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Heterogeneity Effects of Improved Tomato Farmers' Technical Efficiency in Southwest, Nigeria: An Unconditional Quantile Regression Approach.

Julius Olumide Ilesanmi[1*], Sadiat Funmilayo Arifalo[2]

[1] Department of Agricultural Science and Technology, School of Agriculture and Agricultural Technology, Bamidele Olumilua University of Education, Science and Technology, Ikere-Ekiti, Nigeria.

[2] Department of Agricultural and Resource Economics, School of Agriculture and Agricultural Technology, Federal University of Technology, Akure, Nigeria.

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***Corresponding author:** Julius Olumide Ilesanmi.

Department of Agricultural Science and Technology, School of Agriculture and Agricultural Technology, Bamidele Olumilua University of Education, Science and Technology, Ikere-Ekiti, Nigeria.

Abstract

Nigeria's present economic situation has raised production costs and directly affected the affordability of farm inputs, endangering both the sustainability of output and the improvement of farmers' efficiency. Furthermore, the consequences of climate change are becoming more noticeable, and one of the industry's most at risk is agriculture. Therefore, to alleviate all of these problems, improved tomato varieties and sustainable farming techniques must be developed to boost farmers' output. Therefore, the study aimed to measure the efficiency of the farmers and to examine the effects of improved tomato varieties cultivated and sustainable agricultural practices on the efficiency of the farmers. The study was carried out in Osun and Ekiti States based on the density of improved tomato farmers. Data Envelopment Analysis (DEA) model was used to measure the technical efficiency of the farmers while Unconditional Quantile Regression (UQR)was used to determine the heterogenous effects of SAP and variety cultivated on the efficiency of the farmers. DEA model employed to assess the technical efficiency of tomato growers revealed that the Variable Return to Scale Technical Efficiency (VRSTE) output of the tomato farmers in the examined area achieved an average technical efficiency of 0.93, indicating a higher level of technical efficiency among them. The assessment of efficiency is based on analyzing the input amounts used by the tomato farmers about the volume of tomatoes produced and it became apparent that the farmers applied a greater quantity of fertilizer (mean slack of 1.64kg) to provide essential nutrients to the crops and enhance their yield. The model also indicated a mean slack of approximately 0.13ha of land among the farmers in their agricultural activities.

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The UQR findings revealed that the factors at various quantile levels suggested that there is heterogeneity among the quantiles, as the strength of the coefficients varied as well. Soil quality and income level had a significant impact across all quantiles. Family size, years of experience, land ownership, planting period, income level, and access to credit displayed negative coefficients across the quantiles, while age, marital status, gender, education level, access to extension agents, number of sustainable agricultural practices, and number of varieties grown presented positive coefficients across the quantiles. The implementation of SAP exerted a negative influence on efficiency at the τ.50 quantile, where it was not statistically significant. This suggested that a one-unit rise in the number of SAP adopted at the τ.50 quantile would lead to a 0.82% decrease in farmer efficiency. Furthermore, an increase of one unit in SAP adoption would result in efficiency improvements of 0.001% and 0.002% for farmers at the τ.25 and τ.75 quantiles, respectively, indicating a minimal effect on the efficiency of the local tomato farmers. The number of hybrid tomato varieties cultivated positively influenced efficiency at all quantile levels, and it reached statistical significance at all quantile levels. This indicated that for every additional unit of varieties grown, farmer efficiency is expected to rise by roughly 0.08%, 0.03%, and 0.05% at the τ.25, τ.50, and τ.75 quantiles, respectively.

Keywords: *Improved Tomato Varieties; Unconditional Quantile Regression (UQR); Efficiency; Data Envelopment Analysis (DEA); Heterogeneity effects; Sustainable Agricultural Practices (SAP).*

