Journal of Economics and Behavioral Studies (ISSN: 2220-6140)
Vol. 18, No. 3, pp. 29-42, 2026

Estimating Technical Efficiency and Yield Losses Among Smallholder Coffee Farmers in Uganda: A Stochastic Frontier Analysis

*Phiona Natuha[1,2], Onesmo Selejio[3], Aloyce S Hepelwa[4]
[1]School of Economics, University of Dar es Salaam, Dar es Salaam, Tanzania
[2]Makerere University Business School, Kampala, Uganda
[3]Department of Applied Economics, University of Dar es Salaam, Dar es Salaam, Tanzania
[4]Department of Agricultural Economics and Business, University of Dar es Salaam, Dar es Salaam, Tanzania
E-mail: *natuhaphiona@gmail.com, oselejio2@gmail.com, ahepelwa@yahoo.com
Corresponding Author: Phiona Natuha

Abstract: This study examines technical efficiency (TE) and identifies determinants of inefficiency among smallholder Robusta and Arabica coffee farmers in Uganda while quantifying yield losses associated with inefficiency. The study utilized pooled cross-sectional data from 1,283 smallholder coffee farmers drawn from three survey waves (2015/2016, 2018/2019 and 2019/2020) of the Uganda National Panel Survey (UNPS). A one-step Stochastic Frontier Analysis (SFA) with a translog production frontier is applied to jointly estimate technical efficiency and its determinants. The approach further quantifies yield losses attributable to inefficiency, disaggregated by coffee farmer type. Mean technical efficiency is 76.5 percent for Robusta and 73.1 percent for Arabica, implying potential output gains of 23.5 percent and 26.9 percent, respectively, using existing inputs. Efficiency variations are associated with group membership, off-farm income, cropping systems, soil type, and plot proximity, with effects differing by coffee type. Yield losses due to inefficiency averaged 113.0 kilograms for Robusta and 138.6 kilograms for Arabica per farmer. Policies should promote location-specific agronomic practices like intercropping and soil fertility management tailored to coffee type and ecological conditions. Capacity-building initiatives including input use, pest and disease management, and sustainable farming can reinforce efficiency gains. Supporting farmer groups and cooperatives could enhance knowledge sharing, coordinated input use, and market access, thereby reducing transaction costs and improving resource-use efficiency. The study employs a one-step SFA to estimate technical efficiency separately for Robusta and Arabica farmers, incorporating farm-level, institutional, and environmental factors to examine efficiency differentials across coffee types in Uganda.

Keywords: *Technical efficiency, Stochastic frontier analysis, Frontier Output, Smallholder coffee farmers, Yield losses*

1. Introduction

Globally, coffee is a high-value commodity supporting over 125 million livelihoods across more than 60 tropical countries and providing important export earnings for developing economies (FAOSTAT, 2023). Production is dominated by Arabica and Robusta, accounting for about 60 percent and 40 percent of global output, respectively (ICO, 2020). Despite rising demand, smallholder farmers, who produce nearly 80 percent of global coffee, remain exposed to price volatility, rising input costs, and climate risks. (Massrie, 2025). Africa contributes about 10–12 percent of global production, led by Ethiopia, Uganda, Côte d'Ivoire, Tanzania and Kenya, and supplies both Arabica and Robusta to international markets. Uganda ranks second in Africa after Ethiopia, largely due to its comparative advantage in Robusta (ICO, 2023). However, low productivity, ageing trees, production variability and limited value addition continue to constrain the sector (Addisie & Tebarek, 2023; Kawuma, 2016).

Uganda's coffee sub-sector is a cornerstone of the national economy, sustaining more than five million livelihoods and contributing about 16-20 percent of the country's foreign-exchange earnings (ILO, 2024; UCDA, 2023a). Recognizing this strategic importance, the Government of Uganda, through the Uganda Coffee Development Authority (UCDA), launched the 2017 Coffee Roadmap, which aims to raise annual coffee production to 20 million 60-kg bags by 2030. This target is reinforced by complementary initiatives such as Operation Wealth Creation, the Coffee Replanting program and the Parish Development Model, all designed to enhance on-farm production and productivity (UCDA, 2023b). Despite these ambitious interventions, recent trends raise concerns about the sector's long-term sustainability. Uganda's national coffee production expanded steadily from 166,968 metric tons in 2008 to a peak of 414,007 tons in 2021 before declining to

384,000 tons in 2022 (FAOSTAT, 2023; UBOS, 2023). Over the same period, average yields per hectare exhibited a fluctuating trend from 0.6125 tons in 2010 to 0.5304 tons in 2015, then increased to 0.5798 tons in 2019 and declined again to 0.5473 tons in 2023 (FAOSTAT, 2023; UBOS, 2023). This persistent low and unstable productivity could reflect underlying inefficiencies in resource use and structural constraints that hinder farmers from achieving optimal technical efficiency levels.

While previous studies have examined technical efficiency among coffee farmers, they have largely focused on the production-side performance of Arabica coffee systems (Ngango & Kim, 2019; Sebatta et al., 2020; Tamirat & Tadele, 2023). As a result, the efficiency dynamics of Robusta coffee, Uganda's dominant variety, remain underexplored (ILO, 2024). This study extends beyond single-variety assessments by comparing Robusta and Arabica farmers, recognizing that their distinct agroecological conditions, production systems, and input-use requirements may shape different efficiency outcomes. Understanding farmers' technical efficiency is crucial for policymakers to prioritize interventions that improve agricultural productivity. The remainder of the paper is organized as follows. Section 2 reviews related literature. Section 3 presents the methodology, including data sources, sample selection, sampling strategy, and the analytical framework for estimating technical efficiency and its determinants. Section 4 reports the empirical results on technical efficiency, associated yield losses, and drivers for inefficiency. Section 5 concludes and presents policy implications for improving technical efficiency.

