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Technical Efficiency of Mushroom Production Among Smallholder Farmers in Uasin Gishu County, Kenya

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Abstract

Mushroom cultivation is an emerging crop in Kenya with significant potential to alleviate poverty and food insecurity among smallholder farmers. However, low production levels in regions like Uasin Gishu County indicate potential technical inefficiencies that limit its market potential. This study was carried out to analyze the technical efficiency (TE) of smallholder mushroom farmers in Uasin Gishu County, Kenya, and to identify the determinants influencing that efficiency. The study utilized a cross-sectional survey design. Data were collected from a sample of 114 farmers from a target population of 162 mushroom farmers, primarily growing Oyster and Button species. The sampling technique employed was Stratified Random Sampling with Proportional Allocation. Both primary (survey data collected via semi-structured questionnaires) and secondary data were used. The collected data was analyzed using descriptive statistics and a Stochastic Frontier Analysis (SFA) model. The SFA model was estimated using Maximum Likelihood Estimation (MLE), assuming a half-normal distribution for the inefficiency term. The descriptive results showed that the majority of farmers had limited access to institutional support, with 60.5% lacking access to agricultural extension services. The mean age of household heads was 52 years, with an average farming experience of 4 years. The SFA model revealed significant technical inefficiency, with TE scores ranging from 29% to 89%, and a mean

TE of 67%. This implies that farmers could increase their current output by 33% without changing the existing technology or input levels. Frontier analysis showed that Man-hour Labour (β=0.665) was the most critical constraint to output, while inputs like fertilizer and wheat straw were found to be over-utilized. Analysis of the inefficiency determinants revealed that Access to Extension Services (increasing TE by 48.8%), Price of Mushroom Output (increasing TE by 33.5%), and Access to Credit (increasing TE by 8.1%) were the most significant factors in reducing technical inefficiency. However, distance to the Market was found to increase inefficiency significantly. The study concludes that substantial potential exists for mushroom output improvement in the short run. It recommends that county agricultural sectors prioritize strengthening extension service delivery and providing tailored credit facilities to enhance input allocation, close the efficiency gap, and maximize the economic benefits of mushroom production.

Keywords: Technical efficiency, mushroom production, farmers, stochastic frontier production function, Kenya

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Introduction

Mushroom is a fleshy spore bearing fruiting body of the Kingdom Fungi, subdivision of Basidiomycotina, and the class Hymenomycetes (Lincoff, 2011). Historically, the Chinese published record show that *Auricularia* was the first ever cultivated mushroom in 300 before Christ (B.C), followed by the straw mushroom, *Volvariella volvacea* in 1000 (B.C). A systematic approach towards their cultivation commenced after the white button mushroom (*Agaricus bisporus*) was first grown in France around 1650 Anno Domini (A.D), which was later on commercialized to become an industrial venture in many countries of the world (Nelson, Chourey and Chang, 1978).

According to the study on Natural History Museum by Toomsalu, Pärnsalu, Tapfer and Mesila (2015), the estimated global species of fungus are 1.5-5.1 million. However, 64,000 species found in tropical rainforests have been studied so far. Many fungus species from the tropic areas may have disappeared before scientific exploration on them. These have been caused by the global climate change. Global mushroom production has expanded substantially over the past decades, growing more than 30-fold since 1978. Current worldwide production stands at roughly 17.25 million tonnes per year, with projections reaching over 32 million tonnes by 2032. The global market is expected to see continued robust growth with a Compound Annual Growth Rate (CAGR) of about 9–10% through 2030, fuelled by consumer demand for functional and health-promoting foods (Food and Agriculture Organization, 2014; Mushroom Market Size, Share, Trends Analysis Report, 2030). China is the overwhelmingly dominant producer, accounting for approximately 80% of global output (over 5 million metric tons in 2024. Other major producers include Italy, the United States of America, UK, Spain, and France. The most cultivated species globally are: Shiitake (*Lentinula edodes*); Oyster (*Pleurotus spp.*); Button mushroom (*Agaricus bisporus*) and Enoki (*Flammulina velutipes*) (Royse, Daniel, Johan & Qi 2017).

In the African continent, South Africa is the leading mushroom producer in Africa, ranking 22nd globally with a production volume of approximately 24,070 metric tons in 2021. Production is projected to reach nearly 28,000 metric tons by 2026, sustained by a growth rate of around 2.5% year-on-year. Most production is concentrated in the provinces of Gauteng, Western Cape, and KwaZulu-Natal (South Africa Mushroom Industry Outlook 2022-2026, 2022). The dominant varieties cultivated are white button and brown mushrooms (*Agaricus species*), which make up the vast majority of production for the fresh market. Interest in exotic (oyster, shiitake) and medicinal mushrooms is growing but remains a small niche segment.Mushroom farming in South Africa is technologically advanced, requiring detailed knowledge of climate control, substrate preparation, and strict hygiene. Unlike in some overseas markets where compost is purchased from specialized companies, South African farms typically produce their own compost on-site, adding to operational complexity and costs. There has been recent research into innovative production methods, such as containerized farms to enhance sustainability and access for small-scale growers (South Africa Functional Mushroom Market Size & Outlook 2024 – 2030, 2024). The industry serves both domestic fresh markets (especially supermarkets and hospitality) and exports a portion of produce to neighboring countries such as Namibia and Mauritius. Less than 5% of mushrooms are processed (canned, sauces), as fresh consumption dominates consumer preference. (Revolutionising mushroom growing in SA May,2025). Key company Producers: Kulu Mushrooms, Mushrush and Tropical Mushrooms (South Africa Mushroom Industry Outlook 2022 – 2026).

In Kenya, mushroom cultivation was introduced in the 1970s, but the production is slowly and steadily picking up (Kimenju et al., 2009). It is a steadily growing sector driven by rising domestic demand, health awareness, and emerging export opportunities. The exotic mushrooms currently cultivated in Kenya are the white button (*Agaricus bisporous*), Oyster (*Pleurotus spp*) and Shiitake (*Lentinula edodes*). Shiitake is both edible and medicinal.Shiitake is grown at very low scale, mainly for hotel industry that caters for foreign and high end clients. Reishi (*Ganoderma lucidun*) is grown on small scale for their medicinal value. Among the three verities, a good deal of scientific information is available with regard to white button mushroom which is successfully cultivated commercially in several parts of Kenya especially Central, Rift valley and Western parts (Sigot, 2014). Kenya produced approximately 480 tons of mushrooms in 2023, up 20% from the previous year, with *Agaricus bisporus* (button, cremini, and Portobello) constituting over 93% of production, followed by oyster mushrooms at about 6.25%. Annually farm-gate value stands at Kenya shillings (KSh) 255 million and a retail value of Ksh.340 million. Despite growth, local production still falls short of demand, leading to imports mainly from neighboring Rwanda. The country imports about 81.5 million tonnes of dried mushroom worth Ksh.9.8 million and exports 16 tonnes of mushroom worth Ksh.3.9 million. From a food security standpoint, Kenya is a net importer of mushroom, which means that the availability aspect cannot be sustainable due to the dependence on other sources. The market is projected to grow at a compound annual growth rate (CAGR) of around 11-17% between 2025 and 2029, reflecting expanding health-conscious consumer bases and increased urbanization (Kenya Mushroom Cultivation Market Size Growth Rate 2022-2028, 2022). The bulk of marketed mushroom comes from large scale farms which constitutes 90-95% of the total production. In Kenya, the major farms that produce mushroom are Agridutt Kenya Ltd (35%), Rift Valley Mushrooms (30%), Olive Farm (20%) and Devan (10%) (Waiganjo, Ngeli, Gateri and Muriuki, 2008) Small scale production is concentrated mainly in Kisumu, Kakamega, Mombasa and Malindi Counties.

