Credit access and technical efficiency of smallholder farmers in Northern Ghana

Double bootstrap DEA approach

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Abstract

Purpose – The purpose of this paper is to examine the relationship between credit access and technical efficiency of smallholder crop farmers in northern Ghana.

Design/methodology/approach – The study uses a random sample of 445 farming households in the three northern regions of Ghana. The two-stage double bootstrap DEA approach was used to consistently estimate technical efficiency scores as well as the determinants.

Findings – The results revealed that, given the current technology, there is substantial yield or productivity gap among the sample of producers in northern Ghana used for the study. This is because producers can reduce input use by over 50.0 percent while still achieving the same output levels. It is further revealed that proportion of household income from off-farm activities, distance of farm from homestead, location and credit access are significant determinants of technical efficiency.

Originality/value – The current study differs from previous studies in two basic ways. First, it takes into account the fact that smallholder farmers practise mixed or inter-cropping by using value of output so that various crops on a given plot of the farmer can be aggregated; and second, a nonparametric approach is adopted so that the inherent inconsistencies in using the two-step model within a parametric framework can be avoided.

Keywords Technical efficiency, Ghana, DEA, Credit, Truncated model

Paper type Research paper

1. Introduction

Like many other developing countries, Ghana’s economy is agrarian and the agriculture sector is predominantly a rural phenomenon with 71.3 percent of the rural working population engaged in it as against only 18.2 of the urban working population (GSS, 2014a). Poverty in developing countries is also a rural phenomenon. For example, while the national incidence of poverty stood at 24.2 percent for Ghana in 2012/2013, incidence for urban areas stood at 10.6 percent with that of rural areas being 37.9, or rural areas accounted for 78 percent of the national poverty incidence (GSS, 2014b). In addition, the incidence of poverty among food crop farmers is relatively very high. Available evidence indicates that rural agricultural workers are the poorest in the country (GSS, 2014a; Quartey et al., 2012). Further, the incidence of poverty in the three northern regions of Ghana remains as high as 44.4, 50.4 and 70.7 percent in the Upper East, Northern and Upper West regions, respectively (GSS, 2014b), and the World Bank (2011, p. 10) also notes that almost half of Ghana’s poor is concentrated in the three northern regions alone. An important way, thus, of alleviating poverty and propelling inclusive and sustainable economic growth and development, in Ghana (as envisaged in a number of Ghana’s development strategy documents)[1] and specifically in the three northern regions – that is, Northern, Upper East and Upper West – is through improving agricultural productivity.

Agricultural productivity can be improved in several ways, including adoption of new and improved technology, increasing the use of inputs such as bringing more land under cultivation and improving farmer technical efficiency. Availability of improved technology emanates

JEL Classification — O12, Q12, Q14
directly from research and development; use of additional inputs hinges very much on availability of funds or credit; and technical efficiency, depicting the ability to produce maximum output from a given set of inputs, is affected by farmers’ socio-economic circumstances such as managerial capability, access to credit/finance, access to information, among others. Despite the existence of structural rigidities in Ghana’s economy hampering improved productivity, improving input use and farmer technical efficiency remain feasible options to increasing agricultural productivity. Increasing agricultural productivity at the national level will directly result in reducing the national agricultural imports bill, which progressively rose from an annual average of $114m between 1979 and 1981 to $1,879.4m by 2013 (FAO, 2007, 2015a), thereby freeing some resources to be used in funding development activities. It will also enhance rural incomes and ultimately reduce poverty, deprivation and hunger.

Credit availability improves farmers’ liquidity situation thereby improving access to new technology, and inputs in particular, for increased productivity. Unfortunately, smallholder farmers in developing countries face critical credit shortages in their farming activities (Hussain and Thapa, 2015) due to several reasons, the major one being the lack of or inadequate collateral in the form of property and stable employment (FAO, 2015b)[2]. Indeed, Dittoh (2006) notes that credit access is a critical and topmost priority for smallholder farmers in northern Ghana. This, he notes, emanates from the unacceptably high poverty levels of the people; high cost of agricultural inputs such as services for land preparation, seeds and fertilizers; and the fact that yields cannot be improved without credit services.

