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PROMOTING IMPROVED AGRICULTURAL TECHNOLOGIES TO INCREASE SMALLHOLDER FARM PRODUCTION EFFICIENCY: GHANAIAN STUDY OF CASSAVA FARMERS

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Abstract

Our study provides empirical answer that verifies increase in productivity, if any, through promotion of improved agricultural technologies among smallholder food crop farmers in Africa. We specifically examined Root and Tuber Improvement and Marketing Programme (RTIMP) technology effect on improving the production efficiency of cassava farmers in Ghana. we stratified RTIMP cassava farmers into above average adopters and below average adopters based on their adoption intensity scores and further examined differences in their efficiency levels which we estimated by employing the stochastic frontier production model (SFA). In order to empirically establish if RTIMP technology has actually had effect in improving productivity of the cassava farmers, we estimated an adjusted regression model (average treatment effect and average treatment effect on the treated models). Our results show that the potential outcome mean technical efficiency of about 69% achieved by the above average RTIMP technology adopters is significantly higher than that of the below average technology adopters which was found to be about 64%. Our Average Treatment Effect on the Treated (ATET) estimates confirm that there has been significant increase in the technical efficiency of cassava farmers attributable to the adoption of the RTIMP cassava technology.
***Key words**: Average treatment effect model, technical efficiency, technology adoption, cassava farmers, Ghana*
Jel Codes: *C21, D13, D24, Q12, Q16*

1. Introduction

In many developing countries agriculture is a major contributor to the gross domestic product and export earnings. However, majority of the labour force found within the agricultural sector, especially rural farmers are often described as being in a low-income or poverty trap as result of the persistent low farm level productivity (Schneider, & Gugerty, 2011; Amare, Cissé, Jensen, & Shiferaw, 2017; Hasselberg, 2017; De Janvry, & Sadoulet, 2010; Gassner, et al., 2019). This suggests that addressing the issue of low farm level productivity could significantly move farmers out of the low-income or poverty trap. Premised on this, several policies and programmes to foster higher productivity growth at the farm level has been proposed. However, one that has been asserted to have a direct impact on productivity growth at the farm level is the adoption of new and improved agricultural technologies by rural farmers (Acheampong, et al., 2017; World Bank, 2008; Muzari, Gatsi, & Muvhunzi, 2012; Haregewoin, et al., 2018; Gebeyehu, 2016; Abdullahi, Mahieddine, & Sheriff, 2015; Rehman, Jingdong, Khatoon, Hussain, & Iqbal, 2016). In the Ghanaian economy, the goal of improving agricultural productivity has been a major policy focus by the central government acting through relevant state institutions. As food security and poverty reduction concern, substantial emphasis has been placed on food crop production; key among them is the root and tuber subsector. Evidences suggests that the adoption and continuous use of improved agricultural technologies is one thing that could generate significant growth in agricultural productivity; moving national economies from low productivity subsistence agriculture to a high productivity agro-industrial economy (Acheampong, et al., 2017; World Bank, 2008). In response to this, several efforts have been initiated by national government to developed and disseminate new and improved agricultural technologies to farmers. For instances, as effort towards achieving significant increases in farm productivity, income and food security status of food crop farmers in rural areas of Ghana, the government of Ghana in partnership with International Fund for Agricultural Development [IFAD], instituted the Root and Tuber Improvement and Marketing Programme [RTIMP] to introduced and trained farmers in the adoption and use of improved technologies (Ministry of Food and Agriculture [MoFA], 2018). RTIMP as an intervention package introduced improved planting materials of recommended varieties of cassava, yam, cocoyam and sweet potato to farmers. In addition to this, farmers were also introduced to technologically enhanced agronomic practices for a more sustainable root and tuber crops production. Credit to the RTIMP intervention, several rural farming communities across the regions of Ghana have received technical supports in terms of provision and distribution of improved crop varieties and agronomic practices in root and tuber crops production (MoFA, 2018). As with every agricultural intervention, the success of it lies in the ability of the programme to significantly change the status quo situation of farmers, by moving them out of poverty and food insecurity. Achieving this, lies in the ability of the technologies introduced to farmers through the intervention to significantly moved farmers from low productivity to high productivity potential on a more sustainable basis. This is because increasing farm productivity enables farm households to generate more income and food stock which consequently could move them out of poverty and food insecurity. This of course requires that the technological intervention is target specific as well as goal specific.

To lend empirical support to the needs for more target based agricultural technological innovations, several studies has been conducted to evaluates the impact of technology adoption on the productivity and income of farm households. However, the literature shows that majority of the studies mostly relied on the comparison of average incomes and outputs between the adopters and non-adopters, and the use of before and after analytical procedures, especially within the African context (see for example Bimpeh, 2012; Wiredu, Mensah-Bonsu, Andah, & Fosu, 2010; Kasamoko, 2004; Afidjah, 2004). These approaches however, have been found to give bias estimate of true welfare gain of technology adoption under a non-experimental survey context (Kassie, Zikhali , Pender, & Köhlin, 2010; Nabasirye, Kiiza, & Omiat, 2012; Acheampong et al., 2017; Acheampong, 2015). This is because the evaluation of welfare gains of technology adoption using a non-experimental or survey data is characterised with selection problem (Acheampong et al., 2017; Tesfaye, Bedada, & Mesay, 2016; Dandedjrohoun, Diagne, Biaou, & N'Cho, 2012). In view of this challenges, to be able to have a direct and true impact assessment of any agricultural intervention on the productivity and livelihood of farmers using a survey data, treatment effect modelling is considered much appropriate and offers better policy benefit (Haregewoin, et al., 2018; Acheampong, et al., 2017; Tesfaye, et al., 2016; Dandedjrohoun, et al., 2012). The approach presents an opportunity to know if the new technological innovation did present some benefits to adopters of the innovation as compared to non-adopters of the innovation. Additionally, the use of treatment effect model help strengthens causal argument in survey data by minimising selection and endogeneity biases. Although some studies have used treatment effect models (TEM) to assess the impact of technology adoption in Ghana, empirical evidences on the use of TEM to assess the effect of technology adoption on technical efficiency remains rare, even though technical efficiency is a better prediction of productivity gains. For instances, Acheampong and Owusu, (2015) using a treatment effect model, evaluated the impact of adoption on farm income and reported that the adoption of improved cassava varieties by cassava farmers in Ghana increased total crop incomes of women by GH¢3173 and men by GH¢ 149 per hectare respectively. In a similar study by Acheampong, et al. (2017), it was found out that, the adoption of improved sweetpotato variety by farmers in Ghana resulted in total income increases of GH¢1267 per hectare.

Despites these efforts, we find the use of income and yield as outcome variables in the TEM by these studies as quiet straight forward target of potential impact from the used of the technology. This is because the outcomes variables considered in these studies fails to tell whether farmers are opertating at their optimum potentials or not and to what extent that could be attributed to adoption. Thus there is the needs for the use of an outcome variables that is able to tell the defferentials between the potential performance and actual performance of the farm units and how technology adoption can contributes to addressing the performance differentials. In this regard, we find the use of technical efficiency as the outcome variable to give added advantage in establishing empirical evidence of technology adoption impact. Furthermore, a surf of literature suggest that not much adoption impact studies within the Ghanaian context have followed this estimation approach thereby leaving substantial knowledge gap on the appropriateness of the use of TEM in assessing adoption impact on farm productivity, especially on technical efficiency. To butress the claim that the use of TEM is much robust and accurate in impact assessment of techology adoption in Ghana given the huge investment in the development and distribution of technologies, there is the need for more independent studies focusing on key project initiatives such as RTIMP. As effort to contributes to literature on the use of TEM in assessing the impact of technology adoption on farm productivity in a developing country context, we adopts the average treatment effect (ATE) and average treatment effect on the treated (ATT) models to assess the direct impact of the adoption of RTIMP cassava technologies on technical efficiency using cross-sectional data from cassava farmers in the Techiman Municipal Assembly in the Bono East Region of Ghana. This we believe will provide the national government solid empirical evidence on the actual welfare gain from the development and distribution of agricultural technology, and on how to have a more pragmatic policies to effect desired change in the agricultural sector through technology adoption.

