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Full Length Research Paper

Gender difference and farm level efficiency: Metafrontier production function approach

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Gender mainstreaming has, for some time now, been identified as a paramount issue in development of resource-poor societies, and particularly, the women whose access to productive resources is limited due to tradition, culture and other socio-economic constraints. This research paper investigates the influence of Gender in management on the level of efficiency of food crop farms in Ghana. The study specifically: compares the technical efficiency scores of farms with male entrepreneurs and those with female entrepreneurs; examines the determinants of technical efficiency of food crop farmers; and compares technological gaps of farms with male entrepreneurs and those with female entrepreneur. The study involved 90 male food crop farmers and 90 female food crop farmers in the Juaboso District in the Western Region of Ghana. The respondents interviewed were selected using stratified random sampling technique. Stochastic metafrontier production function was used to estimate the efficiency scores in each group and multiple regression models was estimated to verify the determinants of technical efficiency. Survey was conducted with structured interview schedules to collect data. The estimated technical efficiencies indicate that food crop farmers in the Juaboso District of Ghana are, in general, less efficient in their production. Although farms under male farmers management had higher mean value of production figures relative to the female farmers' farms, the farms under female farmers management were found to be more efficient and also nearer to the potential output defined by the metafrontier production function compared to the farms owned by males. We also found technical efficiency to be influenced significantly by gender, age, household size, years of farming experience, access to credit, education and consultation with extension staff.

Key words: Gender of farmers, metafrontier, food crop production.

INTRODUCTION

Food security, the situation of having enough food to provide adequate nutrition for healthy life, for several years has been a critical issue in the developing world. Report by Pinstrup-Anderson (1993) indicates that if current agricultural trends continue, by the year 2020 sub-Saharan Africa's food shortage will increase twenty times, to 250 million tons. This poses a challenge in developing countries as to how initiatives can be taken to improve farm productivity for increased food production.

Gender advocates have called for social intervention programmes to increase women economic role in rural areas to engage them in food production where they are expected to perform better on the farm. Women are encouraged to own and control farm lands, cultivate food produce (mainly staples), and use the return to support their family in addressing households food security threats. This argument has been buttressed by the assertion that female farmers are equally efficient as male farmers, once individual characteristics and input levels are controlled for (Moock, 1976; Bindlish and Evenson, 1993; Saito et al., 1994). Furthermore, most of the technology adoption studies reviewed revealed that better educated farmers, regardless of gender, are more likely to adopt new technologies. Increasing the educational

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level of female farmers has higher marginal effects on the probabilities of adoption than increasing the educational level of male farmers, due to the generally lower levels of female education in most rural areas. However, according to Nelson (1981), it is wrong to assume that an effective development programme for males will automatically translate into an effective programme for females as well, and care must be taken if women were going to be encouraged to engage on the farm independently. This implies that men and women have different needs and desires. Gamble and Gamble (2002) asserted that men and women perceive different realities, have different expectations set for them, and that while women are typified as emotional, men are classified as rational. This complicates the advocacy role in favour given equal high priority to women economic participation and survival in food production, and thus calls for rigorous studies into measuring and compares technical efficiency of male and female food crop farmers on the field to guide policy direction. The measurement of gender differences in agricultural productivity is complicated by differences in farming systems and social and cultural institutions. It may be possible to estimate gender differences in efficiency in farming systems where men and women manage separate plots, as in many African farming systems (Boserup, 1970), but it is more difficult to isolate managerial efficiency differences in agricultural settings where plots are cultivated jointly by male and female family members and hired labor. In the latter setting, found in the "male" farming systems of Asia and Latin America, the farm manager is usually assumed to be the male head of the household, regardless of the actual contribution of women to decision making and farm labor.

In some of the places where it is possible to identify the gender of the plot manager, direct estimates of gender differences in technical efficiency have been made. The production function studies either estimate male and female production functions separately, or estimate a pooled regression with a dummy variable for the gender of the farm manager. Coefficients from these production functions have also been used to estimate gender differences in labor productivity. Since labor is usually measured in time units, it is assumed to be homogeneous within a category. However, many of the earlier studies did not consider endogeneity of input choices with respect to farmer characteristics. A production function is a technical relationship between inputs and outputs that specifies the maximum level of output possible, given input levels. Technical efficiency reflects the ability of a manager to produce output, given input levels and technology. Suppose that male and female farmers have the same production technology but male farmers are more technically efficient. Stochastic frontier production functions have been used extensively in the past two decades to analyze technical efficiency (Travers and Ma, 1994; Fan et al., 1994; Wang et al., 1996a and b; Xu and Jeffrey, 1998; Fan, 1999; Tian and Wan, 2000). The original models of Aigner et al. (1977) Meeusen and Van den Broeck (1977) have been modified and extended in a number of ways. One development has been to express inefficiency as an explicit function of farm-specific variables. Such a model can be estimated in a two-stage technique, where the stochastic frontier is obtained first and the predicted efficiencies are then regressed upon the farm-specific variables. Battese and Coelli (1995) proposed a simultaneous estimation procedure that has the advantage of providing consistent and efficient estimates that is commending.

