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Agricultural Informatization and Technical Efficiency in Maize Production in Zambia

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Received: 21 March 2019; Accepted: 19 April 2019; Published: 25 April 2019

Abstract: The cropland productivity gap between Africa and the rest of the world is widening. Fortunately, increasing farmers' access to useful agricultural information reduces the costs of searching for information, thereby leading to higher agricultural productivity and sustainability. This study investigates the association between the adoption of mobile phones to collect agricultural information and farmers' technical efficiency (TE) in Zambia. Different from previous studies, we focus on the actual use of mobile phones by farmers rather than mere ownership. Farmers were selected using a two-stage sampling procedure, and the Cobb-Douglas (CD) production function is adopted to estimate the association using two approaches—the conventional stochastic production frontier (SPF) and propensity score matching-stochastic production frontier (PSM-SPF) model. In both cases, we found that the use of mobile phones is significantly and positively associated with farmers' TE. However, the conventional SFP model exaggerates the TE scores by 5.3% due to its failure to mitigate biases from observed variables. Regarding the agricultural growth indicators (income and output) related to TE, a close inspection reveals that increasing mobile phone use to close the TE gap between the two groups could result in a 5.13% and 8.21% reduction in severity of poverty and extreme poverty, respectively. Additional research is essential to corroborate the findings and analyze the potential causal mechanisms. Our study provides strong evidence to promote mobile phone use in agricultural production in rural Zambia.

Keywords: agricultural informatization; mobile phone use; maize production; technical efficiency; sample-selection model: Zambia

1. Introduction

Enhancing agricultural productivity in Africa is indispensable given revelations by the World Bank that the continent remains food-insecure amidst a burgeoning population [1,2]. Further evidence indicates that poverty, hunger, and malnutrition continue to be rampant [3], and climate change poses a high risk to the agriculture sector [4]. The bottom line is that Africa is still behind the rest of the world in terms of agricultural cropland productivity [5], despite already reported increased cropland productivity [6]. In light of this, most countries in Sub-Saharan Africa (SSA) have come up with ways of supporting poor farmers, with the aim of eradicating poverty and hunger. The promotion and provision of disease-resistant and high-yield seeds are among the strategies employed to increase agricultural output [7]. To the disappointment of many, these strategies have not made much difference, and the efficiency of farmers has been called into question.

Kibaara [8] discloses that agricultural output is a function of inputs and efficiency, and for the most part efficiency is the most critical. Therefore, modern agriculture that makes use of various innovations in enhancing agricultural productivity is expected. In response to this, the use of a mobile phone to collect agricultural information (agricultural informatization) is the intelligent, flexible and innovative solution because farmers are able to conveniently access information relevant to their agricultural tasks. In this research, we define agricultural informatization, after Li [9], as the degree and process of transforming the agriculture sector through the effective use of information and communication technology (ICT) in agricultural operations, production, and management. With the speedy development of ICT and the deployment of mobile phones in agriculture, information is generated, stored, analyzed, and disseminated effectively with the aim of supporting farmers and farming communities at a national or regional level to become more productive [10].

Cash [11] postulates that the agriculture sector in Sub-Saharan Africa has become increasingly information-dependent especially that information empowers farmers to be more knowledgeable about the various agricultural practices available and sources of quality inputs, as well as enabling them to make informed decisions quickly and allocate resources efficiently. Consequently, farmers' access to information has significantly improved driven by the new opportunity to overcome transaction and search costs that has been seized through persistent progress in mobile phone coverage [12]. With the expansion of rural electrification and an increase in literacy levels, mobile phone technologies are a significant medium of communication in rural Zambia today. They have the potential to narrow the gap in the adoption of beneficial agricultural technology resulting in higher crop productivity, which is crucial to eradicating food insecurity, hunger, as well as poverty. This is why Batchelor, et al. [13] conclude that mobile phones accelerate endorsement of sustainable agriculture.

Maize is dominantly produced by smallholder farmers and is a pronounced staple food crop of Zambia. It is also among the top 10 products exported by the country [14]. While maize production in the landlocked nation has been fluctuating, the mobile phone subscription rate has been growing drastically (Figure 1). Maize production performance has been so bad that it is believed to be one of the underlying reasons which led to the country being declared the third most hungry nation in the world [15]. For instance, in the 2017/18 farming season, Zambia's maize production was 2.4 million tonnes which is 34 and 20 percent down on the previous year and five-year crop record, respectively. This level of production is 14 percent lower than the country's consumption [16]. In view of the aforementioned issues, Zambian farmers are looking for ways to access different agricultural information to increase their maize output. For this purpose, mobile phones are becoming successful in aiding farmers to access desired information, such as weather forecasts, pest attacks, improved cultivation practices, pest and disease management, and input prices. As a platform for receiving voice-message information and text messages (SMS), mobile phones facilitate connection of Zambian smallholder farmers to new information sources and highly customized knowledge with the opportunity of real-time access. This guarantees improvement in farmers' knowledge on most issues regarding their farming tasks and prudent decision-making, which may increase farmers' technical efficiency.

