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Exploring Productivity Dynamics and Drivers among Maize Farmers in Nigeria

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Abstract

This study investigated productivity dynamics among maize farmers in Nigeria using panel data from the General Household Survey (GHS-P) Waves 1 and 4. Farmers were classified into low, medium, and high productivity categories using a Total Factor Productivity (TFP) index. Between Wave 1 and Wave 4, the share of farmers in the high productivity group increased from 38.20% to 42.11% indicating moderate progress, while those in the low productivity group declined from 39.56% to 32.77%. Tobit regression results revealed that access to credit, mobile phones, and remittances significantly enhanced productivity, while non-farm enterprise participation and increased farming experience negatively affected it. The findings suggested that engagement in non-farm activities diluted farm efficiency, and older farmers were less inclined to adopt new technologies. Markov transition analysis showed both upward and downward mobility, with many farmers remaining in low-productivity states due to systemic constraints. Based on these insights, the study recommended that policymakers should have strengthened agricultural extension systems to promote the adoption of modern technologies, encouraged the formation of farmer cooperatives to reduce input costs, addressed the trade-offs between non-farm and farm activities through integrated livelihood strategies, and expanded rural financial and digital infrastructure to improve access to resources and information for sustainable productivity growth.

Introduction

Maize plays a central role in the global agricultural economy, ranking as the most extensively cultivated cereal grain with a global production volume reaching approximately 1.16 billion tonnes in 2020. It is the leading cereal crop by weight and, together with wheat and rice, accounts for more than half of total global cereal production (FAO, 2023). Within the maize category, two primary subtypes exist: yellow and white maize. Yellow maize predominates globally, driven by its extensive animal feed and ethanol production use. While yellow maize dominates international markets primarily as livestock feed and industrial input, white maize is more prevalent in regions such as Sub-Saharan Africa, Latin America, and South Asia where it serves as a principal staple food and is directly consumed by households (FAO, 1997; Shiferaw *et al*., 2011).

Global maize production has followed a relatively flat trend since the 2013/14 marketing year, with only modest year-on-year growth. However, a notable increase occurred in the 2019/2020 period, when output reached approximately 1,140 million metric tonnes harvested across about 190 million hectares of land (Shiferaw *et al*., 2022; FAO, 2023). This growth is largely attributable to production booms in Asian countries. In Africa, on the other hand, despite maize serving as a dietary mainstay for nearly half of the sub-Saharan population, the continent contributes a modest 7% to the global maize production. A 2021 analysis conducted by PricewaterhouseCoopers (PwC), using available FAO data, indicates that Africa generated 81.9 million metric tons (MMT) of maize in 2019, compared to 89.3 million metric tons in 2017 (PwC, 2021). This decrease has been attributed to a misplaced

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focus on expanding harvested area rather than productivity improvements (Nevin *et al*., 2021a).

Yield disparities across regions can be attributed to a combination of varietal differences and resource constraints. For example, North America achieves yields of approximately 11 tons per hectare (t/ha), Europe around 7 t/ha, Asia about 6 t/ha, and South America close to 6 t/ha (Nevin *et al*., 2021b). While improved and high-yielding varieties contribute significantly to these differences, limited access to essential inputs such as quality seeds, fertilizers, irrigation, and mechanization remain a major constraint, particularly in Africa. Addressing these resource gaps is critical for African governments to enable local farmers to enhance productivity and close the yield gap with their global counterparts.

According to Nevin *et al*. (2021b), intra-continentally, maize farming in Africa is predominantly focused on in certain locations, with East Africa at the forefront. This region produces over 30 million metric tons (MMT) per year, which accounts for about 37.6% of the continent's total maize output. West Africa and Southern Africa subsequently produce an average of 19 MMT and 12 MMT per year, respectively. In 2019, South Africa, Ethiopia, and Nigeria emerged as the foremost maize producers, representing almost 39.0% of Africa's maize production.

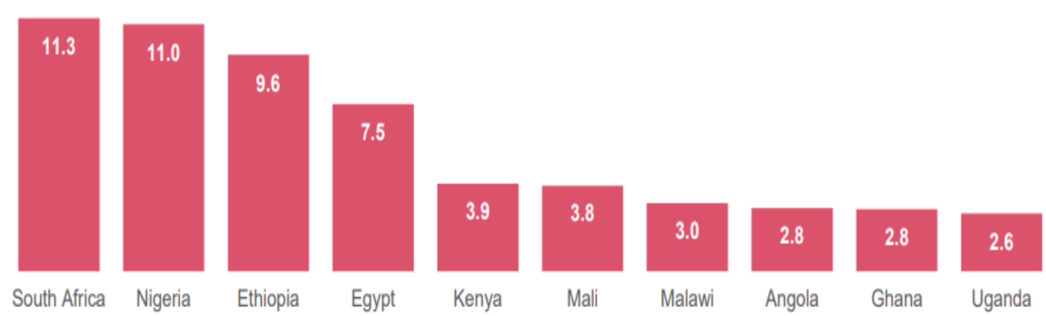

Figure 1: Africa's top 10 largest maize producers
Source: PwC (2021)

Maize is a predominant crop in Nigeria, leading the country's coarse grain production. It is cultivated across nearly all agroecologies, but production is mainly concentrated in 10 states, contributing about 64% of Nigeria's total maize yield. After South Africa, Nigeria is the biggest maize producer in Africa. FAO reports that in 2019, Nigeria produced approximately 11 million metric tons (MMT) of maize, an increase of 49% from the previous decade.