In Uasin Gishu County, mushroom farming is mostly dominated by smallholder farmers who grow mainly Oyster and white button species of mushroom with production meant for the local markets (Uasin Gishu County Integrated Development Plan 2018-2022, 2018). White button variety is currently gaining a lot of popularity in this region than Oyster due to its good market price. For instance, a kilogram of oyster and white button fetches Ksh 400 and Ksh 600 respectively but middlemen pay farmers Ksh 350 per kilogram, denying farmers their full profits (Osmani & Hossain, 2015). Mushroom production in Uasin Gishu County has dropped from 10,000kg in 1997 to 3,130kg in 2018 (Agriculture, Livestock and Fisheries Development Report, 2019). Over the years, total yield realized from mushroom cultivation has been inconsistent as shown in figure 1. For instance, in 1985, the total yield realized from mushroom steadly rose from 1,932kg in 1985 to 10,000kg in 1997 which was the highest pick; then yield declined to 2,000 kg in 2009 and then rose to 3,130kg in 2018. The observed substantial decline and inconsistency in total yield over time, despite the high market price and potential for profit, strongly suggests a problem of inefficient resource use at the farm level, specifically technical inefficiency (TE). Despite the potential of the crop and the observed production decline, there is a paucity of empirical studies analyzing the level and determinants of technical efficiency among smallholder mushroom farmers in Uasin Gishu County. Therefore, this study was carried out to analyze the technical efficiency of mushroom production among smallholder farmers in Uasin Gishu County, Kenya, and to identify the factors contributing to technical inefficiency.

Methodology

The Study Area

The study was conducted in Uasin Gishu County, Kenya as shown in figure 2. The county is located in the former Rift Valley province in Kenya. The county shares common borders with Trans Nzoia to the North, Elgeyo Marakwet County to the East, Koibatek to the South East, Kericho County to the South, Nandi County to the South West and Lugari Sub-County to the North West. The county covers a total area of 3,327.8Km^2. The county is divided into six sub-counties namely Ainabkoi, Soy, Kapseret, Moiben, Kesses and Turbo (KNBS, 2010). The county is a highland plateau with an altitude that fall gently from 2,700m above sea level at Timboroa in the East to about 1,500m above sea level at Kipkaren in the West (CIDP, 2018-2022, 2018).

The county is divided into two broad physiographic regions agricultural lands and forest lands. The topography of the county is higher in the East and declines towards the western borders. The average rainfall received in the county ranges between 624.9mm-1,560.4mm and this occurs between the months of March and September with two distinct peaks in May and August. Temperatures range between 8.4^{o}C and 26.1^{o}C. An estimated 90 percent of the land area in the county is arable, out of which about 2,000 km^2 is classified as high potential and about 1,000 km^2 is medium potential. There are four major soil types in the county for agricultural production. These include red loam, red clay, brown clay and brown loam. The county is basically agricultural, producing about one-third of the total wheat produced in Kenya. Maize, a staple food for most Kenyans, is also produced in the county in large quantities, second to wheat (Lagat *et al.,* 2012).

According to the national census of 2019 by KNBS, (2019), the county's population was 1,163,186, with an annual growth rate of 3.35% per annum. The county population growth rate is higher than the national average of 2.9% per annum (KNBS, 2019). According to report by the Department of land, Housing, physical planning and Urban development (2019), in Uasin Gishu County, large-scale farmers have an average land holding of between 10-15 hectares while small-scale farmers have an average land holding of 0.5 – 5 hectares, which is owned by 14% and 86% of the total households, respectively.

To promote crop diversification, the county has categorized mushroom as one of the high-value crops that is commercially grown. The county has also considered it a type of horticultural farming that can highly contribute to food security and nutrition (Uasin Gishu County Integrated Development Plan, 2018-2022, 2018). Mushroom consumption per capita is projected to grow from 1.0 kg in 2008 to 2.4 kg in 2020. As a result, the total demand for mushrooms is projected to increase from 3,130 kg /year in 2017 to 7,500/year by 2022 (Palapala, Otieno & Onyango, 2015).

Research Design

Descriptive Research Design was used in this study. According to Wiersma and Jurs (2009), in descriptive research design no experimental variables are manipulated variables are studied as they exist in the situation. Descriptive research design describes the phenomena in numbers and measures, instead of words (McMillan and Schumacher, 2010). According to Kothari (2004), the major purpose of descriptive research is the description of the state of affairs as it exists at present. Mugenda (2009), explains descriptive studies as the study performed within communities with the main aim of establishing the extent of the range of problems, issues or concerns that have not been investigated earlier.

Target Population

According to report by the National Farmers Information Services, (2017) Uasin Gishu County has a total of 162 mushroom farmers, with Kapseret Sub-County having the highest number of mushroom farmers. The respondents for this study were smallholder mushroom farmers particularly those who planted in the 2018 and 2019 cropping seasons. Therefore, the distribution of the 162 smallholder mushroom farmers in the six sub counties of Uasin Gishu County is as shown in Table 1.

Table 1: Population of Smallholder Mushroom Farmers in Uasin Gishu County

Sub-County	Target Population
Soy	24
Moiben	29
Ainabkoi	28
Tarbo	27
Kapsaret	35
Kesses	19
Total	**162**

Source: Ministry of Agriculture (2019)

Sample Size Determination

The required sample size for smallholder mushroom farmer household was determined using Krejcie and Morgan (1970) table. The proportionate size sampling technique is as shown in equation 1.

$$S = \frac{X^2 NP(1-P)}{d^2(N-1) + X^2 P(1-P)} \quad \text{...... (1)}$$

Where *S* is the required sample size, X^2 is the table value of chi-square for 1 degree of freedom at the desired confidence level (3.841) i.e. 1.96 x 1.96 = 3.84416; *N* is the population size; *P* is the population proportion (assumed to be 0.50 since this would provide the maximum sample size); and *d* is the degree of accuracy expressed as a proportion (0.05). Therefore, fitting the values to equation 1 gives the sample size of 114 as shown below.

$$S = \frac{1.96^2 * 162 * 0.50(1-0.50)}{0.05^2(162-1) + 1.96^2 * 0.50(1-0.50)} = 114$$

Therefore, from the computation, 114 smallholder mushroom farmer households were sampled and used for analysis in this study.

Sampling Procedure

The population of interest constituted all farmers who practiced mushroom farming in Uasin Gishu County. The study used multistage cluster sampling procedure. To achieve the study objectives, the county was clustered into six sub counties namely; Soy, Moiben, Ainabkoi, Tarbo, Kapseret, and Kesses. Since the number of respondents in each of the sub counties was few, a simple random sampling procedure was used to select the 114 respondents to represent the whole county. A list of the respondents was obtained from the county agricultural office and the names of the farmers in the list were then serially numbered and randomly ordered and then picked using simple random sampling technique. The complete list of the respondents of interest was then proportionately distributed to the sub counties as shown in the Table 2. This technique gave each of the farmers an equal opportunity of being selected and therefore increased the chances of obtaining an appropriate and representative sample size.

The study adopted Kothari formula for computing proportion of population included in stratum (Kothari, 2004). The formula is empirically expressed in equation 2.

$$s = \frac{S}{N} * n \quad \text{.. (2)}$$

Where:

s= sample size for the individual stratum

S=stratum size i.e. (total farming household in each County)

N= Aggregate target population size i.e. 162 smallholder farmers in 6 Sub- counties
n = Overall sample size i.e. 114 smallholder mushroom farmers.

