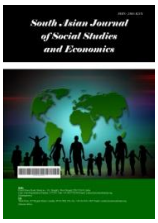

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Access to Credit and Farm Efficiency in Cameroon: A Data Envelopment Analysis Approach

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Author's contribution

The sole author designed, analyzed, interpreted and prepared the manuscript.

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ABSTRACT

The aims of this paper is to analyze the effect of access to credit on the technical efficiency of farms in Cameroon's rural area. Using a sample of 545 farm households, we first estimate a Data Envelopment Analysis (DEA) model with constant returns to scale; then a censored TOBIT model enabling us to identify factors of efficiency, especially the effect of access to credit on efficiency. Two main results emerge from our analysis. First, we find that on average, the level of technical efficiency of farms is 56.78%; showing therefore the possibility of substantial efficiency gains. Second, farm size, association membership, and fertilizer expenditure negatively affect technical efficiency, while access to credit, age and education increase it. Based on these results, we believe that it's interesting for farm householders to organize themselves in associations to benefit from available credits and financial facilities and to share their experiences in the agricultural field in order to improve their efficiency.

Keywords: Technical efficiency; farm households; access to credit; DEA; Cameroon.

1. INTRODUCTION

Agriculture occupies an important place in the Cameroon's economy (about 30% of GDP), especially in rural zones where about 81.8% of households live from agricultural activities compared to 20.6% in urban zones (INS, 2016). The rural zone constitutes a crucial sector in

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economic development, the fight against malnutrition and poverty in developping countries. In Cameroon, despite its important contribution and the government actions for its development, this sector has not seen any real progress in order to effectively fight against poverty (still very high in rural areas).

The poor performance of this sector is partly attributable to the low level of technical equipment and innovation, very limited access to credit, the predominance of archaic agricultural techniques and practices that degrade natural resources [1,2]. These constraints are further accentuated by the effects of climate change and a poor spatio-temporal distribution of rainfall affecting negatively the agricultural productivity (Kabore, 2016).

Therefore, increasing agricultural productivity is widely seen as an important driver of socio-economic transformation in Sub-sahharan African (SSA) countries, and the use of modern inputs is a way to promote increased productivity [3]. Elsamma and George [4] define production as the transformation of goods and/or services into finished products (i.e. the relationship between inputs and outputs). However, in order to be effective, this transformation must meet a certain number of conditions, notably control of the technical itinerary, control of climatic changes and markets, and above all, the availability of financing for the purchase of inputs necessary for production in order to be efficient.

Hazarika et al. [5] define efficiency as the ability of producers to obtain the maximum amount of output possible from a given amount of inputs (capital and labor). According to the authors, this concept derives from a particular interpretation of the notion of the production frontier. They believe that the efficiency of a farm is centered on its ability to produce the maximum possible output from a given quantity of inputs [6].

Koopmans [7] and Debreu [8] were the first to work on the concept of efficiency. Therefore, Koopmans [7] highlighted the measurement of this concept and Debreu [8] verified it empirically by highlighting the coefficients of the resources used, thus giving a numerical evaluation of the losses associated with the non-optimal situation. However, the economic literature identifies three main types of efficiency, namely technical (or productive) efficiency[1], allocative efficiency[2] and economic efficiency[3] (Chaari, 2006,Torkamani and Harder, 1996); [9,10].

Farrell [11] was the first author to give a clear definition of the notion of economic efficiency by distinguishing the concept of technical efficiency from that of allocative efficiency, and to show an approach to estimating the efficiency frontier. Farrell's [11] work built on the work of economists such as Koopman [7] through the definition of efficiency and Debreu [8] through the measurement of technical efficiency [12 cited by Kotsemir, 2013; Minkoa Nzie, 2009). According to Koopman [7], technical efficiency is a vector of inputs (or outputs) achievable when it is technically impossible to increase one output (or reduce one input) without simultaneously reducing another output (or increasing another input).

Compared to Africa, there is a vast empirical literature on farmer efficiency in developed and Asian countries in order to assess the exact level of efficiency achieved by these farmers (Battese, 1992, Coelli, 1995); [10]. However, numerous studies on farm efficiency show that farmers in both developed and developing countries are often not able to use their technical potential and/or allocate their productive resources efficiently (Nyemeck, 2008); [1,10,14-16]. As for Cameroon, little work has been done there.