2. Literature Review

Empirical evidence demonstrates that technical efficiency (TE) among smallholder coffee farmers is generally substantial but exhibits considerable variation across regions and production systems. In Uganda, for instance, Sebatta et al. (2020) reported that Arabica coffee–banana farmers in the Mt. Elgon region realized only around 50 percent of their potential output, with efficiency limited by low input use, inadequate soil fertility, and labor constraints. Similarly, Bongers et al. (2015) identified substantial differences in productivity across coffee-based farming systems, noting that banana–coffee systems achieved higher yields per tree, indicative of greater technical efficiency. In contrast, van Asten et al. (2011a) found that coffee yields were largely unaffected by intercropping in both Arabica and Robusta farms, highlighting that the effects of cropping arrangements on efficiency are highly context-dependent. These findings motivate the inclusion of cropping system and soil type in the inefficiency model to capture differences in farm management and production conditions.

Cross-country studies indicate that human capital and institutional factors play a key role in technical efficiency. In Rwanda, Ngango and Kim (2019) reported that education, access to extension services, adoption of improved coffee varieties, monocropping, and land consolidation positively influenced farm efficiency. Consequently, schooling and training are expected to reduce inefficiency by enhancing farmers' technical knowledge and ability to apply recommended production practices. In Ethiopia, Ajema and Nigussie (2021) found that coffee–enset intercropping improved resource-use efficiency and land productivity. The age of coffee trees is a recognized determinant of productivity, with older trees generally associated with lower technical efficiency (Nalunga, 2021). However, some studies report mixed effects, indicating that the impact may vary with farm and household characteristics and environmental conditions (Nado et al., 2021). Relatedly, off-farm income and household characteristics have also been linked to efficiency outcomes. Getachew and Temesgen (2018) observed that off-farm income, household demographics, and plot distance positively impacted technical efficiency among Ethiopian coffee farmers, while female-headed households demonstrated higher efficiency, likely due to better resource management. Similar positive effects of off-farm income have been documented in other contexts (Abebe, 2014; Tamirat & Tadele, 2023). These findings highlight the relevance of household size, plot distance, and tree age in explaining technical inefficiency, while off-farm income reflects the influence of household liquidity and labor allocation on farm efficiency. Membership in cooperatives and access to credit are generally associated with higher technical efficiency (Tambi, 2023). However, in contexts with limited external support, the effects of group membership on efficiency may be insignificant or even negative (Binam et al., 2003; Lutonja, 2023). This variation reinforces the importance of testing the effect of group membership within the Ugandan coffee-farming context.

Despite extensive research, evidence on the determinants of coffee farmers' technical efficiency remains limited and context-specific. Key determinants such as education, extension services, cooperative membership, access to inputs and off-farm income exhibit varying effects across regions, countries and coffee varieties, with few

comparative analyses between Arabica and Robusta producers. Additional factors including age of the tree, household size, farm experience, crop diversification, soil type and plot location also show mixed effects across contexts. Methodological inconsistencies further hinder comparability, as previous studies have primarily employed two-step stochastic frontier approaches using Cobb-Douglas or Translog functional forms alongside DEA, often producing divergent efficiency estimates. To address these limitations, this study employs a single-step stochastic production frontier approach using pooled cross-sectional data across survey waves to jointly estimate the production frontier and the inefficiency effects model.

3. Methodology

Data Sources

This study utilized secondary data from the Uganda National Panel Survey (UNPS) implemented under the World Bank's LSMS-ISA program. The analysis draws on the 2015/16, 2018/19 and 2019/20 survey waves, which contain harmonized agricultural modules with information on coffee production, input use and quantities harvested. These waves were selected to enable consistent analysis of coffee variety-specific performance among farming households. The three waves were pooled, yielding a sample of 1,283 coffee-farming households: 443 from 2015/16, 284 from 2018/19 and 556 from 2019/20, providing a larger and more representative sample for the empirical analysis. Pooling of data was adopted because panel diagnostics revealed that the household identifier for the coffee households did not provide repeated observations across the selected waves, limiting the applicability of panel estimation.

Sample Size and Sampling Strategy

The study utilized a subsample of coffee-farming households drawn from the UNPS for 2015/16, 2018/19 and 2019/20. These were selected from the agricultural modules based on the study's inclusion criteria, focusing specifically on Robusta and Arabica coffee farmers. The resulting sample comprised 1,283 coffee-farming households, including 443 in 2015/16, 284 in 2018/19, and 556 in 2019/20. Of the total sample, 567 were Robusta, and 716 were Arabica farmers. The selected sample provided the basis for the analysis of technical efficiency and its determinants across the two coffee varieties.

Analytical Framework of Technical Efficiency

The concept of technical efficiency was first introduced by Farrell (1957) who measured a farm's actual output relative to the output of an efficient "frontier" farm using the same set of inputs. Technical efficiency can be estimated using several approaches, including Data Envelopment Analysis (DEA), the Malmquist Index, and stochastic production frontiers (SPF). DEA and the Malmquist Index are non-parametric and cannot account for random shocks such as weather events or pest outbreaks. In contrast, the SPF is parametric and addresses technical inefficiency while explicitly incorporating random shocks through a "composite error" structure, decomposing the error term into a stochastic component and an inefficiency component. This makes the SPF approach relevant for Uganda's coffee sector where deviations from the production frontier arise from both farm-specific factors and external environmental influences. Following Aigner et al. (1977), the stochastic frontier production function model is specified as:

$$Y_i = f(X_{ji}, \beta, \tau) \exp(\varepsilon_i) \quad \text{i = 1,..., N} \qquad (1)$$

Where Y_i measures the quantity of output produced by the *i*-th farming household head; X_j is the amount of input *j* used in the production of farm *i*, β is a vector of parameters to be estimated and τ represent dummies capturing the effect of topography and use of improved seedlings. According to Aigner et al. (1977), ε_i is an error term composed of:

$$\varepsilon_i = v_i - \mu_i \qquad (2)$$

where v_i is the systematic random error caused by factors outside the scope of the farmers, including weather, natural disasters, measurement errors, and other statistical noise. μ_i represents the one-sided disturbance term used to represent inefficiency factors and is assumed to follow a truncated normal distribution, N (0, ${\delta_\mu}^2$).

