Soil and Water Conservation Practices and Smallholder Farmer Multi-Activity Technical Efficiency in Northern Ghana

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Abstract

A greater number of the people of northern Ghana are peasants and poor, depending heavily on natural resources for their livelihoods. The poverty is caused partly by inadequate water availability and deteriorating soil conditions. As a result, various organizations promote the use of soil and water conservation practices in the area, but the link between the use of the practices and farmer multi-activity technical efficiency is yet to be shown empirically. The current study thus investigates this link using data from 445 households in the area. The study uses a stochastic input distance function and the results show adoption of conservation practices exerts positive effect on technical efficiency. The results further reveal significant diversification economies in smallholder production with complementarity effects in crop-livestock and livestock-off-farm combinations, and substitutability effects in crop-off-farm combination thereby highlighting the need for a holistic development of both the farm and off-farm sectors.

Keywords: Soil and Water Conservation, Technical Efficiency, Diversification Economies, Instrumental Variables, Northern Ghana

Introduction

The economies of a number of developing countries are predominantly agrarian relying heavily on earnings from agriculture exports with majority of their populations depending on the natural environment for their livelihood and subsistence (Barbier, 2010). But the agricultural sector has long been identified as a cause of environmental degradation and this trend is not expected to change at least in the next half century (Millennium Ecosystem Assessment, 2007). As a result, these countries face the difficult task of simultaneously increasing

agricultural productivity and maintaining the natural resource base supporting agricultural production in their development planning.

Northern Ghana, which comprises Northern, Upper East and Upper West regions, is a major food production area and the poorest in the country despite the fact that it is known to abound in so many resources including gold deposits, especially in the Upper East and West regions. According to the most recent nationwide household survey, the incidence of poverty in the three northern regions of Ghana remains as high as 44.4%, 50.4%, and 70.7% respectively in the Upper East, Northern, and Upper West regions as against the national average of 24.2% (GSS, 2014). The World Bank (2011) also notes that almost half of Ghana's poor is concentrated in the three northern regions. The area experiences over seven months of dry spells even though a large portion of it is drained by the Volta River. The primary activity in the area is farming, and this is constrained by the rather long period of dry spells.

The high levels of poverty in northern Ghana is caused partly by inadequate water availability for crop, livestock and other enterprises as well as deteriorating soil conditions as this puts a major strain on the livelihoods of the people (IRG, 2005). As a result, farmers have devised and continue to devise various ways of managing the scarce natural resources, sometimes with external support, so they can continue to produce. While about 69.0 percent of the total land area of Ghana is said to be prone to erosion estimated at a cost of 2.0 percent of GDP (MoFA, 2007) and about 35.0 percent estimated to be vulnerable to desertification (IRG, 2005), the majority of the areas under this classification are located in the three northern regions (IRG, 2005; MoFA, 2007). Again, while declining soil fertility is seen as a major constraint to agricultural production in Ghana (FAO, 2004), the situation is worsened in the Coastal, Guinea, and Sudan savannah zones by annual burning and removal of crop residues (EPA, 2003). Against this background, governmental and non-governmental organizations in northern Ghana are engaged in promoting soil and water conservation practices among farmers so as to increase agricultural productivity in the area.

Formally, not very many studies have been conducted to assess the efficiency of smallholder farmers in the area. Besides Bhasin's (2002) study which considered technical efficiency of vegetable growers, other studies (such as Abdulai and Huffman, 2000; Al-hassan, 2008; Martey et al., 2015) have concentrated on the efficiency of rice or maize growers, probably because each of these is an important food or commercial crop. However, to improve the lot of the poor peasants in the area calls for an understanding of the efficiency and productivity of resources in the production of not only crops like rice and maize, but also the other equally important staples such as sorghum, millet as well as vegetables and also taking into

account livestock production and off-farm activities in the area. Again, to the best of the author's knowledge, there is no any empirical study in the area that attempts to quantify the effects of the adoption of soil and water conservation practices on smallholder multi-activity technical efficiency.[11]

Against this background, the current study investigates formally how the adoption of the conservation practices (such as stone and soil bunding, composting) impacts farm household multi-activity technical efficiency. The study attempts to do so by explicitly using the smallholder household, in northern Ghana, as the unit of analysis. This approach is justified by the argument made by Chavas et al. (2005) that smallholder agricultural production in developing countries faces various constraints including technological jointness and labour market rigidities, and subsequently deriving a model grounded in the theory of agricultural household production to study production efficiency in The Gambia. Deriving inspiration from these authors, Fletschner (2008) and Solís et al. (2009) also maintain that the appropriate unit of analysis in such situations is the household, rather than the farm, as it allows for capturing the effect of off-farm activities and also a more appropriate examination of production and labour allocation decisions.

It has been observed that the relationship between environmental conservation and farm efficiency has received very little attention in the literature (Solís et al., 2009). Two studies, Wadud and White (2000) and González and Lopez (2007), examine this issue indirectly and come to the conclusion that farms located in highly eroded areas are less efficient. Solís et al. (2009) contribute to the literature by investigating the relationship between farmer participation in two resource management programmes and their level of technical efficiency in Central America. Other studies that have considered a slightly different issue of environmental conditions in farmer efficiency analysis are Rahman and Hasan (2008) and Sherlund et al. (2002). The current study adds to this apparently thin literature in a unique way, by explicitly assessing the effect of conservation adoption on farmer efficiency in the multi-output framework using the parametric stochastic distance function.

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11   A study by Anríquez and Daidone (2010) for the whole of Ghana, not specifically for the three northern regions, to have assessed household efficiency in its production activities only examines the linkages of the farm and nonfarm sectors. Another study by Ofori-Bah and Asafu-Adjaye (2011) explores technical efficiency of cocoa agroforestry systems in Ghana, and since cocoa is not grown in the north, the study focuses on the south. Nkegbe (2012) examines the relationship between adoption of resource conservation practices and farmer technical efficiency in crop production only in northern Ghana; this paper thus extends that study.

Literature on Multi-Output Studies

Anríquez and Daidone (2010) studied the complementarity or otherwise of the farm and nonfarm sectors in rural Ghana using distance function with the data envelopment analysis approach. Using a subsample of 2,289 households from the fourth round of the Ghana Living Standards Survey and classifying outputs and inputs into four categories each, they find that the nonfarm sector offers significant diversification economies for rural households, it does not adversely affect technical efficiency, and that the sector stimulates the demand for agricultural inputs thereby supporting the hypothesis that the nonfarm sector helps ease household cash constraint. The study also finds smaller farms are more efficient than larger farms. However, in sharp contrast to the results of other studies reporting the efficiency levels of smallholder Ghanaian farmers to range from 51.2 to 88.7 (see, for example, Abdulai & Huffman, 2000; Ofori-Bah & Asafu-Adjaye, 2011), this study estimates the average technical efficiency of the sample to be as low as 18.2 percent. Notwithstanding the fact that some of the other studies used the single-output stochastic frontier function and also geographically spanned just the Northern and Upper East regions of Ghana for which reason the results might not be directly comparable, the fact that in the same study the rather not favoured half-normal stochastic distance model gives an average technical efficiency estimate of over 99.0 percent gives cause for concern. As demonstrated by Nkegbe (2011), the results should be expected to be very close when the parametric and nonparametric approaches are applied to the same data set. It is, thus, likely that some sample selectivity effects still remain given the study used a subsample, even though an inverse Mills ratio to check for selection bias in the study was not significant.

To examine technical efficiency among farmers practising cocoa agroforestry systems in Ghana, Ofori-Bah and Asafu-Adjaye (2011) used a sample of 340 smallholder producers from the Ashanti, Eastern and Western regions of Ghana. Applying a stochastic input distance function involving two outputs and four inputs they report an average technical efficiency of 86.0 percent for those growing multiple crops, and an average index of 47.0 percent for mono-crop cocoa farmers using a stochastic frontier model. They find presence of shade trees on the farm, farmer's age and engagement in farming on fulltime basis to be significant determinants of technical efficiency among their sample. They also report evidence of scope economies between cocoa and the other crops produced by the farmers.

In a study to examine female labour contribution to crop production in Bangladesh, Rahman (2010) employed a stochastic input distance function in which he classified inputs into seven categories and outputs into four categories. Applying the model to

a sample of 1,839 households from 16 villages he reports that besides contributing over a fourth of the labour requirement in crop production, female labour also contributes significantly to productivity and efficiency. The results of the study further reveal average technical efficiency among the sample to be 90.0 percent, with the educational levels of both male and female, family size, farmer's age, and share of women's labour having significantly positive effect on technical efficiency.