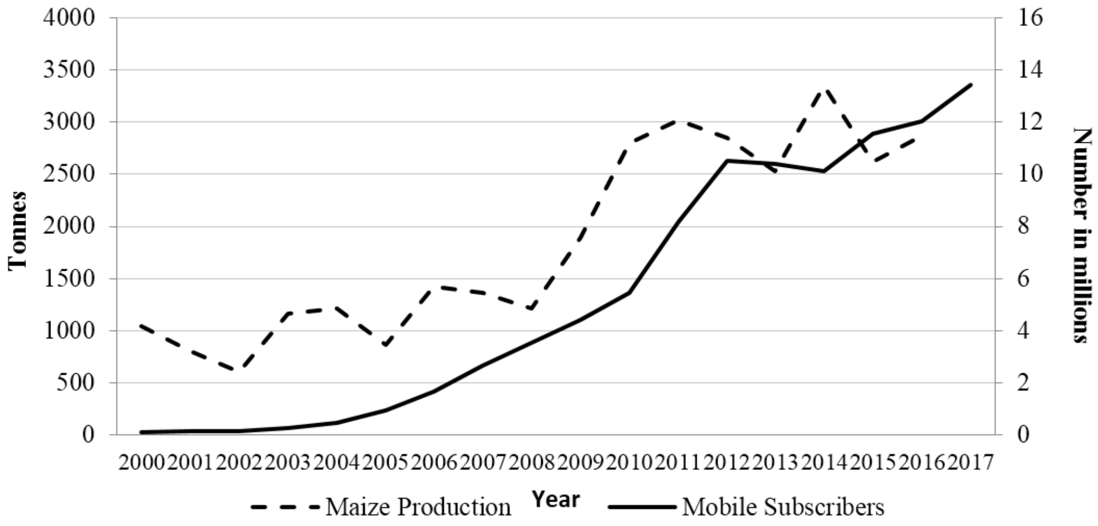

Figure 1. Mobile phone subscription and maize production trend in Zambia. Source: Statista [17] and FAOSTAT [18].

Fischer, et al. [19] underscore that mobile phone use in agriculture should be accorded the same significance given to the biotechnology revolution because mobile technologies have significantly improved farmer's access to information [12,20], functioning of markets [21–23], marketing decisions [24], input and output prices [25], agricultural production patterns [26,27], household income [28,29], gender equality and nutrition [30], greater market participation [31] and diversification to high-value crops [32]. Eventually, it is predicted that the use of mobile phones will impact the behavior pattern of farmers, facilitating the adoption of improved practices leading to higher yields [33]. While a few recent studies [26,34] have conceptually discussed how mobile phones could translate to higher crop productivity, empirical evidence is scarce.

The objective of this paper, therefore, is to analyze the association between mobile telephone use and technical efficiency among smallholder maize farmers in Zambia. The overarching aim is to make available evidence of the technological prospects being converted into economic welfare at the farm level. This paper addresses the following specific research questions: (1) Do farmers who use mobile phones to access information have higher technical efficiency than those who do not? (2) Is the difference in maize output/income between users and non-users significant? Overall, our results suggest that improved access to information via mobile phone technology could generate certain socioeconomic benefits in rural agricultural settings. Understanding such associations of mobile phone use is critical, specifically against the background of the Sustainable Development Goals (SDG) 1 and 2, which advocate for profound change in food production to alleviate hunger and poverty.

Our study contributes to the literature in six ways: First, this paper tries to link access to agricultural information via the mobile phone to technical efficiency in an attempt to promote mobile phone use beyond regular communication in farming communities. This is essential for the farming communities to focus on current and readily available information that ensures timely and informed decision making. Second, to the best knowledge of the researchers, no study has empirically dealt with the association of mobile phone use and technical efficiency. Little is known about whether access to information through the mobile phone facilitates the improvement of technical efficiency in maize production. Third, this study focuses on the collection of information through the mobile phone in a rural setting only, thus providing policymakers with target-specific evidence on the role of information accessed via mobile phone on maize production and the challenges experienced. Fourth, unlike previous studies, we do not use mobile phone ownership to evaluate the association between access to information via mobile phone and technical efficiency but rather the actual use of mobile phones. Fifth, we apply a method that can overcome the methodological limitations of the conventional approach regarding technical efficiency estimation. In our case, this procedure ensures that factors influencing mobile phone adoption, productivity and technical efficiency of farmers is evaluated without any biases from observed variables. Therefore, the results are beneficial for policymakers, extension agents, and other stakeholders interested in enhancing mobile phone adoption in crop production. Finally, we also calculate the associated differences in output and income per capita between the two groups, which are critical agricultural growth indicators with policy implications regarding poverty eradication and attaining agricultural sustainability.

The remainder of this paper is organized as follows: Section 2 gives details of the data and explains the methodology; Section 3 presents empirical results and discussion; and Section 4 provides conclusions and policy implications.

2. Data and Methods

2.1. Data

Cross-sectional data from a 2018 household survey in central Zambia, Mkushi district, are used in this study. The country's agriculture is characterized by vast areas of well-watered land appropriate for animal husbandry and various kinds of farming. Maize is among the primary crops grown, and subsistence farming is predominant. Mkushi farmers are considered surplus producers of maize in the Central province of the country, which could be due to suitable climatic conditions (rainfall of 800–1000 mm and temperature 15–32 °C) and good soil quality. The area has 22 farming camps, and the target participants are mobile phone user and non-user maize growers.

A two-stage sampling technique was employed in selecting the sample. In stage one, three farming camps with the same farming systems and agro-ecologies were purposefully nominated from the 22, namely, Nshinso, Lweo, and Fiwila. The selection was based on network availability for mobile phone use and easy accessibility to the area. Since 2010, the area is covered by all three mobile network operators (MNOs) in the country (MTN, Airtel and ZAMTEL). The MNOs provide mobile money services, SIM registration, weather forecast information dissemination, job alerts, and internet access. The network coverage is reasonably good for the camps near the town centers while those further away (about 23 percent of subscribers) have difficulty to access it. This has led to a mobile penetration rate of 53.73% which is lower than the national reported penetration of 81.92%. While the market penetration of mobile phones is unknown, the area has many sellers of the device in most parts of town centers and markets [35]. For the second stage, 201 households were randomly selected from the farmers' list obtained from the Ministry of Agriculture offices in the area selected in stage one.