The production of maize in Nigeria faces an array of challenges that hinder its full potential. Key among these factors are the usage of antiquated agricultural practices such as inefficient weed control, inadequate plant stands, and non-application of fertilizers or organic manures (FAO, 2003). Additionally, the degradation of soil conditions and adverse climate change impacts exacerbate farmers' vulnerabilities, particularly in the African context (UNFCCC, 2007). Soil erosion, leading to nutrient depletion, further compounds the problem. Financial constraints due to limited access to credit make it difficult for farmers to invest in essential farming inputs. This inability to invest subsequently impedes achieving optimal yields.

Further exacerbating the issue is the rural-urban migration of young, energetic individuals who could potentially bring innovation to farming practices. Such migration not only depleted rural labour but also hampered the adoption of modern farming technologies (Abebaw and Haile, 2019). Moreover, inadequate water management poses irrigation challenges, hindering any prospects for production enhancement. Despite maize's vital role in Nigeria's economy and food security, the production levels remain insufficient to meet both food and industrial demands (Onuk *et al*., 2010). Factors such as elevated input costs, widespread pest infestations, and insufficient storage infrastructure have consistently undermined maize production, limiting yield potential and post-harvest value (Idowu *et al*., 2024).

Based on the foregoing, this paper answers the following research questions: (1) What is the production level of maize in Nigeria? (2) What is the nature of changes in maize production over time in Nigeria? (3) What factors influence its productivity among maize farmers in Nigeria?

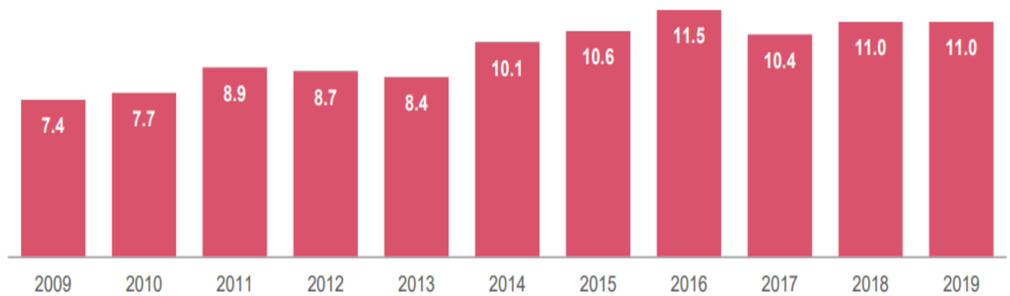

Figure 2: Trends of Nigeria's maize production (MMT)
Source: PwC (2021)

Theoretical Framework: Concepts of Productivity Growth and Technical Progress in Agriculture

The theoretical framework in this study focuses on basic theories of productivity growth and its measurement. The fundamental concept of productivity has been defined as the relationship between the number of goods and services produced and the number of resources used or the ratio of the aggregate output index to an aggregate of factors used in the index (Ajao, 2011; Adeleke *et al*., 2017). According to Shih-Hsun *et al*., (2003) and Adeleke *et al*. (2017), productivity growth is a major source of growth of aggregate agricultural output and this growth can occur in three main ways: an increase in the use of farm production resources, advancement in production technologies, and combination of changes in inputs and productivity. Consequently, increased productivity arises as a result of rise in the ratio of total outputs to inputs. Traditionally, two often utilized measures of productivity are Partial Factor Productivity (PFP) and Total Factor Productivity (TFP). Partial Factor Productivity: the ratio of output and one of the inputs used.

In mathematical form, this can be expressed as:

$$PFP = \frac{Y}{X_i} \tag{1}$$

Where Y is output, and X is input *i*. An important limitation is that it does not control for the level of other inputs employed (Walter *et al.*, 2003).

Total factor productivity: the ratio of output and total inputs employed.

$$TFP = \frac{Y}{\sum P_i X_i} \tag{2}$$

Where Y is revenue derived from output, and Σ *Pi* X*i* is the summation of all costs of variable inputs used. Total factor productivity is a generalization of single-factor productivity. However, methods of production change over time, and it is important to be able to account for the effects of such changes on output. These effects can be captured in a production function, where output Q depends on capital input (K) and labour (L). This can be expressed as:

$$Q = f(K, L) \tag{3}$$

This implies that Q depends on how much K and L are used. An increase in K and L is expected to lead to changes in Q. However, improved technology can cause Q to increase using the same level of K and L. Thus, this output growth due to technical progress is attributed to factors other than growth in conventional input quantity (Walter *et al*., 2003). This change reflects a shift in the production frontier and can be expressed as:

$$Q = A(t)\, f(K, L) \tag{4}$$

Where A(t) represents all the drivers (extension services, education, infrastructure, technology innovation, government intervention, agricultural research, and development) of Q besides K and L. Furthermore, a change in A(t) is referred to as technical progress over time. According to Walter *et al*. (2003), technical change may influence output by affecting all inputs and not just a single input, which is referred to as neutral technical progress. Furthermore, technical change may also enhance either capital (capital-augmenting technical progress) or labour (labor-augmenting technical progress) in order to affect output. These two cases can be represented as:

$$Q = f[A(t)K, L] \tag{5}$$

This represents the capital-augmenting technical progress

$$Q = f[K, A(t)L] \tag{6}$$

This represents the labour-augmenting technical progress

Generally, agricultural productivity and specific components of productivity or crop growth have been decomposed into two components: technological progress (factor-neutral) and intensification (or input/factor substitution) (Rudel *et al.*, 2009; Nelson *et al.*, 2014;). Figure 2 illustrates these components. The movement of the isoquant indicates technical change, representing the transition from point A to point B, while intensification is represented by movement along the isoquant from point A to C represents intensification.