Solís et al. (2009) also implemented the stochastic input distance function to examine the relationship between two resource management programmes and technical efficiency among participating farm households in El Salvador and Honduras using a sample of 639 producing three categories of outputs with five input groups. The results of the study show that the average technical efficiency among the sample is 78.0 percent, technical efficiency is positively influenced by the adoption of the resource management practices, with gender, education, extension and membership in farmer organization also impacting farmer efficiency positively. They also report decreasing returns to scale among the sample, with significant diversification economies of output.

In characterising the coffee production system in 24 districts (municipios) of the state of Veracruz, Mexico, for the period 1997-2002, Vedenov et al. (2007) used a stochastic input distance function with three outputs and four inputs, and a sample of 120 observations. Their results show average technical efficiency for all the districts to marginally increase from 87.5 percent to 89.0 percent over the period. They also report complementarity effects between staple crop and coffee production as well as staple crop and other cash crops, and substitution effect between coffee and other cash crops. Further, the study identifies positive effect of population density, roads network and altitude on technical efficiency, with a higher ratio of other cash crops having a negative effect on technical efficiency. An earlier study by Coelli and Fleming (2004) among smallholder mixed food and coffee farmers in Papua New Guinea reports findings similar to that of Vedenov et al. (2007). Using stochastic input distance function with three outputs and four inputs they report weak diversification economies between subsistence crop production and the production of either food cash crop or coffee, and non-significant diversification diseconomies between cash food crop and coffee production. The study further reports an average technical efficiency of 78.0 percent among the sampled farmers, with specialization and social obligation respectively influencing the level of technical efficiency negatively and positively.

González and Lopez (2007) in their study of the interrelationship between political violence and farm household technical efficiency using data from 822 households in Columbia with a stochastic input distance function in which households are

assumed to produce three outputs utilizing seven inputs, estimate the technical efficiency of the sample to be about 87.0 percent with political violence adversely affecting the level of technical efficiency both directly, with disproportionate effects on larger farms, and indirectly through its disruptive effect on rural labour markets. Factors like level of education, landlessness and road density are reported to have positive effect on household efficiency in the study. Like Wadud and White (2000), they report that households located in areas prone to soil erosion are less efficient thereby emphasizing the potential positive effects of using soil conservation methods in the study areas; an issue which is directly investigated by the current study in the Ghanaian context.

A study by Irz and Thirtle (2004) to characterise technology in the agriculture sector of Botswana using a district level panel data of 342 observations for the period 1979-1996 from the 18 districts of Botswana with a two-output seven-input stochastic input distance function finds the commercial technology is more productive than the traditional technology, technological regression for the traditional agriculture subsector over the period, and that the technology gap between the two subsectors is fast widening; outcomes also showing in their total factor productivity analysis. They report an average technical efficiency of 85.0 percent for the two subsectors over the period with time trend indicating a positive effect on technical efficiency for the traditional technology while the commercial technology exhibits a declining trend, and districts with large share of livestock output being more efficient. They thus conclude that Botswana's agriculture sector is dualistic in nature.

A number of key lessons from the review of empirical studies on efficiency in the multi-output framework are relevant to the current study. Results from some of the studies emphasise the importance of environmental conditions and in particular improvement in soil fertility to efficiency analysis. This thus lends support to the focus of the current study. Again, it is revealed that the few multi-output efficiency studies on Ghana have not considered the important issue of how use of conservation practices impacts smallholder technical efficiency. As a result, the study attempts to shed some light on this important issue.

Framework and Econometric Model

To examine farm household multi-activity technical efficiency and how it is influenced by the adoption of soil and water conservation practices, the distance function framework (proposed by Shephard (1953, 1970) and further developed by Färe and Primont (1995)) is seen to be more appropriate since the household

production technology is characterised by the use of multiple inputs to produce multiple outputs (see, for example, Kumbhakar & Lovell, 2000; Rahman, 2010). The stochastic distance function is closely linked to the concept of production frontier, and it is normally cast in an input or output orientation or both. In an input orientation it is called a stochastic input distance function and it considers a minimal reduction in all inputs that takes the production unit to the frontier isoquant while the output orientation, referred to as the stochastic output distance function, describes the maximal increase in outputs attainable with input quantities fixed (Coelli et al., 2005; Kumbhakar and Lovell, 2000). The use of output-oriented distance function to measure technical efficiency is appropriate if outputs are endogenous (as in revenue maximization case) and inputs are exogenous or if production units have more control over outputs than inputs, while the use of input-oriented distance function becomes appropriate if inputs are endogenous (as in the case of cost minimization) and outputs exogenous or if production units have more control over inputs than outputs (Coelli et al., 2005; Kumbhakar et al., 2007). Following other studies (such as González and Lopez, 2007; Rahman, 2010; Solís et al., 2009), the input distance function is employed as it relies on a framework of cost minimization which has been observed to be a plausible behavioural hypothesis for farm households in developing countries' context (Solís et al., 2009).

If farm households produce M outputs, $y = (y_1, \ldots, y_M) \in R_+^M$, using a vector of K inputs, $x = (x_1, \ldots, x_K) \in R_+^K$, so that $L(y) = \{x \in R_+^K : x \; can \; produce \; y\}$, then the input distance function can be defined as:

$$D_I(x, y) = max\{\lambda : (x/\lambda) \in L(y)\}. \tag{1}$$

where $L(y)$ is the feasible input set x that can produce output vector y, λ is an efficiency score, and $D_i(x, y)$ is the input distance function which has been shown to be non-decreasing, positively linearly homogenous (of degree 1) and concave in inputs, and non-increasing in outputs (see, for example, Coelli et al., 2005; Färe & Primont, 1995; Hailu & Veeman, 2000).[12] The distance function takes a minimum value of one if the input vector is an element of the feasible input set, i.e. $D_I(x, y) \geq 1 \; if \; x \in L(y)$. For an efficient frontier or if x is located on the inner boundary of the feasible input set, the value of the distance function is unity, i.e. $D_i(x, y)=1$ (Coelli & Perelman, 1999, 2000).

As noted earlier, in the definition of the input distance function, the dual to the input distance function is the cost function, and this duality is usually cast in terms

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[12] These are properties that are said to be inherited from the parent (i.e. cost function) technology (Färe & Primont, 1995; Irz & Thirtle, 2004).

of the minimization problem given as (see, for example, Färe & Primont, 1995; Irz & Thirtle, 2004):

$$C(w, y) = \underset{x}{Min}\{wx: D_I(x, y) \geq 1\}, \quad w > 0 \tag{2}$$

where w is a vector of input prices. Following Irz and Thirtle (2004), if equation (2) is expressed in logarithmic terms, two important derivative properties germane to the interpretation of the empirical results of this study can be obtained. First, taking the log derivative of the input distance function with respect to the kth input, and bearing in mind $x^*(\blacksquare)$ represents vector of cost-minimizing input quantities, yields its cost share as follows:

$$S_k = \varepsilon_{D_I, x_k} = \frac{\partial \ln D_I}{\partial \ln x_k} = \frac{w_k x_k^*(w, y)}{C(w, y)}. \tag{3}$$

The cost share above defines the relative importance of the given input in producing the vector of outputs,. The other property is obtained if the envelop theorem is applied to the log form of equation (2) with respect to the vector of outputs, y. It yields the result below:

$$\varepsilon_{D_I, y_m} = \frac{\partial \ln D_I(x^*(w, y), y)}{\partial \ln y_m} = -\frac{\partial \ln C(w, y)}{\partial \ln y_m} \tag{4}$$

Thus the elasticity of the input distance function with respect to a given (desirable) output yields the negative of the cost elasticity of that output, and its absolute value reflects the relative importance of the given output (Irz & Thirtle, 2004).

Another relevant property of the log form of the distance function is the fact that it yields returns to scale when the inverse of the negative sum of partial derivatives with respect to the outputs vector, y, is taken (see, for example, Anríquez & Daidone, 2010; Coelli & Fleming, 2004), that is:

$$\varepsilon_{rts} = \left[-\sum_{m=1}^{M} \partial \ln D_I(x, y) \Big/ \partial \ln y_m \right]^{-1}. \tag{5}$$

The production technology is said to exhibit constant returns to scale if $\varepsilon = 1$, but it displays increasing (or decreasing) returns to scale if $\varepsilon > 1$ (or $\varepsilon < 1$).

