



Received: 06 April 2020
Accepted: 04 October 2020

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FOOD SCIENCE & TECHNOLOGY | RESEARCH ARTICLE

Estimating technology adoption and technical efficiency in smallholder maize production: A double bootstrap DEA approach

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Abstract: The study examined how farmers' technological choice affects technical efficiency (TE) in small-scale maize production in northern Ghana. A random sample of 340 respondents took part in the study. A binary probit modeling was applied to analyse adoption decision, while double bootstrap data envelopment analysis was relied upon to evaluate TE. Truncated regression was used to assess the sources of inefficiency. The results indicated a bias-corrected TE of 57% under variable returns to scale assumption and 52% when constant returns to scale was assumed. Accounting for potential endogeneity of the adoption variable, the findings indicated that technical efficiency increased with technology adoption. Technical efficiency improved with herd size but decreased with educational attainment, number of household members, access to extension, frequency of weeding, and size of cultivated land. The study, therefore, recommends that making improved seeds available and affordable to small-scale producers and training farmers on effective weed management could be potential measures to enhance the farm-level technical efficiency.

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PUBLIC INTEREST STATEMENT

Low agricultural productivity is a major concern in smallholder agriculture because of the important role agriculture plays in rural livelihoods and socio-economic development in developing countries. A major factor contributing to low agricultural productivity is low adoption of improved technologies including improved planting materials. Despite efforts by research institutions to develop and disseminate improved technologies to smallholders, adoption of these technologies has been low in many developing countries. This study, therefore, assessed the factors influencing adoption of improved maize seeds and the impact of adoption on technical efficiency of smallholder farmers in Ghana. The study adopted a non-parametric efficiency approach. The results indicated a positive and significant effect of improved variety adoption on technical efficiency. Hence, there is the need to encourage farmers to adopt improved varieties and follow recommended practices to optimize farm output. Improving farmers' access to input subsidy is required to promote technical efficiency of maize production.

Subjects: Agriculture & Environmental Sciences; Development Studies; Sustainable Development; Rural Development; Development Economics

Keywords: Adoption; bootstrapping; data envelopment analysis; technical efficiency; Tolon district

1. Introduction

Agricultural growth through higher productivity is a topical issues that has gained global attention for the past decades because of its influence on food and nutrition security (FNS) and long-term expansion of the economy (Collier & Dercon, 2014). Typically, developed countries have been able to enhance productivity at the farm level by adopting improved technologies and access to productivity-enhancing resources such as credit, land, and markets. Improved agrarian technologies adopted include improved crop varieties, weed, insect pest management, farm equipment, and conservation agriculture (Asfaw et al., 2012; Reardon et al., 2009; Sheahan & Barrett, 2017). According to Lee (2005), the adoption of agricultural technologies has the potential to increase farm yields, increase farmers' income, and ensure food security. Despite the benefits of improved agricultural technologies, adoption is low in several less-developed countries (Abebe et al., 2013; Jayne & Rashid, 2013; Sheahan & Barrett, 2017), including Ghana.

Ghana is an agrarian economy, with the agricultural sector providing jobs to about 71% of rural dwellers (Ghana Statistical Service, 2014a). In most rural communities, where agricultural production is the predominant livelihood, poverty, and food insecurity are rife (Ghana Statistical Service, 2014b). Agricultural development is therefore pivotal to eradicate poverty and enhance economic development. Indeed, promoting agricultural productivity can improve the welfare of rural farm households through higher income (Asfaw et al., 2012). Evidence suggests that the uptake of improved planting materials improves yield and thus household welfare as well as food and nutrition security (Donkor et al., 2016; Sheahan & Barrett, 2017).

The government of Ghana has put in place initiatives to improve the productivity of smallholder farming. The Food and Agriculture Sector Development Policy (FASDEP II) was initiated in 2007 to enhance productivity. Similarly, the Ghana Shared Growth and Development Agenda (GSGDA 2010–2013) and Medium-Term Agriculture Sector Investment Plan (METASIP 2010–2015) have all acknowledged the importance of boosting agricultural productivity of staple crops by providing farmers access to improved technologies and other productive resources such as credit and irrigation facilities. The most recent of the comprehensive strategies set up by the government is the Planting for Food and Jobs (PFJ) programme increase the production and yield of maize and other crops such as rice, soybeans, sorghum, and vegetables through the provision of subsidized inputs such as fertilizer, improved planting materials, and extension advice (MoFA (Ministry of Food and Agriculture), 2017).

