Kehinde *et al. Agriculture & Food Security* (2024) 13:12
https://doi.org/10.1186/s40066-023-00464-y

Agriculture & Food Security

REVIEW

Open Access

Impact of participation in social capital networks on the technical efficiency of maize producers in Southwest Nigeria

Ayodeji D. Kehinde[1,2*], Temitope O. Ojo[1,2] and Abiodun A. Ogundeji[2]

Abstract

Maize is a staple food and one of the important sources of starch for many households. However, maize yield in Nigeria remains one of the lowest in sub-Saharan Africa. Providing agricultural credit to farmers cannot be disregarded because it has a significant impact on maize productivity. As a result of this capital investment through social capital networks is needed to improve maize productivity. This study investigated the impact of participation in social capital networks on the technical efficiency of maize producers in Southwestern Nigeria. The multistage sampling procedure was to select about 300 respondents for the study. The data were analysed using Hurdle Negative Binomial (HNB) and Endogeneity Stochastic Frontier models. According to the first hurdle result, the decision to join social capital networks is significantly influenced by age, age square, household size, gender, and access to credit. According to the second hurdle results, the level of participation in social capital networks is significantly influenced by age, age squared, household size, experience, gender, and access to credit. The Endogeneity Stochastic frontier model shows that the average technical efficiency of 65% in maize production. Maize seed, fertilizer, agrochemicals, labour, and farm size influence the technical efficiency of maize farmers. However, participation in social capital networks, as well as socioeconomic characteristics of the farmers including household size, years of education, years of experience, and extension contact, are the sources of technical inefficiencies in maize production. The study concludes that participation in social capital networks has a positive and significant effect on the technical efficiency of maize farmers. This study recommends that agricultural programmes targeted at efficient maize production should consider maize farmers participating in social groups. Therefore, more social capital networks should be established and participation of maize farmers in the social capital networks should be encouraged to access social capital and improve their production.

Keywords Maize farmers, Southwestern Nigeria, Endogeneity, Social capital, Technical efficiency

Introduction

Maize is a crop of notable interest for food security in many parts of sub-Saharan Africa (SSA) (Kehinde and Tijani 2022); [1–3]. As in other countries of SSA, maize is an important crop in Nigeria, where it is largely cultivated by smallholder farmers over 6.5 million hectares of land [4–6]. Murphy [7] and Nazifi et al. [8] indicated that growing maize by smallholder farmers can overcome food insecurity in their households. These smallholder farmers make up to 80% of farmers in Nigeria,

*Correspondence:
Ayodeji D. Kehinde
kehindeayodeji8@gmail.com
[1] Department of Agricultural Economics, Obafemi Awolowo University, Ile Ife, Osun State, Nigeria
[2] Disaster Management Training and Education Centre for Africa, University of the Free State, Bloemfontein, South Africa

they produce a substantial percentage of food consumed by Nigerians, particularly maize crops. Maize is one of the important grains in Nigeria, not only based on the number of farmers that are engaged in its cultivation, but also on its economic value [9, 10]. It is by far the largest cereal crop in terms of area and production volume and is the most consumed staple food in Nigeria [5]. Nigeria is tagged the largest maize producer accounting for 16% of harvest in the continent [11]. Similarly, Nigeria is the largest African producer of maize with over 33 million tons, followed by South Africa, Egypt, and Ethiopia [11, 12]. In 2019, maize production in Nigeria was 11,000 million tonnes [13]. In addition to vitamins A and C, it is an excellent source of protein, vitamin B, minerals, and carbohydrates for individuals. [14]. Apart from cooking or producing raw food for human consumption, it also produces processed feed for animals, especially cattle [15, 16]. Despite the economic importance of maize, Nigeria could not meet maize demand for its teeming population, livestock and poultry feed industries [17]. Available statistics revealed that Nigeria imported about 215,000 tonnes of maize as of 2016 [18]. Also, in 2020, maize worth 54,685 (thousand US dollars) was imported into Nigeria [19]. This poses a serious threat to the social and economic status of small-scale farmers (Kehinde and Tijani 2022).

Nigeria is currently churning out about 10.5 million metric tons per annum with a demand of 15 million metric tons, leaving a supply–demand gap of 4.5 million tons per annum [15, 20]. The demand–supply gap, has a significant impact on the capacity of maize to end hunger and achieve food security [21]. Nigerian maize production is characterized mostly by its poor yield, which is thought to be the cause of the discrepancy [22]. Many factors contribute to low maize yields, including poor soil and land management practices, unfavourable climate change, a lack of farm tools, high input costs, resistance to new technology, a lack of improved varieties, and the presence of pests and diseases [23, 24]. Nevertheless, farm production can be increased by utilizing existing technology more effectively or introducing new ones [25]. In light of the aforementioned, the government focused its efforts on developing and disseminating new technologies through the National Maize Research Programs and the International Institute for Tropical Agriculture (IITA) to assist maize farmers in maximizing the potential of maize production. Despite these concerted efforts, the average maize production in Nigeria (1.6 t ha^{-1}) is still much less than projected (5.1 t ha^{-1}) when compared to other countries in the world where maize is grown [135]. This may be explained by the fact that effective use of productive resources is necessary for them to function at their highest levels of production. This implies that increasing maize production in Nigeria depends on the ability of farmers to efficiently integrate the available resources or their technological prowess.

According to available studies, maize farmers in Nigeria are inefficient at allocating or combining resources for maize production [26–29]. The main cause of the inefficient use of productive resources is a lack of financial resources to cover these costs [30–32]. To these farmers, access to credit is a key complementary input to success in maize production. Providing credit for farmers is one of the tools used to build the productive capacity of farmers so that they can efficiently produce and contribute to the economy of the country [33, 34]. Credit allows producers to have the necessary resources they need to cover the financing needs induced by the production cycle. Farmers are particularly in need of agricultural credit, because of the seasonal pattern of their activities and the important uncertainty they are facing [35]. The reasons for limited access to agricultural credit from formal sources are that, each credit source has its constraints that limit either the ability of a farmer to obtain credit from the source or the amount of credit the farmer wishes to borrow. For instance, Owusu-Antwi and Antwi [36] state that formal financial markets often require collateral in the form of land or houses as a prerequisite for granting loans to borrowers which are often out of reach of the majority of the farming population. As a result, most poor smallholders are often unable to invest in new technologies or inputs such as fertilizer, improved seeds, etc. [37, 38].

However, the farmers can finance these investments by utilizing their social capital [39, 40]. Thus, a perceived alternative for raising financial capital needed for transforming the available natural resources into physical assets is through the construction of social capital. This includes benefits accrued to individuals by membership and participation in the activities of social capital networks. Social capital is a series of processes of human relations that are supported by networks, norms and trust that enable efficiency and effectiveness of coordination and cooperation for mutual benefit [40]. Social capital can be best understood as a means or a process for accessing various forms of resources and support through networks of social relations. Social capital is an intangible livelihood asset in agricultural production that plays a key role in sharing information and resources [41, 138]. Social capital reduces transaction costs through social collateral to access credit and another productive asset to improve efficiency in agricultural production [42]. This is achieved by the ability of the poor to access credit based on social collateral through the social networks to which they belong to replace physical collateral. It creates avenues for individuals to improve performance through collective efforts or social relationships with friends, colleagues, or families to explore opportunities to use collective financial and human capital. The availability of social capital allows greater use of purchased inputs, which increases farmers' production and subsequently their income. Specifically, access to social capital enables maize farmers to: undertake efficient land preparation, purchase farm inputs, adoption of improved technologies and on-farm technical efficiency [43–48]. Thus, without access to social capital, optimal agricultural productivity might not be realized [49]. Social capital, therefore, can improve the technical efficiency of maize producers.

However, several empirical studies, including those by Abdulai et al. [50], Adhikari et al. [51], Payang et al. [52], Ali et al. [139], Belete [53], Mdoda et al. [54], Kongolo [55], and Wu et al. [56], have assessed the technical efficiency of maize production in Nigeria. Similar research has been done on the impact of social capital on income [57, 58], productivity [41, 59], alleviating poverty [60, 61], technology adoption [62, 63, 140] and food security [64–67]. None of these studies investigated the participation in social capital networks while evaluating the technical efficiency of maize producers. A few studies (for instance, [68]) investigated the impact of social capital on the technical efficiency of farmers without taking into account the endogeneity nature of social capital. On the other hand, if the endogeneity of social capital is not taken into consideration, the characteristics and assets of friends, acquaintances, and organizations may influence individual findings, leading to biased or inconsistent assessments. This methodological issue might lead to incorrect findings concerning the relationship between participation in social capital networks and the technical efficiency of maize producers. Therefore, this present study is conducted to fill this gap in the literature. In line with the economic theory of production, investigating the endogeneity impact of participation in social capital networks on the technical efficiency of maize farmers is the main objective to be explored in the study. In an attempt to do this, the study provided answers to the following research questions: what are the socioeconomic characteristics of maize farmers by participation in social capital networks? What are the factors affecting the probability and level of participation of maize farmers in social capital networks? and What is the impact of participation in social capital networks on the technical efficiency of maize farmers? These findings will enable academics and other society's actors such as policymakers to obtain adequate, sufficient and reliable data for analysis geared towards meaningful policy formulation for maize production in Nigeria. The study will also make a major contribution to the existing literature on social capital networks. The remainder of this paper is organized as follows. The second section reviews the literature. The third section elaborates on the data and method employed in the analysis. The fourth section is the finding and discussion. The last section is the conclusion.

Literature review

A framework for this study is based on the economic theory of production, as used by the majority of agricultural technical efficiency studies. Putting it simply, efficiency is the absence of waste in the accomplishment of a farm firm's goal. Economists have developed many efficiency theories based on the idea of "no waste". All efficiency assessments, however, are based on the fundamental idea of the quantity of goods and services per unit of input. If a production unit produces too little given a set of inputs, it is technically inefficient. The classical approach and the frontier approach are the two basic ways to evaluate efficiency. The conventional method, known as single-factor productivity, is based on the ratio of output to a specific input. In reaction to their frustration with the shortcomings of the traditional methodology, economists created modern econometric approaches for analysing efficiency. According to the frontier measure of efficiency, efficient firms are considered to operate at the production frontier. Efficiency is dependent on the degree to which a firm departs from its production frontier. Efficiency is the state in which the economy produces goods and services at the lowest possible price, according to Case et al. [141]. Therefore, the relative effectiveness of the processes used to convert given inputs into outputs is the main focus of the idea of efficiency. At least three different levels of efficiency are identified by Farrell's economic theory [69]. Technical, economic, and allocative efficiency are involved. Allocating efficiency is the process of deciding which inputs are the best fit given the relative factor prices. In other words, allocative efficiency refers to the ability of the firm to utilize its inputs in the most effective combinations, given their costs. Technical efficiency demonstrates the capacity of the firm to use the "best practice" within a specific industry, requiring the least amount of a given set of inputs to achieve the best output level [70]. Economic efficiency is a result of both allocative and technological efficiency. Therefore, the farmer seeks to produce as much as possible for the smallest possible cost.

