Estimation and Determinants of Technical Efficiency of Smallholder Cashew (*Anacardium*) Farmers in Dassa District, Benin: a Bootstrap Data Envelopment Approach

Raoul Akanro

People's Dynamics and Sustainable Development Laboratory, Benin Centre for Scientific Research Innovation

Abraham AMOUSSOUGA GERO (✉ gerolandry@hotmail.fr)

National University of Agriculture <https://orcid.org/0000-0001-6052-4250>

Marie-Odile Attanasso

People's Dynamics and Sustainable Development Laboratory, Benin Centre for Scientific Research and Innovation

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**ESTIMATION AND DETERMINANTS OF TECHNICAL EFFICIENCY OF
SMALLHOLDER CASHEW (ANACARDIUM) FARMERS IN DASSA DISTRICT,
BENIN : A BOOTSTRAP DATA ENVELOPMENT APPROACH**

Raoul Akanro, Abraham Amoussouga Gero* and Marie-Odile Attanasso

Correspondence: gerolandry@hotmail.fr, School of Agribusiness and Agricultural Policy,
National University of Agriculture, Benin, P.O. Box 01BP55 Porto-Novo, Benin

Summary

Cashew nut production is becoming more important in Benin's economy and helps improve rural populations' living conditions through the income it provides. However, production is characterized by an obsolete technology and a low farm productivity. This paper examines cashew producers' technical efficiency in Dassa District in Benin using survey data collected from 100 farms in 2020. The research relied on the bootstrap modelling of Data Envelopment Analysis (DEA) while a censored Fractional Regression Model (FRM) was applied to assess the determinants of producers' technical efficiency. The results show that farms are 34.56% technically efficient. Factors affecting technical efficiency include experience, access to credit, age of farm managers, sale of cashew apples, and expenditure on education. Policies to promote cashew farm efficiency need to focus on promoting formal education in rural areas, establishing a financial literacy training programme for farm managers, and promoting the expansion of agricultural extension for farmers. In addition, producers should also set up a system for cashew apples' conservation and sale as production waste in order to increase their income.

Keywords: Bootstrap, Cashew, Data Envelopment Analysis, Productivity, Technical efficiency and Benin

1. Introduction

Measuring and determining the factors that influence efficiency in resource use remain important steps in improving agricultural productivity (Abate et al., 2019; Anang, 2021; Awunyo-Vitor et al., 2016). Technical efficiency is defined as the situation in which a maximum output is produced using a given set of inputs or the application of a minimum amount of resources to obtain a given level of output (Battese, 1992; Battese and Coelli, 1992; Farrell, 1957). In the agricultural sector, a farm is considered technically efficient when, given its use of inputs, it produces the maximum possible output. The more efficiently they produce, the closer they are to the efficient production frontier and the more productive they are in using their limited resources. In other words, the production frontier is reached when the available inputs are used in optimal level.

However, the quantification of a firm's ability to transform inputs into outputs has been subject to several controversial debates in economic analysis. For example, according to the neoclassical theory, productivity gains are assessed using the changes achieved in output that are not explained by the main inputs such as labour and capital stock (Solow, 1957). Thus, Total Factor Productivity (TFP), which is defined as the residual, is initially interpreted by Solow (1957) as a technical progress (shifting to the production frontier). However, this approach qualified as the growth accounting approach had some weaknesses as it required firstly the definition of a functional form for production, secondly assumptions about the market structure and finally the assumption that the market is perfect (Del Gatto et al., 2011). Thus, to overcome these difficulties, Farrell (1957) introduces the Data Envelopment Analysis (DEA) approach. This approach consists in determining the optimal combinations of inputs-outputs in order to obtain an approximation of the production frontier (best practice). The latter will identify the share of technological progress and technical efficiency in productivity growth. Therefore, productivity growth is achieved by increasing three factors: capital accumulation, technological

progress, and efficiency (Kumar and Russell, 2002). The concept of efficiency is central to the production's microeconomic theory. Therefore, inputs optimal use and the important role that efficiency plays in increasing agricultural productivity have been recognized by several researchers. Indeed, improving efficiency in resources use by producers is important for achieving the goal of sustainable agricultural production for food security and rural household incomes.