Recognizing that smallholder farmers face credit constraints, the government has made various attempts at increasing access to agricultural finance. A number of such attempts have been outlined in FAO (2015b). First, government established the Agricultural Development Bank in 1965, with lower lending rates to farmers. However, low and unimpressive repayment rates have resulted in a lower lending share to agriculture. Financial institutions’ lending share to agriculture appears not to be impacted by a steady increase in the number of leasing companies in Ghana since the early 2000s, with just below 1.0 percent of the total leasing value devoted to agriculture. Second, the government established a Collateral Registry in 2011, subsidized by the Central Bank and charging low fees to its users. The rationale is to provide information about assets registered by borrowers as collateral for the purpose of borrowing so that lending institutions can recover defaulters’ assets for sale without having to go to court. Third, the government launched the two complementary programs of the Agriculture Mechanization Services Enterprises Centers (AMSECs) in 2007 and the Block Farm in 2009 with some credit components. The AMSECs program is a credit facility aimed at assisting selected private sector companies to purchase tractors at subsidized price and interest rate which will then be rented to smallholder farmers at affordable prices. The Block Farm, on the other hand, was launched as a component of the Youth in Agriculture Program to provide large blocks of land for production of selected crops. Under the program, block farms are provided with a bundle of subsidized mechanization services and inputs as well as extension services which are repaid in kind after harvest.

Despite these measures, credit to farmers remains very low. As such, a pertinent question to ask is whether access to credit will increase output and thus technical efficiency of smallholder farmers. To the best of our knowledge, two studies (Martey et al., 2015; Abdallah, 2016) have attempted answering this question, but they both focused on maize producers and also employed the stochastic frontier model. While the two are important studies, it is difficult to appreciate fully the results as smallholder farmers in Ghana, and northern Ghana in particular, are typically mixed croppers (MoFA, 2016) growing various combinations of crops on given plots. Further, to deal with perceived endogeneity and/or selection bias in examining the effects of credit, Abdallah (2016) used a two-step approach within a parametric framework. However, this approach is criticized as the estimation of first stage credit model to derive credit scores, assumed to correct for endogeneity in credit access, is not accounted for in the
likelihood function for the stochastic frontier model (see e.g. Greene, 2010; Kumbhakar et al., 2009). As a result of the identified weaknesses, the current study differs from the previous studies in two basic ways. First, it takes into account the fact that smallholder farmers practise mixed or inter-cropping by using value of output, following Coelli and Fleming (2004) and Chavas et al. (2005), so that various crops on a given plot of the farmer can be aggregated; and second, a nonparametric approach is adopted so that the inherent inconsistencies in using the two-step model within a parametric framework can be avoided.

The rest of the paper is organized as follows. The next section reviews relevant literature on the subject under study. This is followed by a brief description of the methodology employed in Section 3. The penultimate section presents the empirical results and the final section presents the concluding remarks.

2. Review of relevant literature

2.1 Nature of agricultural credit in Ghana
Agricultural credit is usually in cash or in kind. Most of the in-kind credits come as a result of project support with farm inputs, such as improved maize seeds, agrochemicals and technical support, for production which are repaid after harvest either in cash or in kind using farm produce (see e.g. Iddrisu et al., 2018). The cash credit system for farmers’ credit is usually operated by bank or non-bank financial institutions under the supervision of the Bank of Ghana. The formal banking financial sector comprises commercial banks which offer opportunity to farmers, but usually commercial producers, with the required collateral for the credit. The semi-formal non-bank credit system, such as microfinance institution, operates in a form of savings from the farmers’ income through credit unions which give farmers opportunity to receive credit from their contributions. The informal financial sector consists of moneylenders, traders, family members, friends, neighbors and the traditional susu system, where farmers borrow money usually insufficient for purposes of farm production. However, the in-kind credit system is the most common system, usually patronized by smallholder farmers, due to lack of collateral and low income of farmers (FAO, 2015b).