Farms aim to accomplish these objectives by increasing output at a certain level of cost or decreasing cost at a certain level of output. The distribution of inputs and the choice of technology in these two optimization issues are both governed by the same strategy. There are numerous ways to achieve production goals, thus the production theory provides the theoretical and empirical framework to assist in selecting the best alternative among the available options for any one goal of the farmer, or for a set of goals. Economists contend that prioritization should take into account the need to maximize efficiency when working with limited resources. Decision-makers frequently struggle to strike a balance between the growing demand for various services and the available resources. In 1957, Farrell asserted that the firm's efficiency could be determined empirically and provided a ground-breaking approach for gauging the efficiency frontier using actual production measures. The nature and purported characteristics of the gap between the observed production and the ideal production can be used to categorize the frontier estimate methods in addition to the frontier's intended shape and the estimation technique used to obtain it. The categorization based on the frontier form allows for differentiation to be made between parametric and nonparametric methodologies. The efficiency of a farm can be determined using a variety of parametric and nonparametric methods, with the main difference being the assumptions of residue. A production or cost frontier will be parametric if we employ a deterministic functional form (Cobb–Douglas, Translog, etc.) and assume that any discrepancy between the estimated function and the data is brought on by the producer's inefficiency. If a producer's inefficiency and a few unpredictable random events are both contributing elements in a frontier gap, that discrepancy is said to be stochastic. In contrast to nonparametric approaches, which place less structure on the frontier but presume the absence of random mistakes, parametric approaches impose a functional form that takes the shape of the frontier. The parametric technique (Cobb–Douglass, CES, Translog, etc.) yields a function with discrete parameters. The parametric technique presents a function with stated parameters, according to Aigner et al. [71]. Many econometric and non-econometric methods can be used to estimate the production or cost border parameters in the case of a parametric function, such as the least-squares method or the maximum likelihood method. Data envelopment analysis (DEA) [72] and the stochastic frontier production function approach [71, 73] are the two methods that are most frequently used to determine technical efficiency. In agricultural production, where data are anticipated to be significantly impacted by systematic errors brought on by weather, climate change, diseases, etc., the stochastic frontier technique is thought to be more suitable than the DEA approach. The stochastic frontier production function was first proposed in 1977 by Aigner et al. and again in 1988 by Meeusen et al. The original specification contained a production function with cross-sectional data requirements and an error term with two components, one for random effects and the other for technical inefficiency.

The stochastic frontier production function, according to Battese [74], can be written as the following equation:

$$Y_i = f(x_i;\beta)\exp(v_i - u_i), \tag{1}$$

where $i = 1, 2, \ldots, N$ and Y_i indicate the potential output level for the ith sample unit; $f(x_i;\beta)$ is an appropriate function (such as Cobb–Douglas or Translog) of the vector, x_i of inputs for the ith unit, and a vector; is a vector of estimated parameters; and N denotes how many units were included in the cross-sectional survey. The phrase "stochastic frontier" refers to the property of this model where the probability of production Y_i is above bound by the stochastic quantity $f(x_i)\exp(V_i)$. In addition, V_i is the symmetric error term that accounts for random variations in output brought on by external variables like weather, disease, bad luck, and measurement error, while U_i represents technical inefficiency in relation to the stochastic frontier, which only accepts positive values. The assumption is that the distribution of the symmetric error component V has the form $N\left(0, \delta_u^2\right)$. However, it is assumed that the distribution of the one-sided component u is half normally distributed $(u > 0)$ as $N\left(0, \delta_u^2\right)$ and thus measures production shortfalls from its hypothetical maximum level. If $u = 0$, the farm is efficient and operating at a profit or producing below the frontier function; the distance between Y_i and Y^* indicates the degree of the farmers' technical inefficiency [75]. If $u > 0$, the farm is inefficient and operating at a loss. Therefore, the farm becomes more inefficient the larger the one-sided error is.

According to current technology, a single producing unit's technical efficiency is defined in terms of the ratio of observed output to equivalent frontier output [75]. The unit i's technical efficiency is therefore expressed by the following sentence in terms of the stochastic frontier production function:

$$\mathrm{TE}_i = \exp(-u_i), \tag{2}$$

$$\mathrm{TE}_i = \frac{Y_i}{Y_i^*} = \frac{f(x_i;\beta)\exp(v_i - u_i)}{(x_i;\beta)\exp(V_i) = \exp(-U_i)}. \tag{3}$$

Y_i is an observed output and Y_i^* is the frontier output. $(x_i;\beta)$, and V_i are as defined earlier. In this case, Y_i achieves its maximum value of $f(x_i;\beta)\exp(V_i)$ if and only if $\mathrm{TE_i} = 1$. Otherwise, $\mathrm{TE_i} < 1$ provides a measure of the shortfall of observed output from the maximum feasible output in an environment characterized by stochastic elements that vary across producers.

The stochastic frontier production model has been widely used in agricultural research to determine how technically efficient, the farmers are. For instance, Bamlaku et al. [76] looked at the technical efficiency of farmers. While access to credit, literacy, close proximity to markets, and livestock are found to have positive and significant effects, age, sex, extension services, and off-farm activities are found to have little to no impact on the technical efficiency of farmers. Additionally, Endrias et al. [77] examined the technical efficiency of maize producers. Agroecology, oxen holding, farm size, and usage of modified maize varieties are found to be important predictors of technical efficiency, while age, education, family size, and loan access are found to be minor determinants. The primary problem with the study, however, is the choice of the input variables and dependent variables. The majority of research fails to take into account important inputs like seed, compost, herbicides, and insecticides in the choice of input variables, which could result in the wrong conclusion. This research can still solve some of the flaws of the preceding research by carefully examining the potential input and external variables. Furthermore, if the model has an endogeneity problem, the standard maximum likelihood estimation for stochastic frontier models (SFMs) produces contradictory parameter estimates. This necessitates using the appropriate instrumental variable (IV) strategy to solve the endogeneity issue. One common approach to solving this problem is to first maximize the related log-likelihood before modelling the combined distribution of the left-side variable and endogenous variables. The error term in SFMs has unique characteristics, making this task more challenging than it would be in normal maximum likelihood models that only incorporate two-sided error terms.

Material and methods

Area of study

This study was conducted in the southwest of Nigeria (Fig. 1). A geographical region known as Southwestern Nigeria is located between latitudes 6° 21′ N and 8° 37′ N and longitudes 2° 31′ E and 6° 00′ E. The region's boundaries are defined by the States of Kogi and Kwara in the North, the Atlantic Ocean in the South, the Republic of Benin in the West, and the States of Edo and Delta in the East. It has a population of about 27,581,992. Even within the same State, there are many dialects, yet Yoruba is the language that is used most frequently in the region. The dry season and the wet season are two separate climatic seasons. A long-wet season that lasts from March to October contrasts with a shorter dry season that lasts from November to March. Temperatures range from 21.0 to 34.0 °C, with annual precipitation amounts between 1500 and 3000 mm. Due to the good temperature and soil conditions, more than 70% of the inhabitants decided to pursue farming. There are permanent and food crops grown. The environment is ideal for growing crops including maize, yams, cassava, millet, rice, plantains, cashews, and cocoa.

Sampling procedure

A multistage sampling method was used to select respondents for the study. The first stage was the simple random selection of two (2) States from Southwest Nigeria. These States are the Ondo and Osun States. The second stage involved the purposive selection of three (3) Local Government Areas (LGAs) from each selected State based on the concentration of maize production in the State. The third stage entailed a simple random selection of five (5) villages from a list of maize-growing communities of each LGA. In the fourth stage, ten maize farmers were selected from each village using simple random sampling. The sample size of the study is about 300 maize farmers.

Estimation procedure

Firstly, descriptive statistics was used to describe the socioeconomic characteristics of the cocoa farmers. Then, the data were analysed using the Hurdle negative binomial model, and the Endogeneity stochastic frontier model.

Hurdle negative binomial model

The Hurdle Negative Binomial (HNB) model was used to determine the probability of farmers participating in social capital networks and the level of their participation in social capital networks. The decision to join a social group and the number of social capital networks in which maize farmers participate are used as proxies for the probability of participation and level of participation in social capital networks, respectively. The model was used because of the features of the data captured in the objectives of the study. The second hurdle uses a count variable with an extremely large zero-inflated distribution as the dependent variable. Following Adekunle et al. [78], the HNB model incorporates both binary choice models like the probit model and zero-truncated negative binomial (ZTNB) models, which investigate the variables influencing the probability of participation and level of participation in social capital networks, respectively. However, the two objectives are not estimated simultaneously.

When expressed, HNB models look like this (Eq. 4):

$$P(Y=y)=\begin{cases}\text{Binomial}(\pi) & y=0\\ \text{ZTNB}(\mu)(1-\pi) & y=1,2,3\ldots N\end{cases}. \tag{4}$$

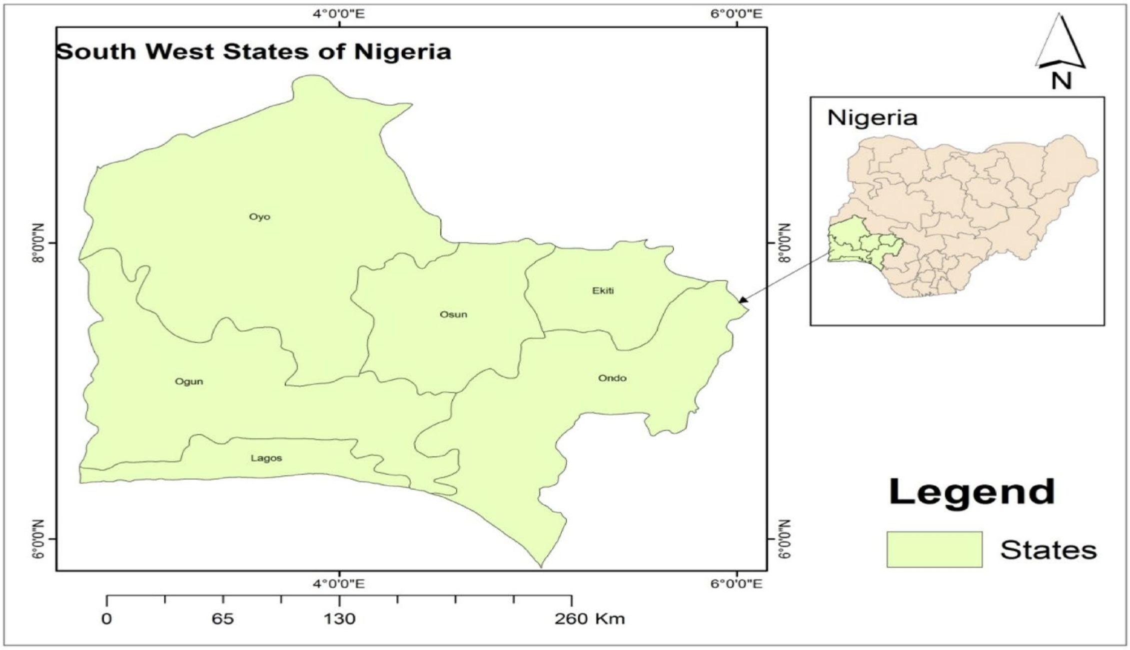

Fig. 1 Map of Southwestern Nigeria showing the study areas (Source: Google Map, 2019 Accessed from https://www.researchgate.net/figure/Map-of-Southwest-States-Nigeria-Sourcearticlesapuborgsors_fig1_3226616026/5/2019)

A binary choice model uses a binary outcome of 0 or 1 to determine the first hurdle; if the outcome is larger than 0, the 'Hurdle' is then passed to the second hurdle, which is determined by ZTNB.

