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Technology adoption intensity and technical efficiency of maize farmers in the Techiman municipality of Ghana

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This paper analyses the determinants of the intensity of adoption of improved maize technology, technical efficiency and constraints farmers faced in the Techiman Municipality of Ghana. To achieve the objectives, cross-sectional data were collected from 407 maize farmers. The data collected were analyzed using descriptive statistics and econometric models such as the Poisson model and the stochastic frontier model. The study found a positive and significant influence of extension contact, formal training, land ownership, hired labour, farm size and mobile phone ownership on the intensity of adoption of improved technology. The stochastic frontier model estimates also found maize farmers to be on, average, 70% technically efficient with increasing returns to scale of 1.26. The intensity of adoption, age, land ownership, livestock ownership and perception of soil fertility by the farmers with household size were found to statistically contribute to the technical efficiency of farmers. The study concludes that intensity of adoption of improved maize technology package elements increases productivity, and, therefore, recommends that subsidy packages and credit should be made available to farmers through government and other financial institutions to increase adoption intensity. This study addresses the gap in the use of improved and multiple maize technology in Ghana.

Keywords: Kendall coefficient, Poisson model, technology adoption, technical efficiency

Introduction

Agricultural production has become the source of livelihood for most African countries, including Ghana, due to the role it plays in food security, poverty reduction, and employment generation, and as a source of raw material for growing industries. Despite these massive contributions from the agricultural sector, a report by the World Bank (2015) suggests that sub-Saharan African (SSA) countries still lag behind other countries on the continent in terms of agricultural productivity. This makes it impossible for African countries to achieve food security and poverty reduction. This was confirmed by Mensah-Bonsu et al. (2017) who stated that the contribution of the agricultural sector in SSA countries is far behind expected potential levels. The study attributed the productivity gap to the inability of SSA countries to take advantage of the technological progress that is being experienced globally. This raises the question of how farmers in SSA countries can increase productivity through enhanced adoption of improved agriculture technology and modernized farm inputs.

The Ghanaian economy, like other African countries depends largely on the agricultural sector for its role in the growth and development of the country. From 2006 to 2009, the agricultural sector contributed over 30% to the country's GDP and also employed over 50% of the country's labour force during these periods. This was confirmed by World Bank (2010) country report, which indicated about 33.7% contribution of the agriculture sector to GDP and over 56% provision of livelihood of Ghana's total labour force. Also, 90% of Ghana's food needs are supplied by the agricultural sector, according to the Food and Agriculture Organization (FAO 2010). In recognition of the importance of agricultural production in Ghana, the Government through the Ministry of Food and Agriculture (MoFA) initiated long-term policy interventions geared towards improving growth in the agricultural sector. Notable among the policies were the Food and Agricultural Sector Development Policy (FASDEP I, 2007 and FASDEP II, 2010). In 2011, the Medium Term Agriculture Sector Investment Policy (METASIP) was adopted as the investment plan of FASDEP II, with the aim of intensifying the use of improved technologies in order to increase the productivity of selected crops (maize, cassava, rice, yam and cowpea) (MoFA 2010).

Cereals have been identified by Kuwornu, Suleyman, and Amegashie (2011) as the most widely consumed food in Ghana. This is seen by the total production of cereals of about 3 million tonnes in 2016 (FAO 2017). Among the cereals consumed in Ghana, maize is the largest food staple, accounting for at least 50% to 60% of overall cereal production, according to the 2015 report on complete curriculum and guide to maize production in Ghana (Voto 2015). It is one of the major food crops cultivated in large quantities in Ghana. As of 2014, it was the first staple food crop in the country and the second-largest food crop after cocoa with a planted area of 1,018,936 hectares (SRID & MoFA 2015). Maize production is mainly dominated by smallholder farming households who produce on a small scale and mostly reside in rural areas. Its cultivation serves as a staple crop for sales and food for human consumption as well as a feed for the poultry industry. Mashingaidze (2004) described maize as the major source of protein and calorie intake as well as a primary source of weaning for babies. A study conducted by Tweneboah (2000) also reported maize as a major determinant of household food security in Ghana.

In spite of the government's vision of agriculture modernization through the use of improved technology, agricultural productivity is still characterized by low improved technology adoption and technical inefficiency in production, leading to low productivity. Salifu, Alhassan, and Salifu (2015) however, reported that the prerequisite for achieving food security without food aids in Ghana is by increasing agricultural productivity through the use of improved agricultural technologies. Due to this, attempts were being made to increase farmers' adoption of improved technology, productivity and technical efficiency through cereal crops since they are the major contributors to agricultural production in Ghana. Several improved technology packages of seed, agronomic practices, timely harvesting, proper storage and applying chemicals on the stored grain in the storage crib have been recommended by CSIR and MoFA for use by farmers.

Thus, researchers have paid much attention to improved technology adoption in recent times, since it is believed to be the basis for production, increased productivity and income growth (Minten and Barrett 2008). To assess the impact of these technologies, several studies have been conducted by various researchers on how maize productivity can be increased through the use of improved maize technologies and efficient utilization of resources. For instance, Mensah-Bonsu et al. (2017) used the count data model to examine the intensity of adoption of land and water management practices in Ghana. The study found a positive influence of extension visits, credit, and the experience of severe food shortage on adoption with education and land per capita having a negative impact. Alhassan, Salifu, and Adebanji (2016) also studied the influence of farmer's socio-demographic and varietal characteristics of maize on adoption of improved maize varieties. Oppong, Onumah, and Asuming-Brempong (2016) estimated technical efficiency and production risk of maize production in Ghana and found that seeds, land, the cost of intermediate input and herbicides have decreasing returns to scale effect on maize output with a mean technical efficiency of 0.62. Kuwornu, Amoah, and Seini (2013) also investigated the technical efficiency of maize farmers in the Eastern Region. By employing a multi-stage sampling procedure, the study found the mean technical efficiency of the farmers to be 0.51 with negative returns to scale based on farm inputs such as seed, fertilizer, and family labour.

These studies, however, targeted the adoption of improved maize seed varieties and fertilizer use, and neglected other recommended agronomic practices in the improved maize technology package such as crop density and spacing, weed control, zero tillage and other soil fertility management practices that need to accompany the improved maize variety and fertilizer application in order to achieve maximum yield. However, findings by Aikins, Afuakwa, and Owusu-Akuoko (2012) have shown that adoption of an improved maize variety and chemical fertilizer application alone cannot solve the yield gaps that Ghana is currently experiencing. The study further proposed the need to evaluate farmers' adoption of recommended agronomic practices such as seeding rate and spacing, timely planting, proper crop density, weeds and pesticide control and other land use and management practices recommended in the improved maize technology package. MoFA (2011) also attributed the low production of maize in the country to the low technology adoption.

