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Panel Predictive Modeling of Agricultural Production Among States In Nigeria

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Abstract: *This research seeks to fit panel regression predictive models on agricultural productivity in Nigeria using data from 36 states and Federal Capital Territory, Abuja (37 cross-sections) from 2006 to 2015 (10 periods). Data were collected on crop production output, agricultural area, fertilizer used, and employment in crop farming, farmgate prices and cost of seeds/seedlings as provided by each state in Nigeria. Crop production is used as a proxy for measuring the level of agricultural productivity for each state of the Federation. The result of the analysis shows that static panel models are the best models in modelling crop production in Nigeria, especially panel least squares with fixed effect cross-section and fixed effect period, followed by Panel EGLS with fixed effect cross-section and random effect period. The analysis shows that 97.5% of the variation in crop production can be explained by the variations in the explanatory variables included in the model. The area planted, employment in crop farming, farmgate prices and cost of seeds/seedlings are significantly positively related to the level of crop production in Nigeria except for fertilizer usage, which has a significant negative relationship. Government and all other stakeholders should provide more agricultural land for crop production, more employment in crop farming, consider farmgate prices and cost of seeds/seedlings as they all have significant positive effect on crop production.*

Keywords*: Panel data, Predictive model, Static panel, Dynamic panel, Pooled regression*

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I. Introduction

Different types of data are generally available for empirical analysis, namely, time series, cross section, and panel. A data set containing observations on a single phenomenon observed over multiple periods is called time series. In time series data, both the values and the ordering of the data points have meaning. In cross-section data, values of one or more variables are collected for several sample units, or entities, for the same period. Panel data sets refer to sets that consist of both time series and cross section data. This has the effect of expanding the number of observations available, for instance if we have 10 years of data across 37 states, we have 370 observations. Although, there would not be enough to estimate the model as a time series or a cross section, there would be enough to estimate it as a panel (Baltagi, 1980).

Modelling agricultural production in this period of high cost of living, low standard of living in Nigeria, a giant of Africa is sacrosanct. If only Nigeria can key into statistical modelling, maybe we would have moved passed the level we are now. The economy of Nigeria consists of the trade, industry, agriculture, and human resources. As of 2015, approximately 182.2 million people were living in 36 states including the federal capital territory in Nigeria (NPC, 2016). Nigeria is a resource-rich country but many Nigerians are poor. Recently, the growth in GDP has reduced to its decade lowest ever. The percentage of agriculture contribution to Nigeria GDP is nowhere near crude oil contribution to GDP. Africa is the world's poorest inhabited continent and Nigeria, which is supposed to be a rich country in Africa is now facing economic down turn because of neglect of agricultural production as measured by Gross Domestic Product (GDP) per capita. (Marcantonio et, al, 2014).

The United Nation Millennium Development Goals of reducing poverty by half, between 1995 and 2020, the proportion of people whose income is less than one dollar a day has energized the school of thought calling for Africa to redefine the importance of agricultural development. Since Africa is land abundant, especially Nigeria will always have larger primary sector and smaller manufacturing sector than the land scarce regions of Asia and Europe (Wood 2002).

Zakari et. al (2014), in their work mentioned that food insecurity is a major challenge for Niger and for many African countries. The purpose of their study is to investigate the factors influencing household food security in Niger, based on this, they collected data on 500 households, drought, high food prices, poverty, soil infertility, disease and insect attacks are reported by the respondents to be the main causes of food insecurity. Their empirical results from logistic regression revealed that the gender of the head of household, diseases and pests, labour supply, flooding, poverty, access to market, the distance away from the main road and food aid are significant factors influencing the odds ratio of a household having enough daily rations. Another important finding was that female-headed households are more vulnerable to food insecurity compared to male-headed households. Their findings provided evidence that food insecurity continues to affect the Nigerien population.

Marcantonio et. al (2014), employed the relationship between policy, market access, country governance indicators and food production in 41 African countries based on a cross-country panel sample, using a fixed-random effect model to test the hypothesis that beyond agricultural inputs and macroeconomic reforms other exogenous factors could foster food production. Their findings show that improving food-agricultural inputs enhance production, while conflicts, food aid and geographic location such as landlocked countries negatively affect food production. Exogenous factors influencing production response include rainfall, market access, and education. Both governance and education can indirectly improve food production by enhancing growth, through investment in infrastructures, and human capital.