In Benin, difficulties experienced by cotton, the main export crop, through the decline in international prices have shown the vulnerability of an economy based on a single export crop. Thus, several programmes and projects such as the Agricultural Sector Development Strategic Plan (PSDSA) and the Support Programme for Agricultural Diversification (PADA) have been implemented in order to make agricultural diversification a national priority. It is within this framework that cashew nuts have been classified among the priority sectors with high added value able to improve public revenues and producers' incomes. Indeed, cashew nut production allows the supply of cashew nuts and cashew apples, which are products for which local and international demand keeps increasing. In addition, from an environmental point of view, it reduces carbon dioxide emissions, the destruction of plantations by bush fires, water consumption and soil erosion. The average area is 1 hectare, while about 60,000 households and 200,000 actors depend on this production. Furthermore, the cashew industry contributes for 3% to the Gross Domestic Product (GDP), 7% to the agricultural GDP and provides 8% of Benin's export earnings. Globally, Benin is ranked as the 9th largest exporter of cashew nuts and the 3rd largest exporter in Africa (PSDSA, 2017) . These different characteristics show the opportunity that cashew production represents in agricultural diversification in Benin. However, despite its advantages, cashew nut production faces some difficulties. Low productivity of trees per hectare with an average annual cashew yield of 356 kg per hectare in 2019, which is much lower than in Ghana and Asian countries, which are respectively 800 and

more than 900 kilograms per hectare (Gbaguidi, 2020) ; poor quality of storage equipment and insufficient control of production costs. In view of these difficulties, the question arises as to know whether there are factors that influence the technical efficiency of cashew producers' resource allocation in Benin.

This research's objective is to identify cashew farms' efficiency determinants in Benin. The contributions of this article can be summarized as it follows. Firstly, it will, not only help to fill in the gap of research on the determinants of cashew nut producers' technical efficiency in Benin, but also, highlight the economic utility of cashew apples considered as production waste. Secondly, it will inform public policy on the factors that should be emphasized on to increase cashew nut productivity in Benin.

After the introduction, which outlines the problematic of this article, the second section presents the literature review on the technical efficiency of agricultural producers. The third section presents the Data Envelopment Approach (DEA) and the Fractional Regression Model (FRM), which allows us determine the factors that influence producers' technical efficiency. The fourth section deals with the model application results' analysis and interpretation. Finally, the fifth section presents the conclusion and policy implications.

2. Literature Review

The notion of efficiency appeared in economic literature with the reflections of Carlson (1939), Hicks (1935) and Samuelson (1947). However, this notion was developed in the work of Debreu (1951) on the empirical measuring of resource use of Koopmans (1951), on the measurement of efficiency and of Shephard (1981) who introduced the distance function to measure inefficiency. Farrell (1957), drawing on the work of Debreu (1951) and Koopmans (1951), considers that efficiency is composed of Allocative Efficiency (AE) and Technical Efficiency (TE). As stated earlier, TE is the ability of the firm or farm to produce the maximum possible

output from a given set of inputs, while AE is the ability of a firm or farm to produce a given level of output using cost-minimizing input ratios (Farrell, 1957). Charnes and al., (1978), in showing that Farrell's (1957) model was a special case of programming, developed the research in the field of operations research that gave rise to the DEA which is described as a non-parametric approach. The main advantage of this model is that it allows several outputs and inputs in the production process. Secondly, it imposes no restrictions on the functional form and no distributional assumptions on firm-specific efficiency, but it is extremely sensitive to variable selection and errors. The main criticism of DEA is that it gives all deviations from the frontier to inefficiency (Coelli, 1995). As a result, it is sensitive to measurement errors and random effects, leading to an overestimation of inefficiencies (Del Gatto et al., 2011).

Parametric approaches, on the other hand, are based on econometric techniques with a specification of the functional form. In this approach, the Stochastic Frontier Approach (SFA) proposed by Aigner and al., (1977) and Meeusen and van Den Broeck (1977) is widely used in the economic literature to estimate firm efficiency and its determinants. The SFA separates random errors that are outside the control of the Decision Making Units (DMU) from inefficiency deviations and allows the estimation of standard errors and hypothesis testing (Banker, 1996; Coelli, 1998, 1995; Grosskopf, 1996). Comparing the results of the parametric and non-parametric approach, most researchers point out that if the chosen functional form is closed to the production technology, the SFA is the best performing method. Otherwise, the DEA method is more appropriate. Several empirical researches have measured technical efficiency and its determinants in agricultural production in developing countries (Adamie et al., 2019; Geffersa et al., 2019; Nsiah and Fayissa, 2019; Pradhan and Mukherjee, 2018). Anang (2021) in studying groundnut farmers' technical efficiency in Ghana using the DEA and Tobit model finds that on average farmers are technically efficient at 50 and 70% under the returns to scale hypothesis; female farmers, farming experience, household size, off-farm activities