Following Adeyemo and Kehinde [15], the probit element of the model is defined as follows (Eq. 5):

$$f(y_i) = \frac{1-g(0)}{1-h(0)}h(y) \quad \text{if } y_i \geq 1;\ g(0) \quad \text{if } y = 0, \tag{5}$$

where the probability $g(0)$ determines the zeros, and the probability function $h(y|y>0) = h(y)/\{1-h(0)\}$ determines the positive counts. To ensure that the probabilities add up to one, a truncated probability function is multiplied by "$\{1-g(0)\}$," which indicates the likelihood of passing the hurdle.

The zero-truncated negative binomial model was employed in the second hurdle to account for overdispersion brought on by unobserved heterogeneity.

The contribution to the likelihood (Eq. 6) is

$$l_i^H = g(0)^{(1-d)} \times \left[\{1-g(0)\}\frac{h(y)}{1-h(0)}\right]^{d_i}, \tag{6}$$

where d_i represents whether farmers i successfully overcome the obstacle. The maximization technique can be broken down into two steps, presuming that both functions are independent conditional on covariables. First, a binary model with d_i as the dependent variable can be maximized using the entire sample. Second, a reduced regression can be used to estimate the parameters of h separately using only observations with positive counts.

Endogeneity stochastic frontier model

The endogeneity stochastic frontier model was adopted to determine the impact of participation in social capital networks on the technical efficiency of maize producers. It is noteworthy to mention that, in contrast to the conventional control function techniques that involve two-stage estimations as employed by Abdulai and Abdulai [79] and Khanal et al. [80], the model utilized in this investigation estimates the parameters in a solitary stage. This model conveniently takes into account random errors that are outside the control of farmers as well as measurement inaccuracies. The stochastic frontier estimation strategy is thoroughly documented in the literature.

Using Aigner et al. [71] as a guide, the implicit statement of the Cobb–Douglas functional form of the stochastic frontier model was as follows (Eq. 7):

$$\ln Y_i = \beta_i \ln X_i + (V_i + U_i), \tag{7}$$

where Y_i is the output of the ith maize farmer, X_i is the input quantities of the ith maize farmer, β is the unknown parameters to be estimated, V_i is random error which is independent of the U_i, and U_i is a non-negative random variable called technical inefficiency. The value of U_i may be obtained from the observable value of $V_i - U_i$ with the assumption that the composed error $V_i - U_i$ is known and is the best predictor for technical efficiency. The technical efficiency of an individual maize farmer is defined as the ratio of the observed output to the corresponding frontier output, conditional on the level of input used by the farmer.

The component of the model representing technical inefficiency is represented as follows (Eq. 8):

$$\varepsilon_i = V_i - U_i. \tag{8}$$

The error component v_i is a pure random component which accounts for factors beyond the farmers' control and omitted variables with measurement error; u_i is the systematic and non-negative component accounting for inefficiency.

The corresponding output-oriented technical efficiency measure is expressed as (Eq. 9):

$$\mathrm{TE}_i = \exp(-u_i) \in |0, 1|. \tag{9}$$

The increase in output for maize farmers TE would be expressed in Eq. (9) depending on the degree of input used. In this instance; however, it is assumed that there is no connection between predetermined variables and the stochastic error of the model, therefore the estimation is unaffected by simultaneous equation bias.

It is presumable that u_i has a half-normal distribution and that v_i has a normal distribution (Eq. 10):

$$\text{Thus, } \operatorname{cov}(v_i u_i) = 0. \tag{10}$$

If either of these conditions are violated then the MLE will be biased and most likely inconsistent. Yet, it is not difficult to think of the presence of endogeneity in the model. For example, social capital is generated through interactions of networks of people which improves the well-being of people participating in the social groups. Although social capital is an individual asset, it is sourced from the interaction of people in a group. Due to this fact, the characteristics and resources of friends, contacts, and groups may affect individual outcomes. Hence, this relationship causes the causality between technical efficiency and participation in social capital networks, leading to the correlation between x and v_i. The novelty in this study is that the study envisages that the policy variable, participation in social capital networks in the model, by its nature, correlates with the basic efficiency error term:

$$\mu^0 = E\left(u_i^0\right) = m\sqrt{\frac{2}{\pi}}\delta_u \text{ and } u_i^0 = u_i^0 - \mu^0. \tag{11}$$

Finally, μ^0 is a random component that is independent from both v_i and ε_i, and is specific to farmers.

We used the likelihood method to the relevant equation in the manner of Kutlu [81], Tran and Tsionas [82], Amsler et al. [83], and Amsler et al. [84] to address the endogeneity issue in production function estimation. This strategy makes use of Cholesky decomposition.

Estimating participation in social capital networks cannot be done straightforwardly, as the decision to participate in social capital networks may be influenced by inherent characteristics that could also impact the technical efficiency of maize farmers. As a result, this gives rise to the correlation of error terms, which in turn leads to partiality in parameters that signify the impact of participation in social capital networks on technical efficiency. The impact of participation in social capital networks on technical efficiency may be subject to unreliable estimates due to the potential influence of unobservable characteristics of farmers and their farms. These factors may impact both the decision to participate in social capital networks and the resulting technical efficiency. The resolution of the endogeneity issue necessitates the utilization of an appropriate instrumental variable (IV) methodology. The endogeneity issue in participation in social capital networks was addressed by utilizing ethnic group membership as an instrumental variable (IV). Membership in ethnic groups has the potential to facilitate farmers' access to credit facilities. This suggests that the actions of ethnic groups bear a resemblance to those of social capital networks. In Nigeria, it is customary for farmers to be affiliated with at least one farmers' group in order to obtain loans or financing for agricultural operations and expansion. Kutlu [81], Tran and Tsionas [82] and Amsler et al. [84] are notable contributors to the field of stochastic frontier analysis, particularly in the development of models that account for endogeneity.

In accordance with Amsler et al. [84], the u_i is independent of $\psi_i = \frac{u_i}{\eta_i}$. We prepare the instrument with, w_i (Eq. 12).

Hence,

$$f(y, x_2|w) = f(y|x_2, w).f(x_2|w). \tag{12}$$

The following is the current form of the log-likelihood function:

$$\ln l = \ln l_1 + \ln l_2, \tag{13}$$

where $\ln l_i$ is $f(y|x_2, w)$ and $\ln l_2$ is $f(x_2|w)$.

However,

$$\ln l_i = -\left(\frac{\pi}{2}\right)\ln\sigma^2 - \frac{1}{2\sigma^2}\sum{}_{i=1}^{n} e_i^2 + \sum{}_{i=1}^{n} \ln\left[\phi(-\lambda_c e_i/\sigma)\right],$$

$$\ln l_2 = -\left(\frac{n}{2}\right)\ln|\sum\eta\eta| - 0.5\sum{}_{i=1}^{n}\eta_{i'}\sum{}_{\eta\eta}^{-1}\eta_i. \tag{14}$$

By maximizing the likelihood function $\ln l$, the model's estimation, that is, the process of acquiring the model parameters $(\beta, \sigma_v^2, \sigma_u^2, \Gamma, \sum v\eta)$ is done. By examining the combined significance of the terms' component parts η, the endogeneity test is conducted. The presence of endogeneity in the model is demonstrated if η is significant. If not, efficiency can be calculated by Aigner et al. [71] using traditional SFM (Table 1).

Specification checks

Participation in social capital networks and proposed trade credit instruments were compared using correlation analysis. The instrument employed as the instrumental variable for participation in social capital networks in the SFA model had the highest correlation coefficient with participation in social capital networks and was uncorrelated with the usage of technical efficiencies. The proposed instruments include ethnic group membership, cooperative membership, and access to extension services. The rationale behind the selection of these variables was based on the review of the literature. According to Kehinde et al. [40], cooperative membership, access to extension services and ethnic group membership influence farmers' participation in social capital networks and might not significantly influence the dependent variable in question (technical efficiency of maize farmers). Furthermore, following Howley et al. [85] and Kehinde and Ogundeji [86], the Sargan over-identification test was also conducted for the IV models. If the *P*-value is not significant, it means that the instrument is not correlated with the error term and therefore it is valid [40].

Results and discussion

Profile of socioeconomic characteristics of maize farmers by participation in social capital networks

Table 2 presents the socioeconomic characteristics of maize farmers by participation in social capital networks. The findings of the *T*-test revealed that maize

Table 2 Profile of socioeconomic characteristics of maize farmers by participation in social capital networks. Source: Field survey, 2021

Variable	Members of social capital networks (67)	Non-members of social capital networks (33)	*T*-test
Age	50.22 (10.80)	52.54 (18.26)	2.12**
Age^2	2631.06 (181.36)	2826 (173.27)	2.76***
Household size	7.23 (1.806)	6.85 (1.62)	2.52**
Years of education	9.25 (3.76)	8.56 (3.43)	2.35**
Years of experience	24.06 (17.89)	23.89 (17.09)	1.72
Male (%)	91.25	87.14	
Extension (%)	87.51	81.43	
Access to credit (%)	90	72	
Maize yield	165.13 (74.07)	146.58 (66.96)	5.13***
Farm size	2.55 (1.99)	2.36 (1.72)	3.52***
Maize seed	78.20 (34.22)	74.74 (32.27)	2.84***
labour	55.93 (24.37)	36.14 (17.73)	1.13
pesticides	17.08 (9.46)	15.22 (8.57)	1.19
Fertilizer	18.73 (7.31)	12.95 (5.91)	4.40***
Asset	94,277.47 (14,284.30)	53,188.20 (17,728.97)	2.66***

Figures in parenthesis indicate the standard deviation

***, ** and * represent significance levels at 1%, 5% and 10%, respectively

Table 1 Definition of variables in ESF model and a prior expectation. Source: Author's computation

Variables	Definition	Expected sign
Maize output	Measured in kilogram	±
Seed	Measured in kilogram	±
Fertilizer	Measured in kilogram	±
Pesticides	Measured in litres	±
Labours	Measured in Man-days	±
Farm size	Cultivated land occupied by maize in hectares	±
Age	Measured in years	±
Age^2	Square of age measured in years	±
Household size	The number of persons in a household (count)	±
Years of education	Number of years spent in school	±
Years of experience	Number of years in farming	±
Gender	1 = if a farmer is male	±
Extension visit	1 = if the farmer is visited by an extension agent	±
Access to credit	1 = if the farmer has access to credit	±
Asset	Asset owned by the farmers in Naira	±

farmers who are members of social capital networks and those who are not, differ significantly in terms of age, age squared, household size, maize yield, farm size, maize seeds, fertilizer, asset ownership and years of schooling. This suggests that maize farmers who are members of social capital networks typically have larger homes, live longer, are more educated, and are older than non-members. Similarly, farmers who participate in social capital networks achieve higher maize yield, use more production inputs such as maize seeds and fertilizers and also own more assets than farmers who do not participate in social capital networks. This proves that endogeneity and selection bias are problems with the sample. According to descriptive statistics on maize farmers, those who belonged to social capital networks had a little bit better access to loans and extension services than those who did not. Male farmers belong to more social capital networks than female farmers do and this is in line with the prior hypothesis of the study and the socio-cultural environment of Africa. This result corroborates the findings of Ogunleye et al. [87] and Adeyemo and Kehinde [88].

