RAAE

Review of Agricultural and Applied Economics
The Successor of the Acta Oeconomica et Informatica
***ISSN 1336-9261, XIX* (Number 2, 2016): 39–50**
doi: 10.15414/raae/2016.19.02.39-50

REGULAR ARTICLE

TECHNICAL EFFICIENCY OF TECHNOLOGY ADOPTION BY MAIZE FARMERS IN THREE AGRO-ECOLOGICAL ZONES OF GHANA

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ABSTRACT

Using a farm household data from 3 agroecological zones of Ghana, this paper investigates the causal relationship between the adoption of improved maize variety and technical efficiency or productivity. The empirical results show a positive relationship between the adoption of improved maize variety and technical efficiency or productivity of farmers in the Semi-deciduous forest and Guinea Savannah zones. Generally, adopters of improved maize variety are about 6% to 8% more efficient than non-adopters. The estimated percentage increase in productivity due to the adoption of improved maize variety is about 53%. In the Semi-deciduous forest agroecological zone, adopters of improved maize variety are about 25% to 36% more efficient than non-adopters whilst in the Guinea Savannah agroecological zone, adopters of improved maize variety are about 15% to 26% more efficient than non-adopters. The estimated percentage increase in productivity due to adoption of the improved maize variety is about 8% in the Semi-deciduous forest zone and about 11% in the Guinea Savannah zone. The impact of adoption on technical efficiency in the Transitional zone is however negative. Adopters of improved maize variety are 7% to 8% less efficient than non-adopters and the estimated percentage decrease in productivity due to adoption of the improved maize variety is about 15%. Food safety net policies should pay attention to increased development and dissemination of improved crop varieties suitable to different agroecological zones.

Keywords: Food security, Ghana, Impact assessment, Technology adoption, Technical efficiency
JEL: D24; Q15; Q18

INTRODUCTION

Improving agricultural productivity has always been a major policy goal in Ghana and in most parts of sub-Saharan Africa. This has gained increasing significance over the last two decades, partly because of chronic food insecurity. Low agricultural productivity and food insecurity are partly due to inefficiency of resource-use in agricultural production and low adoption rates of improved agricultural technologies or crop varieties **(Doss and Morris, 2001; Doss, 2006).** Agriculture still employs about 60 percent of the economically active population in Ghana **(ISSER, 2010**) where poverty is reported to be highest (59%) among food crop producers who find it difficult to afford, or adopt improved agricultural technologies to boost food production **(Seini, 2002; GPRS, 2003).**

In Ghana, maize remains the number one staple food crop with domestic production and demand increasing over the years **(ISSER 2010)** from an average of 296,700 tonnes per year in 1977-78 to over 1 million tonnes per year in 1997-98 **(MoFA, 2009)**. The average maize yield in Ghana is estimated to be 1.7 metric tons/hectare (**MOFA, 2013**). Despite an estimated achievable yield of around 6 Mt/ha, the domestic maize supply deficit is expected to average about 12 percent **(MoFA, 2013)**. The adoption of improved maize varieties is critical for improving productivity and overall output to meet the increasing domestic demand.

The adoption of improved crop varieties and improvement in resource-use efficiency in agricultural production have been widely advocated as policy measures required to improve the productivity levels, increase the overall food production and contribute to reducing hunger and malnutrition in Ghana **(Doss, 2006**). Improved crop varieties are high yielding and disease or pest resistant (or tolerant) crops with high nutritional quality and low input requirements. The Council for Scientific and Industrial Research (CSIR) and its affiliate institutions such as the Food Research Institute (FRI) and the Crop Research Institute (CRI) develop and release improved crop varieties to farmers in Ghana. Notably, an improved maize variety known as "Obatanpa" was released to farmers in the mid-1990s, with the aim of improving the yields and household food security of the farmers (**Ragasa et al., 2013**). Found to be the best amongst the improved maize varieties, the Government of Ghana (GoG), the Ministry of Food and Agriculture (MoFA) and the Canadian International Development Agency (CIDA) under the Ghana Grains Development Project (GGDP) have advocated its dissemination and adoption over the past two decades.

The food production potentials of different agroecological zones in sub-Saharan Africa have been widely documented (**Adiku et al. 2009; Ragasa et al., 2013**). For instance, with the exception of the Sudan Savannah zone, maize thrives best in almost all the agroecological zones of Ghana **(Adiku et al. 2009).**

Despite the possible impacts of agroecological zones on technology adoption and resource-use efficiency, farmers tend to be treated as if their constraints and opportunities in the different agroecological zones are similar. Improved technological packages may be similar but they are often targeted at farms and communities with different agroecological conditions where different levels of infrastructural development and human capital exist. Ignoring the agricultural production environments of smallholder farmers and their implications on resource allocation and productivity could be misleading (**Langyintuo and Mekuria, 2008**). As noted by **Sherlund et al. (2002),** agricultural production that neglects heterogeneity in environmental conditions could result in omitted variables bias in the estimation of the parameters of the production frontier.

Studies that have examined the impacts of adoption of improved technologies on household welfare have been widely documented (**Becerril and Abdulai, 2010; Suri, 2011**). Moreover, the empirical literature on adoption decisions of smallholder farmers (e.g., **Feder et al., 1985; Kaliba et al., 2000; Doss and Morris, 2001; Bandiera and Rasul, 2006; Langyintuo, 2008)** did not pay much attention to the relationship between adoption and farm efficiency. The current paper contributes to expanding the literature on adoption of new technologies and efficiency by examining the direct impacts of adoption of improved maize variety on technical efficiency and productivity, using a sample of farm households from three different agroecological zones of Ghana. The paper is relevant in a sense that besides throwing more light on the relationship between adoption and farm efficiency, the influence of agroecological conditions on productivity and efficiency of adoption by farm households is examined.

In this paper, we employ the stochastic frontier model in the empirical analyses to examine farm efficiency, and the propensity score matching (PSM) approach to analyse the impact of adoption on farm technical efficiency and also control for possible self-selection that normally arises when technology adoption is not randomly assigned. The paper generally finds a positive relationship between adoption of improved maize variety and technical efficiency or productivity of farmers in the Semi-deciduous forest and Guinea Savannah zones but significant negative impact of adoption on technical efficiency in the Transitional zone. The remainder of the paper is organized as follows: Section 2 briefly reviews literature on adoption of improved maize variety in Ghana. Section 3 outlines the conceptual framework on adoption of the improved maize variety, the impact of adoption on efficiency using the propensity score matching approach and the computation of technical efficiency with the stochastic frontier model. Section 4 presents the data employed in the empirical analyses. Section 5 discusses the empirical results. The final section provides some concluding remarks.

