Impact of Agricultural Credit on Technical Efficiency and Technological Gap Ratio Among Coffee Farmers in Kenya

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Abstract Extant literature demonstrates that the technical efficiency (*TE*) of coffee farmers is on a downward trajectory but there are scarce resources to link how agricultural credit is directly instrumental in improving technical efficiency. Therefore, this study was conducted in Kiambu County in Kenya to determine the impact of agricultural credit on technical efficiency and the technological gap ratio among coffee farmers. The data for the study from 2017 to 2019 was obtained from Commodity Fund and farmers' cooperative societies. The paper adopted a meta-frontier framework to estimate the technology gap ratios (*TGR*) for participating (*PF*) and non-participating (*NPF*) coffee farmers in the credit program. The empirical results disclose that *PF* and *NPF* adopted heterogeneous production technologies given their dissimilar access to credit that is essential for the acquisition of inputs. The *TGR* for *PF* and *NPF* was 0.969 and 0.747 respectively which indicate that *PF* operated on a loftier frontier in comparison to *NPF*. Thus, *PF* were technically efficient as compared to *NPF* given their very small gap between regional and meta-frontier efficiencies (*MFE*). The Decision-Making Unit inefficiency estimates indicate that the credit program interventions aimed at efficiency improvement in *NPF* should be targeted at enhancing farmers' access to optimal combinations of inputs and advisory services through extension visits. Consequently, this paper recommends policies tailor-made to promote credit access by smallholder farmers to improve *TE* and *TGR*.

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1 Introduction

The coffee sector has continued to play a key role in Kenya's economy accounting for more than 40% of the total value of exports and providing livelihoods to more than 700,000 smallholder farmers (KNBS, 2022). These smallholder farmers produce about 70% of total coffee production yet they are faced with numerous limitations to their farming operations. As a result, the production of coffee has now shrunk substantially from 1985 to 2019 by 0.42% (Wanzala et al., 2022; ICO, 2019). Apart from the international coffee regulatory framework and inept management of the sector locally, the declining productivity of coffee has been blamed on inefficiency in resource use and of which several studies have attested to its roles in undermining households' food security status and income (Chege, 2012). Hence, the Government of Kenya (GoK) formed Commodity Fund in 2006 to provide agricultural credit to smallholder farmers to boost coffee productivity. Nevertheless, statistics by ICO, FAO and the Coffee Marketing Board of Kenya manifest coffee as a moribund sector. These diminishing levels of production coffee with concomitant to—among other things—sub-optimal utilization of feasible input-output combinations due to poor access to credit (Theuri, 2012). Thus, if the GoK is providing credit to smallholder farmers, the central question is: does access to agricultural credit improve the farmers' efficiency and reduce the technological gap ratio (*TGR*) in coffee production? Therefore, the objective of this study is to determine whether access to agricultural credit has an impact on the technical efficiency (*TE*) and technology gap ratios among coffee farmers in Kenya.

Efficiency is a very important factor of productivity growth especially for smallholder farmers who have limited funds and poor access to credit to develop and adopt improved technologies (Vassiloglou & Giokas, 1990). Generally, a firm is technically efficient if it produces a given level of output using a feasible number of inputs (Wadud, 2003). To improve the farmers' productivity, inputs must be used more efficiently with attention paid to attaining maximum production without wastage (technical efficiency) (Skevas et al., 2014). Several approaches like economic analysis (Beltrán-Esteve et al., 2014) and met a production function (Lau & Yotopoulos, 1989; Hayami, 1969) have been developed purposely to analyze firm efficiency. These approaches do not take into consideration the technology gap characterized by the incomparability of data and the differences in the basic economic environment (Villano et al., 2010). Further, it's a challenge to specify an appropriate production function when using these approaches. To overcome this challenge, stochastic meta-frontier and Data Envelopment Analysis (DEA) meta-frontier techniques are used because they can calculate the meta-frontier of all groups' frontier and estimate both the *TE* and *TGR* (Villano et al., 2010). Unlike the stochastic meta-frontier, this study will use DEA because it does not require the specification of a particular functional form for the technology (Rao et al., 2003).

The extant literature on *TE* and *TGR* using the meta-frontier approach is very limited (Ramalho et al., 2010). Even more limited is the literature on the impact of agricultural credit on TE and *TGR* using the meta-frontier approach. Further, most studies that investigate TE use a dummy variable as a proxy for access to agricultural credit (Beltrán-Esteve et al., 2014). However, this study deviates from these past studies and used meta-frontier analysis and real credit data from 2017 to 2019 collected from Commodity Fund. The result of this study contributed to efficient decision-making at the farm level and assisted policymakers in the devising of relevant policies geared to improve coffee productivity. The study findings also avail pertinent information on the impact of agricultural credit on *TE* and *TGR* to academia and agricultural extension workers.

2 Theoretical Framework

The theoretical framework for this study is grounded on the theory of the firm that presupposes that firms exist and make decisions with an intention to maximize profits (Debertin, 2012). The firms are interested in the market because it offers them with an opportunity to make both supply and demand decisions after which they are able to allocate resources economically and efficiently in line with the models ensuring maximization of the net profits (Ogada et al., 2014). According to Farrell (1957) school of thought, economic efficiency consists of allocative and technical efficiency. That in order for a firm to be economically efficient, it first needs to be technically efficient. This means that a firm that is technically efficient will utilize the right combinations of inputs (labour, fertilizer, agrochemicals) to get the right output mix given the prices of the commodity in the market. Thus, the relationship between technical and allocative efficiency can be illustrated by Fig. 1.