This paper analyzes the effect of access to credit on the technical efficiency of farms in Cameroon's rural zones using the DEA (Data Envelopment Analysis) method and a censored TOBIT model to determine the factors that explain the observed inefficiencies. Such an

[1] *According to Farrell [11], it measures the ability of a production unit to obtain the maximum output from a given set of inputs. In fact, a farmer is technically efficient if, for a given level of factors and products used, it is impossible to increase the quantity of one product without increasing the quantity of one or more factors or without reducing the quantity of another product. A farmer is said to be technically more efficient if, for an equal level of output, he uses the least amount of inputs.*

[2] *Also called "price efficiency", it evaluates the way in which the firm chooses the best proportions of the different inputs in relation to the market price, which is assumed to be competitive. Theoretically, the production process is said to be allocatively efficient if the marginal rate of substitution between each pair of factors is equal to the proportion of their price (Albouchi et al., 2005). This is the optimal combination, or the best proportion of resources given their relative prices [3].*

[3] *Economic efficiency, also known as "total efficiency", is jointly determined by technical efficiency and allocative efficiency. It corresponds to the products of these two types of efficiency (Coelli et al., 1998). A farm is thus said to be economically efficient if it is both technically efficient and allocates its productive resources efficiently.*

analysis is relevant in that it can inform the government on the policies to be implemented in the agricultural sector in order to achieve its objectives in terms of targeting, and the potential effects of the various programs implemented in this sector. Thus, this article will first present the literature review (section 2), then the methodology and tools analysis used (section 3), followed by the results (section 4) and finally the conclusion and recommendations.

2. LITERATURE REVIEW

The analysis of the effect of access to credit on the technical efficiency of farms has not been mutually agreed upon by economists. These studies reach different conclusions; while some find a positive impact of credit on technical efficiency, others show a negative impact [17,18]. In addition, some authors have shown that access to credit has no effect on the technical efficiency of farms.

The evolution of production systems is conditioned by population density and access to markets. The general framework for analyzing the causes that can explain the low rates of adoption of agricultural innovations in developing countries and stipulates that population density and access to markets are, among other things, the main factors that determine the adoption of agricultural innovations [19].

As a result, it is not surprising that rural farms in Cameroon seem "paralyzed" and "inert" with respect to most of the innovations introduced, given that this area is largely made up of poor small farmers. The latter have neither sufficient equity to self-finance their activities, nor the collateral to benefit from the credit needed to improve their efficiency (Ngono, 2007); [1,20].

Still, for traditional microeconomic theorists, technical or economic efficiency studies are not relevant insofar as the producer is assumed to be rational and therefore called upon to maximize his profit under the cost constraint. According to them, each operator would always be on the production frontier or on the cost frontier. But in reality, many studies highlight the fact that generally and in most cases, farmers rarely (if ever) find themselves on the production and cost frontiers [15].

However, Kumbhakar et al. [21] were the first to highlight the determinants of inefficiency. These include limited access to finance and production inputs such as fertilizer, pesticides, and technological innovation. In the same vein, Nkamleu [1] considers that the inefficiency of agricultural productivity in Sub-Saharan Africa is linked to the lack of adoption of new agricultural technologies.

Nyemeck et al [20] assessed the technical efficiency of smallholder monoculture and intercrop groundnut and maize farmers from a sample of 450 farms in 15 villages in Cameroon. Using a parametric stochastic production frontier (SFA) approach, they found average technical efficiencies of 77%, 73%, and 75% for the three types of producers, respectively, and concluded that technical inefficiencies are due mainly to credit, soil fertility, access to supervision, and road infrastructure.

These results are similar to those of Nyoré (2009) who, using the same method on a sample of 104 family farms oriented towards plantain cultivation in the southern Cameroon region, shows that smallholders operating in the plantain-based cultivation system are relatively more technically efficient with a minimum level of technical efficiency estimated at 61.3%. This study also shows that farmers' technical efficiency is positively influenced by their level of education, extension services and smallholder support through access to finance [3,22]; (Khan et al., 2010).

Simonyan et al [23] highlight the relationship between gender and technical efficiency through the analysis of relative technical efficiency and determinants in the case of maize production in the Akwa Ibom region of Nigeria. Using the descriptive tools and SFA method, the authors arrive at the results that access to credit, farm size and household size represent the most important variables positively impacting farmers' efficiency in Essien Udim community [24,25]. According to these authors, male farmers would be technically less efficient (i.e., 93%) than female farmers in the farm (estimated at 98%). This is in accordance with the finding of Tasila Konja et al. [3] and Yiadom-Boakye et al. [26] who state that farmers who have access to credit are more technically efficient than those without.

Conversely, some work has highlighted the negative effect of access to credit on farm efficiency. Alwarritzi et al. [27] analyzed the effect of smallholder farm efficiency on palm oil production as well as the determinants of the technical efficiency of these productions in

Indonesia. The authors, using an SFA model and the 2013 production data of 271 smallholder palm oil farmers show the negative and insignificant impact of access to credit on the technical efficiency of smallholders and justify these results by the fact that these farmers would have used the credit obtained for other purposes and not injected into agriculture. In other words, farmers tend to use the credit facility available to them, which is intended to improve the productivity of their current farm, to meet their daily needs instead of using it to increase their efficiency. This finding is consistent with the conclusion of the work of Nyemeck et al. [20] that if farmers could manage the benefit of the credit facility appropriately, it would likely enhance their ability to adopt new farming techniques and improve their productivity. This result is consistent with the conclusion of the work of Nyemeck et al. [20] that if farmers could appropriately manage the benefit of the credit facility, it would likely enhance their ability to adopt new farming techniques and improve their productivity [27].