Adoption of improved maize variety in Ghana

Maize is the most important cereal crop in Ghana (**Alderman and Hingis 1992; Morris et al., 1999; MoFA. 2009)**. It is grown by a vast majority of rural households in almost all parts of the country**.** The cropping systems and production technologies of maize however vary in the six agroecological zones of Ghana. These agroecological zones are the Sudan Savannah and the Guinea Savannah in the North, the Coastal Savannah in the South, the Semi-Deciduous and Evergreen Forest (High Rainforest) zones in the South and the Transitional zone, which is sandwiched between the Guinea Savannah and the Semi Deciduous Forest zones.

The Guinea and Sudan Savannah zones have a single rainy season in April or May where maize is grown on permanently cultivated fields located close to homesteads, as well as in more distant plots **(Morris et al, 1999).** Sorghum and millet are the dominant cereals in the Sudan and Guinea Savannah zones but maize is intercropped with small grains, groundnut, and/or cowpea. A major constraint to maize production in the Sudan Savannah zone is the hostile agroecological environment such as irregular rainfall pattern, soil infertility and periodic drought (**Whitehead, 2006**). The mean annual rainfall in the forest zones is about 1,500 mm where maize is planted in both the major (March) and the minor (September) rainy seasons usually on scattered plots and intercropped with cassava, plantain, and cocoyam. The transitional zone also has a bimodal rainfall and predominantly deep and friable soils, and relatively sparse tree cover that allow maize to be planted as a monocrop or intercropped with yam and/or cassava.

Various institutions and organizations are involved in the release, transfer and adoption of improved maize varieties in Ghana. Between 1979 and 1998, over twelve improved maize varieties were released to farmers by the Council for Scientific and Industrial Research (CSIR) under the Ghana Grains Development Project (GGDP) funded by the Government of Ghana (GoG) and the Canadian International Development Agency (CIDA). Some of the improved maize varieties released to farmers include "Abeleehe", "Aburotia", "Dobidi", "Dorke", "Golden Crystal", "Mamaba", "Obatanpa", "Okomasa" and "Safita" (**Morris et al., 1999**). Four improved varieties, including, "Aziga", "Golden Jubilee", "Akposoe" and "Etubi" were then released in 2007. Five hybrid varieties, including, "Mamaba", "Cidaba", "Dadaba", "Etubi", and "Enibi" were released by the Crop Research Institute (CRI) and Savannah Research Institute (SARI) in 2010. Another six varieties namely, "Aseda", "Opeaburoo", "Tintim", "Nwanwa", "Odomfo" and "Honampa" were released in 2012 (**Ragasa et al., 2013**). Although these recent releases of improved maize varieties have occurred in Ghana, the "Obatanpa" variety continues to be the most popular not only in Ghana but in other countries in sub-Saharan Africa as well because of its medium-maturing open-pollinated characteristics and its adaption to the growing conditions in the lowland tropics (**Sallah et al. 2003**). According to **Morris et al. (1999),** the "Obatanpa" maize variety has received much patronage among smallholder farmers in Africa due to its high amino acids content (lysine and tryptophan). The efforts toward the transfer and adoption of improved maize varieties in Ghana are supported by the Grains and Legumes Development Board (GLDB), the Ministry of

Food and Agriculture (MoFA) and the International Institute of Tropical Agriculture (IITA).

Adoption of improved maize varieties is linked to farmer's productivity and real incomes. Farmer and household characteristics such as gender and schooling are also hypothesized to influence adoption of improved maize variety **(Langyintuo and Mekuria, 2008**). According to **Doss and Morris (2001),** male and female farmers take the same adoption decisions if they are in male-headed households. This indicates that female-headed households face certain constraints which are not faced by male-headed households. Apart from the head of the household, adoption of improved crop varieties is enhanced if other household members have higher number of years of schooling (**Asfaw and Admassie, 2004).**

Adoption of improved agricultural technologies is hypothesized to be influenced positively by policy relevant variables such as access to capital (cash), access to information and availability of labour markets**.** Lack of credit is an indication of market failures and constraint to adoption. When farmers have information on new agricultural technologies, they would be ready to adopt them. The availability of labour is likely to exert a positive effect on adoption of agricultural technology, the relationship must be examined on case by case basis because of the existence of different policy environments (**Doss, 2006).** Other relevant variables such as resource ownership (total land owned and maize area cultivated), and access to technology in terms of extension contacts could also influence improved maize variety adoption in Ghana**.**

The growing body of literature on adoption of improved maize varieties in Ghana **(Morris et al., 1999; Doss and Morris, 2001; Badu-Apraku et al. 2005; Braimoh and Vlek, 2006; Adiku et al., 2009; Wiredu et al., 2010; Ragasa et al., 2013)** has not quantified the direct impact of improved maize variety adoption on technical efficiency or productivity of farmers. To examine this efficiently, one needs to ensure that there is no reverse causality between adoption of improved maize variety and productivity or technical efficiency. The reverse causality leaves one in limbo as to whether the most performing farmers are adopting new technologies or farmers adopting new technologies are more productive or technically efficient. As noted by **Doss (2006)**, it is difficult to compare the productivity gains between adopters and non-adopters of improved agricultural technologies since adoption decision is correlated with other factors affecting productivity. The reverse causality as argued by **Barrett et al. (2004)** could be avoided if productivity differences across plots are controlled while holding observed and unobserved characteristics constant.

CONCEPTUAL FRAMEWORK

This section presents a simple framework on adoption of improved maize variety, and how the impact of adoption on technical efficiency or productivity can be captured using the propensity score approach. Computation of technical efficiency scores with stochastic frontier model is then discussed.