1.0 Introduction

Tomatoes are one of the most significant vegetables and may be consumed both raw and cooked, according to Giovannoni (2007). In addition, it contains fiber, antioxidants, vitamins, and minerals. Klee and Giovannoni (2011) asserted that it is also an excellent model system for research on sustainable agriculture. Nigeria has the potential to lead the globe in tomato exports since it is now the 11th-largest tomato-producing country in the world. Olanrewaju, Jacob, Suleiman, and Abubakar (2017) state that Nigeria is the continent's second-largest producer of fresh tomatoes, accounting for 10.8% of total production. The country was the 14th largest tomato grower in the world in 2016 with 2.3 million tons produced (PWC, 2018). NGF (2015) states that in 2016, this only made up 1.2% of the world's production. Over the last ten years, Nigeria has produced an estimated 2.3 million tonnes of fresh tomatoes, a 25% increase from 1.8 million tonnes. Nonetheless, the continuous growth of the tomato harvesting area—which rose from 265,000 hectares to 668,292 hectares during the same period of time—has largely contributed to this increase. Tomato yields between 2006 and 2016 averaged 5.47 tonne/ha, which was exceedingly low compared to the global average of 38.1 tonne/ha. Lack of Sustainable Agricultural Practices (SAP), the use of antiquated seedling varieties, weed and insect invasion, and insufficient soil fertility have all been linked to insufficient tomato output (Sahel Research, 2017). According to Idoko (2023), farmers in Nigeria are mostly ignorant of the advantages and long-term effects of sustainable agricultural practices, which adds up to a lack of awareness of ecologically friendly approaches. Among the difficulties facing sustainable farming in Nigeria are restricted access to contemporary farming methods, insufficient funding for farmers, and the effects of climate change on agriculture, which could have been avoided with the adoption of climate-smart agricultural practices. Tomato, as a staple crop in Nigeria, are pivotal for both nutritional and economic sustainability. However, the tomato farming sector is marred by inefficiencies, particularly in the realm of sustainable agricultural practices and the adoption of improved varieties. While substantial research has been undertaken on general agricultural productivity and sustainability (Dossou et *al*., 2007; Onifade et al., 2013), specific investigations focusing on the efficiency of improved tomato production in the unique context of Southwest Nigeria remain sparse. This study aims to fill this critical research gap by examining the impact of sustainable practices on the efficiency of tomato farms in this region, which is characterized by its diverse agro-ecological zones and economic conditions (Sahel Research, 2017). The sustainability of production and the enhancement of farmers' efficiency are in danger due to Nigeria's current economic circumstances, which have increased production costs and directly impacted the affordability of farm inputs. Additionally, the effects of climate change are becoming more apparent, and agriculture is one of the most vulnerable sectors. The development of sustainable agricultural practices and improved varieties to increase farmers' productivity in tomato production are thereby necessary to alleviate all of these issues. A number of studies have been done on the efficiency of tomato farmers and sustainable agricultural practices; however, very few have specifically examined the desire of large- and small-scale farmers to address issues of inefficiency for optimal output and to adopt good agricultural practices for sustainable production in order to combat food poverty. Any productive farmer's general objective is to maximize profit from the limited resources acquired while minimizing costs at different phases of production. This research will provide detailed insights into the dynamics of tomato farming in Southwest Nigeria, exploring how local environmental and socio-economic factors influence agricultural efficiency (Olanrewaju et al., 2017). This study was aimed to measure the efficiency of the farmers and to determine the heterogenous effects of SAP and variety cultivated on the efficiency of the farmers.

2.0 Methodology

2.1 Study Area

The study covered the two major tomato-producing states in southwest Nigeria; Osun State and Ekiti State. Southwest Nigeria has rainy and dry seasons, and its climate is tropical. The Southwest Monsoon Wind from the Atlantic Ocean is related with the rainy season, and the North-East Trade Wind from the Sahara Desert corresponds with the dry season. The three primary agro-ecological zones in the region are the Guinea Savannah in the North, the tropical rainforest in the middle belt, and the swamp on the Atlantic coast. Freshwater swamps and mangrove forests make up the vegetation in the Southwest of Nigeria, while secondary forest is found closer to the northern boundary, where the Southern Savannah exists. The lowland in forest extends inland to Ogun State and a portion of Ondo State (Agboola, 1979). The bulk of the population relies mostly on rain-fed agriculture for their

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subsistence. The locals mostly grow maize, cocoa, oil palm, plantains, bananas, pineapples, cowpeas, cashews, kola nuts, cassava, and other crops (Oyekale, 2009).

2.2 Data Source and Data Collection

In order to gather primary data for this study, a well-structured questionnaire comprising both closed-ended and open-ended questions was administered, and respondents in the study area were interviewed in person.

2.3 Sampling Procedure and Sampling Size

Throughout the research process, a multi-stage sampling technique was used. In the first phase, Osun and Ekiti States were specifically chosen among the six Southwest Nigerian states because of their sizable tomato-producing populations (Oyedokun, Yesufu, Ayorinde, and Ogunmola, 2020). The second phase also required the deliberate selection of three (3) Local Government Areas (LGAs) from each state based on the density of tomato producers in order to determine a total of six (6) LGAs for the research. Based on the stated concentration of tomato producers in those villages as indicated by ADP in the state, five (5) villages were specifically chosen from each LGA identified in the second phase to make a total of thirty (30) villages included in the research. Three hundred (300) tomato growers were polled in the last stage, which included choosing ten (10) farmers at random from each village. Simple random sampling was used to clean out researcher bias and guarantee equitable gender representation.

2.4 Data Analysis and Model Specification

The study employed analytical methods including Unconditional Quantile Regression (UQR), Data Envelopment Analysis (DEA), and descriptive statistics like percentage and frequency tables to draw conclusions regarding the correlations between the data variables.

2.4.1 Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) was employed to measure the efficiency of tomato farmers in the study area who are growing the improved variety (objective iv). The DEA is a non-parametric technique. It is a linear programming model that is used to measure technical efficiency under the assumption that there are no random errors. A farm is considered efficient if it generates a certain number of outputs while using a given number of inputs, or if it uses the same number of inputs or less to generate the same number of outputs. The DEA approach is used to set a benchmark and evaluate efficiency when there are many inputs, multiple outputs, and no market price. Although Farrell (1957) and Debreu (1951) laid the groundwork for the approach, Charnes, Cooper, and Rhodes (1978, 1981) are the canonical references.