In spite of these efforts, the type of seed use by farmers remains a major challenges affecting farm productivity. For instance, farmers' uptake of improved maize varieties (IMVs) is still below expectation, with production at the subsistence level. In Ghana, there are several seed types available and used by farmers. These include certified inbreds seeds, hybrid seeds, and farmers' recycled seeds or what is tagged as ordinary seeds. In the context of this study, IMVs are those certified inbreed seeds and hybrid seeds released and introduced to farmers by national research bodies such as Savanna Agricultural Research Institute (SARI) and the Crops Research Institute (CRI). These are open pollinated varieties and quality protein maize with higher yielding potential (usually 3.5–5.5 tons/ha) and early maturing (75–110 days). Other features include drought, pests and disease tolerance, resistant to lodging and *striga* infestation, among others. Although most of the IMVs released can be cultivated across almost all the agro-ecologies in Ghana, some are most suited to the Sudan and Guinea savannah, which constitute the northern part of Ghana. Some of the varieties most suited and hence, are mostly used by farmers in northern Ghana, including the

study area include Dodzi, CSIR-Abonem, Sanzal-sima, Ewu-boyul, Wang-dataa, Bihilifa, Tigli, and Obaatanpa, among others. It is expected that farmers adopt these varieties to increase farm productivity, and subsequently improved their livelihoods.

However, low adoption of these IMVs by smallholders has contributed to farm-level inefficiencies. Thus, efforts geared towards identifying the drivers of IMV adoption and its effect on production efficiencies are critical in enhancing the productivity of farmers. This is because the judicious use of productive resources required to enhance smallholder production systems, thus promoting economic growth. This study, therefore, aimed at investigating the influence of adopting IMVs on farm efficiencies in the Tolon district, Ghana.

Some empirical investigations have examined the influence of adopting modern technologies on farmers' technical efficiency (TE) levels. Principal among such studies that are similar to this study are Asante et al. (2019), Azumah et al. (2019), Rahman and Norton (2019), and Abdulai et al. (2018). The point of departure from this study is that Asante et al. (2019) employed the meta-frontier model and found the adoption of fertilizer to increase maize farmers' technical efficiency level in Ghana. Azumah et al. (2019) applied stochastic frontier analysis (SFA) and reported that the adoption of an irrigation system enhanced the technical efficiency level of Ghanaian rice producers. Rahman and Norton (2019) also used the SFA and found that the decision to adopt integrated pest management (IPM) did not influence the technical efficiency level of Bangladeshi eggplant growers. Nkegbe (2018) used the double bootstrap data envelopment analysis (DEA) approach to estimate the impact of agricultural credit on smallholders' TE in northern Ghana. The study was a pioneering work in terms of the estimation of technology adoption within a non-parametric technical efficiency framework in relation to Ghanaian agriculture. The study, however, did not account for endogeneity of the credit variable. This study extends the literature further by evaluating the impact of IMV adoption on the technical efficiency of maize farmers within a non-parametric framework, specifically the data envelopment analysis. Also, we accounted for endogeneity of the adoption variable by including the predicted adoption scores rather than the observed adoption variable in the estimation.

2. Literature review

TE is attained when an economic agent is able to apply minimum quantities of production factors to realize a given output quantity (i.e., input-oriented), or for an economic agent to obtain feasible maximum output using a given set of resources (i.e., output-oriented) (Coelli et al., 2002). The ability to produce efficiently is important because most smallholders are resource-constrained and depend largely on agriculture for their livelihoods. According to Singh et al. (2002), a smallholder farmer is a producer who cultivates an average of 2 ha. Improving the TE of production will improve the level of productivity thus enhancing farm income and household food security. Estimating the level of efficiency provides insight into the resource-use efficiency of farmers, while evaluating the sources of inefficiency gives insight into the measures necessary to reduce inefficiency in production. Theoretically, the two main approaches for TE estimation are stochastic frontier analysis (SFA) and data envelopment analysis (DEA). The SFA model is parametric in nature, accommodates noise in the data, and based on defining a functional form and a model for the source of inefficiency (Kumbhakar et al., 2009). DEA on the contrary, is non-parametric and requires no *a priori* assumption of the relationship between inputs and outputs. The DEA approach is however deterministic in nature and does not require a model identifying the sources of inefficiency.

Motivated by these arguments, various empirical studies have been conducted using the input-oriented DEA technique to evaluate the efficiency of firms or economic agents. Balcombe et al. (2008) applied the DEA double bootstrap technique and found a mean technical efficiency of 64% (at constant returns to scale, CRS) and 59% (at variable returns to scale, VRS) for rice farmers in Bangladesh. They observed that access to credit, extension, and higher education increased farmers' technical efficiency, while age decreased efficiency. Using the DEA double bootstrap

approach, Wouterse (2010) found that continental migration increased the TE of Burkinabe farmers. Also, Mitra and Yunus (2018) applied the DEA double bootstrap procedure and observed the mean TE of tomato producers in Bangladesh to be 83%. The study revealed that efficiency increased with education, and training but decreased with age. These studies, and many others, indicate that farmers are not making efficient use of their scarce resources as revealed by the presence of inefficiency in production. Furthermore, the studies reviewed highlight several sources of inefficiency in production, including farm and farmer characteristics, socio-economic and institutional factors. Our choice of variables for evaluating the factors affecting technical efficiency of Ghanaian smallholders was informed by previous studies and a priori expectation.