Self-selection into adoption of improved maize variety

Following the literature on adoption decisions of agricultural households, it is assumed that the adoption of improved maize variety is a dichotomous choice, where the improved variety is adopted, if the net benefits from adopting the improved variety are greater than that from non-adoption. The difference between the net benefits from adoption and non-adoption may be denoted as D^*, such that $D^* > 0$, implying the net benefits from adoption exceeds that of non-adoption. Although D^* is not observable, it can be expressed as a function of observable elements in the following latent variable model (Eq. 1).

$$D_i^* = \alpha Z_i + \mu_i, \ldots. D_i = 1\,[D^* > 0] \qquad (1)$$

where D_i is a binary variable that equals 1 if the household *i* adopts the improved variety and 0 otherwise, α is a vector of parameters to be estimated, Z_i is a vector of household and plot level characteristics and μ_i is an error term assumed to be normally distributed. The probability of adoption of the improved maize variety can be represented by Eq. 2.

$$\Pr(D_i = 1) = \Pr(D_i^* > 0) = \Pr(\mu_i > -\alpha Z_i) = 1 - H(-\alpha Z_i) \qquad (2)$$

where H is a cumulative distribution function. The functional form of H may follow a logistic distribution. To link the adoption of improved maize variety to farm technical efficiency or farm productivity, consider a linear specification of the level of efficiency Y_i as a function of a vector of explanatory variables *Z* and a dummy variable *D* that captures the adoption status of the farmer. The relationship between technical efficiency or farm productivity (Y_i) and adoption may then be expressed as Eq. 3.

$$Y_i = \beta_1 Z_i^{'} + \beta_2 D_i + \xi_i \qquad (3)$$

where Y_i is technical efficiency or productivity of the sampled maize farmer i, ξ_i is a normal random disturbance term and D_i is a dummy variable indicating $D_i = 1$ if the farm household adopts the improved variety and $D_i = 0$, otherwise. The vector, *Z* summarizes the individual and household characteristics as well as farm and location-specific characteristics.

From the treatment equation (1) and the outcome equation (3), the relationship between adoption of the improved maize variety and technical efficiency or productivity may be interdependent, resulting in selection bias. The implication of this is that treatment assignment is not random, with the group of adopters being systematically different. Selection bias normally occurs if unobservable factors influence both error terms in the adoption specification (μ_i) and the technical efficiency or productivity equation (ξ_i), resulting in correlation of the error terms in the two specifications. The error terms of the treatment and the outcome variables then become correlated such that $corr(\mu, \xi) = \rho$. When $\rho \neq 0$, any standard regression technique such as OLS applied to the regression models produces biased results. The problem of self-selection can be overcome by employing statistical matching approach, which involves the pairing of adopters and non-adopters of the improved maize variety with similar observable characteristics **(Dehejia and Wahba, 2002).**

Stochastic production frontier

As indicated previously, computation of technical efficiency scores is done with the stochastic frontier model, which can be specified as Eq. 4. Given that several farmers in the sample were subsistence farmers, we chose to estimate only technical efficiency, since the specification of allocative efficiency could result in biased estimates. As argued by **Barrett (1997),** allocative efficiency estimates tend to overstate the inefficiency of remote farms or others facing substantial transaction costs since their shadow prices are free to deviate more from an allocative efficiency benchmark based on market prices than will those of persons participating in the market.

$$\ln Q_i = X_i \beta + v_i - u_i \tag{4}$$

where Q represents the yield, X denotes the factors of production and β represents the unknown parameters to be estimated. The $v's$ are assumed to be independent and identically distributed random errors having $N(0,\ \sigma_v^2)$ distribution. The $u_i's$ are non-negative random variables, associated with technical inefficiency of production, which are assumed to be independently distributed, such that u_i is obtained by truncation (at zero) of the normal distribution with variance σ_u^2 and mean μ_i **(Coelli et al., 1998).**

The output-oriented measure of farmer specific technical efficiency is the ratio of observed output to the corresponding stochastic frontier output **(Battese and Coelli, 1988)**. A producer who is technically efficient is able to avoid waste of inputs by producing as much output as the inputs under the current state of technology**.** The allocative efficiency refers to the ability of the producer to obtain an optimal allocation of the inputs available at the prevailing output and input prices **(Tzouvelekas et al., 2001).**

Since the output is expressed in natural logarithm, the technical efficiency is defined as Eq. 5.

$$\begin{aligned} TE_i &= Q_i / \exp(X_i\, \beta + v_i) \\ &= \exp(X_i \beta + v_i - u_i) / \exp(X_i\, \beta + v_i) = \exp(-u_i) \end{aligned} \tag{5}$$

To predict farmer-specific technical efficiency after the frontier has been fitted to the data, we disentangle the inefficiency component u_i by utilizing the conditional mean function $E(u_i/\varepsilon_i)$ as Eq. 6.

$$E\left[u_i \middle| \varepsilon_i\right] = \frac{\sigma_u \sigma_v}{\sigma} \left[\frac{f(\varepsilon_i \lambda_i / \sigma_i}{1 - F(\varepsilon_i \lambda_i / \sigma_i} - \frac{\varepsilon_i \lambda_i}{\sigma_i} \right] \tag{6}$$

where $\lambda = \frac{\sigma_u}{\sigma_v}$ and $\sigma^2 = \sigma_u^2 + \sigma_v^2$, and f and F are the standard normal density function (PDF) and the standard normal distribution function (CDF), respectively. The parameters of the stochastic frontier model are estimated by the maximum likelihood procedure. The farm specific technical efficiency is between 0 and 1 and is inversely related to the level of the technical inefficiency.

The propensity score matching technique

To examine the direct causal effect of adoption of improved maize variety on technical efficiency or farm productivity, the propensity score matching approach is employed. As indicated previously, the advantages of using the propensity score matching model is to control for self-selection bias that arises when adoption of improved maize variety is not randomly assigned. Moreover by using propensity score matching, we assume that both adopters and non-adopters of improved maize variety have similar characteristics. Therefore we are able to avoid the possible reverse causality between adoption of improved maize variety and farm household technical efficiency or productivity.

The propensity score $p(Z)$ is the conditional probability of adopting the improved maize variety, given pre-adoption characteristics **(Rosenbaum and Rubin, 1983)**. Thus (Eq. 7)

$$p(Z) \equiv Pr\{D = 1 | Z\} = E\{D | Z\} \tag{7}$$

where $D = \{0,1\}$ is the indicator of exposure to adoption of the improved maize variety and Z is the vector of pre-adoption characteristics. The estimated propensity scores are used to estimate the Average Treatment Effect on the Treated (ATT), which is the parameter of interest as in Eq. 8.

$$\begin{aligned} \delta &\equiv E\{Y_i^1 - Y_i^0 \mid D_i = 1\} \\ &= E\{E\{Y_i^1 \mid D_i = 1, p(Z_i)\} - E\{Y_i^0 \mid D_i = 0, p(Z_i)\} \mid D_i = 1\} \end{aligned} \tag{8}$$

where $p(Z_i)$ is the *p*-score, Y_i^1 and Y_i^0 are the potential outcomes (technical efficiency or productivity) in the two counterfactual situations of receiving treatment (adoption of the improved maize variety) and no treatment (non-adoption of the improved maize variety).