However, in their study of tobacco production in Malawi, Hazarika et al. [5] found no evidence of a positive correlation between access to credit and production efficiency, but they do conclude that improving farmers' access to credit would likely enhance their production (the extensive margin).

3. METHODOLOGY

3.1 Specifications of the Models used

The economic literature notes that the methods used to estimate the production frontier depend on the estimation technique used to obtain it, the expected shape of the frontier, and the nature of the gap between observed and optimal output (Albouchi et al., 2005; Kane, 2010). Still, there are two approaches to efficiency estimation, namely the parametric and the non-parametric approach.

The parametric approach especially the deterministic and parametric approach was by Farrell [11]. This approach can be subdivided into two broad categories depending on whether the frontier is deterministic or stochastic and whether the method of estimating the frontier is Ordinary Least Squares (OLS) or Maximum Likelihood (ML). The production frontier is said to be deterministic if any observed deviation is solely due to inefficiency. It is said to be stochastic or compound error if, in addition to technical failure, another random term is taken into account, including possible measurement errors, model misspecification errors, omission of certain explanatory variables and consideration of events whose occurrence is not dependent on the operator (Aigner et al., 1977; Meeusen and Van Den Broek, 1977; Jondrow et al., 1982).

It is worth noting that it was following serious criticisms highlighting the limitations dictated by the deterministic nature of the production frontier that the stochastic approach was implemented [13]. Thus, the estimation of the production frontier is done either by Maximum Likelihood, Least Squares or the Method of Moments.

Basically, the parametric approach is different from the non-parametric approach in that it is based on an explicit statistical model materialized by the use of a particular functional form unlike the non-parametric approach. It uses more information than the non-parametric approach and therefore its results should be more accurate. However, this approach presents a risk of choosing an inappropriate functional form, which can influence the results [28]. The non-parametric method, on the other hand, avoids these errors related to the wrong choice of production function. Thus, in our study the non-parametric method especially the DEA method is choosen.

3.1.1 The DEA model

To estimate efficiency, we use the DEA method, the most popular of the non-parametric method integrating into the analysis the multi-factor character that characterizes the farms studied (Hasnain et al., 2015). The DEA method is a method for measuring the efficiency of decision-making units that uses linear programming techniques to wrap the observed input-output vectors as tightly as possible [29]. It allows several outputs and inputs to be considered at the same time without any assumptions about the distribution of the data; and in each case, efficiency is measured in terms of the proportional change in inputs or outputs. According to Blancard and Boussemart (2006), the DEA approach is particularly well suited for modeling a primal technology with multiple inputs and multiple outputs, without going through the double cost function assuming no technical efficiency. However, the DEA model can be subdivided into an input-oriented model that minimizes inputs while satisfying at least the

given output levels and an output-oriented model that minimizes outputs without requiring more observed input values.

DEA models can also be subdivided in terms of returns to scale by adding weight constraints. As a result, the two most widely used variants of the DEA model are: the model originally proposed by Charnes et al [30] known as the CCR model which measures the efficiency of production units at constant returns to scale (CRS) when operating at their optimal scale; and later, the model introduced by Banker et al. [31] known as the BCC model which measures efficiency at variable returns to scale (VRS). However, in both cases, a distinction is made:

- **Input-oriented models:** Here, efficiency is analyzed in terms of inputs. In other words, here we are interested in inefficiency in terms of excess inputs.
- **Output-oriented models:** Here efficiency is analyzed in terms of outputs. In other words, here we are interested in inefficiency in terms of insufficient outputs.

Following the analysis of Coelli (1996) taken up by Nyemeck [14], let us assume that we have K inputs and M outputs for each of the N farms.

Let us note: X = the matrix of inputs (a matrix of K rows and N columns); Y = the matrix of outputs (a matrix of M rows and N columns); x_i = the vector of inputs (K rows, 1 column); y_i = the vector of outputs (M rows, 1 column); v' = the vector of weights associated with the inputs (K,1); u' = the vector of weights associated with the outputs (M,1). In other words, the matrices of inputs X (K, N) and outputs Y (M, N) group together the information relating to all the farms; the vectors -columns xi and yi represent respectively the information relating to the ith farm.