Technological advancement can signify intensification if it enables the production of equivalent agricultural output on the same land area with reduced inputs. Intensification can occur independently of technological developments; as alternative variables supplant land in reaction to fluctuations in relative pricing. Intensification may also arise from a modification in the product mix that is unaffected by technical advancements. This transpires when more efficient commodities supplant less efficient ones due to alterations in relative product prices and market prospects (Nelson *et al*., 2014). Figure 3 illustrates this.

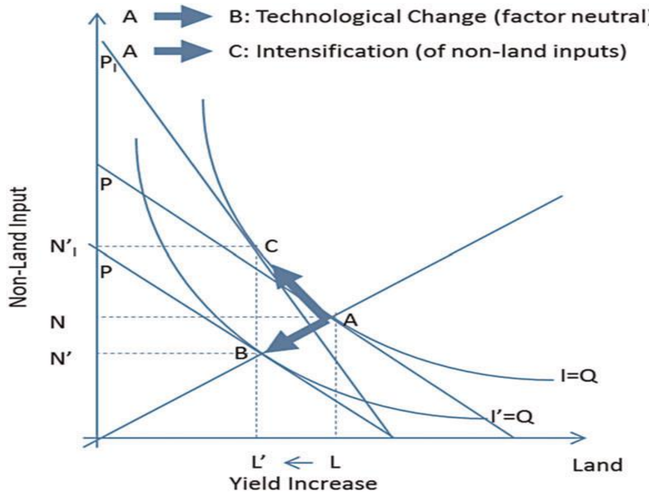

Figure 3: Decomposition of productivity growth into intensification and technological progress (Nelson *et al*., 2014).

Notes: (a) shift of the isoquant represents technological change (b) movement along the isoquant represents an intensification.

Empirical Review of Productivity Drivers among Maize Farmers

Ezeaku *et al*. (2010) explored the resource use efficiency for maize production in north-central Nigeria to optimize output in the future. Data from 2009-2011 maize production years and socioeconomic surveys of 90 farmers from 3 communities, as well as soil samples, were analyzed. The result revealed that the properties of soil varied across locations but shared similar lithology. Regression analysis demonstrated that yield improvement was linked to optimal input levels, with decreasing returns to scale observed for most inputs except fertilizer. The study recommended reducing the use of variable inputs with returns below costs. It also emphasized educating farmers on innovative technologies to promote efficiency and sustainability.

Furthermore, Adesiyan (2015) examined factors affecting maize production in 2 Local Government areas in Osun state. The study identified land use, labour, the quantity of fertilizer, and the education level of farmers as significant factors influencing maize output positively. However, the use of the quantity of maize seeds, insecticides, and herbicides negatively influences maize output. Akerele (2012) in a similar study, explored the socio-economic determinants of maize production in Ogun state, Nigeria. The findings revealed that men dominated maize farming, with most farmers aged between 18 and 45 years. Also, more than half had formal education, with household sizes ranging between 1 and 5. It identified limited access to capital, high transportation costs, poor road infrastructure, and poor farming equipment as key constraints. The study suggested efficient input management and addressing these challenges to improve maize production.

In addition, Ammani *et al*. (2010) analyzed how the present dual fertilizer distribution and Nigerian fertilizer sector liberalization affect the production of maize in Nigeria using time series data ranging from 1990 to 2006. The study utilized a multiple regression model using a dummy variable to capture liberalization effects. The study reported a negative relationship between the 1997 liberalization policy and aggregate maize production, which was attributed to a decline in the use of fertilizer during this period. Furthermore, the study found that the dual fertilizer distribution led to a statistically significant decline in maize production in Nigeria.

Similarly, Abu (2016) investigated how maize productivity and rural poverty in Nigeria are affected by fertilizer market liberalization. Data from the pre-liberalization period, 1990 to 1996, and the liberalization period, 1997 to 2006, were analyzed using Data Envelope Analysis (DEA). The result of this study shows that fertilizer market liberalization has not led to increased yields or improved smallholder farmers' income. It concluded that liberalization failed to deliver anticipated benefits and may not be suitable for economies that are dominated by resource-constrained smallholder farmers. Instead, it recommended reintroducing targeted fertilizer subsidies to support smallholder farmers in fighting food insecurity by improving productivity. Furthermore, ensuring timely access to subsidized fertilizer is important.

Lastly, Oyewo *et al*. (2014) examined factors affecting maize production in Oyo State, focusing on Oluyole Local Government Area. It reported that male farmers were more than female farmers, and a large percentage had some formal education exposure. More than half of the farmers produced between 6 to 10 bags (50 kilograms per bag) of maize, and more than half of the farmers relied on hired labour. The study highlighted the significance of extension visits, which positively influence productivity. However, labour and practices like bush burning, zero tillage, bush fallow, and herbicide usage had negative effects on productivity. The study recommended strengthening extension services to educate farmers on better farmland management practices and discouraging bush burning.

Conceptual Framework for the Study

The conceptual framework for this study explores the interrelationship between maize productivity growth, as well as variables that affect maize productivity and the welfare status of maize farming households in Nigeria. As shown in Figure 4, the independent variables are grouped as socioeconomic factors and maize production inputs or factors.