For efficient and unbiased estimates, the balancing property and the Conditional Independence Assumption (CIA) of the propensity score matching shouldn't be violated. Testing for the balancing property ascertains if household behaviour within each group is actually similar. The Conditional Independence Assumption (CIA) propound that once the set of observable characteristics, are controlled for, the adoption of improved maize variety is random and uncorrelated with the technical efficiency or productivity of the farmer. A further requirement is the common support condition which requires that persons with the same values of covariates Z have positive probabilities of being both adopters and non-adopters **(Heckman et al., 1999)**. Thus, all individuals in the common support region actually can exist in all states ($0 < P(D=1|Z) < 1$).

Data Description

The data employed in this paper were collected from 453 maize farm households comprising of 151 farmers each in the Semi-deciduous Forest, the Transitional and the Guinea Savannah agroecological zones of Ghana in 2009. A three-stage sampling procedure was used in the study. In the first stage, Bekwai Municipality (located in the Semi-deciduous forest), Nkoranza district (located in the Transitional zone) and Gushiegu district (located in the Guinea Savannah zone) were randomly selected from all the districts with high levels of maize production.

This was followed by a random selection of 9 villages from the Bekwai Municipality, 8 from Nkoranza district and 9 from the Gushiegu district. In the third stage, 151 maize farmers were randomly sampled from each of the 3 selected agroecological zones. In addition to the 41 sampled farmers from Bekwai town, 15 farmers each were selected from the rest of the 9 sampled communities in the Bekwai Municipality. In addition to 46 sampled farmers from Nkoranza town, 15 farmers each were selected from the rest of the 8 sampled communities in the Nkoranza District. Also in addition to 31 sampled farmers from Gushiegu town, 15 farmers each were selected from the rest of the 9 sampled communities in the Gushiegu District.

The farmers were randomly sampled with the assistance of Agricultural Extension Agents (AEAs) from the Ministry of Food and Agriculture (MoFA) and crop breeders from the Crop Research Institute (CRI) in Kumasi, Ghana, who provided a list of maize farm households in the sampled communities. Structured questionnaires comprising of individual and household, and farm-specific characteristics, institutional and environmental factors and location-specific characteristics were used to solicit the relevant information for the study. Input-output data for the stochastic frontier model comprised of quantity and cost of inputs such as land, labour, fertilizer and seed, and quantity of maize produced in 2009.

Adoption of improved maize variety was measured as a dummy variable indicating 1 if the farmer adopted, and zero otherwise. The outcome variables are the predicted technical efficiencies from the stochastic frontier model and the productivity levels of the farm households measured as output (kg) per hectare (ha). Table 1 presents the descriptive statistics of the variables used in the stochastic frontier and inefficiency models for adopters and non-adopters of the improved maize variety. The significance levels suggest some differences between adopters and non-adopters with respect to household and farm-level characteristics, as well as location-specific characteristics. With regards to the outcome variables, there appear to be statistically significant differences between household productivity levels and technical efficiencies of adopters and non-adopters. However, mean differences do not account for the effect of other characteristics of farmers and cannot be taken as evidence for the specific effects of adoption. Matching should normally be based on variables that influence both treatment assignment and outcomes and are not affected by the treatment (**Caliendo and Kopeinig, 2008)**. Economic theory and sound knowledge of previous research and information about the institutional settings are crucial in the choice and specification of the model (**Smith and Todd, 2005**). Selection of variables in this study were based on previous empirical work on the determinants of adoption of improved maize varieties **(Morris et al., 1999; Doss, 2006).** To control for the differential effects of the three sampled agro-ecological zones, separate models representing the Guinea Savannah zone, the Transitional zone and the Semi-deciduous Forest zone were estimated.

RESULTS AND DISCUSSION

The maximum likelihood estimates of the stochastic frontier production function and the inefficiency effect model for the three agroecological zones are presented in Table 2. The estimated sigma square (σ^2) parameters in the estimated stochastic frontier productions are significantly different from zero, indicating goodness of fit for the models and appropriateness of the normal distribution assumption. The estimated lambda ($\lambda = \sigma_u / \sigma_v$) parameters are significantly different from zero, implying that technical inefficiency effects are significant in determining the level and variability of improved maize yield. The predicted technical efficiencies of the farmers are shown in Fig. 1. Majority of the farmers in the Semi-deciduous Forest zone have higher predicted technical efficiencies whilst those in the Guinea Savannah zone have low technical efficiencies. The estimated mean technical efficiency for maize producers in the Semi-deciduous Forest, Transitional and Guinea Savannah agroecological zones of Ghana are 0.722, 0.826 and 0.607, respectively, indicating some differences in the technical efficiencies among the farmers across the different agroecological zones. The technical efficiency for the whole sample of farmers is 0.642. These findings suggest that agroecological conditions matter with regards to technical efficiency of farmers and that environmental and ecological conditions need to be accounted for in the estimation of technical efficiency (**Sherlund et al., 2002; Adiku et al. 2009**).

A logit model was employed in the prediction of the propensity scores. The analysis was conducted for the entire sample, and for the farmers within the Semi-deciduous forest, Transitional and the Guinea Savannah agroecological zones.

Table 1 Descriptive statistics of variables used in the stochastic frontier and inefficiency models