Finally, following Coelli and Fleming (2004) and Vedenov et al. (2007), diversification economies in the production of the various outputs is reflected by taking the second cross partial derivative of the distance function with respect to any two outputs. This is given by:

$$\frac{\partial^2 \ln D_I(x, y)}{\partial \ln y_m \ln y_n} \gtreqless 0, \quad m \neq n, \quad m, n = 1, \dots, M. \tag{6}$$

Relation (6) depicts diversification economies between outputs m and n which can be positive or negative. If the cross partial derivative of the stochastic input distance function with respect to the two outputs is positive then they are said to be complements as it implies that increasing the production of one also increases the marginal product of the other, but they are substitutes if it is negative since increasing the production of one will decrease the marginal product of the other.[13]

Implementation of the distance function requires that a functional form be specified. Following Coelli and Perelman (1999), a general form of the translog input distance function for the N farm households producing M outputs with K inputs can be stated as:

$$\ln D_{Ii} = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln Y_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln Y_{mi} \ln Y_{ni} + \sum_{k=1}^{K} \beta_k \ln X_{ki}$$

$$+ \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln X_{ki} \ln X_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M} \gamma_{km} \ln X_{ki} \ln Y_{mi}, \tag{7}$$

where i signifies the ith farm household (given as i = 1, 2, …, N). Like many other studies (for example, Hailu & Veeman, 2000; Irz & Thirtle, 2004; Morrison-Paul et al., 2000; Morrison-Paul & Nehring, 2005; Rahman, 2010; Vedenov et al., 2007), this study employs the translog functional form because it is both flexible and allows for direct estimation of substitution effects or diversification economies. The homogeneity and symmetry restrictions that need to be imposed on the specified translog distance function are respectively given by:

$$\sum_{k=1}^{K} \beta_k = 1, \quad \sum_{k=1}^{K} \beta_{kl} = 0, \quad \sum_{k=1}^{K} \gamma_{km} = 0, \quad (k = 1, \dots K; \ m = 1, \dots, M) \tag{8a}$$

and

$$\alpha_{mn} = \alpha_{nm} \ \text{ and } \ \beta_{kl} = \beta_{lk}, \quad (m, n = 1, \dots M; \quad k, l = 1, \dots, K) \tag{8b}$$

Following the practice in the literature, imposing the above restrictions involves normalizing the translog function in equation (7) by one of the inputs. If, for example, the first input is selected, then the function becomes:

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13 Detailed discussion on this is found in Carree, M., Lokshin, B. and Belderbos, R. (2011). A note on testing for complementarity and substitutability in the case of multiple practices. *Journal of Productivity Analysis*, 35(3), pp.263-269 and Stern, D. (2011). Elasticities of substitution and complementarity. *Journal of Productivity Analysis*, 36(1), pp.79-89, and the references therein.

$$\ln\left(\frac{D_{Ii}}{X_{1i}}\right) = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln Y_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\alpha_{mn}\ln Y_{mi}\ln Y_{ni} + \sum_{k=1}^{K-1}\beta_k \ln X_{ki}^*$$

$$+\frac{1}{2}\sum_{k=1}^{K-1}\sum_{l=1}^{K-1}\beta_{kl}\ln X_{ki}^*\ln X_{li}^* + \sum_{k=1}^{K-1}\sum_{m=1}^{M}\gamma_{km}\ln X_{ki}^*\ln Y_{mi}, \qquad (9)$$

where $X_k^* = X_k/X_1$. The equation above can be written in a more compact form as follows:

$$ln\, D_{Ii} - ln\, X_{1i} = TL(X^*, Y) \quad or \quad -ln\, X_{1i} = TL(X^*, Y) - ln\, D_{Ii} \qquad (10)$$

Stochastic elements can be introduced into the model above, in the spirit of the Aigner et al. (1977) stochastic frontier formulation, by adding a symmetric error term to the function to capture statistical noise, while noting that the distance from the frontier can be understood to be technical inefficiency, i.e. $lnD_{Ii} = u_i$ (Färe & Primont, 1995) or $-lnD_{Ii} = -u_i$ (Morrison-Paul & Nehring, 2005). This then leads to the estimable *stochastic input distance function* below:

$$-ln\, X_{1i} = TL(X^*, Y) + v_i - u_i \qquad (11)$$

Equation (11) is a typical stochastic function with the composed error term $\varepsilon_i = v_i - u_i$, which can be estimated using maximum likelihood procedure. The inefficiency term, , can be assumed to possess any one of the distributions of half-normal, truncated normal, exponential or gamma (see, Greene (2008), Kumbhakar & Lovell (2000), Stevenson (1980), Aigner et al. (1977) and Meeusen & van den Broeck (1977), Greene (1980a, 1980b, 1990) and Stevenson (1980)). The individual technical efficiency will thus be $TE_i = exp\,(-u_i)$, and the mean defined by:

$$\mu = \delta_0 + \sum_{l=1}^{L}\delta_l Z_{li} \qquad (12)$$

The empirical model that is estimated in this study to depict farm household multi-activity production structure is specified with a translog functional form as follows:

$$-\ln X_{1i} = \alpha_0 + \sum_{m=1}^{3}\alpha_m \ln Y_{mi} + \frac{1}{2}\sum_{m=1}^{3}\sum_{n=1}^{3}\alpha_{mn}\ln Y_{mi}\ln Y_{ni} + \sum_{k=2}^{5}\beta_k \ln X_{ki}^*$$

$$+\frac{1}{2}\sum_{k=2}^{5}\sum_{l=2}^{5}\beta_{kl}\ln X_{ki}^*\ln X_{li}^* + \sum_{k=2}^{5}\sum_{m=1}^{3}\gamma_{km}\ln X_{ki}^*\ln Y_{mi} + v_i - u_i \qquad (13a)$$

and

$$u_i = \delta_0 + \sum_{l=1}^{4}\delta_l Z_{li} + \epsilon_i \qquad (13b)$$

where the dependent variable is the total area of land under cultivation during the 2008/09 agricultural production season X_1, X^* is the set of four other inputs (*viz.*, purchased input, household labour, capital and off-farm labour) normalised by

the X_i variable, Y is a set of three output variables (crops, livestock and off-farm income), v is the symmetrical error term, u is the asymmetric non-negative error term, and α, β and γ are parameters in equation (13a) to be estimated. In equation (13b), δ is a set of parameters to be estimated in the inefficiency part of the model, Z is a set of variables (namely, level of education of household head, proportion of household income from off-farm engagement, access to credit, and a variable reflecting adoption of conservation practices) affecting technical (in) efficiency, and ϵ is the error term in the inefficiency component assumed to have a half normal, exponential or gamma distribution. The variables in model (13) are discussed in the next section.

Selectivity and/or endogeneity involving the conservation adoption variable remain(s) a statistical issue to be resolved in the model. Technology adoption has been observed in the literature (see, for example, Faltermeier & Abdulai, 2009; Khanna, 2001; Langpap, 2004; Solís et al., 2009) not to be random. As a result, the conservation variable used in the inefficiency component of the frontier is likely to be correlated with the error term. To deal with a potential selectivity issue, the analysis was first pursued within the framework developed by Greene (2006; 2010) for incorporating selectivity into frontier models in a consistent manner. It was thus first estimated as a single-output stochastic frontier. But there was no evidence of selection bias. A natural second step thus involved a test for endogeneity of the conservation variable, which produced evidence to that effect. On the basis of the evidence and following, for example, Huang et al. (2002) and Solís et al. (2009), the study employs the instrumental variables approach to mitigate the effects of the endogeneity of the conservation variable on the models. Thus the conservation variable in the inefficiency part of the model is a predicted value of the endogenous conservation variable.

The estimated translog stochastic input distance function should satisfy certain regularity conditions to adequately represent a production technology, i.e. it should adequately exhibit the properties inherited from the parent (cost function) technology. The monotonicity conditions require that (see, for example, Sauer et al., 2006; Vedenov et al., 2007):

$$\frac{\partial D_I(x,y)}{\partial x_k} \geq 0, \ k = 1, \dots, K, \quad and \quad \frac{\partial D_I(x,y)}{\partial y_m} \leq 0, \ m = 1, \dots, M. \qquad (14)$$

The above implies the function should be non-decreasing in inputs and non-increasing in outputs. These, together with the curvature properties, are checked.

