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TECHNICAL EFFICIENCY AND TECHNOLOGICAL GAP RATIOS OF TOMATO PRODUCTION IN NORTHERN NIGERIA: A STOCHASTIC META FRONTIER APPROACH

Obianefo Chukwujekwu Aloysius[1,3*]
Uchemba Uzochukwu Victor[2]
Ezeano Ike Caleb[3]
Anumudu Oluchi Odinaka[3]

ABSTRACT

The study on technical efficiency and technological gap ratios of tomato production in Northern Nigeria used a stochastic meta-frontier approach to compare the technical efficiency (TE) and technological gap ratios (TGRs) of farmers after establishing the existence of heterogeneous technology adoption among farmers. Data were collected from a cross-section of 359 randomly selected farmers. A trans-log production function model proved more appropriate through a likelihood ratio test, therefore, stochastic frontier analysis and meta-frontier analysis approach were used. The study revealed that Plateau farmers are more technically efficient than Kano and Taraba counterparts respectively. Furthermore, the mean TGR associated with Taraba farmers is tangential to the meta-frontier output, this implies that Taraba farmers adopted the most advanced technology in the industry, while Plateau and Kano farmers need to close up 0.5% and 1.2% gap respectively in order to produce at the optimal output. By policy implication, Plateau and Kano farmers need to be educated on the need to adopt the best agricultural technology to increase their production. This calls for intensification of extension effort in Plateau and Kano state.

Keyword: Analytical model, hypothetical assumptions, efficiency, meta-frontier, tomato, Nigeria

I. INTRODUCTION

Tomato (*Solanum Lycopersicum*) is one of the vegetable crops produced in Nigeria; abundant in Northern parts due to their favourable climates for the crop and better irrigation system to support all year production. Srinivasan (2010) noted that the crop is rich in minerals, vitamins and antioxidants. Corroboratively, Ambecha *et al*. (2012); Umar *et al.* (2017) accentuate that tomato is rich in sugar, essential amino

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[1]IFAD Assisted Value Chain Development Programme, Anambra State.
[2]Department of Agricultural Economics and Extension, Chukwuemeka Odumegwu Ojukwu University, Igbariam
[3]Department of Agricultural Economics and Extension, Nnamdi Azikiwe University, Awka

[*]*Correspondence: Obianefo Chukwujekwu Aloysius, Department of Agricultural Economics and Extension, Nnamdi Azikiwe University, Awka. Email: obianefoca@gmail.com*

acids, iron, and dietary fibres among others. Umar *et al.* (2017) further reported that Nigeria produces an estimated 1.93 million metric tonnes of tomato from 517,000 hectares of land averaging 3.7 tons per hectare, equally, the Food and Agricultural Organization (FAO, 2016) estimated a 2.33 million metric tonnes consumption in Nigeria, creating 17.20% deficit demand-supply gap. Insecurity in Nigeria widened the demand-supply gap to above 20% in the year 2019 which explains the hike in the price of tomato products in the country.

The above necessitates the need to improve tomato production in Nigeria by making frantic effort to resolve the factors causing inefficiency to the utilization of farm inputs in the tomato industry (Asfaw *et al.*, 2010), at this Mensah and Brümmer (2016) suggested that it will be economically helpful to train farmer's managerial capabilities as well as agronomic skills. Abate *et al.* (2019) noted that such factors causing inefficiency in production may include input management, limited modern technologies, and weak supportive infrastructure (extension, road, marketing, agricultural policy, insecurity among others); these variables creates production gap due to heterogeneous technology adoption. This gave room for the existence of inefficiency in tomato production caused either by factors under control or those beyond the farmers. Wahid *et al.*, (2017) suggested that there is an urgent need to examine the technical efficiency of agricultural production particularly among smallholder tomato farmers in the developing countries. This examination will help to improve the productivity of farmers through an increase in input utilization and increasing technical efficiency level (Mbogo *et al.*, 2020; Ochilo *et al.*, 2019).

The study of Obianefo *et al*. (2020) viewed technical efficiency as the ability of farmers to obtain the highest possible output from given production resources using a particular technology. Only when the level of technical efficiency and its determinants are identified that policymakers will tailor training to improve production capacity that will lead to self-sufficiency in demand and supply in the country. Nnamdi *et al*. (2016) gave a better impression of technical efficiency by trying to quantify their approach, they alleged that technical efficiency is the extent of time, effort and cost management intended for a specific task. Ajayi *et al.* (2018) defined it as the success of producing a large amount of output as possible from the set of input available.