Table 2: Distribution of Mushroom Farmers in Uasin Gishu County

Sub-County	Target Population of mushroom farmers	Proportionate Size Sample
Soy	24	17
Moiben	29	20
Ainabkoi	28	20
Tarbo	27	19
Kapsaret	35	25
Kesses	19	13
Total	162	114

Source: *Author's Computation from the County Agriculture, Livestock and Fisheries Development Report, 2019.*

Data Types and Sources

Primary and secondary data was used in this study. Primary data was collected using semi structured questionnaires administered by trained enumerators. Primary data that was collected included smallholder mushroom farmers' socio-economic characteristics, all the factors of production used in mushroom production, production and their respective costs, as well as mushroom yields, output sold, and sale prices. For the farm and farmer characteristic variables, the data collected comprised of the farmer's age, gender, education level, household size, mushroom house size, occupation, farmer experience in mushroom farming, farmer's income source, land availability, land size, labour size, land ownership, method of sterilization used, temperature regulation method, amount of spawn used, association membership, access to agricultural extension services, access to credit, access to the market, distance to market, price of input, price of output, source of market information, and availability of market. This quantitative data was collected for the period 2019/2018 cropping season. Secondary information was obtained from the national and county government publications, journals and published theses, economic surveys, economic journals, statistical abstracts, conference reviews, books, magazines, national and county development and strategic plans, national and county ministry of agriculture, livestock and fisheries annual development reports, private agricultural companies reports, National Bureau of Statistics publications, desktop literature and internet sources.

Instruments of Data Collection

This study used personal interviews that involved face to face encounter with the respondent. A structured questionnaire was administered to all farmers. The questionnaire captured information on different factors and activities relevant to mushroom production. A separate interview schedule was be used to collect information from different stakeholders participating in the mushroom industry. These stakeholders included outreach centre for research and innovation at the University of Eldoret, Uasin Gishu County extension staff, private consultants that included Dels and Rose mushroom consultancy farms and merchant buyers (Elgon groceries and Amina Agro buyers) in Eldoret town.

Pre –Test

The research instrument was pre-tested in order to standardize them before the actual study. The pre-test study was done using West Kabras ward, Kakamega County using simple random sampling. This helped in identifying problems that respondents might encounter and to determine if the items in the research instrument would yield the required data for the study. Simple random sampling was used to sample of 11subjects equivalent to 10% of the study sample size of 114 subjects. According to Mugenda and Mugenda (2003), a sample equivalent to 10% of the study sample is enough for pre-testing the study instruments. After responding to the questionnaires, necessary corrections were made and adjustments of the instruments to increase their reliability.

The reliability of the instruments is determined using Cronbach Alpha coefficient. A reliability coefficient of 0.7 to 1 indicates that the data collection instruments are reliable (Santos, 1999).

This study used Cronbach Alpha coefficient to computer reliability coefficient as adopted from Bland and Altma (1997). Cronbach's Alpha coefficient expressed mathematically is as shown in equation 3.

$$\alpha = \frac{N\bar{c}}{\bar{v} + (n-1)\bar{c}} \quad \text{.........................} (3)$$

Where:

α is the Cronbach's Alpha coefficient, $\bar{c}$ is the average inter-item covariance among the items, $\bar{v}$ is the average variance and N is equal to the number of items/ observations (the 10% of the study sample).

After calculating the Cronbach's Alpha coefficient for this study, a reliability coefficient of 0.727 was achieved as shown in Table 3, which falls within the acceptable reliability range of 0.7 to 1.

Table 3: Questionnaire reliability statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	No. of Items/observations
0.727	0.832	11

Source: *Author's Estimates from Pre-Test Survey Data, 2020.*

For the interview schedule, the Cronbach's Alpha value was used to compute the 11 observations. A reliability coefficient of 0.801 was obtained as shown in Table 4 which falls within the accepted coefficient range of 0.7 to 1.

Table 4: Interview schedule reliability statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	No. of Items
0.801	0.857	11

Source: *Author's Estimates from Pre-Test Survey Data, 2020.*

Data Analysis and Presentation

Upon receipt of the filled questionnaires and after cross-checking, there were no incomplete data sources, thus none was discarded. The next stage was the initial screening of data by sorting, coding and cleaning. The questions were numbered and coded using a coding frame ready for entry and analysis using STATA version 12.0 computer program. The descriptive statistics were used to describe the primary data collected and the analyzed socio-economic characteristics. The results were then presented in form of tables and charts from which inferences were drawn. The primary analytical model used in this study was the Stochastic Frontier Analysis (SFA). The SFA model was chosen to address the primary goals of the study: (1) to estimate the Cobb-Douglas SFA model to determine technical efficiency scores for each farmer and overall efficiency, and (2) to identify the significant farm-specific and socio-economic variables (Z variables) that determine technical inefficiency. The estimation of the technical efficiency scores and their determinants was achieved by employing the one-step Maximum Likelihood Estimation (MLE) approach, as formalized by Battese and Coelli (1995). This approach simultaneously estimates the parameters of the production frontier and the parameters of the inefficiency effects model, offering a statistically consistent and efficient alternative to the inefficient two-step procedures. The Cobb-Douglas functional form (double log) was specified for the stochastic frontier production function. This choice was based on its simplicity in estimation and interpretation, requiring fewer data points compared to the more flexible Translog function. Furthermore, the selection was supported by the fact that results from a preliminary Likelihood Ratio (LR) test failed to reject the null hypothesis that the Translog model reduces to Cobb-Douglas, indicating the simpler form was statistically adequate for the data. Therefore, the objectives in this study were analyzed as follows:

- Objective One used descriptive statistics and multiple linear regression to analyze the relationship between one dependent variable and multiple explanatory variables.
- Objective Two used the one-step Stochastic Frontier Model (Cobb-Douglas linear production function, double log) to estimate technical efficiency scores for each farmer and the overall technical efficiency.
- Objective Three used the inefficiency effects component of the one-step Stochastic Frontier Model (Battese and Coelli, 1995) to identify the factors contributing to technical inefficiency among smallholder mushroom farmers.

Theoretical Models

To determine the level of technical efficiency of mushroom production among smallholder mushroom farmers in the study area, a stochastic frontier model (Cobb Douglas linear production function-double log) was estimated from which the technical efficiency scores of each farmer and the overall technical efficiency was obtained. The Stochastic Frontier Analysis (SFA) according to Aigner *et al*. (1977) is considered most applicable in determining the technical efficiency in agriculture, especially in developing countries, where the data are prone to be heavily influenced by the measurement errors and the effects of weather conditions, and diseases. Thus, following Aigner *et al.* (1977) and Meeusen and van den Broeck (1977), Cobb Douglas linear production function-double log consists of two-part error terms: an inefficiency component (u_i) and a purely random component (v_i). Therefore, this stochastic frontier production with two error terms can be modeled as shown in equation 5.

$$Y_i = f(X_i, \beta)\exp(V_i - U_i) \quad \text{.............. (5)}$$

Where;

Yi is the mushroom output of the i^{th} farm (in Kg); $i = l, 2, 3, ..., n$, x_i is a $(l\times k)$ vector of known functions of input quantities used by the i^{th} mushroom farmer, β is a $(k\times l)$ vector of unknown parameters to be estimated, V_{is} are random errors assumed to be independently and identically distributed $N(0, \delta_v^2)$ and independent of U_{is}, U_{is} are non-negative random variables, associated with technical inefficiency in production also assumed to be independently and identically distributed. The first error component V is intended to capture the effects of random shocks outside the farmer's control, measurement error and other statistical noise. The second error component *U* is intended to capture the effects of technical inefficiency.

Equation 4 also specifies the stochastic frontier production function in terms of the original production values. The technical inefficiency effect, U_{is} in the stochastic frontier model could be specified in equation 5. According to Battese and Coelli (1995), the technical inefficiency effects, U_i can be expressed as in equation 6.