Though attractive for estimating production technology in the case of multi-input, multi-output relationships, a criticism levelled against the distance function

(both input and output) is a potential simultaneity bias arising from the use of endogenous inputs (outputs) as regressors in input (output) distance function, leading to the use of instrumental variables to address the potential endogeneity issue by some authors (see, for example, Cuesta & Orea, 1998). However, Coelli and Perelman (1996) argue that, for example, the normalization of all other inputs by one of the inputs in the input distance function introduces input ratios as regressors which can be assumed to be exogenous.[14] Coelli (2000) further demonstrates that under an assumption of cost minimizing behaviour estimating the input distance function using ordinary least squares procedure gives consistent parameter estimates. The argument thus appears to settle the criticism since it can, as well, be generalized for the maximum likelihood estimation procedure.[15] This argument notwithstanding, certain authors (for example, Atkinson et al., 2003; Atkinson, Färe & Primont, 2003; Sickles et al., 2002) have proceeded to employ the instrumental variables approach on the basis of the suspected endogeneity, without demonstrating its nature and source (an observation also made by Coelli (2000)).

Survey Data and Variables

Data for the study were obtained from a survey of 445 households in the three northern regions (namely Northern, Upper East and Upper West) of Ghana. The three northern regions are located mainly in the Guinea and Sudan savannah agro-ecological zones of Ghana dominated by grassland with scattered draught resistant trees. By their location they are very close to the Sahara and experience an annual average rainfall of about 1000 mm (FAO, 2005; IRG, 2005), which is unimodal and tends to be very variable. The rainy season lasts from April or May to October. Due to the vegetation in the area, the major land use systems are annual food and cash crops, and livestock. The major crops grown are maize, sorghum, millet, rice, cowpea and cotton, while the livestock include cattle, sheep and goats, as well as pigs and poultry. The major off-farm activities in the area include charcoal production, trading, hunting, craftsmanship such as masonry and carpentry, teaching and other professions.

The survey was undertaken between November 2009 and March 2010, but covered production activities for 2008/2009 agricultural year. The households were drawn using a multi-stage sampling procedure which involved identifying a district in

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14 This is the analogous argument made by Coelli and Perelman (1996); they actually made the argument for the output distance function which also holds for the input distance function.

15 Several other authors (including, Morrison-Paul & Nehring, 2005; Rahman, 2010) have found defence in this argument.

each of the regions, randomly selecting 5 communities from each district and finally randomly selecting up to 30 households from each community.[16] The list of districts and communities sampled is provided in Appendix A.1.

To measure the effect of soil and water conservation practices on the technical efficiency levels of farm households in their various production activities, a stochastic input distance function is employed. Following previous studies (such as, Coelli and Fleming, 2004; González and Lopez, 2007; Irz and Thirtle, 2004; Solís et al., 2009) the study assumes that households produced three outputs (y_M) using five inputs (x_N) in the 2008/2009 agricultural year. The outputs are: *Crops* (y_1) representing the total value (in GH¢)[17] of all crops grown by the household; *Livestock* (y_2) representing the value (in GH¢) of animals produced by the household and this comprises animals sold, quantity used for own consumption and all other products derived from livestock; and *Off-farm Output* (y_3) which is wage income (in GH¢) earned by all household members from engaging in off-farm work and/or from working on other households' farms.

The inputs in the model include *Land* (x_1) measured as the total area of land under cultivation in hectares, with the major part of this variable being land owned by the household. The *Purchased Input* (x_2) variable includes the value of all inputs bought such as fertilizer, seed, insecticide, disinfectants, and veterinary drugs, and conservation related expenses and labour hired. *Household Labour* (x_3) is the total man-days spent by household members and self-help labour on-farm, including that used for maintaining soil and water conservation structures.[18] Following the view held by Taylor and Adelman (2003, p.46), and echoed by Solís et al. (2009), that family and hired labour may not be perfect substitutes in developing countries, *Household Labour* could have been divided into hired and non-hired or family labour. However, doing so in this study leads to estimation difficulties when a flexible functional form is used; the hired labour category is thus added to the purchased input variable in line with some other view held in the literature (see, for example, Barbier, 2010, p.649). The *Capital* (x_4) variable, which is general operating capital, reflects value of services obtained from capital assets, farm implements, livestock assets and other livestock related expenses such as animals purchased for purposes of maintaining stock. It includes the value of costs, such as depreciation and

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16   Details of the survey, including sample size calculations, are found in Nkegbe (2011).

17   The average exchange rate for the local currency in 2009 stood at GH¢2.2024 and GH¢1.4132 respectively to GB £1 and US $1 as quoted in the 'Bank of Ghana Annual Report 2009' (BoG, 2010, p.51) and can be accessed from www.bog.gov.gh.

18   Labour man-day is the adult equivalent of about 8 hours of work per day, and self-help labour is a reciprocal labour exchange arrangement among farmers in which they take turns to work on one another's farm.

interest, related to the ownership of all farm implements used in the 2008/2009 agricultural year. It also includes cost of tractor hire and animal hire services. The *Off-farm Labour* (x_5) variable captures the total man-days spent by all household adult members working off-farm.

Four variables (z_k) are incorporated in the model to explain the inefficiency/ efficiency levels of farm households in northern Ghana. The variable *Education* (z_1) measures the effect of the level of formal education of the head of household in years to capture the effects of human capital on efficiency. The variable *Proportion Off-farm* (z_2) captures the effects of engagement in off-farm work on farm household technical efficiency. This variable is the percentage of total household income generated from activities other than farm work by household members. The *Credit* (z_3) variable is a dummy which takes a value of 1 if household had access to credit and 0 otherwise. It is noted that in the literature evidence on the exogeneity or endogeneity of credit remains inconclusive, but authors (including, Chavas et al., 2005; Solís et al., 2009) have commonly treated this as exogenous. As a result, credit is treated as being exogenous in this study.

The *Conservation* (z_4) variable captures the effect of adoption of soil and water conservation practices and it is the proportion of cultivated area under conservation practices such as stone bunding, agroforestry, cover crops, soil bunding, grass strip and composting. Appendix A.2 indicates that 88.1% of surveyed households practise at least one conservation technique with 56.6%, 55.7%, 31.5%, 15.1%, 13.3% and 8.8% using stone bund, soil bund, grass strip, agroforestry, composting and cover crops, respectively.

As mentioned earlier, it has been observed that the decision to adopt soil and water conservation practices or technologies is a choice variable (see, for example, Faltermeier & Abdulai, 2009; Solís et al., 2009) and so it is likely to be correlated with the error term in the inefficiency equation. Consequently, the conservation adoption variable is considered endogenous; a position further justified by the results of both a Durbin-Wu-Hausman and a Wu-Hausman tests (shown in the first panel of Appendix A.3). Following the literature (examples are Huang et al., 2002; Rios & Shively, 2005; Solís et al., 2009), this study thus employed the instrumental variables approach to address the endogeneity issue. Length of time (in years) a farmer has been practising soil and water conservation practices (*LT_PRAC*), average index for major soil type (*SOILDEX*) on all plots (scored from 1 to 5, with 1 being most fertile and 5 the least fertile/desirable) and *VISDEG*, average index for visible signs of degradation on all plots also ranked from 1 to 5 depending on whether there is no degradation to the existence of deep gullies or even worse, were used to instrument the decision to adopt soil and water conservation in the 2008/2009

agricultural year. These were used as a set of explanatory variables to estimate a first step reduced form equation (Adkins & Hill, 2008; Cameron & Trivedi, 2010; Hill et al., 2008). The *Conservation* variable used in the inefficiency model is therefore the predicted value of the proportion of cultivated land under conservation practices obtained from the reduced form equation shown in Appendix A.4.[19] The chosen instruments meet the requirements for a good instrument (Cameron & Trivedi, 2005), since as shown in Panels B and C of Appendix A.3, the tests reveal the instruments are uncorrelated with the error term or valid, and are also not weak. Thus the three instruments are relevant (Stock & Yogo, 2005).

The summary statistics of the variables used in the model are in Table 1. The table indicates that the average land size cultivated by the sampled farmers in the 2008/2009 agricultural year is 1.95 hectares, but those using the soil and water conservation practices cultivated relatively larger plots with a mean land size of 1.99, against the mean of 1.68 cultivated by those not using the conservation practices. Whilst the level of capital use by both groups of farmers is about the same, the mean years of formal education for the non-adopters is marginally higher than that for the adopters even though the general level of education amongst the heads of household is very low – 2.27.