In tomato industry, it is very doubtful for all the farmers to produce at a frontier level considered as industrial efficiency or boundary, this is so because operating in a homogenous industry does not deny heterogeneous technology adoption. This singular act creates technological gap not minding that farmers use similar production resources which might differ in application and also influenced by other exogenous or external factors. This gap is widened if environmental influence is more. Prusty *et al*. (2016) suggested that this gap can be reduced through training, continuous monitoring and timely supply of farm inputs. For more information on a technological gap, Ng'ombe (2017) contend that a technological gap ratio of one means that the farmers are producing tangential to the frontier output, on the other hand, Korotoumou *et al.* (2019) noted that a technological gap ratio far from one means that the farmers did not adopt the most advanced technology available. Hence, this study specifically hopes to: i) describe the tomato farmer's variables used for the frontier analysis, ii) estimate the state/regional-specific stochastic frontier model, iii) estimate the tomato industry stochastic meta-frontier model, and iv) ascertain the level of technical and meta technical efficiency, as well as the technological gap ratio in the industry. Before the study will adopt the stochastic meta fromtier; the Kumbharkar (2015) likelihood ratio test will be carried out to test the existence of different or heterogenous technology adoption among tomato farmers from different locations.

Empirical Review

Many researchers came up with a more interesting report on technical efficiency of tomato production with some adopting a meta-frontier approach but, to the best of my review, none pointed to the Northern Nigeria which makes this study helpful to policymakers and scholars. Umar *et al.* (2017) in comparison of Cobb-Douglas and Tran-slog frontier models in the analysis of technical efficiency in dry-season tomato production found that fertilizer and labour were significant under Cobb Douglas function, while seed and agrochemical were significant under Trans-log function. The mean technical efficiency (TE) for CD was 89% and 54% for Trans-log. Study by Mwangi *et al.* (2020) in technical efficiency in tomato production among smallholder farmers in Kirinyaga County, Kenya revealed that their inputs used for tomato farming were; fertilizer (236.50kg), seed (54.21kg), agrochemical (8.34 lit), labour (349.7 man-days) which was combined to produce 7043kg of tomato per ha. The fertilizer, seed and farm land were the significant input and out combination variables with 71.22% efficiency score. Household size was found as the determinant of TE. Recent study by Malawal and Ueasin (2020) in the Study of Technical Efficiency in Tomato Production: a case study of Mekong River Bank Thailand adopted stochastic frontier analysis with a restrictive Cobb Douglas approach. The study receorded an output of 12,910kg/ha and an average farm land of 0.5 ha. Farm land (ha) and agrochemical (lit) were the significant input variables in the study.

Najjuma *et al.* (2016) in the assessment of technical efficiency of open-field tomato production in Kiambu County, Kenya (stochastic frontier approach) revealed the production inputs as farm land (1.46 ha), fertilizer (211 kg), agrochemical (3.7 lit), seed (0.15 kg), labour (416) which was combined to yield 3879 kg/ha. The inputs with significant relationships from the frontier anlaysis include: fertilizer, labour, agrochemical and seed. Again, the determinants of TE were experience, education and household size. The study of Haryanto *et al.* (2016) estimated the technical efficiency and technology gap, as well as the determinants of Indonesian rice farming. DEA Meta-frontier and Tobit regression analysis was applied respectively for the first and second objective. Fifteen rice–producing provinces in Indonesia were sampled. The study revealed that the result of MTE is slightly lower than the TE based on group specific frontier estimation to signal the existence of technological gap. The determinants were found as net income, education, and irrigated rice field. Furthermore, Korotoumou *et al.* (2019) in stochastic meta-frontier analysis of smallholder rice farmers' technical efficiency observed the technical efficiency (TE), Meta technical efficiency (MTE) and technological gap ratio (TGR) of the system of rice intensification (SRI) and Conventional Rice Production System (CRPS). Their result produced TE of SRI (96.4%), and CRPS (79.2%). The study also revealed the MTE for SRI (94.6%) and CRPS (87.9%), and TGR for SRI (98.5%), and CRPS (91.8%). Their study thought that SRI is more technically efficient than CRPS.

II. MATERIALS AND METHODS

Northern Nigeria was the study area, the Northern Nigeria comprises of nineteen (19) States out of the thirty-six (36) States of the federation and Capital Territory (FCT). The north has a total of 660,000km^2 land area from the 923,768km^2 which represents 71.4% of the total land area in the country. The area is divided into three geopolitical zones of Northeast (Adamawa, Bauchi, Borno, Gombe, Taraba, and Yobe), Northwest (Jigawa, Kaduna, Kano, Katsina, Kebbi, Sokoto, and Zamfara) and North-central (Benue, Kogi, Kwara, Nasarawa, Niger, Plateau and FCT). Northern Nigeria is a semi-arid area in the far north and progressively rainier moving southwards. The annual highest rainfall in the north is about 840 mm (Akinibiyi *et al.*, 2019). Northern Nigeria is blessed with all year round agricultural activities due to a well-developed irrigation system in the zone. It is located on a latitude of 10°.30' N and longitude 7°.25' E.

One state was conveniently selected from each geopolitical zones: Northeast (Taraba), North-central (Plateau), and Northwest (Kano). The convenient state selection was as a result of rising insecurity issues in the region. A multi-stage sampling technique was adopted to select the study representatives. In stage one, two local government areas (Plateau; Langtang North and Wase, Kano; Bichi and Gabasawa, and Taraba; Gashaka and Zing) were randomly selected which was later proceeded with random selection of two communities per LGA. Furthermore, four villages were randomly selected from each community to make it a total of sixteen (16) villages per state where a sample of 10 tomato farmers was randomly selected to make it 160 sample size per state and 480 for the entire study area. Table 1 reflect the questionnaire return rates.