However, in Ghana empirical literature from the studies involving estimate of efficiency in farming systems is limited, and also it is hard to come by any study on ascertaining gender differences in technical efficiency in farming systems where men and women manage separate plots, as in many African countries including Kenya, Nigeria, and Ivory Coast. This study adds to the literature on farm level efficiency in Africa. Moreover, knowledge of how gender difference affects farm level efficiency is important in determining strategies and formulating policies for agricultural development. It is in this light this study investigates into gender of farm entrepreneur and farm level efficiency in food crop farming in the study area in Ghana.

OBJECTIVES OF THE STUDY

The main purpose of this study is to investigate the influence of gender in farm management on the level of efficiency in food crop farming in Ghana. That is whether male-managed farms are more efficient than their female counterparts.

The specific objectives are:

i) Compare the technical efficiency scores of farms with male entrepreneurs and those with female entrepreneurs.
ii) Compare technological gaps of farms with male farmers and those with female farmers.
iii) Examine the determinants (for example gender, age, years of farming experience, education access to credit, household size, and consultation with extension staff) of technical efficiency of food crop farmers.

THEORETICAL FRAMEWORK

Stochastic frontier metaproduction approach

Further developments of the stochastic frontier model led to the stochastic metaproduction frontier model. Hayami (1969), Hayami and Ruttan (1970) introduced the concept of metaproduction function for the assessment of efficiency. They defined the metaproduction function as “the envelope of commonly conceived neoclassical production functions”. Thus, it is a common underlying production function that is used to represent the input-output relationship of a given industry (Lau and Yotopoulos, 1989). The metaproduction function concept is based on the hypothesis that all producers in different groups have potential access to the same technology. However, each producer may choose to operate on a different part of it depending on circumstances such as the natural endowments, relative prices of inputs, and the economic environment (Lau and Yotopoulos, 1989). Recent extensions and modification of the stochastic frontier metaproduction function approach is found in Battese and Rao (2001), which is thus reviewed.

The stochastic metaproduction model by Battese and Rao (2001)

Battese and Rao (2001), showed how technical efficiency scores for firms across regions can be estimated using a stochastic frontier metaproduction function model, and used a decomposition result to present an analysis of regional productivity potential and efficiency levels. If stochastic frontier models are defined for different regions within an industry, and for the jth region, there exist sample data on firms that produce one output from the various inputs. The stochastic frontier model for this region is specified as:

$$Y_{ij} = f(x_{ij}, \beta_j) e^{V_{ij} - U_{ij}}, i = 1, 2...., N_j \quad (1)$$

It is assumed that the V_{ij} s are identically and independently distributed as $N(0, \sigma_v^2)$ -random variables, independent of the U_{ij} s, which are defined by the truncation (at zero) of the $N(0, \sigma_v^2)$ -distributions. Omitting the subscript j to simplify the model for the jth group gives:

$$Y_i = f(x_i, \beta) e^{V_i - U_i} \equiv e^{x_i \beta + V_i + U_i}. \quad (2)$$

The stochastic metaproduction frontier function model for all firms in all regions of the industry is defined as

$$Y_i = f(x_i, \beta^*) e^{V_i^* - U_i^*} \equiv e^{x_i \beta^* + V_i^* - U_i^*}, i = 1, 2...., N \quad (3)$$

Where $N = \sum_{j=1}^{R} N_j$ is the total number of sample firms in all (R) regions.

The maximum-likelihood estimates of the parameters of the above stochastic frontier metaproduction function do not necessarily result in the estimated function being an envelope of the individual regional production functions. This is because if the assumptions for the regional frontiers are satisfied, those associated with the stochastic frontier metaproduction function may not be satisfied. However, Battese and Rao (2001) discussed that it is possible to constraint the estimation of the metaproduction function (equation 3) such that it is an envelope of observations for efficient farms in all regions. Battese and Rao (2001) showed that the model for the jth group and the stochastic frontier metaproduction function yields the following identity relationship:

$$1 = \frac{e^{x_i \beta}}{e^{x_i \beta^*}} . \frac{e^{V_i}}{e^{V_i^*}} . \frac{e^{-U_i}}{e^{-U_i^*}}, \quad (4)$$

where the three ratios on the right-hand side of the above equation are called productivity potential ratio (PPR), the random error ratio (RER) and the technical efficiency ratio (TER), respectively:

$$PPR_i \equiv \frac{e^{x_i \beta}}{e^{x_i \beta^*}} \equiv e^{-x_i(\beta^* - \beta)}, RER_i \equiv \frac{e^{V_i}}{e^{V_i^*}} \equiv e^{V_i - V_i^*}, \text{ and}$$

$$TER_i \equiv \frac{e^{-U_i}}{e^{-U_i^*}} \equiv \frac{TE_i}{TE_i^*} \quad (5)$$