The estimation of technical efficiency (*TE*) in this study follows a framework based on agricultural production theory where a smallholder coffee farmer (*SHCF*) are presumed to use owned and bought inputs to produce coffee. The rational *SHCF* is assumed further that to produce coffee he embraces production technology which utilizes a set of inputs; $(x_1, \ldots, x_m \epsilon \mathfrak{R}_+^n)$ to produce a positive set of outputs $(y_1, \ldots, y_m \epsilon \mathfrak{R}_+^m)$. The collection of all set of the feasible input-output (or production possibility set) for *SHCF* is the subset T of the space $\mathfrak{R}_+^{m+n}$ is therefore represented as:

$$T = \left((YX)X \text{ can produce } Y \in \mathfrak{R}_+^{m+n}\right) \tag{1}$$

The *SHCF* can devise any production plan from any input-output combination thereof. However, given that this is an optimization problem centered on the available inputs and outputs, analysis of the efficiency of a coffee farm requires estimation strategy that selects a combination of inputs which yields maximum output as per its achievable output set (Varian & Varian, 1992). Theoretically, the
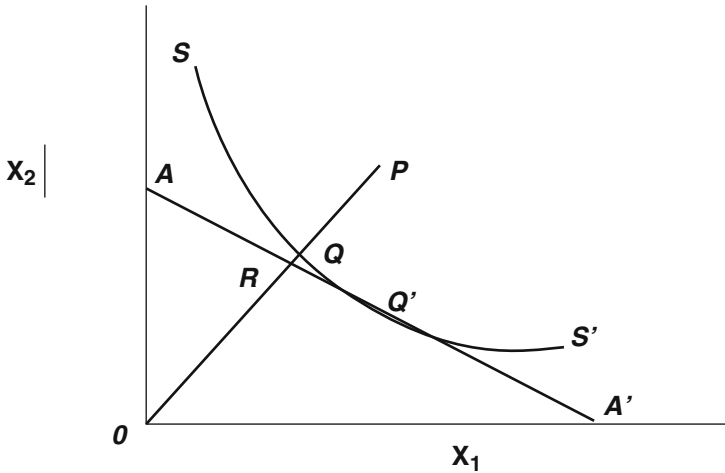
Fig. 1 The relationship between technical and allocative efficiency

production function exemplifies the optimum output that can be obtained from a given set of inputs (Jehle & Reny, 2011), and can be stated as:

$$Y = F\left(X^{t^i}, Z^{t^i} \mid \sum_i Z^{t^i}, \overline{M}\right) \tag{2}$$

Where, Y is a vector of coffee production, X, W and Z is set of inputs such as land, labour and fertilizer respectively that is purchased. The t^i indicates the seasonality and progressive nature that characterizes coffee production phases as dictated by biological physiognomies. Such a recursively distinguishable arrangement of the production procedure implies for example that labor used for pre-harvest activities such as pruning, fertigation and weeding is different from labor used to harvesting activities. The M on the other hand denotes a set of optimum use of services made possible by the fixed stock of *SHCF*-controlled inputs in each step of the production process. The Eq. (2) illustrates that there are some exceptional characteristics that exemplify coffee production and the extent to which the characteristics occur in agriculture has insinuations on how they can be portrayed mathematically (Karagiannis, 2014).

The inputs-output behavioral relationship can further be characterized by returns to scale (RTS) in production whereas farm's technology can exhibit constant returns to scale (CRS) or variable return to scale (VRS) (Debertin, 2012). In CRS production technology, a given percentage increase in inputs leads to the equal percentage increase in output while in the VRS, a given percentage increase in inputs is characterized by less than or more than proportionate rise in output (Daraio & Simar, 2007). Representation of returns to scale in agricultural production analysis indicates whether any efficiency gains can be obtained by modifying the scale of

operation of a farm (Tolga et al., 2009). The theoretical foundation is that a production function connotes the boundary of the PPS and a farm can be said to be efficient in utilization of inputs if it's operating on this production function (Ogada et al., 2014). In this perspective, efficiency in coffee production reflects the selection of production technology that results into optimum output given available combination of possible input set. This in tandem with the description of *TE* in conventional economic theory.

The efficiency scores obtained from SFA will be used to analyze variations in the scores across *SHCF*. There are many factors which causes variation in the *TE* scores which include farm and agency, agent and structural and policy and institutional factors (Yoshiko, 2011). The marketing channels for the sale of coffee beans, access to extension and credit services constitute the policy and institutional factors. The farm specific factors include area under coffee cultivation, age of the coffee tree, coffee variety planted, the overall farm size and number of coffee trees per acre. The *SHCF* characteristics which may affect efficiency include the household head education level, *SHCF′s* age, size of the household and labour structure in coffee farming.

2.1 Empirical Review

Extant literature is dominated by studies focusing on the technical efficiency of agricultural and livestock production and their associated factors influencing the *TE* levels (Geffersa et al., 2022). Meaningful empirical research on *TE* and *TGR* is scanty (Danso-Abbeam & Baiyegunhi, 2020). This is especially after the seminal papers of Battese and Rao (2002), Battese et al. (2004), and O'Donnell et al. (2008) who used the meta-frontier model to estimate technology gaps for entities embracing diverse available technologies. This study was conducted as a result of very few studies that have been dedicated to providing in-depth insights on agricultural productions under different technological formations, especially credit programmes. So far, there is even less research that examined *TE* and *TGR* on coffee productivity, especially in Kenya. Given that studies using meta-frontier models on coffee are scanty, this study reviewed empirical studies focusing on other crops.

