FINAL

Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

Do Age and Education Determine the Technical Efficiency? Evidence from Onion Farmers in Cameroon

Dr Martial Bindoumou

University of Ebolowa
bindoumoumartial@yahoo.fr

Accepted 9 /5/2025 **Published 28/5/2025**

Abstract

This study contributes to the literature by highlighting the interaction between education and adoption of new agricultural techniques, as well as the age threshold effect of the onion farmers in the North and Far North regions of Cameroon. Since the empirical evidence concerning age effects on technical efficiency is still weak, this study further contributes to the literature attempting to bridge this gap. Data collection was carried out in three phases over the course of an agricultural year for the period August 2023-May 2024. The simultaneous estimation of a stochastic frontier and technical inefficiency function is carried out on a sample of 309 onion farmers. The study unveiled an inverted U-shaped relationship between age and technical efficiency. The interaction between education and adoption of agronomic techniques has a significant and negative effect on the level of efficiency. The least efficient producer and the most efficient producer in the sample must respectively increase their production by 62% and 5.28% using the same level of inputs to be fully efficient. The support and development programme for the agricultural sector should therefore focus on the appropriation of novel agronomic techniques by farmers with secondary education and above.

Keywords: age; education; technical efficiency; stochastic frontier

Journal of Agricultural Economics, Extension and Rural Development : ISSN-2360-798X Vol 13: (5):

1. INTRODUCTION

Agriculture in Africa, and specifically in Cameroon, remains predominantly traditional, limiting its ability to significantly reduce rural poverty. To address this, the Malabo Declaration in June 2014 emphasised the need to double agricultural productivity by 2025. In alignment with this goal, Cameroon has implemented initiatives such as the Support Project for the Development of Agricultural Sectors (PDAS) through the International Fund for Agricultural Development (IFAD) since 2014. One of the major aims of the PDAS is to increase rice and onion production (Sakatai et al., 2021). This programme targets strategic crops, including rice and onion, to strengthen rural livelihoods by boosting incomes, enhancing food security, and promoting modern farming practices. It aims at increasing production from 140,000 tonnes in 2013 to over 200,000 tonnes by 2026 (Ministry of Agriculture and Rural Development, 2020). The onion sector, which is Cameroon's leading vegetable crop, plays a vital role in the fight against poverty and food insecurity in the Northern region of Cameroon, as this region is the main production area (Jacques et al., 2020). Despite efforts, yields remain low in the rural area, averaging between 7.9 t/ha and 11 t/ha (Sakatai et al., 2021). To counter these challenges, PDAS has provided smallholder farmers with resilient seeds, efficient land and water management techniques, and tools to reduce their reliance on rain-fed agriculture and ensure sufficient and sustainable food production. At least three conditions are to be met to achieve these socio-economic objectives. Firstly, small-scale farmers should optimally use the available resources to overcome resource constraints in the agricultural sector (Ghorbani et al., 2020). Secondly,

FINAL
Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

farmers need to be skilled and equipped with knowledge and principles of rational use of resources to raise productivity. Finally, farmers need to be technically efficient to maximise production at farm level.

In economics, the idea of efficiency is intricate and multifaceted (Debertin, 2012). However, Farrell (1957) established the foundation by differentiating between technical and allocative efficiency. A producer is deemed technically efficient when maximum output is achieved from a given set of inputs. Allocative efficiency, on the other hand, arises when inputs are used in minimum proportions relative to their prices to generate a specific amount of output. The combination of these two aspects defines economic efficiency. Lampach et al. (2021) further contextualise productive efficiency in microeconomic theory as the maximum output achievable using a specific set of inputs and technologies. It is typically measured as the ratio of observed production to maximum potential production or the ratio of observed inputs to the minimum inputs needed to achieve a given output. Since the 1960s, extensive research has been conducted on the gaps between current and potential outputs and the factors influencing these gaps. Human capital is very frequently identified in the literature as a determinant of these gaps (Biwas et al., 2021; Hoang-Khac, L., et al., 2022). Human capital includes education, age, farming experience and health of the farming household. But these findings underscore the complex relationship between age, education, and technical efficiency, shaped by local contexts and access to resources. First, while extensive research exists on the determinants of technical efficiency, limited attention has been given to the age threshold effect. Specifically, the literature on the effect of age on technical efficiency is still unclear or divided. Second, although younger farmers are generally more receptive to adopting new technologies and leveraging extension services, older farmers often are averse to technological changes. Some studies (Audibert et al., 1999; Kouamé et al., 2020; Diatta, 2023) suggest that age positively influences technical efficiency, whereas others (Battese and Coelli, 1993; Olivier and Sardan, 1995; Chetto, 2020) argue that ageing impedes innovation adoption within farming households. Additionally, contrasting evidence exists regarding the significance of age threshold effects, with some studies identifying a notable impact (Audibert et al., 1999; Gwazani, 2022), while others find no such influence (Krasachat, 2023). In order to fill in these gaps, this study looks into the dual effects of the age threshold and the interaction between education and the adoption of new production techniques on technical efficiency.

Notably, this research is among the first to explore these effects comprehensively. Its significance is underscored by the need to enhance agricultural productivity in rural areas to boost employment and alleviate poverty. In Cameroon, existing studies have predominantly focused on measuring technical efficiency and its determinants. However, little to no research has explored onion production, a critical cash crop for farm households and a strategic sector for poverty reduction. Finally, measuring household technical efficiency in onion production is of crucial importance because it helps in identifying the determinants for generating information, making an intervention and enhancing the existing level of efficiency (Abdi et al., 2022).

The structure of the article is as follows: The materials and procedures are described in Section 2, and the results are shown and discussed in Section 3. Section 4 discusses sensitivity analyses, and Section 5 concludes the study.

The rest of the article is organised, as follows: Section 2 reviews existing theoretical and empirical work; section 3 describes the methodology. The results are presented and discussed in section 4. Section 5 addresses sensitivity analysis, and section 6 concludes the paper.

2. LITERATURE REVIEW

2.1 – Theoretical Foundation of Efficiency

The neoclassical theory of production implicitly posits that all production activities operate on the frontier of the feasible production set, with minimal deviations attributed to random errors. This framework assumes that producers are rational economic agents who aim to maximise profit or output or minimise production costs (Kumbhakar et al., 2015). However, this assumption has been challenged by numerous studies, which demonstrate that inefficiencies are more common than uncommon (Battese, 1992).

The concept of efficiency in economics is a complex and difficult one (Debertin, 2012). But the seminal work of Farrell (1957) tried to lay the groundwork for the definition of efficiency in a relative sense and distinguished allocative efficiency and technical efficiency. Efficiency is

FINAL
Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

a departure from the best practices of a peer group of producers that is indicative of the industry. Allocative efficiency happens when resources are used in a way that maximises producer earnings based on input prices. On the other hand, a company is considered technically efficient if it can produce the most with a specific set of inputs. In that way, technical efficiency is the ratio of observed to maximum potential output obtainable from the given inputs or the ratio of the minimum potential to observed inputs required to produce the given output (Sadoulet and Janvry, 1995). These two concepts are explained in figure 1 below.