The introduction of the DEA method in the form of a ratio is an intuitive way of proceeding (ratio between all the outputs and inputs of each farm; i.e. $u'y_i/v'x_i$). The ratio obtained measures, for a given farm, the technical efficiency, and a set of constraints is imposed so that the ratio of each farm is always less than or equal to 1. It is therefore necessary to determine the optimal weights for each farm, using the following mathematical program (for the CCR ratio):

$$\begin{cases} \max_{U,V}\left(u'y_i/v'x_i\right), & (1) \\ sc \\ \quad u'y_j/v'x_j \le 1 \qquad j = 1,\dots,N \\ \quad u, v \ge 0. \end{cases}$$

That is to say, the efficiency of the i-th farm is obtained as a ratio between outputs and inputs, with the condition that for all the other farms observed, this ratio is equal to or less than 1. The difficulty with this fractional form is that its optimization is difficult; and this form also admits an infinite number of solutions. However, by defining a constraint that $v'x_i = 1$, it is possible to make the fractional form linear. The linear program can then be written as follows:

$$\begin{cases} \max_{\mu,\vartheta},\left(\mu'y_i\right) & (2) \\ \textbf{sc} \\ \quad v'x_i = 1 \\ \quad \mu'y_j/\vartheta'x_j \le 0 \qquad j = 1,\dots,N \\ \quad \mu, \vartheta \ge 0. \end{cases}$$

Where, u and v have been replaced by μ and ϑ to indicate that this is a different linear program. The fractional linear program developed by Charnes and Cooper [30] favored choosing a representative solution in each equivalence class (duality in linear programming) and the associated dual linear program is as follows:

$$\begin{cases} \min_{\theta,\lambda} \theta & (3) \\ \textbf{sc} \\ \quad -y_i + Y\lambda \ge 0 \\ \quad \theta x_i - X\lambda \ge 0 \qquad j = 1,\dots,N \\ \quad \lambda \ge 0. \end{cases}$$

Where θ is a scalar that measures the technical efficiency score of the considered farm ($\theta \le 0$); λ is a vector (N, 1) of constants called multipliers. These multipliers indicate how the farms combine to form the frontier against which the ith farm will be compared; they are given the name "peers" in reference to the efficient $(\lambda > 0)$ farms forming each segment of the efficiency frontier.

The problem is to be solved N times, once for each farm in the sample ; and therefore generates N optimal values of θ and λ. However, if θ =1, the observed farm is efficient in the Farrell sense, i.e. it is on the frontier. On the contrary, it will be technically inefficient if $\theta < 0$.

In DEA (3), the performance of the farmer is assessed in terms of his ability to decrease his factor vector to the level of the observed best practice. However, it turns out that the constant returns to scale assumption is only really appropriate if the firm is operating at an optimal scale [32]. In other words, this assumption is appropriate when farms produce at an optimal scale. This is not always the case in situations of imperfect competition, liquidity constraints, etc. that may prevent the objective of optimal production. In order to counter this limitation, Banker et al. [31] proposed the BCC model, which makes it possible to determine whether production takes place in a zone of increasing, constant or decreasing returns. It is an extension of the DEA model with constant returns to scale in order to take into account situations of variable returns to scale.

These authors decompose their model of technical efficiency into pure technical efficiency and scale efficiency. As a result, the CCR model can be modified by taking into account the hypothesis of variable returns to scale. This can be done by adding a constraint: $N1'\lambda=11$ to program (3); we then obtain:

$$\begin{cases} \min_{\theta,\lambda} \theta \\ \textbf{sc} \\ \quad -y_i + Y\lambda \geq 0 \\ \quad \theta x_i - X\lambda \geq 0 \qquad j = 1, \dots, N \\ \quad N1'\lambda = 1 \\ \quad \lambda \geq 0. \end{cases} \tag{4}$$

Where N1 is a unit vector of dimension (N, 1).

The difference between the technical efficiency index obtained by the CRS DEA model and that of the same farm by the VRS DEA model is a good measure of the scale efficiency of the farm considered (Coelli et al., 1998). Furthermore, this model allows the decomposition of technical efficiency into total technical efficiency and pure technical efficiency. The assumption of constant returns to scale leads to the determination of total efficiency, while the assumption of variable returns to scale leads to that of pure efficiency.

Following this presentation of DEA models, we will focus on the TOBIT model. Indeed, according to Ji and Lee [33], the predominant method in the literature to search for the determinants of the censored efficiency scores at the decision making units is to use a TOBIT regression method given that the efficiency scores are censored at their maximum value.

3.1.2 The TOBIT model

In order to explain the inefficiencies of farms in Cameroon, a censored TOBIT model is used Goldberger (1964). Here, the dependent variables have an upper bound (1) and a lower bound (0). The choice of the TOBIT model is justified by the fact that the dependent variables that will be the indices of inefficiencies (1 - efficiency) are continuous and take values in the interval [0 1[. The form of the model is as follows:

$$\begin{cases} Y_i = X_i\beta + u_i \\ \text{with} \begin{cases} Y_i = Y_i^* \text{ if } Y_i^* > 0 \\ Y_i = 0 \ \text{Otherwise} \end{cases} \end{cases} \tag{5}$$