In terms of empirical studies on the impact of adoption of agricultural technologies on the TE level of farmers, different econometric techniques, crop types, and agricultural technologies have been used with conflicting results. For example, Benedetti et al. (2019), based on stochastic frontier analysis (SFA), found that the adoption of a fertigation system increased the level of TE among Italian farmers. In a similar study, Rahman and Norton (2019) applied SFA and found no significant influence of adoption of integrated pest management (IPM) on the TE level of eggplant growers in Bangladesh. Using the meta-frontier model, Asante et al. (2019) found that the adoption of fertilizer increased the technical efficiency of maize farmers in Ghana. Azumah et al. (2019) employed the SFA correcting for sample selection bias and found the adoption of irrigation system to increase the technical efficiency level of Ghanaian rice producers. These studies highlight different approaches used in estimating the impact of technology adoption on TE. Most of the studies reviewed are aligned to the SFA tradition. In this study, we apply the DEA methodology to assess the effect of technology adoption on TE of smallholder farmers in the context of a developing country.

Although there are existing studies on technology adoption by smallholder farmers in Ghana, the results are conflicting and relate to different technologies and crops. Importantly, there is the need for scientists to regularly update their research findings because the factors affecting technical efficiency are specific to time, geographic location and crop type (Donkoh, 2011).

3. Methodology

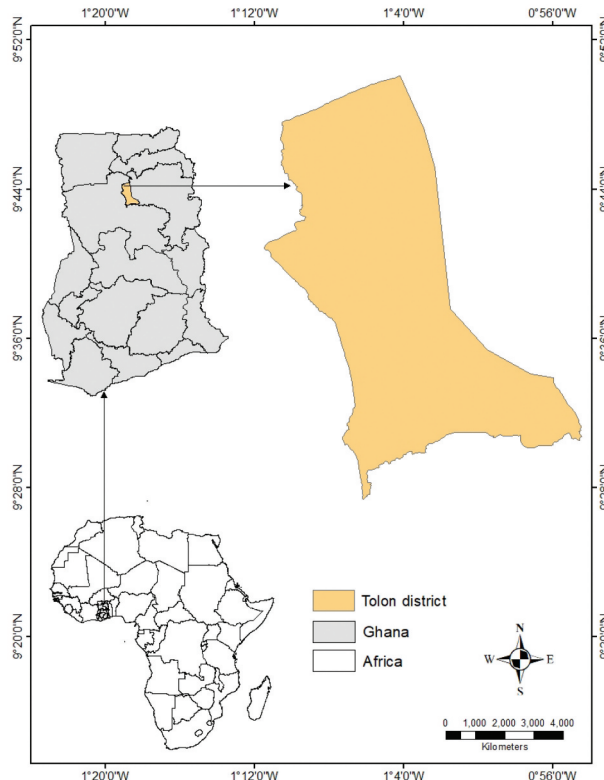
3.1. Study area and data

Maize is Ghana's major staple food crop and the most significant source of food security (Wongnaa & Awunyo-Vitor, 2018). Also, maize production is an essential source of income in areas where it is cultivated and has featured significantly in most national public documents because it has the potential to enhance food security (MoFA (Ministry of Food and Agriculture), 2017). Despite these roles of maize, Ghana has experienced average shortfalls in domestic maize supplies. This is primarily due to low productivity, as yields remain low around 1.99 metric tonnes per hectare for Ghanaian farmers in 2016 instead of an achievable yield level of 5.5 metric tonnes per hectare (MoFA (Ministry of Food and Agriculture), 2016).

The study was conducted in the Tolon district (Figure 1), which is located in the Northern region of Ghana. Tolon is a rural district, with the majority of the people engaged in crop farming (97.5% of households), predominately as small-scale producers (Ghana Statistical Service, 2014c). Maize is widely cultivated by small-scale farmers in the district, which per the 2010 national population census, had 72,990 inhabitants (Ghana Statistical Service, 2014c). Located in the dry savanna zone, the district experiences one rainy season, from April/May, and ends in October/November. Average daily temperatures are very high (reaching over 40 degrees Celsius during the peak). Crop production depends mainly on natural rainfall which does not exceed 1,200 mm per annum.

Cross-sectional data were obtained from 340 smallholder maize farmers from 11 communities in the district for the 2018 farming season. Multistage sampling was used for data collection. Stage one involved selection of the Tolon district as a major maize cultivating districts in the Northern

Figure 1. Study area showing map of Tolon district.