Ratio-based efficiency measurement is the most often employed approach. Their shortcoming is that just a small portion of the variables influencing a producing unit's total efficiency are reflected in them. Assuming that there are n productive decision-making units (DMU) in our population (DMU_1, DMU_2, …, DMU_n). Each unit produces 's' outputs while consuming 'm' inputs. We have

input matrix X = [xij, i = 1, 2, …, m, j= 1, 2, …, n] and

output matrix Y = [yij, i = 1, 2, …, s, j= 1, 2, …, n].

The q-th line – i.e. Xq and Yq – of these matrixes thus shows quantified inputs/outputs of unit DMUq. The efficiency rate of such a unit can then be generally expressed as:

$$\frac{weighted\ sum\ of\ outputs}{weighted\ sum\ of\ inputs} = \frac{\sum_{i=1}^{s} U_i y_{iq}}{\sum_{j=1}^{m} V_j x_{jq}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

where:

V_j, j = 1, 2, …, m, are weights assigned to j-th input,

Ui, i = 1, 2, …, s, are weights assigned to i-th output.

A homogeneous group of decision-making units (DMUs), in this example tomato producers, have their relative efficiency measured using the multi-factor productivity analysis model known as DEA. According to Coelli (1995), the two primary benefits of DEA are that it does not need the distributional assumption of the inefficiency element or the assumption of a functional form to explain the link between inputs and outputs. According to Fraser and Cordina (1999), the former suggests that one can avoid needless limitations on functional design that might bias analysis and efficiency measures. According to Coelli, Rao, and Battese (1998), the DEA model's Constant Returns to Scale (CRS) model is only suitable when the farm is running at its ideal scale. However, this is thought to be unfeasible for a variety of reasons, such as limited resources, unsatisfactory competitiveness, and insufficient agricultural inputs, among others. Compared to a CRS DEA, a Variable Return to Scale (VRS) DEA is more adaptable and tightly encapsulates the data. Thus, Banker, Charnes, and Cooper (1984) created the VRS DEA model. The technical efficiency of tomato farms in the study area was estimated using an input-oriented VRS DEA model. According to Coelli et al. (1998), the following is the specification of an input-oriented variable return to scale DEA model for technical efficiency estimation:

$$min_{\theta,\lambda}\,\theta,$$

Subject to: $-y_i + Y\lambda \geq 0$ ……………………………………...(2)

$$\theta X_i - X\lambda \geq 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$N_1/\lambda = 1$$

$$\lambda \geq 0$$

Where Y = Tomato yield (kg) for N farms

= The input technical efficiency score has a value 0 ≤ ≤ 1

x = an input matrix for N farms

λ = N by 1 vector of weights which defines the linear combination of the peers of ith farm

= quantity of tomato output of ith farm

The input considered are:

X_1 = farm size (ha)

X_2 = Seed quantity (kg)

X_3 = Herbicide (litres)

X_4 = fertilizer (kg)

X_5 = Fungicide (litres)

X_6 = Insecticide (litres)

2.4.2 Unconditional Quantile Regression (UQR)

The distributive impact of variety cultivation and sustainable agricultural practices on the productivity of tomato growers in the research area were examined using the UQR. Similar to Timothy

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Park's (2015) study, who used the UQR to examine the impact of direct marketing participation on the entire distribution of farm sales; the UQR revealed the distributional effects that arise when tomato producers in the study area align with particular SAP and tomato cultivars with regards to efficiency. Regression analysis of the (recentered) impact function of the outcome variable's unconditional quantile is performed on the explanatory variables as part of the methodology (Firpo et al. 2006). One often used tool in robust estimating that is simple to construct for each quantile of interest is the influence function. Similar to how regression coefficients are utilized in the case of the mean, the estimated regression model may be used to infer the effect of changes in explanatory variables on a given unconditional quantile. The Recentered Influence Function (RIF) is the foundation of the unconditional quantile method (Hampel, Ronchetti, Rousseeuw and Stahel, 1986). Without requiring a new calculation of the distributional statistic, v(F), such as the median, interquartile range, or any quantile, the influence function (IF) evaluates the effect of a single observation on that statistic. Unconditional Partial Effect (UPE) assume that dχ, the boundary of the support χ of X, is such that if ∈ dχ , then () = 0. Then the vector α(v) of partial effects of small location shifts in the distribution of a continuous covariate on $v(F_Y)$ can be written as:

$$\alpha(v) = \int \frac{dE[RIF(Y;v)|X=x}{dx} . dF(x) \ldots\ldots (4)$$

Turning to the specific case of quantiles, consider the τth quantile $q_\tau = v_\tau(F_Y) = inf_q(q: F_Y(q) \geq \tau)$

$$RIF\left(Y; q_\tau\right) = q_\tau + \frac{\tau - I\,(y \leq q_\tau}{F_Y(q_\tau)} = C_{1,\tau} . 1(y > q_\tau) + C_{2,\tau} \ldots\ldots (5)$$

Where, $C_{1,\tau} = {}^{1}/_{F_Y(q_\tau)}$, $C_{2,\tau} = q_\tau - C_{1,\tau} . (1 - \tau)$ and $F_Y(q_\tau)$ is the density of Y evaluated at q_τ , thus

$$E[RIF(Y; q_\tau)|X = x] = C_{1,\tau} . P_r\,[Y > q_\tau|\, X = x] + C_{2,\tau} \ldots\ldots (6)$$