2. Methodology

2.1. Study Setting and Data Collection Process

The study was conducted in the Techiman Municipal Assembly, located in Brong Ahafo Regions of Ghana. The area was selected because of its significant role in the root and tuber crops commodity chain, particular in crops such as yam and cassava (MoFA, 2016). It was also one major area where the RTIMP programme technology was promoted and implemented among cassava farmers. The area is located in the northern part of the Region between longitudes 1°49’ East and 2°30' West and latitudes 8°00' North and 7°35' South. The area is characterized by a bimodal rainfall pattern. The mean annual rainfall ranges between 1250mm and 1650mm. The average temperature ranges between 30°C and 20°C. The study area is characterized by three main vegetation zones; which are the guinea savanna woodland, the semi-deciduous zone and the transitional zone. These agro-ecological zones extend to many parts of the Sub-Saharan Africa making the choice of the study location and the farming conditions therein a good representation to study in the African farm settings. The Ghana’s 2010 population and housing census puts the population of the Municipality at 206,856 with a population density of 343 people per square kilometres. The Techiman Municipality is one of the agricultural areas in Ghana where agriculture accounts for about 57% of the labour force. The study location is the home of the famous agricultural Market, which happens to be the largest food crops market in Ghana and one of the major commercial centres. *(GhanaDistrict.com, accessed: January, 2017).* Due to its significant contribution to agricultural production, the Municipality has seen a lot of agricultural interventions including the RTIMP programme intervention (MoFA, 2016). The target population for our study was all cassava farmers in the operational areas of RTIMP in the Techiman Municipality. These are farmers among whom the RTIMP technology was promoted to and implemented with based on the comparative advantage they have for cassava production which is one of the major food crop RTIMP targeted in Ghana.

We sampled 450 farmers through multi-stage sampling technique to partake in our survey. The determination of the sample size was done following the Yamane’s statistical sample size determination formula. This helped to estimate the appropriate sample size for the study as well as maximize the degree of representativeness (Yamane, 1967). The formula adopted to compute the sample size is as follows:

$$n = \frac{N}{1+N(e^2)}$$

Where “n” represents the suitable sample size to be used for the study; “N” is sample frame obtained from the target population and “e” is the precision {a precision of 0.05, that is 95 percent confidence interval, was assumed. With the assistance of the Techiman Municipal Department of Agriculture, the sample frame was obtained to be about 3000 active cassava farming households in the study area. Substituting this into the Yamane’s formulae, gives an estimated sample size of about 375 farmers. This suppose that any sample size equal to or greater than 375 would be sufficient for our study. With assistance from Municipal Department of Agriculture and RTIMP offices, we identified forty-five (45) communities as operational areas where the RTIMP intervention had covered in the study location and treated each of the operational areas as separate clusters. We then applied the simple random sampling technique to select ten (10) famers from each cluster to be part of the study resulting in obtaining 450 selected farmers. This sampling approach helped us to cover the entire study location in terms of the coverage of the RTIMP intervention and to have good representation of our study population. The selected individual farmers were then contacted and interviewed one-on-one using a structured interview schedule as research instrument. The instrument consisted of both open and closed ended questions. This was to ensure that sufficient responses are obtained. In addition, the choice of the instrument was to ensure that each respondent was presented with exactly the same questions/items in an order manner. The instrument also gave room for further probing by the interviewer so that reliable responses were obtained.

2.2. Analytical Methods

Following the quantitative research approach, we collected cross-sectional data which was subjected to the appropriate analytical estimation to arrive at our study results. With our chosen research approach, we are able to be precise knowing what we wanted to measure (technology adoption quantitative effect on technical efficiency level). Further the research approach helps us to achieve the research objective through covering of large and representative data with which we could conduct robust and efficient statistical analysis based on which we make valid inferences about our study population. Analytically, the average treatment effect and the average treatment on the treated effect models were used to investigate the effect of RTIMP technology adoption on improving productivity (efficiency) of smallholder cassava farmers. To measure the production efficiency of the cassava famers, we estimated the stochastic frontier model.

2.2.1. Formal Presentation and Empirical Specification of the Treatment Effect Model

Programme evaluation efforts have had to battle with issues that concerns the nature of intervention or treatment. Especially with socio-economic programme interventions, random assignment of treatment is hardly ever since people usually chosen to be eligible can and in fact sometimes do opt out (Agula et al 2018; Acheampong and Owusu 2015). Accordingly, there is a potential component of self-selection that makes it important to recognise and deal with selection bias between treatment and comparison groups in programme evaluation. This suggests that estimating intervention impacts based on simple difference between treatment and comparison groups might fail to capture the actual intervention's effect (Agula et al 2018; Acheampong and Owusu 2015). This possible evaluation problem that could arise can be addressed by estimating the regression adjustment average treatment effect model (consistent with Agula et al 2018; Akudugu et al 2016; Acheampong and Owusu 2015; Wooldridge 2009; Li, Racine and Wooldridge 2008). We note also that employing average treatment effect estimation technique is useful when there is presence of treatment heterogeneighty as the case in our study. Here, assuming a binary treatment and an outcome variable of interest (which in our study case is technical efficiency of cassava farmers) for each population unit, there would be two possible outcomes: Y(0) (i.e. the outcome without treatment and Y(1) (i.e. the outcome with treatment). Given the binary treatment indicator, W; W=1 denotes "treatment". The nature of Y(0) and Y(1), which in our is a continuous measure of technical efficiency levels, could also be discrete or some mix ((Wooldridge 2009). Now for each population unit i, the causal effect of the treatment is measured as below:

$$Y_i(1) - Y_i(0) \tag{1}$$

Here, the problem could be simplified by just averaging the gains across the random sample if these gains could be observed from the random sample. However, since for each population unit i, only one of $Y_i(0)$ and $Y_i(1)$ can be observed in a cross-sectional data like ours, we would have a missing data problem even though there had been random sampling of units. This become the case since it is impossible to assign same units to both treatment and control groups. Accordingly, it becomes vital to estimate the average treatment effect in the total population. Therefore, given the treatment indicator and the counterfactual outcomes, we estimate the population average treatment effect (ATE) in the total population which can be formally defined as follows:

$$Y_{ATE} = E[Y_i(1) - Y_i(0)] \tag{2}$$

In economics and evaluation studies, given the fact that it is not always possible to have randomized experiment, it is critical to ensure absence of selection bias and thus preferable to estimate average treatment effect on the treated, ATET (i.e. units who actually received the treatment). This gives the implicit quantifiable effect of intervention on only those who have received the intervention (Verbeek 2008; Wang, Nianogo and Arah 2017) given a vector of individuals socio-economic characteristics, X_i. The formal mathematical definition of ATET to be estimated is given as follows:

$$Y_{ATET} = E[Y_i(1) - Y_i(0) \mid X_i;\ W_i = 1] \quad (3)$$

Where in the empirical context of our current study, Y_{ATET} is average treatment effect on the treated, given $Y_i(1)$ - as potential outcome of technical efficiency estimates for i^{th} farmers if above average RTIMP technology adopter and $Y_i(0)$ – as potential outcome of technical efficiency estimates for i^{th} farmers if below average RTIMP technology adopter, X_i – as characteristics of the i^{th} farmer, and W_i – define the treatment category (i.e. whether i^{th} farmer is above average RTIMP technology adopter, $W_i = 1$ or otherwise). The specific variables that we specified to estimate through maximum likelihood estimation of the empirical model to arrive at our study findings are: Sex, Age (years), Household size, Years of experience, Years of formal education, Membership to association, Frequency of access to extension service, Revenue from sale of farm output (GHS), and Credit access. These farmers' socio-economic variables were chosen to be captured in our model estimation because they are being considered to also influence farmers' productivity capacity and production outcomes consistent with empirical literature (see for example Guo, Li, McAleer, and Wong 2018; Osun, Ogundijo and Bolariwa 2014; Dadzie and Dasmani 2010; Battese and Coelli 1992).