Table 1: Questionnaire return rate (n = 480)

State	Expected return	Observed return	Percentage return	General return rate
Plateau	160	135	84.4	
Kano	160	120	75.0	74.79
Taraba	160	104	65.0	
Total	480	359		

Analytical model

Stochastic frontier and technical efficiency

A stochastic frontier analysis (SFA) with the Cobb Douglas production function is a restrictive and convenient approach especially where one cannot afford to lose the degree of freedom, whereas the Trans-log function is more flexible though has issue with data convergence due to the problem of multi-collinearity and heteroscedasticity. Malinga *et al.* (2015) contend that the stochastic frontier allows one to differentiate between random error and inefficiency effects; this is what separate parametric approach from none parametric that uses data envelop analysis. Interestingly, Cobb Douglas allows for a hypothetical test, it is equally efficient for inputs modelling since it takes care of multi-collinearity and heteroscedasticity. Aigner *et al.* (1977) was the first to work on stochastic frontier analysis and has severally been used by Battese and Coelli (1992) to refer to firm productivity and performance. Specifying the stochastic function decomposed the error term into non-negative random error (U_i) that is associated with technical efficiency (TE) of the *i*th firm and the normal error term (V_i) that represents random variation. The stochastic function is stated in equation 1 as used in Najjuma *et al.* (2016):

$$Y_i = f(X_i;\beta)\ exp(V\text{-}U),\ i = 1, 2, \dots n \ \dots\dots\dots\dots \quad (1)$$

Where: Y_i is output level of the *ith* farm, X_i is the vector of inputs of the *ith* farm, β is the vector of the unknown parameters, *Vi* is asymmetric error term that accounted for random variation in tomato output due to exogenous factors (weather, disease outbreak, etc.) identically distributed (Obianefo *et al.*, 2020; Nnamdi *et al., 2016.*), *Ui* is a non-negative error term that represents a stochastic shortfall in optimum output (Osawe *et al*., 2018).

Stochastic frontier adopted a maximum likelihood estimation (MLE) technique to yield estimator for Sigma (σ) and Gamma (γ).

$$\sigma^2 = \sigma^2_u + \sigma^2_v \ \dots\dots\dots\dots \quad (2)$$
$$\gamma = \sigma^2_u / \sigma^2 \ \dots\dots\dots\dots \quad (3)$$

The parameter γ stands for the total variation of output from the frontier attributed to technical inefficiency which lies between zero to one ($0 \leq \gamma \leq 1$).

On the other hand, technical efficiency (TE) represents the maximum possible output that can be produced from each input used or minimum input used to produce a certain level of output. This approach helps to describe the current state of technology adoption in the *ith* farm (Ogunniyi and Oladejo, 2011). The study of Martin *et al.* (2017); Ogada *et al.* (2014) suggested that TE is influenced by factors classified into agent (those associated with farm management; level of education, age etc.) and structural factors (on-farm; farm type, farm location, farm size, fertility, etc. and off-farm; infrastructure, etc.). The TE of the *ith* farm is specified in terms of observed output (Y_i) to expected output (Y^*) which is premised on the level of input used. Therefore TE is stated mathematically as:

$$TE = Y_i / Y^* \quad \ldots\ldots (4)$$

$$TE = \frac{f(Xi;\beta)\exp(V-U)}{f(Xi;\beta)\exp(V)} = exp(-U) \quad \ldots\ldots (5)$$

Stochastic meta-frontier analysis

Production of tomato in a different environment even when all farmers in the industry are given similar inputs does not guarantee homogenous technology adoption. Heterogeneous technology adoption is bound to exist in such a case, this acts invalidates the use of SFA and validated the adoption of Stochastic meta-frontier (SMF) analysis as the best approach (Nguyen *et al.,* 2019). Based on Huang *et al.* (2014) approach, SMF was adopted to estimate the maximum output of tomato farming industry in Northern Nigeria. This SMF is used to examine technical efficiency of farmers operating under different technology or heterogeneous technology. A two-step approach that differentiates Haung *et al.* (2014) from the classical meta-frontier was used. The first step produced technical efficiency for each *ith* farm as used in equation 1, the second step saw the estimation of the meta-frontier with special consideration to the exogenous factors as shown in equation 6:

$$f^j(X^j{}_i;\beta) = f^T(X^j{}_i;\beta)e^{-U^T{}_{ij}} \quad \ldots\ldots (6)$$

Where $f^T(.)$ is the $U^T{}_{ij}$ is the difference in the frontier of each group to the difference in the frontier of all group. Good to note that meta-TE measures the distance between the actual outputs of the i^{th} farm and the meta-frontier production function. The ratio between the technology of i^{th} farm in the j^{th} group and the best technology available for all group frontier is what is known as the technological gap ratio (TGR_{ij}) and is defined by:

$$TGR_{ij} = \frac{f^j(X_{ij})}{f^T(X_{ii})} = e^{-U^M{}_{ij}} \quad \ldots\ldots (7)$$