Region. This was followed by the random selection of 11 communities in the district. In each community, 30–35 maize producers were randomly selected, based mainly on geographical spread of the communities. Without an existing sampling frame, the sample size was determined using the 2010 Population Census estimate of the district’s population. Cochran’s procedure for sample size determination indicated that a sample size of 340 is representative of the population engaged in farming. The respondents were interviewed using face-to-face interviews using semi-structured questionnaires. The majority of the respondents were interviewed in the local dialect with the assistance of interpreters. The information collected from respondents covered input and output quantities, farm-specific variables, socioeconomic, demographic, and institutional factors.

3.2. Technology adoption model

Following Khonje et al. (2015), farm households’ choice of IMVs is analysed under the random utility theory. It posits that rational economic agents (i.e. farm households) will choose to plant IMVs if the utility derived from adoption (W_{i1}) exceeds the utility from non-adoption (W_{i0}). However, the utilities are unobservable and the maximum benefit derived from adoption (M_i) is an unobservable variable related to farmers’ socio-economic factors, as presented in Equation (1):

$$M_i = X_i\beta + \varepsilon_i \text{ with } M_i = \begin{cases} 1 & \text{if } M_i > 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where M_i is binary and equals 1 if farmers adopt IMVs and 0 otherwise, β represents unknown parameters, X_i represents farmer/farm-specific and institutional factors, ε_i is the error term that has a normal distribution. Thus, the likelihood to adopt is presented as

$$\Pr(P_i = 1) = \Pr(P_i^* > 0) = \Pr(\varepsilon_i > -X_i\beta) = 1 - F(-X_i\beta) \quad (2)$$

where F is the cumulative distribution function for ε_i . Estimation of equation (2) is done by employing the probit model (Wooldridge, 2010). The model to estimate the probability of observing a farmer adopting IMVs is expressed in Equation (3):

$$P(Y_i = 1|x) = F(X_i\beta) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right) dz \quad (3)$$

Empirically, the probit model used to estimate adoption is represented as follows:

$$Y_i = \beta_0 + \sum_{n=1}^{11} \beta_n X_{ni} + u_i \quad (4)$$

where X_i represents the factors influencing adoption, and u_i is a random error term. The explanatory variables include farmer's age and its quadratic term, educational level, household size, extension contact, degree of specialization in maize production, soil fertility status, access to credit, farmer group membership, herd size, and participation in off-farm work. After obtaining the probit model estimates, the predicted probability of adoption of IMV was estimated and used as an independent variable in the efficiency model to control for endogeneity.

3.3. DEA model

The study relies on DEA methodology to evaluate technical efficiency and how it is influenced by technology adoption. Unlike the parametric stochastic production frontier approach, the DEA approach does not assume *a priori* functional form for the input-output relationships and distributional assumptions of the inefficiency term (Farrell, 1957; Fraser & Cordina, 1999). Specifically, the DEA input-oriented approach was used because maize farmers do not have much control over the level of their output as compared to their inputs. Following Farrell (1957), the input-oriented model for individual farm unit or DMU is calculated by using the following model:

Minimize TE_j

Subject to: $\sum_{j=1}^n y_j \lambda_j - y_j \geq 0; \lambda_j \geq 0$ for j ,

$$x_{ij} TE_j - \sum_{i=1}^m x_{ij} \lambda_j \geq 0 \quad (5)$$

where : $x_i, y_j \leq 0; \lambda_j \geq 0$ and $0 \leq TE \leq 1$

TE_j is a scalar indicating technical efficiency scores of the j th maize farmer or DMUs in the sample, λ_j represents a vector of weight of each firm that is not situated on the efficient frontier, and x_{ij} is an $m \times n$ input matrix, representing the quantity of use of the i th input on the j th maize farm. y_j is the quantity of output on the j th maize farm. For this specification, $TE_i \leq 1$, where a value of 1 indicates that the j th farmer is fully efficient.

The above specification denotes constant returns to scale (CRS), which is ideal given that all farms are operating at their optimum scale. The assumption of CRS is therefore regarded as restrictive, which can be relaxed by including additional constraints. Additional constraint of $\sum \lambda_j = 1$, $\sum \lambda_j \leq 1$ or $\sum \lambda_j \geq 1$ to Equation (5) enables technical efficiency to be estimated under assumptions of variable, decreasing or increasing returns to scale.