2.2 Empirical evidence of effects of agricultural credit on output and technical efficiency
In northern Ghana, smallholder farmers operate at subsistence levels, primarily for household consumption (Iddrisu et al., 2018). This then compels farmers to sell some of the crops at harvest at very low prices to be able to raise funds to meet their cash needs. Access to credit is regarded as an important intervention for improving the incomes of the rural population, mainly by mobilizing resources to more productive uses (Masuku et al., 2015). Empirical research has argued that agricultural productivity increases depend on better access to agricultural credit (Iddrisu et al., 2018). According to Abdallah (2016), availability and thus access to credit provide the ability for farmers to diversify by undertaking investment in new technologies. Again, credit helps households with binding liquidity constraints to confidently invest in their production activities because it gives them more choices and alternative routes of meeting expected expenditures and dealing with unexpected shocks (Schindler, 2010). However, the findings of Akudugu (2016) support the argument that credit provision should be a key component of interventions targeting productivity improvements in African agriculture. Akudugu (2016) recommended that efforts to promote agricultural productivity in Africa in general and Ghana in particular should focus on finding the appropriate farm sizes for farmers taking into consideration the context within which farmers operate to be able to produce. This will enable them produce at the pareto optimal levels.

However, the findings of Iddrisu et al. (2018) using the propensity score matching (PSM) procedure on farmer participants in a project in northern Ghana revealed that, even though farmers who participated in the project (supported with inputs such as seeds and agrochemicals) tended to have higher overall output and yield, they were not relatively better
off than the non-participants in terms of net output or income, especially farmers whose outputs were not enough to pay for the cost of input received from the project after harvest.

It is held that utilization of modern agricultural inputs by relaxing credit constraint would improve productivity of agriculture, which has far-reaching implications on ensuring sustainable livelihood of traditional farmers (Laha, 2007). The relationship between technical efficiency and agricultural credit has been widely studied with different estimation methods depending on the underlying assumptions. While some (such as Abate et al., 2014; Martey et al., 2015) have used the PSM methods, other studies (like Amaza and Maurice, 2005; Abdallah, 2016; Chandio et al., 2017) have measured impact of credit using the stochastic production frontier.

Martey et al. (2015) revealed that participation in the Agriculture Value Chain and Mentorship Project had positive impact on technical efficiency and farm income of farm households in Northern region of Ghana. Their study suggests that participation in the development project does not necessarily improve farm income, though impact may be realized in the long run with continuous use of the knowledge acquired from the project.

The work of Abdallah (2016) reveals that access to credit by smallholder farmers increased their output and efficiency than those without credit access. Laha (2007) reiterated that farmers having access to credit achieved a higher efficiency level by adopting improved technology which brought about enhanced agricultural production and productivity. Jack (2013) and Meyer (2015), using 2SLS approach, showed that credit inefficiency can serve as a major barrier to the adoption of yield-enhancing technologies which imply that if credit markets such as banks, microfinance institutions and moneylenders consider scaling up their activities, more households are likely to benefit.

2.3 Empirical application of DEA in efficiency studies

Nonparametric data envelopment analysis (DEA) technique has been applied to empirically determine the efficiency of various units in producing a single output. In a study to examine the efficiency of small scale rice producers in Bangladesh, Coelli et al. (2002) employed DEA and reported mean technical, allocative, cost and scale efficiency estimates of their sample to be 69.4, 81.3, 56.2 and 94.9 percent, respectively, for the dry season with these estimates not substantially different from those obtained for the rainy season. Using a second-stage Tobit regression, they find larger family size, experience in farming, limited access to inputs markets emanating from poor infrastructure and intensive engagement in off-farm work to significantly constrain efficiency levels of the farms.

Applying the DEA double bootstrap, proposed by Simar and Wilson (2007), to a sample of 295 farms to examine technical efficiency among smallholder rice farmers in Bangladesh, Balcombe et al. (2008) reported average technical efficiency of 64.0 and 59.0 percent for the farmers under wet season cultivation, respectively, under constant and variable returns to scale (VRS). They claimed that their technical efficiency estimates appear to be lower, albeit slightly, than that obtained by Coelli et al. (2002) because their procedure corrects for inherent bias in the DEA estimates obtained using the conventional two-stage approach[3]. They found that education, extension and access to credit positively influence farmer technical efficiency, with age being a negatively significant determinant. Wouterse (2010) also applied the double bootstrap DEA to study the effect of migration on technical efficiency of cereal producers in Burkina Faso with the results indicating a positive relationship between continental migration and technical efficiency while intercontinental migration shows no effect.