Where in relation (5) X_i is the vector of explanatory variables; β is the vector of parameters to be estimated and Y_i^* is the threshold at which the variables X_i affect the efficiency of a farm (it is a latent variable). In this study, the efficiency variable is the dependent variable; it is continuous and bounded at zero.

u_i: the disturbances. However, assuming that the latter are identically distributed (idd) according to a normal distribution $(0, \sigma_u^2)$, we use log likelihood maximization to estimate the censored TOBIT model (5). Thus, the log likelihood maximization can be written as follows:

$$\begin{aligned} & log\, L \\ & = \sum_{i=1}^{n} log[1 - \Phi X_i\beta/\delta] \\ & + \sum_{i=1}^{n} log\left(\frac{1}{\sqrt{2\pi\sigma}}\right) \\ & - \frac{\sum_{i=1}^{n}(Y_i X_i \beta)^2}{2\sigma^2} \end{aligned} \tag{6}$$

Where n is the number of observations, and δ is the standard deviation.
Once the presentation of the models to be used in our study is done, it is appropriate to present the variables involved in the different models to be estimated.

3.2 Data and Presentation of Variables

3.2.1 The data

The sample is made up of farms in Cameroon's rural zones. This choice is justified by the crucial role of the agricultural sector both in the GDP and the fight against malnutrition and poverty in Cameroon. Agriculture constitutes the main

activity of households in rural zones in the ten (10) regions of the country. Here, we consider a secondary sample of 4774 agricultural households from the ECAM 4 (Fourth Cameroonian Household Survey) database focusing on agricultural products (cash crops and food crops) which include the most cultivated and consumed products in Cameroon (ECAM 4); [34]. ECAM 4 is provided by the Cameroon's National Institute of Statistics.

3.2.2 Presentation of the variables

3.2.2.1 Variables used to measure efficiency

Data analysis was carried out with the DEA method incorporating three inputs and two outputs based on the Cooper et al. (2006) method used by Ji and Lee [33].

- **Input 1:** Size of the farm (in hectares).
- **Input 2:** Labour (work) : this will be evaluated in terms of the number of workers on the farm.
- **Input 3:** Seed (in FCFA)
- **Output:** agricultural productivity (in FCFA/ha).

The choice of these variables is justified according to Nyemeck [14] cited by Kane et al. (2012) by the fact that they are generally used for the estimation of agricultural production frontiers in developing countries and constitute the basic inputs for any farm especially in Cameroon.

Technical efficiency scores measurement : To calculate the technical efficiency scores in our study, we use the DEAP computer program (DEAP 2.1) which have been written by Coelli (1996) to conduct DEA for the purpose of calculating efficiencies in production.

Spearman's test: In order to observe the similarity of the results between the different indicators (efficiency scores: constant or variable returns to scale, input or output oriented), we used the rank correlation coefficient (Spearman correlation coefficient). This method measures the correlation between the ranks of efficiency values. It evaluatee the strength of a monotonic link (or of monotonic dependence) between two variables. This strength of dependence is measured by the Spearman correlation coefficient (ρ) which takes its values in the interval [-1; 1]; this highlights two situations: the variation of the two variables in the same direction when the coefficient is positive; and their variation in the opposite direction in case of a negative coefficient. This coefficient is defined from the sum of the squared distances between the variables taken two by two ($\sum_{i=1}^{n} \boldsymbol{d_i^2}$**).** Hence the following formula:

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)}$$

With $d_i = [R(X_i) - R(Y_i)]$and -1≤ρ≤1 ; ρ=0 when the variables are independent.

The more |ρ| converges to 1, the stronger the correlation between the two variables; conversely, the more it tends towards -1, the closer the rankings are to opposition, and finally, the more it tends towards 0, the more uncorrelated the vectors are (close to independence).

The hypotheses for the Spearman correlation test are as follows:

H0: ρ=0, there is no relationship between the two variables (independent rankings);

H1: ρ≠0, there is a relationship between the two variables (non-independent rankings).

However, the closer the absolute value of the coefficient is to 1, the stronger the monotonic dependence relationship between the two variables. 1 in absolute value means that the data classified by line are perfectly linear; the sign of the coefficient indicates the direction of the relationship. Thus, the coefficient will be positive if the two variables tend to increase (or decrease) together, and the line representing the correlation will slope upwards. Conversely, the coefficient will be negative if one variable tends to increase when the other decreases, and the line representing the correlation will slope downwards.

The results of these correlations are presented in the table.