The maximum efficiency is 1; hence, $1 - TE_i$ is the proportion by which producers can potentially reduce input utilization to attain the same production. Truncated regression is subsequently applied to estimate the factors influencing farmers' efficiency, where the response variable is the estimated TE score. A notable feature of the Simar and Wilson DEA approach that we employ in this study is the double bootstrap, which provides bias-corrected TE scores. According to Simar

and Wilson (2007), this procedure, unlike the traditional censored regression, corrects for serial correlation between the efficiency scores. The truncated regression model is expressed as

$$\widehat{TE}_i = \gamma_0 + \sum_{j=1}^{11} \gamma_j Z_{ji} + w_i \quad (6)$$

where \widehat{TE}_j is the DEA scores that have been corrected for bias, $\varepsilon_j \sim (0, \sigma_\varepsilon^2)$ with right truncation at $1 - Z_j \gamma$, γ represents unknown parameters, and Z_j denotes farmer/farm-specific and socioeconomic factors hypothesized to affect technical efficiency. The explanatory variables in the vector Z_j include the predicted adoption score, farmer's age and its quadratic term, household size, educational level, degree of specialization in maize cultivation, engagement in off-farm work, farmer group membership, size of herd, farm size and frequency of weeding. These explanatory variables were adopted from previous studies (Asante et al., 2019; Azumah et al., 2019; Kassie et al., 2013; Khonje et al., 2015; Konja et al., 2019). To address potential endogeneity of the adoption variable, the predicted adoption score was appended as an independent variable in the efficiency model. For this study, 2000 bootstrap replications were used. The data were analysed using Stata version 15.

A common method in efficiency analysis is to use a Tobit model to assess the factors influencing efficiency due to the censored nature of the TE scores. Such an approach has however been criticised because it lacks a well-defined data-generating process. Also, there are serious serial correlations between the estimated TE scores that make conventional approaches to statistical inference invalid. Simar and Wilson (2007), therefore suggested truncated regression as a better approach for the second-stage analysis.

The double bootstrap approach employs a data-generation process that seeks to address the challenges associated with estimating Equations (5) and (6). The approach follows the following steps: (i) estimate each farm's efficiency scores using Equation (5); (ii) Estimate the truncated regression using Equation (6); (iii) calculate a set of bootstrap estimates; (iv) calculate each farms' TE score adjusted for bias; (v) the TE scores adjusted for bias serves as the response variable in a truncated regression to estimate the factors affecting TE (vi) conduct a series of bootstrapping to provide bootstrap estimates; and (vii) calculate new confidence intervals based on the bootstrap estimates.

The description, unit of measurement, and expected signs of the explanatory variables in the probit and truncated regression models are shown in Table 1.

4. Results and discussion

4.1. Characteristics of the respondents

Table 2 presents the summary statistics of the sampled farmers. Adopters had significantly higher maize output and used higher input quantities (labour, fertilizer, and agrochemicals) in production than non-adopters. As expected, the number of visits from extension agents was higher for adopters. On average, farmers received one extension visit during the farming season, which is very low. On the other hand, adopters allocated less of their total agricultural land to maize production. In other words, adopters had a lower degree of specialization in maize production in the study area. Furthermore, adopters were older and had more years of formal education. Adopters also had smaller household sizes and were more likely to participate in off-farm work. The respondents had on average 10 household members.

The respondents had an average farm size of 3.8 acres and a mean maize output of 1253 kg. Furthermore, 42% of the respondents adopted IMVs, while 46.5% participated in a farmer group organization. The adopters of IMVs have a significantly higher average age (40 years) than non-adopters (37 years). The average age of both groups implies that most of the sampled farmers are within their active and productive years. Adopters had more years of formal education and fewer

Table 1. Description and expected signs of the explanatory variables in the models

Variable	Definition	Effect on adoption	Effect on efficiency
<i>Output and inputs variables</i>			
Maize output	Maize output in kilograms	+	+
Farm size	Maize farm size in acres	±	+
Quantity of seed	Quantity of seed in kilograms	+	+
Total labour	Quantity of labour in person-days	+	+
Quantity of fertilizer	Quantity of fertilizer in kilograms	+	+
Total agrochemicals	Quantity of agrochemicals in litres	-	+
<i>Socioeconomic variables</i>			
Age	Age of farmer in years	±	±
Education	Years of formal education	+	+
Household size	Number of household members	±	+
Herd size	Number of cattle owned	+	+
Participation in off-farm work	Dummy: 1 = participant, 0 = otherwise	+	±
Degree of specialization	Proportion of land allocated to maize	+	+
<i>Policy/institutional variables</i>			
Extension contact	Number of extension visits	+	+
Credit access	Dummy: 1 = access, 0 = otherwise	+	+
Farm group membership	Dummy: 1 = member, 0 = otherwise	+	+
<i>Farm-specific variables</i>			
Weeding	Frequency of weeding	-	+
Soil fertility status	Dummy: 1 = fertile, 0 = otherwise	+	+
Adoption score	Estimated adoption score		+

members per household relative to non-adopters. Also, a significantly higher proportion of adopters engaged in off-farm income-generating activities while the respondents had approximately one extension contact during the cropping season, with a minimum of zero and a maximum of five. The respondents also owned an average of two cattle and allocated 52% of the total agricultural land to maize cultivation. Access to agricultural credit did not differ between adopters and non-adopters. On average, the respondents weeded their farms twice during the cropping season, while 54% of the respondents perceived their soils to be fertile.