3. Methodology

3.1 DEA model

The DEA model is employed in this study to examine technical efficiency in crop production and how it is affected by access to credit in a nonparametric framework. The non-specification
of functional form on the production relationships between inputs and outputs, and
distributional assumptions on firm-specific inefficiency effects are the main strengths of the
DEA approach (see Wouterse, 2010), which are exploited in this study. A major limitation of the
DEA approach is the fact that because of its deterministic nature, it attributes all the variation
from the frontier to inefficiency and the estimates derived from it are likely to be sensitive to all
kinds of noise in the data (Wouterse, 2010). Related to this point is the observation by Simar
and Wilson (2007) that efficiency estimates from conventional DEA are serially correlated as a
result of which standard inference procedures based on the DEA are statistically invalid.
To deal with these shortcomings, the current study employs the double bootstrap procedure
developed by Simar and Wilson (1998, 2007, 2008) and applied by Balcombe et al. (2008) and
Wouterse (2010). The method is set out below.

If there are \( N \) farms, producing \( M \) output(s) using \( K \) inputs, then the linear programming
problem for calculating the efficiency of each production unit relative to a “peer group”
defined as a linear combination of efficient units is given by (see e.g. Coelli et al., 2002; Daraio
and Simar, 2007; Murillo-Zamorano, 2004):

\[
\text{Min} \eta_i \psi_i
\]

\[
\text{s.t. } -Y_l + \sum_{j=1}^{n} \eta_j Y_{lj} \geq 0, \quad l = 1, \ldots, M
\]

\[
\psi X_i - \sum_{j=1}^{n} \eta_j X_{ij} \geq 0, \quad i = 1, \ldots, K
\]

\[
\eta_j \geq 0,
\]

where \( \psi_i \) is a scalar and \( \eta \) is the intensity variable or weight of each farm not located on the
efficient frontier for which a vector \( \pi = (\eta_1, \ldots, \eta_N) \) is defined. The objective function
above seeks to minimize the proportion, \( \psi_i \), of inputs used by farms in a peer group to
produce the same level of output. An optimal value of \( \psi_i \) thus defines the (constant returns
to scale (CRS)) technical efficiency score of the \( i \)th farm, and this is then solved for each farm
in the sample. It satisfies the condition \( \psi_i \leq 1 \), with 1 indicating the \( i \)th farm operates on the
piecewise linear frontier, and thus fully (technically) efficient.

However, the assumption of CRS is rather restrictive since the differential effect of size is
not accounted for. As a result, an additional constraint of \( \sum \eta_j = 1 \) or \( \sum \eta_j \leq 1 \) or \( \sum \eta_j \geq 1 \)
added to Equation (1) allows for VRS, non-increasing returns to scale or non-decreasing
returns to scale, respectively.

The \( \psi_i \) are the efficiency estimates generated, with \( 1 - \psi_i \) representing the proportion by
which inputs can be potentially reduced to achieve the same level of output. These non-negative
estimates, truncated above 1, are used as a dependent variable in a second-stage truncated
regression to determine the correlates of technical efficiency. The regression model is given by:

\[
\psi_i = \rho_0 + \sum_{l=1}^{4} \rho_l Z_{li} + \epsilon_i,
\]

where \( \rho \) is a vector of parameters to be estimated, \( Z \) is a vector of variables (i.e. level of education
of household head, proportion of household income from off-farm engagement, access to credit,
gender of household head and distance to farm variables) assumed to influence technical
efficiency in this study, and \( \epsilon \) is a continuous random (error) term.

A procedure commonly employed in the literature is to analyze the determinants of
efficiency using Tobit regression, since the calculated technical efficiency scores are
censored at 1. However, Simar and Wilson (2007) identified two problems associated with this approach. First, the procedure does not describe a consistent data-generating process (DGP). And second, conventional approaches to statistical inference in such studies are invalid due to some complicated serial correlation emanating, for example, from the fact that the calculation of efficiency for a given farm household necessarily involves all other households in the sample (Wouterse, 2010). The upshot of these problems is that the efficiency scores are likely to be biased in finite samples.

The DGP that provides the rationale for the Simar and Wilson (2007) double bootstrap to solve the identified problems is the DEA model represented by Equation (1) and the second step truncated regression model in Equation (2). The double bootstrap consists of the following steps: standard DEA scores are calculated for all the farm households in the sample using Equation (1); Equation (2) is estimated using truncated maximum likelihood procedure; a set of bootstrap estimates are calculated; compute the bias-corrected, $\hat{\psi}_i$, efficiency estimates for each farm household; employ truncated maximum likelihood procedure to regress $\hat{\psi}_i$ on the explanatory variables; employ a number of bootstrap replications $L$ to yield a set of bootstrap estimates; and use the bootstrap estimates in Steps 5 and 6 to construct confidence intervals for the efficiency scores and the regression parameters.