Variable	Definition of variables	Semi-deciduous Forest Non-Adoption (N=7)	Semi-deciduous Forest Adoption (N=144)	Transitional Non-Adoption (N=126)	Transitional Adoption (N=25)	Guinea Savannah Non-Adoption (N=115)	Guinea Savannah Adoption (N=36)
Techeff	Technical efficiency	0.58 (0.13)	0.73 (0.18)	0.85 (0.13)	0.71 (0.23)	0.57 (0.25)	0.72 (0.21)
Yield	Output from maize production (kg/ha)	2017.9 (777)	2586.7 (846)	1608.7 (1619)	1281.1 (694)	1027.1 (552)	1175.9 (488)
Fertilizer	Quantity of fertilizer used (kg/ha)	0.00 (0.00)	4.86 (8.61)	27.46 (11.38)	32.40 (12.00)	19.04 (15.16)	21.11 (11.66)
Labour	Labour input in maize production (man-days/ha)	546.4 (195)	733.1 (407)	450.1 (503)	365.4 (472)	212.3 (187)	185.3 (113)
Farmsize	Area under maize cultivation (ha)	0.91 (0.45)	1.00 (0.53)	2.03 (1.64)	3.30 (2.23)	1.96 (1.22)	1.68 (1.21)
Seeds	Quantity of seeds used (kg.ha0	2.91 (0.30)	3.73 (0.46)	3.24 (0.64)	3.42 (0.99)	2.36 (0.45)	2.44 (0.57)
Gender	1 if farmer is a male and 0 otherwise	0.29 (0.49)	0.65 (0.48)	0.74 (0.44)	0.80 (0.41)	0.99 (0.09)	1.00 (0.00)
Age	Age of the farmer (years)	42.14 (6.07)	46.19 (10.30)	41.06 (10.76)	45.88 (11.28)	41.3 2 (11.28)	42.78 (9.53)
Household size	The number of people in the household	9.43 (3.87)	7.20 (2.33)	6.27 (3.23)	7.08 (3.49)	14.91 (8.52)	11.19 (5.43)
Education	The number of years of schooling (years)	7.29 (1.60)	7.30 (2.23)	4.85 (3.73)	5.52 (3.28)	2.40 (3.30)	2.06 (3.35)
Owner-cultivator	1 if farmer cultivates owned plot, 0 otherwise	0.43 (0.53)	0.31 (0.47)	0.44 (0.50)	0.36 (0.49)	0.73 (0.45)	0.58 (0.50)
Mono-cropping	1 if farmer practices mono-cropping farming system, 0 otherwise	0.00 (0.00)	0.35 (0.48)	0.56 (0.50)	0.44 (0.51)	0.35 (0.48)	0.58 (0.50)
Extension contact	1 if farmer receives extension visits, 0 otherwise	0.71 (0.49)	0.82 (0.39)	0.12 (0.33)	0.36 (0.49)	0.32 (0.47)	0.69 (0.47)
Credit access	1 if farmer has access to credit for farming, 0 otherwise	0.43 (0.53)	0.63 (0.49)	0.13 (0.34)	0.32 (0.48)	0.09 (0.28)	0.11 (0.32)
Farm distance	The distance from home to the farm (km)	4.14 (1.57)	3.49 (1.11)	3.83 (3.18)	3.89 (2.23)	4.95 (3.39)	4.91 (1.77)
Market distance	The distance from farm to the nearest market (km)	7.43 (2.64)	6.90 (1.81)	5.97 (3.53)	4.62 (3.02)	5.92 (3.23)	5.94 (2.49)
FBO	1 if farmer is a member of farmer-based organization, 0 otherwise	0.14 (0.38)	0.16 (0.37)	0.02 (0.15)	0.20 (0.41)	0.19 (0.40)	0.28 (0.45)
Off-farm work	1 if farmer participates in an off-farm work, 0 otherwise	0.29 (0.49)	0.22 (0.41)	0.24 (0.43)	0.40 (0.50)	0.08 (0.27)	0.03 (0.17)
Soil fertility	Fertility of plot	3.14 (0.38)	3.17 (0.47)	2.01 (1.03)	2.76 (1.30)	2.90 (0.43)	2.94 (0.47)
Herbicide usage	1 if farmer uses herbicides for weed control, 0 otherwise	0.43 (0.53)	0.92 (0.27)	0.86 (0.35)	0.92 (0.28)	0.57 (0.50)	0.75 (0.44)
Tractor use	1 if farmer uses tractor for ploughing, 0 otherwise	0.00 (0.00)	0.01 (0.08)	0.82 (0.39)	0.96 (0.20)	0.62 (0.49)	0.72 (0.45)

Figures are means and those in parentheses are standard deviations.
Source: Own calculation

The descriptive statistics of the variables used in the regression models as well as the results from the propensity score matching analyses are reported in Tables 3 and Table 4, respectively. Since the propensity score only serves as a device to balance the observed distribution of covariates across the treated and untreated groups **(Smith and Todd, 2005**), a detailed discussion of the empirical results is not undertaken. However, variables such as education, access to credit and markets exhibit positive influence on the probability of the farmers to adopt the improved maize variety. The common support condition was imposed and the balancing property was set and satisfied in all the estimated regression models at 1% level of significance.

The effects of adoption of improved maize variety on technical efficiency and productivity were estimated for the whole sample, and then for samples disaggregated according to agroecological zones (see Table 5). The empirical results on the average treatment effects on the treated (ATT) from the calliper (1.5), nearest neighbour (NNM) (2) and kernel-based matching (KBM) methods for the whole sample, as well as the estimates for the three agroecological zones are presented in Table 5.

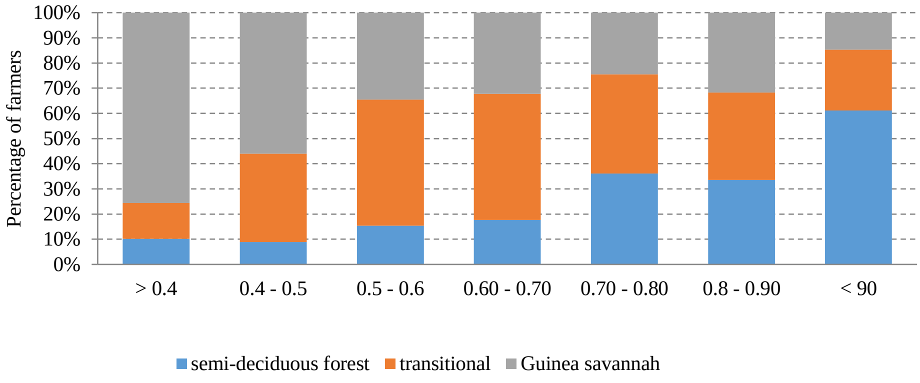

Figure 1. Distribution of technical efficiencies of maize farmers in the 3 agroecological zones
Source: Own calculation

Table 2. Maximum likelihood estimates of stochastic frontier and inefficiency models