4.2. Determinants of improved maize variety adoption

Table 3 presents the results of the adoption model. The association between the age of the respondents and adoption was positive and significant at 1%. Older farmers, who are premised to be more experienced in production, are therefore more likely to adopt IMVs. A unit increase in age increases the likelihood of adoption by 0.043. However, the quadratic term of the age variable indicates that adoption increases at a decreasing rate. In other words, beyond a certain threshold, adoption begins to decline with age. The positive effect of age on adoption of IMV agrees with Anang (2019) and Danso-Abbeam et al. (2017) in their studies in northern Ghana but disagrees with that of Islam et al. (2012) in their study in Bangladesh.

Farmers' educational level had a positive correlation with adoption, implying that additional years of formal education positively influenced farmers' decision to cultivate IMV. An additional year of education has the likelihood to enhance adoption by 0.017. This result resonates

Table 2. Characteristics of respondents

Variable	Full sample (n = 340)		Adopters (n = 144)		Non-adopters (n = 196)		Mean diff.
	Mean	SD	Mean	SD	Mean	SD	
<i>Output and inputs variables</i>							
Maize output (kg)	1253	879	1373	1033	1165	737.6	207***
Farm size (acres)	3.84	2.83	3.94	3.24	3.77	2.50	0.17
Quantity of seed (kg)	21.72	14.71	20.91	15.54	22.31	14.07	-1.40
Total labour (person-days)	97.36	61.53	108.6	70.73	89.09	52.45	19.6***
Quantity of fertilizer (kg)	427.4	327.1	463.7	391.5	400.8	268.1	62.95*
Total agrochemicals (litres)	4.46	3.98	5.24	4.96	3.89	2.96	1.35***
<i>Socioeconomic variables</i>							
Age (years)	38.44	11.96	39.75	11.09	37.47	12.50	2.28**
Education (years)	2.31	4.29	2.91	4.81	1.88	3.81	1.03*
Household size (count)	10.40	5.09	10.38	5.23	10.41	5.00	-0.03*
Herd size (count)	2.36	4.76	2.19	4.25	2.48	5.12	-0.29
Off-farm work (= 1 if participant)	0.29	0.46	0.33	0.47	0.27	0.44	0.07**
Degree of specialization	52.0	18.45	49.20	18.98	54.05	17.82	-4.85**
<i>Policy/institutional variables</i>							
Extension contact (frequency)	0.72	1.26	0.96	1.34	0.55	1.18	0.41***
Credit access (= 1 if access)	0.40	0.49	0.39	0.49	0.40	0.49	-0.01
Farm group (= 1 if member)	0.47	0.50	0.44	0.50	0.48	0.50	0.04
<i>Farm-specific variables</i>							
Weeding (frequency)	2.00	0.41	1.99	0.45	1.94	0.38	0.05
Soil fertility status (= 1 if fertile)	0.54	0.50	0.54	0.50	0.54	0.50	0.001

***, **, and * denote significant levels at 1%, 5% and 10%, respectively.

Table 3. Determinants of improved maize variety adoption

Variable	Coefficient	Std. Error	Marginal effect
Age	0.111***	0.032	0.043
Age squared	-0.001***	0.000	-0.0004
Years of formal education	0.043**	0.017	0.017
Household size	-0.012	0.015	-0.005
Degree of specialisation	-0.009**	0.004	-0.365
Extension contact	0.239***	0.068	0.093
Credit	0.107	0.162	0.042
Farmer group membership	-0.336**	0.166	-0.130
Herd size	0.008	0.017	0.003
Off-farm work	0.165	0.159	0.065
Soil fertility status	0.354**	0.173	0.137
Constant	-2.569***	0.757	-

***, **, and * denote significance at 1%, 5% and 10%, respectively. Log likelihood = -211.8; pseudo R² = 0.086.

with other empirical studies (see Ahmed, 2015; Anang, 2019; Deepa et al., 2015; Ghimire et al., 2015) on the adoption of agrarian technology, which points to a positive significant influence of formal education on farm technology adoption. On the other hand, farmers who allocated a higher proportion of their farmland to maize production were less likely to adopt improved varieties at 5% significance level. A unit increase in the proportion of land allotted to maize cultivation decreases the probability of adoption by 0.365. As farmers allocate a greater proportion of their farmland to maize cultivation, the cost of adoption is expected to rise, which may deter cash-constrained farmers from adopting IMVs.