Factors influencing the probability and level of maize farmers participating in social capital networks

The double hurdle negative binomial regression results are presented in Table 3. The results of the hurdle model are presented in two parts. The first hurdle shows the results of factors that influence the decision to participate in social capital networks, while the second hurdle shows the results of factors that influence the level of participation in social capital networks. The number of social capital networks, the maize farmers are actively belonging to, is used as a proxy for the level of participation in social capital networks. This is based on the fact that farmers decide to participate in numerous social capital networks to enjoy a high level of social capital. The statistical significance of the overall goodness of fit of the model has been determined to be at a 1% probability level through the utilization of the likelihood ratio test [likelihood ratio test of alpha (Chibar)]. This shows that the entire model is the best fit and is significant at 1%. The first hurdle has a significant log-likelihood ($P = 0.000$) and LRChi^2 of 33.16, indicating a high level of explanatory power. This shows that the entire model is the best fit and is significant at 1%. According to the findings of the first hurdle, the desire of maize farmers to participate in a social capital network is significantly influenced by their socioeconomic characteristics, including their age, age squared, household size, farm size, asset ownership, gender, and access to credit. In furtherance to that, the age of the farmers has a positive and significant effect on the decision to participate in a social capital network.

Table 3 Factors affecting the participation of the maize farmers in social groups. Source: Field survey, 2021

Variable	First hurdle (decision to participate in a social group)	Second hurdle (level of participation in social group)
	Coefficient (*Z*)	Coefficient (*Z*)
Age	0.185*** (2.69)	0.133*** (3.16)
Age^2	0.159** (2.43)	0.162*** (2.60)
Household size	0.072* (1.70)	0.058** (2.01)
Years of education	−0.012 (−0.72)	0.004 (0.30)
Years of experience	0.295 (0.31)	0.155** (2.20)
Gender	0.355*** (3.41)	0.278** (2.24)
Access to credit	0.701*** (3.37)	0.776*** (5.39)
Extension	0.160 (0.73)	0.236 (1.20)
Farm size	0.117*** (4.56)	0.528*** (3.03)
Fertilizer	0.715 (0.22)	0.178 (0.58)
Asset	0.927*** (3.27)	0.788***(4.11)
Constant	4.901*** (2.78)	3.610*** (3.40)
LRChi^2	33.16	57.17
Log-likelihood	−190.698	−437.947
Prob > Chi^2	0.0001	0.000
Likelihood ratio test of alpha (Chibar2(01))		7.38
Prob > chibar2		0.003
Observations	300	300

Figure in parenthesis indicates the *Z* values

***, ** and * represent significance levels at 1%, 5% and 10%, respectively

This implies that older farmers have a higher probability of participating in social capital networks. Also, the age squared of the farmers has a positive and significant effect on the decision to participate in social capital networks. This implies that farmers with active economic life have a higher probability of participating in social capital networks. Household size has a positive and significant effect on the decision to participate in social capital networks. This implies that farmers who have large households have a higher probability of participating in social groups. Also, gender has a positive and significant effect on the decision to participate in social capital networks. This implies that male farmers have a higher probability of participating in social capital networks. Similarly, access to credit has a positive and significant effect on the decision to participate in a social capital network. This implies that farmers with access to credit have a higher probability of participating in social capital networks. The asset has a positive and significant effect on the decision to participate in a social capital network. This implies that farmers who own asset have a higher probability of participating in social capital networks.

Interestingly, in the second hurdle, the likelihood ratio test of alpha strongly rejects the null hypothesis that the errors do not exhibit overdispersion. Thus, the zero-truncated Poisson regression model is rejected in favour of its generalized version, the zero-truncated NB regression model. Therefore, the zero-truncated NB regression model gives an unbiased and consistent estimate than the zero-truncated Poisson model. The second hurdle has a significant log-likelihood ($P=0.000$) and LRChi^2 of 57.17, indicating a high level of explanatory power. This shows that the entire model is best fit and significant at one percent. The result of the model shows that socioeconomic characteristics such as age, age squared, years of experience, household size, gender, farm size, asset and access to credit are significant in determining the level of participation in social capital networks. Sequel of this, the age of the farmers has a positive and significant effect on the level of participation in social groups. The result suggests that an increase in the age of farmers increases the level of participation of maize farmers in social capital networks. This implies that older farmers participate in many social capital networks. Also, the age square of the farmers has a positive and significant effect on the level of participation in social capital networks. The result suggests that an increase in the age square of farmers increases the level of participation of maize farmers in social capital networks. This implies that farmers with active and economic life participate in many social capital networks. Household size has a positive and significant effect on the level of participation in social capital networks. The result suggests that an increase in the household size increases the level of participation of maize farmers in social capital networks. This implies that farmers that have large households participate in many social capital networks. Years of experience have a positive and significant effect on the level of participation in social capital networks. The result suggests that an increase in years of farmers' experience increases the level of participation of maize farmers in social capital networks. This implies that farmers with many years of experience participate in many social capital networks. Also, gender has a positive and significant effect on the level of participation in social capital networks. The result suggests that increasing the number of male farmers increases the participation of maize farmers in social capital networks. This implies that male farmers participate in many social groups. Farm size has a positive and significant effect on the level of participation in social capital networks. The result suggests that increasing the hectares of farm increases the participation of maize farmers in social capital networks. This implies that farmers with large farms participate in many social capital networks. Asset ownership has a positive and significant effect on the level of participation in social capital networks. The result suggests that increasing the number of assets owned by farmers increases the participation of maize farmers in social capital networks. This implies that farmers with many assets participate in many social capital networks. Similarly, access to credit has a positive and significant effect on the level of participation in social capital networks. The result suggests that an increase in credit sources increases the level of participation of maize farmers in social capital networks. This implies that farmers with access to credit participate in many social capital networks.

The plausible reason for the positive effect of age and age squared on the probability of farmers participating in social capital networks could be that older farmers are likely to join social capital networks in order to secure a market for their increasing output or for old age reasons. This may be due to the fact that as farmers mature, they may amass cash and other resources and come to appreciate the value of using social networks to actively participate in the commitments and activities that such networks share. Again, this may be expected because older farmers may come across as more trustworthy in group settings than younger ones who tend to be more assertive, which in turn influenced their decision to join social capital networks later in life. Furthermore, some social capital networks prefer older members because they seem to be more credible in group formations than their younger counterparts who tend to be more aggressive. On the other hand, older farmers may want to join social capital networks to seek assistance because they may not be energetic enough to participate in other fund-generating activities. The study corroborates the studies of Kehinde and Ogundeji [86, 89], Mbagwu [90], Mojo et al. [91], Mugabekazi [92], Othman et al. [93], Adong et al. [94]. The positive relationship between household size and participation in social capital networks shows that large households are more likely to join social capital networks. Large households can contribute more family efforts so that they can produce more maize according to some requirements of social capital networks. Larger households tend to require more labour for maize cultivation in rural agricultural settings. Hence, large households are more likely to become members of social capital networks because these households are more likely to meet the high-quality requirements of social capital networks which involve the need for more labour. Additionally, larger households are more likely to participate because it is easier for them to spare one family member from working on the farm and send it to those meetings. As expected, the years of farming experience determine the level of participation in social capital networks. Farmers with more experience have a better understanding of the costs and benefits of belonging to social capital networks. Hence, farming experience is likely to influence positively the membership decision of maize farmers. The participation of farmers in social capital networks is significantly and positively affected by gender as well. Due to the practice of joining clubs and cooperatives, men may be more interested in joining social capital networks. In addition, male farmers attend membership campaign meetings, leaving women at home to take care of household duties. This is because women frequently have household responsibilities to attend to, leaving little time for social engagement. Access to credit positively influenced the likelihood of farmers' participation in social capital networks. It implies that farmers join social capital networks because they can access credit services from them, and that social capital networks are more dependable sources of credit than formal lending institutions because they do not require collateral. The result agrees with studies of Mugbabekazi (2014), Woldegebrial et al. [143], and Gasana [95], where access to credit influenced farmers' decision to join cooperatives. The possibility of participation in social capital networks is significantly and positively affected by the size of the farm. This is acceptable because larger farms typically have more resources and the ability to increase agricultural productivity, which motivates farmers to join social capital networks so they can sell their goods and have easier access to farm input [96–101]. In addition, farmers use large land assets as informal safeguards to join cooperative societies. The plausible reason for the positive effect of asset ownership on the probability of farmers participating in social capital networks could be that households with better access to assets have less financial stress and a higher propensity to fulfil their membership responsibilities, such as monthly cash contributions and dues, as well as membership obligations, such as buying fertilizer and chemicals [96, 99–104].

Are instrumental variables valid?

Correlation test

An investigation of the relationship between participation in social capital networks and proposed instruments was done using a correlation test to determine the validity of the instrumental variables utilized in the ESF model. The proposed instruments include ethnic group membership, cooperative membership, and access to extension services. The results of the correlation analysis are presented in Table 4. Ethnic group membership has significant correlations with participation in social capital networks, but an insignificant correlation with the technical efficiency of maize farmers. It also has the highest significant correlation coefficient (0.715) with participation in social capital networks, which satisfies the theoretical relevancy requirement for instrument validity. This shows that our IVs are not weak [137].

Sargan test of instrumental variables

Sargan test of over-identification was also run to validate the instrument. The proposed instrument must not only be uncorrelated with the dependent variable and error term (valid), but also with the endogenous explanatory variable [142, 136]. Membership in ethnic groups was identified using a correlation approach. The next challenge is meeting the requirements of the Sargan test of over-identification. The Sargan standard over-identification test for instrument validation was conducted in this regard. The satisfying condition is that the p-value of the

Table 4 Correlation values of instrumental variables with access to trade credit and use of EU-approved pesticides. Source: Field survey, 2021

Variables	Ethnic group membership	Cooperative membership	Access to extension service
Participation in social capital networks	0.715 (0.000)	0.668 (0.001)	0.506 (0.002)
Remarks	Significant	Significant	Significant
Technical efficiency of maize	0.813 (0.766)	0.769 (0.336)	0.772 (0.001)
Remarks	Not significant	Not significant	Significant

Figures in parenthesis are the p-values

***, ** and * represent significance levels at 1%, 5% and 10%, respectively

Table 5 Sargan test of instrumental variable. Source: Field survey, 2021

Variable	Technical efficiency of maize farmers	
	Probit model	OLS model
Participation in social capital networks	0.278*** (3.05)	0.576** (2.27)
Sargan estimates		0.44 (0.79)

Figures in parenthesis are the *t*-values

***, ** and * represent significance levels at 1%, 5% and 10%, respectively

instrument must exceed a significance value of 0.1, to be a valid instrument [89, 105] [137]. The over-identification test result for Sargan is shown in Table 5, and Membership in an ethnic group is reported to be a valid instrument because its *p*-value is more than the significance threshold of 0.1. As a result, our estimates would be objective and consistent, since we have an instrument, i.e. membership in an ethnic group that is sufficiently accurate to resolve any endogeneity issues that could come from both the membership in ethnic groups and the technical efficiency of the maize farmers.