3.2 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 survey covered production activities for 2008/2009 agricultural year and was undertaken between November 2009 and March 2010. The households were drawn using a multi-stage sampling procedure which involved identifying a district in each of the regions, randomly selecting five communities from each district and finally randomly selecting up to 30 households from each community[4]. The households are smallholder producers growing cereals like maize, millet, sorghum and rice; and other crops like groundnut, cowpea and soy bean under rain-fed conditions. These crops are produced mainly for home consumption, but surpluses are marketed to meet other household needs.

To measure the effect of access to credit on smallholder technical efficiency in crop production, the DEA model is used in which the dependent variable ($y$) is the total value (in GHS)[5] of all crops (i.e. cereals, legumes, roots and tubers, and vegetables) grown in the 2008/2009 agricultural year. A number of variables have been hypothesized to determine both the production part of the model and the inefficiency part. These variables and their descriptive statistics are presented in Table I.

Farm households’ off-farm income as a proportion of total income is uniform for those with access and those without access to credit as shown in the table. The observation is similar for years of education of household head, distance of farm from homestead and age of household head (Table I). There is a difference in the level of household labor use on farm by households with and without access to credit. The combined sample mean is about 333 man days with the mean for those accessing credit and those not accessing being about 415 and 322 man days, respectively. Further, while land area cultivated for those accessing credit stands at 2.42 ha, that of those not accessing credit is 1.89 ha and the difference is statistically significant at the 1 percent level. The total output (in value terms) obtained by the two households is also statistically significant at the 1 percent level. The results also indicate that just about 12 percent of the sampled households accessed credit prior to the interview.

The explanatory variables for the DEA model are basically production inputs broadly classified into four groups. Land ($x_1$) is measured as the total area of land under cultivation in hectares. The Purchased input ($x_2$) variable includes the value of all inputs bought (in GHS) such as fertilizer, seed and insecticide, and expenses on other activities and labor hired. Labor ($x_3$) is the total man days spent by household members and reciprocal labor
exchange among farmers, also known as self-help labor, on-farm during the 2008/2009 agricultural year[6].

The Capital ($x_4$) variable reflects value of services (in GHS) obtained from capital assets and farm implements. It is the value of costs, such as depreciation and interest, related to the ownership of farm implements like hoe, cutlass, axe and other farm implements used in the 2008/2009 agricultural year. It also includes cost of tractor hire and animal hire services. Farm implements are typically used over a production year as a result depreciation was calculated using the straight-line method while interest on capital consumption for the year was calculated using the central bank’s average policy rate for 2009 (i.e. 18.0 percent). These thus constitute the cost of replacing such implements.

Following the literature (e.g. Gorton and Davidova, 2004) and also on the strengths of the available data, seven variables ($z_i$) have been incorporated to explain smallholder farm efficiency. The level of education of the farmer in years (Education ($z_1$)) has been added to the inefficiency component to explain the effect of human capital on efficiency. The variable Proportion off-farm ($z_2$) captures the effects of engagement in off-farm work on farm efficiency. This variable is the percentage of total income generated from activities other than farm work by farmers. Gender ($z_3$), as a variable, captures the effect of gender of household head on technical efficiency. Age of household head ($z_4$), as noted by Wouterse (2010), depicts a variety of features that can likely affect economic activities of the household. Among other things, it reflects the level of experience of the farm operator and can also influence management decision making through its effect on the farmer’s physical ability to manage given enterprises. Location effects are captured using Northern ($z_5$) and Upper West ($z_6$) regions with Upper East region as the control. Distance ($z_7$), measured in km, is used to capture the effect of distance on technical efficiency.