Experienced and well-trained enumerators collected the data using a structured pre-tested questionnaire. The instrument used was substantially rich in content as it included many variables related to institutional center access, information searching, farming practices, farming inputs, actual production, and revenue from maize sales. To realistically and correctly comprehend the role of mobile phones in accessing agricultural information, a question on the use of the device in searching for information was asked explicitly to avoid using mobile phone ownership. Tadesse and Bahiigwa [24] warn that using ownership is inappropriate because some farmers who own a mobile phone do not use them for accessing agricultural information on account of network coverage, education level, access to power and language barriers. Other demographic and socioeconomic information was also collected. The explanatory variables and factors of production selected based on previous literature are presented in Table 1.

2.2. Measurement of Key Variables

Mobile phone use is the primary explanatory variable and is captured through a dummy variable. We consider a household as a mobile user if at least one adult member in the household owned and used the mobile phone to collect agricultural information during the survey year.

Regarding the outcome variable, we focus on the technical efficiency levels of the households which are derived from the estimation of the CD model using conventional SPF and PSM-SPF model as explained in Section 2.3 The ultimate goal is to establish whether an association between mobile phone use and technical efficiency exists. It is not within the scope of this study to evaluate the causal effect of mobile phone use on maize production in Zambia.

2.3. Empirical Strategy

A one-step stochastic frontier analysis (SFA) is adopted to model farmers' productivity of maize using two procedures—conventional SPF and PSM-SPF model. Then, income and output for users and non-users are compared to derive any socioeconomic implication of the differences.

2.3.1. Stochastic Frontier Analysis-Conventional Approach

Stochastic Frontier Analysis (SFA), formulated by Aigner, et al. [36], is a parametric approach on which efficiency measurements rest; the general form is as follows:

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

where Y_i is the output of the i-th farmer, x_i is a vector of inputs, β is a vector of parameters to be estimated, and V_i~N $(0,\delta_v^2)$ and U_i~$N^+[f(\mu,\alpha),\delta_u^2]$, are the random error and the inefficiency term, respectively. The inefficiency term u follows a positive truncated normal distribution with a constant variance δ_u^2 and a location parameter μ that depends on additional explanatory variables. Technically, $\mu = \alpha z$, where α is a vector of parameters to be estimated. In the standard approach, the determinants of technical efficiency can be estimated simultaneously using the production frontier given in Equation (1) and an equation for inefficiency effects which Battese and Coelli [37] specified as follows:

$$u_i = \mathrm{f}\,(\mu_i,\ \alpha). \tag{2}$$

Ultimately, the technical efficiency of the i-th farmer $\mathrm{TE_i}$ is given by:

$$\mathrm{TE_i} \;=\; \frac{y_i}{y_i^*} = \frac{\mathrm{f}(x_i,\beta)\,\exp(\mathrm{v}_i - u_i)}{\mathrm{f}(x_i,\beta)\,\exp(\mathrm{v}_i)} \;=\; \exp(-u_i) \tag{3}$$

where $y_i = \mathrm{f}(x_i,\beta)\exp(v_i - u_i)$ is the observed production with inefficiency and $y_i^* = \mathrm{f}(x_i,\beta)\exp(v_i)$ is the frontier output quantity with no inefficiency.

In our study, we take the CD production function, which is a first-order approximation of any unknown function, to model the production behavior of maize producers in Zambia. We adopt the CD rather than the translog production function for two reasons: first, we only have 200 observations, and translog function has many more parameters to be estimated which require more degrees of freedom to obtain a precise estimation; second, results from the CD model are consistent with theory and production reality in Zambia. We use this procedure to estimate the efficiency of farmers for the pooled sample. The CD function and its respective inefficiency function are specified as follows:

$$lnY_i = \beta_0 +\ \beta_i \sum\nolimits_{i=1}^{4} lnX_i + v_i - u_i, \tag{4}$$

$$u_i =\ \alpha_0 + \alpha_1 MP\ use_i + \sum \alpha_i m_i + z_i, \tag{5}$$

where Y_i is the output of maize, X_i is a vector of the four classical inputs (land, fertilizer, seeds, labor), β_0, α_0, α_1, α_i and β_i are parameters to be estimated, m_i is a vector of other determinants of technical inefficiency other than MP use, u_i is a non-negative inefficiency component that follows a truncated-normal distribution and v_i is a random error following a normal distribution for the production function while z_i is a random error for the inefficiency model.

In order to detect the existence of the inefficiency, Battese and Coelli [37] recommend the use of the gamma (γ) after SFA estimation. The log-likelihood function is parameterized in terms of $\delta^2 = \delta_v^2 + \delta_u^2$ and $\gamma = \delta_u^2/\delta^2$ with the range $0 < \gamma < 1$. The value γ is widely used as an indicator to measure the influence of the inefficiency component in the overall variance [38], in which case γ close to 1 implies deviations from the frontier dominates total variance, and γ = 0 denotes no technical inefficiency. Bear in mind that gamma is not the contribution of inefficiency in total variance, because the variance of the truncated normal random variable u_i is $(\frac{\pi}{2} - 1)\delta_u^2$.