Battese and Rao (2001) defined the productivity potential ratio as the potential productivity increases for the given region, according to currently available technology for firms in a given region relative to the technology available in the whole industry. The technical efficiency of farm i, relative to its regional frontier, $TE \equiv e^{-U_i}$ is estimated by $T\hat{E} \equiv E(e^{-U_i} / E_i \equiv V_i - U_i)$ and the technical efficiency of firm i, relative to the metaproduction frontier is estimated as:

$$T\hat{E}_i^* \equiv E(e^{-U_i^*} / E_i^* \equiv V_i^* - U_i^*).E_i^* \equiv E_i - x_i(\beta^* - \beta) \quad (6)$$

Stochastic metafrontier approach

The stochastic metafrontier model is an extension of the metaproduction function model. The technique proposed by Battese and Rao (2002) is used for the measure of technical efficiency ratios as well as technology gap ratios for farms in a group relative to the best practice in the industry. In a similar way as the stochastic frontier metaproduction function, the stochastic metafrontier function is expressed as in Equation (3). However, Battese and Rao (2002) explained that the metafrontier function is an envelope of the stochastic frontiers of the different groups such that it is defined by all observations in the different groups in a way that is consistent with the specifications of a stochastic frontier model. Observations on individual farms in the different groups may be greater than the deterministic component of the stochastic frontier model, but deviations from the stochastic frontier outputs are due to inefficiency of the farms in the different groups.

The stochastic frontiers for the different groups and that of the metafrontier would generally be assumed to be of the same functional form (for example Cobb-Douglas or translog), but there are no problems of aggregation as with the relationship between firm and industry functions. It is easily identified that the identity relationship in Equation (2) of the stochastic frontier metaproduction function also holds for the stochastic metafrontier function. However, for the stochastic metafrontier function, the three ratios on the right-hand side of Equation (2) are called the technology gap ratio (TGR), the random error ratio (RER) and the technical efficiency ratio (TER). Thus:

$$TGR_i \equiv \frac{e^{x_i\beta}}{e^{x_i\beta^*}} \equiv e^{-x_i(\beta^*-\beta)}, RER_i \equiv \frac{e^{V_i}}{e^{V_i^*}} \equiv e^{V_i-V_i^*}, \quad \text{and} \quad TER_i \equiv \frac{e^{-U_i}}{e^{-U_i^*}} \equiv \frac{TE_i}{TE_i^*} \qquad (7)$$

According to Battese and Rao (2002), the technology gap ratio indicates the technology gap for the given group according to currently available technology for farms in that group, relative to the technology available in the whole industry. The technical efficiency of farm i, relative to its regional frontier, $TE \equiv e^{-U_i}$, is estimated by $T\hat{E} \equiv E(e^{-U_i} / E_i \equiv V_i - U_i)$, and the technical efficiency of farm i, relative to the metafrontier is estimated as $T\hat{E}^* \equiv E(e^{-U^*_i} / E_i^* \equiv V_i^* - U_i^*)$. The identity $E_i^* = E_i - x_i(\beta^* - \beta)$ is satisfied.

The metafrontier model by Battese et al. (2004)

If we denote i = 1, 2,…, N as an index of firms in a group j, t = 1, 2,…, T to index time periods, according to Battese et al (2004), if inputs and outputs for firms in a given industry are such that stochastic frontier production function models exist for R different groups (j= 1, 2,…, R) within the industry, then the stochastic frontier model for the jth group is defined as:

$$Y_{it(j)} = f(x_{it(j)}, \beta_{(j)}) e^{V_{it(j)} - U_{it(j)}} \qquad (8)$$

where $Y_{it(j)}$ is the performance or output of firm i in period t for the jth group, $x_{it(j)}$ is the vector of inputs or functions of inputs used by the ith firm in the tth time period for the jth group, $\beta_{(j)}$ is a vector of parameters associated with the x-variables for the stochastic frontier for the jth group involved, $V_{it(j)}$s are statistical noise terms assumed to be independently and identically distributed as $N(0, \sigma^2_{v(j)})$ random variables, independent of the $U_{it(j)}$s, defined by the truncation (at zero) of the $N(\mu_{it(j)}, \sigma^2_{(j)})$ distributions, where the $\mu_{it(j)}$s are defined by some appropriate inefficiency model. The model for the jth group is thus simplified as:

$$Y_{it(j)} = f(x_{it(j)}, \beta_{(j)}) e^{V_{it(j)} - U_{it(j)}} \equiv e^{x_{it}\beta_{(j)} + V_{it(j)} + U_{it(j)}} \qquad (9)$$

From the above expression, it is assumed that the exponent of the frontier production function is linear in the parameter vector, $\beta_{(j)}$ so that X_{it} is a vector of functions of the inputs for the ith firm in the tth time period (Battese et al. 2004). They define the metafrontier function as "a production function of specified functional form that does not fall below the deterministic functions for the stochastic frontier models of the groups involved". The stochastic metafrontier model for firms in all groups of the industry is expressed by:

$$Y_i = f(x_i, \beta^*) e^{V_i^* - U_i^*} \equiv e^{x_i\beta^* + V_i^* + U_i^*} \quad i = 1, 2.....N \qquad (10)$$

where β^* is the vector of parameters for the metafrontier function such that $X_i\beta^* \geq X_i\beta$ and $N = \sum_{j=1}^{R} N_i$ is the total number of sample firms in all R groups and the assumptions for the V_i^*s and the U_i^*s are analogous to those for the $V_i s$ and the $U_i s$ respectively.