The study by Adeleke et al. (2021) used a stochastic meta-frontier approach to assess the technological gap ratio of the different food crops. The study randomly sampled 1678 food crop farmers from General Household Survey-Panel Wave 2 from the National Bureau of Statistics for the six geo-political zones in Nigeria. The mean *TE* and mean *TGR* of the food crop farmers were 56.3 percent and 71.6 percent respectively indicating sub-optimal production of food crops than the potential output in Nigeria. Aloysius et al. (2021) used stochastic meta-frontier analysis to scrutinize *TE* and *TGR* of tomato production in Northern Nigeria. The study randomly sampled 359 farmers in Plateau, Kano and Taraba. The study indicated that farmers from the Plateau region were more technically efficient than their counterparts in Kano and Taraba. However, the *TGR* mean for Taraba farmers was

tangential to the meta-frontier output indicating that these farmers used innovative farming technology. The *TGR* mean of Plateau and Kano farmers was less than the optimal output by 0.5% and 1.2% respectively. The study concludes that there is a need for sensitization of Plateau and Kano farmers on sound agricultural technology for optimum production.

In the study conducted by Majiwa and Mugodo (2018) on *TE* and *TGR* among rice farmers in Kenya, a stochastic meta-frontier model was used to estimate *TE* and *TGR*. The results indicate a lower mean between different rice growing regions; that is, Mwea (0.556), West Kano (0.475), Ahero (0.402), and Bunyala (0.45). Their study also discovered a wide gap between rice-producing regions. Specifically, the *TGR* values for Mwea, West Kano, Ahero, and Bunyala were 0.998, 0.605, 0.482, and 0.48, respectively. This study digressed from the above studies by focusing on coffee and using a quasi-experimental design.

2.2 Theoretical Basis of Efficiency Estimation

2.2.1 Data Envelopment Analysis

Efficiency is a very important factor of productivity growth especially for small-holder farmers who have limited funds and poor access to credit to develop and adopt improved technologies. It is described as the ability of DMU to produce optimum output(s) with the least combinations of feasible inputs relative to competitors subject to available resource limitations and operational settings (Coelli & Perelman, 1999). The efficiency of DMUs can be examined by using either the parametric (SFA) or non-parametric techniques (DEA). Due to the agility of DEA and data limitations, this study employed DEA in efficiency estimation. The DEA can be estimated by using an input-oriented approach (IOA) and an output-oriented approach (OOA). The IOA to *TE* estimates the degree to which a DMU can minimize resources to produce the same level of output. As such, IOA denotes the resource intensity of DMU relative to optimum practice. The output-oriented approach (OOA) assesses the degree to which a DMU can maximize the output level given the same quantity of inputs. A DMU is said to be inefficient if it does not operate along the optimum practice frontier and efficient if vice versa. Therefore, for OOA, the linear programming problem for the ith firm can be estimated as:

$$Max \ \theta_1$$

Subject to:

$$\theta_1 b_{w,u} \leq \sum_{w=1}^{W} z_w b_{w,u} \qquad\qquad \forall u \qquad\qquad (3a)$$

$$\sum_{w=1}^{W} z_w b_{w,v} \leq a_{w,v} \qquad\qquad v \in \pi \qquad\qquad (3b)$$

$$\sum_{w=1}^{W} z_w b_{w,u} = \eta_{w,v} a_{w,v} \qquad\qquad v \in \widehat{\pi} \qquad\qquad (3c)$$

$$\eta_{w,v} \geq 0 \qquad\qquad v \in \widehat{\pi} \qquad\qquad (3d)$$

where v is a scalar indicating the extent by which the farmer can increase output; $b_{w,u}$ is the output u by farm w; $a_{w,v}$ is the input v used by farm w and z_w are weighting factors. The resources encompass of both variable and fixed factors delineated by the set as $\widehat{\pi}$. To estimate the capacity of output quantity, lessening restrictions of the bounds on the sub-vector of variable inputs $a\widehat{\pi}$ is necessary. The lessening restrictions of the bounds on the sub-vector is realized by permitting the inputs to continue unconstrained by introducing a measure of the input utilizing rate ($\eta_{w,v}$) assessed in the model for each farm w and variable input v (Färe et al., 1994). The technically efficient capacity utilization (TECU) grounded on observed output (u) becomes:

$$\varpi = \frac{b}{b^*} = \frac{b}{\theta_1 b} = \frac{1}{\theta_1} \qquad\qquad (4)$$

where b^* is the capacity-output grounded on observed outputs b. The ϖ measure ranges from zero to one, with one implying full capacity utilization (i.e., 100% of capacity) which assumes efficient use of all the inputs exists at their optimal capacity. Efficiency measures of less than one indicates that the firm operates at less than full capacity given the set of fixed inputs.

2.2.2 Meta-frontier Analysis

The input and output sets are linked with meta-technology set (Eq. 3) with the output set is hereby defined for any input vector a as:

$$p = \{(b) : (a,b) \in \mathcal{T}\} \qquad\qquad (5)$$

Equation ss holds if and only if a inputs will produce b outputs by utilizing one or more of the definite technologies $\mathcal{T}^1, \mathcal{T}^2, \ldots, \mathcal{T}^k$ associated with a particular region. It is anticipated that the meta-technology would meet all the requirements of both convexity axiom and production axioms, articulated as the convex hull of the pooled region-specific technologies as follows:

$$\mathcal{T}^* \equiv Convex\ Hull\left(\mathcal{T}^1 \cup \ldots \mathcal{T}^2 \cup \ldots \mathcal{T} \cup^k\right) \qquad\qquad (6)$$
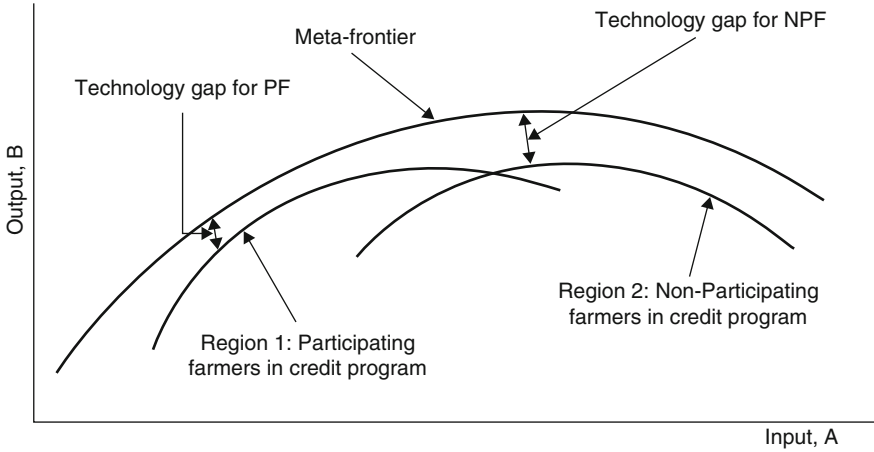
Fig. 2 Meta-frontier illustrating technology gap between PF and NPF

Thus, using the meta-technology $\mathcal{T}^*$ and if the input-output distance function is known, the results of any specific region of a given output $\left(D_o^*(a,b)\right)$ and input distance functions $\left(D_i^*(a,b)\right)$ would be follows:

$$D_o^k(a,b) \geq D_o^*(a,b),\qquad k$$
$$= 1,2,\ldots,n \qquad\qquad\qquad iff\ \ D_i^k(a,b) \leq D_i^*(a,b) \qquad (7)$$

Thus, the output-oriented *TGR* (denoted in equation as: ξ) between the region k technology and the meta-technology is computed as follows:

$$\xi_o^k = \frac{D_o^*(a,b)}{D_o^k(a,b)} \qquad (8)$$

The *TGR* when considering the output-oriented technical efficiency measure (ϖ) is specified as follows:

$$\xi_o^k = \frac{\varpi_o^*(a,b)}{DE_o^k(a,b)} \qquad (9)$$

The relationship between participating and non-participating coffee farmers in the credit program is illustrated by two regional frontiers (Region 1 and Region 2 respectively), meta-frontier and technology gap in Fig. 2. Thus, the DEA approach was used to estimate the efficiency of coffee productivity for and non-participating coffee farmers in the credit program and the meta-frontier approach was used to determine technology gap ratios. The output meta-frontier refers to the boundary of this output set which fulfills the typical regularity characteristics (Färe & Primont, 1995).

2.3   Regression Analysis of Determinants of Efficiency

The problems concomitant to embracing either Tobit or linear models in the DEA framework prompted Papke and Wooldridge (1996) to develop fractional regression model (FRM). The FRM is hailed for being able to overcome the limitation of dependent variables defined on the unit interval, irrespective of whether boundary values are observed (Ramalho et al., 2010). Further, it captures nonlinear data thus yielding better estimates. Finally, it helps predict response values within the interval limits of the dependent variable and last. As a result, Ramalho et al. (2010) commend use of the FRM to estimate determinants of efficiency in the second stage. However, FRM assumes a functional form of b which applies that the preferred constraints on the conditional mean of the regressand, as follows:

$$E(b|a) = \Phi(A\psi) \qquad (10)$$

where $\Phi(.)$ represents a nonlinear function which fulfils the condition $0 \leq \Phi(.) \leq 1$. Note that FRM can be estimated using either of the four link functions of conditional mean (logit, loglog, probit or complementary log) whose partial effects is specified as:

$$\frac{\delta E(b|a)}{\delta x_j} = \psi_{j\Phi}(A\psi) \qquad (11)$$

The efficiency scores of one-part and two-part models are usually dissimilar given that one-part models assume that:

$$E(\psi|w) = \Phi(w\delta) \qquad (12)$$

where $\Phi(.)$ signifies a probability distribution function $(w\delta)$. Since δ is unknown parameter, it is approximated by quasi-maximum likelihood which is specified as:

$$LL(\psi)_{max} = \sum_{i=1}^{n} (\widehat{\psi}_i \, log(\Phi(w_i\delta)) + (1 - w_i) \, log(1 - \Phi(w_i\delta))) \qquad (13)$$

In the two-part models, the whole sample is used to estimate the model:

$$Prob(\psi_i = 1|w) = F\left(w_i'\beta\right) \qquad (14)$$

Where probability distribution function and unknown parameter are represented by β and F respectively. It is assumed that $(\widehat{\psi}_i|w_i) = \Phi\left(w_i'\delta\right)$ for the responses in (0, 1) for the second part. The inefficiency determinants were six: age, gender and education of the coffee farmer. Further, number of extension visits, variety of the coffee and cropping system. The *TE* scores were regressed not only against age, gender and education of the coffee farmer but also number of extension visits, variety of the

coffee and cropping system. It was anticipated that some variables could influence efficiency either in a positive or negative way.