Maize production inputs such as land size, labour, maize seeds, pesticides, and herbicides are basic factors of maize production, and these are all essential for maize farming activities. The quantity and quality of these maize production inputs fundamentally determine the level of expected maize output, regardless of the socioeconomic status of the farmers.

Moreover, socioeconomic status, such as sex, age, marital status, and level of education of maize farmers, which are intrinsic parts of the maize producers, could contribute tremendously to the expected maize output. Other factors, such as extension services, use of improved seeds, and credit accessibility, also have some levels of influence on maize productivity growth as well as transitions.

Data Source and Selection of Observations Used

In this study, General Household Survey Panel Data (GHS-P-P) from the Living Standard Measurement Survey-Integrated Survey of Agriculture (LSMS-ISA) were utilized. This data was collected repeatedly from the same set of farmers in 2010 and 2018. The National Bureau of Statistics, in collaboration with the National Food Reserve Agency, the Federal Ministry of Agriculture, the Bill and Melinda Gates Foundation, and the World Bank,

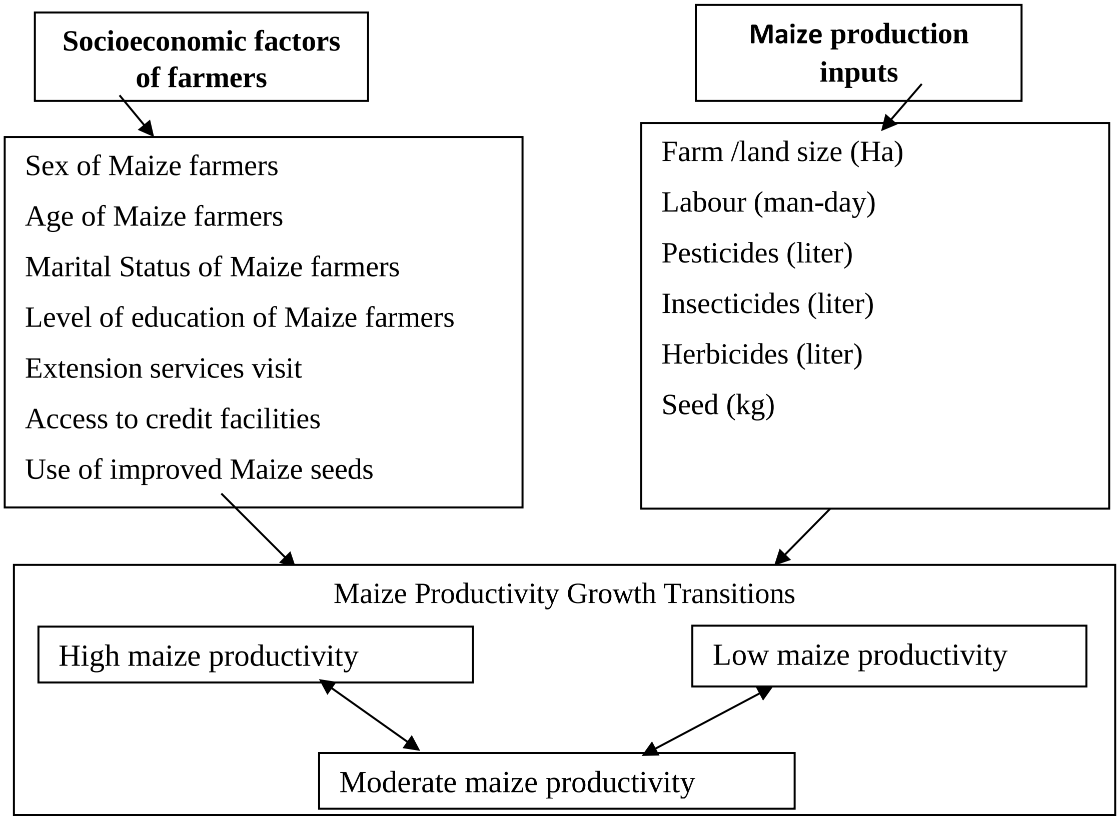

Figure 4: Conceptual Framework for the Study

conducted this survey. The GHS-P-P panel remains a vital database as it tracks the same households longitudinally.

The GHS-P-P is a nationally representative survey of households throughout Nigeria. The GHS-P panel was collected annually at two-year intervals and consisted of data on households, their characteristics, welfare, and their agricultural activities. For this study, information such as maize farmer households' socioeconomic characteristics, maize farmer households' income and expenditure, and maize input and output data would be sorted and analyzed to achieve the set objectives of this study.

A two-stage stratified sample selection process was utilized in the GHS-P panel survey. Firstly, they selected enumeration areas (EAs) as the primary sampling units. In each state, EAs were picked using probability proportional to size. Secondly, 10 households were selected from each EA, and a sampling interval was calculated by dividing the total number of listed households by 10.

More specifically, for this study, further sampling procedures were performed; thus, all the farm households in the data set (GHS-P) were sorted with the aid of STATA 12 commands, and the next step involved matching of variable files to the corresponding respondents' data identifiers. Also, maize farmers' socioeconomics, income, expenditure, inputs, and output variables were sorted and matched using the STATA command. Lastly, maize farmers with a complete data set were used in the actual analysis.