Efficiency level and technology gap

From Battese et al. (2004), an alternative expression for the output that is observed for the ith firm in the tth time period, which is defined by the stochastic frontier for the jth group, is given by:

$$Y_i = e^{-U_{i(j)}} \times \frac{e^{X_i \beta_j}}{e^{X_i \beta^*}} \times e^{X_i \beta + V_{i(j)}} \tag{11}$$

The first term on the right-hand side of Equation (11) is the technical efficiency relative to the stochastic frontier for the jth group:

$$TE_i = \frac{Y_i}{e^{X_i \beta_{(j)} + V_{i(j)}}} = e^{-U_{i(j)}} \tag{12}$$

The second term on the right-hand side of Equation (11) is the technology gap ratio for the observation for the sample firm involved,

$$TGR = \frac{e^{X_i \beta_{(j)}}}{e^{X_i \beta^*}} \tag{13}$$

The technology gap ratio has values between zero and one, and measures the ratio of the output for the frontier production function for the jth group relative to the potential output defined by the metafrontier function, given the observed inputs.

In an analogous way to Equation (12), the technical efficiency of the ith firm, for the tth observation relative to the metafrontier $\hat{TE}_i$ is the last term on the right-hand side of equation (11), which is the metafrontier output adjusted for the corresponding error,

$$TE_i^* = \frac{Y_i}{e^{X_i \beta^* + V_{i(j)}}} \tag{14}$$

It follows from Equation (11) to (14) that, the technical efficiency relative to the metafrontier is alternatively expressed as:

$$TE_i^* = TE_i \times TGR_i \tag{15}$$

Equation (15) implies that the technical efficiency relative to the metafrontier function is the product of the technical efficiency relative to the stochastic frontier for the group involved and the technology gap ratio (TGR). Battese et al. (2004) presented the estimation procedures and also proposed two methods for the identification of the best envelope $(\hat{\beta}^*)$: The minimum sum of absolute deviations and the minimum sum of squares of deviations.

MATERIALS AND METHODS

This section considers a stochastic metafrontier production function to investigate the technical efficiency of the farms in different groups, thus male-managed farm and female-managed farms that may not have the same level of technology. The stochastic metafrontier method is appropriate for this study because the metafrontier function concept is the best option for groups that have differences in technology. Most stochastic frontier methods put the data for the different groups together to estimate the efficiency scores. However, the fact that there are differences in technology which may be evident in the Ghanaian situation, could lead to an estimation bias. The following procedures were used to assess the efficiency of the food crops farms that are managed by females and males farmers separately: estimate stochastic frontier for each of the two groups (that is, one with female farmer as managers and the other with male farmers as managers): perform Likelihood Ratio (LR) tests to determine whether the technological difference between the two categories of farms is statistically significant: construct the metafrontier if the test indicates significant difference: estimate Technology Gap Ratio (TGR) and Technical Efficiency Ratio (TER) and estimate a Logit model to verify the determinants of technical efficiency.

Specification of the stochastic frontier

Following Battese et al. (2004), the stochastic frontier production function model for the groups in the manufacturing industry is presented in this section. The transcendental logarithm was adopted because it was assumed to specify the production technology of the entrepreneurs. We specified a transcendental logarithm stochastic frontier production function for the firms with male-managers and the firms with female-managers as follows:

$$Y_{gi} = \alpha_g + \beta_{1g} k_{gi} + \beta_{2g} l_{gi} + \beta_{3g} l_{gi}{}^2 + \beta_{4g} k_{gi}{}^2 + \beta_{5g} l_{gi} k_{gi} + V_{gi} - U_{gi} \tag{16}$$

Where Y_g is a vector of valued of production for farms managed by females Y_f and males Y_m, which can be defined as output less cost of raw materials and indirect inputs; K_g denotes a vector of physical capital, l_g is a vector of labor which consist of permanent and casual farm labourers were employed by the managers, i is a farm specific index; V_g is a vector of two-sided error term assumed to be identically and independently distributed; U_g is a vector of non-negative technical inefficiency component of the error term; α and β are vector of parameters to be estimated. All the variables are in natural logarithms. The stochastic frontiers would be estimated from equation (16), using the Stata 9.0 software for the two groups, that is farm managed by female and male entrepreneurs.

The likelihood ratio tests

The likelihood ratio test was used to determine whether the metafrontier is really necessary for estimating the efficiency levels of the firms. If the two groups (farms with female managers and with male managers) have similar technology in terms of food crop production, then the stochastic frontier production model is enough to estimate the efficiency of the farms. (That is we do not have to estimate separate regressions for the two groups.) A likelihood ratio (LR) statistic, which has the null hypothesis that the stochastic frontier models for the two groups are the same, was calculated.

