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EFFECT OF HUMAN CAPITAL ON THE TECHNICAL EFFICIENCY OF AGRICULTURAL PRODUCERS IN BURKINA FASO

ABSTRACT

The objective of this research is to analyse the effect of the non-formal education component of human capital on the technical efficiency of agricultural households in Burkina Faso. To this end, the production frontier of the distance output function with technical inefficiency effects was applied to a sample of 890 households from data collected as part of the second National Land Management Programme in 2017. Our results reveal an average technical efficiency score of 0.62, which means that agricultural households could increase their production levels by 38% without increasing their production factors. Our results show that literacy and agricultural training have positive and significant effects on farmers' technical efficiency. To improve the performance of the agricultural sector, authorities must promote literacy and strengthen agricultural training for farmers.

Key words: human capital; technical efficiency; distance-output function; Burkina Faso

JEL Classification J24; O4; C21

1. INTRODUCTION

Agriculture is an essential pillar of the economy, as Johnston and Mellor (1961) noted. Improving its productivity stimulates economic growth and helps reduce poverty. Despite its importance, increasing agricultural productivity remains a major challenge for sub-Saharan African countries, where this sector employs more than half of the working population.

In Burkina Faso, public policies have implemented numerous projects and programmes, such as the Support for the Promotion of Agricultural Sectors (PAPFA) project, to address this challenge. However, despite these efforts, agricultural yields remain low, which compromises food security (Zahonogo, 2016).

The World Bank (2020) estimates agricultural productivity at 1.5 tonnes per hectare in sub-Saharan Africa, whereas the global average is 4 tonnes per hectare. Fuglie and Rada (2013) estimate that over the period 1985–2008, the growth rate of agricultural productivity remained low, at approximately half the average for all developing countries, or approximately 1% per year.

In Burkina Faso, average yields of the main agricultural crops have increased slightly over the last decade. Between 2011 and 2020, the average maize yield increased from 1,521 kg/ha to 1,753 kg/ha, and that of white sorghum increased from 939 kg/ha to 1,028 kg/ha. The millet yield increased from 749 kg/ha to 906 kg/ha, and that of cotton increased from 1,111 kg/ha to 1,230 kg/ha (MAAH, 2020). These figures show limited progress in agricultural productivity, highlighting the persistent challenges in this key sector.

This low agricultural productivity is the result of several factors, namely, climatic hazards, low levels of education among farmers, lack of training for agricultural stakeholders, low public spending on agriculture, etc.

According to the World Bank report (2008), the impact of low public spending on agricultural performance could have been mitigated if rural populations had a higher level of education. Education increases agricultural production by improving productive capacity and enabling farmers to choose optimal levels of inputs and outputs (Welch, 1970).

Human capital is defined as the set of skills, knowledge and competencies acquired through education, training and experience. The theory of human capital arose from the observation that traditional factors of production (land, capital, labour) explain only part of economic growth. Two American economists, Schultz (1961) and Becker (1964), were the originators of this concept. The fundamental assumption at the heart of this theory is that education is an investment (private or social) that increases the productivity of those who receive it. Therefore, training has a positive effect on individuals' productivity by enabling them to increase their knowledge and skills and thus their ability to work (Schultz, 1961; Becker, 1964).

In Burkina Faso, several studies have investigated the relationship between human capital in terms of formal education and the technical efficiency of agricultural producers (Savadogo *et al*., 2016; Wouterse, 2011). Our contribution to this study is to consider non-formal education, namely, literacy and agricultural training, rather than formal education, which can have adverse effects on agricultural productivity (labour leaving for other promising sectors). We also consider four crops, namely, cotton, which is the primary cash crop, and maize, sorghum and millet, which are the main crops and account for approximately 57% of household energy availability (MAAH, 2020).

Burkina Faso was chosen as the study area, mainly because of the importance of agriculture in this region. Indeed, the agricultural sector employs more than 82% of the working population and contributes approximately 35% of GDP (MAAH, 2020).