2.3.2. Stochastic Frontier Analysis-PSM-SPF

As a robustness check, we also adopt the approach advanced by Bravo-Ureta, Greene and Solís [38] in part. In comparison to the conventional approach in Section 2.3.1, this approach circumvents the methodological weakness by addressing biases stemming from unobserved and observed variables. First, a group of mobile phone non-users is generated using PSM, with observed characteristics comparable to the group of users. This aids to mitigate bias arising from observed variables and is also a necessary condition to elicit an accurate measure of the impact according to Monteiro [39]. A "1-to-1 nearest neighbor matching without replacement" is employed and the advantages are that the condition of common support is imposed as every user is matched with a non-user [40], compared to all the alternatives has the most intuitive interpretation and is easy to implement [41]. The probability of receiving treatment conditional on covariates is expressed as:

$$p(S_i) \equiv \Pr(T_i = 1 \middle| X_i = E(T_i \middle| X_i), \quad (6)$$

where $p(S_i)$ is the probability of a farm i having been assigned to a treatment and this is called a propensity score.

Second, the model introduced by Greene [42] is utilized to deal with biases from unobserved variables. Unlike the model proposed by Heckman [43] to correct selection bias, this model is internally consistent as it incorporates selection bias in the stochastic frontier model. The model posits that the noise in the frontier is correlated with the unobserved characteristics in the selection model.

However, we do not employ the second stage in our analysis for two reasons. First, under the assumption that the frontier is the same in each analysis for all observations, our interest is to compare pooled estimations in both conventional SPF and PSM-SPF. Second, given the size for each matched group, the degrees of freedom do not warrant accurate estimations that are theoretically consistent. In view of this, we only implement stage one to derive a matched sample which is used in technical efficiency estimation. It is important to note that, other potential issues of selection bias may occur when using this approach and as such results should not be over-interpreted in a causal sense.

2.3.3. Difference in Income and Output

The association of mobile phone use with technical efficiency could be linked to income, and maize output realized. Therefore, we also establish whether the differences in income and output between the groups are statistically and socioeconomically significant. For statistical evaluation, we employ the t-test to test the differences in the means between users and non-users while poverty measures and the average daily maize requirement (364 grams according to Chapoto, et al. [44] and FAO [45]) are used to gauge the socio-economic relevance of the difference.

3. Empirical Results and Discussion

The results are presented with a controversial question as a subtitle so that the discussion is not futile. We begin by presenting descriptive statistics.

3.1. Descriptive Statistics

Table 1 presents the descriptive statistics of the unmatched and matched variables used in the study. We find that users have more years of formal education compared to their counterparts and rate the use of mobile phones as necessary unlike non-users, which is consistent with common sense and reality as the use of mobile phones demands higher levels of interest and technical abilities. In support, Tadesse and Bahiigwa [24] find that technical abilities are essential for effective use of mobile phones. Interestingly, we also find that non-users are relatively wealthier in reference to landholding per capita and subscribe more to cooperatives, which is an alternative information source [46–50]. This could also partly explain the non-usage of mobile phones to search for information. An assessment of the agricultural inputs reveals that while non-users cultivate more land for maize production than users, they use the same level of seeds, fertilizer, and labor-days. This is inconsistent with reality or theory as more cultivated land would require relatively more production inputs. Fisher and Kandiwa [51] contend that such a scenario would impose real costs on society in connection with misused potential in agricultural production.

After the matching procedure, all the 41 users were paired with 41 non-users out of 159. Following Leuven and Sianesi [52], we conducted *t*-tests before and after matching to gauge whether the means of observed characteristics between the two groups were equal. While the differences in the unmatched sample are significant, the balancing property of covariates is satisfied after matching as the means between users and non-users is insignificant. According to Caliendo and Kopeinig [53], a good match is achieved when covariate means for the control and treated groups are equal. Also, Rosenbaum and Rubin [41] recommend checking *t*-test for insignificant differences because if the covariates used in the match are randomly distributed, the significance level should be insignificant. Regarding visuals, Figures 2 and 3 shows the achieved region of common support due to the satisfactory balancing of characteristics between users and non-users.

Table 1. Description of the variables.

Category	Description	Unmatched Sample (N = 200)			Matched Sampled (N = 82)		
		Pooled	Users	Non-Users	Pooled	Users	Non-Users
		Explanatory Variables					
Gender	Sex of HHH (1 = male)	0.83 (0.06)	0.86 (0.03)	0.86 (0.02)	0.82 (0.043)	0.83 (0.06)	0.80 (0.06)
Education	Number of years of formal education of the HHH	5.24 (0.25)	8.62 (0.28)	4.35 (0.26) ***	6.91 (0.34)	8.58 (0.28)	7.24 (0.50)
SpEducation	HHH's spouse with basic education (1 = has basic education)	0.52 (0.04)	0.69 (0.07)	0.48 (0.04) **	0.62 (0.05)	0.71 (0.07)	0.63 (0.07)
Cooperative	HHs who are members of a cooperative (1 = member)	78.57 (0.06)	0.97 (0.01)	0.79 (0.07) ***	0.85 (0.04)	0.92 (0.04)	0.88 (0.07)
Family size	Number of people in a HH	6.14 (0.23)	6.30 (0.50)	6.09 (0.26)	5.99 (0.31)	6.37 (0.51)	5.61 (0.34)
Farmexp	Years of the HHH's farming experience	21.71 (0.87)	18.07 (1.53)	22.67 (1.01) **	19.68 (1.21)	20.07 (1.53)	21.29 (1.85)
Landholding	Total land possessed per capital	1.62 (0.09)	1.15 (0.17)	1.74 (0.10) ***	1.27 (0.11)	1.15 (0.17)	1.38 (0.14)
		Agricultural Inputs					
Fertilizer	Amount of fertilizer used in kg	580.45 (47.90)	607.14 (92.48)	573.40 (55.53)	545.12 (53.54)	612.20 (94.62)	478.05 (49.33)
Land	Land cultivated for maize production	1.75 (0.09)	1.45 (0.17)	1.84 (0.11) *	1.68 (0.14)	1.64 (0.17)	1.81 (0.21)
Labor	The hours of labor used in labor-days	134.74 (6.26)	134.86 (19.38)	134.71 (6.08)	133.24 (11.33)	136.40 (19.79)	130.09 (11.28)
Seed	Amount of maize seed used in kg	26.57 (1.41)	26.42 (3.37)	26.60 (1.55)	26.46 (2.11)	26.59 (3.45)	26.34 (2.46)