The procedure is as follows. A stochastic frontier function for each of the two groups will be estimated, and another for the pooled data from all the two groups. The LR statistic is defined as:

$$LR = -2\left\{Ln\left(\frac{LH_0}{LH_1}\right)\right\} = -2\left\{Ln\left(LH_0\right) - Ln\left(LH_1\right)\right\} \quad (17)$$

where $Ln\left(LH_0\right)$ the value of the log likelihood function for the stochastic frontier is estimated by pooling the data for all the two farm groups, and $Ln\left(LH_1\right)$ is the sum of the values of the log likelihood functions for the two stochastic production functions estimated separately.

Construction of the metafrontier

This step is about obtaining the vector of estimate of the metafromtier parameters (that is, β^*). This is done in such a way that the estimated function best envelops the deterministic components of the estimated stochastic frontiers for the different groups. Battese et al (2004) proposed two methods to identify the best envelope: the minimum sum of absolute deviation and the minimum sum of squares of deviation. Minimum sum of absolute deviations in the construction of the metafrontier will be employed. The use of this method involves solving the following linear programming (LP) problem of the form:

Minimize $$L^* \equiv \bar{X}_i \beta^* \quad (18)$$

Subject to $$X_i \beta^* \geq X_i \hat{\beta}_{(g)} \quad (19)$$

where $\bar{X}$ is the row vector of means of the elements of the X_i vector for all observations in the data set and β_{igs} are the estimated coefficients of the group stochastic frontiers and β^* are parameters of the metafrontier function.

Technology gap ratio (TGR) and technical efficiency ratio (TER)

The technical efficiency from the stochastic frontier for each group is estimated as:

$$TE_{gi} = {Y_i}\Big/{e^{\alpha_g + \beta_{1g} k_{gi} + \beta_{2g} l_{gi} + \beta_{3g} l^2{}_{gi} + \beta_{4g} k^2{}_{gi} + \beta_{5g} l_{gi} k_{gi} + V_{gi}}} = e^{-U_{gi}} \quad (20)$$

The technological gap ratio is also estimated as:

$$TGR_i = \frac{e^{\beta_{1g} k_{gi} + \beta_{2g} l_{gi} + \beta_{3g} l^2{}_{gi} + \beta_{4g} k^2{}_{gi} + \beta_{5g} l_{gi} k_{gi}}}{e^{\beta^*{}_{1g} k_{gi} + \beta^*{}_{2j} l_{gi} + \beta^*{}_{3g} l^2{}_{gi} + \beta^*{}_{4j} k^2{}_{gi} + \beta^*{}_{5g} l_{gi} k_{gi}}} \quad (21)$$

Thus, the technical efficiency relative to the stochastic frontier over the technical efficiency relative to the metafrontier.

The technical efficiency relative to the metafrontier is estimated as:

$$TE^*{}_i = \frac{Y_i}{e^{\alpha_g + \beta^*{}_{1g} k_{gi} + \beta^*{}_{2g} l_{gi} + \beta^*{}_{3g} l^2{}_{gi} + \beta^*{}_{4g} k^2{}_{gi} + \beta^*{}_{5g} l_{gi} k_{gi}}} \quad (22)$$

Thus the technical efficiency relative to the metafrontier is alternative defined from equations (20 to 22) as the product of the technical efficiency relative to the stochastic frontier for each group involved and the technology gap ratio (TGR) defined below

$$TE_i^* = TE_{gi} \times TGR_{gi} \quad (23)$$

The multiple regression model

The Ordinary Least Square estimation procedure had been adopted in determining factors influencing the technical performance of the food crop farmers. This was due to the fact that, the procedure had been used in a number of studies, which was consistent and had provided satisfactory results. The determinants of technical efficiency was specified as,

$$TE_i^* = \gamma + \theta h_i + \mu_i \quad (24)$$

Where γ is the intercept, h_i is the firm characteristics, μ_i is the disturbance term in the model. But $h_i = f(Sx, Ag, Ex, Fs, Hhs, Es, FI, Ed, Ac, UIs, OS)$ are the determinants of technical efficiency of the manufacturing firms: Sx represent the sex of the farmer: Ag is the age of the farmer: Ex years of farming experience: Fs is the farm size: Hhs is the household size: Es is a dummy variable indicating whether the farmers have consultation with extension staff: FI denotes off-farm income: Ed is the level of education of the farmer: Ac is a dummy indicating whether the farmer has access to credit: UIs denotes the use of improved seeds: OS represent the ownership status and μ_i. And $\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7, \theta_8, \theta_9, \theta_{10}, \theta_{11}$ are unknown scalar parameters to be estimated and coefficients would help the researchers in identifying the variables which influence the technical efficiency of the farmer.