$U_i = Z_i \delta + W_i$ .... (6)

Where *W,* are random variables, defined by the normal distribution with zero mean and variance σ^2 *u,. Zi* is a vector of farm specific variables associated with technical inefficiency, δ is a *(mxl)* vector of unknown parameters to be estimated. The technical efficiency of the i^{th} sample farm denoted by *TE;* is given as shown in equation 3.7.

$$TE_i = \exp(-U_i = \frac{Y_i}{f(X_i \beta)\exp(V_i)} = \frac{Y_i}{Y_i^*}$$

.... (7)

Where Y_i^* = f(X_1 β,) exp(V_i) defines the maximum possible output (the frontier) for given inputs and random shocks. f(X_1,β) is the deterministic part of the production function. X_i is a vector of inputs (like land, labor, fertilizer), and β is a vector of technology parameters that describe how inputs are transformed into output. exp(V_i): This term captures random shocks or statistical noise affecting production that are beyond the control of the producer, such as weather, pests, or measurement errors

If Y_i is equal to Y_i^* then TE_i =1, reflects 100% efficiency. The difference between Yi, and Yi* is embedded in U_i.. exp(−U_i): Represents the technical efficiency of producer i (ith farmers), Ui≥0 is a non-negative random variable capturing technical inefficiency. If Ui=0, the producer is fully efficient; if Ui>0, the producer is technically inefficient; U_i<0 is not possible in this model; inefficiency is always non-negative.

The basic structure of the stochastic frontier model in equation 5 is depicted in graphical illustration in Figure 3.1 in which the productive activities of two firms, represented by I and j, are considered. Firm i uses inputs (land, labor, fertilize, spawn etc) with values given by (the vector) x_i and obtains the output Yi, (Mushroom yield), but the frontier output, Y_i*, exceeds the value on the deterministic production function, f(X_1, β), because its productive activity is associated with "favourable" conditions for which the random error, V_i, is positive. However, firm j uses inputs (land, labor, fertilize, spawn etc) with values given by (the vector) x. and obtains the output, Y_j(Mushroom yield) , which has corresponding frontier output, Y_j* (Maximum possible Mushroom outpu)t, which is less than the value on the deterministic production function, f(X_j,β), because its productive activity is associated with "unfavourable" conditions for which the random error, V_j, is negative. In both cases the observed production values are less than the corresponding frontier values, but the (unobservable) frontier production values would lie around the deterministic production function associated with the firms involved.Given the assumptions of the stochastic frontier model in equestion 3.5, inference about the parameters of the model can be based on the maximum-likelihood estimators because the standard regularity conditions hold.

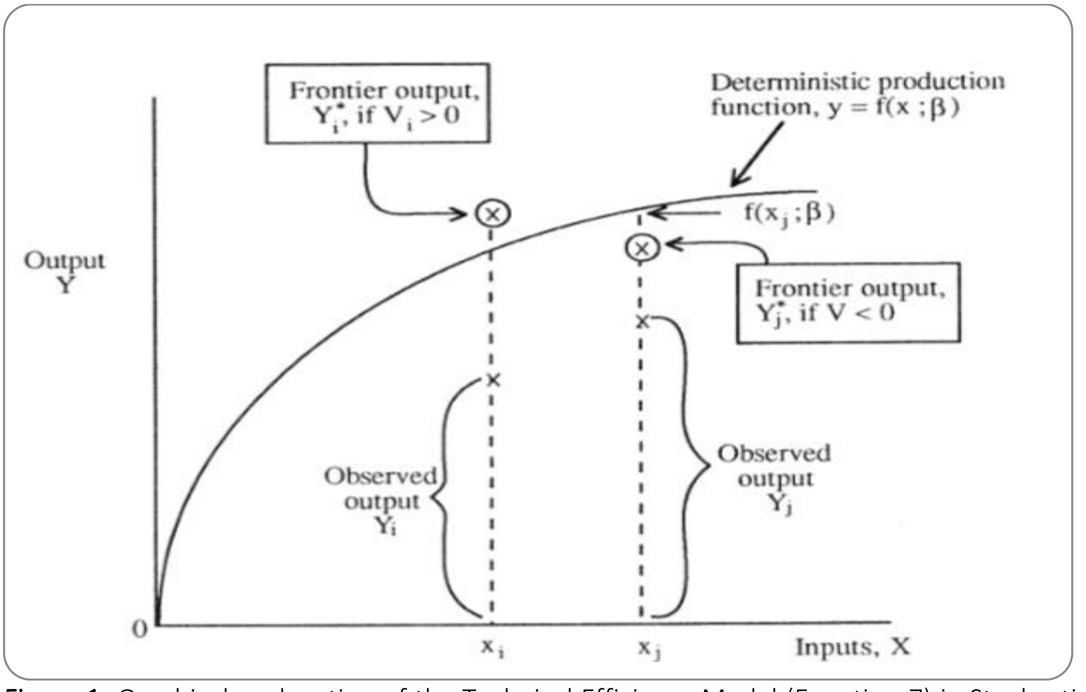

Figure 1: Graphical explanation of the Technical Efficiency Model (Equation 7) in Stochastic Frontier Production Function

Source: Author's Computation adopted from Adpoted from Aigner, Lovell and Schmidt (1977); Meeusen and van den Broeck (1977)

The maximum likelihood estimates (MLE) of the parameters of the model are defined by equations 7 and the generation of farm-specific characteristics. The efficiencies are estimated using a predictor that is based on the conditional expectation of *exp (-U)* (Battese and Coelli, 1993). In the process, the variance parameters $\sigma^2 u$, and $\sigma^2 v$, is expressed in terms of the parameterization as shown in equation 8 and 9.

$$\delta^2 = (\delta^2 v + \delta^2) \text{..............................}(8)$$

$$\gamma = \frac{\delta^2 v}{\delta^2} \text{..}(9)$$

The value of γ ranges from 0 to 1 with values close to 1 indicating that random component of the inefficiency effects makes a significant contribution to the analysis (Coelli & Battese, 1996). Therefore Cobb-Douglas production function (stochastic frontier production function) was then fitted with all variables used in determination of technical efficiency and expressed as shown in equation 10.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + e_{vu} \text{...} (10)$$

Where Y is mushroom output, β_0 is a constant or intercept and β_1, β_2, β_3, β_4, β_4, β_5 ,β_6,β_7 are the coefficients to be estimated, X_1,X_2 ,X_3,X_4,X_5 ,X_6 ,X_7 are the input varraibles and e_{vu} is the stochastic two error terms i.e. *V* and *U* where *V* is the Stochastic error term, an error term that is independently and normally distributed with mean zero and constant variance of $\varepsilon_i \sim N(0, \sigma^2)$. *U* is the technical inefficiency effect predicted by the model.

Diagnostics Test and Model Specification

Diagnostic test results provide information on how these raw data may be modelled. When a model is estimated, diagnostic tests on model residuals yield information about model adequacy (Kuan, 2008). For the purpose of this study, heteroscedasticity test was performed to check for correctness of the estimates. A test on heteroscedasticity was done based on ordinary least square residuals. Also, one of the assumptions made about residuals/errors in OLS regression is that the errors have the same but unknown variance. This is known as constant variance or homoscedasticity. When this assumption is violated, the problem is known as heteroscedasticity. Therefore, for this study, heteroscedasticity test was performed to test whether the variance of the errors from the regression are dependent on the values of the independent variables. Godfrey, (1978) and Breusch and Pagan, (1979) independently proposed testing for heteroscedasticity based on squared least squares residuals.