The results contained in Table 1 show that the signs of the different Spearman correlation coefficients are positive, indicating that the relationships between the variables are positive and significant. In conclusion, H0 is rejected. In the results above, we note the existence of ties in the ranking of Spearman's rho coefficients of agricultural productivity. The correlation coefficients between VRS_output and CRS_input and between VRS_output and CRS_output are

Table 1. Spearman correlation matrix

	CRS_in	CRS_ou	VRS_ou	VRS_in
CRS_in	1			
CRS_ou	1,000***	1		
VRS_ou	0,816***	0,816***	1	
VRS_in	0,702***	0,702***	0,347***	1

*** $p \leq 0.001$

Source: Author's data analysis results

the highest. However, following this test and based on some arguments from the literature, we choose an input orientation of the DEA model. According to Coelli (1996), the orientation should be chosen according to the quantities of inputs and outputs that farmers are able to control. Indeed, farmers are better able to control inputs : labor and the size of the farm than outputs. Therefore, the orientation chosen in this case is the input orientation (CRS_input) (Kane et al., 2012).

3.2.2.2 The variables that explain technical efficiency

The full empirical form of the TOBIT model that will be estimated is as follows:

$$Y_i = \beta_0 + \beta_1 Niv\_Edu + \beta_2 Age + \beta_3 Tail\_Exp + \beta_4 M\_Asso + \beta_5 Acces\_Cred + \beta_6 Engrais$$

However, the variables that may affect the efficiency of the farmers in the sample are presented in the following table:

Table 2. Presentation of variables

Variables	Definition	Type	Code and description
Dependent variable			
Technical efficiency		Continuous	
Independent variable			
Acces_Cred	Access to credit	Binary	1= Yes et 0= No
Age	Head of household's age	Continuous	
Niv_Edu	Level of education	Categorical	0= primary ; 1= secondary and 3= higher education
Tail_Exp	Farm size (in ha)	Continuous	
M_Asso	Member of an association	Binary	1= Yes et 0= No
Engrais	Fertilizer	Continuous	

Source: Author's data analysis results

3.3 Statistical Description of Model Variables

Table 3. Descriptive statistics of the variables used in the study

Titles			Mean
Variables	**Type**	**Code and description**	
Output	Continuous	PAG=agricultural productivity (in FCFA)	270,167
Input 1	Continuous	Total land area	2.04
Input 2	Continuous	Labour (number of people working on the farm)	3.20
Input 3	Continuous	Seeds (in FCFA)	14,112.17
Acces_cred	Binary	1= Yes et 0= No	0.03
Age	Continuous		47.98
Niv_Edu	Categorical	0= primary ; 1= secondary and 3= higher education	1.49
M_Asso	Binary	1= oui et 0=non	0.44
Achat d'engrais	Continuous	Purchase of fertilizer	20,599.77
Achat_pesticide	Continuous	Purchase of pesticid	14,588.62
Tail_Expl	Continuous	Farm size (in ha)	1.97

Source: Author's data analysis results

The variables used to calculate the efficiency indices: On average, farms in rural zone in Cameroon (cultivating one or more of the 34 products cultivated in the country) record 270,167 FCFA/ha in terms of productivity. Yet, there is a great disparity between these farms justified by the minimum and maximum productivity (3,225 FCFA and 2,380,000 FCFA respectively). This may be related to the variability of the farms' resource endowments and the use of selected seeds by some production units.

As for the inputs used, the average values of total area (land), labour (work) and seed expenditure (capital) are respectively 2.04 ha, 3.20 workers and 14,112.17 FCFA. However, the average farmer's access to credit is 0.03.

The variables of technical efficiency factors: In Cameroon's rural zone, the average age of the heads of agricultural households in the sample is 47.98 years. The education level (Niv_Edu) is one of the factors that most favors productivity because, as it increases, labor productivity increases (Weir, 1999); Gari Baker shares this point of view. Indeed, the majority of household heads have completed their primary school education. Less than half of them are members of a peasant association (44%).

Concerning the farm size, the cropping system sampled reports that the average size of the cultivated area is 1.97 ha. The use of small areas (less than 5 ha) by farmers could be justified by the dominant practice of subsistence farming (Kane et al., 2012).

4. RESULTS

For the purpose of this analysis, the results obtained assume that all farms in the sample are subject to the same conditions and use the same inputs and outputs to produce.

4.1 Technical Efficiency of Farms in Rural Areas

Technical efficiency indices: The average level of technical efficiency for the sample of farms is 56.8%. Thus, an efficient use of all production factors would result in an average reduction in inefficiency of 43.2% by keeping the volume of production constant. These results show that farms are slightly above average in terms of average efficiency level, reflecting a clear increase in the average efficiency level of farmers compared to 2007 (48.31%).

Table 4 above, shows a great disparity between farms that are on the frontier and the others ; in this regard, the minimum level of efficiency is 0.21. Thus, the least efficient farm in this sample could reduce its resource use by 79%, while maintaining the same level of production. There is a significant improvement in rural efficiency levels between 2007 (99.06%) and 2014.