2.2.2. Estimation of Cassava Farmers' Technical Efficiency Levels Using Stochastic Frontier Analysis (SFA)

2.2.2.1. Theoretical Specification of the Stochastic Frontier Model

In the agricultural industry, performance evaluation of production unit is aimed at addressing bottlenecks to productivity growth and improvement. Theoretically, the estimation of farm-level productivity has followed the application of technical efficiency. Estimation of technical efficiency dates back to the scholarly work of Koopmans (1951) and Debreu (1951). However, Farrell in building on the work of Koopmans and Debreu provided a sound theoretical and empirical measure of productive efficiency (Farrell, 1957). Technical efficiency estimation generally assumes that production units are able to increase output at existing technology without absorbing additional resource (Inkoom & Micah, 2017). In estimating technical efficiency of farm units, two different approaches under the rubric of mathematical programming approach (Data Envelopment Analysis [DEA]) and econometric approach (Stochastic frontier Analysis [SFA]) have been used by researchers (Guo, Li, McAleer, & Wong, 2018; Inkoom & Micah, 2017; Osun, Ogundijo, & Bolariwa, 2014). DEA is non-parametric and deterministic ascribing all deviation from the efficient frontier to technical inefficiency effect. As Greene (2007) and others have pointed out, the non-stochastic nature of DEA leads to findings that are considered incomprehensive and unsustainable, thus motivating researchers to often opt for the econometric method (i.e. SFA). Theoretically, the SFA is often favoured because of its ability to distinguish in efficiency estimation the effect of technical inefficiency and stochastic effects. Thus, in the context of production estimations, the stochastic frontier model was proposed to account for the impact of technical inefficiency by accommodating random or stochastic errors (Guo, et al., 2018; Wang, 2008; Inkoom & Micah, 2017). The preference for SFA has also been significantly enhanced due to the possibility of obtaining producer-specific output estimates (Coelli, Prasada, O'Donnell, & Battese, 2005; Kumbhakar, & Lovell, 2000). In the efficiency literature, the stochastic frontier model is attributed to the combined effort of Meeusen and Van der Brock (1977) and Aiger, Lovell, and Schmidt (1977). Given the stated advantage of the SFA over the DEA and the inherent stochastic characteristics that are associated with agricultural production activities, the current study employed the standard stochastic production frontier which is considered as the appropriate SFA techniques for estimating technical efficiency. Following Meeusen and Van der Brock (1977) and Aiger, Lovell, and Schmidt (1977), we specify the standard stochastic production frontier for estimating technical efficiency as follow:

$$y_i = f(x_i, \beta) + \varepsilon_i \qquad \{\varepsilon_i = v_i + u_i;\ i = 1,2,\ldots,n\} \tag{4}$$

$$y_{ij} = f\left(x_{ij}, \beta_j\right) + v_i - u_i \tag{5}$$

The variables in equation 4 and 5 are explained as follows. The y_i represent output level for the *i^th^* cassava farmer using x amount of inputs. The x_i represent vector of inputs used by the *i^th^* cassava farmer. The β s represent unknown parameters to be estimated. The ε_i stands for the composed error term consisting of two independent factors. The v_i term denotes the stochastic noise and other factors outside the control of the farmer; u_i term denotes the non-negative technical inefficiency term (Coelli, Rao, O'Donnell & Battese, 2005). Fundamentally, the estimation of the production frontier assumes that the boundary of the production function is defined by the "best practice" firm. Thus the stochastic frontier production function as expressed in equations 4 and 5 differentiates the observed output (y_i) from the frontier output (y_i^*). Accordingly, we estimated the measure of technical efficiency of the i^{th} farm relative to the production frontier with the specification below:

$$TE_i = \frac{y_i}{y_i^*} = \frac{x_i\beta + v_i - u_i}{x_i\beta + v_i} = exp(-u_i) \tag{6}$$

From theory, technical efficiency score depends on the value of the unobservable $-u_i$ (i.e. the technical inefficiency term) being estimated. The estimated value of TE is thus expected to lie between the value between 0 and 1. A value of 1 implies the production is technically efficient, hence operating on the optimal frontier. A value 0 suggest that the production unit is technically inefficient, hence operating below the optimal frontier. Given, this the level of technical efficiency or inefficiency of the production unit (i.e. the cassava farmer) is described by extent of point deviation (radial distance) below its production frontier at the existing technology; all other things being equal.

Under the SFA estimation technique, the composed error terms are assumed to have a distributional assumption where $v_i \sim iid\ N(0, \sigma_v^2)$ and $u_i \sim iidN^+(0, \sigma_u^2)$. Also v_i and u_i are assumed to be distributed independently of each other and the regressors (Kumbhakar & Lovell 2000; Battese, Malik, and Gill, 1996). Hence, in estimating firm-specific technical efficiency, the correct estimator must be based on the conditional expectation of the exponential of u_i (Battese & Coelli, 1992). Following Battese and Corra, (1977), the firm-specific technical efficiency cab be reparametrized and expressed as:

$$\gamma = \frac{\delta^2 u}{\delta^2} = \frac{\delta^2 u}{(\delta^2 v + \delta^2 u)} \tag{7}$$

Where the gamma parameter (γ) is bounded between zero and one. A value of $\gamma = 1$ means that the deviations from the frontier are entirely due to technical inefficiency effect. On the other hand, if $\gamma = 0$, it indicates that the deviation from the frontier is entirely due to noise effects. Hence, $0 < \gamma < 1$ indicates that the variability in output is characterized by the combined effect of technical inefficiency and statistical noise.

2.2.2.2. Empirical Specification of the Stochastic Frontier Model

The analytical use of SFA models in literature relies primarily on two functional form specifications (i.e. Cobb-Douglas functional form and Translog functional form). Here, there is no universal consensus in the literature as to which of the two is better. The choice of which functional form depends largely on the suitability of the model to data sets and its consistency with the theoretical basis of the research objectives (Coelli et al., 2005; Kumbhakar & Lovell, 2000; Greene, 2007). Thus, in deciding on the best functional forms, it has been suggested that one takes into consideration the strengths and weakness of the two models to efficiently fit available data. For instance, the Cobb-Douglas functional form exhibits strong algebraic tractability and as well has the ability to explain the substitution between inputs. However, one weakness of the Cobb-Douglas model is its restrictive nature which in any way does not sacrifice the empirical efficiency of the analysis. The Translog functional forms is also known to exhibit strong empirical flexibility and adaptability. The Translog model also permits the assessment of the interactive effects between the inputs and how this impacts output level. One key weakness of the Translog model is, however, the complexity in the model specification and the potential multicollinearity situation. It therefore, becomes appropriate to always subject the data set to the two-modelling estimation approaches to verify which of them efficiently fit the datasets. Taking into consideration the strengths and weaknesses associated with the two models, we decided to subject our dataset analysis to the estimation of the two-functional models and further tested to check which of them best fit out data set in line with the theoretical disposition on which model to choose. To compute the technical efficiency of our sampled cassava farmers, the maximum likelihood estimation approach of the stochastic production frontier model was followed. The empirical model specifications for the Cobb-Douglas (equation 8) and Translog (equation 9) functional forms that we estimated are given as follow:

$$Iny = \beta_0 + \beta_1 In(cap)_1 + \beta_2 In(lab)_2 + \beta_3 In(fms)_3 + v_i - u_i \tag{8}$$

$$\begin{aligned} Iny = {} & \beta_0 + \beta_1 In(cap)_i + \beta_2 In(lab)_i + \beta_3 In(fms)_i + \beta_4 (I(0.5{*}In(cap_i)^2) + \\ & \beta_5 (I(0.5{*}In(lab_i)^2 + \beta_6 (I(0.5{*}In(fms_i)^2) + \beta_7 (I(In(cap_i) * In(lab_i)) + \\ & \beta_8 (I(In(cap_i) * In(fms_i)) + \beta_9 (I(In(lab_i) * In(fms_i)) + \beta_{10} (I(In(cap_i) * \\ & In(lab_i) * In(fms_i)) + v_i - u_i \end{aligned} \tag{9}$$