3 Methodology

3.1 Study Area and Data Sources

Kiambu County has twelve sub-counties where coffee is mostly concentrated within five sub-counties (Kiambu, Thika, Githunguri, Gatundu South and Gatundu North) that have 11 farmers' cooperative societies (FCS). The twelve sub-counties are ecologically homogeneous in terms of climate and edaphic factors. The research design for this study is a non-experimental research design. The study relied on secondary data on credit extended to smallholder coffee farmers in Kiambu County in Kenya in the custody of ComFund. The data was collected from participating and non-participating farmers in the Commodity Fund credit programme.

The data were treated in two ways. Firstly, the data on *SH*CF*s* who received credit from the Fund for coffee cultivation was considered as a treatment group. The treatment was the credit received by *SH*CF*s* from ComFund and not the coffee project itself. The treatment group was in three sub-counties of Githunguri, Gatundu South and Gatundu North. Secondly, the *SH*CF*s* who did not receive credit from the Fund was considered as a control group. The control group was in two sub-counties of Kiambu and Thika. To minimize potential spillovers of agricultural inputs to the control group in their sublocations, the selected sublocations whereby farmers received agricultural credit were mapped. Whereas other studies have used a 1 km buffer zone for example, (Chung et al., 2018), this study used a 6 km buffer zone to separate the treatment and control groups' sublocations. This is consistent with existing literature (Banerjee et al., 2010; Miguel & Kremer, 2004).

3.2 Population and Sample

The study targets *SH*CF*s* in Kiambu County who obtained credit from ComFund. The sample size was determined as follows. The initial step entailed obtaining a list of all *SH*CF*s* in Kiambu County who got credit from ComFund from 2016 to 2020. From the ComFund database, 15,003 *SH*CF*s* from Kiambu County who applied for credit in this period (2016–2020). According to the subject matter specialist at the Ministry of Agriculture, custodian of data at ComFund and our knowledge on the ground, all these farmers were financially constrained and had failed to access credit from commercial banks. ComFund on the other hand had limited funds and could only advance credit to only a few numbers of *SH*CF*s* who applied for their credit at any given time. Therefore, ComFund advanced credit to only 3589 *SH*CF*s* in this period which translates to 23.9% of those *SH*CF*s* who received credit and 76.1% of

*SH*CF*s* who did not receive credit. This scenario creates a natural experiment for impact evaluation. Of the 3589 *SH*CF*s*, 87 farmers were maintaining records of coffee production.

In consistency and reliability of the data and in consultation with the subject matter specialist at the Ministry of Agriculture and custodian of data at ComFund, going forward only these 87 farmers with records were included in the study as the treatment group. Using these inclusion criteria, 87 farmers were found to be commercially oriented and had a credit portfolio between KShs. 100,000 to KShs. 1,000,000. The credit range (KShs. 100,000 to KShs. 1,000,000) provided a sufficient census size to conduct an impact evaluation and to answer convincingly the policy question of interest. To identify the quasi-control group, the 87 farmers were selected using a propensity matching score (PMS) which runs a logistic regression of observable characteristics.

These characteristics were the overall size of the land, land under coffee, the ratio of coffee trees over the size of the land under coffee, the number of hired laborers over the size of the land under coffee, the farming system, credit from other sources, the ratio of cost of agrochemicals over the size of land under coffee, the ratio of cost of inputs over the size of land under coffee, and the ratio of coffee harvest over size of land under coffee. Similarly, only those farmers in the control group who maintained coffee production records were considered in the study. Therefore, the total manageable sample size for the study is 174. To limit digression on the objective of the study, neither empirical processes nor theoretical underpinnings on PSM are provided but can be availed on request.

3.3   Smallholder Coffee Farmer Characteristics

In Table 1, the mean age difference of negative 2.53 between participants and non-participants *SHCFs* was statistically significant at a 5% level. This indicates that age has a negative correlation with *SHCFs* participating in credit scheme. The mean gender and education differences between participants and non-participants *SHCFs* were 1.08 and 0.76 respectively. These two mean differences were statistically significant at a 1% level of significance. Therefore, it can be deduced that

Table 1 Summary results for mean difference of SHCFs characteristics

Demographics characteristics	Participants (n = 87) Mean	Non-Participants (n = 87) Mean	Mean difference	t-statistic
Age	48.47	51.00	−2.53**	−2.132
Gender	1.78	0.70	1.08***	11.958
Education	1.89	1.13	0.76***	6.360

*** 1% level of significance, **5% level of significance, *10% level of significance
Source: Authors computation, 2023

Table 2 Summary results for mean difference of output and inputs of SHCFs

Smallholder coffee characteristics	Participants (n = 87) Mean	Non-Participants (n = 87) Mean	Mean difference	t-statistic
Labor cost	271,542.20	187,351.40	84,190.87***	6.184
Structure of labor	0.16	0.27	−0.11***	−8.703
Fertilizer	1508.45	1064.68	443.77***	5.735
Farming area	5.354368	4.47977	0.89**	2.935
Age of the coffee tree	32.30	35.76	−3.46*	−1.663
Agrochemicals	62133.32	44336.21	17797.11***	5.180
Extension visits	1.48	0.92	0.56**	2.737
Coffee variety	0.40	0.79	−0.39***	−5.698
Cropping system	0.79	0.83	−0.05	−0.779
Yield	1909.22	1340.46	568.76***	5.449

*** 1% level of significance, **5% level of significance, *10% level of significance
Source: Authors computation, 2023

gender has a positive correlation with participants *SHCFs* in credit scheme. Further, participant *SHCFs* were more educated than non-participants *SHCFs*.