Rather interestingly, members of the adopter households use more labour in off-farm work than the non-adopter households, when it would have been thought that because the use of some of the conservation practices is labour intensive users would have less time to engage in off-farm work. It is thus not surprising that they earn more income, in absolute terms, off the farm than their non-adopter counterparts. However, earnings from off-farm activities as a percentage of total household income are greater for non-adopters than the adopters (see Table 1). Access to credit from all sources to the sampled households is limited with just about 12.0 percent of the combined sample accessing credit.

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19   Solís et al. (2009) used a similar approach in studying technical efficiency among farmers participating in three natural resource management programmes in Central America.

Table 1: Descriptive statistics of variables in stochastic input distance function

Variable	Units	Adopters		Non-adopters		Combined Sample	
		Mean	SD	Mean	SD	Mean	SD
Outputs							
Crops (y_1)	GH¢	807.56	619.15	649.44	575.48	788.73	615.63
Livestock (y_2)	GH¢	383.58	473.13	384.28	484.71	383.67	473.97
Off-farm (y_3)	GH¢	526.79	898.14	478.78	747.54	521.07	880.94
Inputs							
Land (x_1)	Ha	1.99	1.07	1.68	1.13	1.95	1.08
Purchased input (x_2)	GH¢	178.00	233.53	156.47	245.68	192.85	235.10
Household labour (x_3)	Man-day	331.72	300.33	339.64	391.67	332.67	312.10
Capital (x_4)	GH¢	255.46	312.18	225.27	244.01	251.87	304.78
Off-farm labour (x_5)	Man-day	115.69	148.92	101.35	125.08	113.99	146.23
Inefficiency variables							
Education of household head (z_1)	Years	2.11	4.20	3.49	4.91	2.27	4.31
Proportion off-farm income (z_2)	Percent	28.99	28.79	32.81	30.36	29.44	28.98
Credit (z_3)	Dummy	0.13	0.34	0.04	0.19	0.12	0.32
Conservation (z_4)	Proportion	0.71	0.32	0.00	0.00	0.62	0.37

In the construction of the variables to estimate the input distance function, a particular problem that had to be resolved was zero values recorded for certain inputs and/or outputs. In particular, there were households without livestock or whose members did not engage in any kind of off-farm work, albeit few, for which zeros were recorded for the livestock, off-farm output and off-farm labour variables. Such a situation will render the use of the translog function impossible. As a result, following the commonly used correction approach in the literature (see, for example, Morrison-Paul et al., 2000) a value of 1 was inserted in each case in order to allow for the log transformation of those three variables, after trying with values ranging from 0.1 to 5. The use of 1 only resulted in an infinitesimal numerical change without impacting the result.

Empirical Results

Preliminary Tests

A number of tests were conducted to determine the appropriate functional form to use, whether output could be aggregated, and also to check if inefficiency effects exist to justify the use of a frontier platform. Table 2 shows the results of the various tests. The first test result in the table suggests the more flexible translogarithmic functional form should be used and not the rather popular but inflexible Cobb-Douglas production function. This is because the test rejects the null hypothesis that all interaction terms collectively are not statistically different from zero (i.e. $\alpha_{mn} = \beta_{kl} = \gamma_{km} = 0$ for all k, l, m and n).

Next, a related test, which restricts only the cross-terms between inputs and outputs to zero (i.e. $\gamma_{km} = 0$ for all k and m) is also implemented to test for separability of inputs and outputs in the stochastic input distance function (Irz & Thirtle, 2004). The test result shows the null hypothesis is rejected at the 0.01 level, implying that outputs should not be aggregated since that will lead to inconsistent estimates. This thus strengthens the argument for the use of the distance function, but not the stochastic frontier.

Table 2: Results of hypotheses tests in stochastic input distance function

Type	Null	Test Statistic	p-Value	Outcome
Functional form test	$H_0 : \alpha_{mn} = \beta_{kl} = \gamma_{km} = 0$ for all k, l, m and n	LR=340.25	0.000	Reject H_0: CD is inappropriate
Input-output separability	$H_0 : \gamma_{km} = 0$ for all k, and m	LR=57.09	0.000	Output should not be aggregated
Frontier tests	-	$\sum e_i^3 = -0.002$	-	Frontier, not OLS, is appropriate
	$H_0 : M3T = 0$	$Z = -9.23$	0.000	Reject : Frontier is appropriate
Inefficiency effects	$H_0 : \delta_l = 0$ for all l	LR = 15.32	0.004	Inefficiency effects dependent on variables included
Returns to scale	$H_0 : \sum_1^3 \alpha_m = -1$	Wald (x^2) = 1497.13		Reject H_0: There exists increasing returns to scale

To test between the use of the stochastic distance function and an average response model, a set of two statistics are calculated. It has been observed that a negative skew of the third moment of the OLS residual is an indication of the existence of inefficiency effects (Waldman, 1982), and this is indeed negative. The other test

is the standard normal skewness statistic *(M3T),* proposed by Coelli (1995), also based on the third moment of the least squares residuals. The value of the test statistic is statistically significant at the 0.01 level justifying the use of the frontier framework. This finding is further confirmed by the statistical significance of the estimates reported in Table 3.

Further, following Irz and Thirtle (2004), a likelihood ratio test is implemented to check if inefficiencies are identically distributed across individual observations in the sample. The test result indicates the null hypothesis is rejected at the 0.01 level implying that the inefficiency effects variables included in the model are relevant in explaining technical efficiency differences.

As observed by Coelli et al. (2005), increased flexibility implies estimating more parameters due to the presence of interaction and squared terms, and this may lead to estimation problems like multicollinearity. An inspection of the matrix of variance inflation factors for the variables in the translog stochastic input distance function revealed some level of multicollinearity effects. However, following the view by Gujarati and Porter (2003) that in the case of translog function multicollinearity can be ignored, no remedial measure was taken.

Multi-Activity Production Structure of Smallholders

Results of the estimated stochastic input distance function are shown in Table 3. Three models corresponding to the assumptions of half normal, exponential and gamma distributions for the one-sided error term u_1 were estimated.[20] All variables were mean-centred (i.e. each was deflated by its mean) prior to estimation so that the coefficients of the first-order terms are interpreted as partial production elasticities.[21]

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20 The model with distributional assumption of truncated normal for the one-sided error term could not achieve convergence.

21 When both input and output variables are mean-centred or scaled, the new mean for each scaled variable is 1, so that from equation (7) the partial derivative of the distance function with respect to

X and Y given as $\partial \ln D_I / \partial \ln X_k = \beta_k + \sum_{l=1}^{M} \beta_{kl} \ln X_l + \sum_{m=1}^{M} \gamma_{km} \ln Y_m$ and $\partial \ln D_I / \partial \ln Y_m = \alpha_m + \sum_{n=1}^{M} \alpha_{mn} \ln Y_n + \sum_{k=1}^{K} \gamma_{km} \ln X_k$

reduce to β_k the coefficient of X, and α_m, the coefficient of Y, respectively, since the log of the scaled means will be zero. The first-order coefficients are therefore interpreted as partial production elasticities.