The main objective of this research is to analyse the effects of human capital (non-formal education) on the technical efficiency of Burkinabe producers. More specifically, it aims to analyse the effects of agricultural training on the technical efficiency of farmers, and analyse the effects of literacy on the technical efficiency of agricultural producers.

The rest of the paper is structured as follows: the second section presents the literature review, the third presents the methodology, the fourth analyses and discusses the results of the study, and the last section concludes and proposes economic policy recommendations.

2. STATE OF KNOWLEDGE

2.1. THEORETICAL LITERATURE REVIEW

The theory of human capital emerged in the 1960s owing to the work of Schultz (1961) and Becker (1964). Like other forms of physical capital investment, human capital can contribute to economic and social development by increasing people's incomes. This increase in income linked to labour productivity can be as effective as other investments. Schultz (1961) observes that education accounts for most of the total factor productivity, the portion of growth that neither physical capital nor the volume of labour can explain. Schultz studies the impact of human capital on agricultural productivity and shows that workers' education and training is an essential means of improving productivity and, consequently, agricultural incomes. Later, Welch (1970) distinguished the channels through which human capital has an effect on agricultural productivity. Owing to the education acquired, farmers considerably improved the quality of their work. Human capital plays an important role in the modernisation of agriculture. The ability to cope with the imbalances caused by technological change in agriculture depends heavily on education, and better-educated farmers adapt better than less-educated farmers (Schultz, 1975; Ali and Byerlee, 1991). The accumulation of human capital corresponds to the accumulation of formal training acquired through schooling, education systems, in-depth training, and the knowledge and skills acquired by farmers over time (i.e., experience).

2.2. EMPIRICAL LITERATURE REVIEW

A positive relationship between human capital and agricultural productivity has been theoretically confirmed, but empirical studies remain controversial.

Several authors have analysed the effects of human capital, in terms of advanced training and experience, on farmers' efficiency and productivity (Czyżewski *et al*., 2021; Ndour, 2017). Their conclusions converge towards a positive effect of human capital on agricultural productivity. Furthermore, other studies confirm that education has a positive and significant effect on the technical efficiency of farmers (Addai and Owusu, 2014).

Xayavong *et al*. (2015) found that human capital and the use of innovations in the agricultural sector have significant effects on sector performance. Khadimallah and Akrout (2017) showed that the quality of human capital has a significant effect

on increasing agricultural value added. Nguyen-Van *et al*. (2016) concluded that farmers' contact with agricultural extension agents had a positive and significant influence on agricultural performance. Hoang-Khac *et al*. (2022) reported that human capital (education, experience and practical training) has a significant overall effect on the technical efficiency of food crop producers.

Although it is widely accepted that human capital has a positive effect on agricultural productivity, several empirical studies have shown that human capital has a negative or zero effect on productivity.

Some studies have shown that the variable "education" has no significant effect on farmers' technical efficiency (Nguyen-Van and To-The, 2016). Nyamekye and Fiankor (2016) analysed the effect of human capital through education, experience and access to extension services on maize productivity in Ghana. They concluded that human capital has no significant effect on maize production in sub-Saharan African countries, and show that human capital has no effect on productivity.

Appleton and Balihuta (1996) also revealed that education has no significant impact on agriculture. They attributed this to insufficient data and errors in measuring agricultural production. Savadogo *et al*. (2016) conclude that up to 3.9 years of formal education for farm managers improves the technical efficiency of farms. However, beyond 3.9 years, formal education has a negative effect on technical efficiency. This latter result could be explained by the fact that the most educated workers diversify their activities, especially in favour of non-agricultural activities that offer better opportunities.