Where y denotes the monetary value of the total output of cassava (GH¢) produced. fms_i represents total land under cultivation (hectares); lab_i stands for cost of labour employed per hectare (GH¢); cap_i denotes the cost of other capital inputs per hectare (GH¢). Composite capital input cost consists of ploughing cost, cost of cutlass, cost of hoes, cost of spraying machines and the cost of agrochemical if any. The cost of cutlass, hoes and spraying machines was computed based on their annual depreciation values. We followed the conventional straight-line depreciation method in computing the depreciation values, assuming a salvage value of zero for each of the items. The βs denote unknown parameters to be estimated. v_i and u_i denote composite error term (i.e. random noise effect and technical inefficiency effect respectively) whiles the i notation indicates the individual farmer case.

In the estimation of the two models, we assumed that both Cobb-Douglas and Translog equally fit our data set efficiently and subsequently hypothesised a null that there is no significant difference between the two models with respect to the model goodness of fit and estimation power given our data set. We, therefore, employed the log-likelihood ratio post estimation test to determine which of the Cobb-Douglas and Translog models best fit our data set and gives us the most efficient estimates.

3. Root and Tuber Improvement and Marketing Programme (RTIMP) in Ghana

The RTIMP programme is joint partnership programme that was initiated by the Ghana government and the International Fund for Agricultural Development. The first phase of the programme started in 1999 with the goal of developing the Root and Tuber subsector. The programme implemented initially was the Root and Tuber improvement programme (RTIP) which run from 1999-2005. The focus was essentially on developing root and tuber crop production capacity. Due to some shortfall identified in the RTIP, the programme was packaged to incorporate marketing concept, hence the new name RTIMP. The programme became effective on the 8th November, 2006 and ended in December 2014.The goal of the RTIMP was to enhance income and food security in order to improve livelihood of the rural poor. The programme sought to build a competitive market-based Root and Tuber Commodity Chain (RTCC) supported by relevant, effective and sustainable services that are available to the rural poor. RTIMP works with a wide cross section of stakeholders in order to achieve maximum economic and social impact at all stages of the R&T commodity chains. Its interventions focus especially on improving the outputs, incomes and hence living standards of small-scale R&T farmers, processors and traders, particularly women.

Additionally, as a strategic objective, RTIMP aimed at building a competitive and market-based R&T commodity chains supported by relevant, effective, and sustainable services that are easily accessible to the rural poor. The focus of the intervention has been on establishing and consolidating the services on which the rural poor will rely on to ensure effective participation in the commodity chains. At the local farmers' level, the programme aims to achieve economic growth, improve access of the poor to social services and carry out intervention measures to protect poor and vulnerable groups. At the national level, the programme was designed to achieve food security and stimulate demand for cheaper staple food such as cassava, yam, cocoyam, and sweet potato (Adeniyi, 2009). In all, the programme had as an objective of facilitating the commercialization of roots and tuber production, improving the living conditions, income, food security and nutritional health of poor smallholder households in across the country.

As a result of the programme implementation, most farmers, took advantage to expand their farm sizes to gain high economic benefit. Since its implementation, the programme has introduced improved technology for storage of fresh cassava and yam, improved cassava planting materials and improved seed yam through yam mini sett technology, among others. In addition, action strategies to strengthen downstream activities, check incidences of low prices in producing communities, bridge income disparities, and enhance employment were also incorporated into the programme. The section that follows discusses our respondent farmers' adoption of the four main components of the RTIMP cassava technology in the study area.

3.1. Adoption of Individual Components of the RTIMP Cassava Technology by Farmers

To better evaluate the performance of the RTIMP technology intervention, we considered that, first and foremost the extent of adoption of the technologies introduced to farmers through the intervention is assessed. Table 1 therefore present results on the extent of adoption of the individual components of the RTIMP cassava technology introduced to the farmers. As shown in the table, the RTIMP cassava technology introduced to farmers had four main components. The information as presented in Table 1 reflects the adoption of the individual technology components by the farmers. Here, if a farmer has adopted a particular component, he/she is classified as an adopter of that component. On the other hand, if he/she has not adopted that component, he/she is referred to as a non-adopter of that components.

Table 1. Distribution of Farmers Based on Adoption Level of Individual Technology Components

Technology component	Adopters		Non-Adopters	
	Freq.	%	Freq.	%
Land preparation technology				
Slash and burn	305	81.3	70	18.7
Stumps and stock removal	375	100	0	0
Ploughing	375	100	0	0
Improved planting material (high yielding varieties)				
Plant only the RTIMP cassava planting material:	365	97.3	10	2.7
Tekbankye	193	51.5	182	48.5
Bankye afisiafi	305	81.3	70	18.7
Bankyehemaa	325	86.7	50	13.3
Essam bankye	305	81.3	70	18.7
Planting Technology				
Planting in roll	372	99.2	3	8.0
Use appropriate planting distance of 1 x 1m	373	99.5	2	5.0
Improved Cultural practices				
Early weeding – three weeks after planting	367	97.9	8	2.1
Effective Scouting – three to four time	348	92.8	27	7.2
Effective Rogueing – immediately after identifying disease situation	288	76.8	87	23.2
Spraying with recommended pesticides to control pest and disease infestation	75	20.0	300	80.0
Adopt IPM to control pest and diseases	93	24.8	282	75.2
Cutting planting material nine months after planting for further distribution	207	55.2	168	44.8
Do you apply fertilizer	9	2.4	367	97.6
If yes do you follow the recommended rate	7	77.8	2	22.2

The results in Table 1 shows that, among the land preparation techniques, farmers had adopted stumps and stock removal completely. It can thus be deduced that the adoption rate for land preparation technology is around 93.8 % and this indicates a high level of adoption. In terms of improved cassava varieties, the results show that farmers were growing more than one variety on their farmers. This probably could be considered as a risk coping strategy to mitigate against potential risk due to yield and revenue lost. Bankyehemaa variety saw the highest level (86.7 %) of adoption, which could be attributed to it superb qualities such as early maturity period (9-12months), high yielding (40-50ton/ha), varied uses (fufu, gari and flour) and high resistance to pest and diseases. The results further reveal that, majority of the farmers had adopted row planting (99.2%) and the appropriate planting distance of 1x1m^2 (99.5%). This implies that, per hectare of land the farmers have the recommended and appropriate plant population density which guarantee effective and proper plant growth and high crop yield. Furthermore, it was realised that majority of the farmers had adopted the appropriate cultural practices such as early weeding, effective scouting and rogueing, spraying with recommended pesticides among others. Given this trend one could say that the cassava industry in the study area is doing quite well in enhancing good and hygienic farm environment which is key to output qualities. With this, farmers stand the chance of commending good market price for their products. It was however noted that few (24.8%) of the farmers had adopted the IPM concept in pest and disease control and this could be attributed to the associated cost in effectively implementing the IPM on one's farm. In all we observed that the average farmer had adopted some components of the technology introduced. This therefore suggest that the technology has seen some level of penetration among the farmers.