Analytical Techniques

Objective 1: To profile maize farmers by their productivity levels. Descriptive statistics (such as frequency distribution, mean, and standard deviation) the Total Factor Productivity (TFP) measure were used. The estimation of the TFP of maize farmers followed Fakayode *et al*. (2008) and Ukoha *et al*. (2010), who measured it as the inverse of unit variable cost or the ratio of revenue to variable cost incurred to generate the revenue.

This is so since total factor productivity is a ratio concept. In this study, Total Fixed Cost (TFC) was not included because it does not affect profit maximization

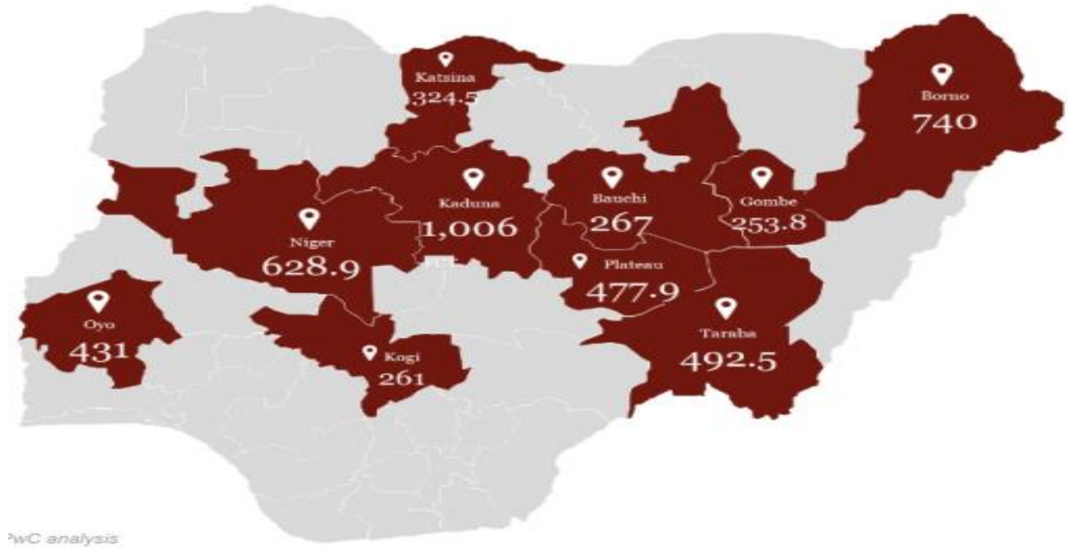

Figure 5 Map of Nigeria showing top maize- producing states (in thousand metric tonnes)

Source: PwC, 2021

and the resource-use efficiency condition. More so, it is a constant (Fakayode *et al*., 2008).

$$TFPI_{it} = \frac{\sum P_{qit} Q_{it}}{\sum P_{xit} X_{it}} \quad (7)$$

Where:

$TFPI_{it}$ = Total factor productivity index of farmer i at time t

$\sum P_{qit} Q_{it}$ = Total revenue of maize farmer i at time t

$\sum P_{xit} X_{it}$ = Summation of the cost of inputs used by maize farmer i at time t

X_{it} = Independent variables at time t, X_i include;

X_1 = Cost of maize stem (₦per bundle)

X_2 = Labour cost (₦ per man-day)

X_3 = Cost of pesticides (₦ per litre)

X_4 = Cost of insecticides (₦ per liter)

X_5 = Cost of herbicides (₦ per litre)

Categorization of Total Factor Productivity Index (TFPI)

To categorize the maize-based performance into low, moderate, and high levels based on farmers' total factor productivity indices, the upper limit of the mean (mean plus standard deviation) value of the total factor productivity index was divided into three points, as outlined by Kumar and Ganesan (2014). Given the upper limit of the mean of farmers' total factor productivity index is φ, then if:

TFPI$< \frac{\varphi}{3}$ the total factor productivity of the farmer is categorized as low

TFPI$\geq \frac{\varphi}{3}$ and $<\frac{2,\varphi}{3}$, the total factor productivity of the farmer is categorized as moderate

TFPI $\geq \frac{2\varphi}{3}$, the total factor productivity of the farmer is categorized as high.

Objective 2: To investigate the drivers of productivity among maize farmers. Utilizing a censored Tobit model, the outcome of the total factor productivity index of the maize farmers was regressed on independent variables that are farm-specific and show productivity variation among different farms. According to Gujarati (2004), Tobit regression is specified as:

$$E* = \delta o + \delta_m Z_{im} + \mu \quad (8)$$

$$\frac{v}{z} \approx normal\ (0, \delta^2)$$

where E^* is a latent variable expressing the efficiency ratings of maize producer farmers. δ is a vector of unknown parameters to be estimated, Z_{im} is a vector of explanatory variables m (m = 1,2, . . ., n) for a farm household, such as:

X_1 = education levels or years of schooling

X_2 = household size in number

X_3 = age of farmers in years

X_4 = farm size in hectare.