The Credit ($z_8$) variable is a dummy which takes a value of 1 if farmer 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; Balcombe et al., 2008; Solís et al., 2009) have commonly treated this as exogenous[7]. As a result, credit is treated as being exogenous in this study.
4. Results
The DEA procedure developed in the previous section was employed to estimate a single output model using two double bootstrap DEA specifications. First, the basic model of Equation (1), i.e. CRS model, was estimated and then modified to accommodate the VRS constraint in an input-oriented framework. The estimates were also bootstrapped using 2,500 iterations in order to obtain bias-corrected estimates (see e.g. Simar and Wilson, 1998, 2008). Using such number of replications, as noted by Balcombe et al. (2008), is enough to engender confidence in the resulting estimates[8].

4.1 Estimates of technical efficiency
The results in Table II indicate that the average bias-corrected technical efficiency for the sample is about 40.0 percent for the DEA CRS model and 47.0 percent for the DEA VRS model. The modal efficiency range is 0.0–50.0 percent for both the CRS and VRS models. The results show that about 71.0 and 62.0 percent of the sample households are at most 50.0 percent technically efficient in crop production for the CRS and VRS models, respectively. Further, it is shown in the table that less than 1.0 and over 4.0 percent of the farmers are classified as being 91.0–100.0 percent technically efficient for the CRS and VRS models. However, the uncorrected estimates in Table AI show that almost 6.0 and 12.0 percent of the sampled households had efficiency scores in the range 91.0–100.0 percent for the CRS and VRS models, respectively, confirming the upward bias of the efficiency scores based on the ordinary DEA model.

The average efficiency scores imply that scope exists for decreasing input use by over half the current levels while achieving the same output levels, whether the CRS or VRS technology is used. The mean technical efficiency indices obtained using the two DEA restrictions, namely, CRS and VRS, diverge from those obtained by authors elsewhere including Balcombe et al. (2008), Coelli et al. (2002), Wadud and White (2000) and Wadud (2003). This difference will be partly explained by the imposition of different constraints on the DEA programming model. From policy point of view, there exists opportunity for improving technical efficiency as a way of closing the rather wide yield gap in crop production in northern Ghana. As a result, attention is now turned to the determinants of the observed technical efficiency.

4.2 Technical efficiency, credit access and other determinants
The sources of technical efficiency in the DEA models are shown in Table III. Unlike in Balcombe et al. (2008) and Wouterse (2010), where the influences of factors are explained through their effects on inefficiency, so that signs are reversed in discussing technical

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### Table II. Technical efficiency averages and distribution for crop production

<table>
<thead>
<tr>
<th>Efficiency levels</th>
<th>DEA CRS</th>
<th>DEA VRS</th>
</tr>
</thead>
<tbody>
<tr>
<td>≤0.50</td>
<td>71.2</td>
<td>61.6</td>
</tr>
<tr>
<td>0.51–0.60</td>
<td>13.7</td>
<td>15.5</td>
</tr>
<tr>
<td>0.61–0.70</td>
<td>9.5</td>
<td>11.4</td>
</tr>
<tr>
<td>0.71–0.80</td>
<td>3.4</td>
<td>5.2</td>
</tr>
<tr>
<td>0.81–0.90</td>
<td>2.0</td>
<td>2.0</td>
</tr>
<tr>
<td>0.91–1.00</td>
<td>0.2</td>
<td>4.3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Efficiency scores</th>
<th>DEA CRS</th>
<th>DEA VRS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.40</td>
<td>0.47</td>
</tr>
<tr>
<td>Median</td>
<td>0.38</td>
<td>0.44</td>
</tr>
<tr>
<td>SD</td>
<td>0.18</td>
<td>0.20</td>
</tr>
<tr>
<td>Range</td>
<td>0.90</td>
<td>0.89</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.02</td>
<td>0.07</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.92</td>
<td>0.96</td>
</tr>
</tbody>
</table>
efficiency, here the effects are explained directly on technical efficiency (as the scores are direct measures of technical efficiency) and hence there is no need to reverse signs. Except the education and gender variables, the rest are statistically significant at least in the CRS model.

Proportion of household income from off-farm activities negatively affects crop production technical efficiency. This result, which is consistent with that reported by Coelli et al. (2002) who employed the DEA method to analyze efficiency among rice producers in Bangladesh, suggests that increased engagement in off-farm activities leads to reallocation of labor away from farm production activities, especially those that will help increase farm productivity such as adoption of new and improved technologies (Abdulai and Huffman, 2000).