From equation 10, the unconditional partial effect, that we denote α(τ) in the case of τth quantile, simplifies to:

$$\alpha(\tau) = \frac{\partial V_\tau(F_Y, t.G_Y^*)}{\delta t} |_{t=0} = C_{1,\tau} . \int \frac{dP_r\,[Y > q_\tau|\, X=x]}{dx} . dF_x(x) \ldots\ldots (7)$$

where the last term is the average of marginal effect from the probability response model $P_r\,[Y > q_\tau|\, X]$. We call the parameter $\alpha(\tau) = E[dE[RIF(Y, q_\tau)|X]/dx]$ the unconditional quantile partial effect (UQPE). UQPE in terms of general structural model, $Y = h(x, \varepsilon)$ where the unknown mapping $h(.,.)$ is invertible and ε is an unobserved determinant of the outcome variable Y, which can also be written as weighted average of conditional quantile partial effect (CQPE), which is the effect of a small change of X on the conditional quantile of Y:

$$CQPE(\tau, x) = \frac{\partial Q_\tau[h(x,\varepsilon)|X=x]}{dx} = \frac{\partial h(x, Q_\tau(\varepsilon)]}{dx} \ldots\ldots (8)$$

$$UQPE(\tau) = E[\omega_\tau(X) . \frac{\partial h(x, \varepsilon_\tau(X)]}{\partial x} \ldots\ldots (9)$$

Y = Technical Efficiency (TE)

X_1 = Age of the farmers (years)

X_2 = Marital Status (Married = 1 and 0, otherwise)

X_3 = Gender (Male = 1, Female = 0)

X_4 = Family Size (Numbers)

X_5 = Farmers' Education (years of schooling)

X_6 = Experience (in years)

X_7 = Farm Workers (Numbers)

X_8 = Size of land (ha)

X_9 = Soil Quality (Good = 1 and 0, otherwise)

X_{10} = Land Tenancy Status (Owned = 1 and 0, otherwise)

X_{11} = Period of Planting (Wet season = 1 and 0, otherwise)

X_{12} = Income Status (High = 1 and 0, otherwise)

X_{13} = Access to Credit (Yes = 1 and 0, otherwise)

X_{14} = Access to Extension Agents (Yes = 1 and 0, otherwise)

X_{15} = Numbers of SAP adopted

X_{16} = Numbers of improved varieties cultivated

3.0 Results and Discussion

3.1 Data Envelopment Analysis (DEA) on Measuring Efficiency of Tomato Farmers

An input-oriented variable returns to scale DEA model was employed for this analysis to assess the technical efficiency of tomato growers. The Variable Return to Scale (VRS) output revealed that the tomato farmers in the examined area achieved an average technical efficiency of 0.93, indicating a higher level of technical efficiency among them. Table 2 demonstrated that the assessment of efficiency was based on six variable inputs: farm size, seed quantity (Kg), herbicide usage (litres), fertilizer application (Kg), fungicide usage (litres), and insecticide usage (litres). The technical efficiency calculated here considers the different inputs involved in tomato production and their interrelationships. Analyzing the input amounts used by the tomato farmers in relation to the volume of tomatoes produced, it became apparent that the farmers applied a greater quantity of fertilizer to provide essential nutrients to the crops and enhance their yield. Since slack represents an excess in input utilization, a farm could decrease its input spending by the slack amount without negatively affecting the output (Oguntade, Fatumbi and Okafor, 2013). In Table 1, out of the 300 tomato farms that were examined, 125 under VRS and 11 under Constant Return to Scale (CRS) are completely productive. Thirty-two (32) farms under VRS and one (1) farm under CRS have their efficiency scores ranges from 0.3 to 0.39. It was discovered that the highest efficiency score was 0.926. CRS and VRS have average total technical efficiencies of 0.749 and 0.926, respectively. About 3.7% and 41.7% of farms, respectively, were determined to be entirely technically efficient under the CRS and VRS specifications under the current circumstances. The observed difference between CRS and VRS measurements also suggested that some farmers were not operating at an efficient size, and that if farmers changed their operational scales, overall efficiency may be improved. The mean technical efficiency score in this study ranges from 0.749 to 0.926. According to these findings, given the existing production situation, technological efficiencies may be raised by at least 80% by making better use of the resources that are available. Under the CRS standard, the group with the lowest technical efficiency score is 0.3 to 0.39 and under the VRS specification, the group with the lowest technical efficiency scores is 0.5 to 0.59 category; This shows that TE scores under the VRS were higher than those obtain under the CRS specification (Alemdar and Oren, 2006; Ogunniyi and Oladejo, 2011). The causes of inefficiency for unproductive farms might be either misallocation of resources or incorrect size.