Empirical expression of heteroscedasticity test model, the OLS assumption that error terms in the regression should all have the same variance holds as shown in equation 11.

$$Var(\varepsilon j|X|) = \sigma^2 \quad \ldots\ldots(11)$$

If this variance is not constant (i.e. dependent on X's), then the linear regression model has heteroscedastic errors and likely to give incorrect estimates. According to MacKinnon and White, (1985), this OLS regression assumption allows the use of white test formulae in testing for heteroscedasticity. The usual calculation of the White test is expressed by letting ? be uncorrelated with the independent variables, X_j, the squares of the independent variables X_j^2 and the cross products of the independent variables X_hX_j, where *j=h*, and *j, h =(1,2,........,k)*. This led to the White test which suggest the inclusion of all the above as covariates in the second step regression. In order to compute white test auxiliary regression must be computed i.e.??^{2} is regressed on all the explanatory variables *(Xj)*, their squares (X_j^2) and all their cross products. This is generally expressed as shown in equation 12.

$$\hat{\varepsilon}_i^2 = \beta_0 + \beta_1 x_1 + \ldots\ldots + \beta_K x_k + \beta_{K+1} x_1^2 + \beta_{K+2} x_1 x_2 + \ldots + e \quad \ldots\ldots(12)$$

The above white test for heteroskedasticity then tests whether all the above parameters are all equal to 0 (zero). Let *m* be the number of regressors in auxiliary regression keep R^2, say $R^2_{\varepsilon 2}$, F-statistics(chi-square statistics) for hypothesis test is then computed as shown in equation 13.

$$F = \frac{\frac{R^2_{\delta^2}}{1}}{\frac{1-R^2_{\delta^2}}{n-2}} \; Or \; \chi^2_m = nR^2_{\delta^2} \quad \ldots\ldots(13)$$

To test for heteroskedasticity, the assumption that the errors are actually homoscedastic holds, and it is what be examined if that is true. Therefore in examining heteroskedasticity in a null hypothesis, the expected value of the errors being zero is still maintained. This means that the variance of the error term is constant thus it can be expressed as shown in equation 14.

$$Var(\varepsilon|x_1,x_2,\ldots\ldots,x_k) = R(\varepsilon^2|x_1,x_2,\ldots\ldots,x_k) = \sigma^2 \quad \ldots\ldots(14)$$

Hence the hypothesis being test is written as shown in equation 15.

$$H_0: = R(\varepsilon^2/x_1, x_2,\ldots\ldots,x_k) = \sigma^2 \quad \ldots\ldots 15$$

If homoskedasticity holds in a null hypothesis, it can be derived by letting ε be the error term in the linear relationship, and assumed to be normal distributed with mean 0 given the independent variables as shown in equation 16.

$$\varepsilon^2 = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots + e \quad \ldots\ldots(16)$$

Therefore, if heteroskedasticity does not exists, the null hypothesis of homoskedasticity, can be written as in equation 17,

$$H_0{:}\beta_1 = \beta_2 = \ldots\ldots = \beta_K \ldots\ldots\ldots\ldots\ldots\ldots\ldots(17)$$

White test is a special case of Breusch–Pagen. White test is more generic and it relies on the intuition that if there is no heteroskedasticity, the classical error variance estimator gives standard error estimates close enough to those estimated by the robust estimators. Therefore, it is able to detect more general form of heteroskedasticity than Breusch and Pagen (1979) test.

Definition of Variables

The variables used in the Stochastic Frontier Analysis (SFA) model are classified into three categories: the dependent variable (Output), the Production Function Inputs (Xj), and the Inefficiency Determinant Variables (Zk).

Output Variable

The dependent variable in the stochastic frontier production function (Equation 9) is the farmer's output.

Table 5: Output Variable

Variable	Description	Units
Mushroom (Y)	Total quantity of mushroom produced	Kilogram (kg)

Production Function Inputs (X_j)

These variables are the determinants of the production frontier in Equation (9). They are specified in their natural logarithmic form for the Cobb-Douglas model. The expected sign is for the β coefficient (on the output, *lnY*). A positive sign (+) indicates that an increase in the input leads to an increase in mushroom output.

Table 6: Production Function Inputs (X_j for *lnY*)

SFA Designation	Variable	Description	Units	Expected Sign on *lnY* (β)
$\ln X_1$	ln(House Size)	Natural logarithm of Mushroom House Size	ln(M2)	+
$\ln X_2$	ln(Spawn)	Natural logarithm of Amount of Spawn Used	ln(kg)	+
$\ln X_3$	ln(Straw Bales)	Natural logarithm of Weight of Wheat Straw Bales (Substrate)	ln(kg)	+
$\ln X_4$	ln(Labor)	Natural logarithm of Labor (Family + Hired, in Man-Days equivalent)	ln(Man-Days)	+
$\ln X_5$	ln(Fertilizer)	Natural logarithm of Amount of Fertilizer (Nutrient Supplement)	ln(kg)	+

Inefficiency Determinant Variables (Z_k)

These variables are hypothesized to explain the technical inefficiency effect (U_i) in Equation (10). The expected sign is for the δ coefficient (on the inefficiency term, Ui). A negative sign (−) means the variable decreases technical inefficiency (implying a positive effect on Technical Efficiency), while a positive sign (+) means the variable increases technical inefficiency (implying a negative effect on Technical Efficiency).

Table 7: Inefficiency Determinant Variables (Z_k for U_i)

SFA Designation	Variable	Description	Units	Expected Sign on Ui (δ)	Implication
Z_1	Age	Age of the farmer	Years	+	Increases Inefficiency (Bad)
Z_2	Education Level	Level of education attained	Ordinal: 1=Primary...4=University	−	Decreases Inefficiency (Good)
Z_3	Farming Experience	Years of experience in mushroom farming	Years	−	Decreases Inefficiency (Good)
Z_4	Technical Assistance	Access to extension services	Dummy: 1=Yes,0=No	−	Decreases Inefficiency (Good)
Z_5	Access to Credit	Access to financial credit	Dummy: 1=Yes,0=No	−	Decreases Inefficiency (Good)

Other Variables

The remaining variables are presented in Table 8 for descriptive analysis, used as input (X_j) or inefficiency determinant (Z_k) variables in the final SFA model specified above (Equations 9 and 10).

Table 8: Description and Measurement of Other Variables

Variables	Description	Units	Expected sign
Gender	Categorical	1=male,0=female	+
Family size	Continuous	Man equivalent	+
Formal Employment (off-farm)	Dummy	1=Yes,0=No	+
Membership to a cooperative association	Dummy	1=Yes,0=No	+
Distance to the market	Continuous	Km	+/−
Land availability	Dummy	1=Yes,0=No	+
Occupation of the respondent	Ordinal	1=Farmer,...	+
Type of substrate	Ordinal	1=Maize stock,...	+/−
Access to market	Dummy	1=Yes,0=No	+
Price of output	Continuous	Kenya shillings	+
Type of temperature regulation	Ordinal	1=Regular misting,...	+
On- farm income	Dummy	1=Yes,0=No	+
Off -farm income	Ordinal	1=Non-farm work,...	+
Market information	Ordinal	1=local dealers,...	+

Results and Discussions

Socio-Demographic Profile of Mushroom Farmer

Results in Table 9 reveal that the youngest and the oldest smallholder mushroom farmer household head were aged 28 and 76 years respectively, with a mean of 52 years. From previous studies, it has been found that age is an important factor in technology adoption. According to the findings by Akudugu, Guo and Dadzie (2012), on adoption of modern agricultural production technologies by farm households in Ghana, they found out that rate of adoption of modern agricultural production is low for both the younger and older ages. However, the young household heads have a higher probability of adopting new technologies as compared to the older household heads. According to the study by Asfaw, Shiferaw, Simtowe and Lippe (2012), on impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia, they found out that at a younger age of 33 year, the farmer may not have adequate resources needed to adopt modern agricultural production technologies especially capital intensive ones, while the older farmer at 59 years have accumulated many years of farming experience through experimentation and observations and may not want to jeopardize such experiences by trying completely new technologies. The current finding is in convergence with the study findings by Donovan, Bailey, Mpyisi, and Weber (2003), in their study done on the effects of prime-age adult morbidity and mortality on household income, agricultural production, and food security strategies in rural Rwanda. They found out that the majority of mushroom farmers were between 25-55 years. This is in contrast with the findings by Akudugu et al., (2013) who found that the majority of mushroom farmers were aged between 40-60 years, which is also dissimilar to the current study findings.