In Table 2, the mean difference of the cost of labor (KShs. 84,190.87), fertilizer (443.77 Kg), agrochemicals (KShs. 17,797.11) and yield (568.76 Kg) was statistically significant at a 1% level. Further, each of these four variables (cost of labor, fertilizer, agrochemicals and yield) had a positive correlation with *SHCFs* participating in the credit scheme. Yield is a common yardstick used to assess the performance of agricultural activities and the mean difference indicates that the *SHCFs* participating in credit scheme obtained higher yields than non-participating *SHCFs*. The size of land under coffee cultivation and the number of extension visits for participants were more than non-participants by 0.89 ha and 1 (~0.89) and it was significant at a 5% level. The non-participating *SHCFs* had a 11% more of their family members in their labor structure than participating *SHCFs*. Further, the age of trees maintained by the non-participating *SHCFs* was three and a half (3.46) years more than the participating *SHCFs*. Nevertheless, although the mean difference of crop variety is statistically significant at a 1% level, it has a negative value (−0.39) with *SHCFs* participating in the credit scheme. This might be because the seedlings might be more expensive than the traditional variety and the biological dimension between planting and the first harvest. There was no significant difference in the cropping system between the *SHCFs* participants and non-participants of the credit program.

4   Results and Discussion

4.1   Hypothesis Testing for Technical and Scale Efficiency

To find out whether mean *TE* was statistically different across the *PF* and *NPF* frontiers, a Kruskal Wallis Test was undertaken. The null hypothesis that means *TE* of *PF* and *NPF* was not significantly different from each other was tested. From Table 3, the result shows that the mean *TE* was statistically different across the *PF* and *NPF* given that the null hypothesis ($p - \text{value} = 0.028$) was rejected at a 5% level of significance. This suggests that efficiencies between *PF* and *NPF* is different which paves way for the computation of *TGR* between *PF* and *NPF*.

4.2   Pooled and Regional Meta-Frontiers for Participating and Non-Participating Farmers in the Credit Program

Table 4 summarizes meta-frontier efficiencies (MFE) results for *PF* and *NPF* for the pooled data. The *TE* of *PF* and *NPF* was 0.674 and 0.636 respectively.

Table 4 provides the regional efficiencies (RE) and *TGR* of *PF* and *NPF*. In general, a regional frontier that overlaps with the meta-frontier indicates a *TGR* that is equal to 100%. However, the mean *TGR* estimate for *PF* is 0.969, suggesting that the maximum output that is feasible for a farmer with credit is only about 97% of the output that could be realized using the technology represented by the meta-frontier. Therefore, a higher *TGR* value of 97% infers a lesser technology gap between the *PF* frontier (Region 1) and the meta-frontier. Nevertheless, *NPF* produces coffee outputs under conditions that are more limiting than *PF* due to poor access to credit. As a result, a mean *TGR* of 0.747 shows that *NPF* could, at best, produce only 75% of the coffee output that could be obtained using the limited technology or input. Hence, a lower *TGR* value of 75% infers a higher technology gap between the *NPF* frontier (Region 2) and the meta-frontier. Consequently, *TGR* results indicate that *PF* were technically efficient than *NPF* given the very small gap between Region 1 and meta-frontier. On the other hand, *NPF* operate with a higher *TE* and are far away from the meta-frontier. So, to improve their performance, it is essential for *NPF* to follow a strategy that shifts the Region 1 frontier approaching the meta-frontier. Consequently, the *NPF* frontier is more likely to move towards the meta-frontier through accessing agricultural credit to acquire and utilize optimum inputs and new applicable innovative technologies. These results are echoed by Majiwa and Mugodo (2018) who indicate that different regions exhibit different result

Table 3 Hypothesis testing results for technical

Variable	$p - \text{value}$	Conclusion
Technical efficiency	0.0278	Reject

Source: Authors computation, 2023

Table 4 Meta-frontier regional efficiencies estimates from pooled data

	Participating Farmer (Number of DMUs)					Non-Participating Farmer (Number of DMUs)				
	2017	2018	2019	Total	%	2017	2018	2019	Total	%
<0.1	0	0	0	0	0.0	12	0	0	12	4.6
0.1–0.1999	3	0	0	3	1.1	20	0	0	20	7.7
0.2–0.2999	11	0	0	11	4.2	13	2	1	16	6.1
0.3–0.3999	7	6	0	13	5.0	13	0	2	15	5.7
0.4–0.4999	15	14	0	29	11.1	8	1	1	10	3.8
0.5–0.5999	7	16	1	24	9.2	8	4	2	14	5.4
0.6–0.6999	3	24	10	37	14.2	4	7	4	15	5.7
0.7–0.7999	12	14	37	63	24.1	1	26	18	45	17.2
0.8–0.8999	14	13	38	65	24.9	2	44	49	95	36.4
0.9–0.9999	15	0	1	16	6.1	6	3	10	19	7.3
1	0	0	0	0	0.0	0	0	0	0	0.0
Mean	0.6746					0.6368				
Std Dev	0.1889					0.2728				
Std Error	0.0117					0.0169				
Minimum	0.1114					0.0432				
Maximum	0.9503					0.9701				
Median	0.7279					0.7615				

NB-% of the Total Number of DMUs
Source: Authors computation, 2023

technology gaps depending on their level of access to technological set used for production (Table 5).

These findings have a significant policy implication linked to the prospects to minimize the productivity gap by increasing *TE* in coffee husbandry. For *PF* in the short run, it is anticipated that *TE* will be responsive to optimum use of the available technological set. But at the same time, this region is, on average, close to the meta-frontier and to move forward is expected to involve more agricultural credit to develop and implement modern technologies. This result is consistent to Adeleke et al. (2021) who attributes different sub-optimal production of food crops to different heterogeneity of technology used by farmers in different zones. As a result, apart from sensitizing farmers to use sound agricultural technology (Aloysius et al., 2021), there is need to facilitate farmers to access credit in order to acquire these technologies.