Supply-driven factors like extension services and farmer-based organizations (FBOs) are critical avenues for information dissemination on productivity-enhancing inputs such as IMV. Smallholders' access to extension services enhanced technology adoption at 1% level, which confirms the findings of other studies (Kassie et al., 2015; Kijima & Sserunkuuma, 2013). The probability of adoption is 0.093 higher for farmers with access to extension than for their neighbours without extension access. However, being a member of a farmers' group was associated with a lower likelihood of adopting improved varieties, while farmers who perceived their soils to be fertile had a higher likelihood of IMV adoption. FBO membership decreased the probability of adoption by 0.13, while the probability of adoption was 0.137 higher for farmers who perceived their soils to be fertile relative to those who perceived their soils to be poor.

4.3. Results of the technical efficiency analysis

The bias-corrected efficiency estimates of the sampled rice farms under both CRS and VRS assumptions are presented in Table 4. Under CRS, TE ranged between 0.1 and 0.91, with a mean score of 0.52. With regard to farm efficiency under VRS, the original scores ranged between 0.21 and 1, with an average score of 0.72, while the estimated scores after bias correction ranged between 0.16 and 0.95, with a mean score of 0.57.

The findings are comparable to other studies. For example, Kirimov (2013) estimated non-bias and bias-corrected efficiency scores of 67% and 59%, respectively, for potato farms in Uzbekistan. However, our results are lower than those obtained from Abatania et al. (2012), where non-bias and bias-corrected TE scores of 86% and 77% were estimated for farms in northern Ghana. The results further reveal that 39% have TE scores not exceeding 50%, while 61% have efficiency scores exceeding 50%. Besides, 23.5% of the respondents had TE levels exceeding 70%. The results indicate

Table 4. Distribution of technical efficiency scores

Efficiency range	DEA CRS assumption		DEA VRS assumption	
	Freq.	Percent	Freq.	Percent
≤ 0.20	1	0.3	2	0.6
0.21–0.30	9	2.6	15	4.4
0.31–0.40	22	6.5	38	11.2
0.41–0.50	67	19.7	79	23.2
0.51–0.60	66	19.4	66	19.4
0.61–0.70	68	20.0	60	17.6
0.71–0.80	51	15.0	47	13.8
0.81–0.90	37	10.9	17	5.0
0.91–1.00	18	5.3	16	4.7
Total	340	100	340	100
<i>Efficiency scores</i>				
Mean	0.52		0.57	
Minimum	0.10		0.16	
Maximum	0.91		0.95	

that there is a large scope to enhance the TE of the respondents through improvement in resource allocation at the farm level.

4.4. Determinants of technical efficiency

Farmers’ managerial style and practices guide their less efficient counterparts in production; hence, the need to identify the drivers of inefficiency in production. The factors influencing TE are presented in Table 5. Although the results from both CRS and VRS are presented, the focus of the discussion will be on the result under the VRS assumption. This is because agriculture faces several external environmental and policy-driven conditions. Thus, it is not tenable to assume CRS for many farmers. The study followed Farrell’s (1957) input-oriented approach in estimating the TE of the respondents. Using this procedure, a positive coefficient of the explanatory variables corresponds to an increase in technical efficiency, and vice versa. To account for endogeneity of IMV adoption, the predicted adoption score rather than the actual (observed) value of adoption was used as the explanatory variable in the model.

The results indicate that adoption enhances technical efficiency. This result is supported by the findings of other authors such as Owusu (2016) who reported a 6%–8% increase in technical efficiency as a result of IMV adoption by Ghanaian smallholders. Similarly, Ahmed et al. (2017) observed that adopters of IMV in Ethiopia were 4.2% more technically efficient than non-adopters. Obayelu et al. (2016) also noted that Nigerian smallholders who adopted improved protein maize recorded higher technical efficiency than those who did not adopt.

Furthermore, years of formal education and farmers’ technical efficiency were inversely related at 1% significance level, suggesting that being less formally educated enhanced farmers’ technical efficiency. The result is at variance with a *priori* expectation but consistent with that of Anang et al. (2016) on rice production in northern Ghana. Similarly, household size and technical efficiency were inversely related at 10% significance level. The implication is that households with fewer members are more technically efficient, possibly because, an increase in household size puts pressure on the scarce cash resources available to the farm household. Moreover, the larger the size of the family, the larger the dependency ratio, which could lead to this finding. The result agrees with Mango et al. (2015), who found a negative association between the number of household members and technical efficiency of maize production in Zimbabwe.