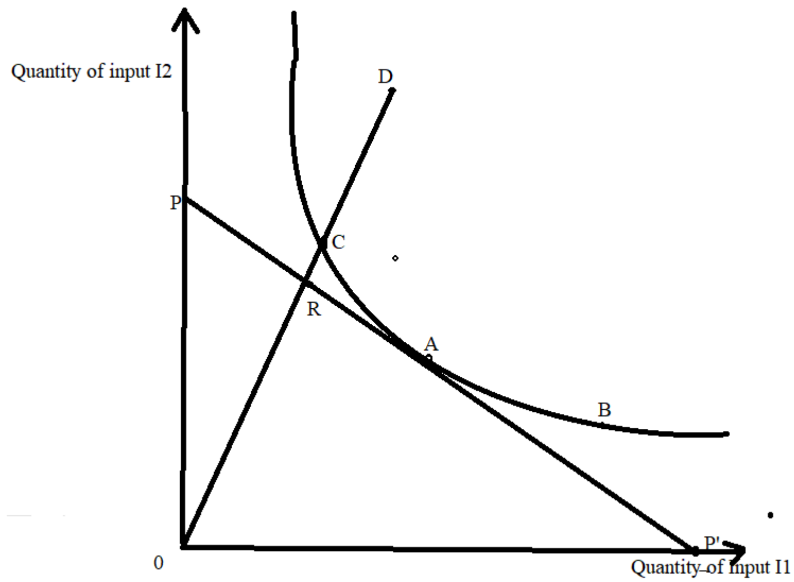

Figure 1. Input-orientated measure of Farrell's efficiency indices
Source: modified from Farrel (1957)

On the basis of the above definition, farmers A, located both on the isoquant and isocost; B and C, who are located only on the isoquant, use the least amount of inputs I1 and I2 to produce a unit of output and are said to be technically efficient, but farmer D is not technically efficient since he or she can reduce the used amount of both inputs and still yield the same level of output or commodity. The distance CD represents the technical inefficiency of the farmer, which depicts the amount by which all inputs could be lowered proportionately without lowering input levels. That is, the technical efficiency of the farmer is measured by the ratio, which accepts a number in the range of 0 and 1. A farmer with a value of one is considered totally technically efficient, whereas one with a value of zero is considered fully technically inefficient. According to Farrell (1957) and Kopp and Diewert (1982), economic efficiency is the ability of a farm to produce a specific amount of output at the lowest possible cost for a given degree of technology. Economic efficiency is demonstrated by the farmer at point A in figure 1.

To measure efficiency, Farrell (1957) distinguishes input-orientated measure (Figure 1 above) from output-orientated measure, which is illustrated in Figure 2 below. The output-orientated metric shows how much output quantities can be increased proportionately without changing the amounts of inputs used (Coelli et al., 2005).

FINAL
Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

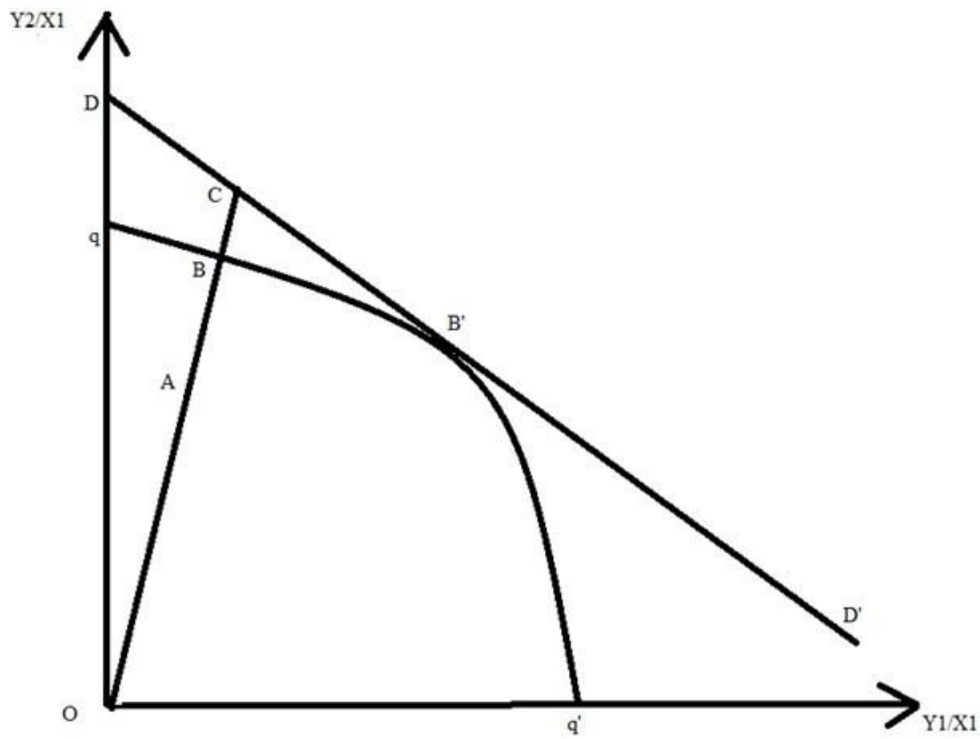

Figure 2. Output-orientated measure of Farrell's efficiency indices
Source: modified from Farrell (1957)

The farmer uses one input to obtain two outputs, Y1 and Y2, in the case of constant return to scale. The unit production possibility curve is depicted by qq'. A farmer located at point A, below qq' is inefficient. Technical efficiency and allocative efficiencies are measured respectively by the and the . The product of the two indices is revenue efficiency.

2.2 Previous Empirical Studies

Studies carried out to determine the size of the gaps between current output and maximum output and the factors determining these gaps have been justified in the literature since the 1960s. Three kinds of variables are used to identify the elements that affect technical efficiency. These include sociodemographic traits like age, education, training, and agricultural extension , as well as unique traits of farmers (Biwas et al., 2021).

Concerning age, which can act as a stand-in for prior farming experience, there is controversy surrounding its effect on technical efficiency. While Khan et al. (2022) reported that age had a negative significant effect on efficiency, the positive effect of age on technical efficiency has been found by Balete (2020) and Abdi etl. (2022), who showed that the age of the household heads has a positive effect on technical efficiency. That is, older farmers increase the yield close to the frontier by improving the efficiency.

As for the education variable, while some authors like Gwazani et al. (2022) discovered that farmers' technical efficiency is unaffected by education, others discovered that it has a notable and beneficial impact. The effect of education on production efficiency is dual, as shown by Ngom et al. (2018). Indeed, according to the authors, education increases the probability of adopting new technologies through the assimilation of new knowledge. It also enables farmers to make an effective and efficient allocation of the available resources. This is why the use

FINAL
Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

of agronomic techniques positively affects technical efficiency. These results align with findings by Ali et al. (2022), who unveiled that education had a significant and positive influence on technical efficiency. These findings were also reported by Karimov (2023) and Islam et al. (2023), who demonstrated that farmers with greater education levels made better use of inputs and that technical inefficiency decreases with school years and rises with farmer age.

These previous studies highlight the indeterminate role of education and age in technical efficiency. For some studies, education and age contribute to increasing farmers' technical efficiency, while for others, when these contributions are not negative, they don't affect their technical efficiency. None of these studies has yet examined the interaction between education and the adoption of agronomic techniques, and few have highlighted the long-run effect of age on productivity in general and specifically on technical efficiency.

3. METHODOLOGY

3.1 – Data Sources

Both primary and secondary data are used in this investigation. Seven locations were used to gather primary data: Pitta, Touboro and Lopéré in the North; and Domayo, Mesquin, Mowo, Salak and Ziling in the Far North. In each locality, information was collected on farming techniques, inputs, infrastructure, land use patterns, and the difficulties and constraints faced by producers in the study area. In addition, data collection was carried out in three phases over the course of an agricultural year for the period August 2023-May 2024. The first survey phase was carried out in August 2023 during the nursery setting. The second phase involved collecting information during October 2023 corresponding to the transplanting period. Finally, the third phase covered the harvesting period from February to March 2024. As for the secondary data, they allow us to take into account the demographics of onion farmers in the study area and set the survey quotas. Three multiple sampling methods were used, namely purposive sampling; using both random and cluster sampling, a representative sample is obtained. Following Norman et al.(2023) and on the basis of 31902 households benefiting from PADFA II (PADFA, 2019), Yamane's (1967) formula was used to determine the sample size using the formula below:

$$n = \frac{N}{\left(1 + Ne^2\right)} \qquad (1)$$

n is the sample size, N is the population size and the margin of error equal to 0.05. The sample then contains 395 onion producers, 199 from the North and 196 from the Far North. Processing outliers led to the removal of 86 outlier households. These outliers declared zero or very low yields, or production costs beyond yield, resulting in negative net farm incomes. In addition, farmers who overestimated or underestimated the distance between the farm and the main road were excluded. Finally, those who gave high acreages were also excluded. Data processing was carried out using SPSS software, with some additional Excel calculations. In the end, 309 onion producers in the research region were chosen.