Data source and collection

The target population for the study was all food crop farmers in the Juaboso Dististrict in the Western Region of Ghana. The district MOFA office was contacted for a list of some food crop farmers through which a snow balling approach was use to identify more farmers and a sample frame of 530 was obtained. The sample frame involved 280 male farmers and 250 female farmers. Sampling of the respondents was done using stratified random sampling technique (lottery approach). The study involved 180 respondents (90 male farmers and 90 female farmers). Data was collected using structured interview schedule which was pre-tested before the main field survey. With the help of Stata computer software, collected data was analyzed. For easy and fast

Table 1. Summary statistics of socio-economic and institutional variables

Variable name	Male-managed farms		Female-managed farms	
	Mean	**Standard deviation**	**Mean**	**Standard deviation**
Value of production	30.5	11.3	24.4	4.5
Capital	1,870.00		1,208.50	
Labour	510.45	205.50	281.15	65.60
Age	45.4	8.9	42.5	10.8
Education	7.6		4.5	
Household size	5.41	1.90	6.21	2.11
Farm size	15.6	2.81	9.0	1.33
Number of years in farming	12.5	6.2	8.5	11.3
Household income	608.50	11.60	426.32	286.93
	Frequency	**Percent**	**Frequency**	**Percent**
Engagement in other activities	47	52.2	66	73.3
Access to credit	77	85.6	44	48.9
Extension service	70	77.8	39	43.3
Ownership status	64	71.1	43	47.8

comparison of male-female entrepreneurs' production activities, descriptive statistics (frequencies, percentages, means and standard deviations) was run to obtain the summary of the data.

RESULTS AND DISCUSSION

Socio-economics and institutional characteristics of respondents

Table 1 shows that the mean value of production from the male managed farms is GH¢ 3,050.00 compared with the GH¢2,440.00 mean value of production from the female-managed farms. The result also indicates that on average, the value of capital used on the male-managed farms is GH¢610.00 higher than the value of capital used on female-managed farms. Furthermore, the average labour cost incurred on male managed farms was comparatively higher than labour cost on female-managed farms that is GH¢510.45 and GH¢281.15 respectively. These results suggest that more input were used on male-managed farms comparatively; and this might justify why the value of production from male-managed farms was greater than value of production from female managed farms. This is also consistence with the result on farm size which depicts an average size of 15.6 acres for male-managed farms compared with an average size of 9.0 acres for female-managed farms (Table 1). The standard deviations for all the four variables discussed are lower than their respective means in all the two farmer-groups, and this indicates no wider or significant variations.

It can further be seen in Table 1 that on average, the entrepreneurs of both groups of farms were above 40 years of age, and have involved in the food crop farming on average for 8 years. This stand to reason that the two farmer groups interviewed have similarities in their age distributions; and the average age above 40 years implies that there is inadequate number of youth in agriculture in the study area. The table also shows that the average years of formal education received by both male and female entrepreneurs was about 8 years and 5 years respectively (that is at most, junior high school level). This means that the farm entrepreneurs interviewed generally, have low level of education which might have implication for the efficiency with which they will operate. The average household size of the male-entrepreneurs' households was 6 people compared with about 7 people in the households of female farm entrepreneurs. The measures of dispersions around the means were found to lower than the means (that is 1.90 and 2.11 respectively for male and female entrepreneurs' households). This implies that there were no wider variations in the household sizes in the two farmer groups' households.

The results in Table 1 again portrays that on average, the off-farm income of GH¢608.50 per annum for male entrepreneurs was greater than the annual off-farm income of GH¢426.32 for female farm entrepreneurs. This suggest that male farm entrepreneurs are likely to re-invest proceeds from their business than their female counterparts and thus stand the chance of early adopting improved technology and inputs to be more efficient. According to Elsasser (2006), in recent years, there has been a growing recognition that lack of access to financial resources represents a major barrier to adoption of improved technology and inputs for increased of

Table 2. Estimates of stochastic frontier for the two-farmer groups.

	Male-managed farms		Female-managed farms	
Explanatory variable	**β coefficients**	**Standard errors**	**β coefficients**	**Standard errors**
Capital (K)	0.984	0.520*	0.487	0.187
Labour (L)	-1.885	0.941**	0.168	0.281*
K^2	0.077	0.306**	-0.019	0.013
L^2	0.097	0.11	0.089	0.070
K*L	-0.206	0.216*	0.045	0.148*
Constant	11.966	2.392**	8.103	2.047**
Mean efficiency	0.287		0.213	
Standard deviation	0.115		0.184	
Minimum	0.042		0.014	
Maximum	0.6290		0.765	
Log Likelihood	-98.270		-72.836	

improved technology and inputs for increased production and productivity. From the Table 1, majority (85.6%) of male managed farms had had access to credit facilities compared with only less than half (48.9%) of the female-managed farms who had accessed credit facilities. This buttresses the fact that women are more constraint by cultural factors from controlling resources and having more active economic roles ((Adam et al., 2003); an assertion that is also consistence with the result in Table 1 on the entrepreneurs' ownership status. The result on the ownership status depicts that 71.1% of the male entrepreneurs operate on their own farms whereas only 47.8% of the female farm entrepreneurs owns their farms.