The variation in technical inefficiency across farms can be estimated simultaneously within the stochastic frontier framework using a maximum likelihood approach. The technical inefficiency component is Battese and Coelli (1995) specified as follows:

$$\mu_i = \delta z_i + w_i \qquad (3)$$

Where z_i is a vector of variables including socioeconomic, farm-specific characteristics, institutional and environmental factors, δ refers to the parameters to be estimated, w_i vector of unobservable random variables. Thus, the farm-specific technical efficiency (TE) can be defined as the ratio of the observed output (Y_i) to the corresponding frontier output (Y_i^*) conditional on the levels of inputs used by the *i*-th farming household head, given as:

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{E(y_i|\mu_i, x_i)}{E(y_i|\mu_i = 0, x_i)} = E[\exp(-\mu_i)\,|\varepsilon_i] \quad (4)$$

Where ε_i is the standard error term, while μ_i is the measure of efficiency that follows a truncated normal distribution such that $0 \leq TE \geq 1$. Hence, if coffee farmers achieve their maximum output, then they would be technically efficient, and this means that. μ_i = 0. The δ parameters in equation (3) indicate the effects of variables in z on technical inefficiency, where a negative coefficient implies a positive influence on TE and a positive coefficient implies a negative influence on TE.

Empirical Estimation of Stochastic Frontier Production Function

In this study, a Stochastic Production Frontier Approach (SPFA) was employed to estimate the technical efficiency of coffee farmers using pooled cross-sectional data from the UNPS waves of 2015/16, 2018/19 and 2019/20. This approach was adopted due to its ability to accommodate the stochastic nature of agricultural production by decomposing the error term into random noise and technical inefficiency. The approach provides consistent estimates of farm-specific technical efficiency while accounting for exogenous shocks that may affect output of the farmer (Aigner et al., 1977; Battese & Coelli, 1995; Coelli et al., 2005). The empirical translog stochastic model of sampled coffee farming households was specified as equation (5):

$$\text{Ln}\, Y_i = \beta_0 + \sum_{j=1}^{4} \beta_j \,\text{Ln}\, X_{ji} + \frac{1}{2}\sum_{j=1}^{4}\sum_{k=1}^{4} \beta_{jk}\left(\text{Ln}\, X_{ji}\, \text{Ln}\, X_{ki}\right) + \sum_{i=1}^{2} \tau_i\, dummies + v_i - u_i \quad (5)$$

Where:

Y_i= represents the total amount of ripe cherries (in kilograms) produced by the *i*-th farming household head, X_{ji}= inputs ($j = 1, \ldots, 4$) is a set of the amounts of production inputs (X_1 =Land size, X_2 = Hired labor, X_3 =Fertilizer and X_4= pesticide), β's are parameters of the inputs,τ_1 = coefficient of topography (1= gentle slope) and τ_2= coefficient for improved seedling (1= use of improved seedling), v_i is the random error and u_i is the error term that reflects the technical inefficiency term. All variables in the translog production frontier were mean-centred before estimation to reduce multicollinearity among quadratic and interaction terms and allow the first-order coefficients to be interpreted as elasticities evaluated at the sample mean. The appropriate functional form in equation (5) was tested using the log-likelihood ratio test (LR) statistic in equation (7). The empirical technical inefficiency effects u_i is specified as:

$$\mu_i = \delta_0 + \delta_1 Z_{1i} + \delta_2 Z_{2i} + \delta_3 Z_{3i} + \delta_4 Z_{4i} + \delta_5 Z_{5i} + \delta_6 Z_{6i} + \delta_7 Z_{7i} + \delta_8 Z_{8i} + \delta_9 Z_{9i} + \delta_{10} Z_{10i} + \varepsilon_i \quad (6)$$

Where δ's are unknown parameters to be estimated and ε_i is the disturbance term. The expected signs of these technical inefficiency variables are summarized in Table1.

Table 1: Description and Measurement of Variables in the Inefficiency Model

Variable	Definition	Measurement Unit	Expected Sign (δ)
Z_1	Sex of the household head	1= Female	+
Z_2	Household Size	Number	-
Z_3	Schooling	Number of years	-
Z_4	Distance between home and plot	1=Less than 1 km	-
Z_5	Cropping system	1= Mixed	-
Z_6	Tree Age	Number of years	+
Z_7	Soil Type	1= Sandy-Loam	+
Z_8	Membership in a group	1= Member	-
Z_9	Farmer trainings	1=Participated	-
Z_{10}	Income sources	1= Off-farm income	-

Whether or not the inefficiency effects existed was also verified using the log-likelihood ratio (LR) test statistic computed from equation (7) as:

$\chi^2 = -2[\log(L(H_0)) - \log(L(H_1))]$ (7)

Where χ^2 has a chi-square distribution; $L(H_0)$ and $L(H_1)$ denote the values of the likelihood function under the null hypothesis (Cobb-Douglas Production Frontier) and the alternative hypothesis (Translog Production Frontier model), respectively.