Table 4. Descriptive statistics for total technical efficiency

	Technical efficiency level
Mean.	56.78%
Std. Err.	0.16
Minimum	0.21
Maximum	1

Source: Author's data analysis results

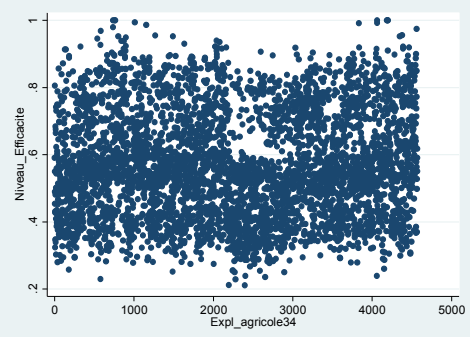

Fig. 1. Total technical efficiencies relative to the border
Source: Author's data analysis results

Fig. 1.1 shows that in terms of efficiency levels, there is a high concentration of farms in the interval [0.4 0.8]. This is even more pronounced in the interval [0.4 0.6], particularly around 0.5 (hence the average technical efficiency level estimated at 56.78%). However, less than 1% of the sample is on the efficiency frontier (3 farms).

Scale efficiency and input slacks: Our analysis shows an average scale efficiency of 0.689. The level of scale efficiency is on average neither too low nor too high. This suggests that, from a technical efficiency perspective, the farms in the sample suffer from suboptimal size. As a result, optimal use of farm size would result in an average reduction in cultivated area of 31.1% in Cameroon while maintaining the same level of productivity. Farms that have a scale efficiency equal to 1 have an average production area of about 2 ha. Therefore, the optimal farm size would cancel out the wastefulness of this factor.

Concerning excesses in the use of production inputs measured by the "input slacks[4]" (percentage of their level of use), the results show that labour is the most used factor in excess on average in our sample (with an additional excess of 98.4%) compared to the seed and farm size factors (Table 5). Thus, on average, farms could reduce their labour use by 141.62% (43.22%[5] plus 98.4%[6]), while maintaining the same level of production. These results reflect the aforementioned overuse of labour, and could be justified by the abundance of this factor (Kane et al., 2012). Talking about seed and farm size, farms could, on average, reduce their use of these factors by 47.82% and 46.52% respectively while maintaining the same level of production. Indeed, compared to other factors, the farm size is the least overused input in Cameroon.

Table 5. Additional factor excesses

Input	Percentage of factor level used
Seeds (%)	4.6
Farm size (%)	3.3
Labour (%)	98.4

Source: Author's data analysis results

The results of the technical efficiency analysis show that there are still considerable potential gains to be made in the use of production inputs for farms in Cameroon. In other words, there is significant scope for increasing agricultural productivity in rural areas based on current resource use. Farmers don't make optimal use of inputs (waste of resources).

4.2 Determinants of the Technical Efficiency of farms in Cameroon

It is important to analyze the factors that influence efficiency in order to limit the waste of resources and at the same time to identify the levers needed to improve farms efficiency.

4.2.1 Estimation of the censored TOBIT model

Table 6. Tobit results: Determinants of farms total technical efficiency

Variables	Coef.	Std. Err.
Tail_Expl	-0.019**	0.001
	(-2.83)	
Age	0.001**	0.001
	(2.31)	
M_Asso	-0.043***	0.013
	(-3.23)	
Niv_Edu	0.017	0.013

[4]*Input slacks measure the additional excess of input used.*
[5]*Proportional reduction highlighted by technical efficiency.*
[6]*Non-proportional reduction highlighted by the additional excesses, i.e. applicable to workforce input only*

Variables	Coef.	Std. Err.		
	(1.25)			
Acces_cred	0.007	0.063		
	(0.11)			
c_engrais	-4.28e-07**	1.56e-07		
	(-2.73)			
_cons	0.576***	0.034		
	(16.94)			
/sigma	0.173	0.003		
Number of observations		545	Number of uncensored observations	542
Number of left-censored observations		1	LR Chi2(6) =	35,85
Number of right-censored observations :		2	Prob > Chi2 =	0,0000

Note: Dependent variable: Level of farm efficiency (aggregate output)
**** (**) {*} significant at 1%; 5% and 10%. Values in parentheses are Student's t tests.*
Source: Author's data analysis results

5. DISCUSSION

The estimates of agricultural productivity are globally significant at 1% Prob > Chi2=0.0000. Indeed, the model for estimating efficiency indices is globally significant at the 1%. The variables that explain the farms technical efficiency in the sample are: farm size, access to credit, level of education of the head of household, age of the head of household, membership in a peasant association, and fertilizer expenditure.

Therefore, the farm size affects negatively the technical efficiency of farms. Thus, the smallest farms are the most efficient, "ceteris paribus". In fact, when the cultivated area is large, farmers are not able to make optimal use of their resources (waste due to the excessive use of land); an increase of one unit of cultivated area would lead to a decrease in farm efficiency of 1.9%. This result corroborates those of Chirwa [34] in the case of Malawi, Dlamini et al. (2010) and Fo and al. (2020). Dlamini et al (2010) showed that appropriate land use increases production. Some studies found contrary results namely Nyemeck et al. [14]; Baloyi et al. (2011); Raheli et al. [35]; Abdulai et al. [36]; Amaechina and Eboh [37] and Tasila Konja et al. [3].