Impact of participation in social capital networks on technical efficiency of maize farmers

The present study employs an endogeneity-corrected stochastic frontier model to examine the influence of participation in social capital networks on the technical efficiency of maize farmers. The percentage of participation in social capital networks of the sample is 67, suggesting that a significant proportion of the respondents included in the study are affiliated with a social capital network or the other. Ma et al. [106], Olagunju et al. [107] and Kehinde et al. [40] have noted that the decision to participate in social capital networks may not be random and could be influenced by inherent characteristics, such as managerial skills and attitude of farmers. This could lead to potential endogeneity issues. Hence, it is crucial to consider the endogeneity issues to guarantee unbiased and consistent estimations from the SFA model. To address the issue of endogeneity concerning participation in social capital networks, the study employed ethnic group membership as an instrumental variable for participation in social capital networks. This finding is grounded on the observation that the variable exhibits a noteworthy correlation with participation in social capital networks while displaying an inconsequential correlation with the technical efficiency of maize farmers. This is consistent with the research results of Adepoju and Oni [42] and Kehinde and Ogundeji [86]. We estimated the equation using the Cobb–Douglas production function. The results of the estimation are presented in Table 6. Model EX represents the model that disregards endogeneity, and Model EN represents the model that accounts for endogeneity. Interestingly, the two models show similar results in terms of significant variables and magnitude. However, the endogeneity test (η) indicates that social capital is an endogenous variable and the problem of endogeneity has been taken care of in the model. Therefore, we discounted Model EX and reported Model EN. The result reveals that the mean technical efficiency score was 0.646. By implication, the average technical efficiency of 65% suggests that an average maize farm in Southwestern Nigeria requires about 35% additional existing resources to operate at the optimum level. This suggests that an average maize farmer lost 35% of their output as a result of technical inefficiency. We assume that a farmer is said to be effective when he obtains an index that is higher or equal to the average efficiency score (65%). In light of this reasoning, the study

Table 6 Impact of social capital on the technical efficiency of maize farmers. Source: Field survey, 2021

Variable	Model ex	Model en
Frontier model		
Constant	3.68** (2.31)	3.69*** (7.86)
Seed	0.481*** (4.17)	0.473*** (10.53)
Fertilizer	0.717*** (3.29)	0.725*** (12.32)
Agrochemical	0.880*** (2.89)	0.728*** (9.61)
Labour	0.260*** (7.38)	0.087*** (4.82)
Farm size	0.339** (6.60)	0.337*** (7.59)
Inefficiency model		
Age	−0.083 (−0.75)	−0.225 (−0.42)
Age^2	0.109 (1.03)	1.806 (0.04)
Household size	−0.309*** (−2.61)	−0.152*** (−3.21)
Years of education	−0.101*** (−3.07)	−0.592*** (−3.34)
Years of experience	−0.04*** (−2.66)	−0.187*** (−2.78)
Gender	0.523 (0.52)	0.192 (1.12)
Extension visits	−0.645** (−2.18)	−0.450*** (−2.25)
Access to credit	0.699 (0.19)	0.330 (0.28)
Asset	0.320 (0.51)	0.407 (0.22)
Dependent variable: $\ln(\sigma^2 u)$		
Constant	2.988*** (3.24)	3.151*** (4.54)
Social capital	−0.571*** (5.54)	−0.423*** (10.33)
Dependent variable: $\ln(\sigma^2 v)$		
Constant	0.881*** (4.15)	
Dependent variable: $\ln(\sigma^2 w)$		
Constant		24.060*** (7.31)
η		4.182*** (7.54)
η Endogeneity test ($X^2=15.18$)		$P>X^2=0.000$
Mean technical efficiency	0.681	0.646
Log-likelihood	−937.927	−3155.156

Figures in parenthesis are the *t*-values

***, ** and * represent significance levels at 1%, 5% and 10%, respectively

suggests that given the current technology and resources (inputs) in the study area, maize production may still be increased by roughly 35%. To increase their income and profit from the production of maize, farmers in the study area should concentrate on making efficient use of the available resources and technology. Improved resource management contributes to improved output, yield, and, eventually, profit. The value of returns to scale (RTS), the sum of the coefficients of variables in the frontier model, was 2.550. This implies that the maize production is in "an increasing return to scale" stage. A 100% increase in the resource used for maize production in Southwestern Nigeria will generate a 255% increase in maize output. This further collaborated the technical efficiency result that maize farmers are yet to attain the optimum level of the combination of the resources because the farmers are still in the first stage of production. This result is consistent with the findings of Adeyemo et al. [108].

The model comprises two panels; the first being the technical efficiency panel which explains the technical efficiency of farmers and their drivers. The second panel is the technical inefficiency model which explains the variation in technical inefficiency of farmers. An increase in technical efficiency decreases the technical inefficiencies. Interestingly, all the variables are significant and positive in the frontier model. This result is consistent with the estimates of Abdulai and Abdulai [109] who also found positive and significant effects of frontier variables on the output of maize farmers in Zambia. The coefficient of maize seed was significant and positive. This implies that a percentage increase in kilogram of maize seed will increase the technical efficiency of maize farmers by 47.3%. This study is similar to the results of the study found by Abdulai [110], which suggests that an increase in rice output can be achieved through seed intensification and the engagement of more labour. The coefficient of fertilizer was significant and positive. This implies that a percentage increase in kilogram of fertilizer will increase the technical efficiency of maize farmers by 72.5%. This finding agrees with the work of Abdulai [110], Weldegebriel [111], Osanyinlusi and Adenegan [112], and Opata et al. [113] who stated that fertilizer is a vital land supplement because it improves land fertility by increasing per hectare yield of rice. The coefficient of agrochemicals was significant and positive. This implies that a percentage increase in a litre of agrochemicals will increase the technical efficiency of maize farmers by 72.8%. Therefore, paying more attention to investment in agrochemicals such as pesticides can enhance the levels of maize output. This result is consistent with the studies of Sienso et al. [114] and Opata et al. [113] which observed a positive and significant relationship between the quantity of agrochemicals and output. The coefficient of labour was significant and positive. This implies that a percentage increase in man-days of labour will increase the technical efficiency of maize farmers by 8.7%. This implies that maize farming is labour-intensive and uses traditional technology that relies heavily on labour usage. This is in line with the findings of Etim and Okon [115], Dlamini et al. [116] and Olowa and Olowa [117]. Improved maize seed varieties are typically more expensive for the farmer, thus they want to minimize wastage that could come from using family labour, hence they heavily rely on hiring labour. Due to the labour-intensive nature of maize production, extra labour will be needed, particularly for weeding and harvesting tasks [118]. The conclusions of Abawiera and Dadson [119] and Dlamini et al. [116] are refuted by this finding. The coefficient of farm size was significant and positive. This implies that a percentage increase in a hectare of farm size will increase the technical efficiency of maize farmers by 33.7%. When the farmers have higher land holdings, they invest in improving land productivity. This study is similar to the results found by Oyewo [120] and Weldegebriel [111]. A better distribution of the aforementioned resources increases yield and subsequently production. To increase the amount of maize seed produced, farmers should concentrate on making judicious use of the resources and technologies already available.

However, in order to determine the impact of participation in social capital networks on the technical efficiency of maize farmers, we considered the following variables: age, age squared, household size, years of education, years of experience, gender, extension visit and participation in social capital networks in the inefficiency model. The result reveals that participation in social capital networks, household size, years of education, years of farming experience, and extension visits significantly influence the technical inefficiency of maize farmers. Household size has a negative and significant effect on the technical inefficiency of maize farmers. This implies that a percentage increase in household size will increase technical efficiency of maize farmers by 84.8%. This means that large households are technically more efficient than smaller ones. This could be explained by the fact that large households will tend to give their best of them to produce more in order to ensure the consumption of maize for their members. In addition, this type of household has a larger workforce (family labour), all things being equal. This result is consistent with the work of Kabore [121] and Ouédraogo et al. [122], who finds that extended-type households tend to be more efficient because they have the advantage of being an important source of labour. Years of education of farmers have a negative and significant effect on the technical inefficiency of maize farmers. This shows that the more years the farmer spent in formal schools the less technical inefficiency and more productivity. This is an indication that the farmer's level of inefficiency declines as he/she acquires more education in the study area. This implies that a percentage increase in years of education will increase the technical efficiency of maize farmers by 40.8%. The fact that education level and technical efficiency are positively correlated may also be explained by the fact that farmers with relatively higher levels of education are thought to have had more exposure to agricultural technology and agronomic practices (such as inspection, rouging, thinning, spacing, and weeding), which may have a positive impact on the technical efficiency of maize production. Since more educated farmers are more likely to utilize modern technology effectively, this could increase farm productivity per hectare [53]. Additionally, educated people are in a better position to take in, process, interpret, and react quickly to new information. Years of experience have a negative and significant effect on the technical inefficiency of maize farmers. This shows that the more the farming experience, the less the technical inefficiency and the more the technical efficiency and productivity. This implies that a percentage increase in years of experience will increase the technical efficiency of maize farmers by 81.3%. This implies that experienced maize farmers are more productive and efficient. The findings of Kumbhakar et al. [123] that farmers with more experience tend to be more efficient in output because new skills are developed with time are supported by this result. This finding is in line with Olarinde's [124] observation that farmers with more experience are better able to get the knowledge and skills required for selecting the right new agricultural technology over time in order to be more productive and efficient.

Extension contact has a negative and significant effect on the technical inefficiency of maize farmers. This implies that a percentage increase in contact of maize farmers with extension agents will increase the technical efficiency of maize farmers by 55%. This indicates households who receive more extension visits by extension workers appear to be more technically efficient than their counterparts. This result is also similar to those obtained by Jude et al. [125] and Mbanasor and Kalu [126]. The reason for this is that maize farmers that receive more extension visits were able to adopt better farm management practices in maize growing because they were better informed about new technological breakthroughs. They utilized resources more effectively as a result than individuals who were not able to receive any extended visits. This finding supports those of Abawiera and Dadson [119], Addai et al. [127], Yiadom-Boakye et al. [128], and Onumah et al. [129] who found that farmers with higher levels of technical efficiency sought out technical information and had adequate extension contact. Primarily, agricultural extension agents report the needs of farmers to researchers and in turn disseminate new research findings to farmers and so one would expect their contact with farmers to enhance efficiency. In particular, this dual function of extension service is more important in the use of production inputs such as improved varieties of seeds released into the market by research organizations. Idiong [130] also noted that farmers who got extension services displayed better levels of efficiency. He went on to explain that informal teaching and learning sources assisted farmers in modernizing their farming practices, which in turn had a beneficial impact on efficiency level. Farmers who use extension services are better informed about how to use resources (inputs), gain technical knowledge about producing maize, and learn about the market, all of which may result in increased technical efficiency. Additionally, extension assistance helps farmers choose the most cost-effective combinations of production inputs and produce the maximum amount of output using those inputs. Also, agricultural extension services are meant to increase productivity by bridging the knowledge gap between farmers and the available technology and technical expertise. This result agrees with Begum et al. [131] and Abate et al. [132], who supported the idea that farmers' efficiency levels will increase with properly managed extension services.

Finally, participation in social capital networks has a negative and significant effect on the technical inefficiency of maize farmers. This implies that a percentage increase in participation in social capital networks will increase the technical efficiency of maize farmers by 57.7%. According to the study, farmers who are members of social capital networks are more technically proficient than their counterparts who are not. They will probably gain by having easier access to opinions and knowledge about best practices. In other words, members of these communities engage with one another, share knowledge about farming methods, and gain insight from one another's experiences. A similar observation was made by Nyagaka et al. [133], Kehinde and Olatidoye [134], Kehinde and Adeyemo [39]. This is explained by the fact that social capital networks give farmers, researchers, private organizations, and extension agents a forum for interaction in order to improve agricultural techniques and methods to increase maize production. This suggests the exchange of ideas and information between farmers and other interested parties in order to enhance local maize farming and boost maize production through the use of more effective production input combinations.