The parameters of equations (5) and (6) are estimated simultaneously using a one-step maximum likelihood estimation with Frontier 4.1 (Coelli, 1996). The total variance is decomposed as:

$\sigma^2 = \sigma_v^2 + \sigma_u^2,\ \gamma = \frac{\sigma_u^2}{\sigma^2},\ 0 \leq \gamma \leq 1$ (8)

Where σ^2 represents the combined variance from random noise (σ_v^2) and technical inefficiency (σ_u^2). The parameter γ captures the relative contribution of inefficiency to output variation. A value near 0 indicates that deviations from the production frontier are primarily due to stochastic factors, whereas a value close to 1 implies that inefficiency is the dominant source of variation.

4. Results and Discussion

Socioeconomic, Farm-Level, Institutional and Environmental Factors

Results in Table 2 reveal the characteristics of Robusta and Arabica coffee farmers in Uganda. Participation of female-headed farming households is comparable across the two production systems, representing 27.69 percent of Robusta and 29.75 percent of Arabica farmers, indicating a similar gender distribution in both production contexts. A higher proportion of Arabica farmers (57.3%) cultivate plots on suitable sandy-loam soils compared to 45.4 percent of Robusta farmers, reflecting agro-ecological differences between highland Arabica and lowland Robusta regions (Jena et al., 2012). In contrast, group membership is almost similar across both groups, indicating widespread integration into farmer organizations (Ssebunya et al., 2019). Distance to coffee plots shows a significant variation, with 46.51 percent of Arabica farmers reporting shorter travel times compared to 38.45 percent of Robusta farmers. This is in agreement with potential delays reported in field management for Robusta farmers (Chiputwa et al., 2015).

Cropping systems differ, as 87.4 percent of Arabica farmers are more likely to practice mixed cropping systems compared to 78.7 percent of Robusta farmers (see Table 2). This could be attributed to Robusta farmers' emphasis on yield stability and risk mitigation in contrast to Arabica farmers' focus on specialized high-quality plots for export markets. Participation in agricultural training is significantly higher among Arabica farmers, with 66.8 percent involved compared to 58.4 percent of Robusta farmers. This suggests that Arabica-growing regions benefit more from targeted capacity-building programs aligned with government and donor initiatives to improve coffee quality and export competitiveness (Chiputwa et al., 2015). Finally, off-farm income is also more prevalent among Arabica farmers (60.61%) compared to Robusta farmers (50.79%) at the 1 percent level. This result aligns with findings by Wairegi et al. (2018) who highlight that diversification of income sources is a common strategy among Arabica farmers to enhance household resilience and financial stability.

Table 2: Summary Statistics of variables used in the study

Variables	Robusta (n=567)		Arabica (n=716)		P-value
	Percent (%)		Percent (%)		
Sex of household head	27.69		29.75		0.419
Soil Type	45.39		57.32		0.000
Membership in group	52.03		51.12		0.746
Distance to plot	38.45		46.51		0.004
Cropping system	78.66		87.43		0.000
Farmer trainings	58.38		66.76		0.002
Income sources	50.79		60.61		0.000
	Mean	Std.Dev	Mean	Std.Dev	
Schooling	5.57	3.24	6.05	3.18	0.011
Household size	5.54	3.77	5.03	2.59	0.001
Tree age	19.72	7.44	12.45	4.44	0.000

Source: Author's own computation from UNPS data

Results in Table 2 indicate that Arabica farmers have slightly higher schooling levels, averaging 6.1 years compared to 5.6 years for Robusta farmers, a difference significant at the 5 percent level. However, the average years of schooling for both groups remain below Uganda's national average of 6.2 years, indicating relatively low educational attainment among coffee-farming household heads (UNICEF, 2024). However, household sizes for both farmer categories exceed Uganda's national average of 4.6 persons, with Robusta having a significantly larger average household size (5.5 persons) compared with Arabica households (5.0 persons)(UBOS, 2024). Tree age also differs significantly between the two coffee types, with Robusta farms having older trees (20 years) than Arabica (13 years). This difference could be attributed to variation in varietal longevity, replanting cycles, and farm management practices. Robusta trees are generally retained for longer periods due to their resilience and relatively stable yields, whereas Arabica farms tend to undergo more frequent replanting to sustain productivity (Wintgens, 2012).

Analysis of Coffee Output and Input Use among Robusta and Arabica Farmers

Table 3 presents summary statistics for key farm inputs and outputs among Robusta and Arabica coffee farmers. On average, Robusta farmers harvested 380.79 kilograms (Kgs) of coffee, which is significantly higher than the 301.59 kg harvested by Arabica farmers ($p < 0.01$). This difference in output may be attributed to variations in agronomic practices. Robusta is typically planted at higher densities, regularly pruned, and is more resilient to challenging weather conditions, allowing it to thrive in hotter climates, while Arabica's shade tolerance and pest susceptibility can limit yields (ILO, 2024). The average land area under coffee cultivation was slightly larger for Robusta farmers (1.70 acres) than for Arabica farmers (1.58 acres), although this difference was not statistically significant. Similarly, total hired labor measured in man-days was slightly higher for Arabica farmers (1.8 days) than for Robusta farmers (1.6 days), and the difference was not significant. These results indicate that variations in farm size and labor allocation are relatively minor between the two coffee types and may not be the primary drivers of observed yield differences.