Furthermore, the meta-TE is the distance between the actual output of i^{th} farm in group j and the meta-frontier production function which is therefore defined as:

$$MTE_{ij} = TGR_{ij} * TE_{ij} \quad \ldots\ldots (8)$$

Model specification

The study adopted Haung *et al.* (2014) two-step procedure, the first approach was to estimate the *ith* farm group-specific stochastic frontier production. The second further estimated the stochastic meta-frontier by pooling the samples. The Kumbhakar, Wang and Horncastle (2015) Likelihood ratio test method was used to check for the choice of trans-log model over a Cobb Douglas (CD) frontier option which was defined in equation 9 as:

$$LR\text{-}stat. = -2[L(H_o) - L[(H_1)] \quad \ldots\ldots (9)$$

Where *LR-stat*. is the calculated result of the test, $L(H_o)$ is the log-likelihood ratio of CD and $L(H_1)$ is the log-likelihood ratio of trans-log function.

Table 2: Hypothesis on the choice of model

State	CD	Trans-log	Degree of freedom	LR-stat.	Chi-square @ 0.001	Remarks	Decision
Plateau	469.570	589.898	15	240.651	37.667	Rejected	Trans-log used
Kano	182.983	220.500	15	75.034	37.667	Rejected	Trans-log used
Taraba	235.851	341.373	15	211.044	37.667	Rejected	Trans-log used
Northern Nigeria	478.610	505.504	15	53.788	37.667	Rejected	Trans-log used

A flexible trans-log stochastic production function model was used for all the states as well as for the Northern Nigeria, this flexible trans-log function used in the analysis relates to the type proposed by Alemu, Nuppenau and Bolland (2009) and Ng'ombe (2017) as:

$$LnY_{it} = \alpha_0 + \sum^5_{j=1}\beta_j LnX_{jit} + 1/2\sum^5_{j=1}\sum^5_{k=1}\beta_{jk}LnX_{jit}LnX_{kit} + (V_{it} - U_{it}) \ldots\ldots\ldots (10)$$

Huang *et al.* (2014) defined meta-frontier model from environmental-specification as:

$$LnY_{hart} = \alpha_0 + \sum^5_{j=1}\beta_j LnX_{jit} + 1/2\sum^5_{j=1}\sum^5_{k=1}\beta_{jk}LnX_{jit}LnX_{kit} + (V_{it} - U_{it}) \ldots\ldots\ldots (11)$$

Where Ln = natural logarithm, Y_{it} = tomato output in kg/ha for the *ith* farm at time t, α_o = farm specific fixed effect measuring heterogeneity, β_j *and* β_{jk} = parameter to be estimated, X_{jit} = inputs (X_1 is labour in man-day, X_2 is the seed in kg, X_3 is agrochemical in lit, X_4 is fertilizer in kg and X_5 is Field area in ha) j of the ith farm at time t, V_{it} = random error, U_{it} = time varying inefficiency term. It is assumed that V_{it} is independently and identically distributed at:

$$N(0,\sigma_V^{j2});\ U_{it} \sim N^+(U^j(Z_{it}), \sigma^{j2}) \ldots\ldots\ldots (12)$$

where Z_{it} = farm specific variables.

The influence of group-specific variables causing inefficiency in tomato production followed the model estimated jointly with the SF model in a single-stage maximum likelihood estimation (MLE) approach as used in (Coelli, 1996):

$$U_i = \delta_0 + \delta_1 Z_1 + \delta_2 Z_2 + \delta_3 Z_3 + \delta_4 Z_4 + \delta_5 Z_5 \ldots\ldots\ldots (13)$$

Where Z_1 is age (year), Z_2 is education (years), Z_3 is the household size (no), and Z_4 is a farming experience (years).

Test of hypothetical assumptions

Before proceeding with a stochastic meta-frontier (SMF) analysis, it is very important to establish the existence of some hypothetical theorem or assumptions that must hold waters. A Likelihood ratio (LR) statistics result has to be compared over a table Chi-square (χ^2) distribution at a particular critical value say 0.001 probability level as used in the study. The LR statistics defined in kumbhakar *et al.* (2015) was used. The researcher(s) failed to reject the null hypotheses any time the LR-statistics calculated is less than the table critical value (*LR cal. < LR tab.*).