negatively affect ET unlike extension. Tetteh Anang et al. (2020) combining the double bootstrap DEA and probit model show that maize farmers' technical efficiency increases with technology adoption, herd size and decreases with education level, household size, access to extension, weeding frequency and area cultivated. Balogun and al. (2017) using the SFA showed that cassava farmers have an average technical efficiency of 81.8% in South West Nigeria. They also find a positive impact of land fragmentation on ET in contrast to distance between farms. Njikam and Alhadji, (2017) in analysing the technical efficiency of rice farmers using SFA in Cameroon find that technical efficiency and the impact of socio-economic characteristics vary across agro-ecological zones. Ahmed and al. (2018) have examined the efficiency of maize production in Ethiopia. Their results indicate that the mean values of technical efficiency, allocative efficiency and economic efficiency were 82.24%, 37.07% and 28.97% respectively. They also concluded that extension services, cooperative membership, distance between farm and home, labour, improved seeds and off-farm activities have a positive impact on technical efficiency. This is confirmed by Abate and al. (2019) who also find that age, education level, household size, land fragmentation, market information and access to credit have a positive impact on technical efficiency.

In Benin, Kinkingninhou-Médagbé and al. (2010) found, using the SFA, that female rice farmers are discriminated in adherence to the irrigation system, access to land and equipment. The results also show a positive impact of experience and distance to the irrigation channel while planting dates have a negative impact on technical efficiency. Similarly, Singbo and Lansink (2010) using the DEA bootstrap find that the average inefficiency of rice farmers which is 34.9% is positively influenced by age, water control, high land area and negatively by experience, household size and education. Singbo et al. (2014) showed that there is 13.7% inefficiency in vegetable production. Soil fertility, extension, credit, formal education,

experience have a positive impact on technical efficiency. Lawin and Tamini (2019) show that the technical efficiency of smallholder farms is 71% with higher efficiency for non-landowners.

3. Methodologies

3.1. Data envelopment analysis

In our research, we use the input-oriented DEA model to assess the extent to which a farm can reduce its input use compared to the best farmers. We chose this specification because Benin's farmers find it much more difficult to acquire inputs at lower cost. Hence it would be important to determine inputs efficiency in order to reduce production costs.

Bootstrapping is a method of testing the reliability of the original data by creating a pseudo-replicated data set. This method determines whether the distribution has been influenced by stochastic errors and can be used to build confidence intervals for point estimates, which cannot be derived analytically. In this context, Simar and Wilson (1998) introduced the DEA bootstrap where the data generation process is repeatedly simulated by resampling the sample data and applying the original estimator to each simulated sample (Simar and Wilson, 2000a, 2000b). The DEA bootstrap method is based on the idea that the bootstrap distribution will mimic the original unknown sampling distribution of the interest estimators (using a non-parametric estimate of their densities). Therefore, this measure can simulate the Data Generation Process (DGP) using the Monte Carlo approximation and can provide a reasonable estimator of the true unknown DGP. In addition, the non-parametric DEA approach has the advantage of having less stringent constraints than non-parametric methods.

The efficiency for a data point (x_k, y_k) is $\theta_k = \min\{\theta | \theta x_k \in X(y_k)\}$ where $X(y_k)$ is a set of input requirements. If $\theta_k = 1$, unit k is efficient in its use of inputs. Then, $\theta_k \leq 1$ represents the proportional achievable reduction in inputs that the DMU could achieve if y_k were produced efficiently. (Simar and Wilson, 1998) define the level of input efficiency corresponding to an

173 output y_k as $x^\theta(x_k|y_k) = \theta_k x_k$. Note that θ_k is a radial measure of the distance between
 174 (x_k, y_k) and the corresponding frontier. Unfortunately θ_k is unknown because $X(y)$ and $\theta_k x_k$
 175 are unknown.

176 Let's suppose that the DGP of P generates a random sample $\chi = \{(x_k, y_k) | k = 1, \dots, n\}$. Using
 177 the data χ with a non-parametric method:

$$178 \quad \widehat{\theta}_k = \left\{ \theta | y_k \leq \sum_{i=1}^n \gamma_i y_i | \theta x_k \geq \sum_{i=1}^n \gamma_i x_i | \sum_{i=1}^n \gamma_i = 1, \gamma_i \geq 0 | i = 1, \dots, n \right\} \quad (1)$$