Tesfaye (2014) mentioned that despite the critical importance of agriculture in SSA countries; there are constraints behind, between, and beyond the border that directly and indirectly affects agricultural export performance of these countries. His paper attempted to explain theoretically and assessed empirically the demand and the supply side factors affecting agricultural export of SSA countries. Specifically, the study focused on analyzing the relative importance of the two major factors in determining the countries agricultural export performance. Panel data set with fixed effects estimation technique was used to address the question. The data set covers 47 SSA countries over the periods 2000-2008. The estimation result showed that on the supply side, factors such as real GDP, real GDP (lagged) of exporting country and lagged agricultural input use positively and significantly affects agricultural export of the SSA countries. The study also indicated that on the demand side the effect of per capita GDP of US, the major trading partner of SSA countries, is positive and significant. Moreover, the effect of US import tariff imposed on agricultural products from SSA countries is negative and significant. Therefore, the overall result reiterated that both supply side and demand side factors are equally important in determining agricultural export performance of SSA.

This research is therefore concerned in finding some relationships that exist among variables that can help to formulate predictive models that will be suitable for forecasting agricultural production among states in Nigeria. This model, if relied on would help to maintain steady growth in agricultural production and agricultural export in Nigeria.

In this research, crop production level is used as a proxy to measure agricultural productivity of Nigeria. It is expected that the higher the crop production level of a nation, the more improved the food production wellbeing of the people. The remaining sections of this research are organized as follows. Section two contains the material and research methodology and the models used were specified, in section three, we empirically analyzed the data and discussed the result of the analysis while in section four we concluded the research and give necessary recommendations to all stake holders.

Aim and Objectives of the Study

This research aimed at formulating panel predictive models for crop production among states in Nigeria. In order to achieve this aim, the following objectives are stated.

1. To study the behavioural pattern of agricultural productivity among states in Nigeria and know the state and period that has highest agricultural productivity in Nigeria.
2. To formulate panel predictive models for predicting and forecasting agricultural productivity among states in Nigeria
3. To identify the predictor variables, which have significant effect on states' agricultural productivity
4. To select the most adequate panel predictive model for forecasting agricultural productivity for individual states in Nigeria.

II. Materials and Method

In this section, we addressed the issue of the data used and how it was collected and the method of analysis. Secondary data was collected on 37 states in Nigeria and for ten years covering 2006 to 2015. The panel data model is adopted for modeling agricultural productivity in Nigeria. Crop production level is used as a proxy for agricultural productivity.

2.1 Data Description

The variables of interest in this research are crop production level (in thousand metric tons ('000 metric tons)), which provides information on the level of growth in agriculture of the states in Nigeria. The crops included in the analysis are cowpea, cassava, maize, cocoyam, groundnut, rice, yam, rice, melon, soybeans, sesame seed and palm oil. Other variables that are of concern are area planted (in thousand hectares ('000 ha)), fertilizer usage (in metric tons), employment in crop farming (in number of persons), farmgate prices (in naira per kilogram) and cost of seed/seedlings (in billion of naira). The data was retrieved from National Bureau of Statistics (NBS) published transcript. The data in the transcript was collected by NBS through the two data collection infrastructure; National Integrated Survey of Household (NISH) and National Integrated Survey of Establishment (NISE). NISH Master Sample was constructed from the frame of EAs of 2006 Housing and Population Census by National Population Commission (NpopC). The household listing of the EAs were and stratified into farming and non-farming household and the sample size was taken from the farming through randomization. The NISE has a well-complied frame of corporate farms from where the sample was taken. The data which collection started in 2006 was made available up to 2015. All the 36 states of the federation were involved in the analysis including the Federal Capital Territory, Abuja, making 37 cross-sections.

2.2 Panel Data Predictive Model (PDPM)

In a typical symbolic representation, time series variables are usually denoted by subscript t while cross-sectional variables are denoted by subscript i. Since panel data have both time series and cross-sectional dimensions, their variables are represented by subscript *it*. Using the proposed model for this research, we can specify the following models in respect of this data set below:

$$y_t = \alpha + \sum_{w=1}^{k} \beta_w X_{wt} + e_t, t = 1, 2, \dots, T \quad (1)$$

$$y_i = \alpha + \sum_{w=1}^{k} \beta_w X_{wi} + e_i, i = 1, 2, \dots, n \quad (2)$$

$$y_{it} = \alpha + \sum_{w=1}^{k} \beta_w X_{wit} + e_{it}, i = 1,2, \dots, n;\ t = 1, 2, \dots, T \quad (3)$$

where y denotes outcome variable, X represents the explanatory variables, t is time series dimension, i is the cross-sectional dimension and w is a counter for the explanatory variable while k is the number of the explanatory variable used. Equation (1) above follows a time series framework, equation (2) follows a cross-sectional frame work while equation (3) follows a panel data framework (Drukker ,2003).