The huge yield gap between the actual and the potential yield of maize production in Ghana, calls for the need to address the low adoption of improved maize technology in Ghana (Wongnaa et al. 2019). The purpose of this study is to analyze the factors that determine the intensity of adoption of improved maize technology package elements and the technical efficiency achieved by farmers in the Techiman Municipality. The study further examines the sources of the technical inefficiency and the constraints farmers experienced in the adoption of the improved technology package. The Poisson regression model was used to study the intensity of adoption of improved maize packages while the stochastic frontier was employed in the estimation of the technical efficiency. This study contends that the partial adoption of the recommended CSIR maize technology packages suggests that the available technology is underutilized. Increasing intensity of adoption of the technology package elements and efficiency of farmers is essential, and a better option to grow outputs than introducing new maize technologies. This study adds to the extant literature on technology adoption and technical efficiency in Ghana (Abukari, Hussein, and Katara 2015; Alhassan, Salifu, and Adebanji 2016; Oppong, Onumah, and Asuming-Brempong 2016). It also fills the gap in the intensity of adoption of improved technology in Ghana.

Literature review

Technology adoption and determinants

Doss (2003) defined adoption as the prolonged use of suggested practices by farmers over an extended period of time. Dasgupta (1989), however, noted that adoption is not a perpetual behaviour by farmers. This is because, adopters can resolve to abolish their use of a given technology or innovation for various reasons such as personal characteristics, social, institutional characteristics and knowledge of a new technology that is more rewarding than the initial one. Adoption of improved agricultural technology has become a major concern in agricultural production in both developed and developing countries. It is believed that invention of an improved technology brings about a high adoption expectation by farmers or producers which play a vital role in agricultural productivity. Several studies have been undertaken on technology adoption and technical efficiency in developing countries. Most of these identified several factors that affect the adoption process based on the contextual applicability and underlying specific local condition in the study locales.

Wongnaa et al. (2019) examined the influencing factors of adoption of improved maize production technologies in Ghana using a multinomial model. The study found technology adoption to be influenced by educational level, age, agricultural extension contact, access to credit, initial capital outlay, experience, land fragmentation, group membership, and previous year's price of maize and availability of ready market. Mensah-Bonsu et al. (2017) used the count data model to examine the intensity of adoption of land and water management practices in Ghana. The study found a positive influence of extension visit, credit, the experience of severe food shortage on adoption, while education and land per capita had a negative influence on technology adoption. In a related study, Johnson (2013) used the count data to estimate the intensity of technology adoption of small-scale oil palm producers in the Western Region. Extension contact, access to credit, hired labour and type of shareholder were found to positively influence the intensity of technology adoption, which confirms the findings of Mensah-Bonsu et al. (2017).

Employing a panel dataset, Olwande, Sikei, and Mathenge (2009) examined the determinants and intensive use of fertilizer adoption in Kenya. The study observed a highly positive influence of age, gender, education of the farmer, dependency ratio, the presence of a cash crop, access to credit, distance to a fertilizer market and extension officer and agro-ecological potential on the adoption and intensive use of fertilizer. Similarly, a logit model was extensively used by Mureithi and Ojiem (2000) to assess the determinants of adoption of maize production technologies. The findings showed a positive influence of gender, hired labour, extension services and access to credit facilities on maize production technology adoption in Kenya. Kaliba, Verkuijl, and Mwangi (2000) also employed the Tobit and Probit models to examine the determinants of adoption of improved technologies such as maize seeds and inorganic fertilizer in Tanzania. The study found extension services availability, rainfall, variety characteristics and on-farm field trials and rainfall to have a significant influence on the intensity of adoption of improved technology.

Technical efficiency and determinants

Uri (2002) defined technical efficiency as the commensurable decrease in a number of inputs used by firms in order to achieve a given output level, measured as the efficient use of the input. Technical efficiency simply is the physical proportion of output to input. The larger the proportion obtained, the greater the achieved technical efficiency. To obtain the technical efficiency of a farmer, there is the need to equate the observed output of the farmer to its corresponding frontier output (potential output) based on a number of inputs used by the farmer (Ogundari and Ojo 2007). Farrell (1957) proposed a number of frontier models for efficiency measurement broadly classified into two categories, namely the parametric frontier technique and the non-parametric frontier technique. The parametric frontier technique is further divided into the deterministic frontier technique (Aigner and Chu 1968) and the stochastic frontier technique (Aigner, Lovell, and Schmidt 1977). Data envelopment analysis (DEA) has been widely used in relation to the non-parametric frontier technique (Coelli et al. 2005).

Past empirical studies employed either the parametric or the non-parametric techniques to measure efficiency (Endrias et al. 2010; Ephraim 2007). Aye and Mungatana (2011) and Headey, Alauddinb, and Rao (2010) used both efficiency techniques while paying keen attention to their predictive capability. The findings revealed distributional variations in the pattern of the estimated efficiency. Both studies, however, maintained the two approaches as the preferred choice for efficiency analysis. Coelli and Battese (1996) argued in favour of the parametric approach as the most suited for studies that are related to agriculture. The study justified its conclusion on the fact that exogenous factors and measurement errors are intrinsic in agricultural production and since the non-parametric approach does not account for them, it is most appropriate to prefer the parametric approach against the non-parametric approach.

Ahmed et al. (2018) evaluated the technical, economic and allocative efficiency of maize farmers in the Eastern Ethiopia with the help of a cross-section data from 480 maize plots. By employing stochastic production function fitted on a Cobb–Douglas production function, the study found the amount of seed, land and DAP (Diammonium phosphate) as the factors that influence maize production in the study area. The study further found the potential of farmers to increase economic efficiency to depend more on allocative efficiency than technical efficiency. Oppong, Onumah, and Asuming-Brempong (2016) estimated technical efficiency and production risk of maize production in Ghana and used 232 farms from the Brong–Ahafo Region. The study found a decreasing return to scale effect of seeds, land, the cost of intermediate input and herbicides on maize output with a mean technical efficiency of 0.62. While farm size contributes to technical inefficiency negatively, ploughing, on the other hand, affects technical inefficiency positively.

Kuwornu, Amoah, and Seini (2013) investigated the technical efficiency of maize farmers in the Eastern Region. By employing a multi-stage sampling procedure, they selected 226 farmers from four geographical areas. The study found the mean technical efficiency of the farmers to be 0.51 with negative returns to scale based on farm inputs such as seed, fertilizer and family labour. The study also found extension visit, farmer training in maize farming, membership of a farm-based organization, cash and in-kind credits and frequency of meetings of farm-based organizations as the main determinants of technical efficiency in the Eastern Region of Ghana.