Table 3: Estimates of stochastic input distance function

Category	Variable	Normal-Half Normal		Normal-Exponential		Normal-Gamma	
		Coefficient	*Standard Error*	*Coefficient*	*Standard Error*	*Coefficient*	*Standard Error*
	Constant	0.1868***	0.0253	0.1445***	0.0115	0.1273***	0.0143
Outputs	$\ln y_1$	-0.0398*	0.0208	-0.0456***	0.0145	-0.0449***	0.0140
	$\ln y_2$	-0.4546***	0.0194	-0.4424***	0.0116	-0.4441***	0.0113
	$\ln y_3$	-0.0104	0.0229	-0.0096	0.0103	-0.0092	0.0097
Inputs	$\ln x_2$	0.0159	0.0173	0.0091	0.0084	0.0072	0.0080
	$\ln x_3$	0.0175	0.0220	0.0108	0.0099	0.0086	0.0096
	$\ln x_4$	0.4548***	0.0228	0.4591***	0.0128	0.4620***	0.0125
	$\ln x_5$	0.0162	0.0269	0.0079	0.0127	0.0051	0.0118
Output-output	$0.5(\ln y_1)^2$	-0.0549	0.0404	-0.0820***	0.0233	-0.0793***	0.0227
	$0.5(\ln y_2)^2$	-0.1135***	0.0104	-0.1057***	0.0076	-0.1033***	0.0080
	$0.5(\ln y_3)^2$	0.0036	0.0076	0.0035	0.0032	0.0043	0.0031
	$\ln y_1 \ln y_2$	0.0786***	0.0151	0.0880***	0.0119	0.0858***	0.0121
	$\ln y_1 \ln y_3$	-0.0317**	0.0154	-0.0223***	0.0078	-0.0228***	0.0076
	$\ln y_2 \ln y_3$	0.0122*	0.0072	0.0098**	0.0044	0.0097**	0.0044
Input-input	$0.5(\ln x_2)^2$	0.0037	0.0114	0.0059	0.0051	0.0054	0.0047
	$0.5(\ln x_3)^2$	0.0237	0.0183	0.0092	0.0102	0.0042	0.0096
	$0.5(\ln x_4)^2$	-0.0976***	0.0256	-0.0862***	0.0162	-0.0877***	0.0161
	$0.5(\ln x_5)^2$	-0.0210	0.0245	-0.0218**	0.0093	-0.0250***	0.0090
	$\ln x_2 \ln x_3$	-0.0048	0.0118	-0.0002	0.0045	-0.0010	0.0041
	$\ln x_2 \ln x_4$	0.0104	0.0148	0.0062	0.0071	0.0069	0.0069
	$\ln x_2 \ln x_5$	0.0038	0.0116	-0.0033	0.0057	-0.0060	0.0055
	$\ln x_3 \ln x_4$	-0.0049	0.0211	0.0042	0.0108	0.0079	0.0104
	$\ln x_3 \ln x_5$	0.0018	0.0152	0.0065	0.0091	0.0041	0.0086
	$\ln x_4 \ln x_5$	0.0523***	0.0163	0.0453***	0.0093	0.0505***	0.0091
Output-input	$\ln y_1 \ln x_2$	0.0049	0.0191	0.0099	0.0089	0.0092	0.0083
	$\ln y_1 \ln x_3$	0.0154	0.0216	0.0202*	0.0111	0.0190*	0.0105
	$\ln y_1 \ln x_4$	-0.0570***	0.0208	-0.0681***	0.0142	-0.0656***	0.0141
	$\ln y_1 \ln x_5$	0.0428**	0.0218	0.0276**	0.0111	0.0281***	0.0108
	$\ln y_2 \ln x_2$	-0.0112	0.0110	-0.0098*	0.0056	-0.0103*	0.0054
	$\ln y_2 \ln x_3$	-0.0191	0.0159	-0.0173**	0.0084	-0.0184**	0.0082
	$\ln y_2 \ln x_4$	0.0991***	0.0172	0.0900***	0.0114	0.0890***	0.0115
	$\ln y_2 \ln x_5$	-0.0242**	0.0113	-0.0229***	0.0062	-0.0245***	0.0061
	$\ln y_3 \ln x_2$	0.0012	0.0080	0.0043	0.0041	0.0059	0.0039
	$\ln y_3 \ln x_3$	0.0005	0.0111	-0.0042	0.0065	-0.0028	0.0061
	$\ln y_3 \ln x_4$	-0.0349***	0.0114	-0.0262***	0.0065	-0.0285***	0.0064
	$\ln y_3 \ln x_5$	0.0036	0.0109	0.0033	0.0041	0.0034	0.0039
Inefficiency Effects							
	Constant	-2.8011***	0.3148	-	-	-	-
	Education	0.0374**	0.0159	0.0304**	0.0136	0.0330*	0.0179
	Proportion off-farm	0.0073**	0.0028	0.0042**	0.0019	0.0045**	0.0023
	Credit	0.2667	0.1866	0.1825	0.1499	0.2112	0.1904
	Conservation	-0.8220**	0.4068	-0.4108*	0.2878	-0.4885*	0.3527
	θ			7.3724***		5.8724***	
	P					0.7056***	
	σ_v			0.0385***		0.0445***	
	Log-likelihood	341.381		347.723		348.594	
	AIC	− 1.345		− 1.374		− 1.373	
	BIC	− 0.959		− 0.987		− 0.977	

Note: ***, ** and *, significance at 1 percent, 5 percent and 10 percent levels respectively.

Also, given an input distance function is used, imposition of the homogeneity condition is achieved by normalizing all input variables with the *Land* (x_1) variable.

Since three models corresponding to the distribution of the inefficiency term were estimated, a discussion of the structure of household production is preceded by the selection of an appropriate model. Given the exponential model does not nest the basic half normal model, choice between the two could be carried out using the information criteria, i.e. Akaike (AIC) and Bayesian (BIC). From the results, both the AIC and the BIC favour the exponential model since the values for both criteria for the exponential model are less than that of the half normal model.

The choice between exponential and gamma distributions for the one-sided error term depends on whether the parameter *P* in the gamma model equals 1. The results in Table 3 show the estimate for this parameter is 0.7056 and statistically significant at the 0.01 level, meaning the gamma distribution for the asymmetric error term fits the underlying technology better than the assumption of exponential distribution. The gamma model is thus preferred to both the half normal and the exponential models, and so subsequent discussion is based on the results of this model.

Following Vedenov et al. (2007), the theoretical consistency properties of the selected model are checked. As discussed earlier, the monotonicity conditions require that the input distance function be non-decreasing in inputs and non-increasing in outputs. The curvature properties also require that the function be at least quasi-concave in the inputs which shows up in the bordered determinant with respect to the inputs being negative semi-definite (Chiang and Wainwright, 2005), while the bordered determinant with respect to the outputs need to be positive semi-definite to ensure the function is at least quasi-convex in the outputs. All these requirements for the regularity conditions are satisfied at the means of the sample (see results in Appendix A.5)[22].

The results for the stochastic input distance function with the inefficiency effects component reported in Table 3, show over half of the total estimates in the preferred gamma model are statistically significant at least at the 0.1 level. As stated already, the coefficients of the first-order terms are partial production elasticities. As expected, the elasticities of the three outputs in the input distance function are all negative with that of crops (y_1) and livestock (y_2) being statistically significant at the 0.01 level. This implies that increasing the production of any

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22   The results were obtained using the procedure outlined in Appendix 2 of Hajargasht, G., Coelli, T. and Rao, D.S.P. (2006). *A Dual Measure of Economies of Scope*. CEPA Working Paper WP03/2006, Centre for Efficiency and Productivity Analysis, University of Queensland, Australia.

one of the outputs results in increased cost. Following Irz and Thirtle (2004) and as shown in equation (4), these elasticities are also interpreted as the negative of the cost elasticities of those outputs. Thus from the results the cost elasticity of crops, livestock and off-farm outputs are respectively 0.04, 0.44 and 0.01, implying that a 1.0% increase in each of crop and off-farm outputs increases cost by 0.04% and 0.01% respectively while such an increase in livestock output results in 0.44% increase in cost. These findings show that in the economy of northern Ghana, livestock remain very important followed by crops and then off-farm production activities. This formally provides empirical evidence to agronomic and meteorological evidence from research stations in the area pointing to the fact that it is well suited for animal production, and the popular view that given the rather lengthy dry season in the north, productivity could be enhanced if livestock production, medium or large scale, is vigorously promoted. Irz and Thirtle (2004) also reported dominance of livestock production in their study of Botswana agriculture.

The input elasticities obtained from the stochastic input distance function are all positive as expected, albeit just one is statistically significant, a situation that is likely caused by the presence of multicollinearity in the model. These elasticities, as shown in equation (3), represent cost shares and so reflect the relative importance of the inputs in producing the various outputs (Irz & Thirtle, 2004). The results show that the elasticity for each of purchased input (x_2), household labour (x_3) and off-farm labour (x_5) is about 0.01, with that of capital (x_4) and land (x_1)[23] being 0.46 and 0.51 respectively, implying that land and capital stock are the most important inputs in household production activities in northern Ghana. The results show that land alone accounts for more than half of the production cost in the study area even though respondents maintained they did not pay for the use of land. It is likely the case that transactions relating to land in the area are done in kind which are not reported by respondents. The importance of the land variable in the production process agrees with the finding of Rahman (2010) in his study of efficiency in Bangladeshi agriculture. Given the importance of livestock production in the northern Ghanaian economy, it is not surprising that the capital stock variable, which includes animal purchases for the purposes of stock maintenance, is the next largest cost element in household production activities in the area.