3.2. Estimating the Adoption Intensity of RTIMP Technology by Cassava Farmers

As can be seen from Table 1, the average farmer had at least adopted some components of the RTIMP cassava technology presented to them. With this it become necessary for us to focus on exploring the extent to which these RTIMP cassava technologies package has been adopted by each respondent-farmers which enabled us to compute individual farmers' adoption intensity scores. The adoption intensity scores were expected to fall between 0 and 1 (where the farmers' intensity of adoption increasing from 0 to 1). This was computed by taking the ratio of actual counts of the RTIMP technology components adopted by i^{th} farmer to the total count of technology components expected to be adopted by the i^{th} farmer. As could be seen in the Table 2 above, the total count of technology components expected to be adopted by the i^{th} farmer was 17 which are spread under four broad component areas (i.e. land preparation component, improved planting material or high yielding varieties component, planting technology component, and improved cultural practices component). Using the distribution of the farmers' intensity of adoption scores, we grouped farmers into above average adopters and below average adopters (see Figure 1). Above average adopters were farmers with adoption intensity score greater or equal to the mean adoption intensity score. Below average adopters were farmers with adoption intensity score less than the mean adoption intensity score.

The estimated average adoption intensity score in percentage was found to be about 74% on a range of about 20% to 100% adoption intensity. Our result suggests that on average farmers uptake of the RTIMP cassava technology in totality is around 74 percent. Accordingly, we resolved that the average adoption intensity become a threshold minimum score for adoption of RTIMP technology in the study area based on which to judge and categorised farmers according to their adoption decisions. As the figure 1 portrays, majority (about 67%) of our sampled farmers were found to be above average adopters and the remaining few (about 33.1%) were found to be below average adopters. Here, we consider the above average adopters to have had an appreciable technology adoption intensity necessary enough to generate a higher impact gains on farm productivity; whereas the below average adopters are considered not to have had an appreciable intensity of adoption necessary enough to generate a higher impact gains on farm productivity. From the mean adoption intensity, it could also be inferred that the diffusion rate of the complete RTIMP cassava technology among the farmers stands at about 74% and that there is still significant (i.e. about 26%) marginal fall below the optimum adoption intensity. By implication, there is still about 26 percent adoption gap with respect to the RTIMP cassava technology among the farmers. This adoption gap, we consider to be substantive enough to warrant concern by stakeholders, especially to policy makers in fashioning out appropriate policies to address this gap so as to achieve a higher and a more acceptable productivity and livelihood improvement.

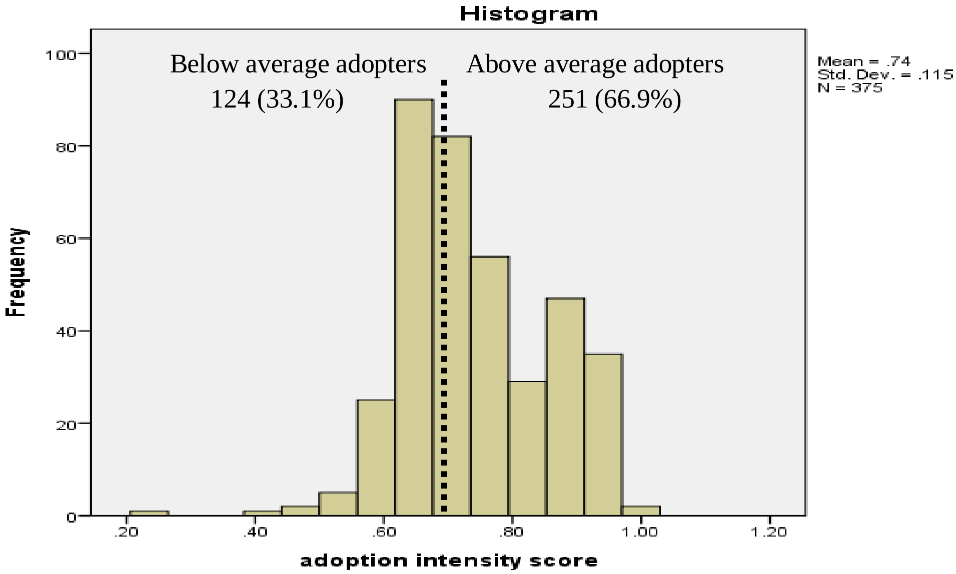

Figure 1. Distribution of Farmers Based on RTIMP Technology Adoption Intensity Scores

3.3. Socio-Economic Characteristics of RTIMP Cassava Farmers

Table 3 presents results on selected socio-economic characteristics of respondents which were used in the predictive models in this study. Here, we compare characteristics of below average technology adopters and above average adopters to verified the extent of heterogeneity in the two identified groups of the technology adopters. As shown in the table, the average age of farmers in the pooled data was 43.9years, with a range of 20 to 74years. The mean age of the below average adopters was 44.8 years compared to 43.7 years for the above average adopters These results show that on the average, sampled farmers were within the active labour force and as expected have the potential to effectively manage their farm business. Additionally, there is the potential for productivity improvement, all other things being equal. The results in the Table 3 also show that more than half (68.0 %) of the cassava farmers were females while 32% were males. Consistent with the distribution found in the pooled data, more females than males were in both below average adopters and above average adopters of the RTIMP technology (i.e. 71.8 compared with 28.2 of below average adopters; and 66.1 compared with 33.9 of above average adopters for females and males respectively). The results therefore suggest that more females than males in the study area were into cassava production. From this, women empowerment policy can target cassava production as the key to addressing poverty eradication in the study area.

Table 3: Description of Demographic Variables of Respondents Used as Explanatory Variables (Univariate Analysis)

		Pooled Data (n=375)		Below average adopters (n=124)		Above average adopters (n=251)		t-test for Equality of Means	
Continuous Variables		**Mean**	**Std. Dev**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**t-value**	**p-value**
Age (years)		43.9	9.9	44.8	10.3	43.7	9.1	1.031	0.303
Household size		6.0	3.0	5.8	2.5	5.97	2.8	-0.557	0.578
Years of experience		7.9	2.3	7.98	3.3	7.8	3.5	0.408	0.684
Years of formal education		8.1	4.4	8.4	4.4	7.9	4.5	1.048	0.295
Frequency of access to extension service		5.0	2.2	4.5	2.0	5.2	2.5	-2.648	0.009
Revenue from sale of farm output (GHS)		6202	4732	5159	3574	6719	5139	-3.417	0.000
Categorical Variables				**Sex**		**Membership to association**		**Credit access**	
Respondents Pooled data				Male	Female	Yes	No	Yes	No
	Frequency			120	255	325	50	329	46
	Percent			32	68	86.7	13.3	87.7	12.3
Below average adopters	Frequency			35	89	112	12	110	14
	Percent			28.2	71.8	90.3	9.7	88.7	11.3
Above average adopters	Frequency			85	166	212	39	219	32
	Percent			33.9	66.1	84.5	15.5	87.3	12.7
Chi-square test	Pearson Chi-Square			1.213		2.426		0.164	
	Asymp. Sig.			0.271		0.119		0.685	

In terms of education, the results showed that on the average, cassava farmers in the study area had attain about 8years (also, average years of education of 8.4 years and 7.9 years respectively for below average and above average adopters) of formal education with a range of 0 to 16 years. Further probing from the results indicates that 85.9% of the farmers have had formal education whiles 14.1% have had no formal education. The above results on education stands to reason that there is an acceptable level of literacy among the cassava farmers in general. This therefore implies that, the probability of the average farmer's ability to understand and appreciate technical information passed on to them is quite substantial. Furthermore, the average household size was found to be 6 members with a range of 1 to 16 members in the pooled data. The average household size of the below average adopters was found to be 5.8 and that of the above average adopters was about 6; all converges to about 6, same as the general average household size. This suggest that, on the average all other things being equal, the household labour capacity of the farm household stands at about 6. The study also revealed that the cassava farmers had an average farming experience of 7.9 years (pooled data) where the average for the two adoption categories were 8 and 7.8 years respectively for below average and above average adopter. This implies that the average farmer has acquire enough experience and therefore the high potential of productivity improvement through effective and efficient ways of carrying out production activity and decision-making.