Theoretical framework and empirical model

Technology adoption decisions by farmers are contingent on several factors. One of these factors is the utility farmers derive from making their adoption decisions. Farmers as rational consumers of improved agricultural technologies have been envisaged to select improved technology package elements that maximize their profitability. This study adopts the Von Neumann-Morgenstern's (VMN) Utility Theory propounded in 1947 which is the basis for an expected utility theory. By applying the Von Neumann-Morgenstern's Utility Theory, the study assumes that smallholder farmers are rational and thus decide to maximize their utility (Von Neumann and Morgenstern 1947).

According to Batz, Peters, and Janssen (1999), the expected utility from the adoption of a new technology is affected by the attributes of the technology (TC), characteristics of the farmer (FACH), the farming system (FSCH) and the farming circumstances (FC). By denoting the utility obtained from the new technology as *Un*, utility from the traditional technology as *Ut* and the adoption status of technology as D_i, the expected utility from the adoption of a new technology is modelled as:

$$Un = f(\text{TC},\ \text{FACH},\ \text{FSCH},\ \text{FC}) \tag{1}$$

$$D_i = 1 \quad \text{if} \quad U_n > U_t \quad \text{or} \quad (U_n - U_t > 0) \tag{2}$$

Farmers will adopt a new technology only if the returns from adoption are relatively high in terms of profit compared to the existing technology. Also, adoption will be possible in situations where the new technology has a relatively low risk compared to previous technology (Doss and Morris 2001).

Materials and method

Study area

This study was carried out in the Techiman Municipality, one of the 26 districts in the Brong-Ahafo region of Ghana which lies between latitude 8° 00′ N and 7° 35′ S and longitudes 1° 49′E and 2° 30′ W. With a total land area of 669. 7 km^2, the Municipality has a total population of 147,788 as of the 2010 Population and Housing Census, representing 6.4% of the total population in the region with a sex distribution of 51.5% males and 48.5% females. The Municipality has three vegetation zones, namely the Guinea Savannah Woodland, the Transitional zone and the Semi-deciduous zone located in the North-west, South-East and the North respectively. Both tropical conventional and Semi-Equatorial climates are experienced in the Municipality, which is characterized by moderate to heavy rains. Annual mean rainfall in the Municipality ranges from 1260 and 1600 mm with humidity of 75%–80% and 70%–72% during rainy seasons and dry seasons respectively and an average Temperature of 28°C. The majority of the people in the Municipality engaged in agriculture farming as their main source of livelihood. Apart from crops, the Municipality also reared livestock such as goat, sheet, guinea fowls and chicken. The Municipality has the largest market in the sub-region, which trades with traders from Togo, Benin and Burkina Faso thus making it an international market.

The study employs two different econometric tools to analyze the determinants of intensity of adoption of improved maize technology package elements and technical efficiency due to the dual nature of the objectives of the study. Most adoption studies have used the Logit and Probit model to estimate the determinants of technology adoption based on the dichotomous nature of the decision where ‘1’ represents adopters and ‘0’ for non-adopters (Assefa and Gezahegn 2010; Moti et al. 2013). A Multinomial model used by Moti et al. (2013) is best for evaluating more than two independent technologies adoption decisions while the Multivariate model employed by Hailemariam, Menale, and Bekele (2013) is useful for estimations involving more than two interdependent technologies adoption decisions.

A Count data analysis model which comprises of the use of the Poisson Regression Model (equi-dispersion), the Negative Binomial Regression Model (over-dispersion) or Gamma Distribution (under-dispersion) has been used intensively in previous studies in situations where multiple technologies are to be adopted. According to Sharma, Bailey, and Fraser (2011), the number of elements in a technology package adopted by a farmer is interpreted as the intensity of adoption when count data models are used. Extant literature that used the count data model for technology adoption employs parametric models such as the Poisson model and the Negative Binomial model. Mensah-Bonsu et al. (2017) and Sharma, Bailey, and Fraser (2011) employ the count data model to estimate the speed and intensity of technology adoption. Mensah et al. (2017) used the Poisson and Negative Binomial regression models to estimate the intensity of adoption of land and water management practices in Ghana using maize farmers as a case study.

This study adopts the Poisson regression model to analyse the determinants of the intensity of adoption of improved maize technology package elements after the Cameron and Trivedi (1990) test for over-dispersion was rejected. Elements in the package include improved and certified seed, fertilizer application, crop spacing and row planting, other soil fertilizer management practices, weed control and zero tillage.

Cameron and Trivedi (2009, 1998) and Greene (2003) defined the Poisson regression model as the foundation for count data analysis. It is used to estimate the decision of a farmer on the number of improved maize technology package to adopt. The likelihood of adopting *k* number of improved maize technology elements given *n* independent improved technology package element is represented by the binomial distribution:

$$P(Y = k) = \binom{n}{k} p^k (1 - p)^{n-k} \tag{3}$$

p is the probability of adopting the k maize technology, n is the number of technologies in the package, Y is the number of improved maize technology package elements that are adopted from the package. As n becomes large and p (probability of adoption) becomes small, repetition of a series of binomial choices supported by the random utility formulation converges to a Poisson distribution:

$$\lim_{n\to\infty} \binom{n}{k} p^k (1 - p)^{n-k} = \frac{e^{-\lambda}\mu^k}{k!} \tag{4}$$

The density function of the Poisson regression model is specified as:

$$f(y/x_i) = \frac{e^{-\mu_i}\mu^y}{y!} \tag{5}$$

where the mean parameter expressed as a function of the x_i and β is given as:

$$E(y/x_i) = \mu = \exp(x'\beta) \quad \text{and} \quad y = 0, 1, 2, \ldots..$$

$f(y)$ is the likelihood that y will take a non-negative integer value and μ is log- linear value assumed to be related to X_i.

This study, therefore, adopts the model used by Nkegbe and Shankar (2014) to estimate the intensity of adoption of improved maize technology package as:

$$\text{Prob}(Y_i \equiv y_i|x_i) \equiv f(x_i^p, x_i^{fc}, x_i^{si}) \quad (6)$$

$Y_i =$ Number of elements (count) adopted by farmer i; $x_i^p =$ Personal and household characteristics; $x_i^{fc} =$ Farm/plot and cropping characteristics; and $x_i^{si} =$ Socio-economic and institutional variables.

A farmer is said to be an adopter when he/she adopts at least one of the six (6) elements in the improved maize technology package and a full adopter when he/she adopts all the six (6) elements in the improved maize technology package. A farmer is, however, regarded as a partial adopter when he/she adopts one (1) to five (5) elements from the technology package (Table 1).