Summary statistics result as shown in Table 9 of this study further indicates that the largest and the least smallholder mushroom farmer household had 8 and 2 members respectively with an average household size of 5 persons.

Table 9: Summary of Results of Household Socioeconomic Characteristics

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Age	114	52.47	11.13	28	76
Household size	114	4.85	1.46	2	8
Number of dependent	114	4.57	1.69	3	12
Farmers experience	114	4.33	2.71	1	10
Land size	114	4.84	2.45	0.5	11
On-farm income	114	13,165.59	11,444.14	1,350	46,000

Source: *Author's Computation from Survey Data, 2020*

The size of the household is a very significant factor in maximum family labor utilization. A large household would most likely engage more in agricultural activities due to the readily available cheap family labor as compared to a smaller household. The current findings are similar to the findings by Shapiro (2011), on farm size, household size and composition, and women's contribution to agricultural production in Democratic Republic of Congo, who found that the average household size was 4 members. family members provide labor readily because large households will be able to provide cheap labor that might be required to apply farm inputs such as fertilizer and manure. These large households increase the probability of adopting fertilizer, manure and other labor intensive farm operations. This current study finding is also in convergence with the national average household size of 3.9 according to the 2019 household census report by the Kenya National Bureau of Statistics, (2019)

Summary statistics results further indicate the results on the number of household dependents. The largest smallholder mushroom farmer household had 12 dependents while the smallest had 3 members. The mean household number of dependent was 5 members. The number of dependents in a household is a critical factor in agricultural economic performance of a household. According to the findings by Amponsah (2012), on farm households' adoption of ecofarm integrated agricultural technologies and potential economic effects on livelihoods in Segou, Mopti and Koulikoro regions of Mali, found out that a household with the highest and least dependents were 10 and 3 members, respectively with a mean household dependents of 6 members. The study also asserts that the agricultural potential and economic performance of the household with the lower dependents is greater than that of the households with higher dependents. This is because nuclear family productivity is greater than in the extended family households. Their findings on number of dependents are in divergence with the current study on number of dependents and agricultural economic performance. The agricultural productivity is negatively or positively related to number of dependents in a household depending with the ability of the household to productively use available factors of production and technology (Muzari, Gatsi, Muvhunzi, 2012).

The table of results further shows that the average years of experience of smallholder mushroom farmer is 4 years. The most and the least experience had 10 years and 1 year respectively. Previous studies have shown that farming experience goes hand in hand with age and this translates to motivation to adopt new agricultural technologies. Therefore, more experienced farmers are more motivated in farming hence have physical and economic support to fully engage in more beneficial and rewarding agricultural activities. The current finding is in convergence with the study findings by Panneerselvam, Halberg, Vaarst and Hermansen (2012), on farmers' experience and perceptions of organic farming in Indian, who found out a positive relationship between the farmers' experience and farm yield. The current study finding is also in convergence with the study findings by Swastika and Indraningsih (2020), on strategy formulation of farmers capacity building through technological innovation in disadvantaged regions of Indonesia, who found out that the more number of years of approximately above 3.5 years a farmer is practicing a given farming technology, the higher he or she gains experience, hence higher probability to get more yield compared to least experienced. Therefore, more experienced farmers are more motivated in farming hence have physical and economic support to fully engage in more beneficial and rewarding agricultural activities.

The summary statistics also show that the average land size owned by the sampled smallholder mushroom farmer households was 4.8 acres. The household with the largest and least land parcel had 10 acres and 0.5 acres respectively. Earlier studies have shown that the size of the land owned by a household is a very important factor in agricultural production. Small farms sizes, which are universally characterized by more intense land utilization, are more productive than large farms lands which are underutilized (Pilvere, Nipers and Upite, 2014). The current finding of this study is convergent with the study findings by Muyanga and Jayne (2014), on effects of rising rural population density on smallholder agriculture in Kenya, who founded out that the average land size owned by smallholder farmer rangers from 0.2 to 5.5 acres and that the output per unit area of land has a positive correlation with intensity of investment in the land but not the size of the land. The current study is also in agreement with the study findings by Gaurav and Mishra (2011), farm size and returns to cultivation in India, who also founded out that there is a positive correlation between intensity of investment and output per unit area of land, where the average land owned by smallholder farmer was 5.8 acres hence this translated to high land productivity.

The summary statistics further shows that the average on-farm income of smallholder mushroom farmer is Ksh.13,165.59. The highest and the least on-farm income levels are Ksh.1350 and Ksh.46, 000 respectively. Previous study by Ume and Ezeano, Anozie (2018), on the role of off-farm and on- farm income in agricultural production and its environmental effect in South East, Nigeria, who reported that the average monthly on-income is Ksh 8,962.04 for smallholder farmers, Ksh 18,050.50 for diversified farms and Ksh 4,046.20 for the less or non-diversified farms. This shows that there is a positive and significant relationship between the farmers' on-income and the farm yield. This finding is in agreement with the current study finding.

Table 10 presents the results on gender of the smallholder mushroom farmer household head. From the results, 79.82% of the household heads were male while 20.18% were females. This shows that the mushroom production in the study area was dominated by the male gender. This shows that male gender is more involved in mushroom farming than female gender in Uasin Gishu County.

Table 10: Gender of the Sampled Household Heads

Gender	Frequency	Percentage
Female	23	20.18
Male	91	79.82
Total	114	100

Source: *Author's Computation from Survey Data, 2020*

The results indicate a significant gender gap in mushroom farming leadership at the household level. This may reflect broader social, cultural, or economic factors that influence access to resources, land, training, or decision-making roles in agriculture. The low proportion of female-headed households suggests that interventions aiming to promote gender equity in mushroom farming may be needed. Programs could focus on empowering women through training, access to credit, and support networks. The data underscores the importance of addressing gender disparities in agricultural sectors like mushroom farming. Promoting greater gender equity could enhance household incomes, improve food security, and empower women within rural communities. The findings highlight a clear male predominance among household heads farming mushrooms, with females constituting a minority. Addressing the underlying causes of this disparity could help enhance gender balance and overall productivity in mushroom farming communities. These results concur with those of Mutema, Basira, Savadye and Parawira (2019) who reported that mushroom production is mostly practiced by 80% of the male gender and 20% of the female gender. Therefore, males are more involved in mushroom production practices than their female counterparts.

Figure 1 presents the results on the level of education of the respondents. Education plays an important role in the adoption of innovation and household understanding of market dynamics (Yost, Sudduth, Walthall and Kitchen, 2019). Education will eventually improve the decision making ability of the farmer household. From the results, 40.4% of the mushroom farmer household heads had attained primary level of education, 14.9% secondary education level, 25.4% college education level, 13.2% university level of education while 6.1% had no formal education. The results indicate that the highest percentage of mushroom farmer households had attained the primary and secondary education as their basic education levels. This shows that farmers who have basic levels of education are more likely to be directly involved in mushroom production, which is an on-farm investment and the main source of income in the rural areas. Education also improves on the decision making ability of the smallholder farmer. The current study findings are contrary to the findings by Rosmiza et al., (2018), who reported that, in Ghana, mushroom production was majorly practiced by 27.2% of illiterate households, 65% of the 'ordinary' level educated households (primary and secondary level of education) and 7.8% of tertiary attained (college and university education), which derailed adoption of mushroom production. The current finding of this study is also in contradictory to the findings by Nathanel, Abdulsalam, Rahman and Abdoulaye (2015), on his findings on the socioeconomic factors affecting adoption of early maturing maize varieties by small scale farmers in Safana State, Nigeria, who argued that 68.4% of highly educated smallholder farmers were of significance among farmers group in terms of sharing new skills and introduction of modern biotechnology techniques to other smallholder farmers through group trainings.