3. MATERIAL AND METHOD

3.1. BASIC THEORETICAL MODEL ILLUSTRATING THE TECHNICAL EFFICIENCY OF PRODUCERS

The distance function allows us to assess the ability of a decision-making unit to make the right choices. In other words, it allows us to determine whether a decision-making unit is efficient. This concept of the distance function was developed by Shephard (1970) and taken up by authors such as Färe and Primont (1995), Färe *et al*. (1993), and Coelli and Perelman (2000). Farrell (1957) proposed the development of a method for estimating these gaps called inefficiency scores. There are two types of distance functions (Färe and Primont, 1995): the output-oriented distance function and the input-oriented distance function.

The output distance function is generally defined on the basis of the set of production possibilities, $P(x)$, where $P(x) = \{y \epsilon R_+^M : x\ can\ produce\ y\}$ where $y \epsilon R_+^M$ is a vector of agricultural products obtained from an input vector $x \epsilon R_+^M$.

Assuming that the technology generating all production possibilities satisfies all the regularity conditions of Färe and Primont (1995), the distance output function is defined as follows:

$$D_0(x,y) = min\left\{\theta: \left(\frac{y}{\theta}\right) \epsilon\, p(x)\right\} \quad (1)$$

If $\theta \epsilon (0,1)$, $\frac{y}{\theta}$, y is multiplied by a number >1, y is extended. If this extended y is still feasible, the $min\theta$ that allows the extension is the value of the distance between point x and boundary $P(x)$.

The distance function is nondecreasing, homogeneous in degree 1, linear and convex in y, and nonincreasing in x (O'Donnell and Coelli, 2004; Lovell *et al*., 1994). It measures the highest proportional increase in products while remaining within the same set of technically feasible production possibilities. The output distance function $D_0(x,y)$ therefore takes a value less than or equal to 1 if the vector of actual outputs y is within the set of production possibilities $P(x)$. If $D_0(x,y) = 1$, the vector of outputs y is on the production possibility frontier.

The implementation of the output distance function requires the use of a functional form that takes its properties into account. In the literature, several functional forms have been used to assess technical efficiency (translog, Cobb-Douglas and CES), but the Cobb–Douglas and translog specifications are widely used in agriculture (Kadiri *et al*., 2014). The Cobb–Douglas function is more restrictive, whereas the translog function is more flexible and allows for interaction between production factors. Some authors have used both functions in their work (Yami *et al*., 2013). However, Lovell *et al*. (1994) introduced a methodology that allows a parametric distance function to be estimated in the context of multi-input/multioutput technologies. To do this, they used an output distance function and a translogarithmic form. This form of function is particularly suitable for multiproduct activities. In this research, we use the translog form. It is easy to manipulate and flexible, and allows the properties of homogeneity and symmetry to be imposed. The translogarithmic output distance function in our case consists of 3 inputs and 4 outputs and is written as follows:

$$\ln y_{4i} = \alpha_0 + \sum_{m=1}^{3}\alpha_m \ln\left(\frac{y_{mi}}{y_{4i}}\right) + \frac{1}{2}\sum_{m=1}^{3}\sum_{n=1}^{3}\alpha_{mn}\ln\left(\frac{y_{mi}}{y_{4i}}\right)\ln\left(\frac{y_{ni}}{y_{4i}}\right) + \sum_{k=1}^{3}\beta_k \ln x_{ki} + \frac{1}{2}\sum_{k=1}^{3}\sum_{l=1}^{3}\beta_{kl}\ln x_{ki}\ln x_{li} + \sum_{k=1}^{3}\sum_{n=1}^{3}\gamma_{km}\ln x_{ki}\ln\left(\frac{y_{ni}}{y_{4i}}\right) - \mathrm{u}_i + \varepsilon_i \quad (2)$$

where y_m is the vector of outputs (m=1,2,3,4); for household i for m=4, y_4 corresponds to the quantity of maize. Maize is taken as currency in this study because it is the main product of rural households. The other products considered are millet, sorghum and cotton. The variable x_{ki} is the vector of inputs k=1, 2, and 3 for

household *i*. The inputs considered are land area, labour and chemical fertilisers. The parameters to be estimated are α, β, δ.