From the Table 3, it could be seen that majority (i.e. 86.7% of pooled data, 90.3% of below average adopters, and 84.5% of above average adopters) of the cassava farmers belong to a farmer-based organisation and this is very essential to technology adoption. In the circumstance, the promotion and facilitation of technology transfer among farmers would be better enhanced. Furthermore, the results revealed that on the average, cassava farmers were able to realise a gross revenue of GH¢ 6,202 from the sale of their farm produce within the production period under review. This therefore stands to reason that all things being equal, farmers generally have the average potential of being able to meet their operating expenses from their most liquid asset. Our comparison of the incomes of the two adoption categories shows that the above average adoption group has an average income of GH¢ 1,560 more than that of the below average adopters. For technology adoption to ensure progress in every business, access to financial resources is very important to the liquidity status of the enterprise that determines capacity to commit the needed inputs. Hence, we sought to find out whether cassava farmers have access to credit to finance their farm business. Our results showed that more than half of the farmers (i.e. about 88% from the pooled data as well as 89% of the below average adopters and 87% of the above average adopters) do have access to credit. This therefore means that majority of the farmers would have the ability to readily meet their operating expenses for better productivity growth.

The tests of the differences in the socio-economic characteristics of the two adoption categories suggest that there is no significant differences in the socio-economic characteristics of the below average technology adopters and above average technology adopters except in the cases of differences in income and that of extension contacts (see the results for the t-test for Equality of Means p-values and Pearson Chi-Square Asymp. Sig. values in Table 3). We therefore fail to reject the null that the distribution of the socio-economic characteristics of the respondents is the same across the two adoption categories; exception, however, can be said of the mean difference in income and number of extension contacts in which cases that of the above average adopters were found to be significantly higher than that of the below average adopters. By implication, the sampled cassava farmers were generally homogeneous across the two adoption categories in terms of farmer and farm characteristics. The significant higher income of above average adopter than below average adopters is not surprising. This is because as people who have had high adoption of technology, they were expected to reap the improved productivity and production benefit that is reflected in their higher income gains compared to their low adopter-counterparts.

4. Results and Discussion

4.1. Technical Efficiency Level of Farmers

Using the stochastic production frontier model, the technical efficiency levels of farmers were estimated and the results presented subsequently in Table 4. We employed the frontier package by Coelli and Henningsen (2017) in R to run the stochastic frontier analysis. In the table are the results from the estimations of Cobb Douglass function (Model 1) and the Translog production frontier (Model 2) are presented. These two models' estimations were subjected to test of model fitness using the log likelihood ratio test which empirically helps us to verify which of the two models has superiority in given robust and efficient results for our data set. he log likelihood ratio test provides estimates for odd ratio in favour of one model over its counterpart where the larger log likelihood value implies stronger evidence for empirical support a model has over its competitor (Balcombe, Chalak and Fraser 2009 cited in Dadzie 2016). The log likelihood ratio test results in the Table 4 depicts that the Translog specification model has the larger log likelihood value of -227.77 compared with log likelihood value of -243.96 for the Cobb Douglass function model. This implies that flexibility in the Translog specification model estimation has resulted in increasing empirical support to make the model superior to the Cobb Douglass function model. Accordingly, we proceed to rely on the Translog model estimates to discuss the efficiency results. The estimated sigma square of

0.39845 was found to be significantly different from zero at an alpha level of 1 percent. This by inference, further suggests a good fit of the model as well as the correctness of the specified distributional assumption. Also, the gamma value of 0.7634 was found to be significant at 1 percent alpha level and this indicates the presence of technical inefficiency. With the estimated gamma being 0.7634, we can conclude that both inefficiency effect and noise effect are important in explaining the deviation from the production frontier but that inefficiency is more important than noise. This by implication means that any policy support system targeting managerial abilities of farmers and technical aspects of production will yield a significant impact in improving the production performance of farmers.

Table 4. Maximum Likelihood Estimates from the Stochastic Production Frontier Model

	Model 1: Cobb Douglass			**Model 2: Translog**		
Variables	**Coefficient**	**Standard error**	**Z-value**	**Coefficient**	**Standard error**	**Z-value**
Intercepts	5.7378 ***	0.6847	8.3797	-42.1402***	12.4066	-3.3966
log(cap)	0.2353*	0.1002	2.3477	9.8895***	2.3951	4.1290
log(lab)	0.1703**	0.0529	3.2191	5.8153***	1.7359	3.3500
log(fms)	0.4325***	0.0906	4.7761	-11.6936***	2.7888	-4.1931
0.5 *log(cap)^2				-0.8503***	0.204497	-4.1578
0.5*log(lab)^2				-0.277659*	0.127228	-2.1824
0.5*log(fms)^2				-1.0832***	0.274735	-3.9426
log(cap)*log(lab)				-0657282**	0.251935	-2.6089
log(cap)*log(fms)				1.1067***	0.3294	3.3596
log(lab)*log(fms)				1.0249**	0.3530	2.9036
log(cap)*log(lab)* log(fms)				-0.032612	0.0466	-0.6997
SigmaSq	0.4587***	0.0488	9.4003	0.39845***	0.0441	9.0260
Gamma	0.7999**	0.0438	18.281	0.7634***	0.0531	14.365
Log likelihood value	-243.9626			-227.7672		
Log likelihood ratio test for fitness of Cobb Douglass and Translog functions to the data						
Model	Df	Log likelihood	Df	Chi Square	P-Value	
1: Cobb Douglass	6	-243.96				
2: Translog	13	-227.77	7	32.391	3.437e-05	
*Signif. codes: "0.01 = ***"; "0.05=**"; "0.1 = *"*						

From the production frontier, with the exception of the interaction effect of all the variables in the model (capital, labour and farm size), the beta coefficients in the models all tested significant. The coefficient results suggest that a marginal increased in either capital or labour or farm size will lead to a corresponding increase in output of most farmers; exception however, can be said of farm size which increases rather leads to decreasing output. It can thus be inferred that when it comes to cassava production, effective use of labour and capital inputs is critical for productivity improvement; as such the importance of increasing such inputs productivity to the production process should be held in high esteem as also suggested by Abdul-kareem and Isgin, (2016). Thus, policy supports that target enhancing financial capacity of farmers by addressing bottlenecks to credit access to farmers will impact positively on farm productivity of farmers with a resultant effect on their livelihood improvement. Our findings collaborate the preposition by researchers like Sebastian, (2013) that inputs productivity functions as a compact measure of general status of the agricultural industry. The result for the land factor coefficient implies that any marginal increase in farm size will leads to a corresponding marginal decrease in the output of most farmers. We therefore explain that there was a possibility of an inappropriate allocation of land resource, thus contributing negatively to farm productivity. Accordingly, a radial reduction in land factor allocation in cassava farming will rather have a positive contribution to farm productivity. Furthermore, though not significant, the interaction between capital, labour and land showed negative relationship with output, suggesting a lack of optimal input-combination. Thus, to achieve positive impact, the optimal combination of inputs should be directed at a radial increase in capital and labour against a radial reduction of land input in the appropriate proportions.