Table 3: Descriptive Statistics for Farm Output and Inputs used in Coffee Production

Variables	Robusta (n=567)		Arabica (n=716)		P-value
	Mean	Std.Dev	Mean	Std.Dev	
Quantity of Coffee harvested (kgs)	380.79	335.53	301.59	198.14	0.000
Land size planted (acres)	1.70	1.82	1.58	1.45	0.162
Total Hired Labor (man-days)[1]	1.57	6.15	1.83	6.14	0.453
Quantity Fertilizer (kgs)	31.82	124.00	73.77	186.79	0.000
Quantity Pesticide(litres)	0.61	2.44	0.48	2.02	0.301

Source: Author's own computation from UNPS data

Input use patterns further reveal notable differences in management strategies. Fertilizer application was significantly higher among Arabica farmers (73.8 kg) than among Robusta farmers (31.8 kg), reflecting more intensive input use in Arabica production. The observed pattern suggests that Arabica farmers may rely more heavily on fertilizer to enhance yields, whereas Robusta farmers may achieve higher output with relatively lower fertilizer inputs, possibly due to differences in crop responsiveness, soil fertility, or pest management practices.

[1] Note: Hired labour computed included work days from children, women and men based standard conversion by Pothin et al. (2025). Family labour was only captured in the wave of 2019/20 and excluded in 2015/16 and 2018/19 and thus not used in this analysis.

Model Selection and Existence of Inefficiency Effects

The first hypothesis tested the appropriateness of the Cobb-Douglas production frontier specification. Given the boundary restrictions associated with the null hypothesis in the LR test, the conventional chi-square distribution is not appropriate. Therefore, a mixed chi-square distribution was used to determine the appropriate critical values. The null hypothesis was rejected at the 1 percent level for both coffee varieties (Table 4), supporting the translog specification as a more appropriate representation for the observed data. The second hypothesis tested whether the inefficiency determinants jointly did not affect technical inefficiency. This null hypothesis was also rejected at the 1 percent level, confirming that the ten (10) explanatory variables specified in the inefficiency effects models significantly explain variations in farm-level inefficiency among both Robusta and Arabica coffee-farming households.

Table 4: Hypothesis Tests for Parameters of the SPF and Technical Inefficiency Model

Null hypothesis	LR Statistic	Critical Values	Decision Rule
1. Ho: $\beta_5 = \beta_6 = \cdots = \beta_{16} = 0; i \leq k = 5, \ldots, 16$		**Mixed** $\chi^2_{12,\ 0.01}$	
Robusta farmers	229.836	25.549	Reject Ho
Arabica farmers	229.110	25.549	Reject Ho
2. H0: $\delta_0 = \delta_1 = \cdots = \delta_{10} = 0$		**Mixed** $\chi^2_{10,\ 0.01}$	
Robusta farmers	23.326	22.525	Reject Ho
Arabica farmers	38.556	22.525	Reject Ho
Ho: $\gamma = 0$		**Mixed** $\chi^2_{10,0.01}$	
Robusta farmers	177.555	22.525	Reject Ho
Arabica farmers	213.907	22.525	Reject Ho

***Note*:** Mixed χ^2 Values were taken from Kodde and Palm (1986)

Finally, the third hypothesis tested the absence of inefficiency effects in coffee production, with the null hypothesis specified as H_0: γ = 0 against the alternative H_1: γ ≠ 0. Based on the generalized likelihood ratio (LR) test with the appropriate mixed chi-square distribution, the null hypothesis was rejected at the 1 percent significance level for both Robusta and Arabica coffee farmers (Table 4). This confirms the presence of inefficiency effects and demonstrates the use of the stochastic frontier model over a conventional OLS specification.

Empirical Estimates of the Stochastic Production Frontier and Technical Inefficiency

To identify the factors driving production inefficiency, a technical inefficiency model was jointly estimated with a translog stochastic production frontier using Frontier 4.1 (Table 5). The variance parameters (σ^2 and γ) are highly significant at the 1 percent level for both Robusta and Arabica farmers, confirming the appropriateness of the stochastic frontier framework. This indicates that output deviations are not solely due to random shocks. (Kumbhakar & Lovell, 2000). Robusta farmers exhibited a higher. σ^2 suggesting greater output variability relative to Arabica farmers. The estimated γ values of 0.986 for Robusta and 0.992 for Arabica further indicate that the vast majority of output variation, respectively, is attributable to technical inefficiency rather than stochastic noise, with both estimates significant at the 1 percent level. These findings are consistent with evidence from other coffee-producing countries (Binam et al., 2003). The estimated results for both the production frontier and inefficiency models are presented in Table 5. To facilitate interpretation, the study followed Coelli et al. (2005). All input variables were mean-centred before estimation, allowing first-order coefficients in the translog model to be interpreted as input elasticities evaluated at the sample mean.

The estimated translog production frontiers for Robusta and Arabica farmers in Table 5 reveal differences in input elasticities and productivity drivers. Land has a positive and significant effect on output for both farmer categories at the 1 percent level. This implies that a 10 percent increase in cultivated land area would lead to approximately a 27 percent increase in coffee output, holding all other inputs constant. This finding is consistent with Botiabane et al. (2017) who identified land expansion as a key driver of production, reflecting the extensification pathway common in smallholder farming systems. Elasticity of hired labor for Arabica farmers is negative and significant at the 10 percent level. Specifically, an additional 10 percent increase in hired

labor would lead to an approximate 0.5 percent reduction in coffee output, holding all other inputs constant. Similarly, Bravo-Ureta et al. (2007) noted that labor productivity in smallholder agriculture often declines when farmers increase their dependence on hired workers.