Notes: Figures in parentheses are standard errors of the mean, while *, **, and *** indicate statistical significance levels at 10%, 5%, and 1%, respectively. Labor-days are calculated by dividing total labor hours by eight hours which is a full working day for the farmers in the study area. HHs = households while HHH = household head.

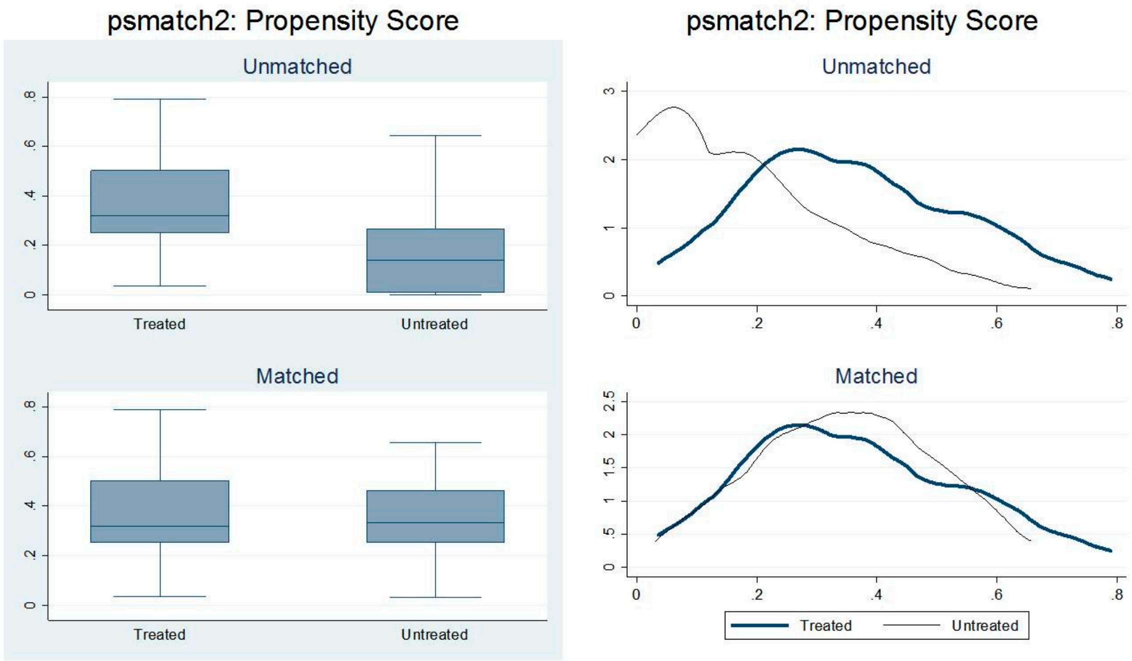

Figure 2. Box plot and probability distribution before and after matching. Source: Authors' estimation.

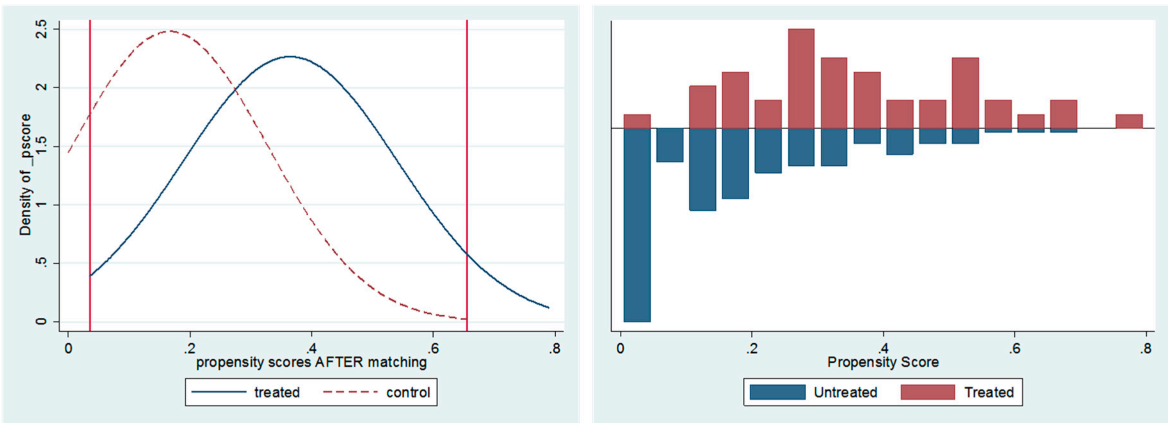

Figure 3. Imposed region of common support. Source: Authors' estimation.