179 To obtain $\widehat{X}(y)$, $\partial \widehat{X}(y)$ it is necessary to estimate its efficiency $\widehat{\theta}_k = \min\{\theta | \theta x_k \in \widehat{X}(y_k)\}$.
 180 Since the DGP of P is unknown, the bootstrap procedure is used to determine the DGP of P as
 181 a reasonable estimator of the true unknown DGP generated by the data. Note that conditional
 182 on χ , the sampling distribution of the estimators $\widehat{X}^*(y)$ and $\partial \widehat{X}^*(y)$ are known since $\widehat{P}$ is
 183 known. Analytically, $\widehat{P}$ could be difficult to calculate, so the Monte Carlo approximation is used
 184 to obtain and to generate B pseudo-samples χ_b^* , where $b = 1, \dots, B$ and pseudo-estimates of the
 185 efficiency scores. The empirical distribution of these pseudo-estimates approximates the
 186 unknown sampling distribution of the efficiency scores.

187 According to Simar and Wilson (1998), a smoothed homogeneous bootstrap procedure is
 188 applied in this research. An algorithm to generate the consistent bootstrap values $\widehat{\theta}_b^*$ from the
 189 b -kernel density estimate is implemented.

190 For a DMU k with input-output data (x_k, y_k) with $k = 1, \dots, n$, θ_k is calculated by the linear
 191 program based on the efficiency estimators.

192 The smoothed bootstrap sample $\theta_1^*, \dots, \theta_n^*$ with $i = 1, \dots, n$ is generated by not considering
 193 $\beta_1^*, \dots, \beta_n^*$, a simple bootstrap sample obtained by uniform drawing with replacement.

$$194 \quad \text{The sequence is defined by: } \widetilde{\theta}_i^* = \begin{cases} \beta_i^* + h\varepsilon_1^* & \text{if } \beta_i^* + h\varepsilon_1^* \leq 1 \\ 2 - \beta_i^* - h\varepsilon_1^* & \text{otherwise} \end{cases} \quad (2)$$

195 And we get the correct bootstrap sample by $\theta_i^* = \bar{\beta}^* + \frac{1}{\left(\frac{\sqrt{1+h^2}}{\hat{\sigma}^2}\right)(\theta_i^* - \bar{\beta}^*)}$ (3)

196 with $\bar{\beta}^* = 1/n \sum_{i=1}^n \beta_i^*$ and $\hat{\sigma}_{\theta}^2$ the sample variance $\hat{\sigma}_1^*, \dots, \hat{\sigma}_n^*$. h is called the bandwidth factor
 197 and ε_i^* is the standard deviation from the standard normal distribution. With these procedures,
 198 the sample values take the same mean and variance as the original values. The bandwidth factor
 199 h is calculated according to a methodological procedure that has been discussed in detail by
 200 Simar and Wilson (2011).

201 Then we use the smoothed bootstrap sample sequence to calculate the new data $x_b^* =$
 202 $\{(x_{ib}^*, y_i) | i = 1, \dots, n\}$, or, $x_{ib}^* = \left(\frac{\theta_i}{\theta_{ib}^*}\right) x_i, \{i = 1, \dots, n\}$ and the bootstrap estimates of the
 203 efficiency $\{\hat{\theta}_k^i | i = 1, \dots, n\}$ are obtained by solving the DEA model for each x_b^* corresponding
 204 to each producer.

205 In this paper, 2000 interactions (B) of the latter two steps were performed to ensure adequate
 206 coverage of the confidence intervals. The bootstrap efficiency scores $\hat{\theta}_k^*$ represent
 207 approximations of the $\hat{\theta}_k$, just as the DEA efficiency scores $\hat{\theta}_k$ represent approximations of the
 208 θ_k

209 Since the bootstrap estimates $\{\hat{\theta}_{k,b}^* = 1, \dots, B\}$ are biased by definition and the $BIAS(\hat{\theta}_k =$
 210 $E(\hat{\theta}_k) - \theta)$, the empirical bootstrap bias for the original estimator $\hat{\theta}_k$ perhaps, calculated as
 211 $BIAS_B(\hat{\theta}_k) = B^{-1}(\sum_{b=1}^B \hat{\theta}_{k,b}^*) - \hat{\theta}_k$. The adjusted DEA scores are obtained by subtracting the
 212 bias from the original efficiency estimates. Since the bias correction introduces additional noise
 213 and could have a higher mean square error than the original point estimates, the analysis
 214 provides corrections to find interval estimates. The percentile method modified by Simar and
 215 Wilson (2000a) was applied to obtain confidence intervals, automatically correcting for bias
 216 without using a noisy biased estimator. Using the bootstrap, we build confidence intervals for