From the Table 2, the mean efficiency score from male-managed farms is about 29% and that of female-managed farms is 21.3%. This implies that food crop farmers in the study area generally operate at low technical efficiency. The result also shows that the constant of the regression, which is an index for the level of technology, is highly significant (see the standard errors, 2.392 and 2.047** respectively; 0.01 alpha level) for both male and female farm managed farms but higher for male-managed farms. Again from the result in the table, the only inputs that show significant for female-managed farms are labour (see the standard errors, 0.281*; 0.05 alpha level) and the interaction between labour and capital (see the standard errors, 0.281*; 0.05 alpha level). With regards to male-managed farms, all inputs except the square of labour showed significance (see the standard error of 0.097 for square of labour; failed test of significant at 0.05 alpha levels). The result portrays that the coefficients for labour and the interaction between labour and capital are negative in the case of male-managed farms. This stands to reason that most of the male-managed farms use excess labour in production of food crops in the study area.

Likelihood ratio test

We computed the likelihood ratio (LR) Statistic to determine whether the data for the two groups (male-managed farms and female-managed farms) could be pooled. The values of interest computed from the stochastic production functions are as follows:

$$\lambda = -2\left\{\ln\left[L(H_0)/L(H_1)\right]\right\} =$$
$$= -2\left\{\ln\left[L(H_0)\right] - \ln\left[L(H_1)\right]\right\}$$

$$\ln\left[L(H_o)\right] = 44.6878$$
$$\ln\left[L(H_1)\right] = 56.8733$$
$$\lambda = 24.371$$

The chi-squared distribution from the table at 99% confidence level is 15.0863. Our estimated value of 20.12883 is outside this range. Based on this result, we failed to accept the hypothesis that the both male-managed farms and female-managed farms used similar technology in production. Therefore, the data for the two farmer groups could not be pooled; and there was the need to use the metafrontier estimation technique to estimate a common technical efficiency scores for the two farm entrepreneurial groups. In Table 3, the mean values for the Metafrontier Technical Efficiencies (MTE) and the Technology Gap Ratios (TGRs) are presented. The result in the table portrays that the female farm entrepreneurs in the food crop production achieved higher mean technical efficiency relative to the metafrontier (that is, 11.8% compared with 7.4% for male entrepreneurs). This stands to reason that male entrepreneurs were less efficient than the female farm

Table 3. Summary statistics for technical efficiencies, technology gap ratios and metafrontier technical efficiencies

Farmer group	Statistic	Group technical efficiency	Technology gap ratio	Metafrontier technical efficiency
Male-managed farms	Mean	0.287	0.465	0.074
	Standard deviation	0.115	0.184	0.067
	Minimum	0.042	0.087	0.004
	Maximum	0.629	1.000	0.345
Female-managed farms	Mean	0.192	0.722	0.118
	Standard deviation	0.184	0.186	0.078
	Minimum	0.014	0.248	0.012
	Maximum	0.765	1.000	0.439

Table 4. Verified determinants of metafrontier technical efficiency estimates

Explanatory variable	Coefficient	t-ratio
Constant	-1.976**	-8.032
Sex (male = 1, female = 0)	-0.398*	-6.082
Age	-0.012*	-1.366
Years of farming experience	0.096*	1.67
Farm size	- 0.003	-.208
Household size	0.110*	2.495
Consultation with extension staff	0.140*	3.602
Off-farm income	0.250	4.694
Education	0.055*	2.011
Access to credit	0.576*	7.454
Use of improved seeds	0.005	0.904
Ownership status	- 0.011	-1.077
Model Summary		
R-Square	0.509	
Adjusted R-Square	0.426	
F	14.83**	
p-value	0.002	

** Significant at 0.01 alpha level; * significant at 0.05 alpha level.

entrepreneurs. Nevertheless, in general, the mean technical efficiencies relative to the metafrontier are very low for both male and female farm entrepreneurs.

The TGRs in the Table 3 also shows that on average, the female farm entrepreneurs produce about 72.8% of the potential output given the available technology to food production in the study area. Male farm entrepreneurs, on the other hand, produce on average below half (that is about 47%) of the potential output given the technology available to food crop production in the study area. This suggests that though male- managed achieved higher mean technical efficiency relative to their group stochastic frontier (that is, 28.7% compared with 19.2%), they operate far from the potential outputs defined by the metafrontier function. The result also shows that the maximum value for the technological gap ratios for both male and female managed farms was 1.00. This implies that the group stochastic frontiers for both male-managed and female-managed farms were tangent to the metafrontier.