Farell (1957) used the reciprocal of the output distance function to measure the technical efficiency (ET_i) of a production unit:

$$D_0(x,y) = \frac{1}{ET_i} \Leftrightarrow \ln D_0(x,y) + \ln ET_i = 0 \tag{3}$$

$$\Leftrightarrow \ln D_0(x,y) = \mathrm{u}_i \text{ where } \mathrm{u}_i = -\ln ET_i$$

where u_i represents the technical inefficiency of production unit i. The technical efficiency of the production unit is measured by $ET_i = e^{-\mathrm{u}_i}$.

The econometric model of the explanatory factors of technical inefficiencies is defined as follows:

$$\mathrm{u}_i = z_i\delta + w_i \tag{4}$$

where z_i is a vector of explanatory factors for technical inefficiencies and where w_i is a vector of random variables representing estimation errors. The assumptions about the errors in the stochastic frontier production model of the output distance function with technical inefficiency effects are as follows: (i) the random errors ε_i are distributed according to the normal distribution $N(0, \sigma_\varepsilon^2)$ and are independent of the random errors associated with technical inefficiencies u_i; (ii) random errors associated with technical inefficiencies u_i are independently distributed according to the normal distribution $N(z_i\delta, \sigma_\mathrm{u}^2)$ and truncated at zero ($u_i \geq 0$); (iii) random errors w_i are distributed according to the normal distribution $N(0, \sigma_w^2)$ and are truncated at $-z_i\delta (w_i \geq -z_i\delta)$.

Under these assumptions, the maximum likelihood method is used to estimate the parameters of the output distance function with technical inefficiency effects and technical efficiency scores.

In the literature, two types of estimation methods are distinguished: the two-step method and the simultaneous estimation method. This two-step estimation is biased since technical inefficiency is considered exogenous in the production frontier and endogenous in the explanation of the level of technical inefficiencies. To overcome this shortcoming, several authors have proposed models that allow simultaneous estimation of the stochastic production frontier and the socio-economic and institutional factors explaining the technical inefficiency of production units. These models were first proposed by Deprins and Simar (1989) in a deterministic frontier context and then adapted to a stochastic frontier context by Kumbhakar *et al*. (1991), and Battese and Coelli (1995).

3.2. DATA AND SOURCES

The data used in this research are those of rural households collected in Burkina Faso as part of the evaluation of the Terroir Management Programme Phase 2 (PNGT-2). The data were collected by the Laboratory for Quantitative Analysis Applied to Development-Sahel (LAQAD-S) of Ouaga II University in 2017.

LAQAD-S uses very rigorous sampling and data collection techniques. Indeed, obtaining observations that are representative of the population depends on a good sampling technique. To this end, regional stratification was used (each region being represented in proportion to the number of municipalities), leading to the selection of a sample of municipalities, villages and households. Sampling was carried out at two levels: at village level in the country and at household level in the village. The municipality was chosen as the basis for selecting villages to comply with the PNGT2 intervention method, which decided to use the municipality as the entry point. The sample in this wave consisted of 90 rural municipalities, from which three villages *per* municipality were selected (270 villages). Within each village, eight households were selected at random and stratified, resulting in a total of 2,160 households.

3.3. DEFINITION OF MODEL VARIABLES

In this study, we capture human capital through two binary variables, namely, literacy and agricultural training. The literacy variable takes a value of 1 if the head of household can read and write in at least one language. The agricultural training variable takes a value of 1 if the head of household has access to extension services and benefits from training and advice from agricultural agents. In the agricultural sector, public authorities implement extension programs to improve farmers' agricultural techniques and knowledge with the aim of promoting more productive agriculture (Wuepper *et al*., 2021). According to Mehdi (2011), training for farmers aims to change behaviour in the workplace to stimulate efficiency and higher performance standards.