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Misallocation of resources refers to inefficient combinations of inputs, whilst inappropriate scale implies that the farm is not being able to benefit from economies of scale. The scale efficiencies in this investigation are relatively great. As a result, inefficient input consumption is the primary cause of efficiency. Table 1 revealed that the tomato farm's mean scale efficiency is 0.819. This outcome demonstrated that the investigated area has some small-scale inefficiency. This suggested that in order to get more productivity given the existing factor combination, the majority of the farm should be smaller than it is now. This research supports the findings of Ogunniyi and Oladejo (2011), who found small-scale inefficiencies in their work. Fertilizer is the input with the largest surplus in Table 2. This is followed by the application of herbicides and fungicides. These findings suggest that sample farms might increase fertilizer use by around 64.02% while maintaining the same level of output. Additionally, a large number of farms (135) use excessive amounts of fungicide. This research revealed overuse of all inputs, particularly fungicides, herbicides, and fertilizers. It was also found that the land slack was 0.126ha. This suggests that in order to get the same level of output, farm size may be decreased by this amount. Moreover, as indicated by the 1.64 kg fertilizer slack, 1.64 kg less fertilizer should be used. Essentially, if the amount of the different inputs were decreased by the corresponding values of slacks among the inputs, the same level of output that was generated from this inputs' utilization could still be produced.

Table 1 Distribution of Technical Efficiency Scores obtained by DEA Models.

Efficiency Scores	CRS	VRS	SCALE
0.30 - 0.39	1(0.3)	32(10.7)	1(0.3)
0.40 - 0.49	6(2.0)	40(13.3)	6(2.0)
0.50 - 0.59	7(2.3)	5(1.7)	1(0.3)
0.60 - 0.69	66 (22.0)	17(5.7)	38(12.7)
0.70 - 0.79	113(37.7)	45(15.0)	72(24.0)
0.80 - 0.89	90(30.0)	20(6.7)	91(30.3)
0.90 - 0.99	6(2.0)	16(5.3)	80(26.7)
1.00	11(3.7)	125(41.7)	11(3.7)
Total	300(100)	300(100)	300(100)
Mean	0.749	0.926	0.819

CRS = Constant Returns to Scale; VRS = Variable Returns to Scale

Source: Computed from field survey, 2024

Table 2 Input Slack and Number of Farms Using Excess Inputs.

Inputs	No of Farms	Mean Slack	Mean input use	Excess input use%
Farm Size	144	0.126	1.189	10.60
Seed Quantity	102	0.117	1.767	6.62
Herbicide	100	0.391	1.832	21.35
Fertilizer	90	1.641	2.563	64.02
Fungicide	135	0.727	1.629	44.64
Insecticide	90	0.365	2.318	15.74

Source: Computed from field survey, 2024

3.2 Determinants of the Heterogenous Effects of SAP and Variety Cultivated on the Efficiency of the farmers

Table 3 presented the results of the heterogenous effects of SAP and varieties cultivated on the efficiency of the farmers at various level of quantiles using the UQR model; and sixteen variables were selected and used for this research. The assessment for multicollinearity was highlighted by the Variance Inflation Factor (VIF) and Tolerance Level (TL). The average values for VIF and TL were recorded at 5.54 and 0.181, respectively, both exceeding the established limits of 4.0 for VIF and 0.10 for TL. The F-value of 3.02 was significant at the 1% probability level, indicating that all predictors were influential on the outcome variables. Additionally, the OLS R-square value of 0.1459 implies that the explanatory factors in the model explain for 14.59% of the variance in the farmers' technical efficiency (Olutumise, Oladayo, Oparinde, Ajibefun, Amos, Hosu and Alimi, 2023). Consequently, the UQR and OLS results presented in Table 3 displayed the coefficients and their significance levels regarding the efficiency of tomato farmers in the area of study and this revealed the heterogeneity effects of the predicted variable. Nine variables had a significant impact on the highest quantile (τ.75), while four variables influenced both the intermediate (τ.50) and lowest quantile (τ.25). it was observed that the highest quantile had more significant variables than the OLS, which had five (5) significant variables. This indicated the presence of heterogeneity across the quantiles, as the magnitude of the coefficients varied as well. Out of the sixteen variables, two variables which are soil quality and income level, significantly affected farmers' efficiency at all quantiles. Family size, years of experience, land ownership, planting period, income level, and access to credit exhibited negative coefficients across the quantiles, whereas age, marital status, gender, education level, access to extension agents, number of sustainable agricultural practices, and number of varieties cultivated showed positive coefficients across the quantiles.

The UQR findings regarding the efficiency of tomato farmers yielded varied results, with all quantile levels demonstrating a significant effect at both the 5% and 1% probability thresholds. The number of Sustainable Agricultural Practices (SAP) implemented had a negative impact on efficiency at the τ.50 quantile and was not statistically significant. This indicated that a one-unit increase in the number of SAP adopted at the τ.50 quantile would result in a 0.82% decline in the farmers' efficiency. Additionally, an increase of one unit of the number of SAP adopted would lead to efficiency gains of 0.001% and 0.002% for farmers at the τ.25 and τ.75 quantiles, respectively; showing a minor impact on the efficiency of the tomato farmers in the area studied. The variety of hybrid tomato grown was seen to be positive and as well significant at all quantile levels. This means that a single unit increase in the number of varieties cultivated will correspond to increases in farmer efficiency of approximately 0.08%, 0.03%, and 0.05% at the τ.25, τ.50, and τ.75 quantiles, respectively. The coefficient for farmers' age was positive and had a statistically significant effect on the τ.50 and τ.75 quantiles at a 5% significance level, indicating that each additional year of a farmer's age leads to approximately a 0.004% and 0.003% increase in farmer efficiency for the τ.50 and τ.75 quantiles, respectively. This was in accordance with the findings of Tuyen and Huong, (2020)