2.2. Measuring Technical Efficiency

Methods for estimating the production frontier and analysing producers' efficiency levels have been extensively developed over the last fifty years. The literature identifies two types of approaches for measuring productive efficiency: non-parametric and parametric.

The Data Envelopment Analysis (DEA) method is employed in the non-parametric approach. This methodology is a linear or quadratic programming technique that calculates an efficiency frontier by optimising the weight ratio of outputs/inputs for each production unit under the constraint that this ratio is at most equal to unity (Kpenavoun et al., 2017b). One of the major drawbacks of using this method is that it assumes the absence of random errors (Kpenavoun et al., 2017a). From this perspective, any measurement error is attributed solely to the inefficiency of the producer. This assumption is inconsistent with the reality of agricultural production, where some factors affecting efficiency are beyond producers' control. These may include the effects of climate change, variations in the market prices of agricultural products and inputs, plant diseases, psychological factors on the part of the producer, etc. This is how this assumption is relaxed in the parametric approach: using the stochastic frontier to take into account random effects on farmers' productivity.

FINAL

Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

In the parametric approach, a functional form of the production function must be specified to estimate the model parameters. The functional form can be the Cobb-Douglas CES, translog, quadratic, normalised quadratic, generalised Leontief, or linear type. This approach distinguishes the deterministic production frontier from the stochastic production frontier. The deterministic method was used by Aigner and Chu (1968) with a Cobb-Douglas specification. In this method, the sole explanation for the error term, a non-negative random variable, is the producer's or farm's technical inefficiency. This method suffers from the same criticisms as the DEA method.

Conversely, the development of a stochastic or compound error production frontier was independently carried out in the work of Lovell and Schmidt (1977) and Meeusen and Van den Broek (1997). Later, this model was adjusted by Jondrow et al. (1982) to introduce the calculation of the technical efficiency index specific to each farm or producer. The method for estimating the stochastic production frontier considers two kinds of errors: one caused by the producer's inefficiency and another random error that comes from unpredictable events outside the producer's control, like weather issues, floods, market price changes, the producer's mindset, and other statistical mistakes. This method can thus distinguish between producer-controlled and uncontrollable factors.

The preference for the stochastic parametric approach in this study is based on several arguments. First, the parametric approach is appropriate for processes producing one output from several inputs, unlike the DEA method, which is suitable for cases where the producer uses several inputs to produce several outputs (Kpenavoun et al., 2017b). In this study, the smallholder only produces onions from several inputs. Secondly, unlike the DEA method, which attributes any departure from the border of production solely to the producer's inefficiency, the stochastic production frontier method has the advantage of highlighting the effect of the producer's technical inefficiency and other factors linked to the climatic and biological risks that characterise agriculture and statistical errors, etc. The parametric approach also allows statistical analysis and testing.

2.3. Technical Efficiency: Stochastic Production Frontier Approach

This model is based on the work of Aigner, Lovelle and Schmidt (1977); and Meeusen and Van den Broeck (1977). Its mathematical form is as follows:

$$\ln Y_i = f(X_i;\beta)+\upsilon_i-\mu_i \qquad (2)$$

Y_i is the farmer's output i, X_i is the column vector of format inputs $K\times 1$, β is a vector of unknown parameters ; μ_i is a non-negative random error attributed to the producer's technical inefficiency i, μ_i is the producer's inefficiency i. The observed output will always be equal to or less than the technically efficient output. Given that $\mu_i \geq 0$, each producer must be on or below its frontier $\left[f\left(x_i;\beta\right)+\upsilon_i\right]$.

According to Kumbhakar and Wang (2015), such a gap is the result of factors that the producer or firm controls such as technical, and economic efficiency, a defective or damaged product, the producer's and his staff's determination and hard work. The frontier can also vary from one farmer to another. In this case, the frontier is stochastic due to the symmetrical random error due to favourable or unfavourable factors that are out of control of the farmers and which are likely to influence his productivity. This symmetrical random error can be less than, equal to or greater than zero. In this framework, the measure of technical inefficiency is the ratio between production assuming technical efficiency and technically inefficient production. The production-based technical efficiency index is calculated by

$$TE_i=\frac{Y_i}{\exp\left(X_i^t\beta+\upsilon_i\right)}=\frac{\exp\left(X_i^t\beta+\upsilon_i-\mu_i\right)_i}{\exp\left(X_i^t\beta+\upsilon_i\right)}=\exp\left(-\mu_i\right) \qquad (3)$$

It is the ratio between observed production and the production corresponding to the stochastic frontier with the same vector of inputs. Its value varies between 0 and

FINAL

Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

1. This index compares the producer's actual output to what a fully efficient producer could achieve with the same input vector. Equation (3) shows the need to estimate the parameters of equation (2). Thus, the calculation of this index is conditional on the estimation of the parameters of the stochastic frontier model (2). The assumptions on the error terms are formulated as follows:

H1- υ_i is distributed independently of μ_i

H2- The two errors υ_i et μ_i are not correlated with the explanatory variables X_i.

H3- $E(\upsilon_i)=0, E(\upsilon_i^2), E(\upsilon_i\upsilon_j)=0, i \neq j, E(\mu_i^2)=constant$, $E(\mu_i)\neq 0$ et $E(\mu_i\mu_j)=0$ for all $i \neq j$

H4- $E(\mu_i)\neq 0$ car $\mu_i \geq 0$.

The estimation method used is the maximum likelihood method. This method, proposed by Aigner et al (1977), is based on two important assumptions about the two error terms:

H5- $\upsilon_i \sim iidN(0,\sigma_\upsilon^2)$: the error υ_i is a normally distributed variable that is independently and identically distributed. On both sides of the production frontier, it is thought to be dispersed.

H6- $\mu_i \sim iidN^{+}(0,\sigma_\mu^2)$: the error μ_i is a random variable assumed to be distributed on only one side of the production frontier and is therefore semi-normally, independently and identically distributed with a scale parameter of σ_μ^2. That said, the probability density function of each error μ_i is a truncated version of a normal random variable with mean zero and variance σ_μ^2. Thus, the parameters of the semi-normal model are

$$\sigma^2 = \sigma_\mu^2 + \sigma_\upsilon^2 \quad (4)$$

et

$$\lambda^2 = \sigma_\mu^2 / \sigma_\upsilon^2 \geq 0 \quad (5)$$

λ measures the share of technical inefficiency in the total variation observed between farmers on the production frontier and survey observations. Thus, a zero value of λ means that there is no effect of technical inefficiency, and that the only error is due to statistical errors.