3.2. Do Farmers Use Mobile Phones to Access Agricultural Information?

Initially, the result of the interrogation as to whether farmers use mobile phones to access information reveals that only 38 percent of farmers who own a mobile phone intentionally access information using it (Table 2). The results confirm that the operation of mobile phone use is linked to mobile phone ownership rather than SIM card ownership. None of the farmers who do not have a mobile phone access agricultural information. This is in contrast with the results of Tadesse and Bahiigwa [24] who investigated the village-level density of mobile phone penetration where households would use their SIM card in another farmer's phone to access information.

Table 2. Percentage of farmers using mobile phones for agricultural information access.

Status of Mobile Phone Ownership	Percentage (Frequency)	% of Farmers Who Use Mobile Phones for Agricultural Information Access
Farmers who do not own a mobile phone	46.5 (93)	0 (0)
Farmers who own a mobile phone	53.5 (107)	38.3 (41)
Total	100 (200)	20.5 (41)

Notes: Figures in parentheses are the number of farmers. Source: Authors' estimation.

Table 3 displays the frequency at which different agricultural information is accessed per month during the production period. To a great extent, Table 3 also discloses how farmers discriminate which information to access by looking at the intensity of access. Intuitively, from the revelation of the intensity of information access by farmers, we can assume that users willingly initiate access to information most of the time [33,54,55]. The different information aspect mostly accessed may also signify that farmers' perceived the source of information as reliable or the information provided is highly critical. These results concur with the revelations from focus group discussions conducted alongside the questionnaire as well as that of Sekabira and Qaim [30], which found that households are actively involved in exchanging text messages, receiving and making calls to agricultural extension officers, farmer organization and fellow farmers, in addition to retrieving information through the Internet (social media platforms such as WhatsApp groups and Facebook groups) and access credit through mobile money services. In this way, mobile phones are beneficial for farmers as they can easily access information on cooperative meetings, agricultural practices, the price of seeds and fertilizer, mobile money transfers, agricultural extension services, and weather—this last aspect is especially important when rain-fed irrigation is the only affordable form of irrigation in this area. In agreement, Muto and Yamano [55] contend that compared to other channels of information access, the spread of information is faster among households that use mobile phones in agriculture. However, this is not without challenges, which include a lack of an information center specifically for agriculture, a lack of access to power for charging phone batteries, network problems, insufficient funds for recharging their phones and language barriers [56–58].

Table 3. Source of information and frequency of information access.

Information Aspect	Information Source	Calls	Messages	Both (Calls and Messages)	Average Frequency Per Month
Agricultural Extension	Ministry of Agriculture	√			4
Prices of maize seeds	Farm Input Suppliers			√	6
Prices of fertilizer	Farm Input Suppliers			√	6
Labor availability related to maize	Farmer Organizations			√	2
Cooperative meetings on maize production	Cooperatives and Farmers			√	18
Weather forecasts	MNOs		√		30
Mobile money	MNOs		√		24

Notes: Ticks indicate the channel used in the information accessed. Source: Authors' estimation.

The mere availability of mobile phones in agricultural communities does not inherently indicate that farmers are making use of them as a solution to their information problems. Supply side and demand factors are the determinants of using a mobile phone in searching for agricultural information [59,60]. Apart from the amount of cropland available and farmers' realization regarding the significance of information, the demand for information via the mobile phone during planting also relates to the farmer's ability to use a mobile phone. The supply-side factors, in contrast, are to a large extent related to the presence of an accessible and reliable information source [24,56,61]. In this case, access is stronger than supply in explaining the use of mobile phones for information. Therefore, farmers with knowledge of where, why, when, and how to search for information are the ones making use of mobile technology.

3.3. Is the Use of Mobile Phones Associated with Technical Efficiency?

The empirical results of the SFA estimated by maximum-likelihood for the conventional SPF and PSM-SPF are presented in Table 4. The overall fitness of the model is guaranteed by model specification tests already established. The values of lambda being significantly greater than zero is an expression of the significant effects of inefficiency in maize production and is consistent with the values of gamma which suggests technical inefficiency is a vital contributor to the variation in observed output [38,62] and is indeed stochastic. The scale elasticity is insignificantly different from 1, indicating a constant return to scale in maize production. This finding is similar to that of Fufa and Hassan [63] and Musaba and Bwacha [64]. All the classical inputs positively and significantly contribute to maize output, except fertilizer and labor which are insignificant. This is attributed to the over-utilization of these factors of production [65]. The models also show different input elasticities. For instance, land is a significant driver in the conventional SPF, while seed is the most important production factor in PSM-SPF. This is explained by the difference in the observations used in both models.

Table 4. SFA Maximum likelihood estimates.

Variables	Conventional SPF	PSM-SPF
Constant	6.707 (0.595) ***	5.964 (0.453) ***
lnFertilizer	0.126 (0.079)	0.106 (0.114)
lnLand	0.609 (0.129) ***	0.345 (0.055) ***
lnLabor	0.028 (0.039)	0.026 (0.047)
lnSeed	0.258 (0.063) ***	0.548 (0.159) ***
Technical Inefficiency Function		
Constant	0.373 (0.173) **	0.080 (0.238)
MP use	−0.293 (0.101) ***	−0.342 (0.097) ***
Family size	0.039 (0.012) ***	0.049 (0.015) ***
Gender	−0.052 (0.047)	−0.141 (0.141)
Farmexp	−0.008 (0.003) **	−0.013 (0.006) **
Education	−0.013 (0.024)	−0.008 (0.043)
SpEducation	0.116 (0.098)	0.277 (0.145) *
Cooperative	0.054 (0.091)	0.127 (0.192)
Landholding	0.002 (0.021)	0.090 (0.047) *
Model Diagnostics		
Returns to Scale	1.021	1.026
Gamma	0.82	0.93
sigma_u	0.194 (0.047) ***	0.238 (0.054) ***
sigma_v	0.092 (0.035) ***	0.060 (0.027) **
lambda	2.112 (0.075) ***	3.945 (0.079) ***
Log-likelihood	35.523	23.260
Wald chi2 (4)	933.76 ***	1157.42 ***
N	197	82

Notes: Figures in parentheses are standard errors of the coefficient, while *, **, and *** indicate statistical significance levels at 10%, 5%, and 1%, respectively. Source: Authors' estimation.