Table 1

Description of variables

Variables	Description
Production function variables	
Area	= number of hectares sown
Labour	= total amount of labour
Chemical fertilisers	= quantities of NPK and urea in kilograms
Technical inefficiency variables	
Literacy	=1 if the head of household is literate and 0 otherwise
Agricultural training	= 1 if the farmer has access to extension services, training and advice, and 0 otherwise.

Table 1 (continued)

Access to credit	= 1 if the household has access to credit and 0 otherwise
Gender	= 1 if the head of the household is male, 0 otherwise.
Access to information	= 1 if the head of household has access to information
Organisational membership	= 1 if the household is a member of an association and 0 otherwise
Access to a market	= the distance in kilometres between the farm and a market

Source: Author's analysis from the literature.

The basic theoretical model of the translog distance function highlights two types of variables: those related to the production function and those related to technical inefficiencies.

4. RESULTS AND DISCUSSIONS

4.1. DESCRIPTIVE STATISTICS OF THE MODEL VARIABLES

Table 2 highlights a low literacy rate, with 28.62% of household heads in the sample able to read and write in at least one language. Statistics show that few (8.87%) farmers receive guidance from extension service agents. Furthermore, the results show that 29.06% of farmers have access to credit and are predominantly male, accounting for 96.57% of the sample. Table 2 reveals that 18.07% of farms have access to information through sources such as radio and television. The statistics also show that only 25.81% of farmers are members of a farmer organisation.

Table 2

Descriptive statistics of the model variables

Variable	**Percentage/ average**	**Standard deviation**
Literacy	28.62	0.442
Training received in agriculture	8.87	0.2844
Access to credit	29.06	0.462
Gender of head of household	96.57	0.1833
Access to information	18.06	0.3849
Membership of an organisation	25.81	0.4378
Quantitative variable		
Cotton	2843.973	3861.57
Corn	1688.545	5930.42
Sorghum	1,227.485	1236.28
Millet	772.241	889.34
Distance -market	8.36	8.49
Age of head of household	47.57	13.73
Observations	890	

Source: Calculations on the basis of PNGT-2 data, 2017.

Furthermore, statistics on quantitative variables show that, on average, a household produces 2,843.97 kg of cotton. As regards cereals, maize production is the most important, with the entire study sample engaged in its production, with an average production of 1,688.545 kg. Sorghum ranks second among cereals, with an average production of 1,227.485 kg. Millet is the least cultivated crop, with a low production level of 772.24 kg on average. The table shows that the average age of farmers is 47.57 years.

4.2. ROBUSTNESS TESTS

In this part of the study, we test the hypotheses concerning the choice of the stochastic production function and the specification of the inefficiency model.

From the relationship in equation (2), we can see that the existence of technical inefficiency is conditioned by a positive gamma value (γ) that is different from zero and significant (0.96). This indicates that 96% of the deviation of production from the frontier is due to the technical inefficiency of farmers. This step allows us to justify the value of considering a stochastic frontier rather than a deterministic frontier, since the latter neglects the effects of random factors. Furthermore, Savadogo *et al*. (2016) reported a high gamma value (0.97) in a study on the impact of social services on agricultural productivity in Burkina Faso. Similarly, Ngom, Sarr and Fall (2016) reported a gamma (0.99) when measuring the technical efficiency of rice farmers in Senegal.

Functional form: On the basis of the results of the various tests recorded in Table 3, the null hypotheses were not accepted. Test 1 on the functional form shows that the translog form is more appropriate for the model. The likelihood ratio value allows us to conclude that the model is globally significant.

Presence of stochastic inefficiency: The third hypothesis specifying the absence of technical inefficiency is rejected. We can conclude that the model includes inefficiency effects. Similarly, the second hypothesis specifying that inefficiency effects are non-stochastic is also not accepted. Test 2 allows us to conclude that the inefficiency effects are stochastic in nature. This is confirmed by the gamma value (0.96), which is significant at the 1% level.