The absence of inefficiency is verified by the test on λ : $\begin{cases} H_0 : \lambda = 0 \\ H_1 : \lambda \succ 0 \end{cases}$. The test statistic is $z = \dfrac{\lambda}{se(\lambda)} \sim N(0,1)$, with λ the maximum likelihood estimator of λ

2.4. Empirical Specification

Following some authors (Gwazani et al, 2022; Muzeza et al, 2023; Rodrigues et al, 2023), we adopt a Cobb-Douglas type specification. This specification does not suffer from the severity of multicollinearity or a low degree of freedom (Rahman et al., 2012). Moreover, Kopp and Smith (1980) and Ahmad and Bravo-Ureta (1996) show that functional form has no significant impact on estimated technical efficiency. Moreover, for Taylor et al. (1986), the Cobb-Douglas function is an appropriate representation of production technology. It is formulated as follows:

$$LnY_i = \beta_0 + \sum_{j=1}^{4}\beta_j \ln X_j + \beta_5 D + \beta_6 Z + \upsilon_i - \mu_i, \quad (6)$$

β_i is the vector of parameters to be estimated and represents the elasticities of production with respect to production factors. Y_i is onion production in kilograms. X represents the factors of production used by the producer such as land measured by the area cultivated in hectares; labor measured by the total working time of family and hired labor required for cultivation and harvesting operations in man-days; and capital measured by both the quantity of fertilizer used in kilograms and the quantity of seed used in kilograms, D represents the adoption of agronomic techniques. If the producer accepts it, the value of this binary variable is 1, and if not,

FINAL

Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

it is 0. Z is the use of the bullock plow, a binary variable that, if used by the producer, returns 1; else, it returns 0. The producer's technical inefficiency model is

$$\mu_i = \theta_0 + \theta_1 Age_i + \theta_2 Distance_i + \theta_3 Education_i + \theta_4 Education_i \times Agronommictechnique$$
$$+\theta_5 Age_i^2 + \theta_6 Cashcredit_i + \varphi_i$$
(7)

where Age is the age (Baruwa & Omodara, 2019; Biswas et al., 2021; Djomo et al., 2023) of the head of the farm household whose expected coefficient sign is negative, is measured in years. Distance is the distance from the plot to the main road access in kilometers and is expected to positively influence inefficiency (Tabe-Ojong and Molua, 2017); Education (Khatiwad et al., 2022 ; Kodua et al., 2022) is the level of education in years of schooling and is expected to negatively influence the technical inefficiency; Age_i^2 is the square of the producer's age and is expected to positively influence the technical inefficiency; Cash credit (Boateng et al., 2022 ; Fidelis et al., 2023) is access to cash credit, a dummy variable which takes the value 1 if the producer has had cash credit and 0 otherwise ; and the associated coefficient is expected to be negatively influence technical inefficiency. $\theta_0, \theta_1, \theta_2, \theta_3, \theta_4, \theta_6$ and θ_7 are the parameters to be estimated.

4. Results and Discussion

4.1. Descriptive Statistics of the Variables Used

Table 1 outlines the socio-economic variables of households involved in onion production in the study area.

Table 1. Descriptive statistics on the variables used

Continuous Variable	Obs	Mean	Std.Dev.	Min	Max
Age of the head of the household (years)	309	39.55	8.834	20	65
Fertilizers (kg)	309	665.34	129.8	400	980
Distance from farm plot to main access road (Km)	309	2.28	1.83	0.5	8
Improved Seeds (Kg)	309	7.49	3.50	1	24.5
Labor (Mandays)	309	42.02	21.93	12	144
Area of cultivation (Acres)	309	3.35	1.48	2	10
Total production (kg)	309	8745.63	4147.72	2500	22500

Categorical variable	Freq.	Percent	Cum.
Agronomic technique			
0	88	28.48	28.48
1	221	71.52	100
Education			
Illiterate	31	10.03	10.03
Primary	137	44.34	54.37
Scondary and above	86	27.83	82.20
Koranic	55	17.80	100.00
Loan structure			
0	129	41.75	41.75
1	180	58.25	100
Study area	38	12.30	12.30
Domayo			

FINAL
Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

Loppéré	29	9.39	21.68
Meskin	59	10.09	40.78
Pitoa	50	16.18	56.96
Salak	50	16.18	73.14
Touboro	20	6.47	79.61
Zilling	13	4.21	83.82
Mowo	44	14.24	98.06
Doyang	6	1.94	100.00
Plough or animal traction			
0	205	66.34	66.34
1	104	33.66	100

Source: authors based on survey data

The results reveal that onion farming is predominantly conducted by men and adherents of the Muslim faith. Farmers' ages range from 20 to 65 years, with an average age of 39.55 years, suggesting that adult farmers, with substantial experience, dominate onion production. Fertiliser and improved seed usage average at 664.5 kg and 7.49 kg, respectively, across an average farm area of 3.35 hectares, yielding an average onion production of 8,745.63 kg, with total production ranging between 2,500 and 22,500 kg. The variability in fertiliser usage stems from farmers' limited purchasing power, which significantly affects onion production levels. Modern agronomic practices such as mulching, irrigation, and weeding are adopted by 71.52% of farmers, whereas 28.48% still rely on traditional methods due to financial constraints. Additionally, 41.75% of producers lack access to agricultural credit, 33.66% use animal traction, and 79.29% rely on wells for irrigation. These factors likely contribute to the low average onion production. However, 71.52% of farmers have contact with agricultural extension services, 44.34% possess primary education, 27.83% have secondary education or higher, 10.03% are illiterate, and 17.80% have only received Koranic education.

Table 2. Matrix of correlations

	Age	Distance	Fexp	lnF	lnL	lnLd	lnSd	lnY
Age	1.0000							
Distance	-0.2423*	1.0000						
Experience	0.6393*	-0.2874*	1.0000					
lnF	0.1059**	-0.0008	-0.0167	1.0000				
lnL	0.1434*	-0.0478	0.2444*	0.0231	1.0000			
lnLd	0.0103	-0.0128	-0.0570	0.1434**	0.2209*	1.0000		
lnSd	0.3256*	-0.2158*	0.5441*	-0.0683	0.2340*	0.0205	1.0000	
lnY	0.4687*	-0.3404*	0.7115*	-0.1041***	0.3089*	-0.0382	0.7060*	1.000

Source: authors based on survey data
*: significance at 1%; **significance at 5%; *** significance at 10%

FINAL
Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

Table 2 indicates that variables such as labor, seed, farm area, and fertilizer are positively and significantly correlated with total onion production at the 5% significance level. Additionally, fertilizer usage is significantly correlated with labor, seed, and farm area.

Table 3. Results of the VIF multi- colinearity test

Variable	VIF	1/VIF
Experience	2.27	0.440718
Age	1.75	0.572232
lnSd	1.46	0.683229
lnL	1.15	0.871608
Distance	1.11	0.904420
lnLd	1.09	0.915004
lnF	1.05	0.953338
Mean VIF	1.41	

Source: authors based on survey data

A Variance Inflation Factor (VIF) test (Table 3) confirms the absence of multicollinearity, with a VIF value of 1.71, well below the critical threshold of 3.

4.2. Estimating the Stochastic Production Frontier and Technical Inefficiency

The stochastic production frontier was estimated using the maximum likelihood method. Table 4 shows that the model is globally significant, with the Wald statistic rejecting the null hypothesis that, at the 1% level, all variables are jointly insignificant.

Table 4. Maximum likelihood estimates of the stochastic frontier and technical inefficiency functions

Variables	**Estimate**	**Z**
Frontier		
lnSd	0.4276*	10.19
lnLd	-0.0657**	-1.7
lnL	0.0513**	1.79
lnF	-0.0964	-1.48
Agro_tech	0.1276*	2.56
Plough	0.0736**	2.56
_cons	8.8040*	20.06
Mu : technical inefficiency		

FINAL

Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

Age	-0.0400**	-2.31
Distance	0.0215**	2.07
Education	-0.0630*	-1.7
EduAgrotech	0.0791*	2.73
Age2	0.0104***	1.85
credit	-0.5773**	-2.2
_cons	1.3099*	4.05
Usigma		
_cons	-4.0942*	-6.86
Vsigma		
_cons	-3.2207*	-23.8
sigma_u	0.1291*	3.35
sigma_v	0.1998*	14.78
Log likelihood = 31.1625		
Number of obs = 309		
Wald chi2(7) = 186.14		
Prob > chi2 = 0.0000		
Stoc. frontier normal/tnormal model		

Source: authors based on survey data
Parameter significance levels are:* significant at 1%; ** significant at 5%; *** significant at 10%.

Table 5. Descriptive statistics on technical efficiencies

Variable	Obs	Mean	Std. Dev.	Min	Max
Technical efficiency	309	0.8024427	0.177373	0.379038	0.9741881

Source: authors based on survey data

All variables significantly influence onion production except fertiliser, whose non-significant effect can be attributed to small-scale farmers' limited financial capacity to acquire quality fertilisers.