Regarding the inefficiency function, farming experience is significantly and positively associated with technical efficiency in both models. Similar to other studies [65,66], the increase in farming experience has positive impacts on technical efficiency because of the expected acquisition of dexterity owing to the fact that farming is mostly learning by doing. This could also be explained by the appetite for more agricultural information as experience demands better knowledge about the production environment to ensure the right decisions.

In contrast, family size is negatively associated with technical efficiency in both SPFs, which could be attributed to over-utilization of labor as pointed out by Donkoh, et al. [67] and Abdulai and Eberlin [68]. In our case, as family size increases, there is a less equitable labor distribution leading to less concentration on the given task as well as lower production efficiency. Our results do not match with Amos [69] and Haji [70] who found that family size has a positive and significant effect on technical efficiency.

Similarly, education of the spouse has a significantly negative impact on technical efficiency in the PSM-SPF. Contrary to the sign on the education of household head's spouse, it is expected that education should have a positive impact on technical efficiency as exhibited by the sign on household head's education despite not being significant. In explaining this assertion, Jaime and Salazar [71] note that education facilitates learning, improves access to information, promotes forward looking attitudes, and facilitates adoption of new technologies. This conclusion is supported by other studies [72–75]. For the education of the spouse, more research is required to understand the underlying mechanism considering education as a major determinant of technical efficiency [65,76]. However, one possible explanation is that educated spouse would not participate much on the farm as they would most likely settle for off-farm employment.

On landholding, our finding is contrary to the notion that higher levels of efficiency are achieved by large farms owing to derived economies of scale [71,75,77–79]. This implies that the dominance of small farms in the area under investigation may tremendously improve productivity in the region. However, Roco, et al. [80] cautions that this may pose a threat to productivity.

Our analysis reveals a positive and significant association between mobile phone use and technical efficiency, as presented in Table 5. Given the information which farmers' access through the mobile phones presented in Table 3, it is expected that it could translate to higher productivity. The advantages of rapid information dissemination and real-time access to information [28] further drive the potential to adopt useful practices and prevent farmers from making decisions blindly. This reaffirms the assertion of Forero [81] that the deployment of mobile communication networks accelerates farmers' technical efficiency. Considering the fact that mobile phones are only a conduit, effort from households is essential in making sure that the accessed information is used appropriately [21,82,83]. Therefore, focused interrogation is necessary because transmitting information is not the same as transmitting expertise in that the latter is difficult to manage asynchronously. We find strong evidence that using a mobile phone to collect agricultural information is significantly associated with technical efficiency. To adequately comprehend the scenario of technical efficiency between users and non-users, we calculate the distribution of technical efficiency across the groups in different SPFs. Unlike users, the majority of non-users have TE scores lower than 0.7 in both SPFs (Table 5). Particularly, in the PSM-SPF model, there is a sharp contrast between the two groups. While many users are above 90 percent and do not fall below 50 percent, it is the opposite for non-users. In comparison to users, we also observe that the scores of the non-users in conventional SPF are different from PSM-SPF. The trend of the scores seems to be clustered below 70 percent in the former. This is as a result of biases from observed variables not being considered, leading to an exaggeration of the treatment effect.

Table 5. Technical efficiency scores distribution.

TE Category	Conventional SPF			PSM-SPF		
	Users	Non-User	Pooled	Users	Non-User	Pooled
<0.5	4.88	12.82	11.17		21.95	10.98
0.5–0.59	19.51	28.85	26.90	17.07	14.63	15.85
0.6–0.69	4.88	30.13	24.87	9.76	12.20	10.98
0.7–0.79	17.07	23.72	22.34	19.51	21.95	20.73
0.8–0.89	41.46	3.21	11.17	9.76	19.51	14.63
0.9–1	12.20	1.28	3.55	43.90	9.76	26.83

Source: Authors' estimation.

The primary goal of the study is to measure the potential differences in technical efficiency between the two groups (users and non-users) and the effect of controlling for biases stemming from observed variables. Therefore, we also performed *t*-test to relate technical efficiency levels and mobile phone adoption. We found a positive association between them (Table 6). Notably, the mean TE of users is significantly higher than that of non-users at 1% significance level in both SPF models. Since the conventional approach uses variables that have not been matched, this exaggerates the estimates by 5.3 percent as can be observed from the differentials in Table 6. This is consistent with a conclusion by White [84] and Rosenbaum and Rubin [41] that the results are in favor of one group when observable characteristics are not comparable. Lastly, based on TE mean from the PSM-SPF in Table 6, there is potential to increase maize production by 20.8 and 31.9 percent with the current level of inputs for users and non-users, respectively. The average mean TE value is consistent with those reported by Binam, Tonye, Nyambi and Akoa [73] and Addai, et al. [85] but higher than the value found by Chiona, et al. [86] in the same province.

Table 6. Technical efficiency and differentials across models.