4.3   Results for Determinants of **TE**

Table 6 summarizes the technical efficiency estimates from one-part (linear models) and two-part FRM models. In the one-part models (linear models), education of the household head, age of the farmer, number of extension visits, coffee variety and

Table 5 Regional meta-frontier efficiencies estimate for participating and non-participating farmers

	Participating Farmer (Number of DMUs)					Non-Participating Farmer (Number of DMUs)				
	2017	2018	2019	Total	%	2017	2018	2019	Total	%
<0.1	2	0	0	2	0.8	0	0	0	0	0.0
0.1–0.1999	8	0	0	8	3.1	0	0	0	0	0.0
0.2–0.2999	11	0	0	11	4.2	0	0	0	0	0.0
0.3–0.3999	8	1	2	11	4.2	3	0	0	3	1.1
0.4–0.4999	12	1	0	13	5.0	8	0	0	8	3.1
0.5–0.5999	10	0	1	11	4.2	3	0	0	3	1.1
0.6–0.6999	8	6	4	18	6.9	8	1	0	9	3.4
0.7–0.7999	10	34	48	92	35.2	9	21	0	30	11.5
0.8–0.8999	10	45	32	87	33.3	13	51	33	97	37.2
0.9–0.9999	8	0	0	8	3.1	43	14	54	111	42.5
1	0	0	0	0	0.0	0	0	0	0	0.0
Mean	0.695					0.852				
Std Dev	0.199					0.118				
Std Error	0.012					0.007				
Minimum	0.064					0.306				
Maximum	0.949					0.972				
Median	0.776					0.892				
TGR	0.969					0.747				

NB-% of the Total Number of DMUs
Source: Authors computation, 2023

crop system was significant at the 5% and 10% levels, thereby explaining why some farmers were efficient. On the other hand, gender did not explain the inefficiency since the variables were not statistically significant. Similarly, logit and cloglog model at the 5% and 10% levels of significance demonstrate that household head, age of the farmer, number of extension visits, coffee variety and crop system explained the inefficiency. However, gender did not explain the inefficiency since the variable was not statistically significant. At the 10% and 5% significance levels for the logit and cloglog model, household head, age of the farmer, number of extension visits, coffee variety and crop system explained the inefficiency.

An examination of the second part of the two-part models showed that the education of the household head, age of the farmer, number of extension visits, coffee variety and crop system was the reason why some farmers were more efficient (at a 5% significance level for the cloglog and at 10% significance level for the logit model). In examining why some farmers were inefficient, their gender reduced their efficiency scores at the 5% and 1% significance level for all the models. Further, education of household head, age of the farmer, number of extension visits, coffee variety and crop system reduced their inefficiency at the 5% and 10% significance levels for all the models.

Table 6 Summary results for determinants of TE

| Variable | One-part models | | | | Two-part models | | | | | | |
| | | | | | 1st Part | | 2nd Part | | | | |
	Linear	Tobit	logit	loglog	logit	cloglog	Linear	logit	Probit	loglog	cloglog
Intercept	0.671***	0.712***	0.792***	0.959***	0.401	0.270	0.597***	0.331**	0.208**	0.610***	−0.128
	(0.033)	(0.145)	(0.156)	(0.122)	(0.663)	(0.609)	(0.216)	(0.133)	(0.083)	(0.101)	(0.090)
Gender	−0.018	−0.075	−0.101	−0.075	−1.211***	−1.110***	−0.033	−0.068	−0.042	−0.056	−0.040
	(0.018)	(0.079)	(0.086)	(0.068)	(0.346)	(0.318)	(0.075)	(0.066)	(0.041)	(0.050)	(0.045)
Education	0.037***	0.156***	0.165***	0.123***	0.157	0.177	0.136***	0.175***	0.109 ***	0.131***	0.121***
	(0.010)	(0.036)	(0.039)	(0.030)	(0.186)	(0.168)	(0.040)	(0.035)	(0.021)	(0.026)	(0.023)
Age of farmer	−0.001	−0.003	−0.004*	−0.002	−0.047***	−0.046***	−0.004	−0.0004	−0.0002	−0.0002	−0.0004
	(0.0005)	(0.002)	(0.002)	(0.001)	(0.013)	(0.013)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Extension visits	0.011**	0.047**	0.044***	0.033**	0.145	0.101	0.049*	0.069***	0.043***	0.051***	0.049 ***
	(0.005)	(0.019)	(0.021)	(0.016)	(0.105)	(0.097)	(0.025)	(0.016)	(0.010)	(0.011)	(0.011)
Crop system	0.032*	0.135*	0.150**	0.118**	1.363***	1.259***	0.134*	0.020***	0.012***	0.016***	0.012***
	(0.017)	(0.071)	(0.076)	(0.058)	(0.470)	(0.447)	(0.077)	(0.063)	(0.039)	(0.047)	(0.043)
Variety	0.077***	0.334***	0.362***	0.274 ***	0.739*	0.792**	0.243***	0.341***	0.213***	0.256***	0.234***
	(0.023)	(0.088)	(0.096)	(0.078)	(0.396)	(0.354)	(0.077)	(0.081)	(0.050)	(0.063)	(0.053)