Figure 2 presents results (see A, B and C) for the distribution of farmers' technical efficiency estimates. Figure 2A presents efficiency estimates distribution for the pooled data whiles Figures 2B and C entails efficiency estimates distribution for below average and above average technology adopters respectively. In general, the results show that farmers were not fully efficient in production. The technical efficiency estimates for the pooled data ranged from 0.0946 (9.5%) to 0.9342 (93.4%) with a mean of 0.6766 (67.7%). The distribution of the farmers' efficiency estimates in the histogram suggest that most of the farmers operate at technical efficiency level above the average. The results further show that although none of the farmers was found to be fully efficient in production, a cursory look at the results suggests that majority of the farmers operate at efficiency levels between 0.5 and 0.93 (i.e. 50-93% efficient). This therefore suggests, the operational and managerial ability of most of the farmers can be said to be okay and that any small technical supports in terms of training will yield a significant impact on the production activity of most farmers; making them realised optimal productivity improvement. The results from our study confirms the findings of previous studies involving cassava farmers (see for example, Abdul-kareem & Isgin, 2016; Taiwo, Dayo, & Bolariwa, 2014; Okeke & Emaziye, 2017). Our results generally imply that the most efficient farmer was operating at about 7 percent below the frontier output and the average least efficient farmer was operating at about 90 percent below the frontier output. The average farmer is said to be operating at about 33 percent below the frontier output. We therefore concluded that the average farmer is generally experiencing about 33 percent productivity gap, which we consider to be quite substantial enough to impact negatively on the livelihood of the farmer by reducing potential income. In following Inkoom and Micah (2017), if the average farmer moves to be efficient as that of his most efficient colleague, he could achieve about 28 percent cost saving {i.e. [1-(67/93)]}. In the same manner, if the least efficient farmer moves to be efficient as his most efficient colleague, he could achieve about 90 percent cost saving {i.e. [1-(9/93)]}. Furthermore, the mean technical efficiency of 67 percent suggests that about 33 percent of output level is lost to technical inefficiency. It further implies that at the existing technology, farmers could increase their output level by 33 % without additional employment of resources.

The distribution of the efficiency estimates of the above average adopters (see Figure 2B) compared with that of below average adopters (see Figure 2C) reveals that most of the above average adopters have efficiency estimates above the general average of 67% with a group efficiency average of 69%. On the other hand, relatively smaller number of the below average adopters have efficiency estimates above the general sample average of 67% with a group efficiency of 62%. This suggests that an above average technology adopter on average is about 7% technically efficient than his below average technology adopter counterpart. We further subjected this efficiency mean difference to statistical test of significance (independence sample t-test statistic) in order to enable us to draw conclusion on the null that there is no significant difference in the mean technical efficiency level of above average adopters and that of below average adopters; the results for the independence sample t-test are presented in the

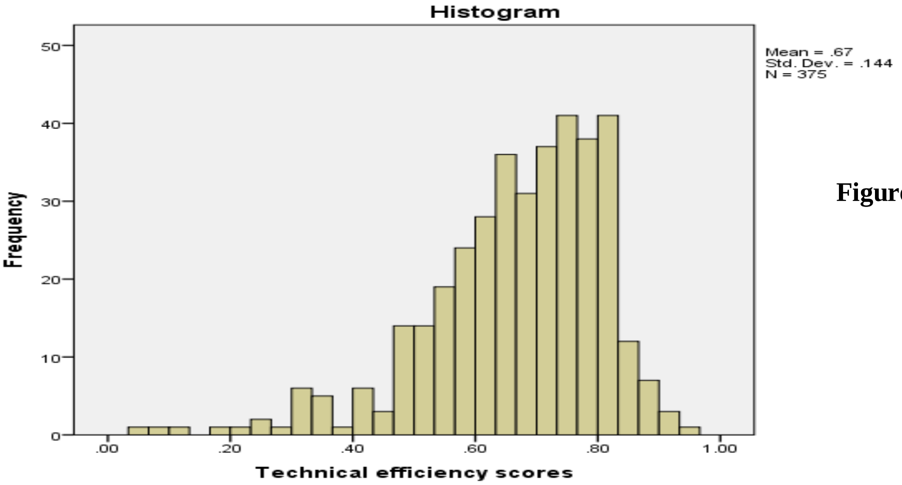

Figure 2A

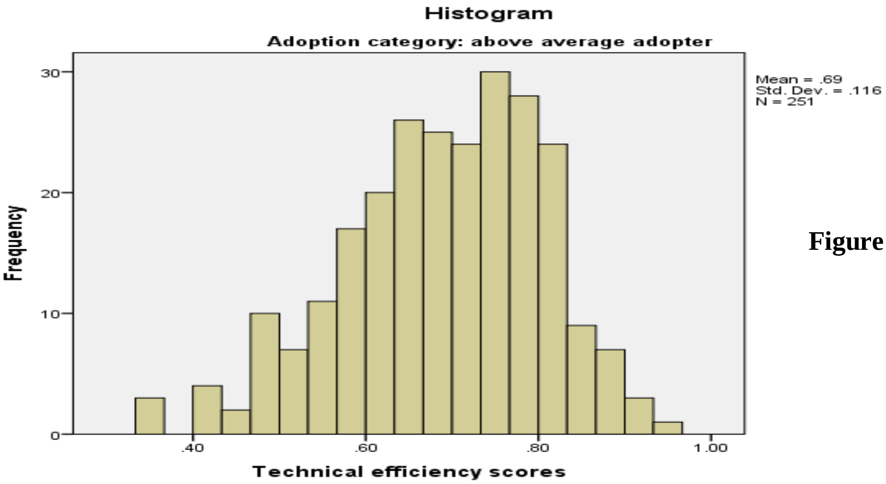

Figure 2B

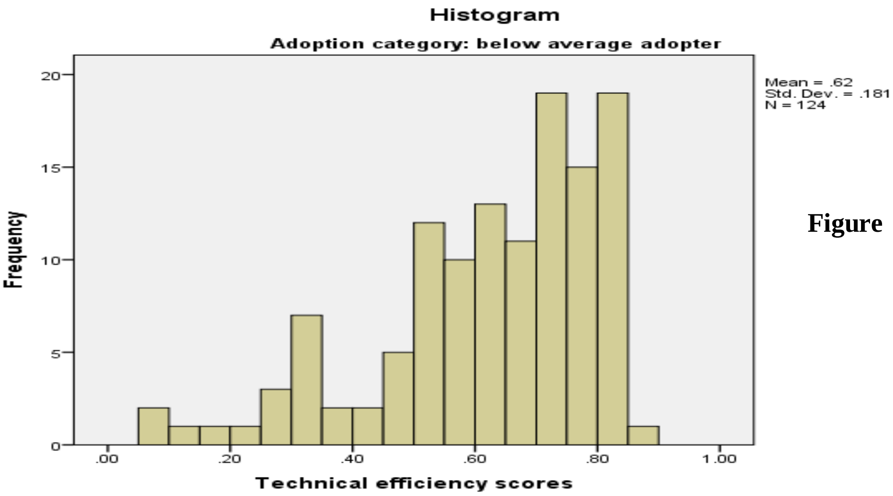

Figure 2C

Figures 2A-C: Distribution of Farmers Based on Their Technical Efficiency Scores

Table 5. As shown in the table, the test of equality of means resulted in a significant difference in the mean technical efficiency level of above average technology adopter and below average technology adopters (i.e. t-value =4.36; sig. p-value= 000). This provide empirical basis to reject the null hypothesis to conclude that on average the technical efficiency level of above average technology adopter is significantly higher than the technical efficiency level of below average adopter in the study area. This by implication means that above average technology adopter on average is technically efficient than the below average technology adopter in the study location.