Table 5: Estimated Results for the Translog SPF for Coffee Farmers in Uganda

Variables	Parameters	Robusta (n=567)		Arabica (n=716)	
		Coeff	Std. error	Coeff	Std. error
Production Frontier		Translog		Translog	
Constant	β_0	3.917***	0.042	3.752***	0.043
LnLand(X_1)	β_1	2.639***	0.068	2.667***	0.074
LnHired Labour(X_2)	β_2	0.036	0.030	-0.049*	0.025
LnFertiliser(X_3)	β_3	-0.003	0035	0.035*	0.020
LnPesticide(X_4)	β_4	-0.002	0.069	-0.015	0.049
Ln(X_1) x Ln(X_2)	β_5	0.071**	0.024	0.006	0.021
Ln(X_1) x Ln(X_3)	β_6	0.007	0.013	-0.021**	0.007
Ln(X_1) x Ln(X_4)	β_7	0.066	0.097	-0.174	0.113
Ln(X_2) x Ln(X_3)	β_8	0.006	0.005	0.003	0.003
Ln(X_2) x Ln(X_4)	β_9	-0.011	0.018	0.028*	0.015
Ln(X3) x Ln(X4)	β_{10}	-0.006	0.007	0.003	0.006
½ (LnX_1)^2	β_{11}	-1.143**	0.055	-1.185***	0.063
½ (LnX_2)^2	β_{12}	-0.076**	0.023	0.032	0.021
½ (LnX_3)^2	β_{13}	-0.001	0.014	-0.007	0.007
½ (LnX_4)^2	β_{14}	-0.089	0.194	0.233	0.191
Topography	β_{15}	0.627***	0.022	0.716***	0.022
Improved seedling	β_{16}	0.379***	0.024	0.246***	0.019
Variance parameters					
Sigma squared	σ^2	0.574**	0.285	0.368***	0.091
Gamma	γ	0.986***	0.006	0.992***	0.003
LR test of δ_μ	χ^2	177.554***		213.907***	
Mean TE	μ	0.765		0.731	
Inefficiency Model					
Constant	δ_0	-0.256	0.814	-0.569	0.452
Sex of household head	δ_1	-0.098	0.121	-0.018	0.079
LnHousehold size	δ_2	-0.217	0.140	0.031	0.400
LnSchooling years	δ_3	0.132	0.090	0.075	0.060
Distance to plot	δ_4	-0.596**	0.263	-0.046	0.084
Cropping system	δ_5	-0.454*	0.243	-0.216*	0.117
LnTree age	δ_6	-0.004	0.172	0.150	0.111
Soil Type	δ_7	0.157	0.173	-0.686***	0.184
Group Membership	δ_8	-0.241	0.181	-0.161**	0.081
Farmer trainings	δ_9	-0.413**	0.205	-0.067	0.071
Income sources	δ_{10}	-0.282*	0.170	-0.012	0.070

Source: Author's own computation from UNPS data
Note: **, ** and *** show significance at 10, 5 and 1% levels, respectively.*

The elasticity of fertilizer use is positive and significant at the 10 percent level for Arabica farmers, suggesting that increased fertilizer application enhances output. Specifically, when fertilizer usage is increased by 10 percent, output would also increase by 0.4 percent, holding all other inputs constant (Table 5). A study on coffee systems shows that balanced fertilizer application enhances coffee growth and yield by improving nutrient availability, particularly in soils affected by nutrient depletion (van Asten et al., 2011b). In contrast, for Robusta

farmers, the negative and insignificant fertilizer elasticity indicates that fertilizer use contributes little to productivity, possibly due to inefficient fertilizer application practices. Table 5 further indicates that input interactions differ by coffee type. For Robusta, land and labor exhibit positive complementarity, whereas the negative land–fertilizer interaction for Arabica suggests potential inefficiencies from excessive input use. The quadratic terms indicate diminishing marginal returns to key inputs consistent with a well-behaved production function in which output rises at a decreasing rate as input use intensifies.

The positive and significant coefficients on topography and access to improved seedlings indicate that these factors shift the production frontier upward. For Robusta farmers, cultivating coffee on gentle slopes and accessing improved seedlings are associated with potential output increases of approximately 62.7 percent and 37.9 percent, respectively, holding all other inputs constant. Similarly, for Arabica farmers, production on gentle slopes and access to improved seedlings increase potential output by about 71.6 percent and 24.6 percent, respectively, holding other factors constant (Table 5). This finding aligns with Bote and Struik (2011) who show that favorable agroecological conditions, particularly suitable topography, enhance coffee productivity. A study by Kathurima et al. (2009) demonstrates that improved coffee varieties increase yields through superior genetic potential, pest and disease resistance, and greater climate adaptability. Results from Table V indicate that the sum of partial output elasticities (returns to scale), evaluated at the sample mean, is estimated at 2.67 for Robusta and 2.64 for Arabica, indicating increasing returns to scale (IRTS) at the sample mean in coffee production. These results imply that a proportional expansion of production inputs would generate more than proportional increases in output at the sample mean. However, returns to scale alone do not capture technical efficiency, which reflects the gap between actual and maximum potential output.

Level of Technical Efficiency among Coffee Farmers in Uganda

The distribution of technical efficiency scores reveals notable differences in performance between Robusta and Arabica coffee farmers. Robusta farmers exhibit significantly higher mean technical efficiency (0.77) than Arabica farmers (0.73), with efficiency ranges of 0.21–0.98 and 0.12–0.98, respectively (Table 6). These estimates suggest that under existing technology and input use, output could be increased by approximately 23 percent for Robusta and 27 percent for Arabica farmers through improved efficiency.