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who in their study revealed that age was significant and positively correlated to the household income per capital at both τ.50 and τ.75 quantiles. Meanwhile, gender positively impacts farmers' efficiency across all quantiles, with statistical significance achieved at the 1% level for both τ.50 and τ.75 quantiles. This suggests that being a male farmer could enhance efficiency by 0.02%, 0.06%, and 0.03% at the τ.25, τ.50, and τ.75 quantiles, respectively. The coefficients associated with marital status across all quantile levels indicated that being married positively impacts farmers' efficiency, although this effect was not statistically significant at every quantile level. In contrast, factors such as years of experience, family size, and tenancy status negatively affect farmers' efficiency at all quantiles, showing that an additional year of experience decreases efficiency by 0.005%, 0.01%, and 0.008% at τ.25, τ.50, and τ.75 quantiles, respectively. Similarly, a rise in family size also leads to a reduction in farmers' efficiency, with decreases of 0.006%, 0.01%, and 0.001% at τ.25, τ.50, and τ.75, respectively. Land ownership status falls into the same category, indicating that possessing land does not correlate with farmers' efficiency and results in a reduction of 0.001% at τ.25 and τ.75 quantiles. The coefficient for farm workers was only positive at the τ.50 quantile, suggesting that an increase of one farm worker enhances efficiency for tomato farmers by approximately 0.008%, whereas at the other quantile levels (τ.25 and τ.75), adding a farm worker decreases efficiency by 0.003% and 0.001%, respectively. The quality of soil positively affects efficiency at the τ.25 and τ.50 quantiles and is significant at the 1% and 5% probability levels, respectively, indicating an increase in efficiency of approximately 0.06% and 0.04% with improvements in soil quality. However, at the τ.75 quantile, soil quality, while statistically significant at the 5% level, negatively impacts the efficiency of tomato farmers, showing a decrease in their efficiency by 0.03% even with a unit improvement in soil quality. This demonstrated that ongoing efforts to improve soil quality, like applying fertilizer, will eventually have no discernible impact on output. The income level of the farmers was statistically significant with 1% probability level at τ.25 and τ.75 quantiles and 5% probability level at τ.50 quantile, but across all quantiles, it exhibited a negative correlation with the farmers' efficiency, resulting in a decrease of 0.06%, 0.04%, and 0.03% at τ.25, τ.50, and τ.75 quantiles, respectively, thereby indicating that an increase in income does not lead to higher efficiency, as efficiency pertains to adequate combination of various inputs for output maximization and cost minimization. The timing of planting and availability of credit facilities have a detrimental effect on the efficiency of tomato farmers across all quantile levels. The timing of planting, however, was found to be significant at the 5% probability level, specifically at the τ.25 and τ.75 quantiles. This showed that, although the wet season is a factor for all tomato farmers to enter production, the season does not accurately reflect the farmers' efficiency. The results of access to credit and extension agent were significant at the 5% probability level at the τ.75 quantile, indicating a long-term impact of the variables on the efficiency of the farmers. Furthermore, access to extension agents has a positive effect on farmers' efficiency at all quantile levels; at τ.25, τ.50, and τ.75 quantiles, respectively, a one-unit increase in visits and access to extension agents will increase farmers' efficiency by 0.06%, 0.03%, and 0.13%. This corroborates the findings of Wanglin Ma and Hongyun Zheng (2021) who revealed in their study of impacts of smartphone use on agrochemical use among wheat farmers in china; that contact with the extension agent is also significant at higher quantile level and as well reduced pesticide and fertilizer expenditure by 10 – 16% and 6 – 12% respectively. In contrast, access to credit was found to have a negative effect on farmers' efficiency at all quantile levels; even though it has an effect on farmers' efficiency over the long term, farmers will eventually settle for repayments, which may have an impact on their profit margin.

Table 3: Result of Unconditional Quantile Regression (UQR) Determining the Heterogenous Effects of SAP and variety cultivated on the efficiency of the farmers

