_1	0.00	0.01
Age of the farmer	δ_2	-0.00***	-3.40
Family size	δ_3	-0.03***	-4.03
Highest level of male education	δ_4	-0.02***	-3.75
Highest level of female education	δ_5	-0.01*	-1.90
Share of women labour	δ_6	-0.50***	-3.37
Tenurial status	δ_7	0.21***	5.87
Jessore region	δ_8	-0.03	-0.87
Herfindahl index of crop diversification	δ_9	0.13**	2.31

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