Index	Conventional SPF			PSM-SPF		
	Pooled	Users	Non-User	Pooled	Users	Non-User
Mean TE	0.655 (0.134)	0.762 (0.149)	0.627 (0.114) ***	0.737 (0.166)	0.792 (0.152)	0.681 (0.164) ***
Max TE	0.949	0.933	0.949	0.970	0.964	0.970
Min TE	0.253	0.474	0.253	0.396	0.523	0.396
TE Differential		21.5%			16.3%	

Note: To calculate the TE differential between the two groups, the percentage increase formula was used. Source: Authors' estimation.

3.4. How Significant is the Difference in Maize Income and Output Between the Groups?

According to Kirk, et al. [87] and Rehan Shaukat and Ali Shah [88], the association between information access and technical efficiency can generate significant results, as the former facilitates the adoption of best practices in cropping patterns, which could improve yields and also warrant better price information of inputs. Thus, farmers secure a better position owing to the improved growth indicators (income and yield). Therefore, following the establishment of the association of mobile phone use with TE, we probe the differences in the agricultural growth indicators exhibited by the groups. Table 7 shows that the differences in income and maize production are statistically insignificant. However, the difference is significant in a socio-economic sense. This is better understood by relating the output and income to daily maize requirement in Zambia and poverty reduction measures, as already established in Section 2.3.3. While we do not attribute the gap in the indicators to the causal effect of the use of mobile phones, it is essential to acknowledge that the difference is significant against the background of poverty reduction. If this gap in income per capita per day (0.10 USD per capita/day at an exchange rate of 1 USD = 11 ZMK) is closed through mobile phone use (which is significantly associated to technical efficiency), poverty severity (relative to the 2 USD/day poverty line) and extreme poverty (1.25 USD/day poverty line) would be reduced by 5.13 and 8.21 percent, respectively (Table 7). By dealing with poverty, hunger is also addressed, because the former is the principal cause of the latter.

To keep the conclusion from being a moot point, a gap in output per capita per day of 147 grams indicates relatively more efficiency and sustainability in production as this contributes 40.38 percent to the daily maize requirement. Therefore, getting rid of such an output difference aligns well with food security essentials, i.e., quality, quantity, and availability [89–91]. More investigation is required to thoroughly understand the underlying cause of the differences between users and non-users. In spite of this limitation, we cautiously conclude that mobile phone technologies could improve farm household income and maize yield on account of their association with technical efficiency through the principle of transitivity.

Table 7. Difference in income and maize output between the groups.

Growth Indicators	Non-User	User	Annual Difference	Difference Per Capita Per Day [1]
Output in kgs	4537.74 (243.92)	4864.29 (640.31)	326.55 (576.93)	0.147
Income in ZMK	5524.62 (305.03)	5936.79 (772.70)	412.16 (713.48)	0.186

Notes: Figures in parentheses are standard errors of the means. Annual difference is obtained by subtracting column 2 Figures from column 3. [1] Obtained by dividing the annual difference by 6.1 (average family size which is the same for both groups) and also by 365 which is the number of days in the year.

4. Conclusions and Policy Recommendation

Agriculture is fundamental to the economic and social development of most African countries, and information of satisfactory quality is a prerequisite to its success. The use of mobile phones for accessing agricultural information (part of agricultural informatization) is beneficial for agricultural communities as it assures agricultural sustainability through increased productivity. It enables farmers to make their agricultural practices highly productive. Consequently, reduction of hunger and poverty alleviation could be achieved, which is in agreement with SDGs 1 and 2.

In this study, farm household data from Zambia has been used to analyze associations between mobile phone use and technical efficiency. The findings present substantial evidence of the association. Such empirical evidence is fundamentally beneficial to farmers and policymakers facilitating the implementation of a focused approach equal to the task of meeting the mounting food demand. Technical efficiency in agriculture has been widely used to offer improvement in farm management systems. The idea is for policymakers to harmonize the results with policy aims to facilitate target specific policy measures. Productivity is inextricably linked to technical efficiency, and so to question traditional approaches in agriculture should be an important concern of any policymaker or scientific researcher. Otherwise, the likelihood of fighting against what should be fought for is bound to happen, especially in the case of mobile phones in agriculture because of the general perception of the device. Therefore, we highly recommend the elimination of barriers to mobile phone use in rural agricultural communities to aid expedient food production.

Finally, this study presents a snapshot and not the entire story of the association between mobile telephone use and technical efficiency, i.e., cross-sectional data from only 201 farmers were used. Moreover, other agricultural community structures may have different outcomes. Also, the identification strategy employed is imperfect, prompting the caution not to over-interpret the findings in a causal sense. However, given the dearth of empirical evidence of mobile phone use on technical efficiency, associational analysis is a useful addition to literature and could possibly motivate follow-up studies. Therefore, panel data covering more extended periods, incorporating diverse agricultural communities along with a large sample size and more robust approaches, are strongly advocated for future studies.

Author Contributions: Conceptualization, X.T.; Data curation, G.E.M. and E.J.-P.A.; Formal analysis, S.W. and S.R.; Funding acquisition, X.T.; Investigation, G.E.M.; Methodology, S.W.and X.T.; Supervision, X.T.; Writing—original draft, G.E.M.; Writing—review & editing, X.T.

Funding: This project was funded by the National Natural Science Foundation of China (Project ID: 71473123) and the Priority Academic Program Development of Jiangsu Higher Education Institutions (PAPD).

Acknowledgments: We express sincere gratitude to the Government of Zambia and The People's Republic of China, particularly the Ministry of Agriculture and Higher Education Loans and Scholarship Board (HELSB) and Chinese Scholarship Council (CSC). We also thank profoundly two anonymous reviewers of this journal for their candid and constructive comments.

Conflicts of Interest: The authors have no conflict of interest.

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