Table 3: Test of hypotheses and eligibility of data

No	Hypotheses	LR statistics	LR Critical @ 0.001	DF	Decision	Conclusion
H_{o1}	**Ordinary least square regression model is a better option over the stochastic frontier model**					
	Plateau	265.704	37.667	15	Rejected	SF appropriate
	Kano	107.424	37.667	15	Rejected	SF appropriate
	Taraba	175.044	37.667	15	Rejected	SF appropriate
	Northern Nigeria	71.888	37.667	15	Rejected	SF appropriate
H_{o2}	**There is no existence of heterogeneous technology adoption**	1292.534	73.403	42	Rejected	Proceed with stochastic meta frontier (SMF)
H_{o3}	**There is no presence of inefficiency effects**					
	Plateau State	311.732	37.667	15	Rejected	Inefficiency effect present
	Kano State	219.396	37.667	15	Rejected	Inefficiency effect present
	Taraba State	477.140	37.667	15	Rejected	Ineffiency effect present
	Northern Nigeria	314.704	37.667	15	Rejected	Inefficiency effect present
H_{O4}	**There is no presence of exogenous factors**					
	Plateau State	334.102	42.312	18	Rejected	Exogenous factors influencing
	Kano State	220.756	42.312	18	Rejected	Exogenous factors influencing
	Taraba State	480.978	42.312	18	Rejected	Exogenous factors influencing
	Northern Nigeria	317.086	42.312	18	Rejected	Exogenous factors influencing

The null hypothesis one that chose ordinary least square regression model over the stochastic frontier model was rejected for all the states (Plateau = 265.704, Kano = 107.424, Taraba = 175.044) and Northern Nigeria (71.888). The null hypothesis two tested the existence of homogenous technology adoption which was rejected to give room for SMF approach [LR cal. (1292.534) > LR tab. (73.403)]. The null hypothesis three that assumed the absence of inefficiency effect was rejected for all the states (Plateau = 311.732, Kano = 219.396, Taraba = 477.140) and Northern Nigeria (314.704). The null hypothesis four that assumed the absence of exogenous or external factors were equally rejected for all states (Plateau = 334.102, Kano = 220.756, and Taraba = 480.978) and Northern Nigeria (317.086).

III. RESULTS AND DISCUSSIONS

Description of tomato farmer's variables used for frontier analysis

Table 4 reflects the description of tomato farmer's variables used for the frontier analysis, in Plateau state; tomato output – kg/ha was 4,999.5 and standard deviation (Std. Dev.) of 988.7 high enough to show variability in output across the state, the average land area under cultivation (1.7 ha) with Std. Dev. of 0.8 revealed that farmer's access to land varies in Plateau State. Over time, records have shown that the area is blessed with adequate landmass. Other inputs; labour – man/day (468.92), seed – kg (0.5), agrochemical – lit (6.5) and fertilizer – kg (167.1) were also described. To mitigate the impact of environmental factors on field fertility, farmers invested averagely 3,202.5kg (manure) and 37,438.1 lit (water) to reclaim the field. The study averagely described Plateau tomato farmers as age – yr. (39.34), education – yr. (8.3), household size – no of people (14.8) and farming experience – yr. (20.7).

Interestingly, we found that Kano (4919.7 kg) and Taraba (496.0 kg) tomato output as well as their Std. Dev. are 1012.5 and 687.7 respectively, high enough to show variability in production across the States. In the North, the average age – yr. (39.6), education – yr. (8.8), household size – no of people (13.84), experience – yr. (17.97), land area under cultivation – ha (1.7) and output – kg (4959.6).

State/regional-specific stochastic frontier

The trans-log function (table 5) produced 0.835 (Plateau), 0.921 (Kano), 0.062 (Taraba) and 0.403 (Northern Nigeria) Gamma value that explains the percentage variation in frontier output as a result of the presence of inefficiency effects (group specific variable), the weak Gamma value (0.062) from Taraba which is farther from one is an indication that variation in technical efficiency (TE) of tomato farmers emanated from the random noise instead of the group specific variables, this suggests that external factor (environmental and economic variables) has more influence on tomato production in Taraba than in other Northern States. Thus the above values implies that the inefficiency presence explained 83.5% (Plateau), 92.1% (Kano), 6.2% (Taraba) and 40.3% (Northern Nigeria) variation in technical efficiency of farmers in the study area.

Table 4: Description of tomato farmer's variables used for frontier analysis

	Plateau		Kano		Taraba		Northern Nigeria	
Variables	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age (yr.)	39.3	14.5	39.6	11.9	39.7	9.4	39.6	12.1
Education (yr.)	8.5	2.8	9.1	3.7	8.8	2.4	8.8	3.0
Household Size (no)	14.8	4.7	12.9	5.3	13.8	3.6	13.8	4.6
Experience (yr.)	20.7	7.6	15.2	8.3	18.0	5.6	18.0	7.6
Land area under cultivation (ha)	1.7	0.8	1.7	0.8	1.7	0.6	1.7	0.7
Manure (kg)	3202.5	542.5	3207.8	702.9	3225.8	540.0	3212.0	598.7
Water (lit)	37438.1	11353.7	35230.0	8551.8	36578.0	7271.8	36415.3	9242.4
Labour (man/day)	468.9	155.8	491.3	160.3	5000.0	80000.0	480.1	144.1
Seed (kg)	0.5	0.7	0.6	0.6	0.5	0.4	0.5	0.6
Agrohemical (lit.)	6.5	3.3	7.1	3.2	6.8	2.2	6.8	2.9
Fertilizer (kg)	167.1	72.7	173.6	68.7	170.4	48.2	170.4	64.0
Output (kg/ha)	4999.5	988.7	4919.7	1012.5	4959.6	687.7	4959.6	907.0