Variable	Parameter	Full sample	Semi-deciduous Forest	Transitional	Guinea Savannah
Stochastic frontier					
Constant	β_0	7.168*** (8.728)	8.197** (1.816)	13.892*** (10.047)	7.272*** (7.251)
lnlabour	β_1	-0.098 (-0.445)	-0.300 (-0.274)	-1.803*** (-3.978)	-0.018 (-0.047)
lnfarmsize	β_2	-0.070 (-0.312)	-1708** (-2.157)	-0.494 (-0.926)	-1.558*** (-2.567)
lnseed	β_3	0.469 (0.792)	0.658 (0.214)	-0.216 (-0.207)	0.164 (0.148)
lnfertilizer	β_4	-0.204* (-1.449)	0.166** (1.752)	-0.156 (-0.384)	0.131 (0.540)
lnlabour^2	β_5	0.323** (1.657)	0.046 (0.629)	0.135*** (3.951)	-0.016 (-0.360)
lnfarmsize^2	β_6	0.0441* (1.306)	0.923 (0.996)	0.211*** (3.026)	0.073 (0.959)
lnseed^2	β_7	0.133 (0.901)	0.055 (0.052)	-0.273 (-0.868)	-0.921*** (-2.738)
lnfertilizer^2	β_8	-0.008 (-0.336)	-0562** (-1.723)	0.099** (2.175)	-0.074*** (-2.258)
lnlabour × lnfarmsize	β_9	-0.051* (-1.518)	0.166* (1.392)	0.039 (0.613)	0.117* (1.434)
lnlabour × lnseed	β_{10}	-0.083 (-0.631)	-0.123 (-0.304)	-0.062 (-0.227)	0.383** (1.914)
lnlabour × lnfertilizer	β_{11}	0.592*** (3.426)	-0.031 (-0.788)	0.192*** (3.351)	0.054* (1.571)
lnfarmsize × lnseed	β_{12}	0.096 (0.778)	0.354* (1.432)	-0.001 (-0.004)	0.351* (1.368)
lnfarmsize × lnfertilizer	β_{13}	0.031 (1.222)	-0.034 (-0.875)	0.033 (0.343)	0.146** (2.254)
lnseed × lnfertilizer	β_{14}	-0.114** (-1.882)	0.194* (1.536)	0.173 (0.648)	-0.341*** (-3.924)
Inefficiency model					
Constant	δ_0	0.731** (1.704)	1.077* (1.516)	-0.192*** (-2.354)	-4.143 (-0.538)
Gender	δ_1	-0.047 (-0.232)	0.186 (0.885)	-0.574*** (-2.713)	5.527 (0.716)
Age	δ_2	-0.026*** (-2.682)	-0.158 (-1.172)	0.042 (1.959)	-0.054*** (-3.444)
Household size	δ_3	0.487*** (3.385)	0.032 (0.803)	0.050 (0.597)	0.047*** (2.524)
Education	δ_4	-0.021 (-0.913)	-0.021 (-0.666)	-0.031(-0.697)	0.037 (0.982)
Owner-cultivator	δ_5	0.260* (1.572)	0.209 (1.064)	0.033 (0.109)	0.165 (0.580)
Monocropping	δ_6	-0.368** (-2.247)	-0.793*** (-2.713)	-0.291 (-0.881)	-0.518** (-1.806)
Extension	δ_7	-0.411** (-2.136)	-0.398** (-1.723)	-0.621* (-1.640)	-0.553* (-1.628)
Access to credit	δ_8	-0.443 (-1.968)	-0.285* (-1.422)	-0.858* (-1.432)	0.352 (1.026)
Off-farm work	δ_9	0.522 (2.457)	0.478** (1.865)	0.227 (0.871)	0.234 (0.555)
Variance parameters					
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	σ^2	0.691*** (3.961)	0.204*** (2.680)	0.272** (2.149)	0.752*** (4.088)
$\lambda = \sigma_u / \sigma_v$	λ	0.937*** (48.691)	0.965*** (39.858)	0.399*** (10.086)	0.985*** (87.663)
Log likelihood function		-261.676	-4.294	-89.051	-75.565
LR test of one sided error		155.445	198.922	36.467	67.906
Mean efficiency		0.642	0.722	0.826	0.607

Note: A positive sign of parameter indicates a negative impact on technical efficiency, and a negative sign means the reverse is true. *, ** and *** indicate statistically significant levels of 1%, 5% and 10% respectively. Source: Own calculation

Table 3. Descriptive statistics of variables used in the regression models

Variable	Definition of variables	Semi-deciduous Forest	Transi-tional	Guinea Savannah	Full sample
Techeff	Technical efficiency	0.95 (0.21)	0.17 (0.37)	0.24 (0.43)	0.45 (0.50)
Yield	Output from maize production (kg/ha)	0.72 (0.18)	0.83 (0.16)	0.61 (0.25)	0.72 (0.22)
Fertilizer	Quantity of fertilizer used (kg/ha)	2560.00 (849.06)	1550.00 (1508.9)	1060.00 (540.20)	1725.80 (1216.99)
Labour	Labour input in maize production (man-days/ha)	4.64 (8.47)	28.28 (11.59)	19.54 (14.39)	17.48 (15.25)
Farm size	Area under maize cultivation (ha)	724.00 (401.44)	436.00 (497.60)	206.00 (172.96)	455.43 (436.67)
Seeds	Quantity of seeds used (kg.ha0	1.00 (0.53)	2.24 (1.81)	1.89 (1.22)	1.71 (1.39)
Gender	1 if farmer is a male and 0 otherwise	3.70 (0.48)	3.27 (0.71)	2.38 (0.48)	3.12 (0.79)
Age	Age of the farmer (years)	0.63 (0.48)	0.75 (0.44)	0.99 (0.08)	0.79 (0.41)
Household size	The number of people in the household	46.00 (10.17)	41.86 (10.96)	41.67 (10.87)	43.18 (10.84)
Education	The number of years of schooling (years)	7.30 (2.44)	6.40 (3.27)	14.03 (8.04)	9.25 (6.21)
Owner-cultivator	1 if farmer cultivates owned plot, 0 otherwise	7.30 (2.20)	4.96 (3.65)	2.32 (3.30)	4.86 (3.72)
Mono-cropping	1 if farmer practices mono-cropping farming system, 0 otherwise	0.32 (0.47)	0.42 (0.50)	0.70 (0.46)	0.48 (0.50)
Extension contact	1 if farmer receives extension visits, 0 otherwise	0.34 (0.47)	0.54 (0.50)	0.40 (0.49)	0.43 (0.50)
Credit access	1 if farmer has access to credit for farming, 0 otherwise	0.81 (0.39)	0.16 (0.37)	0.41 (0.49)	0.46 (0.50)
Farm distance	The distance from home to the farm (km)	0.62 (0.49)	0.17 (0.37)	0.09 (0.29)	0.29 (0.45)
Market distance	The distance from farm to the nearest market (km)	3.52 (1.14)	3.84 (3.04)	4.94 (3.08)	4.10 (2.65)
FBO	1 if farmer is a member of farmer-based organization, 0 otherwise	6.92 (1.85)	5.74 (3.48)	5.92 (3.07)	6.20 (2.92)
Off-farm work	1 if farmer participates in an off-farm work, 0 otherwise	0.16 (0.37)	0.05 (0.22)	0.21 (0.41)	0.14 (0.35)
Soil fertility	Fertility of plot	0.22 (0.41)	0.26 (0.44)	0.07 (0.25)	0.18 (0.39)
Herbicide usage	1 if farmer uses herbicides for weed control, 0 otherwise	3.17 (0.47)	2.13 (1.11)	2.91 (0.44)	2.73 (0.86)
Tractor use	1 if farmer uses tractor for ploughing, 0 otherwise	0.90 (0.30)	0.87 (0.34)	0.62 (0.49)	0.79 (0.40)

Figures are means and those in parentheses are standard deviations.
Source: Own calculation

Also presented in Table 5 are the results from the sensitivity analysis on the critical level of hidden bias (Γ), at which the causal inference of significant adoption impact on technical efficiency and productivity may be questioned. In the semi-deciduous forest zone for example, the value of 1.10–1.15 from the caliper (1.5) matching implies that if farmers that have the same Z-vector differ in their odds of adoption by a factor of 10%–15%, the significance of the impact of adoption of the improved maize variety on technical efficiency may be questionable. The mean absolute standardized bias reduction between the matched and unmatched models indicating the balancing powers of the estimations are provided in Table 6. As shown Table 6, the standardized difference before matching is in the range of 35% and 38% for the three agroecological zones, but after matching, the standardized difference indicated substantial bias reductions within the range of 9% and 22%. We also find no systematic difference in the distribution of covariates between adopters and non-adopters of the improved maize variety. The pseudo-R2 are relatively low and the p-values of the likelihood-ratio test indicate joint significance of the regressors after matching.