Overall adequacy: The final hypothesis specifying that exogenous factors do not affect inefficiency is not accepted at the 5% threshold. The results of Test 3 show that exogenous factors are important in explaining variations in technical efficiency.

On the basis of the various tests, we can conclude that the translog form is best suited to the production function and that the stochastic form is more appropriate.

Table 3

Hypothesis tests for validation of the translog function

Tests	Null hypotheses	LR test	Critical value (5%)	Decision
T1	$H_0 : \beta_{jk} = 0$	72.12	32.077	Reject H_0
T2	$H_0: \gamma = 0$	210.44	2.71	Reject H_0
T3	$H_0: \gamma = \delta_0 = \delta_1 = .. = \delta_8 = 0$	109.08	16.27	Rejection H_0
T4	$H_0: \gamma = \delta_1 = \delta_2 = .. = \delta_8 = 0$	100.1	14.85	Rejection H_0

Source: Constructed from test results.

4.3. ANALYSIS OF THE RESULTS OF THE PRODUCTION FRONTIER ESTIMATION

Table 4 presents the results of the simultaneous estimation of the production frontier via the maximum likelihood method.

A production function can be characterised by several ratios. In our study, average elasticities are used to characterise the production function.

The calculation of product elasticities shows that a 1% increase in sorghum production leads to a 0.34% decrease in maize production. Similarly, a 1% increase in millet production led to a 0.54% decrease in maize production, and a 1% increase in cotton production led to a 0.4% decrease in maize production. With respect to the elasticities of production factors, the results show that a 1% increase in land area and labour leads to a 1.7% and 0.82% decrease in production, respectively. On the other hand, a 1% increase in chemical fertiliser led to a 0.067% increase in production.

Table 4

Results of the multi-output production frontier estimation with inefficiencies

Variables	Coefficients	T statistic
Production function		
Constant	5.06	-21.12
Ln cotton	-0.38	-1.67
Ln sorghum	-0.32	-2.54
Ln millet	-0.36	-2.37
Ln sup	1.83	-6.65
Ln work	0.02	0.33
Ln fertiliser	-0.12	1.66
Ln (sorghum millet)	0.24	-2.72
Ln (fertiliser area)	0.17**	-2.54
Ln (labour area)	-0.21	-2.45
Ln (sorghum area)	0.096*	1.69
Ln (sorghum fertiliser)	0.07	-3.93
Ln (millet labour)	0.5	1.4
Technical inefficiency function		
Constant	0.9	0.83
Literacy	-0.83***	-2.56
Agricultural training	-3.02	-2.66

Table 4 (continued)

Access to credit	-0.54	-1.67
Age	0.0025	0.36
Gender	-5.58***	-5.38
Walking distance	-0.05	-3.08
Access to information	-4.94	-4.11
Organisational belonging	-3.98	-3.66
Parameter variances		
Sigma-square	6.48***	4.94
Gamma	0.96***	125.35
LR test (OSE)	210.44	
Log likelihood	1002.96	

Source: Calculations made *via* FRONTIER 4.1 with PNGT2 data, 2017.

4.4. DISTRIBUTION OF EFFECTIVENESS SCORES

Estimating the distance function *via* Frontier 4.1 software enabled us to determine the technical efficiency levels of agricultural households. The results of the estimates indicate that the average technical efficiency is 0.62. This means that Burkinabe farms could increase their production levels by 38% without increasing their production factors. The levels of achieved production consumed resources beyond the necessary level to achieve them. According to the results, 13.24% of farmers have an average technical efficiency level of 0.84. Table 5 reveals that farmers with an average technical efficiency level of 0.71 represent the majority, accounting for 54.43% of the sample. Notably, 19.41% of farmers had an average technical efficiency of 0.52. The minimum technical efficiency score is 0.16 and was achieved by 2.02% of producers.