*** 1% level of significance, **5% level of significance, *10% level of significance
Source: Authors computation, 2023

The result indicates that the gender of the coffee farmer has a positive impact on efficiency. This means that males were more efficient in coffee farming than females. The finding is consistent with other studies (Koirala et al., 2014; Gebre et al., 2021). For example, using 2012 farm-level cross-sectional data from the Central Luzon Loop Survey, Koirala et al. (2014) empirically demonstrate that females are inefficient in farming (Koirala et al., 2014). Research shows that overall, women provide the bulk of low-paid labour in the coffee sector, yet it is men who have control over the majority of the profits (Dijkdrenth, 2015; Lyon et al., 2017; Kangile et al., 2021). Men also control most productive assets, often hold management positions in cooperatives, have more access to credit and market information. This has been caused mostly by deeply rooted societal biases that result in many hindrances for females compared to males (Kangile et al., 2021; ICO, 2018). These inequalities precipitate inefficiencies in coffee productivity because females, who execute vital farm tasks, are not accessing the resources critical in maintaining or improving their output. However, numerous quantitative studies of discrepancy in agricultural productivity demonstrate that males and females are equally efficient farmers when gender differences in respect to utilization of agricultural inputs are normalized (Aguilar et al., 2015; Quisumbing et al., 2014).

The level of education of the farmer was found to have a significant positive impact on efficiency. For instance, after reviewing 18 different types of research conducted in 13 developing countries, Lockheed et al. (1980) also found that the level of education has a positive impact on efficiency and a mean of 4 years of education increases output by 7.4%. This is true especially in technological advancement settings or contemporary conditions such as access to credit (Eisemon & Nyamete, 1988; Ram, 1980). This is maybe credited to skills and knowledge attained from formal education. Such skills assist farmers to develop capacities to efficiently employ the latest technological inputs set that boost agricultural productivity. Other researchers note that empirically there is either no sufficient evidence or weak evidence to demonstrate that education certainly has a positive impact on agricultural productivity (Ferreira, 2018). They argue that access to innovative technologies is also required to synergize education to realize higher agricultural productivity.

The mean age of farmers was 50 years is expected because most youths don't own land and those who have access to land are not interested in farming coffee because they perceive it as not "sexy" or "cool". However, research has shown that youthful farmers often embrace the latest technologies more rapidly than elderly farmers (Nchare, 2007). Consequently, the result of this study indicates that the age of the farmer was found to have a significant negative impact on efficiency. The result is consistent to Wambua et al. (2021) who found that the age of the farmer increased inefficiency among a sample of 376 farmers from 6 cooperative societies. The number of extensions visits was found to have a significant positive impact on efficiency. This is because farmers need information on inputs, sound agronomic practices, expected changes of prices of their products and weather forecasts among others to be efficient (Aker, 2011). Similar results were reported by Ngango and Kim (2019) who found that the number of extension visits by farmers increased inefficiency among a sample of 320 in Rwanda Northern Province.

The result indicates that the crop system has a significant positive impact on efficiency. This means that monocropping was more efficient in coffee farming than intercropping. However, intercropping of cash crops with food crops is deeply entrenched by smallholders' farmers since it influences technical efficiency in the farming operations, productivity gains, acts as a buffer against uncertainties and risks for food security and farm returns (Coelli & Fleming, 2004). The result is consistent with past studies in Colombia and Costa Rica that indicate that monocropping can improve harvested green coffee on average from 575 kg/ha to more than 1250 (Bertrand et al., 2011). On contrary, Sarmiento-Soler et al. (2020) and Acosta-Alba et al. (2020) reported dissimilar results. Sarmiento-Soler et al. (2020) sampled 810 coffee trees from 27 farms in Mt. Elgon in Uganda to investigate the effect of the cropping system on coffee output and found that coffee is intercropped with bananas (which provides intermediate shade) had a higher output per ha than monocropping.

Adoption of improved coffee variety has been established to be crucial to boosting coffee productivity, particularly in Brazil, Colombia and Vietnam. In this study, the farmers who adopted improved coffee varieties (Batian and Ruiru 11) were more efficient than the coffee farmers who planted traditional varieties. The finding is consistent with the majority of the extant literature which finds improved coffee varieties are more efficient than traditional varieties (Ngango & Kim, 2019). This is because traditional varieties are more susceptible to fungal diseases (coffee berries disease (CBD) and coffee leaf rust (CLR)) and insect pests (Wambua et al., 2021). CBD can wipe 100% of the crop while CLR and pests such as berry borer can reduce the productivity of coffee by 30–35% (Alwora & Gichuru, 2014; Lechenet et al., 2017). Thus, investing in improved coffee varieties is instrumental in enhancing coffee productivity.

5   Conclusion and Recommendations

The main objective of this study is to determine the impact of agricultural credit on coffee productivity in Kiambu in Kenya. Meta-frontier analysis was used to estimate the TE and *TGR* for participating (*PF*) and non-participating (*NPF*) coffee farmers in the credit program. Contrary to previous notion emanating from some previous research findings, the *TGR* results empirically demonstrate that agricultural credit has significant impact on coffee efficiency. The *TGR* estimates validate that coffee productivity by *PF* operated on a loftier frontier in comparison to *NPF*. This stalks from the fact that access to credit would results to acquisition of optimal combination of inputs and lead to improvements in technical efficiency and result into a higher output level. The better timing of farm operations (for instance, planting, irrigation, fertilizer application and weeding) may increase real output and actually reduce the gap with the frontier. The Decision-Making Unit inefficiency estimates indicate that the credit program interventions aimed at efficiency improvement in *NPF* should be targeted at enhancing farmers' access to optimal combinations of inputs and

advisory services through extension visits. Consequently, this paper recommends policies tailor-made to promote credit access by smallholder farmers to improve *TE* and *TGR*.

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