Robustness check

The inverse-probability-weighted regression adjustment (IPWRA) was used as a robustness check, to examine the causal effects of participation in social capital networks on the technical efficiency of maize farmers (Table 7). According to the result from the IPWRA estimation (0.531), of participation in social capital networks has a positive and significant impact on the technical efficiency of maize farmers in Southwestern Nigeria. This means that even technically inefficient maize farmers are more likely to participate in social capital networks and invest social capital in maize production. This is based on the idea that participation in social capital networks increases the purchasing power of farmers, allowing them to invest in improved technologies to increase their technical efficiencies. Our results corroborate studies of Olurotimi et al. [68] and Akinola et al. [44].

Conclusion and policy implications

This study investigated the impact of participation in social capital networks on the technical efficiency of maize farmers in Southwestern Nigeria. A multistage sampling procedure was used to obtain data for the study. Data were analysed using the Hurdle Negative Binomial (HNB) model and the Endogeneity Stochastic Frontier model. The first hurdle result showed that age, age square, household size, gender, farm size, asset ownership, and access to credit significantly influence the decision to participate in social capital networks. While, in the second hurdle, age, age square, household size, years of experience, asset ownership, farm size, gender, and access to credit are significant in determining the level of participation in social capital networks. The results of the Endogeneity Stochastic Frontier model show that the average technical efficiency of 65% in maize production. This suggests that an average maize farmer lost 35% of their output as a result of technical inefficiency. In the frontier model, maize seed, fertilizer, agrochemicals, labour, and farm size significantly influence the technical efficiency of maize farmers. In the inefficiency model, social capital along with socioeconomic characteristics such as household size, years of education, years of experience, and extension contact significantly influence the technical inefficiency of maize farmers. The study concluded that participation in social capital networks has a positive impact on the technical efficiency of maize farmers. This study suggests that participation in social capital networks among maize farmers be taken into account in agricultural programmes aimed at efficient maize production. To access social capital and increase their maize output, more social capital networks should be formed, and maize farmers should be encouraged to participate in social capital networks. Additionally, a significant influence on the technical efficiency of maize farmers in southwest Nigeria is education and extension. ADPs should therefore arrange agricultural training programmes aimed at enhancing the technical efficiency of maize producers, with a particular focus on educated farmers. This study advises the local government to step up extension services, especially training programmes, provide ongoing support for widespread hybrid or high-yielding variety propagation and dispersal in collaboration with the private sector, make credit more accessible to farmers, and raise farmers' educational levels through brief technical training.

With a rising population and land scarcity placing pressure on maize production, this paper aimed to extend the body of literature on the technical efficiency of maize farms in developing countries. However, the findings in this study could be interpreted within the context of methodological limitations relating to data collection. Missing variables are the data limitation. For example, machinery, primary occupation, distance to farm, farm income and non-farm income were not available in the data set. These factors are critical to improving technical efficiency. Second, there could be other sources of unmeasured potential sources of heterogeneity caused by persistent technical inefficiency and endogeneity of inputs. Third, the study is limited to the region of the country (southwestern, Nigeria). Therefore, future research should extend the analysis to ensure the generalizability of the empirical findings regarding the extent to which unmeasured potential sources of heterogeneity are caused by persistent technical inefficiency, endogeneity of inputs and other unobservable region-specific features—such as geographical differences. To extend this work, further research should be conducted into the influence of machinery, primary occupation, distance to farm, farm income and non-farm income on the technical efficiency of maize farmers. This would allow a greater understanding of the effect of other agricultural and socioeconomic variables on the technical efficiency of maize farmers.

Table 7 Results of impact models

Variable	Mean	Standard error	*T*-test
IPWRA	0.531	0.269	3.01***

***, ** and * represent significance levels at 1%, 5% and 10%, respectively

Acknowledgements

We owe a debt of gratitude to the farmers who sat quietly for hours answering the questionnaire. We also thank the anonymous reviewers for their insightful remarks, which helped us improve the work.

Author contributions

ADK is responsible for conceptualization, project administration, writing—the original draft, writing—review and editing. AAO is responsible for the formulation or evolution of overarching research goals and aims. TOO is responsible for the application of statistical, mathematical, computational, or other formal techniques to analyse or synthesize study data; for preparation and formatting of the manuscript.

Funding
This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Availability of data and materials
The data that support the findings of this study can be obtained from the authors upon request.

Declarations

Ethics approval and consent to participate
Ethical approval and consent to participate are not applicable to this study.

Consent for publication
The authors transfer to *Journal of Agriculture and Food Security* the nonexclusive rights to publish our manuscript.

Competing interests
There are no known competing financial or personal interests related to this publication, according to the authors.

Received: 29 August 2023 Accepted: 25 December 2023
Published online: 07 March 2024

References

1. Fisher M, Abate T, Lunduka RW, Asnake W, Alemayehu Y, Madulu RB. Drought tolerant maize for farmer adaptation to drought in sub-Saharan Africa: determinants of adoption in eastern and southern Africa. Clim Change. 2015;133(2):283–99.
2. Foltz JD, Aldana UT, Laris P. The Sahel's silent maize revolution: analyzing maize productivity in mali at the farm-level (No. W17801). National Bureau of Economic Research; 2012.
3. van Ittersum MK, van Bussel LGJ, Wolfa J, Grassini P, van Wart J, Guilpart N, Claessens L, de Groot H, Wieb K, Mason-D'Croz D, Yang H, Boogaard H, van Oort PJA, van Loon MP, Saito K, Adimoh O, Adjei-Nsiah S, Agali A, Bala A, Chikowo R, Kaizzi K, Kouressy M, Makoi JHJR, Ouattara K, Tesfaye K, Cassman KG. Can sub-Saharan Africa feed itself? Proc Natl Acad Sci USA. 2016;113(52):1–6.
4. FAOSTAT. Statistical databases and data-sets of the Food and Agriculture Organization of the United Nations. 2022. http://faostat.fao.org/default.aspx. Accessed 7 Aug 2023.
5. Onumah G, Dhamankar M, Ponsioen T, Bello M. Maize value chain analysis in Nigeria. In: Report for the European Union, INTPA/F3. Value chain analysis for development project. VCA4D CTR 2016/375-804). 2021. 155p+ annexes.
6. Pwc. Positioning Nigeria as Africa's leader in maize production for AfCFTA. insights on global maize production and how Nigeria can position itself as Africa's leader in Maize Production. 2021. https://www.pwc.com/ng/en/assets/pdf/positioning-nigeria-as-africa-leader-in-maize-production-for-afcfta.pdf.
7. Murphy S. Changing perspectives: Small-scale farmers, markets and globalisation. London: International Institute for Environment and Development (IIED); The Hague: Hivos. 2010. http://pubs.iied.org/16517IIED.
8. Nazifi B, Bello M, Suleiman A, Suleiman MS. Impact of contract farming on productivity and food security status of smallholder maize farmer's households in Kano and Kaduna States, Nigeria. Int J Agric Environ Food Sci. 2021;5:571–9.
9. Ogunlade I, Olaoye G, Tologbonse D, Alaoye OEA. On-farm evaluation of drought tolerant maize varieties and hybrids in the southern Guinea Savanna Zones of Nigeria. In: Proceedings of the 44th annual conference of the South African society for agricultural extension, May 4–7, 2010, Langebaan, Western Cape, South Africa. 2010. p. 1–5.
10. Olaniyi OA, Adewale JG. Information on maize production among rural youth: a solution for sustainable food security in Nigeria. Library Philosophy and Practice; 2012. http://digitalcommons.unl.edu/cgi/viewcontent.cgi?article=1798&context=libphilprac.
11. International Institute of Tropical Agriculture (IITA). IITA–BIP sets record for maize production per hectare in Nigeria. 2020. https://www.iitabip.org/.
12. United States Agency for International Development (USAID). Improved extension capacity in smallholders' productivity in Nigeria: findings from an ex-post study of market II. 2019. https://www.chemonics.com.
13. Rastogi M, Shrivastava S. Assessment of indigenous fungal biocatalysts towards valorization of delignified physico-chemically pretreated corn cobs and sugarcane bagasse. Biofuels Bioprod Biorefin. 2023;17(1):153–66.
14. Dey JK, Saren BK, Duary B, Pramanik K. Performance of zero-till biomulching on different pulses under maize-legume sequence. Legum Res Int J. 2023;46(2):176–80.
15. Kehinde AD. Does credit access improve adoption intensity of improved maize seed varieties? Cercet Agron Mold. 2020;184:434–44.
16. Lelea MA, Garbaba CA, Guluma A, Hensel O. Gendering post-harvest loss research: responsibilities of women and men to manage maize after harvest in southwestern Ethiopia. Food Secur. 2022;14(4):951–63.
17. Egwuma H, Dutse F, Oladimeji YU, Ojeleye OA, Ugbabe OO, Ahmed MA. Demand and supply estimation of maize in Nigeria. J Agric AgricTechnonol. 2019;5(2):12–20.
18. FAOSTAT. Food and Agriculture Organization of the United Nations. 2018. http://faostat.fao.org/.
19. Knoema. The imports of maize from Nigeria. 2020. https://knoema.com/data/nigeria+maize+foreign-trade-imports.
20. Kehinde AD, Tijani AA. Effect of cooperatives membership on farmers' preference for improved maize variety attributes in Oyo State, Nigeria. Acta Sci Pol Agric. 2021;20(1):3–15.
21. Kabir K, Baldos ULC, Hertel TW. The new Malthusian challenge in the Sahel: prospects for improving food security in Niger. Food Secur. 2023;15(2):455–76.
22. Abdulrahman S, Timothy AJ, Mohammed B, Siewe F. Measurement of efficiency in cocoyam production: an application of data envelopment analysis (DEA) approach. Asian J Agric Ext Econ Sociol. 2015;6(3):204–14.
23. Chivasa W, Worku M, Teklewold A, Setimela P, Gethi J, Magorokosho C, Prasanna BM. Maize varietal replacement in Eastern and Southern Africa: bottlenecks, drivers and strategies for improvement. Glob Food Secur. 2022;32: 100589.
24. Kehinde AD, Tijani AA. Effects of access to livelihood capitals on adoption of European Union (EU) approved pesticides among cocoa producing households in Osun State, Nigeria. Agric Trop Subtrop. 2021;54(1):57–70.
25. Tijani AA, Kehinde AD. Assessing resource use efficiency and investment in small-scale okra production in Osun State, Nigeria. J Agribus Rural Dev. 2022;3(65):219–27.
26. Awotide DO, Agbola PO. Relationship between land fragmentation and maize farmers' productivity in northern Nigeria. Acta Satech. 2010;3:1–9.
27. Okolie PI, Temitope CM, Okolie EC, Oke EK, Agboola KA, Abayomi SO. Physiochemical and quality evaluation of kokoro (a maize-based snack) from blends of yellow maize, fermented AYB and RICE bran flours. Appl Food Res. 2022;2(1): 100104.
28. Sadiq MS, Singh IP, Ahmad MM, Lawal M. Technical efficiency of rainfed sugarcane producers in Kwara State of Nigeria. JIM QUEST. 2019;15(1):36.
29. Salau SA, Adewumi MO, Omotesho OA. Technical efficiency and its determinants at different levels of intensification among maize-based farming households in southern Guinea Savanna of Nigeria. Ethiop J Environ Stud Manag. 2012;5(2):195–206.
30. Adeyemo R, Kehinde AD. Community driven development: the case of FADAMA II cooperatives in alleviating poverty in a developing country. Contemp Agric. 2021;70(1–2):46–53.
31. Kehinde AD. Does investment in poultry egg production yield any profit? Agricultura. 2021;117–118(1–2):116–22.
32. Khan N, Ramzan M, Kousar T, Shafiq MA. Impact of bank specific factors on credit risk: evidence from Islamic and conventional banks of Pakistan. Pak J Hum Soc Sci. 2023;11(1):580–92.