Table 5. Independence Sample T-Test for Equality of Mean Efficiency Levels for Above and Below Average Adopters of RTIMP Cassava Technology

	Statistics		t-test for Equality of Means			
Respondent Category	**Mean**	**Std. Dev.**	**Mean Difference**	**T-value**	**DF**	**p-value**
Below average adopters (n=124)	0.62	0.18	-0.07	-4.36	373	0.000
Above average adopters (n=251)	0.69	0.12				

4.2. Impact of the Technology Adoption on Technical Efficiency

It has been hypothesised that the introduction of any agricultural innovation is to causes a positive change in the status quo. In line with this sought to assess if any, whether there are significant differences in welfare gains of adoption between adopters and non-adopters of the various components of the RTIMP cassava technology, and whether the observed difference is attributable to the adoption intensity of the RTIMP cassava technology among the farmers. This enable us to test the potential impact of full adoption of the RTIMP cassava technology on the productivity gains. To do, we used the ATE and ATT models to explore the impact of the intensity of technology adoption on the technical efficiency level among farmers. The use of the treatment effect models, enabled us to predict the direct causal effect of adoption on the productivity of farmers. In running the treatment effect analysis, we used the ATE package by Haris and Chan , (2015) in R. In this study we based on farmers' adoption intensity scores to group our farmers into above and below technology adopters as indicator of treatment or otherwise (i.e. treatment variable); our outcome variable in the model estimation was technical efficiency estimates of farmers. We considered technical efficiency as an important outcome variable that best captures welfare gains in terms of productivity improvement as it highlights the productivity differential or gap among the farmers. We assigned above average adopters to be the treatment group as they exhibited a high level of adoption intensity and below average adopters to be the control group as they exhibit a low level of adoption intensity. The treatment group were assigned a code of 1 [i.e. Y (1)] and the control group were assigned a code of 0 [i.e. Y (0)]. The model outputs were estimated at two levels, average treatment effect model and average treatment effect on the treated model as presented in Table 5.

Table 5. Average Treatment Effect and Average Treatment Effect on the Treated Estimation Results

Average treatment effect (ATE)			
Variables	coefficient	Standard error	Z-value
E [Y (1)]	0.6934***	0.0075	92.1797
E [Y (0)]	0.6421***	0.0155	41.4705
ATE	0.0513**	0.0173	2.9621
Average treatment effect on the treated (ATT)			
Variables	coefficient	Standard error	Z-value
E [Y (1) |W=1]	0.6898***	0.0073	94.0617
E [Y (0) |W=1]	0.6559***	0.0204	32.1526
ATT	0.0339***	0.0022	15.531
*Signif.codes: "0.01 = ***"; "0.05=**"; "0.1 = *"*			

The coefficients of E [Y (1)] and E [Y (0)] in the Table 5 are estimates of the potential outcome means (POM) for the above and below average technology adopters respectively which indicate predicted averages of the potential technical efficiency of farmers based on their respective adoption categories. These helped us in the estimation process to be able to estimates the causal difference in outcomes under the treatment (i.e. above average adopters) and under the control (below average adopters). Our results show a coefficient of 0.6934 and 0.6421 respectively for POM for the above and below average RTIMP cassava technology adopters; all of which are significant at 0.01 alpha levels. The coefficient of the POM for the above average technology adopters suggests that if all farmers decide to adopt components of RTIMP cassava technology above the average adoption intensity score, then they would have achieved about 69.3% increase in their productivity. On the other hand, the coefficient of the POM for the below average adopters also suggests that if all farmers decide to adopt components of the technology introduced to them below the average adoption intensity score, they would have rather achieve a relatively lower increase in their productivity level (i.e. about 64.2%). The result further revealed that there exists a significant difference in the welfare gain from the adoption intensity on the technical efficiency. Further from the table, the average treatment effect (ATE) coefficient of 0.0513 was found to be significant at 5 percent and this implies that the average causal effect of RTIMP technology adoption was about 5.1 percent. It can thus be deduced that farmers on the average were able to increase their technical efficiency by 5.1 percent with respects to the increasing intensity of adoption. The positive and significant ATE coefficient further suggest that the increasing intensity of technology adoption has a casual effect or significant impact on technical efficiency among farmers; which consequently is expected to impact positively on productivity and livelihood improvement. This is because increases in technical efficiency enhances farmers ability in producing optimum output level that help generate higher income. We further went on to estimate the average treatment effect on the treated (ATET) in order to access the actual mean difference between farmers with above average adoption intensity and their counterfactual. As can be seen in Table 5, the ATET coefficient was found to be 0.0339 and siginicant at 1 percent. By inference, it can thus be said that with an above average adoption intensity, farmers were able to significantly increased their technical efficiency level by a margin of about 3.4 percent as against their counterfactual. Here, we consider the ATET as the true effect of RTIMP cassava technology adoption because the effect is analysed only on farmers who are above average adopters. Accordingly, following from the observation made from our study results, we can confidently say that the potential performance differential (Technical efficiency differential) observed among the farmers can be attributed to the increasing adoption intensity of the RTIMP cassava technology. The results emphasise the importance of adopting more of RTIMP technology components by farmers and how that contributes to improve the technical efficiency and for that matter the productivity of smallholder farmers. This therefore suggest that any policy supports that can direct and induced farmers to increase their adoption intensity level will consequentially leads to improvement in technical efficiency and subsequently productivity and livelihood of the farmers. Our study could be buttressed with previous studies findings (see for example, Abdulai, Zakariah, & Donkoh, 2018; Owusu, 2016; Asante, Villano, & Battese, 2014).

5. Conclusions and Policy Implications

This study employed stochastic frontier analysis and treatment effect models to estimate the technical efficiency of cassava farmers and the causal effect of adoption intensity of RTIMP cassava technology on technical efficiency respectively. The analysis of the data obtained from the study revealed that the average farmer in the study area had adopted some components of the RTIMP cassava technology that had been introduced to them. In addition, we also found out that the mean adoption intensity was found to 29.93 percent, suggesting a 70.07 percent adoption intensity gap among the farmers. Furthermore, the mean technical efficiency estimates for above average adopters and below average adopters were found to be 0.69 and 0.66 under the ATE model and 0.68 and 0.65 under the ATT model respectively. The ATE and ATT were found to be 0.0319 and 0.0244 respectively. From the results we observed that there was a positive and significant impact of adoption intensity of RTIMP cassava technology on farmer's levels of technical efficiency. Our study result is therefore in line with the predicted role of agricultural technology in improving efficiency and ultimately productivity and livelihood. This efficiency gains from RTIMP technology adoption has important policy implications. It suggests that an above average adoption intensity is effective in improving technical efficiency and subsequently farm level productivity. As such we recommend that any policy intervention by the government through its relevant agencies in the food crop sector to yield desire impact, it should try to provoke high adoption intensity. This means that there is the need for enhancing the capacity of the extension division of the Ministry of Agriculture for efficient information and technology dissemination to farmers. Again, given that our results highlight the importance of extension activities in technology adoption and their impact on farmers' performance, a continuous provision of training to farmers is thus recommended to enhance the smooth transformation of adoption efforts into efficient cassava production thereby improving productivity. It can also be gleaned that enhancing access to extension services and programmes can be strengthened, possibly through the establishment of good practice centres in the districts. In the long run, an improvement in cassava technology to make it more cost effective by using locally available materials that are relatively cheap will go a long way to improving adoption and hence efficient production. Furthermore, given that membership of association affected adoption of improved varieties, farmers must be encouraged and induced to join associations especially farmer-based organizations and innovation platforms. With an effective extension service delivery coupled with membership to farmer- based association, the importance of awareness creation in improved technology dissemination will greatly be enhanced to trigger high technology adoption rate among farmer. This consequently as evident from our study findings will impact positively on productivity growth. Again, our study findings give indication for the need to have well-coordinated and efficient research-extension machinery. The implication is that with more efforts by research and extension improved varieties would occupy a large area in Ghana. Government and non-governmental organization should therefore, support the research-extension system to increase their efforts in the development and dissemination of improved agricultural technologies. Additionally, there is the needs for both technology developers and promoters to develop appropriate monitoring and evaluation mechanism to continually access the extent of adoption and as well as identification of the bottlenecks to effective and efficient adoption of the technology. In view of the fact that our findings support the general knowledge of productivity increases of technology adoption, we further recommend that root and tubers farmers should be encourage to adopt more of the RTIMP technology in order to improve their technical efficiency levels and subsequently improve farm productivity and livelihood. In summary, since research and extension are the main body for dissemination of information on improved agricultural technologies, the need for policy to strengthen and leverage research institutions and extension services to promote and create awareness about the existing improved cassava production technology is important.

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