Table 5. Truncated regression estimates of the determinants of technical efficiency ϕ

Variable	DEA CRS assumption		DEA VRS assumption	
	Coefficient	Bootstrap S.E.	Coefficient	Bootstrap S.E.
Adoption score	0.2014*	0.1188	0.2809**	0.1188
Age	−0.0041	0.0061	−0.0076	0.0059
Age squared	0.0000	0.0001	0.0001	0.0001
Years of formal education	−0.0057**	0.0028	−0.0086***	0.0029
Household size	−0.0006	0.0019	−0.0034*	0.0019
Farm size	0.0041	0.0039	−0.0146***	0.0042
Extension contact	−0.0138	0.0123	−0.0234*	0.0127
Farmer group membership	−0.0024	0.0225	0.0351	0.0234
Off-farm work	0.0012	0.0216	−0.0153	0.0221
Herd size	0.0085***	0.0023	0.0065***	0.0024
Frequency of weeding	−0.0939***	0.0244	−0.0706***	0.0247
Constant	0.7219***	0.1167	0.8669***	0.1181
Sigma	0.1607***		0.1629***	
Wald chi-squared	46.12***		47.06***	
Total sample	340		340	

***, **, and * denote significant levels at 1%, 5% and 10%, respectively. Note: 2000 bootstrap iterations were used.

Also, technical efficiency decreased with maize acreage at 1% significance level. This suggests that the scale of operations is crucial in production. Respondents with more extensive farmlands may be operating beyond their scope (decreasing returns to scale), which might lead to inefficient management of productive resources. Similar results have been observed by Etim and Udoh (2014) and Tien and Thong (2014) among crop farmers in Nigeria and Vietnam, respectively. However, the finding of Mango et al. (2015) is contrary to this study.

Contrary to a *priori* expectation, contact with agricultural extension agents had a negative influence on TE at 10% level. As emphasized by many empirical studies (Abdulai et al., 2017; Danso-Abbeam et al., 2018; Evenson, 2001; Gautam, 2000), agricultural extension service is a critical avenue for disseminating information on production technologies, which is expected to enhance productivity. On average, farmers received only one (1) extension visit during the cropping season, which could account for the negative influence of extension services on farmers' efficiency.

The results further indicate a positive influence of herd size on technical efficiency at 1% significance level. Hence, it is commendable to encourage smallholder farmers to keep livestock. The result agrees with a *priori* expectation because draught animals (especially cattle) are useful in smallholder farming systems where they are used in land preparation and carting of farm inputs, and provide manure for soil fertility improvement. Lastly, weeding frequency was negatively correlated with farmers' efficiency. The general recommendation for maize producers is to weed their farms twice. Hence, farmers who carried out more than two weeding activities used more resources than required, reducing their level of efficiency.

5. Conclusion and recommendations

In this study, we have estimated the influence of IMV on the TE of sampled farms in the Tolon District, Ghana. It was observed from the probit analysis that the probability of adoption of IMV is shaped by the combined effects of age, educational attainment, extension contact, membership of farmer group, and perception of soil fertility status. The results from

the DEA analysis showed a mean bias-corrected TE score of 57% under the VRS assumption. The result suggests that the output level could be increased by 43% without additional input requirements. The second-stage truncated regression estimates indicated that adoption of IMV improved the efficiency of the sampled farms in the study area. This suggests that adoption of IMV has been translated into improving the efficiency of maize production by the sampled farmers.

From a policy perspective, this study has two insightful findings that can serve as an empirical basis for the design and implementation of farm-level programmes. First, the fact that farmers' observed output lag behind their potential suggests that improvement in technical and managerial skills among these farmers is critical to boost the productivity of maize farms. Second, farmers should be encouraged to plant improved varieties to enhance their output and productivity levels. This could be achieved by ensuring that farmers have access to subsidized fertilizer and improved maize seeds. Finally, farmers need training on effective weed management to reduce the frequency of weeding.

Abbreviations

CRS	Constant returns to scale
DEA	Data envelopment analysis
DMU	Decision-making unit
FASDEP	Food and Agriculture Sector Development Policy
FNS	Food and nutrition security
GSGDA	Ghana Shared Growth and Development Agenda
IMV	Improved maize variety
MoFA	Ministry of Food and Agriculture
SFA	Stochastic frontier analysis
TE	Technical efficiency
VRS	Variable returns to scale

Acknowledgements

The authors are grateful to the farmers who participated in the study especially for their cooperation and willingness to provide information to the enumerators during the field survey.

Funding

The authors did not receive any direct funding to undertake this research.

Competing interests

Authors declare there are no competing interests regarding this research.

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Citation information

Cite this article as: Estimating technology adoption and technical efficiency in smallholder maize production: A double bootstrap DEA approach, Benjamin Tetteh Anang,

Hamdiyah Alhassan & Gideon Danso-Abbeam, *Cogent Food & Agriculture* (2020), 6: 1833421.

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