	OLS ($\bar{X}$)		τ.25		τ.50		τ.75	
Variable	**Coef.**	**P>|z|**	**Coef.**	**P>|z|**	**Coef.**	**P>|z|**	**Coef.**	**P>|z|**
Age	0.0031**	0.010	0.0009	0.478	0.0036**	0.048	0.0027**	0.028
Marital Status	-0.0020	0.903	0.0078	0.644	0.0072	0.767	0.0087	0.597
Gender	0.0313**	0.019	0.0215	0.115	0.0666***	0.001	0.0390***	0.004
Family Size	-0.0064	0.222	-0.0060	0.264	-0.0120	0.123	-0.0010	0.850
Education	0.0095	0.153	0.0084	0.218	0.0115	0.243	0.0148**	0.028
Experience	-0.0124	0.067	-0.0053	0.445	-0.0143	0.153	-0.0087	0.202
Farm workers	-0.0009	0.827	-0.0032	0.444	0.0078	0.201	-0.0014	0.733
Farm size	0.0028	0.685	-0.0064	0.374	-0.0101	0.334	-0.0098	0.167
Soil Quality	0.0061	0.646	0.0597***	0.000	0.0399**	0.042	-0.0313**	0.019
Land ownership	-0.0017	0.767	-0.0010	0.867	-0.0003	0.975	-0.0014	0.814
Planting period	-0.0573**	0.027	-0.0566**	0.033	-0.0097	0.800	-0.0575**	0.028
Level of income	-0.0577***	0.000	-0.0691***	0.000	-0.0420**	0.035	-0.0397***	0.003
Credit	-0.0626	0.266	-0.0627	0.279	-0.0372	0.656	-0.1318**	0.021
Extension	0.0717	0.204	0.0695	0.233	0.0335	0.690	0.1384**	0.016
SAP Adopted	0.0004	0.904	0.0011	0.718	-0.0010	0.821	0.0021	0.499

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Varieties cultivated	0.0710***	0.000	0.0849***	0.000	0.0370*	0.064	0.0575***	0.000
_cons	0.6812***	0.000	0.6286***	0.000	0.5238***	0.000	0.7327***	0.000
F-Value	3.02							
R^2	0.1459							
Mean VIF	5.54							
Tolerance Level	0.181							

Note: *** = significant at a 1% level; ** = significant at a 5% level; * = significant at a 10% level

Source: Computed from field survey, 2024

4.0 Conclusion

In conclusion, DEA model employed to assess the technical efficiency of tomato growers revealed that the VRSTE output of the tomato farmers in the examined area achieved an average technical efficiency of 0.93, indicating a higher level of technical efficiency among them. It also demonstrated that the assessment of efficiency is based on six variable inputs: farm size, seed quantity (Kg), herbicide usage (litres), fertilizer application (Kg), fungicide usage (litres), and insecticide usage (litres). Analyzing the input amounts used by the tomato farmers about the volume of tomatoes produced, it became apparent that the farmers applied a greater quantity of fertilizer to provide essential nutrients to the crops and enhance their yield. The model also indicated a mean slack of approximately 0.13ha of land among the farmers in their agricultural activities. Additionally, the quantity of improved varieties grown has a favourable impact on efficiency across all quantile levels, meaning that every additional unit of variety grown will undoubtedly boost farmers' productivity. Furthermore, the number of SAP units adopted by farmers has little influence on the productivity of local tomato farmers; at some point, an additional increase in SAP may result in a decrease in farmer productivity, indicating that SAP was not sufficiently implemented in the study area despite having a positive impact on farmers' productivity.

5.0 Recommendation

According to the findings of this study, recommendations were made on the note that Government should increase access of the tomato farmers to extension agents and service to adequately furnished them with the advantages of adoption of sustainable agricultural practices and cultivation of various improved tomato hybrids in order to increase the efficiency of the farmers. Also, encouragement should be given to the Agricultural NGOs, Input dealers, Extension agents, Agricultural professionals and Researchers by the government so as to get closer to tomato farmers and develop means of solving problems they encounter on the farms in respect to their production and efficiency.

References

1. Agboola, S. A. (1979). Agricultural Atlas of Nigeria. OUP Catalogue, Oxford University Press, number 9780195754087, October.
2. Alemdar T., Oren M. N. (2006). Measuring Technical Efficiency of Wheat Production in Southeastern Anatolia with Parametric and Nonparametric methods. Pakistan J. Biol. Sci. 9(6):1088-1094
3. Banker, R. D., Charnes, A. & Cooper W.W., (1984). "Some models for estimating technical and scale inefficiencies in data envelopment analysis". *Management Science 30,* 1078-92. http://dx.doi.org/10.1287/mnsc.30.9.1078
4. Charnes, A.; Cooper, W. W.; and Rhodes, E. (1978) "Measuring Efficiency of Decision-Making Units," European Journal of Operational Research 3, (pp. 429–444).
5. Charnes, A.; Cooper, W. W.; and Rhodes, E. (1981) "Data Envelopment Analysis as an Approach for Evaluating Program and Managerial Efficiency—with an Illustrative Application to the Program Follow Through Experiment in U.S. Public School Education," Management Science 27, (pp. 668–697).
6. Coelli T. J, Rao D. S. P, Battese G. E., (1998). An introduction to efficiency and productivity analysis. *Kluwer Academic Publishers, Boston,* 271. http://dx.doi.org/10.1007/978-1-4615-5493-6
7. Coelli, T. J., (1995), "Recent developments in frontier modelling and efficiency measurement" *Australian Journal of Agricultural Economics,* 39, 219-45. http://dx.doi.org/10.1111/j.1467-8489.1995.tb00552.x
8. Debreu, G. (1951). The coefficient of resource utilization: Econometrica 19, Pg. 273- 292.
9. Dossou, J., Soule, I., & Montcho, M. (2007). Evaluation des caracteristiques physico-chimiques et sensorielles de la puree de tomate locale produite a petite echelle au Benin [Evaluation of the physicochemical and sensory attributes of locally produced small-scale tomato puree in Benin]. Tropicultura, 25, 119–125.
10. Farrell, M. J. (1957). The measurement of productive efficiency. Journal of the Royal Statistical Society, Series A, 120: 253-90.
11. Firpo S., Fortin N. M. and Lemieux T., (2006). Unconditional Quantile Regressions. NBER Technical Working Paper Series. https://www.econ.pucrio.br/uploads/adm/trabalhos/files/seminario/2006/ffl2_oct_14_all.pdf
12. Giovannoni J.J. (2007). Fruit ripening mutants yield insights into ripening control. Curr. Opin. Plant Biol. 2007;10:283–289. doi: 10.1016/j.pbi.2007.04.008.
13. Hampel, F.R., E.M. Ronchetti, P.J. Rousseeuw, and W.A. Stahel (1986): Robust Statistics: The Approach Based on Influence Functions, New York: Wiley.
14. Idoko Nicholas (2023). Introducing Sustainable Farming in Nigeria. *Disciple in Nigeria.* https://disciplines.ng/sustainable-farming-in-nigeria/
15. Klee H. J, Giovannoni J. J. (2011). Genetics and control of tomato fruit ripening and quality attributes. Annu Rev Genet. 2011;45:41–59
16. Nigeria Governors' Forum (2015). DFID-Mapping of Tomato Clusters in Northern Nigeria (GEMS4).