Education significantly reduces technical inefficiency, with a 10% increase in education level reducing inefficiency by 0.63%. This aligns with findings by Nana and Atangana (2012) and Norman et al. (2023), which emphasise that educated farmers are better equipped to adopt efficient practices (Kitila & Alemu, 2014). Age also exhibits a nuanced effect: it initially reduces technical inefficiency but becomes detrimental beyond a certain threshold. Older farmers' inefficiency may stem from physical limitations and a reduced capacity to adopt modern technologies (Bempomaa & Acquah, 2014; Belete, 2020; Biswas et al., 2021; and Djomo et al., 2023). These findings corroborate earlier studies, including those by Audibert et al. (1999) and Coelli and Battese (1996), for whom heads of household who are very often illiterate behave in ways that are not conducive to

FINAL

Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

efficiency and tend to muzzle young people, who are relatively more educated and enlightened. Zhout al. (2021) justify inefficiency at older ages by the fact that in the context of urbanisation and mechanisation, older farmers may have physical handicaps that hinder productivity improvement and access to modern agricultural technologies. In the same vein, Coelli and Battese (1996) and Malinga et al.(2015) in India found that age contributes significantly to the decrease in technical inefficiency in the two villages Aurepalle and Kanzara. On the other hand, for farmers in the Shirapur village, age rather increases the technical inefficiency of farmers, as in the work of Deme et al. (2015) and Norman etl. (2023). Additional research, like those by Audibert (1997), has even shown that age has no discernible impact on a farmer's technical inefficiency. While a positive effect of the interaction between education and agronomic techniques on technical efficiency was anticipated, the results indicate the contrary. The interaction significantly reduces the degree of technical efficiency among growers. However, Ngom et al. (2016) demonstrated in the case of rice farmers in Senegal that education enhances the probability of adopting new technologies by facilitating the assimilation of new knowledge and enabling an efficient allocation of resources. The observed negative effect may be logically explained by Audibert et al. (2003), who found that the most efficient farmers are often those with lower levels of literacy. This phenomenon could stem, first, from the individualism and overconfidence of educated farmers, which make them less open to advice on new agronomic techniques. Second, educated farmers may redirect their efforts toward other income-generating activities, thereby reducing their focus on agriculture. Krasachat (2023) corroborates this, suggesting that diversification into non-agricultural activities often reduces technical efficiency by maximising utility.

The analysis further identified additional determinants of technical efficiency within the study area. Notably, distance from farm plots to access roads and financing availability have a big impact on efficiency levels. Farm distance from the main access road was found to reduce the technical efficiency of small-scale farmers by 5%. Farmers operating farther from access roads face increased logistical challenges, which limits their productivity. Similar findings were reported by Binam et al. (2004) for shifting cultivation areas in Cameroon, emphasising the critical role of infrastructure in agricultural development.

Access to credit emerged as another significant determinant of technical efficiency, with a 10% increase in credit access reducing technical inefficiency by approximately 5.77%. Credit access enables farmers to overcome financial constraints, acquire necessary inputs, and make more efficient production decisions. These results align with findings by Khandker and Koolwal (2016), Afrin et al. (2017), Freitas et al. (2020), Boateng et al. (2022), and Fidelis et al. (2023), all of whom highlighted the role of credit in enhancing producers' technical efficiency. Binam et al. (2004) also noted that credit facilitates resource acquisition for poor households by allowing them to optimise agricultural inputs. However, contrary findings by Rodrigues et al. (2022) suggest that access to credit may, in some instances, reduce technical efficiency, possibly due to inefficient resource allocation or credit mismanagement.

4.3. Descriptive Statistics on Technical Efficiency Estimates and Model Diagnostic Tests

The third and fourth parts of the analysis show how much of the error is due to the producer's technical inefficiency (Usigma) and how much is due to random errors (Vsigma), which are factors outside the farmer's control that can impact productivity. At the 1% significance level, the maximum likelihood of lambda shows that technical inefficiency accounts for 64.61% of the total difference between the highest possible production and the actual production recorded in the survey data (Table 4).

FINAL
Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

Table 5. Descriptive statistics on technical efficiencies

Variable	Obs	Mean	Std. Dev.	Min	Max
Technical efficiency	309	0.8024427	0.177373	0.379038	0.9741881

Source: authors based on survey data

Table 5 reveals that, on average, small onion farmers produce approximately 19.75% below their maximum potential output. This conclusion implies that each farmer, on average, would need to increase production by 19.75%, using the same quantity of inputs, to achieve full efficiency. Furthermore, the least efficient farmer operates at approximately 62% below the maximum production potential, while the most efficient farmer achieves levels just 5.28% below the potential maximum in the northern region of Cameroon.

To assess the relevance of the stochastic frontier model after specifying a one-sided error term representing technical inefficiency, two tests were employed: (i) the classical test on and (ii) the generalised likelihood ratio (LR) test of inefficiency as proposed by Kumbhakar et al. (2015). Calculations based on the values of u sigma and v (Table 4) indicate that technical inefficiency accounts for approximately 29.45% of the variation in onion production in northern Cameroon. These results support the appropriateness of the stochastic frontier model for parameter estimation.

However, Kumbhakar et al. (2015) caution against relying solely on the classical test for rejecting the null hypothesis of no technical inefficiency. UnliUnlike the LR test, the classical test does not incorporate information derived from the distribution functions of the random error.sequently, we applied the LR test, which indicated that the test statistic exceeded 5.412, the critical value at the 1% significance level (Kodde and Palm, 1986). Thus, the null hypothesis that there was no technological inefficiency was disproved, confirming the stochastic frontier model's relevance in capturing the technical efficiency of small onion farmers in the study area.

4.4. Analysis of the Distribution of the Technical Efficiency Index

The spatial distribution of farmers' technical efficiency is needed to estimate the differences in food crop yields between farmers' actual and potential yields in order to identify productive areas (Zhou et al., 2021).

The technical efficiency index is calculated using the formula of the ratio between y_i observed production and the production corresponding to y_i^* the stochastic frontier with the same input vector

$$\exp(-\mu) = \frac{y_i}{y_i^*}. \qquad (8)$$

Figure 3 below illustrates the geographical distribution of average technical efficiency among small-scale onion farmers.