X_5 = marital status

X_6 = food expenditure (₦)

X_7 = sex of household head in dummy (1 if male, 0 if female-headed household)
X_8 = farm experience in years
X_9 = access to credit (1 if farmers received credit, 0 if not)
X_{10} = non-farm enterprise (1 if farmers engaged in off-farm activities, 0 if not)
X_{11} = access to phone
X_{12} = access to remittance
X_{13} = access to association
X_{14} = harvest (₦)
X_{15} = total cost
X_{16} = land ownership
X_{17} = number of extension visits
μ represents the error term, which is independently and normally distributed, characterized by a mean of zero and variance δ^2. Denoting E_i as observed variables,

$$E_i = \begin{cases} 1, \; if \; E_i^* >= 1, \\ 0, \; if \; E_i^* <= 0, \end{cases} \tag{9}$$

Following McDonald and Moffitt (1980), the likelihood function decomposition of marginal effects, the two-limit Tobit model, is as follows:

The unconditional expected value of the dependent variable can be expressed as:

$$\frac{\partial E(y)}{\partial X_j} = [\varphi(Z_u) - \varphi(Z_L)].\frac{\partial E(y^*)}{\partial X_j} + \frac{\partial[\varphi(Z_u) - \varphi(Z_L)]}{\partial X_j} + \frac{\partial[1-\varphi(Z_u)]}{\partial X_j} \tag{10}$$

The expected value of the dependent variable, conditional upon being between the limits, can be expressed as:

$$\frac{\partial E(Y^*)}{\partial X_j} = \beta m.\left[1 + \frac{\{Z_L \emptyset(Z_L) - Z_u \emptyset(Z_u)\}}{\{\varphi(Z_u) - \varphi(Z_L)\}}\right] - \left[\frac{\{\emptyset(Z_L) - \emptyset(Z_u)\}^2}{\{\varphi(Z_u) - \varphi(Z_L)\}^2}\right] \tag{11}$$

The probability of being between the limits is represented as:

$$\frac{\partial[\varphi(Z_u) - \varphi(Z_L)]}{\partial X_j} = \frac{\beta_m}{\sigma}[\emptyset(Z_L) - \emptyset(Z_u)], \tag{12}$$

where $\emptyset(.)$ is the normal density function, φ(.) is the cumulative normal distribution, $Z_L = -(X_i{}'\beta/\sigma)$ and $Z_u = (1 - X_i{}'\beta/1)$ are the standardized variables derived from the likelihood function given the limits of y^*, and σ is the standard deviation of the empirical model.

Objective 3: To examine the movements in productivity status among the farmers over the years. To achieve this objective, the required data was subjected to a Markov transition model.

The system's initial state can be represented as a probability vector:

$$p(o) = (P_1(o), P_2(o), P_3(o)) \tag{13}$$

The initial state vector, $p(o)$, refers to the state of the system, and the complete transition matrix is (P). Using theorems of matrix algebra, the next level or state, $p(1)$ can be obtained by multiplying the initial state vector $p(o)$ by (P).

$$p(1) = p(o)p \tag{14}$$

If the transition probabilities remain constant and the total population remains unchanged, then the distribution of the population for the new state of the system is thus;

$$p(2) = p(1)p = p_{(0)}p^2 \tag{15}$$

Then, in general $= p_{(0)}p^n$ (16)

Alternatively, similar results can be obtained by multiplying the initial state vector by each successive power of the initial transition matrix.

$$p(1) = p(o)p \tag{17}$$

To perform the calculation sufficiently with a high level of certainty, information relating to the observed probabilities of past trends of maize-based farmers was organized into a matrix, which would be the basic framework of a Markov model. Each element in the matrix represents the probability of moving from one state to another. This probability is referred to as the transition probability. Thus, the matrix of transition probabilities describes the probability of movement from one state to another during a specified time interval. Table 1 show that 39.56% of farmers had low productivity, 38.20% had high productivity, and 22.24% had medium productivity in Wave 1. productivity ratios. The TFPI, calculated as the ratio of total revenue to total variable costs, creates natural censoring points when categorized into low, medium,

Table 1: Comparison of Productivity Levels of Maize Farmers in Waves 1 and 4

WAVE 1		WAVE 4	
Productivity	**Percentage**	**Productivity**	**Frequency**
Low (<3.002391)	39.56	Low (<2.1230)+	32.77
Medium (3.002392 – 6.004782)	22.24	Medium (2.123077 – 4.246151)	25.13
High (>6.004783)	38.20	High (>4.246152)	42.11
Mean	**9.01**	**Mean**	**6.40**

Figures in parentheses are percentages

Results and Discussion

Productivity Level of Maize Farmers in Nigeria

The productivity index was used to classify the maize farmers as having low, medium, or high productivity for the production year. The results in

In the fourth wave, the majority (42.11%) of the farmers had high productivity, 32.77% of the farmers had low productivity, and 25.13% had medium productivity. This shows an improvement from the first wave, which had the majority of the farmers having low productivity. However, the mean productivity in Wave 4 is smaller compared to Wave 1.

Drivers of Productivity among Maize Farmers in Nigeria

The Tobit regression results presented in Table 2 analyze the factors influencing productivity growth among maize farmers. A log-likelihood of -4589.1476 and a log-likelihood ratio (LR) chi-square test of 295.167 ($p<0.05$). This confirms that the model provides a good fit for the data. Several independent variables significantly influence maize farmers' productivity, including farm experience, access to credit, non-farm enterprise participation, access to a phone, access to remittances, land ownership, input cost, and sales value.

The choice of Tobit regression is fundamentally justified by the nature of the dependent variable: the Total Factor Productivity Index (TFPI), which is a censored continuous variable with natural lower bounds since farmers cannot have negative productivity ratios. The TFPI, calculated as the ratio of total revenue to total variable costs, creates natural censoring points when categorized low, medium and high productivity levels, making Tobit regression the appropriate econometric technique. Alternative models like OLS would produce biased and inconsistent estimates when applied to such censored data, while logistic or probit models would lose valuable information about productivity magnitudes by treating the outcome as binary rather than continuous.