Determinants of intensity of adoption of improved maize technology package

The empirical regression model used in this study to examine the determinants of intensity of adoption of elements in the improved maize technology package is specified as:

$$\begin{aligned} \text{ADOPT}_i = {} & \beta_0 + \beta_1\text{GEN} + \beta_2\text{AGE}_i + \beta_3\text{EDUF}_i \\ & + \beta_4\text{EXVISIT}_i + \text{B}_5\text{HHS}_i \\ & + \beta_6\text{FTRAIN}_i + \beta_7\text{LANOWN}_i \\ & + \beta_8\text{HLABOUR}_i + \beta_9\text{ACRED}_i \\ & + \beta_{10}\text{FBO} + \beta_{11}\text{OMP}_i + \beta_{12}\text{DMC}_i \\ & + \beta_{13}\text{PPERCEPTION}_i + \beta_{14}\text{TFSi} + u_i \end{aligned} \quad (7)$$

Technical efficiency analysis

Measurement of technical efficiency compares the actual performance to the optimum performance (true frontier). Empirically, the true frontier is not known; hence, the best-practice farmer is used mostly as a proxy for the true frontier. This study employed the parametric approach (stochastic frontier approach) to estimate the technical efficiency of maize farmers in the Techiman Municipality in the Brong–Ahafo Region of Ghana. Selection of the stochastic frontier approach is based on its ability to account for stochastic noise and producer's inefficiency at the same time.

The stochastic frontier production model that Battese and Coelli (1995) propounded in line with the original model by Aigner, Lovell, and Schmidt (1977) is specified as:

$$Y_i = f(X_i; \beta) \quad \exp \quad (v_i - u_i) i = 1, \ 2, \ 3, \ \ldots, n \quad (8)$$

$n =$ the farmers in the cross-sectional survey; $Y_i =$ the output level of the i^{th} farmer; $X_i =$ vector of input quantities from the i^{th} farmer; $v_i - u_i =$ disturbance error where v_i is normally distributed with mean zero and constant variance: $N(0, \sigma_v^2)$, (Coelli et al. 2005) and u_i is a truncated normal distribution with mean μ_i and variance σ_u^2. The parameters of the variance are estimated as: $\sigma^2 = \sigma_u^2 + \sigma_v^2$

$$TE_i = \frac{Y_i}{Y_i^f} = \frac{f(X_i; \beta) \exp (v_i - u_i)}{f(X_i; \beta)\exp(v_i)} = \exp(-u_i) \quad (9)$$

Y_i is the observed output, Y_i^* is the frontier output and the technical efficiency assumed the value between zero and 1, $(0 \leq TE_i \leq 1)$. If $u_i = 0$, it implies $Y_i = Y_i^f$, depicting that the farmers are technically efficient (100% efficient).

Gamma $(\gamma) = \frac{\sigma_u^2}{\sigma^2}$ and it specifies the error that is associated with the technical inefficiency estimates. It ranges from zero (0) to one (1). Where $\gamma = 1$, deviations from the frontier are said to be due to technical inefficiency. Also, $\gamma = 0$ implies deviations are caused by noise effect whilst $0 < \gamma < 1$ means both stochastic and non-stochastic errors are present in the data.

Table 1: Description of variables used in the Poisson model.

Dependent variable	Description of variable	
ADOPTION	Number of improved maize technology package elements adopted by farmer *i*	
Independent variables	Description of variables	Expected sign
GEN	Gender of the farmer	+/−
AGE	Age of the farmer in years	−/+
EDUF	Years of schooling of the farmer	−/+
EVISIT	Extension contact	+
HHS	Household size	+
FTRAIN	Formal training	+
LANOWN	Land ownership by the farmer	+
HLABOUR	Availability of hired labour	+
ACRED	Access to credit	+
FBO	Member of farm-based organizations	+/−
OMP	Ownership of mobile phone	+
DMC	Distance to input market	−
PPERCEPT	Perception of price of improved maize technology package	−
TFS	Total farm size	+

For the production function form, this study employed the translog production function as specified by Battese and Broca (1997).

$$\ln Q_{ij} = \beta_0 + \alpha_1 \mathrm{DDF}_i + \alpha_2 \mathrm{DDA}_i + \sum_{n=1}^{5} \beta_i InX_i + \frac{1}{2}\sum_{n=1}^{5}\sum_{m=1}^{5} \beta_{nm} InX_n InX_m + \varepsilon_i \quad (10)$$

Q_i = Total output per hectare measured in kilogrammes per hectare (Kg/Ha); DDF = Dummy for fertilizer (1 if fertilizer is used, 0 if not used); DDA = Dummy for agrochemical (Dummy, 1 if agrochemical is used, 0 if not used); X_1 = Fertilizer use, measured in Kg/Ha, X_2 = Agrochemical (Pesticides and herbicides), measured in Litres/Ha, X_3 = Quantity of Seed, measured in Kg/Ha; X_4 = Labour, measured in Man-days/Ha, X_5 = Farm size, measured in Hectare; β_j = Parameters to be estimated, $\varepsilon_i = v_i - u_i$.

According to Onumah and Acquah (2010), lack of inclusion of dummies for fertilizer and agrochemicals in the production function is likely to make the coefficient of responsiveness of fertilizer and agrochemicals to maize output biased.

The productivity level of individual inputs (partial elasticity of output) with respect to the inputs from the translog production function is computed as:

$$\varepsilon_q = \frac{\partial InE(Q_i)}{\partial InX_{ji}} = \left\{ \beta_j + \beta_{jj} InX_{ji} + \sum_{i=1}^{5} \beta_{nm} InX_{nm} \right\} = \beta_j \quad (11)$$

Since the coefficients of the translog production function cannot be interpreted directly as elasticity, the variables are rescaled into unit means. As a result of the rescaling, the square term of β_{jj} and β_{jk} equate to zero, whereas β_j is interpreted as elasticities.

This study uses the firm's output elasticity to determine whether the firm is exhibiting constant, decreasing or increasing returns to scale. The summation of the overall partial elasticity equals the returns to scale (RTS). It is specified mathematically as:

$$RTS = \sum \varepsilon_q \quad (12)$$

$RTS = 1$, implies constant returns to scale. $RTS > 1$, increasing returns to scale; $RTS < 1$, decreasing returns to scale.

Empirical model specification for technical inefficiency model

The technical inefficiency model for this study is specified as:

$$\mu_i = \delta_0 + \sum_{i=1}^{13} \delta_i Z_i \quad (13)$$

where Z_i, $i = 1, 2, \ldots, 13$ are the technical inefficiency factors which are defined as adoption, gender, age, age square, formal education, household size, livestock ownership, land ownership, soil fertility perception, extension contact, distance to market centre, farm-based organizations and access to credit.