FINAL

Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

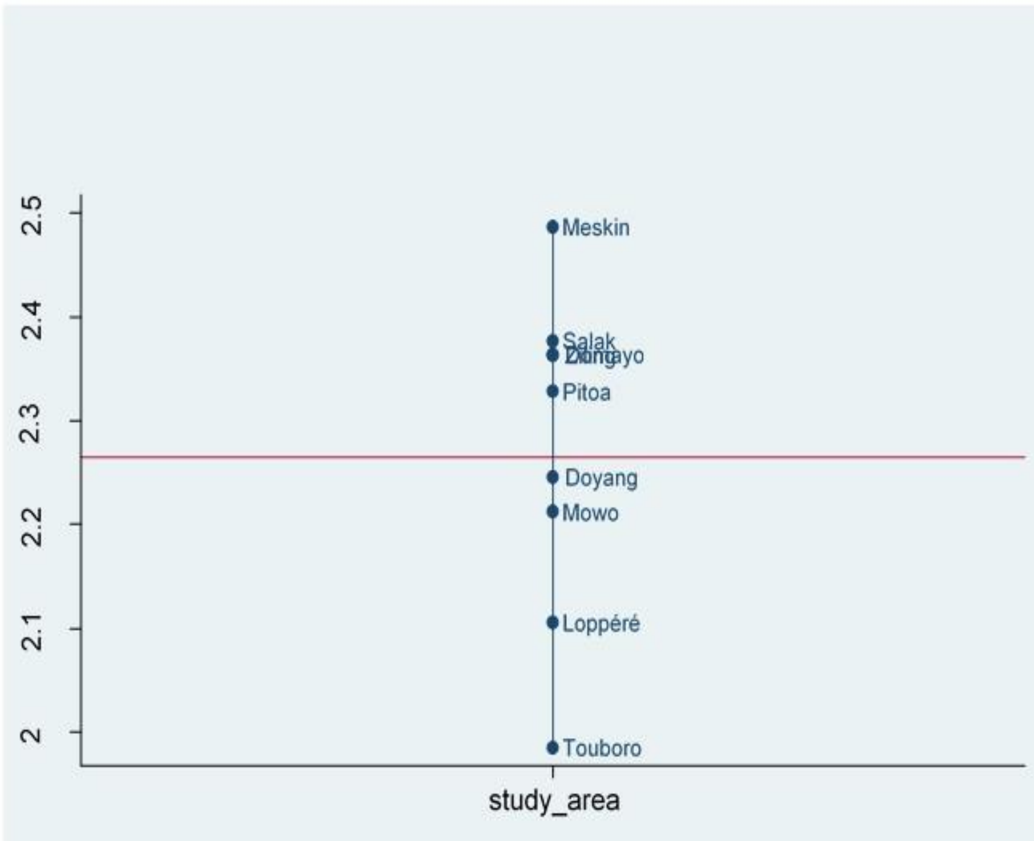

Figure 3. Geographical distribution of technical efficiency index
Source : authors based on the survey data

The findings reveal that farmers in Meskin exhibit the highest levels of technical efficiency, followed by those in Salak, Zilling, Domayo, Pitoa, Doyang, Mowo, Loppéré, and Touboro. These variations in efficiency can be attributed to the determinants of technical inefficiency identified in Table 4. The disparities in technical efficiency among producers are influenced by factors derived from the maximum likelihood estimates obtained from the Cobb-Douglas stochastic frontier and the producers' technical inefficiency. Specifically, farmers in Meskin, Salak, Domayo, Zilling, and Pitoa tend to be older, possess higher levels of education, and have greater access to credit compared to those in the other localities, as evidenced in Table 6.

FINAL

Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

Table 6. Statistics on the determinants of technical efficiency by locality

Study area	Age	Distance	Education				Access_credit	
			Illetrate	*Primary*	*Secondary and Higher*	*Koranic*	*0*	*1*
Meskin	42.90909	2.142424	2	13	16	2	4	29
Salak	43.76	1.542	7	18	16	9	15	35
Domayo	39.62069	1.982759	2	18	7	2	8	21
Zilling	41.875	2.3275	2	17	14	7	13	27
Pitoa	37.48571	1.857143	0	16	10	9	11	24
Doyang	45.25	2.4375	0	1	7	0	3	5
Mowo	44.26316	2.263158	6	6	4	3	9	10
Loppéré	35.08333	2.95625	9	22	6	11	27	21
Touboro	33.91489	2.968085	3	20	12	12	35	12
Total	…………	………….	31	137	86	55	125	184

Source: authors based on survey data

These attributes contribute to their relatively higher levels of technical efficiency.

5. Sensitivity Analysis

Thiam et al. (2001) highlight that the sensitivity of efficiency estimates to the specifications and assumptions imposed on the model remains an issue that has not been fully addressed. The estimation model used in this study is output-oriented, aiming to maximize production while keeping input quantities constant. To assess the sensitivity of the technical efficiency scores, an input-oriented model was also estimated. In this alternative model, input quantities are minimized while continuing to produce at the same rate.

Table 7. Maximum likelihood estimates of the stochastic frontier and technical inefficiency functions for input-oriented model

Variables	Estimate	Z
Frontier		
lnSd	0.4276 *	10.19
lnLd	-0.0657**	-1.70
lnL	0.0513**	1.79
lnF	-0.0964	-1.48
Agro_tech	0.1276*	2.56
Plough	0.0736**	2.56
_cons	8.8040*	20.06

FINAL

Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

Mu : technical inefficiency		
Age	-0.0400**	-2.31
Distance	0.0215**	2.07
Education	-0.0630*	-1.7
EduAgrotech	0.0791*	2.73
Age2	0.0104***	1.85
credit	-0.5773**	-2.2
_cons	1.3099*	4.05
Usigma		
_cons	-4.0942*	-6.86
Vsigma		
_cons	-3.2207*	-23.8
sigma_u	0.1291*	3.35
sigma_v	0.1998*	14.78
Log likelihood = 31.1625		
Number of obs = 309		
Wald chi2(7) = 186.14		
Prob > chi2 = 0.0000		
Stoc. frontier normal/tnormal model		

Source: authors based on survey data
Parameter significance levels are:* significant at 1%; ** significant at 5%; *** significant at 10%.

The estimates from the input-oriented model, presented in Table 7, reveal identical results to those of the output-oriented model. This consistency indicates that the technical efficiency scores and the efficiency frontier remain unaffected by the choice of orientation, affirming the robustness of the model's efficiency measures.

Additionally, a deeper sensitivity analysis was conducted by comparing the results of the stochastic frontier model with those derived from a two-limit Tobit procedure. Given that efficiency scores are bounded between zero and one, the Tobit model serves as a complementary approach. The findings from the Tobit model, presented in Table 8,

FINAL

Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

Table 8:. Tobit model

VARIABLES	(1) model	(2) sigma
Age_Producer	0.02***	
	(0.00)	
distance	-0.01***	
	(0.00)	
Education	0.02***	
	(0.01)	
EduAgrotech	-0.03***	
	(0.00)	
Age2	-0.00***	
	(0.00)	
Access to credit	0.18***	
	(0.01)	
Constant	0.20***	0.07***
	(0.07)	(0.00)
Observations	309	309

Source : authors based on survey data
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Corroborate those of the stochastic production frontier model. All variables in the Tobit model were found to be statistically significant, and the signs of the coefficients align with those of the stochastic production frontier, further validating the robustness and reliability of the efficiency estimates.

6. CONCLUSION AND POLICY IMPLICATIONS

This study aimed to examine the effect of the interaction between the level of education and the adoption of innovative farming techniques on technical efficiency, as well as the threshold effect of age among small-scale onion farmers in northern Cameroon. The findings reveal that, on average, onion farmers in the study area need to increase their production by 19.75% using the same level of inputs to achieve full efficiency. The least efficient farmer would require a 62% increase in production, while the most efficient farmer needs only a 5.28% increase to attain optimal efficiency. Also, how education and the use of farming methods interact, along with age and its limits, greatly affects how efficiently onion producers work. Agricultural support and development programmes should prioritise equipping educated young farmers with innovative agronomic techniques. Emphasis should also be placed on extension services targeting farmers with secondary education and above, as they exhibit a higher capacity to assimilate new knowledge compared to those with limited or no education, who often exhibit counterproductive behaviours. The study also underscores specific localities where production efforts need to be enhanced to achieve maximum output, thereby meeting both the growing domestic and international demand for onions. Labour productivity, currently low, could be improved through better access to agricultural tools such as ox ploughs and motorised pumps.

Given the significant interaction between education and the adoption of farming innovations, future research could explore the inclusion of an index for income-generating activity diversification to assess its direct impact on technical efficiency. This presents an opportunity to investigate how diversifying activities

FINAL

Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

influences the efficiency levels of small-scale onion farmers in the study area.Statements & Declarations

Finding details

No funding nor grants were received to support this study.

Disclosure statement

The authors report there are no competing interests to declare.

Data availability statement.

The datasets used in this study are available from the authors on request.

References

Abdallah, A.-H. (2016). Agricultural Credit and Technical Efficiency in Ghana: Is there A Nexus? Agric. Financ Rev. 76, 309–324.

Abdou, R., Bakasso.Y, Adam.T, Saadou.M, Baudoin.J. P. (2014). Oignon (Allium cepa L) : biologie, système de culture et marqueurs génétiques pour l'analyse de la diversité en Afrique. Thèse, Université de Liège-Gembloux, Gembloux, 151p.