Relative to the stochastic frontier analysis (SFA) for Plateau State tomato farmers, the coefficient of log of labour (0.097) is positively significant at 0.01 level of probability, which implies that a marginal increase in the number of labour employed in the farm will increase tomato output by 0.097 kg. The indication is that tomato farming is labour intensive in Plateau state, thus, the farmers should be careful to employ productive workforce in the field. This result aligns with the report of Umar et al. (2017). Also, the coefficient of log of seedling (0.011) is positively significant at 0.10 level of probability, which implies that a unit increase in the number of seedlings used in the farm will increase tomato output by 0.011 kg. Since tomato production in Plateau is dependent on seedlings, farmers should sort for an improve variety which will help to boost their productivity. Again, the coefficient of log of agrochemical (0.026) was negatively significant at 0.05 level of probability, this implies that a marginal increase in the quantity of agrochemical applied to the farm will reduce tomato output by 0.026 kg. This suggests that farmers should be careful when making a choice on the type of agrichemical to purchase so it does not become toxic to the farm land, this result was in agreement with the work of Mwangi *et al.* (2020). The square coefficient of log of labour (0.021) was negative and significant at 0.01 level of probability which implies that doubling the number of workers in the farm will cause unproductiveness by reducing tomato output by 0.026 kg. The square coefficient of log of seedlings (0.004), agrochemical (0.029) and land (0.007) was positive and significant at 0.01 level of probability which implies that doubling the said input used will increase tomato output by 0.004 kg (seedlings), 0.029 kg (agrochemical) and 0.007 kg (land) respectively. Furthermore, labour and seedlings, seedlings and land, and agrochemical and fertilizer are substitute inputs, while labour and agrochemical, and seedlings and agrochemicals are compliments inputs to each other.

Kano result (table 5) revealed that the square coefficient of log of agrochemical was negative and significant at 0.01 level of probability which implies that doubling the volume of agrochemical applied to the farm will reduce tomato output by 0.077 kg, it is important that the farmers understand the mixing ratio of the chemical to avoid toxicity. On the other hand, the square coefficient of log of land was also negative and significant at 0.05 level of probability which implies that doubling the size of the farm land if other inputs are held constant will reduce tomato output by 0.027 kg. It will be a waste of resources on the farmers to increase their farm land without increasing the quantity of other variable farm inputs applied. Furthermore, it is interesting to note that agrochemical and land are substitute inputs.

Furthermore, Taraba result shows that the coefficient of log of labour (0.484) was positive and significant at 0.10 level of probability which implies that a marginal increase in the number of labour employ to the farm will increase tomato output by 0.484 kg, this is an indication that tomato farming is labour intensive in Taraba state. Also, the coefficient of log of seedlings (0.214) was positive and significant at 0.05 level of probability which implies that a unit increase in the quantity of seedling used in the farm will increase tomato output by 0.214 kg. This also suggests that farmers should make selection of improved seedling to continue with their optimal yield. The coefficient of log of fertilizer (0.913) was negative and significant at 0.01 level of probability which implies that a marginal increase in the quantity of fertilizer used by the farmers will reduce tomato output by 0.913 kg in the area. This reduction in output as a result of fertilizer application could be explained by excess nutrient hence the farmers are using organic mature to reclaim the soil (table 4). This result was in agreement with the work of Mwangi et al. (2020). The square coefficient of log of labour (0.017) was negative and significant at 0.05 level of probability which implies that doubling the number of labour employed in the farm will reduce tomato output by 0.017 kg. This is because this action will introduce redundancy and unproductiveness among workers. Also, the square coefficient of log of seedlings (0.056), fertilizer (0.201) and land (0.041) were positive and significant at 0.01 level of probability which implies that a unit increase in their use will increase tomato output by 0.056 kg (seedlings), 0.201 kg (fertilizer) and 0.041 kg (land) respectively. Still on this, the study found that seedlings and agrochemical, seedlings and fertilizer, and fertilizer and land are substitute to each other.

For the group-specific variables, we observed that the significant and negative coefficient of age (0.055), and education (0.402) increases technical efficiency (TE) of Plateau state tomato farming, while the significant and positive household size (0.239) increases technical inefficiency in tomato production. Also, the significant and negative coefficient of farming experience (0.083 for Kano and 0.276 for Taraba) increase TE.

Estimated output elasticity and return to scale

The researcher(s) found it interesting to clearly present to the readers the various stages of tomato production in Northern Nigeria. This was achieved by summing the output elasticity of individual states. Thus the return to scale of tomato output are 0.101 (Plateau), -0.988 (Kano), -0.199 (Taraba) and Northern Nigeria (2.322). In Plateau state, tomato production is at stage one; that is an increasing stage. At this stage, addition of variable factors of production on a fixed factor (land) is still profitable. Which means that tomato output is increasing at a slow pace of 0.101 unit. Equally, Kano and Taraba tomato production are in stage three. At this stage, the law of diminishing return has set in which suggests that farmers should reduce the inputs used on a fixed factor of production. Generally, tomato production in Northern Nigeria is at stage two. This means that farmers should be careful to know when to stop increasing input use on a fixed factor of production.