To further explain the statistical non-significance of the input variables, the stochastic input distance function estimates using the Cobb-Douglas functional form, which has been rejected in the functional form test (see Table 2), are shown in Appendix A.4. The results in the appendix show that at least one more input

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23   The estimate for land is obtained using the homogeneity condition in equation (8a).

variable is statistically significant when the Cobb-Douglas functional form is used. Specifically, the less favoured normal-half normal model results indicate three input variables are significant with the normal-exponential and the preferred gamma models showing two significant input variables. The results of the Cobb-Douglas functional form thus provide further evidence to the assertion that the statistical non-significance of a number of the input variables is attributable to the presence of multicollinearity in the translog functional form. However, a shortcoming of the Cobb-Douglas functional form, revealed by the results in Appendix A.4, is that the monotonicity condition is violated as the effect of the purchased input variable (x_2) is negative across all the models; when the fulfilment of the condition requires this to be non-negative.

Using equation (5), the returns to scale estimate calculated from the results of the chosen gamma model in Table 3 is about 2.02, indicating the existence of increasing returns to scale. This finding is further strengthened by the formal test of returns to scale reported in Table 2. The Wald test value is 1497.13 and it is statistically significant at the 0.01 level thereby rejecting the null hypothesis of constant returns to scale. Increasing returns to scale implies increasing all inputs by a given proportion will lead to a more than proportionate increase in outputs, a result that suggests productivity among smallholder households in northern Ghana could be improved by increasing input use in all their production activities. The result is in keeping with that of two other efficiency studies (Anríquez & Daidone, 2010; Ofori-Bah & Asafu-Adjaye, 2011) in Ghana and in Bangladesh by Rahman (2010), all of which reported increasing returns to scale among their sample. However, it contrasts the findings of other studies including Chavas et al. (2005) in The Gambia, González and Lopez (2007) in Columbia and Solís et al. (2009) in Central America which observed decreasing returns to scale among their sample.

As shown in equation (6), complementarity effects or diversification economies between outputs are given by the second order cross partial derivatives of the input distance function with respect to any two outputs (Coelli & Fleming, 2004; Vedenov et al., 2007). These measures which are part of the results in Table 3, and are shown to be statistically significant at least at the 0.05 level, are reproduced in Table 4.

Table 4: Output complementarity measures

	Livestock (y_2)	*Off-farm (y_3)*
Crop (y_1)	0.086	-0.023
Off-farm (y_3)	0.010	

The measures in the table show that crop-livestock combination is positive, crop-off-farm combination is negative and livestock-off-farm combination is positive. These imply that while the pair of crop and livestock production activities, and the pair of livestock and off-farm production activities are complementary, that of crop and off-farm production activities are substitutes. The results suggest crop producing households will achieve productivity gains by increasing livestock production, but their productivity will fall if they pursue off-farm livelihood activities. However, households producing livestock could diversify into or increase their engagement in off-farm livelihood activities since that will lead to productivity gains. The largest diversification economies exist between crop and livestock outputs, a result consistent with that of Anríquez and Daidone (2010) who attributed this to the fact that these represented the major activities for diversified rural households in Ghana. At the same time, however, while they found complementarity effects between off-farm activities and all other production activities, including crop production, this study finds substitutability effects between crop production and engagement in off-farm production activities.

Smallholder Multi-Activity Technical Efficiency and Resource Conservation

Levels of multi-activity technical efficiency among the sample can be said to be high. While results of the exponential model show an average technical efficiency estimate of 88.0%, the average for the preferred gamma model is 90.0% (Table 5). The average for the gamma model implies that the average household in the sample can reduce input cost by about 10.0% of the current levels and still produce same levels of outputs. This result is comparable to results obtained in other studies both in Ghana and in other developing countries. Ofori-Bah and Asafu-Adjaye (2011) reported an average technical efficiency of 86.0% for their sample of multi-crop cocoa farmers in southern Ghana, Rahman (2010) reported 90.0% for a sample of Bangladeshi farmers, González and Lopez (2007) obtained an average score of 87.0% for a sample of farmers in Colombia, Vedenov et al. (2007) observed an increase in the average technical efficiency from 87.5% to 89.0% among their sample of coffee producing districts in Mexico for the period 1997-2002, Coelli and Fleming (2004) and Solís et al. (2009) reported an average technical efficiency of 78.0% among their respective samples of farmers in Papua New Guinea and Central America, and Nyongesa et al. (2017) reported an average technical efficiency of 78% among their sample of soya bean farmers in Kenya.

Table 5: Smallholder multi-activity technical efficiency averages and distribution

	Exponential	*Gamma*
Efficiency levels		
≤ 0.50	1.8	1.3
0.51 – 0.60	0.9	1.4
0.61 – 0.70	4.7	4.0
0.71 – 0.80	11.3	9.0
0.81 – 0.90	24.2	19.8
0.91 – 1.00	57.1	64.5
Efficiency scores		
Mean	0.88	0.90
Standard deviation	0.11	0.11
Minimum	0.40	0.41
Maximum	0.99	0.99

Factors explaining the observed levels of technical efficiency are education, share of income derived from off-farm economic activities and adoption of conservation practices (Table 3). The results appear uniform across all the three models, but only the results of the chosen gamma model are discussed. The level of education of the household head has a positive and significant effect on technical inefficiency, which implies that higher levels of education are associated with lower levels of technical efficiency. Generally, education is expected to confer 'allocative ability' on the primary decision maker of the household to easily perceive change, collect and analyse information, and to act decisively to reallocate resources to ensure optimal results (Abdulai & Huffman, 2000; Huffman, 1974). In line with this theory, thus, various studies (such as, González & Lopez, 2007; Rahman, 2010; Solís et al., 2009) have observed positive effect of education on technical efficiency. However, the finding here contradicts the positive role of human capital in production, probably as a result of education offering alternative earning opportunities in off-farm activities which serves to increase the opportunity cost of labour and so compete with labour use for agricultural production (Scherr & Hazell, 1994).

Proportion of household income derived from engagement in off-farm economic activities is also associated with higher levels of technical inefficiency, implying that an increase in this variable significantly decreases the level of household technical efficiency. This suggests households earning greater proportion of their income from off-farm activities have the tendency to reallocate labour away from farm production (Abdulai & Huffman, 2000), the major economic activity in the study area. This finding lends further support to the observation that the negative

effect of education on technical efficiency might be due to the fact that it offers alternative and likely more remunerative earning opportunities off the farm.

The results in Table 3 reveal adoption of soil and water conservation practices is associated with lower levels of technical inefficiency, albeit its effect is marginally significant at the 0.1 level in the preferred gamma model. The result thus suggests that, as expected, adoption of soil and water conservation practices impacts smallholder technical efficiency in their multiple production activities positively. However, a mean test of differences in the levels of technical efficiency between adopter and non-adopter smallholders is statistically not significant (see Table 6). This could be explained by the fact that the analysis here includes livestock and off-farm production activities, besides crop production activities, on which the effect of adoption of conservation practices might not be observed in the short term thereby making it difficult to observe any differences in the levels of technical efficiency between the adopter and non-adopter smallholders.

Table 6: Mean technical efficiency comparison for adopter and non-adopter smallholders[24]

	Adopters	*Non-adopters*	*Mean difference* [a]	*t-Statistic*
Normal-Exponential	0.88	0.88	0.000	0.01
Normal-Gamma	0.90	0.90	-0.002	-0.13
F-test statistic	1.316			
Observations	392	53		

Note: ***, ** and *, significance at 1 percent, 5 percent and 10 percent levels respectively; [a] mean for non-adopters minus mean for adopters.

The observation that adoption of soil conservation practices enhances technical efficiency is in consonance with the finding reported by Solís et al. (2009) that the adoption of resource management practices among their sample of farming households from El Salvador and Honduras participating in natural resource management programmes had positive effect on their level of technical efficiency. It is also in keeping with the observation in Colombia by González and Lopez (2007) that households located in erosion prone areas were less technically efficient, a finding they interpreted as partly pointing to the potential positive effect of adopting soil and water conservation practices.

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24 Averages for the normal-half normal model are not shown because the estimates show all farm households are highly technically efficient ranging from 0.98 to 0.99, thus virtually depicting no variability.

Conclusion

Recent government policy in Ghana has been to minimise the serious impact of agriculture on the environment while improving livelihoods through improved agricultural production, especially for the inhabitants of the three northern regions. This is attested to by the fact that one of the strategies of the Food and Agriculture Sector Development Policy (FASDEP II) is looking at how to sustainably manage natural resources (MoFA, 2007), and a development initiative launched for the Savannah regions of Ghana aims at stemming the tide of environmental degradation in the regions and reducing the incidence of poverty to 20.0% between 2010 and 2030 (GoG, 2010; World Bank, 2011). The results of the current study lead to a number of implications for designing resource management and poverty reduction policies.