Adedeji, I. A., Kazeem, .O. A., Ogunjimi, S.I., Otekunrin, A.O. (2013). Application of Stochastic Production Frontier in The Estimation of Technical Efficiency of Poultry Egg Production in Ogbomoso Metropolis of Oyo State, Nigeria. World Journal Of Agricultural Research, 1(6): 119-123. Doi: 10.12691/Wjar-1-6-5.

Ahmad, M., Bravo-Ureta, B. (1996). Technical Efficiency Measures for Dairy Farms Using Panel Data: A Comparison of Alternative Model Specifications. J. Prod. Anal. 7, 399–416.

AlFraj, N., Hamo, A. (2022). Evaluation of Technical Efficiency of Some Rain-Fed Cerealand Legume Crops Production in Syria: Does Crisis Matter?. Agriculture & Food Security, 11(1), 49.

Ali, S., Murtaza, Bibi, W. A. N., Khan, A., Khan, J. (2022). Does Education and Farming Experience affect Technical Efficiency of Rice Crop Growers? Evidence From Khyber Pakhtunkhwa, Pakistan. Sarhad Journal of Agriculture, 38(3), 1147-1159.

Alvarez, A., Arias. C. (2004). Technical Efficiency and Farm Size: A Conditional Analysis. Agricultural Economics. 30(1), pp. 241-255

Arun, K-C., Tek, B. S., Maharjan, S., Cheerakkollil, N. K., Paresh, S. (2023). Agricultural Emissions Reduction Potential by Improving Technical Efficiency in Crop Production, Agricultural Systems. 207(1). Retrieved from https://doi.org/10.1016/j.agsy.2023.103620

Atkinson, E. S., Cornwell, C. (1994). Estimation of Output and Input Technical Efficiency Using a Flexible Functional Form and Panel Data. International Economic Review, 35(1), pp. 245-255

Audibert, M. (1997 a). Technical Inefficiency Effects among Paddy Farmers in the Villages of the Office in Niger. Journal of Productivity Analysis, 8(1), 379 -394.

Audibert, M. (1997 b). La cohésion sociale est-elle un facteur de l'efficience technique des exploitations agricoles en économie de subsistance ? Revue d'économie du développement, 3, 69-90.

Audibert, M., Mathonnat, J., Nzeyimana I., Henry, M.-C. (1999). Rôle du paludisme dans l'efficience technique des producteurs de coton dans le nord de la Côte-d'Ivoire. Revue d'Économie du Développement, volume spécial « Santé et Développement », vol. 4, p. 121-148.

Audibert, M., Mathonnat, J., Henry M.-C.(2003b). Social and Health Determinants of Technical Efficiency of Cotton Farmers In Northern Côte-d'Ivoire. Social Science and Medicine, 56(1), pp. 1705-1717.

Bagi, F.S. (1982). Relationship Between Farm Size and Technical Efficiency in West Tennessee Agriculture. Southern J. Agric. Econ. 14, 139–144.

Bassole, K., Dieye, P., Durand, A., Guerin, J., Pioffret, T. (2017). Amélioration de la rentabilité du système de

FINAL

Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

culture de l'oignon, au Nord Cameroun. Ecole supérieur d'agro-développement international (ISTOM), 36 p.

Belete, A. S. (2020). Analysis of Technical Efficiency in Maize Production in Guji Zone: Stochastic Frontier Model. Agriculture and Food Security, 9(1), 1–15.

Bempomaa, B., Acquah, H. D. G. (2014). Technical Efficiency Analysis of Maize Production: Evidence from Ghana. Applied Studies in Agribusiness and Commerce, 8(2–3), 73–79. Retrieved from https://doi.org/10.19041/ APS TRACT/2014/2-3/9.

Bera, A. K., Kelley, T. G. (1990). Adoption of High Yielding Rice Varieties in Bangla¬ Desh: An Econometric Analysis. Journal of Development Economics, 33(1), 263 - 285.

Binam, J. N., Tonye, J., Nyambi, G., Akoa, M. (2004). Factors Affecting The Technical Efficiency among Smallholder Farmers in the Slash and Burn Agriculture Zone of Cameroon. Food Policy, 29 (5), 531-545.

Biswas, B., Mallick, B., Roy, A., Sultana, Z. (2021). Impact Of Agriculture Extension Services on Technical Efficiency of Rural Paddy Farmers in Southwest Bangladesh. Environmental Challenges, 5, 100261.

Boateng, V. F., Donkoh, S. A., Adzawla, W. (2022). Organic and Conventional Vegetable Production in Northern Ghana: Farmers' Decision-Making and Technical Efficiency. Org. Agr. 12-47–61. Retrieved from https://Doi.Org/10.1007/S13165-021-00379-7

Bravo-Ureta, B. E., Evenson. E. R. (1994). Efficiency in Agricultural Production: The Case of Peasant Farmers in Eastern Paraguay. Agricultural Economics 10(1), 27–37

Bravo-Ureta, B. E., Pinheiro, A. E. (1997). Technical, Economic and Allocative Efficiency in Peasant Farming: Evidence from the Dominican Republic. The Developing Economics Xxxv (1), 48–67.

Cathala, M., Woin, N., Essang, T. (2003). L'oignon, une production en plein essor au NordCameroun. Cahier Agriculture, 12(1), 261- 266.

Chandio, A. A., Jiang, Y., Gessesse, A. T., Dunya, R. (2019). The Nexus of Agricultural Credit, Farm Size and Technical Efficiency in Sindh, Pakistan: A Stochastic Production Frontier Approach. Journal of the Saudi Society of Agricultural Sciences, 18(3), 348-354.

Chebil, A., Bahri, W., & Frija, A.(2012). Mesure et déterminants de l'efficacité d'usage de l'eau d'irrigation dans la production du blé dur: cas de Chabika (Tunisie). New Medit 12(1), 49-55.

Chebil, A., Bahri, W., Frija, A.(2013). Mesure et déterminants de l'efficacité d'usage de l'eau d'irrigation dans la production du blé dur: cas de Chabika (Tunisie). Institut National de Recherches en Génie Rural, Eaux et Forêts (INRGREF), Ariana, Ecole Supérieure d'Agriculture de Mograne, Tunisie, 1-7.

Coelli, T., Prasada Rao, D.S. Battese, G. E. (1998). An Introduction to Efficiency and Productivity Analysis. 2nd Edition. Boston/Dordrecht/London, Kluwer Academic Press, 274p.

Coelli, T., Prasada Rao, D.S.P., Battese, G. (1998). An Introduction To Efficiency And Productivity Analysis. Kluwer Academic Publishers, Massachusetts.

Coelli, T. J., et Battese, G. (1996). Identification Of Factors Which Influence The Technical Inefficiency Effects Of Indian Farmers. The Australian Journal of Agricultural Economics ,, 40(2), 103-128.

Debreu, G. (1951). The Coefficient of Resource Utilization. Econometrica, 19(3), pp.273-292

Deme, S. G., Matthews, N., Henning, J. (2015). Analysis of factors affecting technical efficiency of smallholder maize farmers in Ethiopia. In Richard Cooksley (Eds.), 20th international farm management congress, Laval University, Québec City, Québec, Canada vol 2, pp. 1–10. Laval University. Retrieved from http://ifmaonline.org/ wpcontent/uploads/2016/01/15_NPR_Deme_etal_ P44-531.pdf.

Djomo, C. R., Ukpe, U. H., Tabetando, R., Gama, E. N., Oben, N. E. (2023). Institutional Micro Credit and

FINAL

Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

Technical Efficiency of Young Small-Scale Root And Tuber Crop Farmers.

Ekanayake, S.A.B., Jayasuriya, S.K. (1987). Measurement of Firm Specific Technical Efficiency: a Comparison of Methods. Agric. Econ. 38, 115–122

Elias, A., Nohmi, M., Yasunobu, K., Ishida, A., Alene, A.D. (2014). The Effect of Agricultural Extension Service on the Technical Efficiency of Teff (Eragrostistef) producers. Am.J. Appl. Sci. 11, 223–239. doi:10.3844/ajassp.2014.223.239.