Data source

The data used for the analysis were sourced from a cross-section questionnaire that was administered to 408 maize farmers in the Techiman Municipality for the 2016 major maize cropping season. The study found one (1) questionnaire to be incomplete and it was rejected, thus 407 maize farmers were used for the analysis. Four stage sampling technique was adopted to collect data. The first stage involved a purposive sampling of the Techiman Municipality as one of the leading maize growing areas in the country. The second stage involves a selection of 6 major maize growing areas in the Municipality out of a total of 9 operations areas. At the third stage, 40 major maize producing communities were selected from the six (6) operational areas while the last stage saw the sampling of 408 farmers through stratified sampling. The questionnaire which has both closed-ended and open-ended questions was augmented with key informant interviewed and focus group discussions to access the authenticity of the information collected from the farmers.

Results analyses and discussion

Descriptive statistics

Results from Table 2 shows the demographic statistics of the variables used in the regression models in the study. They include age, gender, educational level, labour source, formal training in maize farming, extension contact, access to credit, membership of farm-based organization, ownership of the mobile phone, livestock and land. Statistics from Table 2 show that men dominated maize production in the Techiman Municipality with 81%. This is basically due to the fact that maize production is labour intensive as well as cost intensive leading to low participation of women. The results also show that about half of the farmers interviewed do not have formal education which is followed closely by MSLC/JHS with about 31%. The majority of the farmers (96%) have farming as their main occupation while 61% of the farmers employed hired labour for their farming activities. In addition, about 24% of the farmers received credit either from the bank, friends and families or in kind during the 2016 major maize cropping season while about 57% of the farmers were members of farm-based organizations.

It can be observed from Table 3 that total maize production in Techiman Municipality has a mean value of about 1303 which ranges from about 111 to 6227. This is lower than the 1800 kg/ha obtained by Wongnaa et al. (2019). Total fertilizer applied by the farmers also ranges from 0 to 618 kg/ha with an average value of about 112 kg/ha. The mean value of fertility is also lower than the 140 kg/ha obtained in a study by Wongnaa et al. (2019) for maize farmers in the various zones in Ghana. Agrochemical which comprised of the

Table 2: Socioeconomic characteristics of the farmer.

Socioeconomic variable	Item	Frequency	Percentage (%)
Age	15–35	96	23.59
	36–60	262	64.37
	61–80	49	12.04
Gender	Male	331	81.33
	Female	76	18.67
Educational level	No schooling	204	50.12
	Primary school	52	12.78
	MSCL/JHS	127	31.20
	SHS/Voc/Tech	21	5.16
	Tertiary	3	0.74
Labour source	Hired labour	250	61.43
	Family labour	129	31.70
	Exchange	26	6.39
	Others	2	0.49
Occupational status	Main	392	96.31
	Minor	15	3.69
Formal training in maize farming	Yes	307	75.43
	No	100	24.57
Extension contact	Yes	333	81.82
	No	74	18.18
Access to credit	Yes	97	23.83
	No	310	76.17
Membership of farm-based organizations	Members	230	56.51
	Non-members	177	43.49
Ownership of mobile phone	Yes	45	11.06
	No	362	88.94
Livestock ownership	Yes	141	34.64
	No	266	65.36
Land ownership	Family	282	69.29
	Hired	125	30.71

total amount of weedicides and herbicides also have a mean value of 7 litres/Ha with seed quantity (kg/ha), labour (man–days/ha) and farm size (hectares) averaging at about 22, 305 and 2 respectively. The value of agrochemical, seed and labour for this study was, however, higher than the 5.1, 18 and 64 obtained for agrochemical, seed and labour respectively by Wongnaa et al. (2019).

Intensity of adoption of improved maize technology package

The study uses the responses derived from the number of elements adopted by each farmer to construct the dependent variable for the Poisson regression model. Analysis of the data showed that 97% of the farmers are aware of at least five (5) elements of the package. Only 0.25% of the farmers were aware of one element from the package. The number of elements adopted ranges from 0 to 6 where '0' means no adoption and '6' for full adoption. Results from Table 4 show that only 14% of the farmers adopted all the six (6) elements from the package, whereas 2% of the farmers did not adopt any of the elements from the package. The majority of the farmers adopted at least four of the elements of the improved maize technology package with improved seed, other soil fertility management and weed control as the most adopted elements. This implies that farmers adopted improved seed while neglecting other agronomic practices that come with the improved maize technology package. The results concur the findings of Batz, Peters, and Janssen (1999) who carried out a study in Embu District and found that farmers in the District adopted the improved maize variety, but either partially or fully ignored the agronomic practices that come with the package.

Table 3: Summary statistics of variable in the stochastic frontier model and other socioeconomic variables.

Variable	Unit	Mean	Std. D.	Minimum	Maximum
Output	Kg/Ha	1302.952	727.6152	111.1973	6227.046
Fertilizer	Kg/Ha	111.8147	145.1201	0	617.7625
Agrochemical	Litres/Ha	6.8939	5.4126	0	23.06313
Seed quantity	Kg/Ha	22.09646	6.744774	8.236834	88.9578
Labour	Man- days/Ha	304.6112	221.3931	13.6402	963.7095
Farm size	Hectares	1.781813	1.394072	0.4046863	10.11712
Household size	Number	5.7961	3.4627	1	30
Distance to market centre	Hours	1.4326	1.0382	0	5
Extension visit	Number	6.8010	10.3718	0	48
Years of schooling	Years	4.1793	4.6056	0	20

Table 4: Intensity of adoption of improved maize technology package.

Number of elements adopted	Number of adopters	Percentage of adopters
0	7	1.72
1	5	1.23
2	18	4.42
3	104	24.82
4	120	31.20
5	95	22.36
6	58	14.25
Total	407	100.0

Empirical results

Determinants of adoption intensity of improved maize technology package

The study failed to reject the post-estimation test for the equality of the mean and the variance from the Stata diagnostics test. The study, therefore, employed the Poisson regression model to estimate the determinants of adoption of improved maize technology package elements (Table 5).

Results as presented in Table 6 indicates extension contact, formal training, land ownership, hired labour, membership of farm-based organizations, mobile phone ownership, distance to market centre, perception of price of the improved maize package and farm size as the main factors that significantly influence the intensity of adoption of improved maize technology package adoption.