The matching results for the whole sample of farmers in the first column of Table 5 generally indicate that adoption of improved maize variety exerts positive effects on technical efficiency and farm productivity. However, only the estimates from the calliper method produces statistically significant effects on both efficiency and productivity, while all three matching methods show significant impacts on productivity. The causal effects of adoption of improved maize variety on productivity measured in kg/ha are 678, 710, and 661 for the caliper, NNM and KBM respectively. The causal effect of 671kg/ha for instance suggests that yields of adopters of the improved variety are about 671kg/ha higher than non-adopters. The causal effects on the efficiency also suggest that adopters are about 6% to 8% more efficient than non-adopters. The estimated percentage increase in productivity due to the adoption of improved maize variety is on the average, 53%. These findings generally agree with the study by **Morris et al. (1999),** which revealed about 88% increase in maize productivity due to the adoption of improved maize varieties in Ghana.

The results for the Semi-deciduous forest and Guinea Savannah agroecological zones in Table 5 also show that the adoption of improved maize variety exerts positive and significant impacts on technical efficiency and farm productivity, suggesting that adopters are more efficient than non-adopters. The causal effects of adoption on technical efficiency for farmers in the Semi-deciduous forest zone suggest that adopters of improved variety are 25% to 36% more efficient than non-adopters. The causal effects of adoption on technical efficiency for farmers in the Guinea Savannah zone suggest that adopters of improved variety are 15% to 26% more efficient than non-adopters. The estimated percentage increase in productivity due adoption of the improved maize variety in the Semi-deciduous forest zone is about 8% whilst in the Guinea Savannah zone, it is about 11%. However, the estimates for maize producers in the transition zone reveal that non-adopters of improved maize variety are more efficient than adopters. Generally, farmers in the Transitional zone who adopted improved maize variety are 7% to 8% less efficient than non-adopters. We also find that the estimated percentage decrease in productivity due to adoption of the improved maize variety in the Transitional zone is about 15%.

These results are in line with the findings of **Wiredu et al. (2010)**, who reported a positive and significant relationship between the adoption of improved maize varieties and productivity of farmers in the Guinea Savannah agroecological zone of Ghana. The findings on agroecological effects also lend support to the study by **Dermont and Tollens (2004)**, who found 10% yield gains from adoption of Bt maize in the tropical regions, and 5% yield gains in the temperate regions.

Table 4. Logit estimates of propensity of farmers to adopt improved maize variety

Variable	Full sample	Semi-deciduous Forest	Transitional	Guinea Savannah
	Coefficient (z-value)	Coefficient (z-value)	Coefficient (z-value)	Coefficient (z-value)
Constant	-3.0586***	3.5870	-5.4603***	-1.3960
	(-3.98)	(0.73)	(-2.62)	(-1.14)
Age	0.0577***	0.1386*	0.0527	0.0093
	(3.95)	(1.65)	(1.37)	(0.34)
Education	0.1352***	-0.0336	0.1092	-0.0021
	(3.48)	(-0.11)	(1.33)	(-0.03)
Household size	-0.0663**	-0.7119***	-0.1757	-0.0525
	(-2.16)	(-2.70)	(-1.33)	(-1.23)
Farm size	0.0435	0.6374	0.1902***	0.0282
	(1.05)	(0.69)	(2.91)	(0.30)
Farm distance	-0.1042	-1.3615	-0.1153	-0.1219
	(-1.56)	(-1.58)	-(0.93)	(-0.84)
Farmer’s organization	1.1295***	-2.0985	2.7235***	1.0693*
	(2.47)	(-1.20)	(2.64)	(1.85)
Market distance	-0.0464	0.2676	-0.2136**	0.1169
	(-0.81)	(0.45)	(-1.90)	(0.84)
Owner-cultivator	-0.7432	-2.1410	0.0970	-0.8131*
	(-2.64)***	(-1.43)	(0.18)	(-1.66)
Soil fertility	0.5109		-0.1387	-0.7114
	(1.34)		(-0.18)	(-1.04)
Herbicide usage	0.9852***	4.1828***	1.5506	0.2102
	(2.63)	(2.59)	(1.48)	(0.39)
Extension contact	1.8090***	-0.7001	2.1622***	1.6154***
	(5.71)	(-0.43)	(2.92)	(2.53)
Tractor	-2.0495***		0.4547	0.2219
	(-6.36)		(0.39)	(0.37)
Pseudo-R^2	0.4173	0.5120	0.2772	0.1529
Log-likelihood	-181.5065	-13.5381	-48.9783	-70.2537
Observations	450	148	151	151