217 each producer k . If we knew the distribution of $(\hat{\theta}^*(x, y) - \theta(x, y))$, it would be possible to
 218 find a_α, b_α so that $Pr(-b_\alpha \leq \hat{\theta}_k(x_0, y_0) - \theta(x_0, y_0) \leq -a_\alpha = 1 - \alpha)$. Since a_α, b_α are
 219 unknown, we use $\{\hat{\theta}_{k,b}^* = 1, \dots, B\}$ to find values $\hat{b}_\alpha, \hat{a}_\alpha$ such as $Pr(-\hat{b}_\alpha \leq \hat{\theta}_k(x_0, y_0) -$
 220 $\theta(x_0, y_0) \leq -\hat{a}_\alpha | \hat{P}(\chi_n) = 1 - \alpha)$. Finding $\hat{b}_\alpha, \hat{a}_\alpha$ involves arranging the values of
 221 $\hat{\theta}_{k,b}(x_0, y_0) - \hat{\theta}_k(x_0, y_0), b = 1, \dots, B$ in ascending order and then eliminating, a number of
 222 rows equal to a $\left[\left(\frac{\alpha}{2}\right) * 100\right] \%$ at each end of the list and setting $\hat{a}_\alpha \leq \hat{b}_\alpha$ at the ends of the
 223 domain with $\hat{a}_\alpha \leq \hat{b}_\alpha$. The confidence interval $1 - \alpha$ is:

$$224 \quad \hat{\theta}_k(x_0, y_0) + \hat{a}_\alpha \leq \theta(x_0, y_0) \leq \hat{\theta}_k(x_0, y_0) + \hat{b}_\alpha$$

225 This procedure is repeated n times to obtain n confidence intervals, one for each producer with
 226 $\hat{a}_\alpha \leq 0, \hat{b}_\alpha \leq 0$ and $\hat{\theta}_k$ which has values above the confidence interval.

227 3.2. Determinants of effectiveness

228 Producers' socio-economic factors examination influencing DMUs efficiency is estimated from
 229 a second step based on DEA scores regression model. The standard linear model is
 230 inappropriate for this second step because the predicted values of the DEA scores may lie
 231 outside the unit interval. Furthermore, the standard approach of censored normal regressions
 232 use with limits at zero and unity such as the Tobit model is not advisable, as scores obtained
 233 being less than or equal to unity are due to the DEA model rather than censoring. Furthermore,
 234 the domain of the Tobit model varies from the one of the DEA efficiency scores, as scores equal
 235 to zero are not observed (Ramalho et al., 2010). Therefore, as the efficiency scores are bounded
 236 by the interval $[0;1]$ we apply the fractional regression model (FRM) proposed by Papke and
 237 Wooldridge (1996) which allows to keep the predicted values of the conditional mean of the
 238 scores in the unit interval. The FRM requires assumption of a functional form for the y
 239 efficiency scores which imposes a restriction on the dependent mean as follows:

$$E(y|x) = G(x_i\theta) \quad (5)$$

Papke and Wooldridge (1996) propose as a possible specification for $G(x\theta)$ any cumulative distribution function, such as those used to model binary data. The most commonly used functions are the logit and probit functional forms for which $G(x\theta) = e^{x\theta}/(1 + e^{x\theta})$ and $G(x\theta) = \Phi(x\theta)$ respectively. However, there are alternatives such as the loglog and cloglog specifications for which $G(x\theta) = e^{e^{-x\theta}}$ and $G(x\theta) = 1 - e^{e^{-x\theta}}$ respectively (Long and Freese, 2006).

Producers' specific socio-economic characteristics were used as an explanatory variable to identify efficiency's determinants. These are farm manager's gender (x_1), experience (x_2), number of children (x_3), access to credit (x_4), non-farm income (x_5), farm manager's age (x_6), schooling expenditure (x_7), health expenditure (x_8), cashew apples' sale (x_9). In order to determine the correct specification of the functional form the Reset test and the P test proposed by Ramsey (1969) and McKinnon (1963) are used respectively.

3.3. Study area description and data collection

Located between $1^{\circ}41'$ and $2^{\circ}39'$ longitude and $7^{\circ}27'$ and $8^{\circ}31'$ north latitude, Dassa District is bordered to the north by the Districts of Glazoué and Savè, to the south by the towns of Covè, Zagnanado and Djidja, to the west by the town of Savalou and to the east by the District of Kétou. The District of Dassa is one of the six Districts of the department of "Collines" and is also the chief town of the department. It has ten roundings: Dassa I, Dassa II, Akòfojúlé, Gbàfo, Kèrè, Ìkpènyìn, Lèma, Paouignan, Soclogbo, and Tré. According to 2013 census (RGPH-4), the district had 112,122 inhabitants. The district has 3 daily markets and 10 periodic markets which play an important role in the economic life and particularly in marketing. The district's economy is dominated by the primary sector, particularly agriculture. 63.5% of the population of 11,268 farming households, is engaged in the production of cassava, yams, soya, maize and

groundnuts. Cashew nut cultivation is found on all farms. It is practiced by families. It is the main crop, making the department the largest producer in Benin.