Extension contact was found to have a positive influence on intensity of adoption of improved maize technology package elements at 1% level of significance. As farmers have regular contact with extension officers, they receive reliable and timely information on improved technologies which affects their likelihood of technology adoption positively and stimulates their adoption decisions. This finding is consistent with a study conducted by Tura et al. (2010) in Central Ethiopia who found a positive influence of extension contact on improved technology adoption and explained that farmers obtain valuable information when they have regular contact with extension officers. The finding also revealed a positive and significant influence of formal training on intensity of technology adoption at the 5% level of significance. This result concurs with the finding obtained by Kuwornu, Amoah, and Seini (2013) in Ghana and Fikru (2009). According to Fikru (2009), formal training of farmers is an awareness creation platform that encourages farmers to adopt improved maize technology.

The study also found a highly positive and 1% influence of hired labour on the intensity of adoption of improved maize technology package elements. Since adoption of improved maize technology is labour intensive, farmers who have access to hired labour are more likely to adopt improved maize technology. Farmers are able to supplement their family labour with hired labour in order to adopt more improved maize technology. This is consistent with Johnson's (2013) study who found a positive result among oil palm producers in the Western Region of Ghana. Ownership of mobile phone also determined the intensity of adoption of improved technology positively at the 5% level of significance. Farmers who own a mobile phone and use it to access production and market information enriched themselves with better information which increases their technology adoption likelihood. This study agrees with similar results obtained by Kaba (2016) and Solomon et al. (2011). Farm size on the other hand also influenced the intensity of improved technology adoption positively at the 1% level of significance. Farmers with large farm size have a high probability of adopting more elements from the improved maize technology package since large farm holdings come with larger financial resources which enable farmers to devote more lands to improved technology adoption. This result conforms with similar results obtained by Abdul-hanan, Ayamga, and Donkoh (2013) in Ghana.

Land ownership, farm-based organization, distance to market centre and price perception were also found to significantly influence the intensity of adoption of improved maize technology package elements negatively, at 1%, 5%, 1% and 10% level of significance respectively. Farmers who use family-owned lands usually do not have the needed capital to purchase improved technology since most of them operate on a small scale and in some cases subsistence level. This study, however, contradicts the positive, but insignificant results obtained by Mensah et al. (2017) who believed farmers with their own land devoted more lands to improved technology adoption. Interestingly, membership of farm-based organizations has a negative effect on the intensity of technology adoption which contradict the positive sign expected. Where farm-based organizations focus more attention on collecting dues and bargaining for good prices with little time to educate group members about the right technology to adopt, farmers are less likely to receive information about improved technology leading to low or no adoption. The result, however, contradicts the positive finding obtained by Abdul-hanan, Ayamga, and Donkoh (2013) in Ghana.

The negative result obtained for distance to the market centre met its expected sign. Farmers who are closer to the input market centre have low transportation costs in accessing improved maize technology package elements which gives them a greater likelihood of adopting more elements from the package. Mulugeta (2011) also found

Table 5: Test for equality of the mean and variance.

Variables	Test statistics	*P*-Value	Decision
Goodness-of-fit	153.9654	Prob > chi2 (392) = 1.0000	Accept H_0
Pearson good-ness-fit	127.1154	Prob > chi2 (392) = 1.0000	Accept H_0

Table 6: Determinants of Intensity of improved maize technology package.

Variable	Coefficient	Robust S.E	p-value
Constant	1.2630***	0.1268	0.000
Gender	0.0230	0.0413	0.577
Age	−0.0007	0.0013	0.587
Education	0.0030	0.0032	0.350
Household size	−0.0024	0.0042	0.559
Credit	0.0363	0.0354	0.305
Extension contact	0.1813***	0.0518	0.000
Formal training	0.0808**	0.0325	0.013
Land ownership	−0.1350***	0.0331	0.000
Hired labour	0.0785***	0.0284	0.006
Farm-based org.	−0.0724**	0.0367	0.049
Mobile phone	0.0837**	0.0328	0.011
Distance to market centre	−0.0436***	0.0160	0.006
Price perception	−0.0602*	0.0320	0.060
Farm size	0.0312***	0.0096	0.001
Number of observations	407		
Pseudo R^2	0.0270		
Wald chi^2	0.0000		
Wald chi^2 (14)	134.33		
Log pseudo likelihood	−728.4201		

***$p < 0.001$; **$p < 0.05$; *$p < 0.1$

a negative influence of market distance on the intensity of adoption of improved technology in Dale Woreda. The negative result of price perception on the intensity of technology adoption is an indication of how essential price is in the intensity of technology adoption decision-making. Farmers who perceive the price to be high are less likely to adopt more elements from the package than their counterparts. This result is consistent with similar findings by Wandji et al. (2012) who noted that the perception about the characteristics of a new technology has a significant effect on its adoption.

Technical efficiency analysis

Test carried out to determine the appropriate functional form for the stochastic frontier model rejects the Cobb–Douglas production function in favour of the translog functional form at 1% level of significance. The results of the hypothesis tested are presented in Table 7. The hypothesis for the absence of inefficiency effects in the model was also rejected at the 1% level of significance. The study also rejects the hypothesis that the inefficiency model is zero while accepting the hypothesis which specifies the absence of an intercept from the model and analysis.

Estimates of the maximum likelihood analysis found seed quantity, labour and farm size to be positive and significant 5%, 1% and 10% levels of significance respectively. Thus, farmers are more likely to achieve greater output when higher amount of input such as seed, labour and farm size is employed. Wongnaa et al. (2019) also found a positive influence of seed, labour and farm size on maize output in the Guinea Savannah, Transition, Forest and Costal Savannah zones of Ghana. The study also found fertilizer square, agrochemical square, seed quantity square, fertilizer by labour, fertilizer by farm size, seed by labour and seed by farm size to be significant, thus justifying the use of the translog production function. The study further found seed quantity to have the highest coefficient of 0.4504, which implies a 1% increase in the quantity of seed per hectare will increase output by 0.4504%. The positive result for seed quantity and the highest coefficient value concurs with a similar result obtained by Essilfie, Asiamah, and Nimoh (2011) who found a positive and high coefficient value between the quantity of seed used and total output of small-scale maize production in the Mfantseman Municipality of Ghana. While the recommended seed per hectare of land is approximately 25 kg (USAID/IFDC 2015), the study found the average rate of seeds planted per hectare to be approximately 22 kg/ha which shows most farmers do not follow the recommended rate of seed adoption.

Mean technical efficiency was found to be approximately 70% on average, which ranges from 0.09 to 0.93. Thus, maize output of farmers could have likely

Table 7: Results of hypotheses tested.