*** Denotes significant at 1%, ** denotes significant at 5%,* denotes significant at 10%.
Source: Own calculation

Table 5. Average treatment effects

		Full sample		Semi-deciduous Forest		Transitional		Guinea Savannah	
Matching algorithm	Outcome indicator	T.E	Yield (kg/ha)	T.E	Yield (kg/ha)	T.E	Yield (kg/ha)	T.E	Yield (kg/ha)
Caliper (1.5)	ATT	0.042**	677.74***	0.162**	255.88	-0.0543*	-286.84	0.15***	140.82*
		(2.08)	(6.62)	(2.21)	(0.71)	(-1.64)	(-1.21)	(3.75)	(1.74)
	% Change	6.2	52.6	24.9	13.3	-6.6	-18.7	26.2	14.4
	Γ	1.05-1..15	1.45-1.65	1.10-1.15	1.35-1.45	1.05-1..15	1.45-1.60	1.20-1.40	1.45-1.65
Nearest neighbour (2)	ATT	0.057	710.07***	0.2174*	81.501	-0.0677	-169.573	0.1188*	108.094
		(0.94)	(3.88)	(1.84)	(0.15)	(-1.13)	(-0.72)	(1.92)	(0.77)
	% Change	7.9	56.5	33.2	3.9	-8.2	-12.0	19.5	10.7
	Γ	1.25-1.35	1.45-1.60	1.15-1.25	1.30-1.50	1.50-1.65	1.40-1.60	1.20-1.30	1.45-1.50
Kernel matching	ATT	0.041	661.405**	0.2332**	178.0252	-0.0632*	-212.434	0.094**	91.358
		(0.78)	(2.39)	(2.49)	(0.40)	(-1.71)	(-0.83)	(1.99)	(0.87)
	% Change	5.7	50.6	35.6	8.2	-7.7	-14.6	14.9	8.9
	Γ	1.25-1.45	1.70-1.75	1.10-1.15	1.35-1.45	1.25-1.45	1.45-1.60	1.10-1.25	1.20-1.45
Treated	On- support	184	184	16	16	16	16	36	36
	Off-support	21	21	121	121	9	0	-	-
Control	On- support	248	248	7	7	126	126	115	115
	Off-support	0	0	0	0	0	0	-	-

T.E denotes Technical Efficiency
Γ denotes Critical level of hidden bias
*, ** and *** indicate statistically significant levels of 1%, 5% and 10% respectively.
Figures in parentheses are *z*-values.
Source: Own calculation

Table 6. Matching quality indicators of before matching and after matching

Sample	Selected Algorithm	Pseudo R^2 before matching	Pseudo R^2 after matching	*p*-value before matching	*p*-value after matching	Mean standardized bias before matching	Mean standardized bias after matching	Absolute bias reduction
Full sample	Caliper (1.5)	0.413	0.076	0.000	0.134	50.314	45.281	10.003
	NNB(2)	0.413	0.097	0.000	0.342	50.314	13.577	73.016
	Kernel	0.413	0.058	0.000	0.420	50.314	11.906	76.337
Semi-deciduous Forest	Caliper (1.5)	0.512	0.020	0.002	0.707	38.999	22.043	43.477
	NNB(2)	0.512	0.002	0.002	0.600	38.999	20.612	47.147
	Kernel	0.512	0.033	0.002	0.283	38.999	33.320	14.562
Transitional	Caliper (1.5)	0.265	0.013	0.000	0.906	35.036	20.694	40.933
	NNB(2)	0.265	0.072	0.000	0.991	35.036	16.301	53.475
	Kernel	0.265	0.029	0.000	1.000	35.036	9.936	71.641
Guinea Savannah	Caliper (1.5)	0.265	0.014	0.000	0.906	35.036	20.694	40.933
	NNB(2)	0.265	0.072	0.000	0.991	35.036	16.301	53.475
	Kernel	0.265	0.029	0.000	1.000	35.036	9.936	71.641

Note: Outcome indicators are technical efficiency and yield (kg/ha)
Source: Own calculation

CONCLUSIONS

This study investigated the impact of adoption of improved maize variety on farm technical efficiency and productivity, using a sample of farm households from 3 different agroecological zones of Ghana. A propensity score matching model was employed to account for selection bias that normally occurs when unobservable factors influence both adoption of improved maize variety and technical efficiency and farm-level productivity. By explicitly referring to the causal relationship between adoption of improved maize variety and technical efficiency and productivity, the paper seeks to address counterfactual questions that may be significant in predicting the impacts of policy changes.

The results show that with the exception of the Transitional agroecological zone of Ghana, adoption of improved maize variety has a positive and robust effect on technical efficiencies and productivities of farmers. Generally, adopters of improved maize variety are about 6% to 8% more efficient than non-adopters. The estimated percentage increase in productivity due to the adoption of improved maize variety is about 53%. In the Semi-deciduous forest zone, adopters of improved maize variety are about 25% to 36% more efficient than non-adopters whilst in the Guinea Savannah agroecological zone, adopters of improved maize variety are about 15%

to 26% more efficient than non-adopters. The estimated percentage increase in productivity due to adoption of the improved maize variety is about 8% in the Semi-deciduous Forest zone and about 11% in the Guinea Savannah zone. The impact of adoption of improved maize variety on technical efficiency or productivity is negative in the Transitional zone. Adopters of improved maize variety are 7% to 8% less efficient than non-adopters and the estimated percentage decrease in productivity due to adoption of the improved maize variety is on the average, about 15%. The findings from the study indicate that agroecological effects matter in technical efficiency and productivity of farm households regarding adoption of improved crop variety by smallholder farmers in sub-Saharan Africa.

The possible reasons behind the differences in the efficiencies and productivities in the agroecological zones may due to differences in adoption rates of the improved maize variety, input use (fertilizer, herbicide, and certified seed use) and the biophysical environment. The decreases in efficiency and productivity levels in the Transitional zone may come from the longer history of improved maize variety use compared to the other two agroecological zones. It is likely that farmers have been using other improved maize varieties they are already experienced with, in terms of agronomic and management practices. The maize farmers may have compared the "new improved" variety that did not adapt to their cropping system to the "existing improved" variety which they are already experienced with. We also find that on the average, adopters of the improved maize variety in the Semi-deciduous Forest zone tend to be more efficient than the other two agroecological zones. Over the years, extension services in that zone have been biased toward cocoa until recently when attention is being given to other crops. However, we observe lower productivity in the forest zone because the maize farmers may have presumed that their soils were fertile. As noted by **Ragasa et al. (2013),** the highest proportions of fertilizer use seem to occur in the Savannah and Transitional zones compared to the Forest zone even though plots with fertilizer use tend to generate slightly higher yields than those without fertilizer in the agroecological zones of Ghana. The productivity of maize farmers in the Savannah zone is relatively lower than the overall average probably due to low fertilizer use as a result of liquidity constraints and high costs of fertilizer. Since productivity gains in the Guinea Savannah zone may be due to input use, relevant policies that aim at easing the liquidity constraints of farmers and promote the use of these inputs by the smallholder maize farmers must be pursued.

With regards to the biophysical environment, it is likely that existing varieties continued to be used because they are much adapted to the biophysical environment (particularly soil types, rainfall pattern) in the agroecological zone than the new one. Besides, maize farmers in these agroecological zones may not have been using sustainable land management systems, which may have put a lot of stress on the soils there. The findings generally indicate that the growing interest of policy makers in promoting adoption of improved maize varieties, particularly in the rural areas of developing countries is in the right direction, as maize is one of the major food staples is sub-Saharan Africa. In particular, food safety net policies should generally pay more attention to the factors that allow for increased development of new varieties of crops suitable to the different agroecological zones.

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