The relatively low pseudo-R-squared of 0.031 does not invalidate the model choice, as the LR Chi-square test of 295.167 ($p<0.05$) confirms statistical significance, and agricultural productivity data inherently contains substantial unexplained variation due to unobservable factors like weather, soil quality, and management practices. More importantly, the model identifies statistically significant relationships with substantial practical implications, including access to credit increasing productivity by 366.1%, mobile phone access by 345.5%, and remittances by 121.6%, while non-farm enterprise participation decreases it by 164.8%. These findings align with economic theory and provide actionable policy insights, demonstrating that the Tobit model's value lies in causal inference and policy analysis rather than predictive power, making it the most appropriate choice for understanding agricultural productivity dynamics among Nigerian maize farmers.

The results show that farm experience has a negative and significant effect on productivity ($p < 0.10$). Specifically, a unit increase in farm experience leads to a 1.1% reduction in productivity. This may be attributed to the reluctance of experienced farmers to adopt new agricultural technologies, as they may rely on traditional farming methods instead. Similarly, farmers engaged in non-farm enterprises experience a substantial 164.8% decrease in productivity ($p < 0.01$). This suggests that diversifying into other income-generating activities diverts attention and resources away from farming, thereby reducing productivity.

Conversely, access to credit has a positive and significant impact on productivity ($p < 0.05$), with an increase in credit access leading to a 366.1% rise in productivity. This highlights the importance of financial support in enabling farmers to purchase essential inputs such as fertilizers, improved seeds, and mechanized tools. Similarly, access to a mobile phone significantly improves productivity ($p = 0.051$), increasing it by 345.5%. This can be attributed to the enhanced access to market and weather information, which enables better decision-making.

Access to remittances also plays a crucial role in enhancing productivity, accounting for a 121.6% increase ($p < 0.01$). Financial support from family members or external sources helps farmers invest in better inputs and farming techniques. Furthermore, the value of the harvest is positively and significantly related to productivity, reinforcing the direct relationship between farm output and overall efficiency. The total cost of input is also positively significant, indicating that higher production costs are associated with increased productivity. This finding aligns with Ibitola *et al*. (2019), suggesting that farmers investing in high-quality inputs such as fertilizers and improved seeds can achieve better yields. Interestingly, land ownership has a negative and significant effect on productivity ($p < 0.01$), leading to a 159.9% decline. This may be due to land fragmentation or inefficient land use among owner-farmers compared to tenant farmers, who might adopt more intensive cultivation practices.

Linking Productivity and Per Capita Expenditure

Table 3 explains the relationship between the productivity of the maize farmers and their per capita expenditure. It shows that the majority (low-100%, Medium-100%, High-98.67%) of the maize farmers in Wave 1 have their per capita expenditure below 4,000 in all productivity levels and in the high productivity level, 0.89% had per capita expenditure between 4,001-8,000 while 0.44 % had per capita expenditure above 8,000.

Furthermore, according to Table 4, the majority of the farmers in the fourth wave (Low-94.30%, Medium-88.51%, High-92.74%) have their per capita expenditure below 4,000. However, 3.63% of the farmers in the low productivity level have per capita expenditure between 4,001–8,000, and 2.07% have above 8000. Also, 11.49% in the medium productivity level have their expenditure between 4,001–8,000. Among the farmers in the high productivity level, 4.84% had their per capita expenditure between 4,001-8,000, and 2.42% spent over 8,000. This represents an improvement in per capita expenditure compared to Wave 1.

Productivity Transitions among Maize Farmers (Wave 1 to 4)

Table 5 shows the productivity transition of maize farmers from the first wave to the fourth wave using the Markov Transition Matrix. It reveals that 36.91% of the farmers maintained low productivity in both the first and fourth waves. The maintenance of low productivity of the farmers can be attributed to the inaccessibility of the farmers to inputs such as loans, remittances from abroad, subsidies, and improved seeds. The percentage of farmers that improved their productivity to the medium scale and high scale was 22.32% and 40.77% respectively, which might be due to access to inputs, loans, remittances, and access to the right information from their associations.

The farmers who were in the medium productivity of the first wave and moved to low productivity were 22.14%. This might be due to mismanagement of funds or loss of benefits previously available in the first wave. Also, 23.66% and 54.20% maintained medium productivity and improved to high productivity, respectively.

Furthermore, 34.67% and 28.89% of the farmers who were in the high productivity category decreased to the low productivity and medium productivity respectively, in the fourth wave. This negative transition of the maize farmers may be attributed to tribal clashes, and an unfavourable land tenure system as a greater percentage of the farmers do not own farmland but on lease or rent while 36.44% maintained the high productivity in both waves which might be attributed to good maintenance and management of their farm practices. Overall, significant percentages (40.77%, 54.20%, and 36.44%) of farmers in the first wave were able to move to or maintain high productivity.