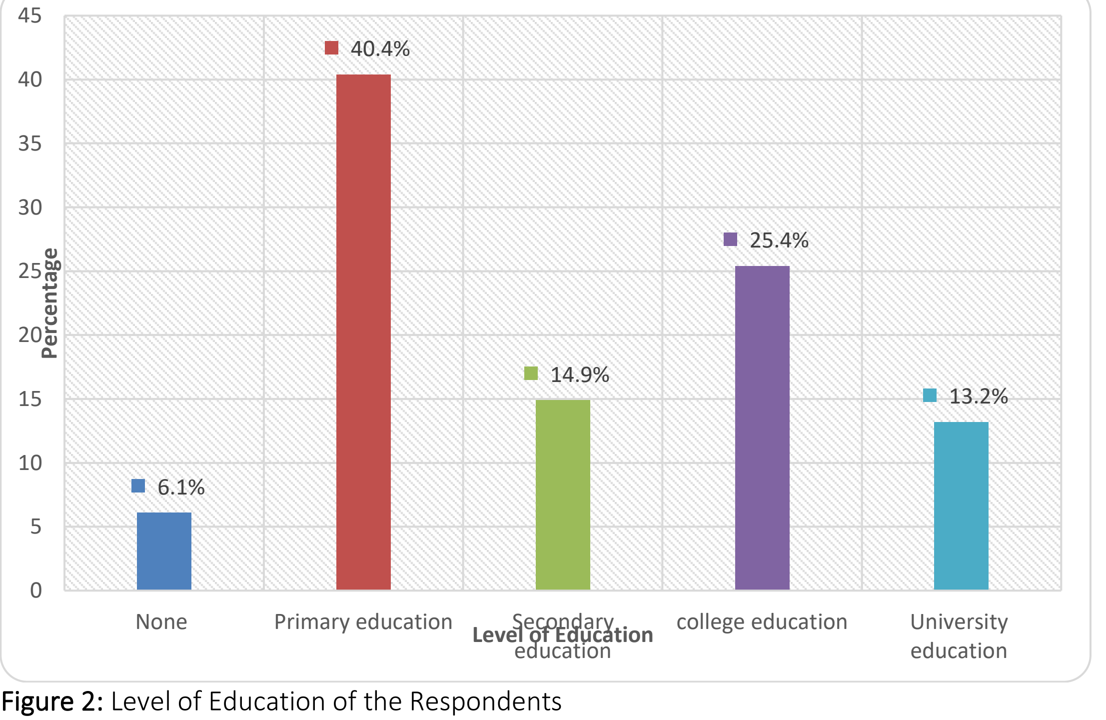

Figure 2: Level of Education of the Respondents
Source: *Author's Computation from Survey Data, 2020*

Econometric Analysis Results

Estimates of Technical Efficiency of Mushroom Production

Table 11 of results shows the coefficient of determination (adjusted R-squared) that was computed to determine the degree to which the input variables (predictors variables) explain the variation of output variables (predicted variable) in the Cobb-Douglas Production Function in Table 12. Results revealed that the R-Squared and Adjusted R-Squared values was 0.84 and 0.83 respectively. The R - Squared results of 0.84 means that that our independent variables for the current study explains 84% of the variability of our dependent variable, whereas the Adjusted R-Squared value of 0.83 means that 83% of the variation in the output variables are explained by the input variables and only 17% lies within the error term in the regression model for this study. This indicates a perfect goodness of fit for the regression model. According to Wooldridge (1991), adjusted R-squared ranges from 0 to 1 and a coefficient of determination of 0.7 to 1 is acceptable.

Table 12: Coefficient of Determination

R	R- Square	Adjusted R –Square	Std. Error of the Estimate
0.914	0.836	0.825	17.23006

Source: *Author's Computation from Survey Data, 2020*

Estimation of the Technical Efficiency of Mushroom Production

Table 13 presents the results of the maximum likelihood estimates of the Cobb-Douglas stochastic frontier production function. From the table of results, the Log likelihood ratio (LR) was found to be -30.937 with a *p*-value of 0.0125 and therefore, statistically significant at 5% level. This Log likelihood ratio test detected a statistically significant inefficiency term in the model, hence indicates that inefficiency exists in the data set. Thus, clear evidence of failure to accept the null hypothesis of no inefficiency component in the model and accept the alternative hypothesis that inefficiency component exits in the model. According to the study by Greene (2003) on econometric analysis of a person's education in India, he found out a Log likelihood ratio (LR) of 0.43 with a p-value of 0.0256, which indicates that inefficiency exists in the data set. The stochastic frontier model used to compute the findings of the study also outlined that output from frontier includes estimates of the standard deviations of the two error components, σ_v and σ_u which are labeled sigma *v* and sigma *u*, respectively. In the log likelihood ratio test, they are parameterized as $ln\ \sigma^2_v$ and $ln\ \sigma^2_u$ and these estimates are labeled /lnsig*2V* and /lnsig*2U* in the output. Frontier also reports two other useful parameterizations, the estimate of the total error variance, $\sigma^2_s = \sigma^2_v + \sigma^2_u$,is labeled sigma^2, and the estimate of the ratio of the two standard errors and it measures the total variation of output from the frontier that can be attributed to technical efficiency $\lambda = \sigma_u \div \sigma_v$ is labeled lambda. It can also be expressed as an estimation of γ which is the ratio of the variance of *u* to the total variance i.e $\gamma = \sigma^2 v \div \sigma u^2$ it must range between 0 and 1. The coefficients of inputs like land (area of mushroom house), labour, additives and spawn were positive in the production function, except the coefficients of wheat straw, fertilizer, substrate and chemical which were negative. The positive effects of inputs on the output were expected because more inputs used in rightful proportions increases production and this agreed with non-negativity assumption in the production function. The coefficients of land area under production (area of mushroom house), labour, additives and spawn were positive implying that increase in the use of any of these factors of production, ceteris paribus, will increase the total production of mushroom.

Summary statistics result of this study also indicates that, the parameter estimates for sigma (σ^2) and lambda (λ^2) squared are 0.2980 and 0.0091 respectively. Lambda is statistically significant at 1% level, indicating a good fitness and correctness of the specified distribution assumption of the composite error terms normal distribution. The lambda is the ratio of the variance of *U* to the variance of *V* in the model, implying that, the one sided error term *U* dominates the error term symmetry *V*. Therefore, variations in the actual output of mushroom are due to differences in smallholder farmers' practices rather than random variation. From Table 13 of results, the derived production elasticity of man-hour labour was significant at 1% level.