Table 5: State/regional-specific stochastic frontier

Variables	Plateau	Kano	Taraba
Log labour	0.097 (11.65)**	-0.856 (-0.81)	0.484 (1.92)*
Log seedlings	0.011 (1.79)*	-0.491 (-1.02)	0.214 (2.68)**
Log agrochemical	-0.026 (-2.20)**	0.207 (0.95)	-0.023 (-0.16)
Log fertilizer	0.018 (1.12)	-0.050 (-0.16)	-0.913 (-4.04)***
Log land	0.001 (0.11)	0.202 (0.65)	0 .039 (0.39)
Square of log labour	-0.021 (-20.58)***	0.108 (0.50)	-0.107 (-2.74)**
Square of log seedlings	0.004 (9.10)***	-0.002 (0.60)	0.056 (16.97)***
Square of log agrochemical	0.029 (22.50)***	-0.077 (-2.97)***	0 .023 (1.05)
Square of log fertilizer	-0.002 (-1.46)	0 .015 (0.23)	0.201 (4.09)***
Square of log land	0.007 (13.10)***	-0.027 (-2.24)**	0.041 (4.73)***
Log labour × log seedlings	-0.002 (-1.68)*	0 .139 (1.06)	-0.006 (-0.54)
Log labour × log agrochemical	0.003 (2.38)**	-0.015 (-0.41)	-0.010 (-0.42)
Log labour × log fertilizer	-0.001 (-0.62)	0.007 (0.10)	0.025 (0.81)
Log labour × log land	-0.000 (-0.10)	0.013 (023)	0.015 (1.07)
Log seedlings × log agrochemical	0.002 (3.46)***	0.021 (-0.56)	-0.023 (-3.26)***
Log seedlings × log fertilizer	-0.002 (-1.35)	-0.060 (-0.88)	-0.038 (-3.06)***
Log seedlings × log land	-0.002 (-3.28)***	-0.012 (-0.17)	0.002 (0.26)
Log agrochemical × log fertilizer	-0.003 (-2.28)**	0.021 (0.56)	0.012 (0.43)
Log agrochemical × log land	-0.001 (-1.06)	-0.074 (-1.87)*	0.022 (0.49)
Log fertilizer × log land	0.002 (1.60)	-0.014 (-0.56)	-0.032 (-1.86)*
Intercept	8.252 (146.58)***	11.145 (3.35)***	8.805 (8.41)***
Group specific variables			
Age	-0.055 (-3.02)***	0.037 (0.93)	0.120 (1.06)
Education	-0.402 (-2.60)**	0.089 (1.13)	0.239 (0.99)
Household size	0.239 (3.23)***	-0.052 (-0.94)	-0.212 (-1.17)
Farming experience	0.030 (0.98)	-0.083 (-2.54)**	-0.276 (-1.72)*
Intercept	-12.361 (-7.44)***	-6.961 (-2.96)***	-11.916 (-2.17)**
Variance and other model statistics			
Sigma (σ^2)	0.000	0.002	0.000
Gamma (γ)	0.835***	0.921***	0.062
Log likelihood ratio	698.967	242.1667	344.614
Obs.	135	120	104

****, **, * represents statistical significance level at 1%, 5% and 10% respectively.*

Table 6: Estimated output elasticity and return to scale

	Plateau	Kano	Taraba	Northern Nigeria
Output elasticity				
Log labour	0.097	-0.856	0.484	-0.253
Log seedlings	0.011	-0.491	0.214	-0.503
Log agrochemical	-0.026	0.207	-0.023	2.892
Log fertilizer	0.018	-0.050	-0.913	-0.492
Log land	0.001	0.202	0 .039	0.678
Return to scale	0.101	-0.988	-0.199	2.322
Stages of production	Stage I	Stage III	Stage III	Stage II

Estimation of tomato industry stochastic Meta-Frontier Model

Table 7 reflects the result of industry stochastic meta-frontier (SMF) model, this approach is used to identify sectorial output. Diagnostically, the Gamma value of 0.951 is an indication that exogenous (environmental and economic) factors explained 95.1% variation in meta-frontier achievable TE in the study. The coefficient of log of seedlings (0.463) was negative and significant at 0.01 level of probability which implies that a marginal increase in the volume of seed used in the farm will reduce tomato output in Northern Nigeria by 0.463 kg. This means that farmers in the Northern Nigeria should stick to improved seed when there is need to increase seedlings use. The square of log of labour (0.044) was positive and significant at 0.01 level of probability which implies that doubling the number of labour employed in the farm will increase tomato output by 0.044 kg. Equally, the log of labour and seedling, and seedlings and agrochemicals are compliment inputs. Also, the log of labour and agrochemical, and labour and fertilizer are substitute inputs. None of the exogenous variable was significant, though manure application to reclaim the soil fertility is nearly significant and negative sign to mean that it increases the Meta technical efficiency (MTE) of the tomato industry (Northern Nigeria). This result is consistent with the study of Najjuma *et al*. (2016); Umar *et al*. (2017) and Mwangi *et al.* (2020).