Fig. 1 Dassa district's Geographical Location (Source : National institute of geography, 2019)

Table 1 below presents the descriptive statistics of the variables used for the DEA model and the socio-demographic variables for the analysis of the determinants of technical efficiency.

The sample is composed of 100 respondent farms in Dassa District.

Table 1 Descriptive statistics of the variables (Source : Own survey result, 2021)

	Mean	Standard deviation	Minimum	Maximum
DEA model variable				
Net income	746182.3	1078452	43000	7107500
Annual investment	185860.2	202400	2000	1432000
Area cultivated	5.9975	5.866195	1	25
Labour employed	9.24	9.73188	1	50
Socio-demographic variables				
Gender of the farm manager (Male=0, Female= 1)	.2	.4020151	0	1
Experience (Age of the farm manager)	19.78	10.48479	5	60
Number of children	6.2	2.546537	2	14
Access to credit (no=0, yes= 1)	.49	.5024184	0	1
Non-farm income (no=0, yes= 1)	.7	.4605662	0	1
Age of farm manager	50.13	8.211417	32	66
Food expenditure	184375	325598.8	0	2132250
Schooling expenses	155011.6	297254.7	0	2132250
Health expenses	88711.4	177709.2	0	1421500
Sale of cashew apples (no=0, yes=1)	.26	.440844	0	1
Observations	100			

4. Results and discussion

4.1. Distribution of effectiveness scores

Table 2 below shows efficiency scores' distribution. Firstly, it can be observed that all producers in the sample have efficiency scores below 100%, which implies that no farm has reached the cashew production possibility frontier. The overall average efficiency score is 34.56%, which means that the same level of production can be obtained by the average cashew producer in Dassa region when he reduces his input quantity by 65.44% given the technology currently available. The average ET of cashew farmers who had access to credit is 28.12%, while that of non-credit takers was 40.74%. In practice, this result shows that by reducing their quantity of inputs by 71.88%, farmers with access to credit would have the same level of production while those without access to credit would have the same level of production by reducing their quantity of inputs by 59.26%. Overall, these results show that farmers without access to credit are more efficient in the optimal use of a quantity of inputs. This result is lower than the efficiency rates of 71% and 74.5% obtained respectively by (Ogundari, 2014) in West Africa and obtained by Mugeru and Ojede (2014) for Africa. Similarly, it is lower than the rates of 67.52% and 71% obtained respectively by Sossou and al. (2014) and Lawin and Tamini (2019) for agricultural farms in Benin. These differences can be explained by the use of the bootstrap method unlike the previous results, which allows for the correction of the bias of the estimators.

Table 2 Technical efficiency's frequency distribution (Source : Own survey result, 2021)

Technical efficiency in %.	All farmers (n=100)		Farmers with access to credit (n=49)		Farmers without access to credit (n=51)	
	Number	Percentage	Number	Percentage	Frequency	Percentage
[0 ; 10]	8	8	7	14.29	1	1.96
]10 ; 20]	18	18	9	18.37	9	17.65
]20; 30]	21	21	14	28.57	7	13.73
]30 ; 40]	23	23	11	22.45	12	23.53
]40 ; 50]	8	8	0		4	7.84
]50; 60]	6	6	4	8.16	6	11.76
]60 ; 70]	6	6	1	2.04	5	9.8
]70; 80]	8	8	2	4.08	6	11.76
]80 ; 90]	2	2	1	2.04	1	1.96

Mean	34.56028	28.12141	40.74664
Standard Error	20.37526	17.73466	20.98561
Minimum	7.27951	7.42843	7.27951
Maximum	86.31032	86.31032	82.07312

Figure 2 below shows scores distribution by gender. Analysis of the distribution of efficiency scores shows that the distribution is much more concentrated on the left and less flat, which means that the majority of farmers, regardless of gender, have scores between about 7% and 40%, while a small number have higher scores. Similarly, it is observed that the probability of obtaining scores below 40% is much higher for men than for women, while the opposite effect is observed when scores are between 40% and 75%. Scores above 75% are only obtained by men. Figure 3 below shows the relationship between area cultivated and technical efficiency. We observe a U-shaped relationship, which means that technical efficiency increases with farms that have high cultivated areas in contrast to farms with small cultivated areas. This shows an excess use of input resources by small cashew farms.