Table 13: Maximum likelihood Estimates of the Cobb-Douglas Production Function (stochastic frontier production function) results

Ln_Yield	Coefficient	Standard error	z	p>|z|
Natural log Area of house(Land Area)	0.0347511	0.584571	0.59	0.552
Natural log Labour	0.6655341	0.008022	7.45	0.000*
Natural log Spawn	0.3040369	0.1577908	1.93	0.054
Natural log Wheat straw	-0.1190761	0.1444397	-0.82	0.410
Natural log Fertilizer	-0.2922318	0.2893605	-1.01	0.313
Natural log Additives	-0.0406499	0.0304734	-1.08	0.279
Natural log Chemicals	-0.0461292	0.0511058	-0.90	0.367
_constant	0.4252176	0.6655247	0.64	0.523
/lnsig*2V*	-2.414941	0.3758476	-6.43	0.000*
/lnsig*2U*	-1.1203	0.3612637	-310	0.002*
Sigma *V*	0.4155554	0.1152354		
Sigma *U*	0.5711233	0.1031631		
σ^2	0.2989525	0.0561803		
λ^2	0.0091041	0.0012782		

Legend

n= 114 Wald chi2(7)=16.24 LR test for: H_0 : Inefficiency component does not exits

Log likelihood = -30.937 Prob>chi2 =0.0125** against Ha: Inefficiency component exits

Notes: *=significant at 1% level,
**= significant at 5% level

Source: Author's Computation from Survey Data, 2020

Man-hour labour had the highest positive coefficient with a value of 0.665. This implies that a unit increase in labour applied in mushroom production will result into an increase in mushroom output by 66.5 percent, ceteris paribus.

Therefore, the highest positive coefficient of labour indicates that it is the most crucial factor of production that greatly determines mushroom output. The result suggests that the more labour a farmer allocated to mushroom farming, the higher the yields obtained. The current finding is in convergence with the findings by Dlamini, Masuku and Rugambis (2018), on technical efficiency of mushroom farmers in Swaziland, who found out that the derived production elasticity of weekly labor was significant at 1% level. Weekly labor had the highest coefficient with a value of 0.378 and therefore, it existed as the most limiting factor that greatly determined what mushroom output would be like. An increase in labor, ceteris paribus, would increase technical efficiency by 37.8%. Labour is the most crucial source of technical efficiency, especially in developing countries where farm mechanization is very limited. This is because agriculture is more labour intensive (Austin & Sugihara, 2014).

Distribution of Technical Efficiency

Table 14 of results shows the results on the distribution of technical efficiency estimates for mushroom farmers in Uasin Gishu County. In this study area, the predicted technical efficiency indices had variations among mushroom farmers that ranged from 0.29 to 1.00.

Table 14: Frequency distribution of technical efficiency of mushroom producers

Efficiency Class	Frequency	Percentage
0.21 – 0.40	36	31.3
0.41 – 0.60	14	12.2
0.61 – 0.80	20	17.4
0.81 – 1.00	45	39.1
Total	114	100.0
Mean Efficiency	0.67	
Minimum	0.29	
Maximum	0.89	

Source: *Researcher's own calculation from survey data of 2020*

From the results, the technical efficiency for the smallholder mushroom farmers in the current study range from 29% and 89% with a mean efficiency of 67%. This implies that, the farmer with the best practice had a technical efficiency of 89%; farmer with the worst practice had a technical efficiency of 29%. This means that mushroom farmers are 29% below the production frontier. The technical efficiency ranges from 0% to 100%. The average technical efficiency score of 67% for this current study indicates that there is a scope for increasing technical efficiency by 33% in the short-run using the current input quantities under the existing technology, so as to be technically efficient at 100%. According to the study by Färel and Lovell (1978), on input and output approach of measuring the technical efficiency of production, a production technology transforming inputs reported that farmers are said to be technically efficient if the minimum and maximum technical efficiencies for farmers are between 80 - 94% and 95-100%, respectively, with a mean technical efficiency falling between 95-98%. Hence only 2-5% of the potential frontier output is not realized due to uncontrollable factors beyond farmer's capabilities. This is a sufficient and necessary condition, if and only if, the production technology is linearly homogenous. Therefore, the results of this current study do not meet the sufficient and necessary condition. This indicates that mushroom famers in Uasin Gishu County are technically inefficient in their production. According to the study by Okoth (2018), on technical efficiency of sugarcane monoculture and sugarcane-soybean intergration among smallholder farmers in Awendo Sub-County, Kenya, found out that the aggregate maximum, minimum and mean technical efficiencies for farmers were found to be 0.83, 0.22 and 0.63 respectively. This implies that the farmer with the best practice had a technical efficiency of 0.83; farmer with the worst practice had a technical efficiency of 0.22 while in general, the farmers had an average technical efficiency of 0.63. The aggregate mean technical efficiency of 0.63 implies that on the average, they were able to obtain a little over 63% of optimal output from a given mix of production inputs and production technology. Therefore, for the current study, there is a scope for increasing technical efficiency by 37 % in the short-run under the existing technology. The findings of the current study is therefore, in convergence with the findings reported by Dlamini, Masuku and Rugambis (2018) on the technical efficiency of mushroom farmers in Swaziland, who found out that the predicted technical efficiency indices varied among mushroom farmers; ranging from 0.38 and 1.00. This means that mushroom farmers are 38% below the production frontier. The mean technical efficiency was estimated to be 65%. This indicates that each farmer can increase mushroom output by 35% using the current input quantities. The most technically efficient participant farmers recorded a score of 100% while the least score was 38%.

Conclusions

The study analyzed the technical efficiency of mushroom production among 114 smallholder farmers in Uasin Gishu County, Kenya, using the Stochastic Frontier Analysis (SFA) model. Descriptive statistics revealed a mean age of 52 years and an average of 4 years of experience in mushroom farming. A significant majority of farmers (60.5%) did not have access to agricultural extension services. The dominant mushroom type cultivated was oyster mushroom (56.14%). Household size was found to be statistically significant and positively affected production. The SFA model confirmed that smallholder mushroom farmers in Uasin Gishu County are technically inefficient in their production. The technical efficiency (TE) scores ranged from 29% to 89%, with a mean TE of 67%. This implies that, on average, farmers could increase their mushroom output by 33% in the short run using the current inputs and technology, simply by adopting the best practices of their most efficient peers. Among the seven inputs used, the derived production elasticity of Man-hour Labour was the only statistically significant input with a positive coefficient (β=0.665). This indicates that labour is the most crucial and limiting factor of production, where a 1% increase in labour would increase mushroom output by 0.665%. However, inputs such as Wheat Straw, Fertilizer, Additives, and Chemicals had negative signs, suggesting that farmers were over-utilizing or misallocating these inputs, causing production to operate in the irrational stage. The study rejected the null hypothesis that farm characteristics, market, and institutional factors do not significantly affect technical efficiency, concluding that inefficiency is controllable. Access to Extension Services (increased TE by 48.8%), Price of Mushroom Output (increased TE by 33.5%), Access to Credit (increased TE by

8.1%), On-farm Income (increased TE by 9.2%), and Labour Size (increased TE by 10.9%). Distance to the Market had a negative coefficient (δ=−0.4194), meaning that longer distances significantly increased technical inefficiency.

Recommendations

Based on the empirical evidence, the following policy and strategic recommendations are provided to help smallholder mushroom farmers close the 33% technical efficiency gap and increase overall output in Uasin Gishu County:

1. Given that Access to Extension Services significantly increases TE by 48.8% and that 60.5% of farmers lack this access, the county and national governments must establish alliances with private agricultural extension companies. Training programs must specifically focus on:
   - Optimal input application rates (e.g., fertilizer and substrate), addressing the current problem of over-utilization indicated by the negative coefficients.
   - Best practices in production, post-harvest handling, and value addition.
2. As labour was identified as the most limiting factor of production, interventions are needed to increase its effective supply and utilisation.
   - Promote the formation of farmer groups or cooperative labour schemes to pool family labour resources.
   - Encourage the use of small-scale, labour-saving technologies for processes such as substrate preparation and temperature/humidity control.
3. To capitalize on the positive impact of price and mitigate the high cost of distance:
   - The county government should invest in creating a reliable market network and organized collection centers to reduce the distance to market burden on individual farmers.
   - Agricultural marketing specialists (e.g., I-Shamba) should be engaged to deliver timely information on favorable prices and quality standards to leverage the positive elasticity of output price.

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