Technical and meta-technical efficiency, and technological gap ratio

Table 8 reflect the result of the technical efficiency (TE), meta-technical efficiency (MTE) and technology gap ratios (TGRs) of tomato farming industry in Northern Nigeria. Results of the TE are 99.8% (Plateau), 96.3% (Kano) and 99.7% (Taraba) respectively which implies that the farmers are operating 0.2% (Plateau), 3.7% (Kano) and 0.3% (Taraba) below their maximum potentials. The MTE results are 99.4% (Plateau), 95.2% (Kano) and 99.8% (Taraba). This result on MTE revealed that Taraba farmers are more technically efficient than their colleagues from Plateau and Kano, while Plateau farmers are more technically efficient than Kano farmers.

Table 7: Estimation of tomato industry stochastic meta-frontier model

Variables	Coefficient	standard error	t-ratio
Log labour	-0.002	0.046	-0.03
Log seedlings	-0.463	0.089	-5.22***
Log agrochemical	0.213	0.164	1.30
Log fertilizer	0.171	0.192	0.89
Log land	-0.075	0.131	-0.57
Square of log labour	0.044	0.017	2.55**
Square of log seedlings	0.030	0.008	3.58***
Square of log agrochemical	-0.026	0.025	-1.04
Square of log fertilizer	0.037	0.024	1.52
Square of log land	0.007	0.009	0.71
Log labour × log seedlings	0.076	0.013	5.86***
Log labour × log agrochemical	-0.040	0.023	-1.71*
Log labour × log fertilizer	-0.060	0.023	-2.62**
Log labour × log land	-0.002	0.019	-0.12
Log seedlings × log agrochemical	0.030	0.014	2.11**
Log seedlings × log fertilizer	-0.013	0.015	-0.88
Log seedlings × log land	0.014	0.012	1.22
Log agrochemical × log fertilizer	0.019	0.024	0.79
Log agrochemical × log land	-0.037	0.020	-1.91*
Log fertilizer × log land	0.032	0.019	1.71*
Intercept	8.136	0.434	18.74***
Industry-specific environmental variables			
Manure	-0.561	0.537	-1.05
Water	0.186	0.422	0.44
Intercept	-2.945	6.408	-0.46
Variance and other model statistics			
Sigma (σ^2)	0.004		
Gamma (γ)	0.951***		
Log likelihood ratio	560.829		
Obs.	359		

***, **, * represents statistical significance level at 1%, 5% and 10% respectively.

Furthermore, we found that Taraba State farmers are producing tangentially to the frontier output which means they have adopted the most advanced technology. The value of TGRs are 99.5% (Plateau) and 98.8% (Kano) which means that Plateau and Kano could increase their production by closing 0.5% (Plateau) and 1.2% (Kano) gap in the area. Above all, we established the sectorial (Northern Nigeria) TE as 95.1% which means that farmers in the entire Northern area of Nigeria are producing 4.9% below their optimal output. This result is consistent with the report of Korotoumou *et al.* (2019) in stochastic meta-frontier analysis of smallholder rice farmers' technical efficiency where it was discovered that system of rice intensification (SRI) had more TGR than the conventional rice production system (CRPS). It is worthy to note that MTE for Plateau and Kano State are slightly lower than the TE based on group specific frontier estimation which signaled the existence of technological gap and was in agreement with the study of Haryanto *et al.* (2016) on technical efficiency and technology gap in Indonesian rice farming.

Table 8 Technical and meta-technical efficiency, and technological gap ratio

Location	Variables	Mean	Std. Dev.	Min	Max
Plateau					
	TE	0.998	0.006	0.937	1.000
	MTE	0.994	0.007	0.940	0.999
	TGR	0.995	0.005	0.964	1.011
Kano					
	TE	0.963	0.054	0.615	0.996
	MTE	0.952	0.070	0.604	1.000
	TGR	0.988	0.046	0.731	1.072
Taraba					
	TE	0.997	0.003	0.983	1.000
	MTE	0.998	0.001	0.997	1.000
	TGR	1.000	0.002	0.996	1.000
Northern Nigeria / tomato industry	TE	0.951	0.045	0.658	0.990
	MTE	0.942	0.072	0.552	0.997
	TGR	0.990	0.059	0.667	1.000

IV. CONCLUSION

The study compared the technical efficiency (TE) and technological gap ratios (TGRs) of tomato production in Northern Nigeria using a stochastic meta-frontier approach. Plateau farmers have higher mean TE, while Taraba farmers are less distant from the meta-frontier than Kano and Plateau farmers. This implies that Plateau and Kano farmers should improve their production. The study revealed that as farmers acquire better education as well as advance in their age and gain more experience in the industry, it will help improve TE level, having access to improved seedlings and experienced labour to execute farm operation will be key to increase tomato production in Northern Nigeria. The negative and significant education, age and farming experience will help the farmers in tomato industry suggest a better way to mitigate risk when confronted, as this will help Plateau and Kano farmers make the best use of existing technologies to increase their regional and meta-frontier tomato output since they still have some gaps to close.

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