33. Kolapo A, Ogunleye AS, Kehinde AD, Odimgbe-James W. Effect of microcredit on investment decision of smallholder farmers in Osun State. Agric Conspec Sci. 2022;87(1):69–75.
34. Ogunleye AS, Kehinde AD, Kolapo A. Effects of social capital on income of cocoa farming households in Osun State, Tanzania. J Agric Sci. 2020;19(2):131–7.
35. Ololade RA, Olagunju FI. Determinants of access to credit among rural farmers in Oyo State, Nigeria. Glob J Sci Front Res Agric Vet Sci. 2013;13(2):23–31.
36. Owusu-Antwi G, Antwi J. The analysis of the rural credit market in Ghana. Int Bus Econ Res J. 2010;9(8):45–56.
37. Conning J, Udry C. Rural financial markets in developing countries. In: Evenson R, Pingali P, editors. Handbook of agricultural economics, vol. 3. Amsterdam: Elsevier; 2007. p. 2858–908.
38. Markelova H, Meinzen-Dick R, Hellin J, Dohrn S. Collective action for smallholder market access. Food Policy. 2009;34(1):1–7.
39. Kehinde AD, Adeyemo R. Effects of social capital dimensions on output and gross margin of cassava farmers in Osun State. Niger J Rural Sociol. 2020;20(1):37–43.
40. Kehinde AD, Adeyemo R, Ogundeji AA. Does social capital improve farm productivity and food security? Evidence from cocoa-based farming households in South-Western Nigeria. Heliyon. 2021;7(3): e06592.
41. Balogun OL, Ogunsina IJ, Ayo-Bello TA, Afodu OJ. Effect of social capital on productivity of cassava farmers in Ogun State, Nigeria. J Agric Sci. 2018;63(1):99–112.
42. Adepoju AA, Oni OA. Investigating endogeneity effects of social capital on household welfare in Nigeria: a control function approach. Quart J Int Agric. 2012;51:73–96.
43. Adjognon SG, Liverpool-Tasie LS, Reardon TA. Agricultural input credit in sub-Saharan Africa: telling myth from facts. Food Policy. 2017;67:93–10.
44. Akinola A, Kehinde AD, Tijani A, Ayanwale A, Adesiyan F, Tanimonure V, Ogunleye A, Ojo T. Impact of membership in agricultural cooperatives on yield of smallholder tomato farmers in Nigeria. Environ Sustain Indic. 2023;20: 100313.
45. Araya MT, Sung-Kyu L. The impact of agricultural package programs on farm productivity in Tigray-Ethiopia: panel data estimation. Cogent Econ Fin. 2019;7(1):1–28. https://doi.org/10.1080/23322039.2019.1631987.
46. Chandio AA, Jiang Y. Determinants of credit constraints: evidence from Sindh, Pakistan. Emerg Mark Fin Trade. 2018;54(15):3401–10.
47. Chandio AA, Jiang Y, Rehman A, Twumasi MA, Pathan AG, Mohsin M. Determinants of demand for credit by smallholder farmers': a farm level analysis based on survey in Sindh, Pakistan. J Asian Bus Econ Stud. 2020. https://doi.org/10.1108/JABES-01-2020-0004.
48. Rehman A, Chandio A, Ali Hussain I, Jingdong L. Fertilizer consumption, water availability and credit distribution: major factors affecting agricultural productivity in Pakistan. J Saudi Soc Agric Sci. 2019;18(3):269–74. https://doi.org/10.1016/j.jssas.2017.08.002.
49. Peprah JA, Koomson I, Sebu J, Bukari C. Improving productivity among smallholder farmers in Ghana: does financial inclusion matter? Agric Fin Rev. 2020;81(4):481–502. https://doi.org/10.1108/AFR-12-2019-0132.
50. Abdulai S, Nkegbe PK, Donkoh SA. Assessing the technical efficiency of maize production in northern Ghana: the data envelopment analysis approach. Cogent Food Agric. 2018;4(1):1–14. https://doi.org/10.1080/23311932.2018.1512390.
51. Adhikari SP, Timsina KP, Brown PR, Ghimire YN, Lamichhane J. Technical efficiency of hybrid maize production in eastern Terai of Nepal: a stochastic frontier approach. J Agric Natural Resour. 2018;1(1):189–96.
52. Payang RSO, Poyearleng C, Ngaisset FJD, Xia X. Analysis of the technical efficiency of maize farmers and its influencing factors in Ombella Mpoko, Central African Republic. Open J Soc Sci. 2019;7(02):216.
53. Belete AS. Analysis of technical efficiency in maize production in Guji Zone: stochastic frontier model. Agric Food Secur. 2020;9(1):1–15.
54. Mdoda L, Obi A, Christian M, Jiba P. Technical efficiency of maize-based farm irrigators in the Eastern Cape province. J Agribus Rural Dev. 2021;62(4):371–81.
55. Kongolo M. Technical efficiency and small scale maize producers in Mwanza Region: a stochastic frontier analysis. Asian J Agric Food Sci. 2021. https://doi.org/10.24203/ajafs.v9i3.6641.
56. Wu Z, Hua W, Luo L, Tanaka K. Technical efficiency of maize production and its influencing factors in the world's largest groundwater drop funnel area, China. Agriculture. 2022;12(5):649.
57. Huang J, Fang Y. Income inequality, neighbourhood social capital and subjective well-being in China: exploration of a moderating effect. Int J Environ Res Public Health. 2021;18(13):6799.
58. Shen J, Bian Y. The causal effect of social capital on income: a new analytic strategy. Soc Netw. 2018;54:82–90.
59. Omotesho OA, Falola A, Oshe AT. Effect of social capital on productivity of rice farms in Kwara state, Nigeria. Sci Technol Arts Res J. 2015;4(1):215–20.
60. Diawara B, Chikayoshi S, Hanson K. Social capital and poverty reduction: empirical evidence from Senegal. Rev Appl Socio Econ Res. 2013;6(2):41–74.
61. Pham ATQ, Mukhopadhaya P. Multidimensionl poverty and the role of social capital in poverty alleviation among ethnic groups in rural Vietnam: a multilevel analysis. Soc Indic Res. 2022;159(1):281–317.
62. Hunecke C, Engler A, Jara-Rojas R, Poortvliet PM. Understanding the role of social capital in adoption decisions: an application to irrigation technology. Agric Syst. 2017;153:221–31.
63. Ntume B, Nalule AS, Baluka SA. The role of social capital in technology adoption and livestock development. Livest Res Rural Dev. 2015;27(9):181.
64. Leddy AM, Whittle HJ, Shieh J, Ramirez C, Ofotokun I, Weiser SD. Exploring the role of social capital in managing food insecurity among older women in the United States. Soc Sci Med. 2020;265: 113492.
65. Nosratabadi S, Khazami N, Abdallah MB, Lackner Z, Band S, Mosavi A, Mako C. Social capital contributions to food security: a comprehensive literature review. Foods. 2020;9(11):1650.
66. Nugroho TW, Hanani N, Toiba H, Sujarwo S. Does social capital improve food security? Evidence from the Indonesian family life survey. Asian J Agric Rural Dev. 2022;12(2):138–47.
67. Sseguya H, Mazur RE, Flora CB. Social capital dimensions in household food security interventions: implications for rural Uganda. Agric Hum Values. 2018;35(1):117–29.
68. Olurotimi PO, Bamire AS, Ogunleye AS. Effects of social capital on technical efficiency of cassava production in Oyo State, Nigeria. Afr J Rural Dev. 2018;3(1):695–704.
69. Farrell MJ. The measurement of productive efficiency. J R Stat Soc. 1957;120(3):253–81.
70. Carlsson B. The Measurement of Efficiency in Production: An Application to Swedish Manufacturing Industries 1968. Swedish J Econ. 1972;76(2):255–258.
71. Aigner DJ, Lovell CAK, Schmidt P. Formulation and estimation of stochastic frontier production models. J Econom. 1977;6:21–37.
72. Charnes A, Cooper WW, Rhodes E. Measuring the efficiency of decision making units. Eur J Oper Res. 1978;2(6):429–44.
73. Meeusen W, Van den Broeck J. Efficiency estimation from Cobb–Douglas production functions with composite error. Int Econ Rev. 1977;18:435–44.
74. Battese GE. Frontier production functions and technical efficiency: a survey of empirical applications in agricultural economics. Agric Econ. 1992;7(3):185–208.
75. Coelli TJ, Rao DSP, Donnell CJ, Battese GE. An introduction to efficiency and productivity analysis. 2nd ed. New York: Springer Science+Business Media Inc; 2005.
76. Bamlaku A, Nuppenau EA, Boland H. Technical efficiency of farming systems across agro-ecological zones in Ethiopia: an application of stochastic frontier analysis. Agric J. 2007;4(4):202.
77. Endrias G, Ayalneh B, Belay K, Eyasu E. Technical efficiency of small holder maize producers in Ethiopia: the case of Wolaita and GamoGofa zones. Awassa: EEA; 2012. p. 2012.
78. Adekunle A, Ayanwale A, Kehinde AD. Determinants of participation in innovation platforms and its sustainability: a case study of sub-Saharan Africa. Trop Subtrop Agroecosyst. 2023;26(2):051.
79. Abdulai AN, Abdulai A. Examining the impact of conservation agriculture on environmental efficiency among maize farmers in Zambia. Environ Dev Econ. 2018;22(2):177–201.
80. Khanal U, Wilson C, Shankar S, Hoang VN, Lee B. Farm performance analysis: technical efficiencies and technology gaps of Nepalese farmers in different agro-ecological regions. Land Use Policy. 2018;76:645–53.