Null hypothesis	Test statistics	Degree of freedom	Critical value	Decision
1. H_0: $\beta_{nm} = 0$	51.350	15	30.578***	Reject H_0
2. H_0: $\gamma = \delta_0 = \delta_1 = \ldots = \delta_{13} = 0$	73.965[a]	15	37.005	Reject H_0
3. H_0: $\gamma = 0$	4.996[a]	1	2.706	Reject H_0
4. H_0: $\alpha_1 = \alpha_2 = 0$	1.542	2	9.210***	Accept H_0
5. H_0: $= \delta_1 = \ldots = \delta_{13} = 0$	66.434	13	27.688***	Reject H_0

Source: Author's compilation from the Survey Data, 2017. [a]Values are a test of one-sided error. The critical values for all test involving γ are obtained from Table 1 of Kodde and Palm (1986, 1246) whilst the critical values for the rest of the hypotheses are obtained from Chi-Square Table. *** represents 1% level of significance.

Table 8: Maximum likelihood estimates of the stochastic frontier model.

Variables	Parameters	Coefficient	Std Err.	*z*-stats	*p*-value
Constant	β_0	5.6154***	0.1668	33.67	0.000
LnFertilizer/hectare	β_1	−0.2260	0.1511	−1.50	0.135
LnAgrochemicals	β_2	−0.1882	0.1327	−1.42	0.156
LnSeedquantity/hectare	β_3	0.4504**	0.2071	2.17	0.030
LnLabour/hectare	β_4	0.3886***	0.1184	3.28	0.001
LnFarmsize	β_5	0.4174***	0.1493	2.80	0.005
0.5 $(\text{LnFertilizer})^2$	β_6	0.3553***	0.1150	3.09	0.002
0.5 $(\text{LnAgrochemical})^2$	β_7	0.1324*	0.0763	1.73	0.083
0.5 $(\text{LnSeedquantity})^2$	β_8	−0.6584***	0.2422	−2.72	0.007
0.5 $(\text{LnLabour})^2$	β_9	0.0606	0.0850	0.71	0.476
0.5 $(\text{LnFarmsize})^2$	β_{10}	0.0782	0.1116	0.70	0.483
LnFertilizer*LnAgrochem	β_{11}	0.0502	0.0397	1.26	0.206
LnFertilizer*LnSeedquan	β_{12}	0.0848	0.1027	0.83	0.409
LnFertilizer*LnLabour	β_{13}	0.0839*	0.0446	1.88	0.060
LnFertilizer*LnFarmsize	β_{14}	0.1577***	0.0497	3.17	0.002
LnAgrochem*LnSeedquan	β_{15}	0.0787	0.1307	0.60	0.547
LnAgrochem*LnLabour	β_{16}	−0.0336	0.0519	−0.65	0.518
LnAgrochem*LnFarmsize	β_{17}	−0.0317	0.0552	−0.57	0.565
LnSeedquan*LnLabour	β_{18}	−0.4778***	0. 1261	−3.79	0.000
LnSeedquan*LnFarmsize	β_{19}	−0.5807***	0.1429	−4.06	0.000
LnLabour*LnFarmsize	β_{20}	−0.0289	0.0809	−0.36	0.721
Sigma square	0.8724				
Gamma	0.9007				
Mean technical efficiency	0.6973				
Log likelihood	−266.857				
Wald $\text{chi}^2(20)$	174.39				

***$p < 0.001$; **$p < 0.05$; *$p < 0.1$

increased if farmers had operated at the optimal output scale. This finding confirms similar results obtained by Abdulai, Nkegbe, and Donkoh (2018) and Wongnaa et al. (2019) in Ghana. The study also found a gamma (γ) value of 0.9007. This portrays that 90% of the variation in output that the farmers obtained was due to inefficiency with random effects accounting for the remaining 10% (Table 8).

Productivity analysis

The degree to which total maize output responds to a change in any of the inputs used in production is essential in analyzing how productive the inputs are in increasing total maize output. Since the production inputs are estimated at the mean, the coefficient obtained from the stochastic frontier model becomes the input elasticity. The study records return to scale of 1.26%, which indicates an increasing return to scale as presented in Table 9. A variation of all inputs in the same proportion of 1% is expected to lead to 1.26% increase in total output. This implies that the use of more inputs of seed, labour and farm size would increase maize output to an efficient level in the Techiman Municipality. The result of increasing return to scale is consistent with the results of a study by Wongnaa et al. (2019) who also found an increasing return to scale among maize farmers in Ghana. The study further shows productivity to be highly responsive to the quantity of seed used which is an indication that productivity is more responsive to seed than labour and land. This result is in conformity with the assumption of Kibaara (2005) which noted that there is a likelihood for maize farmers to improve their maize productivity when they make use of improved seed varieties.

Table 9: Elasticity of production and returns to scale.

Variables	Elasticity	*P*-value
Seed quantity/hectare	0.45	0.030**
Labour/hectare	0.39	0.001***
Land	0.42	0.005***
Returns to scale	1.26	

Determinants of technical inefficiency of maize farmers

Table 10 shows the estimates of the determinants of technical inefficiency of maize farmers in the Techiman Municipality. Adoption, which is a weighted sum of the number of improved technology package elements adopted by the farmers, has a negative coefficient as hypothesized and has a highly significant influence on technical efficiency at the 1% level of significance. This implies maize farmers who adopt more elements from their package accompanied with other best practices of farming are technically more efficient. Abdul-hanan, Ayamga, and Donkoh (2013) and Johnson (2013) found similar results in Ghana and Western Region respectively. The study also found age to influence technical inefficiency negatively, at the 5% level of significance, which implies that older farmers are more technically inefficient compared with younger farmers. Kuwornu, Amoah, and Seini (2013) also confined similar result among maize farmers in the Eastern Region of Ghana.

The negative result of the soil fertility perception at 1% level of significance shows farmers who perceived their soil to be less fertile are more technically inefficient compared with those who perceived their soil to be fertile. Farm ownership also presents a negative influence on

Table 10: Determinants of technical inefficiency.