The level of education of the household head is revealed to have positive, but non-significant, effect on technical efficiency. Even though surprising, Coelli et al. (2002) found a similar effect among their sample of rice producers in Bangladesh. The observation could be attributable to the fact that the average level of education for households heads in the sample is less than four years (see Table I). In the same vein, age of household head has no effect on technical efficiency, implying no generational effect is depicted by the data.

There is evidence of locational effects in the technical efficiency of smallholder crop producers in northern Ghana. For example, the estimates indicate that farmers in the Upper East region are more technically efficient relative to their counterparts in the Northern and Upper West regions. This result can be interpreted as managerial and personal abilities playing more important role in determining technical efficiency than environmental factors. This is because even though all the three regions are in the Guinea Savannah agro-ecological zone, conditions in the Upper East are fast approaching that of Sahel Savannah yet farmers there appear more technically efficient. Distance to the farm from homestead positively affects technical efficiency. The results in Table III show that access to credit has a positive effect on technical efficiency albeit it is significant in the CRS model only, implying the limited access to credit by smallholders in the study area is hampering crop productivity. The finding on credit is in consonance with the observation by Balcombe et al. (2008) that access to credit impacted positively on the technical efficiency among their sample of rice producers in Bangladesh.

Figures 1 and 2 show the distribution of efficiency scores for the two types of households using the two DEA models of CRS and VRS. While Figure 1 (showing the CRS curve) indicates clearly that households accessing credit have higher efficiency scores, depicted by the curve lying more to the right, Figure 2 (showing the VRS curve) shows somewhat mixed results even though the households accessing credit appear to have a slightly higher technical efficiency scores.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient CRS</th>
<th>Bootstrap St error</th>
<th>Coefficient VRS</th>
<th>Bootstrap St error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.4078***</td>
<td>0.0617</td>
<td>0.6137***</td>
<td>0.0595</td>
</tr>
<tr>
<td>Education of head</td>
<td>0.0019</td>
<td>0.0024</td>
<td>0.0013</td>
<td>0.0024</td>
</tr>
<tr>
<td>Proportion off-farm</td>
<td>−0.0020***</td>
<td>0.0003</td>
<td>−0.0005</td>
<td>0.0004</td>
</tr>
<tr>
<td>Gender of head</td>
<td>−0.0065</td>
<td>0.0420</td>
<td>−1.089***</td>
<td>0.0400</td>
</tr>
<tr>
<td>Age of head</td>
<td>0.0007</td>
<td>0.0007</td>
<td>−0.0000</td>
<td>0.0007</td>
</tr>
<tr>
<td>Northern</td>
<td>−0.0615***</td>
<td>0.0239</td>
<td>−0.0917***</td>
<td>0.0260</td>
</tr>
<tr>
<td>Upper west</td>
<td>−0.0457***</td>
<td>0.0231</td>
<td>−0.0770***</td>
<td>0.0245</td>
</tr>
<tr>
<td>Distance to farm</td>
<td>0.0174***</td>
<td>0.0046</td>
<td>0.0102*</td>
<td>0.0052</td>
</tr>
<tr>
<td>Credit</td>
<td>0.0704***</td>
<td>0.0270</td>
<td>0.0195</td>
<td>0.0294</td>
</tr>
<tr>
<td>σ</td>
<td>0.1821***</td>
<td></td>
<td>0.1961***</td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>159.379</td>
<td>112.089</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wald $\chi^2$</td>
<td>75.50***</td>
<td>27.87***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total sample</td>
<td>445</td>
<td>445</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: *2,500 bootstrap iterations used. **p < 0.1; ***p < 0.05; ****p < 0.01
As shown in Table IV, a joint $F$-test of mean difference in technical efficiency indices obtained using the CRS and VRS formulations between households with access to credit and households without access to credit is statistically significant at the 0.05 level, highlighting the important role of credit in raising technical efficiency of smallholder crop producers in northern Ghana.

As shown in Table IV, a joint $F$-test of mean difference in technical efficiency indices obtained using the CRS and VRS formulations between households with access to credit and households without access to credit is statistically significant at the 0.05 level, highlighting the important role of credit in raising technical efficiency of smallholder crop producers in northern Ghana.