Table 2: Tobit Regression Result of the Parameter Estimates of Maize Farmers' Productivity

Productivity	Coefficient.	Standard Error	t-value	p-value	dy/dx
Years of Schooling	-0.037	0.067	-0.560	0.575	0.094
Household size	-0.245	0.293	-0.840	0.403	0.329
Age(years)	0.000	0.000	1.080	0.282	0.001
Farm size(ha)	-0.247	0.531	-0.470	0.642	0.795
Marital status	-0.497	0.858	-0.580	0.562	1.186
Food Expenditure (₦)	0.000	0.000	-1.220	0.222	0.000
Sex	-0.720	0.770	-0.930	0.350	0.791
Access to extension	1.456	1.491	0.980	0.329	4.383
Farm experience	-0.073*	0.043	-1.710	0.088	0.011
Access to credit	1.975**	0.86	2.300	0.022	3.661
Non-farm enterprise	-5.182***	1.801	-2.880	0.004	-1.648
Access to a phone	1.723*	0.883	1.950	0.051	3.455
Access to remittance	7.493***	2.379	3.150	0.002	12.162
Access to Association	-0.337	0.776	-0.430	0.664	1.185
Harvest (₦)	0.000***	0.000	14.69	0.000	0.000
Total cost	0.000***	0.000	-6.730	0.000	-0.000
Land ownership	-3.346***	0.891	-3.760	0.000	-1.599
Number of extension visits	-0.006	0.168	-0.040	0.970	0.323
Constant	11.724	2.318	5.060	0.000	
var	162.084	6.736	.b	.b	
Number of observations	1158				
LR Chi2	295.167				
Prob > chi2	0.000				
Pseudo r-squared	0.031				
Log likelihood	-4589.1476				

Note: *** = significant at 1%, ** = significant at 5%, * significant at 10%

Table 3: Cross Tab of Productivity and Per Capita Expenditure in Wave 1

	Per capita expenditure			
Productivity 1	**<4000**	**4001 – 8000**	**>8000**	**Total**
Low	233	0	0	233
	(100.00)	(0.00)	(0.00)	(100.00)
Medium	131	0	0	131
	(100.00)	(0.00)	(0.00)	(100.00)
High	222	2	1	225
	(98.67)	(0.89)	(0.44)	(100.00)
Total	**586**	**2**	**1**	**589**
	(99.49)	**(0.34)**	**(0.1)**	**(100.00)**

Figures in parentheses are percentages

Table 4: Cross Tab of Productivity and Per Capita Expenditure in Wave 4

Productivity 4	Per capita expenditure			
	<4000	**4001 – 8000**	**>8000**	**Total**
Low	182	7	4	193
	(94.30)	(3.63)	(2.07)	(100.00)
Medium	131	17	0	148
	(88.51)	(11.49)	(0.00)	(100.00)
High	230	12	6	248
	(92.74)	(4.84)	(2.42)	(100.00)
Total	**543**	**36**	**10**	**589**
	(92.19)	**(6.11)**	**(1.70)**	**(100.00)**

Figures in parentheses are percentages

Table 5: Transition Matrix of the Productivity Level of the Maize Farmers

		Wave 4			Total
		Low	**Medium**	**High**	
Wave 1	**Low**	86 (36.91)	52 (22.32)	95 (40.77)	233
	Medium	29 (22.14)	31 (23.66)	71 (54.20)	131
	High	78 (34.67)	65 (28.89)	82 (36.44)	225
	Total	**193 (32.77)**	**148 (25.13)**	**248 (42.11)**	**589**

Figures in parentheses are percentages

Conclusion

In conclusion, while maize productivity among Nigerian farmers has improved over the observed period, substantial productivity gaps remain. These gaps are influenced more by access to critical resources and information than by inherent farmer traits. Improvements in TFP were positively associated with modern enablers such as mobile technology, credit access, and remittances, while traditional constraints like poor extension services, limited mechanization, and engagement in non-farm enterprises hampered productivity growth. The transition patterns across productivity groups reveal promising upward mobility for some farmers, yet persistent challenges prevent many from escaping low productivity tiers. Overall, the evidence suggests that targeted support to overcome these constraints is essential to unlock the full potential of Nigeria's maize sector.

To improve maize productivity and rural welfare, the study recommends the following based on its findings:

Enhancing Financial Inclusion: Policymakers must design and implement low-interest credit schemes tailored to the needs of smallholder farmers. Facilitating timely access to affordable agricultural financing would enable these farmers to invest in productivity-enhancing inputs such as improved seeds, fertilizers, and mechanization, thereby bridging the input-use gap between them and their more resource-endowed counterparts.

Strengthening Agricultural Extension Services: The expansion and professionalization of agricultural extension systems are essential for disseminating modern farming knowledge and practices. Particular attention should be given to engaging older farmers, who may exhibit resistance to innovation, through targeted, context-appropriate training and demonstration activities.

Leveraging Digital Agriculture: Investments in rural telecommunication infrastructure and the promotion of digital literacy are critical to ensuring that farmers can access timely and relevant information. Mobile technologies should be utilized to deliver weather forecasts, input and output price updates, agronomic advice, and market linkage opportunities, all of which contribute to more informed decision-making.

Reforming Land Tenure Systems: Land tenure reforms are necessary to provide farmers with secure and clearly defined property rights. By reducing land fragmentation and uncertainty over ownership, such reforms would incentivize long-term investments in land improvement and sustainable cultivation practices.

Investing in Rural Infrastructure and Storage Facilities: Improved rural infrastructure, particularly road networks, storage facilities, and agro-processing centers, would reduce post-harvest losses, lower transaction costs, and enhance farmers' access to markets. These investments are crucial for increasing farm profitability and integrating smallholders into higher-value segments of the maize value chain.

Declaration of generative AI and AI-assisted technologies in the writing process

The author used artificial intelligence tools in some sections of this manuscript solely for language editing, grammar refinement, clarity, and organization of references. No AI tools were used for actual analysis, interprepation of results, or to generate original ideas. All intellectual material in this article is the original work of the author, who takesfull responsibility for the content of this manuscript.

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