Table 5

Distribution of technical efficiency scores

Interval	Observation	Average	Min	Max
]1;0;8]	118	0.84	0.8	0.995
]0,8;0,6]	485	0.71	0.6	0.799
]0,6;0,4]	173	0.52	0.4	0.599
]0,4;0,2]	97	0.31	0.2	0.399
]0,2;0]	18	0.16	0.11	0.19

Source: Constructed from technical efficiency scores.

4.5. FACTORS EXPLAINING THE LEVELS OF TECHNICAL INEFFICIENCY

The factors explaining the levels of technical inefficiency in agricultural producers are presented in Table 4. (A negative and significant sign indicates a negative impact of the variable in question on the technical inefficiency score and therefore a positive effect on the level of technical efficiency).

The results show that human capital, in terms of literacy and specific agricultural training, contributes to improving the technical efficiency of Burkinabe farms. The results show that literacy (the ability to read and write in at least one language) of the household head has a positive and statistically significant effect on the technical efficiency of agricultural producers.

Similarly, specific agricultural training has a positive effect on the technical efficiency of farmers, with training reducing their level of inefficiency. This result is satisfactory and consistent with that reported by Savadogo *et al*. (2016). Households receiving technical support are technically more efficient than those that do not. On the other hand, Nuama (2006), in researching the sources of increased rice production in Côte d'Ivoire, reported that agricultural training does not improve the technical efficiency of farmers. He explains this by the irregularity of the support service agents and the early duration of the services.

The variable of access to credit has a positive and significant effect on technical efficiency. Access to credit enables producers to acquire factors of production.

The variable of household head gender appears to have a negative and significant influence on technical inefficiency. This means that being male contributes to increased technical efficiency. However, Ngom *et al*. (2016), when analysing the determinants of technical efficiency in rice farmers in Senegal, reported that the gender of the household head increases its inefficiency. In other words, being a woman contributes to reducing inefficiency. One possible explanation is that women are more present in fields and carry out most farming activities, even in fields owned by men. It is therefore understandable that they have a better command of farming practices than men do.

Access to information via radio, television and telephone is a significant variable and has a negative influence on technical inefficiencies. This shows that farmers with access to information are technically more efficient than those without. This result is in line with our expectations and is consistent with that reported by Savadogo *et al*. (2016). Information is crucial in the agricultural sector, as it enables farmers to seize opportunities in terms of prices and production.

Membership of an organisation is significant and negative at the 1% level, indicating that farmers who are members of a farmer organisation are relatively more technically efficient than those who do not belong to a farmer organisation. This result corroborates the work of Boubacar *et al*. (2016). This can be explained by the fact that groups constitute social networks where producers often have access to information that allows them to easily access production opportunities. In addition, membership in an organisation may confer other benefits, such as better access to financing and inputs.

5. CONCLUSIONS

Agriculture plays a dominant role in the economies of most developing countries in general and Burkina Faso in particular. However, it still fails to meet the needs of the population. The objective of this research was to analyse the effect of human capital in its non-formal education component on the technical efficiency of

agricultural producers in Burkina Faso. The data used were collected from rural households across all provinces of Burkina Faso as part of the second National Land Management Programme in 2017. This objective was achieved via the distance output function approach with technical inefficiency.

Our results show that producers have an average technical efficiency score of 0.62. This result implies that better use of available production factors would enable farms to increase their production levels by 38%. With respect to the factors explaining technical inefficiencies, the results reveal that the literacy of the household head, specific training in agriculture (farmer coaching) and membership in a farmer organisation have positive and significant effects on technical efficiency.

In light of the results of the estimates, public decision-makers should first and foremost place greater emphasis on education to slow the decline in producers' technical efficiency. This education must be offered to adults in farming households. However, adults who are already working in agriculture can no longer be directed towards the formal education system. This education can only come from literacy programmes and technical agricultural training. This requires an increase in the number of literacy centres in rural areas and an increase in the number of village agricultural technical agents.

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