Estimates of technical efficiency indicate, given the current technology, there is room for improving productivity through raising technical efficiency. This can be achieved through promoting the adoption of soil and water conservation practices since technical efficiency and adoption are shown to be positively related.

Land is shown to be the most important input in household multiple economic engagements in northern Ghana, implying policies that will ensure well defined rights to land and enforcement of those rights will be germane to the aim of reducing poverty in the area.

The proportion of household income derived from engagement in off-farm economic activities is shown to negatively affect technical efficiency. There should be caution in the interpretation of this result as it might be suggestive of the fact off-farm economic activities are more remunerative in the area than farm production activities so that people with off-farm economic opportunities prefer to focus all their attention on that. This thus makes a case for increasing incentives for farm production activities in order to make them competitive. A way of achieving this is through holistic development of rural infrastructure.

The observation of significant complementarity effects in crop-livestock combination and also in livestock-off-farm combination, but substitutability effects in crop-off-farm combination further emphasises the need to adopt an integrated approach in rural development policy in northern Ghana with livelihood diversification as a major strategy. A balanced development programme for both the farm and non-farm sectors in northern Ghana is required to positively and significantly impact the various livelihood strategies of the people. This thus gives

support to the development initiative being rolled out in the northern Savannah which, among other things, aims at creating a diversified economy in the area.

Two observations from the results point to the need to develop the livestock sector in northern Ghana. First, the livestock sector is shown to play a lead role in the economy of the area. Second, diversification economies between crop and livestock outputs are shown to be the largest. Since crop production is principally for subsistence purposes, developing the livestock, mostly ruminants and poultry, industry in the area will provide avenue for a stable income source for the people throughout the year. This way, the abundant labour available during the rather long dry season will be productively utilised. Also, developing the livestock sector which comes with improved housing will ensure the availability of animal droppings for compost preparation.

The results also reveal increasing returns to scale in smallholder multiple productive activities. This indicates productivity among smallholders in northern Ghana can be raised by encouraging these smallholders to step up their operations.

Finally, a modest empirical contribution of the study is the revelation that animal production plays a pre-eminent role in the economy of northern Ghana. This has been the perception held by many principally because of favourable climatic conditions in the area for animal rearing. But to the best of my knowledge, this perception has not been formally demonstrated hitherto. This finding thus provides an important input to guide both present and future development initiatives in northern Ghana.

It is important to point out a limitation of the current study. Given cross-sectional dataset comprises data on a number of households for just a given time, it is unable to capture dynamic elements. In particular, an important dynamics issue is that long-term returns to certain conservation practices are much higher than in the short-term, which is difficult to capture using cross-sectional dataset. While this limitation should be taken into account in viewing the results of the current study, it at the same time points to the direction of further research in this area. Specifically, it is recommended that further research should concentrate on building and using panel dataset as a way of resolving this difficulty.

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Appendices

A.1: Number of households sampled in various districts and communities

Region	District	Community	No. of households
Northern	Bunkpurugu-Yunyoo	Bimbago	30
		Binde	30
		Kambago	30
		Pagnatik	30
		Yunyoo	30
Upper West	Lawra	Kogle	30
		Kusele	30
		Tolibri	30
		Tongoh	30
		Walateng	30
Upper East	Bongo	Apunwongo	30
		Dua	30
		Kasingo	31
		Saporo	30
		Tankoo	30
Total			451[*]

[*]**Data from 6 households were not usable and so were dropped thereby leaving a total of 445.**

A.2: Proportion of households adopting various conservation practices

Category	Adopter	
	Frequency	Percent
Any one practice	392	88.1
Stone bund	252	56.6
Soil bund	248	55.7
Grass strip	140	31.5
Agroforestry	67	15.1
Composting	59	13.3
Cover crop	39	8.8

A.3: Results of endogeneity test for conservation variable

Test Statistic	Score	Probability	Test Name
Panel A			
H_o: Conservation variable is exogenous			
Chi-square based test	5.137	0.0234	Durbin-Wu-Hausman
F based test	5.103	0.0244	Wu-Hausman
Decision: Reject exogeneity of conservation variable, implies the variable is endogenous			
Panel B			
H_o: Instruments are valid			
Chi-square based test	3.109	0.211	Hansen-Sargan
Decision: Do not reject H_o, implies instruments are valid or uncorrelated with the error term			
Panel C			
H_o: Chosen instruments are weak			
F based test	59.586	0.000	Weak instrument
F based test[a]	51.981	-	Minimum eigenvalue
Decision: Reject H_o, implies instruments are not weak			

Notes: [a] A distortion tolerance level of 5% yielded a critical value of 13.91 (Stock & Yogo, 2005).

A.4: Robust estimates for the reduced form equation (IV estimation)

Variable[a]	Coefficient	Standard Error	t-Statistic
Constant	0.2477[***]	0.0649	3.815
LT_PRAC	0.0132[***]	0.0021	6.203
SOILDEX	-0.0496[**]	0.0242	-2.053
VISDEG	0.2115[***]	0.0182	11.623
Rho[b]	0.51[***]		
Observations	445		

Notes: [***] are statistical significance at the 1%; [a] dependent variable is proportion of total cultivated land under conservation measures; [b] Pearson's correlation coefficient between the *predicted value of conservation* and the *conservation* variable itself.

A.5: Results of regularity conditions check in stochastic input distance function[a]

Input variables		
Regularity conditions check	Monotonicity for inputs $(\partial y/\partial x_i \geq 0)$	Quasi-concavity of input bundle (negative semi-definiteness)
Purchased inputs	0.0072	$\lvert B_1 \rvert = -5.18 \times 10^{-5} < 0$
Household labour	0.0086	$\lvert B_2 \rvert = 2.37 \times 10^{-7} > 0$
Capital	0.4620	$\lvert B_3 \rvert = -1.82 \times 10^{-6} < 0$
Off-farm labour	0.0051	$\lvert B_4 \rvert = 1.00 \times 10^{(-8)} > 0$
Outcome	Satisfied	Satisfied
Output variables		
Regularity conditions check	Monotonicity for outputs $(\partial y/\partial x_i \leq 0)$	Quasi-convexity of output bundle (positive semi-definiteness)
Crop output	- 0.0449	$\lvert B_1 \rvert = 0.0020 > 0$
Livestock inputs	- 0.4441	$\lvert B_2 \rvert = 0.0095 > 0$
Off-farm	- 0.0092	$\lvert B_3 \rvert = 0.0002 > 0$
Outcome	Satisfied	Satisfied

Notes: [a] Analytical derivatives obtained using the procedure outlined in Appendix 2 of Hajargasht et al. (2006, p.28)

A.6: Stochastic input distance function results – Cobb-Douglas functional form

Category	Variable	Normal-Half Normal		Normal-Exponential		Normal-Gamma	
		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
	Constant	0.1912***	0.0144	0.1323***	0.0072	0.1009***	0.0066
Outputs	$\ln y_1$	-0.0725***	0.0144	-0.0197**	0.0083	-0.0191***	0.0070
	$\ln y_2$	-0.3484***	0.0107	-0.4402***	0.0084	-0.4443***	0.0071
	$\ln y_3$	-0.0186***	0.0045	-0.0059	0.0053	-0.0042	0.0041
Inputs	$\ln x_2$	-0.0031	0.0057	-0.0035	0.0035	-0.0059*	0.0031
	$\ln x_3$	0.0409***	0.0063	0.0067*	0.0040	0.0037	0.0038
	$\ln x_4$	0.4057***	0.0143	0.4748***	0.0089	0.4801***	0.0071
	$\ln x_5$	0.0312***	0.0058	0.0104	0.0079	0.0072	0.0059
Inefficiency Effects							
	Constant	-1.7612***	0.1751	–	–	–	–
	Education	0.0220	0.0180	0.0320***	0.0115	0.0358*	0.0194
	Proportion off-farm	0.0014	0.0023	0.0005	0.0015	0.0003	0.0025
	Credit	0.7931***	0.2239	0.2929***	0.1347	0.3310	0.2281
	Conservation	-1.5213***	0.2444	-0.6269***	0.1958	-0.7536**	0.3207
	θ			4.3448***		2.4453***	
	P					0.5055***	
	σ_v			0.0273***		0.0348***	
	Log-likelihood	171.255		266.073		281.249	
	AIC	− 0.707		− 1.133		− 1.197	
	BIC	− 0.578		− 1.004		− 1.058	

*Notes: ***, ** and *, significance at 1 percent, 5 percent and 10 percent levels respectively.*