DOI: 10.5281/zenodo.15033934

https://ngfrepository.org.ng:8443/jspui/handle/123456789/2828
17. Ogunniyi L. T., and Oladejo J. A. (2011). Technical Efficiency of Tomato Production in Oyo State, Nigeria. Agricultural Science Research Journal Vol 1(4) pp. 84 - 91 June 2011 Available online http://www.resjournals.com/arj ISSN-L:2026-6073 ©2011 International Research Journals
18. Oguntade A., Fatunmbi T., and Okafor C. (2013). Effects of Farmers' Field School on the Technical Efficiency of Cocoa Farmers in Nigeria. Journal of Biology and Life Science. ISSN 2157 – 6076, 2013, vol. 4, No1
19. Olanrewaju, T. O., Jacobs, I. A., Suleiman, R. and Abubakar, M. I. (2017). Trend Analysis of Tomato Production in Nigeria (2010 - 2014). International Journal of Agriculture and Development Studies. Vol 2 Issue 1. Pg 63 – 68
20. Olutumise, A.I.; Oladayo, T.O.; Oparinde, L.O.; Ajibefun, I.A.; Amos, T.T.; Hosu, Y.S.; Alimi, I. (2023). Determinants of Health Management Practices' Utilization and Its Effect on Poultry Farmers' Income in Ondo State, Nigeria. *Sustainability* **2023**, *15*, 2298. https://doi.org/10.3390/su15032298
21. Onifade, T.B., Aregbesola, O.A., Ige, M.T. & Ajayi, A.O. (2013). Some physical properties and thin layer drying characteristics of local varieties of tomatoes (Lycopersicon lycopersicum). Agric.Biol.J.N.Americ., 4(3): 275- 279, DOI: 10.5251/abjna.2013.4.3.275.279
22. Oyedokun A. O., Yesufu O. A., Ayorinde V. A., and Ogunmola O. O. (2020). Economic Analysis of Tomato Marketing in Ile Ife, Osun State, Nigeria. Journal of Agriculture and Verterinary Sciences. Volume 12, number 1, 2020. ISSN: 2277 – 0062.
23. Oyekale,T. O., Aboaba, K. O., Adewuyi, S. A., and dada, D. A. (2019). Multidimenssional Poverty Among Rural Housholds in Ogun State, Nigeria. *Journal of Agribusiness and Rural Development, February.* https://doi.org/10.17306/J.JARD.2019.01287
24. Price Waterhouse Coopers (PWC) Limited, (2018). X-raying the Nigerian tomato industry: Focus on reducing tomato wastage. https://www.pwc.com/ng/en/assets/pdf/nigeria-tomato-industry (Accessed June 26, 2024).
25. Sahel Research 2017 - The Tomato Value Chain in Nigeria https://sahelcapital.com/wp-content/uploads/2021/07/Sahel-Newsletter-Volume-15_Tomato.pdf
26. Timothy Park (2015). Direct Marketing and the Structure of Farm Sales: An Unconditional Quantile Regression Approach. Journal of Agricultural and Resource Economics 40(2):266–284. ISSN:1068-5502
27. Tuyen T., and Huong V. (2020). Heterogenous Effects of Livelihood Strategies on Household Well-Being: An Analysis Using Unconditional Quantile Regression with Fixed Effects. Munich Personal RePEc Archive (MPRA). Online at https://mpra.ub.uni-muenchen.de/103849/ MPRA Paper No. 103849, posted 02 Nov 2020 15:41 UTC
28. Wanglin Ma and Hongyun Zheng (2021). Impacts of Smartphone Use on Agrochemical Use Among Wheat Farmers in China: A Heterogeneous Analysis. *Selected Paper prepared for presentation at the 2021 International Association of Agricultural Economics (IAAE) Triennial (Virtual) Conference, August 17-31, 2021* AgEcon Search http://ageconsearch.umn.eduaesearch@umn.edu

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