Fig. 2 Kernel distribution of efficiency scores by gender (Source : Own survey result, 2021)

Fig. 3 Relationship between technical efficiency and the cultivated surface (Source : Own survey result, 2021)

4.2. Efficiency scores' determinants

Table 3 below presents the Reset test and the P test for selecting the correct functional form specification for the second stage of the DEA analysis from the alternative specifications. The results show that only the loglog model is never rejected at the 10% threshold. Therefore, a loglog functional form is preferred to analyse technical efficiency's determinants.

Table 3 FRM functional form selection specification test (Source : Model output, 2021)

	H0 : Logit	H0 : Cauchit	H0 : Probit	H0 : Loglog	H0 : Cloglog
Reset Test	0.0712*	0.0879*	0.0728*	0.2010	0.0383**
H1 : Logit		0.0806*	0.3978	0.3190	0.0497**
H1 : Cauchit	0.4757		0.5524	0.5260	0.4322
H1 : Probit	0.3978	0.0722*		0.3261	0.0321**
H1 :Loglog	0.0703*	0.0251**	0.0887*		0.0224**
H1 :Cloglog	0.1845	0.5042	0.1586	0.4077	

The determinants of technical efficiency from the regression analysis for the second stage using the FRM model are presented in column 1 of Table 4 below. The Tobit, truncated regression and bootstrap truncated regression models shown in columns 2, 3 and 4 respectively were estimated to test the robustness and sensitivity of the results obtained. We observe that, for the most part, all estimates retain their signs and level of statistical significance. However, the effects, whether negative or positive, are higher when estimated using the FRM model. The results show that experience as represented by the number of years of farm operation has a significant negative impact on farms' technical efficiency. This result shows that as the number of years of operation increases, the technical efficiency of cashew farmers decreases. This result is explained by the fact that most cashew farmers in Benin farm the same area of land for several years and also use fertilisers and other chemical products, which decreases the quality of the soil and consequently makes it less productive over the years. In addition, we also note that cashew farmers often stick to old production methods and do not adopt modern innovations that aim at improving efficiency. This result is consistent with the one obtained by Anang (2021) and partially confirms the one obtained by Njikam and Alhadji (2017) who find an inverted U-shaped relationship between producers' technical efficiency and the number of years of experience.

Access to credit has a negative and significant impact on producers' technical efficiency. This could be due to credit use for activities unrelated to cashew production such as maintaining household consumption levels, education and health expenditure. In addition, very high interest rates combined with climatic hazards may lead to the sale of cashew nuts at low prices in order

to repay the credit, resulting in a decrease in the producer's income and a reduction in his productivity for the next production cycles. This result is in line with those obtained by Abate and al. (2019) and Miriti and al. (2021) who find the same results for red pepper and sorghum producers in Africa, highlighting that agricultural loans are used for other purposes by producers. The age of the farm manager also has a negative and significant impact on technical efficiency. This means that over the years, the cashew farmer becomes less efficient and young farmers are more efficient than their older counterparts. This is because older farmers are less energetic and more reluctant to innovate and adopt new production technologies as opposed to younger farmers who participate in extension programmes or other forms of non-formal education that can improve efficiency. This confirms the results obtained by Okoye and al. (2016) in contrast to those obtained by other researches on agricultural efficiency which emphasise that with increasing age, farm managers gain more experience and use their past learning to produce more efficiently with a given level of input (Abate et al., 2019; Dessale, 2019; Tenaye, 2020). The sale of cashew apples has a positive and significant impact on producers' technical efficiency. This means that cashew apples sale, which is considered as a production waste product, improves producers' technical efficiency. Indeed, cashew apples sale provides an additional income not anticipated by producers and consequently improves their productivity. In addition, the increase in cashew juice production has led to an increase in demand for cashew apples, which allows producers to increase their profits through higher prices.

In addition, the results show that schooling expenses have a very small and significant positive effect on cashew producers' technical efficiency. Firstly, schooling expenses allow for the education of household children who constitute a family labour force. As a result, these educated children are able to manage production efficiently, have access to agricultural information in order to explain and adopt new agricultural strategies and practices to farm

managers. This confirms the positive impact of education on the technical efficiency of agricultural producers obtained in the literature (Akamin et al., 2017; Karimov et al., 2014; Tetteh Anang et al., 2020).