Eyoh, D. L. (1992). Reforming Peasant Production in Africa: Power and Technological Cchange in two Nigerian Villages. Development and Change, 23, 37-66.

Farrell ,M. J. (1957). The Measurement of productive Efficiency. Journal of the Royal Statistical Society, séries A, 120, part. 3, p. 253-290.

Fidelis, E.B., Fani, D. C. R., Odufa, E. M. (2023). Technical Efficiency and Poultry Farming in Nigeria. In: Odularu, G.O.A. (eds) Agricultural Transformation in Africa. Advances in African Economic, Social and Political Development. Springer, Cham. Retrieved from https://doi.org/10.1007/978-3-031-19527-3_2

Fortini, R. M., Braga, M. J., Freitas, C. O. (2018). Adoção de práticas conservacionistas e efciênciadaagriculturanoBrasil.https://www.anpec.org.br/encontro/2018/submissao/fles_I/i11-cb3fed81ce 894b66f33bf5093db43499.pdf Acessed 20 November 2020.

Freitas, C. O., Teixeira, E. C., Braga, M. J., Schuntzemberger, A. M. S. (2019). Technical Efficiency and Farm Size: An Analysis Based on the Brazilian Agriculture

Freitas, C.O., Silva, F.A., Teixeira, E.C. (2020). Crédito Rural e Desempenho Produtivo na Agropecuária Brasileira. In: Vieira Filho JER, Gasques JG (eds) Uma jornada pelos contrastes do Brasil: cem anos do Censo Agropecuário. Brasília, IPEA, pp 281–294.

Fried, H., Lovell, C. A. K., Schmidt, S. S. (1993). The Measurement of Productive Efficiency. Techniques and Applications. England, Oxford, Oxford University Press.

Ghorbani, M., Kulshreshtha, S., Radmehr, R., Habibi, F. (2020). Technical Efficiency in Agriculture. In: Kumar, S., Meena, R.S., Jhariya, M.K. (eds) Resources Use Efficiency in Agriculture. Springer, Singapore. https://doi.org/10.1007/978-981-15-6953-1_10

Gurgand, M., (1993). Les effets de l'éducation sur la production agricole. Application à la Côte-d'Ivoire, Revue d'économie du développement, 4, 37-54

Gwazani, R., Gandiwa, E., Poshiwa, X., (2022). Rural Small-scale Aquaculture: An Assessment of Farmers' Perceptions and Technical Efficiency in Masvingo, Zimbabwe. Cogent Food & Agriculture, 8(1), 2139817.
Kouamé, L. M., Koumé, A. H., Ouattara, L., N'guessan, F. K., Aloué-Boraud, M. W., Dje, M. K. (2020). Contraintes liées à la production et à la commercialisation des mangues (Mangifera indica) en Côte d'Ivoire : cas des variétés exportées vers l'Europe », Afrique SCIENCES, vol 17, n°3, pp. 16 – 27.

Islam, S., Mitra, S., & Khan, M. A. (2023). Technical and cost efficiency of pond fish farms: do young educated farmers bring changes?. Journal of Agriculture and Food Research, 12, 100581.

Jacques, H. D., Sounou, A. P., Daïrou, S. (2020). Perte Post-Récolte Dans La Perspective De Stockage Des Bulbes D'oignons (Allium Cepa L.) En Milieu Paysan Dans Le Département De La Bénoué Nord-Cameroun. European Scientific Journal, 16, 124-131.

Jamison, D. T., Moock, P. R. (1984). Farmer Education and Farm Efficiency in Nepal: The Role of Schooling, Extension Services, and Cognitive skills. World Development, 12(1), 67-8

Helfand, S. M., Levine, E. S. (2004). Farm Size and the Determinants of Productive Efficiency in the Brazilian Center-West. Agricultural Economics, 31(1), pp. 241-249.

FINAL

Journal of Agricultural Economics, Extension and Rural Development
Abbreviated Key Title: J. Agric. Econs. Extens. Rural Dev.
ISSN-2360-798X (Print) & Open Access
Vol 13: (5): Pp.: 86-106

Hoang-Khac, L., Tiet, T., To-The, N., & Nguyen-Anh, T. (2022). Impact of human capital on technical efficiency in sustainable food crop production: a meta-analysis. International Journal of Agricultural Sustainability, 20(4), 521-542.

Huang, C. J., Faqir, S. B. (1984). Technical Efficiency on Individual Farms in Northwest India. Southern Economic Journal 51(1), 108–15.

Islam, S., Mitra, S., Khan, M. A. (2023). Technical and Cost Efficiency of Pond Fish Farms: Do Young Educated Farmers Bring Changes?. Journal of Agriculture and Food Research, 12, 100581.

Karimov, A. A. (2014). Factors Affecting Efficiency of Cotton Producers in Rural Khorezm, Uzbekistan: Re-examining the Role of Knowledge Indicators in Technical Efficiency Improvement. Agric Econ, 2(7). Retrieved from https://doi.org/10.1186/s40100-014-0007-0.

Khan, S., Shah, S. A., Ali, S., Ali, A., Almas, L. K., Shaheen, S. (2022). Technical Efficiency and Economic Analysis of Rice Crop in Khyber Pakhtunkhwa: A Stochastic Frontier Approach. Agriculture, 12(4), 503.

Khatiwad, D., Yadav, P., Jaiswal, D. (2022). Technical Efficiency of Ginger Production in Ilam District of Nepal: A Stochastic Production Frontier Approach. Advances in Agriculture, 1–8. Retrieved from https://doi.org/10.1155/2022/ 3007624.

Khan, S., Shah, S. A., Ali, S., Ali, A., Almas, L. K., Shaheen, S. (2022). Technical Efficiency and Economic Analysis of Rice Crop in Khyber Pakhtunkhwa: A Stochastic Frontier Approach. Agriculture, 12(4), 503.

Kopp, Raymond J., and W. Erwin Diewert. (1982). The Decomposition of Frontier Cost Functions Deviations into Measures of Technical and Allocative Efficiency. Journal of Econometrics 19, nos. 2/3: 319–31.

Náglová, Z., Rudinskaya, T. (2021). Factors Influencing Technical Efficiency in the EU Dairy Farms. Agriculture, 11(11), 1114.

Neupane, H., Paudel, K. P., Adhikari, M., He, Q. (2022). Impact of Cooperative Membership on Production Efficiency of Smallholder Goat Farmers in Nepal. Annals of Public and Cooperative Economics, 93(2), 337-356.

Raphael, I. O. (2008). Technical Efficiency of Cassava Farmers in Southeastern Nigeria: Stochastic Frontier Approach. Agricultural Journal, 3(12), 152–156. Retrieved from https:// doi.org/10.1038/s43016-022-00467-1.
Sadoulet, E., Janvry, A. (1995). Quantitative Development Policy Analysis. London: The John Hopkins University Press.

Singh, K., Dey, M. M., Rabbani, A. G., Sudhakaran, P. O. (2009). Technical Efficiency of Freshwater Aquaculture and its Determinants in Tripura, India. Agricultural Economic Research Review, 22(1), 185–195. Retrieved from https://doi.org/ 10.1080/13657300309380329.

Sonny, G. A., Cao, J., Yaa, O. K., Frank, O. F. (2020). The Determinants of Technical Efficiency of Cocoa Production in Ghana: An Analysis of the Role of Rural and Community Banks, Sustainable Production and Consumption. 23(1), pp.11-20. Retrieved from https://doi.org/10.1016/j.spc.2020.04.001.
https://www.sciencedirect.com/science/article/pii/S2352550920300841

Tenaye, A.(2020). Technical Efficiency of Smallholder Agriculture in Developing Countries: The Case of Ethiopia. Economies, 8, 34. https://doi.org/10.3390/economies8020034.