In order to examine the factors that significantly influence technical efficiency of food crop farmers, we estimated a logit model using the metafrontier technical efficiency estimates as the dependent variable and the results are presented in Table 4. Results from the analysis showed that adjusted R square was 0.426. This implied that about 43% of the variation in technical efficiency levels of the food crop farmers was explained by the independent variables in the estimated model. The test of significance indicated an F-value of 14.83 with a p-value of 0.002 and this implies that at the 99% confidence level, the explanatory variables in the estimated model together make significant contribution in predicting technical efficiency of food crop farmers who were studied. The result portrays that sex (male = 1, female = 0), age, years of experience, household size, extension contacts, educational level, and access to credit all have unique significant influence on the efficiency of food crop farmers at 0.05 alpha level. Sex and age showed negative relationship with efficiency of farmers whereas years of experience, household size, extension contacts, educational level, and access to credit depicted positive relationship with efficiency of farmers. With regards to sex, the negative coefficient of the dummy confirms that male-managed farms, on the average, are less efficient than the female-managed farms. The study result is contrary to that of the three studies in Kenya which found that the gender of the farm manager was an insignificant determinant of output per hectare (Moock, 1976; Bindlish and Evenson, 1993; Saito et al., 1994). The result also takes exception from the study in Burkina Faso where the female farmer dummy was found to be negative and significant. The result stands to reason that female farmers are equally efficient as male farmers, once individual characteristics and input levels are controlled. Women may only be more constrained by cultural factors from having more active economic roles, and low levels of education and technical development; resulting in lower input intensities on women's plots, which result in lower yields creating doubt on the assumption of Pareto efficiency (Adam et al., 2003). By addressing differences in the characteristics that contribute to lower yields, earnings or technological adoption of female farmers, appropriate agricultural policy interventions can be better designed.

CONCLUSIONS AND RECOMMENDATIONS

There is a limited number of youth involved in food crop production in the study area. The farm entrepreneurs who were studied in the two groups were, on the average, above 40 years with an average of eight to twelve years of experience in food crop farming. Both male and female farm entrepreneurs had low level of education. More male farm entrepreneurs than their female counterparts had access to both credit facilities and extension services as aid to food crop production in the study area. The amount of both capital and labour inputs used in production by the male-managed farms were found to be relatively higher than their female counterparts.

Consequently, male-managed farms achieved greater value of production than the female-managed farms. Both male-managed and female-managed farms were found to operate at low level of technical efficiencies. However, female-managed farms operated closer to the potential output defined by the metafrontier function than farms managed by male entrepreneurs; given the available food production technology in the study area. We also found out that the stochastic frontiers for both male-managed and female-managed farms were tangent to the stochastic metafrontier.

It is observed from estimates of the multiple regression models that technical efficiency scores were significantly influenced by dummy for sex of the farm entrepreneur, age, years of experience, household size, extension contacts, educational level, and access to credit. The estimates also confirmed the frontier results that, male-managed farms, on the average, are less efficient than the female-managed farms. On the bases of the above major conclusions drawn from the study, we make the following recommendations. Closing the gaps in educational attainment and relieving exogenous constraints in access to markets and resources. Government youth in Agriculture programme should be introduced to the study area; and encouraged young males and females to go into food crops production. Financial services providers like MASLOG, financial NGOs and rural banks must also be encouraged to offer loan/credit assistance to farmers. The positive relationship between access to credit and efficiency of the farmers implies that policies that will make micro-credit from government and non-governmental agencies accessible to these farmers will go a long way in addressing their resource use inefficiency problems.

REFERENCES

Adam ZC, Wallace EH, Scot R (2003): “Technical Efficiency of Modern Grains Production on Chinese Farms. A Stochastic Production Frontier Approach”. Paper prepared for: The Human Resource and Labour economics workshop, department of Economics, Iowa State University.

Aigner D, Lovell CAK, Schmidt P (1977). ‘Formulation and Estimation of stochastic frontier production function models’. J. Econ., 6: 21 – 37

Battese GE, Coelli TJ (1995). ‘A model for technical inefficiency effect in stochastic frontier production function for panel data’. Empirical Economics.

Battese GE, Rao DSP (2001). “Productivity Potential and Technical Efficiency Levels of firms in Different Regions Using a Stochastic Frontier Metaproduction Function Model.” CEPA Working Papers No. 6, School of Economics, University of New England, Armidale.

Battese GE, Rao DSP (2002). “Technology Gap, Efficiency, and a Stochastic Metafrontier Function” Int. J. Bus. Econ.. 1(2): 87-93.

Battese GE, Rao DSP, O’Donnell CJ (2004). “A Metafrontier Production Function for the estimation of Technical Efficiencies and Technology Gaps for Firms Operating Under Different Technologies”. J. Prod. Anal., 21: 91-103.

Hayami Y (1969). “Sources of Agriculture Productivity Gap among Selected Countries.” Am. J. Agric. Econ., 51: 564-575.

Hayami Y, Ruttan VW (1970). “Agricultural Productivity Differences among Countries.” Am. J. Agric. Econ., 60: 895-911.

Lau LL, Yotopoulos PA (1989). “The Meta-production Function Approach to Technological Change in World Agriculture. J. Dev. Econ. 31: 241-269.

Meeusen W, van den Broeck J (1977): " Efficiency Estimation from Cobb – Douglas production Functions with Composed Error". Int. Econ. Rev., 18: 435-456.
Moock P (1976). The Efficiency of women as farm managers: Kenya. Am. J. Agric. Econ., 58(5): 831-835.
Wang J, Cramer GL, Wailes EJ (1996). Production Efficiency of Chinese Agriculture: Evidence From Rural Household Survey Data. Agric. Econ., 15: 17-28.
Yotopolous PA, Lau LJ (1973). A test for relative economic efficiency: Some further results. Am. Econ. Rev., 63(1): 214-223.