Table 4 Determinants of technical efficiency (Source : Model output, 2021)

VARIABLES	(1) FRM	(2) Tobit	(3) Truncreg	(4) Simarwilson
Gender of the farm manager (Female = 1)	0.0328 (0.119)	0.00603 (0.0419)	0.00823 (0.0422)	-0.000538 (0.0535)
Experience	-0.00986** (0.00407)	-0.00360** (0.00172)	-0.00353** (0.00173)	-0.00455* (0.00237)
Number of children	0.00983 (0.0225)	0.00286 (0.00796)	0.00320 (0.00801)	0.00439 (0.0101)
Access to credit (yes= 1)	-0.543*** (0.0933)	-0.185*** (0.0330)	-0.188*** (0.0334)	-0.233*** (0.0444)
Non-Farm income (yes= 1)	0.137 (0.100)	0.0478 (0.0361)	0.0471 (0.0363)	0.0593 (0.0469)
Age of farm manger	-0.0112* (0.00593)	-0.00387* (0.00210)	-0.00373* (0.00213)	-0.00479* (0.00268)
Schooling expenses	8.68e-07*** (2.69e-07)	2.91e-07** (1.22e-07)	2.92e-07** (1.25e-07)	3.38e-07** (1.55e-07)
Health expenses	2.70e-07 (4.11e-07)	2.37e-08 (1.99e-07)	8.12e-08 (2.15e-07)	8.74e-08 (2.60e-07)
Sale of cashew apples (yes= 1)	0.329*** (0.102)	0.101*** (0.0363)	0.107*** (0.0371)	0.124*** (0.0456)
Constant	0.559* (0.318)	0.575*** (0.114)	0.562*** (0.117)	0.605*** (0.148)
Log likelihood	-42.646	43.517	44.084	
Probchi(2)		0	0	0
PseudoR2		-1.4595		
AIC	1.052			
BIC	-403.367			
R2	0.407			

1. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

5. Conclusion

Cashew nut cultivation as a cash crop plays an important role in the economy of developing countries. However, despite all implemented agricultural policies at national and international levels, it remains characterised by farmers' low productivity and inefficiency. Therefore, this paper's general objective of is to identify the determinants of technical efficiency of farmers in the district of Dassa in Benin. The levels of technical efficiency and its determinants were estimated using the DEA Bootstrap method and the Tobit model. The results show that the majority of cashew farms do not make optimal use of available inputs, which makes their production below potential. The average technical efficiency of cashew farmers is 34.56%. In

other words, the same level of production can be achieved by the average cashew producer in the district when he reduces his amount of inputs by 65.44% given the currently available technology. Secondly, the results show that the average ET of cashew farmers who had access to credit is lower than those who did not have access to credit. Concerning determinants, cashew apple sale and expenditure on education, health and food improve technical efficiency in contrast to age, experience and access to credit.

In terms of economic policy recommendations, public policies should focus on producers' capacity building through apprenticeships, professionalization and extension services to improve their competence. Financing institutions should better target credits to the type of farmers, provide financial literacy training to farm managers and ensure regular monitoring of beneficiaries to ensure that credits are used for targeted activities. We suggest that producers set up a system for harvesting, preserving and selling cashew apples in order to increase their income. Finally, policies should continue and extend to cashew producers the implementation of the Human Capital Strengthening Insurance (HCSI) to support schooling expenses.

Abbreviations

AE: Allocative Efficiency; DEA: Data Envelopment Analysis; DGP: Data Generation Process; DMU: Decision Making Units; FRM: Fractional Regression Model; HCSI: Human Capital Strengthening Insurance; SFA: Stochastic Frontier Approach; TE: Technical Efficiency; TFP: Total Factor Productivity

Availability of data and materials

The author want to declare that he can submit the data at whatever time based on your request. The datasets used and/or analyzed during the current study will be available from the corresponding author on reasonable request.

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409 Authors' contributions

410 Both authors provided critical feedback and helped shape the research, analysis and manuscript.

411 MOA was involved in planning and supervised the work and RA and AGA processed the data,

412 performed the analysis, and drafted the manuscript. Both authors discussed the results and

413 commented on the manuscript. Both authors read and approved the final manuscript.

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417 Author information

418 Affiliations

419 People's Dynamics and Sustainable Development Laboratory, Benin Centre for Scientific

420 Research and Innovation, Cotonou, Benin

421 Raoul Akanro & Marie-Odile Attanasso

422 School of Agribusiness and Agricultural Policy, National University of Agriculture, Benin,

423 P.O. Box 01BP55 Porto-Novo, Benin

424 Abraham Amoussouga Gero

425

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