Access to credit affects positively farms' efficiency in Cameroon. Indeed, an increase of 10 credit units would lead to an increase in the farms' technical efficiency of 7%. The hypothesis of our study is partialy verified because this variable has the expected sign but not significant. Thus, the positive sign of the relationship between access to credit and technical efficiency is consistent with economic theory. It shows that access to credit allows farmers to obtain quality inputs (new agricultural techniques, seeds, fertilizer) in order to increase agricultural productivity via farmers' efficiency. Similar results was found by Nyore (2009) in the case of Cameroon, Khan et al. (2010), Obare et al. [24]; Zahidul et al. [25] and Tasila Konja et al. [3]. Howbeit, the insignificativeness of this variable may be justified by the fact that farmers use the credit obtained for other purposes or use it for inappropriate agricultural products (non optimal allocation of credit obtained). These arguments corroborate the reuslts found by some authors [14,18,27]; (Adamu et al.,2015).

The membership to a peasant association affects negatively the technical efficiency of farms. This result is contrary to those of Fo and al. [38]; Nuama [15]; Audibert [39]; Minyono [22] and Kane et al. (2012) in the case of Cameroon who estimate that membership to a peasant association affects the technical efficiency of farms. It could be justified by the limited number and/or low variety (by commodity) of these associations in the rural zone, since the government encourages farmers to put themselves together in associations in order to benefit from facilities from the state and NGOs.

The level of education, although not significant, positively affects the technical efficiency of farmers in Cameroon. The result is consistent with the human capital theory which states that education is an investment that improves productivity. This means that an increase in the year of education of farmers increases technical efficiency level in production. The result is consistent with the findings of Tasila Konja et al. [3]; Danso-Abbeam et al. [40] and Ahiale et al. [41] who also found that access to education affects technical inefficiency negatively. It

corroborates those of Weir and Knight (2000), Nyemeck (1999) [42], Mahdi (2010), Asogwa (2011), Simonyan et al [23] and Coelli and Battese (1996). This contradicts Iwala and al. [43] finding that the level of education has a negative effect on the farmer's efficiency. They think the more educated the farmer is, the more he will seek off-farm employment.

The household head age positively affects the technical efficiency of farms in Cameroon. Thus, older household heads are more efficient than younger ones. This result can be explained by the experience of the older ones. It corroborates those obtained by Tasila Konja et al. [3]; Khan et al. (2010); Kyei et al. (2011); Ishiaku et al. [44] and Raheli [35]. However, this result is contrary to those obtained by Ahiale et al. (2019) who state that as the farmer gets older, technical inefficiency tends to increase, Baloyi et al (2011) confirming Coelli and Fleming's (2004) finding that younger farmers are more efficient than older ones. For these authors, younger farmers are more willing to accept new technologies and extension.

Concerning fertilizer expenses, they affect negatively the farms' technical efficiency. This negative impact is certainly due to factors such as lack of experience, lack of training in agricultural programs and technical itinerary [45]. This result is similar to Nkamleu [46] finding in the case of SSA, which states that technological change has been the main obstacle to achieving high levels of factor productivity. This result also confirms the predictions of human capital theory (human capital formation leads to higher labor productivity) that the use of modern inputs is a way of promoting higher productivity in SSA, but contradicts the result of Anitha and Jayalakshmi [6].

6. CONCLUSION AND RECOMMENDATIONS

The average efficiency level of farms in rural areas in Cameroon is 56.8%, reflecting the fact that an efficient use of all production factors would lead to an average reduction in inefficiency of 43.2% while keeping the volume of production constant. The analysis of the determinants of efficiency shows that the factors level of education and access to credit, although having positive effects, do not significantly explain technical efficiency. Concerning the variable acces to credit, this result may show the fact that farmers use the credit obtained for other purposes or they allocate it to inappropriate agricultural products (non optimal allocation of credit). However, while age increases technical efficiency, farm size, membership in a farmers' association and fertilizer expenditure affect it negatively.

The analysis of the results of our study leads us to propose recommendations in terms of economic policy at two levels, namely at the State level and at the farm level. On the one hand, we suggest that the State emphasize strong collaboration between agricultural research and development institutions / departments in charge of research and development in agricultural fields and the institutions / departments responsible for implementing the results of this research in rural areas via seminars, trainings, conferences, etc. On the other hand, to promote the creation of specific agricultural schools for farmers as well as the frequent organization of seminars in order to develop on the practical level their talents as farmers, their mastery of the technical itinerary and the use of modern inputs and new agricultural techniques. At the level of farmers, we suggest that they gather in associations in order to benefit from available credits and financial facilities, trainings, seminars and share their experiences in the agricultural field.

COMPETING INTERESTS

Author has declared that no competing interests exist.

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