81. Kutlu L. Battese-Coelli estimator with endogenous regressors. Econ Lett. 2010;109:79–81.
82. Tran KC, Tsionas EG. GMM estimation of stochastic frontier models with endogenous regressors. Econ Lett. 2013;118:233–6.
83. Amsler C, Prokhorov A, Schmidt P. Using copulas to model time dependence in stochastic frontier models. Econom Rev. 2014;33:497–522.
84. Amsler C, Prokhorov A, Schmidt P. Endogeneity in stochastic frontier models. J Econom. 2016;190:280–8.
85. Howley P, Buckley C, Donoghue CO, Ryan M. Explaining the economic 'irrationality' of farmers' land use behaviour: the role of productivist attitudes and non-pecuniary benefits. Ecol Econ. 2015;109:186–93.
86. Kehinde AD, Ogundeji AA. The simultaneous impact of access to credit and cooperative services on cocoa productivity in South-Western Nigeria. Agric Food Secur. 2022;11:1–17.
87. Ogunleye AS, Adeyemo R, Bamire AS, Kehinde AD. Assessment of profitability and efficiency of Cassava production among government and non-government assisted farmers association in Osun State, Nigeria. Afr J Rural Dev. 2017;2(2):225–33.
88. Adeyemo R, Kehinde AD. Community-based organisation and land management practices in cassava based small holder farming system in Osun State. Agricultura. 2019;111–112(3–4):270–81.
89. Kehinde AD, Ogundeji AA. Social capital networks (SCNs) reducing the poverty in cocoa producing households: evidence from Osun and Ondo States of Southwestern Nigeria. Trop Subtrop Agroecosyst. 2022;25:082.
90. Mbagwu GNI. Factors influencing membership of farmers' in cooperative societies in Abia state, Nigeria. Sci Pap Ser Manag Econ Eng Agric Rural Dev. 2018;18(1).
91. Mojo D, Fischer C, Degefa T. Social and environmental impacts of agricultural cooperatives: evidence from Ethiopia. Int J Sust Dev World. 2015;22(5):388–400.
92. Mugabekazi D. Evaluation of factors influencing membership in coffee cooperatives in Huye District, Rwanda. MSc thesis, University of Nairobi, Nairobi, Kenya; 2014.
93. Othman H, Asshaari I, Bahaludin H, Tawil NM, Ismail NA. Student's perceptions on benefits gained from cooperative learning experiences in engineering mathematics courses. Procedia Soc Behav Sci. 2012;60:500–6.
94. Adong A, Mwaura F, Okoboi G. What factors determine membership to farmer groups in Uganda? Evidence from the Uganda Census of Agriculture 2008/9 (No. 677-2016-46623). 2012.
95. Gasana G. Exploring the determinants of joining dairy farmers cooperatives in Rwanda: a perspective of Matimba and Isangano cooperatives; 2011.
96. Afolabi SN, Ganiyu YO. Impact of cooperative membership on rural income generation in southwest, Nigeria. REVESCO: Rev De Estud Cooperativos. 2021;138:140–52.
97. Ahmed MH, Mesfin HM. The impact of agricultural cooperatives membership on the wellbeing of smallholder farmers: empirical evidence from eastern Ethiopia. Agric Food Econ. 2017;5(1):1–20.
98. Matchaya GC. Cooperative patronage: the national smallholder farmers' association of Malawi in Kasungu District. Dev South Afr. 2010;27(3):397–412.
99. Nugusse WZ, Van Huylenbroeck G, Buysse J. Household food security through cooperatives in northern Ethiopia. Int J Cooperative Stud. 2013;2(1):34–45.
100. Nugusse WZ, Van Huylenbroeck G, Buysse J. Determinants of rural people to join cooperatives in northern Ethiopia. Int J Soc Econ. 2013;40(12):1094–107.
101. Wossen T, Abdoulaye T, Alene A, Haile MG, Feleke S, Olanrewaju A, Manyong V. Impacts of extension access and cooperative membership on technology adoption and household welfare. J Rural Stud. 2017;54:223–33.
102. Abdul-Rahaman A, Abdulai A. Do farmer groups impact on farm yield and efficiency of smallholder farmers? Evidence from rice farmers in northern Ghana. Food Policy. 2018;81:95–105.
103. Bakare AY, Ogunleye AS, Kehinde AD. Impacts of microcredit access on climate change adaptation strategies adoption and rice yield in Kwara state, Nigeria. World Dev Sustain. 2023;2: 100047.
104. Manda J, Khonje MG, Alene AD, Tufa AH, Abdoulaye T, Mutenje M, Setimela P, Manyong V. Does cooperative membership increase and accelerate agricultural technology adoption? Empirical evidence from Zambia. Technol Forecast Soc Change. 2020;158: 120160.
105. Cawley J, Maclean JC, Hammer M, Wintfeld N. Reporting error in weight and its implications for bias in economic models. Econ Hum Biol. 2015;19:27–44.
106. Ma W, Renwick A, Yuan P, Ratna N. Agricultural cooperative membership and technical efficiency of apple farmers in China: an analysis accounting for selectivity bias. Food Policy. 2018;81:122–32.
107. Olagunju KO, Ogunniyi AI, Oyetunde-Usman Z, Omotayo AO, Awotide BA. Does agricultural cooperative membership impact technical efficiency of maize production in Nigeria: an analysis correcting for biases from observed and unobserved attributes. PLoS ONE. 2021;16(1): e0245426.
108. Adeyemo R, Kehinde AD, Oyenpemi LO. Assessing resource use efficiency and investment in cocoa enterprise: a case of Osun State, Nigeria. Agricultura. 2020;113–114(1–2):260–9.
109. Abdulai AN, Abdulai A. Allocative and scale efficiency among maize farmers in Zambia: a zero-efficiency stochastic frontier approach. Appl Econ. 2016;48(55):5364–78.
110. Abdulai PK. Technical efficiency of maize production in northern Ghana. Afr J Agric Res. 2013;8(43):5251–9.
111. Weldegebriel H. The determinants of technical efficiency of farmers in Teff, Maize and Sorghum production: empirical evidence from Central Zone of Tigray Region. Ethiop J Econ. 2014;13(2):1–36.
112. Osanyinlusi OI, Adenegan KO. The determinants of rice farmers' productivity in Ekiti State, Nigeria. Greener J Agric Sci. 2016. https://doi.org/10.15580/GJAS.2016.2.122615174.
113. Opata PI, Nweze NJ, Ezeibe AB, Mallam M. Efficiency of irrigated and rain-fed (*Oryza sativa*) rice producers in Fadama agriculture, Nigeria. Exp Agric. 2018. https://doi.org/10.1017/S0014479718000212.
114. Sienso G, Asuming-Brempong S, Amegashie DP. Estimating the efficiency of maize farmers in Ghana. Asian J Agric Ext Econ Sociol. Article No. AJAEES. 2014;3(6), http://hdl.handle.net/123456789/2937.
115. Etim NAA, Okon S. Sources of technical efficiency among subsistence maize farmers in Uyo, Nigeria. J Agric Food Sci. 2013;1:48–53.
116. Dlamini SI, Masuku MB, Rugambisa JI. Technical efficiency of maize production in Swaziland: a stochastic frontier approach. Afr J Agric Res. 2012;7:5628–36.
117. Olowa OW, Olowa OA. Sources of technical efficiency among smallholder maize farmers in Osun State of Nigeria. Res J Appl Sci. 2010;5:115–22.
118. Kuwornu JKM, Amoah E, Seini W. Technical efficiency analysis of maize farmers in the Eastern Region of Ghana. J Social Dev Sci. 2013;4:84–99.
119. Abawiera WC, Dadson AV. Technical efficiency of maize farmers in Ghana. Discourse J Agric Food Sci. 2016;4(3):17–20.
120. Oyewo IO. Technical efficiency of maize production in Oyo state. J Econ Int Finance. 2011;3(4):211–6.
121. Kabore DP. Technical efficiency of irrigated rice production in Burkina Faso water control infrastructures: a stochastic frontier approach. Asian J Agric Rural Dev. 2016;6(10):188–200.
122. Ouédraogo BI, Zahonogo P, Ouédraogo S. Determinants of the technical efficiency of maize farmers in Burkina Faso. J Econ Sustain Dev. 2019;10(14):55–67.
123. Kumbhakar SC, Lien G, Hardaker JB. Technical efficiency in competing panel data models: a study of Norwegian grain farming. J Prod Anal. 2014;41(2):321–37.
124. Olarinde LO. Analysis of technical efficiency differentials among maize farmers in Nigeria. The African Economic Research Consortium. Nigeria: Ladoke Akintola University of Technology. 2011. ISBN: 978-9966-023-04-9.
125. Jude C, Benjamen C, Patrick C. Measurement and determinants of production efficiency among smallholder sweet potato farmers in Imo State, Nigeria. Eur J Sci Res. 2011;59(3):307–17.
126. Mbanasor J, Kalu KC. Economic efficiency of commercial vegetable production system in Akwa Ibom state, Nigeria. J Trop Subtrop Agroecosyst. 2008;8(3):313–8.
127. Addai KN, Owusu V, Danso-Abbeam G. Effects of farmer-based-organization on the technical efficiency of maize farmers across various agro-ecological zones of Ghana. J Econ Dev Stud. 2014;2(1):141–61.

128. Yiadom-Boakye EEOS, Nkegbe PK, Ohene-Yankyera K. Gender, resource use and technical efficiency among rice farmers in the Ashanti Region, Ghana. J Agric Econ Dev. 2013;2(3):102–10.
129. Onumah EE, Brümmer B, Hörstgen-Schwark G. Elements which delimitate technical efficiency of fish farms in Ghana. J World Aquac Soc. 2010;41(4):506–18. https://doi.org/10.1111/j.1749-7345.2010.00391.x.
130. Idiong IC. Estimation of farm level technical efficiency in small scale swamp rice production in cross river state of Nigeria: a stochastic frontier approach. World J Agric Sci. 2007;3(5):653–8.
131. Begum M, Ara E, Miah MA, Rashid MA, Hossain MI. Factors affecting the technical efficiency of turmeric farmers in the slash and burn areas of Bangladesh. Agrofor Syst. 2019;93(6):2205–12.
132. Abate TM, Dessie AB, Mekie TM. Technical efficiency of smallholder farmers in red pepper production in North Gondar zone Amhara regional state, Ethiopia. J Econ Struct. 2019;8(1):18.
133. Nyagaka DO, Obare GA, Omiti JM, Nguyo W. Technical efficiency in resource use: evidence from smallholder Irish potato farmers in Nyandarua North District, Kenya. Afr J Agric Res. 2010;5(11):1179–86. https://doi.org/10.5897/AJAR09.296.
134. Kehinde AD, Olatidoye MS. Credit constraint and technical efficiency of smallholder cassava farmers in Osun State, Nigeria. Agricultura. 2019;16(1–2):27–33.
135. FAOSTAT (2019). Food and Agriculture Organization of the United Nations. http://faostat.fao.org/.
136. Burgess S, Dudbridge F, Thompson SG. Combining information on multiple instrumental variables in mendelian randomization: comparison of allele score and summarized datamethods. Stat Med. 2016;35:1880–1906.
137. Ayanwale AB, Adekunle AA, Kehinde AD, Fatunbi OA. Participation in innovation platform and asset acquisitions among farmers in Southern Africa. Environ Sustain Indic. 2023;20:100316.
138. Balogun OL, Yusuf SA, Oloniniyi MT. Effects of Social Network on Production Output of Maize Farmers in Kwara State, Nigeria. Glob Adv Res J Agric Sci. 2017;6(2):031–8.
139. Ali I, HUO XX, Khan I, Ali H, Khan B, Khan SU. Technical efficiency of hybrid maize growers: A stochastic frontier model approach. J Integ Agric. 2019;18(10):2408–21.
140. Husen NA, Loos TK, Siddig KH. Social capital and agricultural technology adoption among Ethiopian farmers. Am J Rural Develop. 2017;5(3):65–72.
141. Case KE, Fair RC, Oster SM. Principles of Economics, 9th edition. Pearson Education Inc., Upper, 2009.
142. Murray MP. Avoiding invalid instruments and coping with weak instruments. J. Econ Perspect 2006;20:111–32.
143. Woldegebrial ZN, Huylenbroeck GV, Buysse J. Determinants of rural people to join cooperatives in Northern Ethiopia. Int J Soc Econ. 2013;40(12):1094–1107.

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.