Table 6: Distribution of Technical Efficiency Estimates and Two-Sample T-test Results

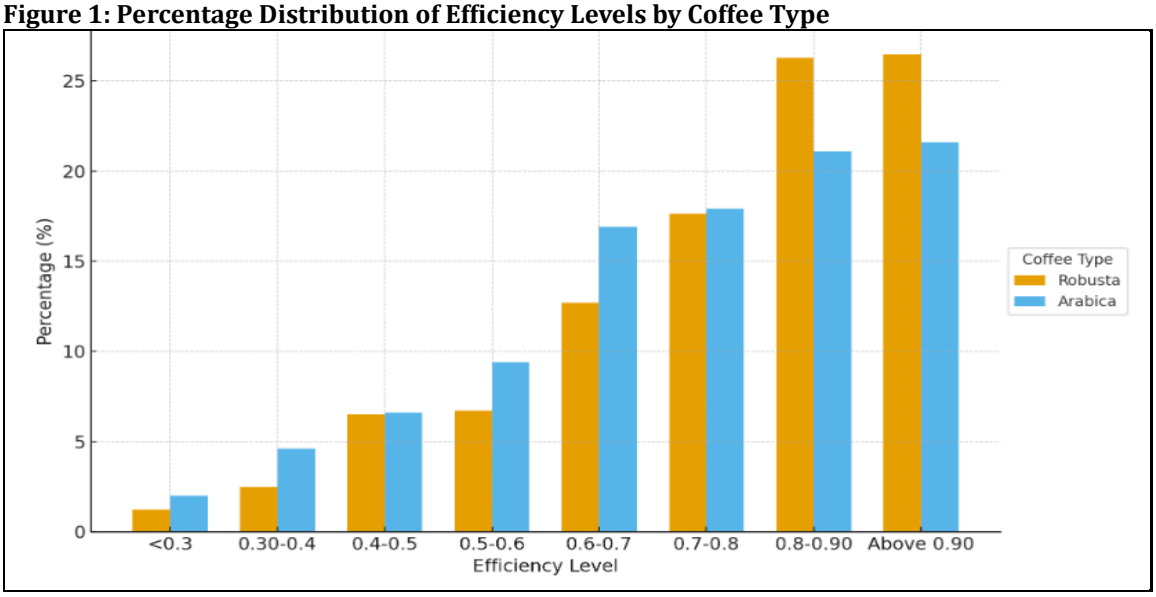
Efficiency level	Robusta farmers (n=567)		Arabica farmers (n=716)	
	Frequency	Percentage	Frequency	Percentage
< 0.3	7	1.23	14	2.0
0.30-0.4	14	2.47	33	4.6
0.4-0.5	37	6.53	47	6.6
0.5-0.6	38	6.70	67	9.4
0.6-0.7	72	12.70	121	16.9
0.7-0.8	100	17.64	128	17.9
0.8-0.90	149	26.28	151	21.1
Above 0.90	150	26.46	155	21.6
Mean	0.765		0.731	
Min	0.208		0.121	
Max	0.977		0.982	
Two-Sample t-test with Equal Mean Technical Efficiencies				
H_0: $\mu_1=\mu_2 = 0$	H_0: Difference (Mean TE Robusta – Mean TE Arabica) = 0			
t-value	3.529		Pr(|T| > |t|) = 0.000	

Source: Author's own computation from UNPS data

Although a notable share of farmers, 26.5 percent of Robusta and 21.6 percent of Arabica achieve efficiency levels above 0.90 and operate close to the production frontier, the majority remain below their potential, indicating substantial scope for efficiency gains. The two-sample T-test further validates that Robusta farmers are significantly more technically efficient than Arabica farmers at the 1 percent level. This efficiency could be driven by Robusta's greater ecological adaptability and lower input constraints, which facilitate more consistent production. Figure 1 further illustrates that Robusta farmers predominantly occupy the higher efficiency

categories, while Arabica farmers are more concentrated in moderate ranges, highlighting the consistently greater technical efficiency of Robusta production systems (Wairegi et al., 2018).

Figure 1: Percentage Distribution of Efficiency Levels by Coffee Type



Source: Author's own computation from UNPS data

Estimated Coffee Yield Loss due to Inefficiency among Coffee Farmers

To estimate yield loss attributable to technical inefficiency, potential coffee output was computed at the farmer level using Equation (4), with harvest loss generated as the difference between computed frontier and observed output. Consistent with the observed efficiency patterns, the findings highlight notable differences in production performance between Robusta and Arabica farmers. Robusta farmers averaged 380.79 kg per farmer, significantly higher than 301.59 kg recorded for Arabica farmers ($p < 0.01$), indicating that Robusta farmers operate closer to the production frontier. The estimated yield frontier under optimal conditions was higher for Robusta than for Arabica, with lower harvest losses for Robusta (see Table 7). These findings indicate that higher technical efficiency among Robusta farmers could be attributed to more effective input use and larger farm sizes, highlighting that better farm-level management practices shape efficiency outcomes (UCDA, 2023b).

Table 7: Estimates of Potential Coffee Production and Yield Loss among Coffee Farmers

Variables	Robusta (n=567)		Arabica (n=716)		P-value
	Mean	Std. Dev	Mean	Std. Dev	
Observed coffee harvested (kg)	380.79	335.53	301.59	198.14	0.000
Technical efficiency estimates	0.765	0.169	0.731	0. 183	0.001
Computed yield Frontier (kg)	493.79	383.05	440.19	321.49	0.007
Computed harvest loss (kg)	113.00	124.62	138.61	175.78	0.003

Source: Author's own computation from UNPS data

Determinants of Technical Efficiency among Robusta and Arabica Coffee Farmers in Uganda

Technical efficiency for Robusta and Arabica farmers was estimated using equations (5) and (6). The sources of technical inefficiency are assessed using the estimated (δ) coefficients reported in Table 5. A negative coefficient indicates lower technical inefficiency and hence higher technical efficiency, while a positive coefficient indicates higher technical inefficiency and lower technical efficiency.