<table>
<thead>
<tr>
<th>Bias-corrected scores</th>
<th>Households with credit access</th>
<th>Households without credit access</th>
<th>Mean difference$^a$</th>
<th>$t$-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEA CRS</td>
<td>0.45</td>
<td>0.39</td>
<td>$-0.059^{**}$</td>
<td>$-2.21$</td>
</tr>
<tr>
<td>DEA VRS</td>
<td>0.48</td>
<td>0.46</td>
<td>$-0.016$</td>
<td>$-0.54$</td>
</tr>
<tr>
<td>$F$-test statistic</td>
<td></td>
<td></td>
<td>$4.215^{**}$</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>53</td>
<td>392</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: $^a$Mean for those without access minus mean for those with access. $^{**}p < 0.05$
5. Conclusions
The double bootstrap DEA procedure proposed by Simar and Wilson (2007) has been employed to examine technical efficiency scores and factors affecting such scores for a sample of smallholder crop producers in northern Ghana. In particular, the study places emphasis on examining the relationship between technical efficiency and access to credit. A couple of important issues emerge from a policy perspective.

First, estimates of technical efficiency obtained from both DEA models indicate that, given the current technology, there is substantial room for improving productivity among the sample of producers in northern Ghana used for the study through raising technical efficiency. Indeed, the yield gaps revealed by the current study appear much bigger than that revealed by studies employing ordinary DEA. Improving technical efficiency among farmers in northern Ghana can help close such yield gaps. Such improvements in technical efficiency can be achieved through increasing farm households’ access to credit since technical efficiency and access to credit are shown to be positively related.

Second, 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. What this result might be suggesting is that 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. One obvious way of achieving this is through improving access to credit. This thus reinforces the important role of credit in the study area.

Notes
2. Other reasons as identified by FAO (2015b) include a history of high default on subsidized loans, issues of land tenure, weather risks and a lack of technical knowledge on risk assessment and management.
3. It should, however, be noted that while these authors used output-oriented measures of technical efficiency, Coelli et al. (2002) employed input-oriented measures, and for which reason the estimates might not necessarily be same, especially if units in the sample do not exhibit constant returns to scale technology.
4. Six households were dropped from an original sample of 451 due to incomplete responses.
5. The average exchange rate for the local currency in 2009 stood at GH¢2.2024 and GH¢1.4132, respectively, to GB£1 and $1 as quoted in the “Bank of Ghana Annual Report 2009” (BoG, 2010, p. 51) and can be accessed from www.bog.gov.gh
6. Labor man day is the adult equivalent of about 8h of work per day.
7. This position is also informed by the observation by Simar and Wilson (2007) that the truncated regression is preferred to the Tobit in modeling the efficiency or inefficiency when using the DEA. Meanwhile, there is still no straightforward way of dealing with endogeneity in truncated regression models, except by using gsem or cmp which then stretches the model beyond the double bootstrap framework.
8. All DEA models were estimated using GAUSS 14.0, while the second-stage truncated regression models were estimated using Stata 15.0.
References


Appendix

<table>
<thead>
<tr>
<th>Efficiency levels</th>
<th>DEA CRS</th>
<th>DEA VRS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate (average)</td>
<td>Bias-corrected (average)</td>
</tr>
<tr>
<td>≤0.50</td>
<td>57.8</td>
<td>71.2</td>
</tr>
<tr>
<td>0.51–0.60</td>
<td>12.3</td>
<td>13.7</td>
</tr>
<tr>
<td>0.61–0.70</td>
<td>9.9</td>
<td>9.5</td>
</tr>
<tr>
<td>0.71–0.80</td>
<td>9.7</td>
<td>3.4</td>
</tr>
<tr>
<td>0.81–0.90</td>
<td>4.5</td>
<td>2.0</td>
</tr>
<tr>
<td>0.91–1.00</td>
<td>5.8</td>
<td>0.2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Efficiency scores</th>
<th>DEA CRS</th>
<th>DEA VRS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.49</td>
<td>0.40</td>
</tr>
<tr>
<td>Median</td>
<td>0.46</td>
<td>0.38</td>
</tr>
<tr>
<td>SD</td>
<td>0.23</td>
<td>0.18</td>
</tr>
<tr>
<td>Range</td>
<td>0.98</td>
<td>0.90</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.00</td>
<td>0.92</td>
</tr>
</tbody>
</table>

Table AI. Distribution of uncorrected and corrected bootstrapped technical efficiency scores

Credit access and technical efficiency


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