Variables	Coefficient	Standard Err.	*z*-value	*p*-value
Constant	3.6839***	1.0316	3.57	0.000
Adoption	−1.9637***	0.4784	−4.10	0.000
Gender	−0.1073	0.1961	−0.55	0.584
Age	−0.0944**	0.0405	−2.33	0.020
Age-square	0.0009**	0.0004	2.25	0.024
Formal education	−0.0267	0.0184	−1.46	0.145
Household size	0.0402*	0.0238	1.69	0.092
Extension contact	−0.1614	0.2192	−0.74	0.462
Credit access	−0.1564	0.1873	−0.84	0.404
Farm-based organization	0.2774	0.2052	1.35	0.177
Distance to market centre	0.1762**	0.0840	2.10	0.036
Soil fertility perception	−0.5006***	0.1670	−3.00	0.003
Land ownership	−0.5211***	0.1893	−2.75	0.006
Livestock ownership	−0.2967*	0.1612	−1.84	0.066

***$p < 0.001$; **$p < 0.05$; *$p < 0.1$

technical inefficiency at the 1% level of significance, suggesting farmers who grow maize on their own lands are more efficient compared with those who used other forms of land. Farmers who plant on their own lands devote more time to their farming activities which translates into increased productivity since they own everything harvested from their crops. Johnson (2013) also found a negative effect of land ownership on technical inefficiency in the Western Region of Ghana. In addition, livestock ownership influenced technical inefficiency negatively, at the 10% level of significance. Farmers who reared livestock in addition to their farming activities were more efficient technically. Ownership of livestock is used as a proxy for measuring the wealth status of farmers. It is also a source of fertilizer manure and income for the purchase of farm inputs and improved technology. Thus, farmers who possess a large number of livestock tend to be technically more efficient. Kaba (2016) also found a negative effect of livestock ownership on technical inefficiency in South-Western Ethiopia.

Household size, the distance to market centre and age square on the other hand have a positive influence on technical inefficiency at the 5%, 10% and 5% levels of significance, respectively. The result of household size corroborates what Yiadom-Boakye et al. (2013) found in the Ashanti Region of Ghana. Though a large household size is regarded as an increased source of family labour for farm activities, it also has the disadvantage of increasing the financial burden on farmers in relation to the consumption expenses of household members and other upkeeps. An increase in the financial obligation of farmers towards their household reduces the number of resources available for farm activities, which increases the technical inefficiency level tremendously. The positive sign of the distance to market centres also met its expected sign and is statistically significant at the 5% significance level. As market distance increases, farmers find it more difficult to easily purchase agriculture inputs and raw materials they need for their farming activities. It also increases the cost of transporting these goods and services to the farm site which makes it difficult for farmers to effectively manage their operations efficiently. Thus, farmers closer to market centres are more efficient technically. This finding confirms the results obtained by Kaba (2016). Abdul-hanan, Ayamga, and Donkoh (2013), however, found a negative influence of market distance to technical inefficiency. According to the study, technical efficiency goes beyond proximity to an input market. It demands undivided attention and whether farmers live in rural, peri-urban areas or urban areas is immaterial.

Table 11: Ranking of constraints faced by maize farmers.

Constraints	Mean rank	Rank
Low selling price of maize	2.15	1
Low rainfall	2.55	2
High input price	2.82	3
Lack of credit	4.90	4
Low soil fertility	5.16	5
Insecure land tenure systems	7.35	6
Shortage of improved seed	7.43	7
Inadequate government incentives	7.45	8
Lack of extension contact	8.54	9
Pest and disease outbreaks	8.62	10
Lack of harvesting and drying equipment	9.02	11
Sample size	407	
Kendall's W	0.611	
Chi-Square	2486.187	
Degrees of freedom	10	
Significance level	0.000***	

***$p < 0.01$

Age square also has a positive influence on technical inefficiency at the 5% level of significance. For every additional year in age, farmers become less productive, which affects their output level and level of technical efficiency. The negative coefficient is in conformity with a similar study by Kuwornu, Amoah, and Seini (2013) who also reported a negative influence of age on technical inefficiency. It, however, contradicts findings by Essilfie, Asiamah, and Nimoh (2011) and Coelli and Battese (1996) who reveal that younger farmers tend to be more reluctant to adopt improved technology and new ways of farming which makes them less efficient.

Estimates from Table 11, which presents the constraint ranking of the maize farmers in the Techiman Municipality, indicates low selling price, low rainfall, high input price and lack of credit as the four most severe constraints out of the 11 constraints listed that maize farmers faced. Other constraints, in descending order, include low soil fertility, insecure land tenure systems, a shortage of improved seed, inadequate government incentives, lack of extension contact, pest and disease outbreaks, and, lastly, lack of harvesting and drying equipment. Results from the Kendall's Coefficient of Concordance also reject the null hypothesis that no agreement exists among the rankings of the farmer at the 1% level of significance with approximately 61% agreement in ranking.

Conclusion and recommendation

The objectives of this study were to analyze the factors that determine the intensity of adoption of an improved maize technology package and the technical efficiency achieved by farmers in the Techiman Municipality. The study also aimed to examine the sources of the technical inefficiency and the constraints maize farmers experienced in the adoption of the improved technology package elements. The Poisson model was employed to achieve the first objective while the stochastic frontier model was used to address the second and third objectives. The fourth objective was estimated using the Kendall Coefficient of Concordance. The study found extension contact, formal training, land ownership, hired labour, farm-based organization, mobile phone ownership, distance to market centre, price perception, and farm size as significant policy variables that influence adoption of improved maize technology package elements in the Techiman Municipality of Ghana. Seed quantity, labour and farm size also emerged as the significant variables that influence productivity, whereas age, age-square, household size, distance to market centre, soil fertility perception, land and livestock ownership contribute significantly to technical inefficiency.

The majority of the farmers were, however, producing on average at 70% of capacity, indicating that they are not operating on the frontier. The implication is that farmers could increase output by 30% if the full set of inputs were employed at their optimal scale. Hence, farmers in the Techiman Municipality were found to be scale inefficient. This resulted in a productivity estimate exhibiting increasing returns to scale of 1.26, indicating a fall in output below the optimal level. The study proposes an all-inclusive approach in policy formulation to increase the intensity of adoption of package elements by farmers to nullify the remaining 30% deficit, with priority given to technical efficiency. Furthermore, there is a need to increase extension contact, provision of incentives to encourage the youth to go into farming, farm-based organizations and improved seeds to enable farmers operate at the optimal scale. Farmers are advised not only to increase their use of farm inputs, but to use them at the recommended rate in order to obtain maximum output from the package elements. The study recommends that farmers be encouraged through incentive packages to adopt more elements from the improved maize technology package since evidence has shown that adoption increases productivity as well as moving farmers closer to the frontier output. Since scale efficiency of maize farmers is higher than their technical efficiency, the study recommends that policies are targeted at encouraging farmers to use improved maize technology and agronomic practices to increase their technical efficiency of maize production. Also, these policies should be geared more towards enhancing technical efficiency than scale efficiency. Thus, where divergent effects exist between adoption intensity and technical efficiency of output, technical efficiency should be accorded higher priority since adoption is only a means to achieving technical efficiency of output. Due to the unavailability of farm-level panel data, this study was carried out with the help of a cross-sectional data. Since a cross-sectional analysis is limited in tracing scale efficiency dynamics, this study recommends future researchers to explore the dynamics of scale efficiency through farm-level panel data in order to track efficiency of farmers over time.

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