Distance to the coffee plot has a negative and significant effect on technical inefficiency among Robusta farmers at the 5 percent level. Specifically, Robusta farmers with coffee plots located within 1 km of their homesteads

are 59.6 percent more technically efficient than those with more distant plots, holding other factors constant. A study by Sebatta et al. (2020) in Uganda found that closer access to coffee plots improves efficiency by facilitating regular supervision, timely input application, and effective farm management. Similarly, findings from other studies such as Binam et al. (2003) and Owusu et al. (2011) reported that greater plot distance reduces technical efficiency by increasing monitoring challenges and delaying farm operations, particularly in labor-intensive crops. These inefficiencies can lower agricultural output and farm profitability, which in turn could constrain household welfare.

Results in Table 5 indicate that membership in farmer groups has a negative and significant effect on technical inefficiency among Arabica farmers at the 5 percent level. Specifically, Arabica farmers who participate in farmer groups are 16.1 percent more technically efficient than non-participants holding other factors constant. The findings suggest that participation in farmer organizations can enhance technical efficiency by improving access to extension services, agricultural information, and knowledge-sharing opportunities. (Sebatta et al., 2020). However, Aheisibwe et al. (2024) found that group membership reduced efficiency among seed potato farmers in Uganda while Owusu et al. (2011) reported limited effects in Ghana due to weak group organization, governance and extension support.

Results in Table 6 also indicate that the cropping system has a negative and significant effect on technical inefficiency among Robusta and Arabica farmers at the 10 percent level. Specifically, farmers practicing mixed cropping were 45.4 percent and 21.6 percent more technically efficient among Robusta and Arabica farmers, respectively, compared to those practicing monocropping systems, holding other factors constant. Consistent with Ajema and Nigussie (2021), Tamirat and Tadele (2023)mixed cropping can improve resource-use efficiency by enhancing shade, maintaining soil fertility, and diversifying production risks. Evidence from Uganda's banana–coffee systems further supports these findings, showing higher yields per tree and increased technical efficiency (Bongers et al., 2015). However, mixed cropping may reduce efficiency where intercrops compete for resources (Binam et al., 2003; Ngango & Kim, 2019).

The coefficient of soil type has a negative and significant effect on technical inefficiency among Arabica farmers at the 1 percent level. Specifically, Arabica farmers cultivating coffee on sandy-loam soils are 68.6 percent more technically efficient than those cultivating on other soil types, holding other factors constant. This finding is consistent with Mekonnen et al. (2015) who highlighted the importance of well-drained soils for Arabica productivity in Ethiopia. However, evidence from Kenya suggests that sandy-loam soils reduce efficiency under low fertility due to increased nutrient leaching and water stress (Mutua-Mutuku et al., 2017). For Robusta, although sandy-loam soils are generally suitable, suboptimal input use and inappropriate spacing and pruning practices may constrain productivity and reduce technical efficiency (Wairegi et al., 2018).

The effect of farmer training on technical inefficiency is negative and significant at the 5 percent level among Robusta farmers. Specifically, Robusta farmers who participate in training programs are 41.3 percent more technically efficient than those who do not participate, holding other factors constant (Table 5). This finding suggests that training could enhance technical efficiency by improving farmers' access to agronomic knowledge, production technologies and better input management practices, enabling more effective utilization of available resources. Similar evidence has been reported in Uganda, where Sebatta et al. (2020) found that access to training services improved coffee farmers' efficiency by strengthening technical knowledge and promoting better farm management practices. Additionally, Abdulai and Huffman (2014) and Binam et al. (2003) showed that farmer trainings enhance technical efficiency by facilitating technology adoption and improving input-use decisions among smallholder farmers. Relatedly, the effect of income source was negative and significant among Robusta farmers at the 10 percent level. Specifically, Robusta farmers with one or more off-farm income sources are 28.2 percent more technically efficient than those without off-farm income sources, holding other factors constant. Previous studies indicate that off-farm income improves farm efficiency by providing financial resources for inputs, hired labor and timely farm operations (Tamirat & Tadele, 2023; Aheisibwe et al., 2018).

5. Conclusion and Recommendations

The study aimed to assess technical efficiency and its determinants among smallholder Ugandan Robusta and Arabica coffee farmers using Stochastic Frontier Analysis (SFA). It identifies significant gaps between actual and potential coffee production among the two farmer types, primarily driven by technical inefficiencies. The mean technical efficiency was 76.5 percent for Robusta and 73.1 percent for Arabica farmers, with Robusta farmers significantly more efficient at the 1 percent level. This implies potential output gains of 23.5 percent for Robusta and 26.9 percent for Arabica using existing inputs and technologies. Among Robusta farmers, technical efficiency was significantly enhanced by proximity of coffee plots to homesteads, mixed cropping, farmer participation in training, and access to off-farm incomes. For Arabica farmers, membership in farmer groups, mixed cropping and cultivation on suitable soil types were associated with higher technical efficiency. The results show increasing returns to scale for both farmer types, indicating that proportional expansion of inputs offers opportunities for productivity gains. These findings point to the importance of targeted policy interventions to enhance coffee productivity and technical efficiency. Optimizing agronomic practices is critical: intercropping and soil fertility management should be tailored to coffee type and local ecological conditions. Complementary capacity-building initiatives, including practical training in input use, pest and disease management, and sustainable farming practices, could reinforce efficiency gains from improved resource use. Promoting collective action through farmer groups and cooperatives can enhance knowledge sharing, coordinated input use, and market access, thus reducing transaction costs and enhancing resource-use efficiency.

Limitation of the Study

The study is limited by the inability of the one-step SFA approach implemented in FRONTIER 4.1 to directly address potential endogeneity among selected inefficiency determinants, including farmer training, group membership, off-farm income and cropping system.

Funding: This study was supported with funding from the African Economic Research Consortium (AERC).

Conflict of Interest: The Authors have no conflict of interest.

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