Panel data models are broadly divided into two, namely static panel models and dynamic panel models. The most notable difference between the two models is the inclusion of the lagged dependent variable as a regressor in the latter. This research focuses on the static panel data models but the dynamic models and pooled regression models will be introduced and be compared with the static models. The difference between a dynamic and static model is that in dynamic model, the lagged dependent variable is also used as one of the independent variables (Ekum et al. 2013). A typical static panel data regression can be expressed as:

$$y_{it} = \alpha + \sum_{w=1}^{k} \beta_w X_{wit} + e_{it} \quad (4)$$

where

$w = 1, 2, \dots, k$ (Regressors); $i = 1, 2, \dots, n$ (Cross sectional units); $t = 1, 2, \dots, T$ (Time periods),

where Y is the dependent variable and X_w are the explanatory variables. The subscripts 'i' and 't' as earlier defined refer to cross-sectional dimension and time series dimension respectively, e_{it} is the composite error term which can be decomposed further into specific effects or individual observations (country effects as in the case of this research) and remainder disturbance term. There are two sets of specific effects namely the individual specific effects and time specific effects. If only one set of specific effects is included in the regression, such is referred to as *one-way error* components model. However, if both sets of specific effects are included, we refer to the model as *two-way error* components model. Equations (5), (6) and (7) show decomposition of e_{it} into one-way and two-way error components.

$$e_{it} = \mu_i + v_{it} \quad (5)$$

$$e_{it} = \lambda_t + v_{it} \quad (6)$$

$$e_{it} = \mu_i + \lambda_t + v_{it} \quad (7)$$

where μ_i and λ_t denote the unobserved individual and time specific effects respectively. We shall limit our empirical applications to the one-way error components.

2.3 Parameter Estimation

From (4) in matrix form we have

$$y = \alpha + X\beta + e,$$

$$y = \alpha J_{nT} + X\beta + Z_\mu \mu + v = Z\delta + Z_\mu \mu + v \quad (8)$$

where Z is $nT \times (K+1)$ and Z_μ, the matrix of country dummies is $nT \times n$.If n is large, (8) will include too many dummies and the matrix to be inverted will be dimension $(n+K)!$ Apart from the herculean task of having to invert such a large matrix, the matrix will also fall into dummy variable trap.

Rather than attempt OLS on (8), we can obtain Least Squares Dummy Variables (LSDV) Estimators of α and β by pre multiplying (8) by Q and performing OLS on the transformed model:

$$Qy = Q\alpha J_{nT} + QX\beta + QZ_{\mu}\mu + Qv \quad (9)$$

but $QZ_{\mu} = QJ_{\mathrm{nT}} = 0$ so that (9) becomes $Qy = QX\beta + Qv$. Square Qv, differentiate the result and equate it to zero to minimize Qv, we have $(Qv)'(Qv) = (Qy - QX\beta)'(Qy - QX\beta)$.

Let $S = (Qv)'(Qv)$, differentiate with respect to β and equate to zero to obtain.

$$\hat{\beta} = (X'QX)^{-1}X'Qy$$

Unbiasedness: $\hat{\beta}$ is an unbiased estimate of β

$$E(\hat{\beta}) = E[\beta] + (X'QX)^{-1}X'QE(v) = \beta$$

Variance of β

$$\hat{\beta} - \beta = (X'QX)^{-1}X'Qv \quad (10)$$

$$V(\hat{\beta}) = E(\hat{\beta} - \beta)(\hat{\beta} - \beta) \quad (11)$$

On substituting (10) into (11), we have, $V(\hat{\beta}) = E\Big[[(X'QX)^{-1}X'Qv][(X'QX)^{-1}X'Qv]\Big]$

Since $QQ' = Q$, we have, $V(\hat{\beta}) = [(X'QX)^{-1}X'Q[E(vv')]Q'X(X'QX)^{-1}]$,

but $E(vv') = \sigma_v^2 I_{nT}$, so that

$$V(\hat{\beta}) = \sigma_v^2 I_{nT}[(X'QX)^{-1}X'QX(X'QX)^{-1}]$$

$$V(\hat{\beta}) = \sigma_v^2 I_{nT}(X'QX)^{-1}$$

The OLS $\hat{\beta} = \beta + (X'QX)^{-1}X'Qv$ is sometimes called the Least Squares Dummy Variable (LSDV).

2.4 Model Specification

In this research, panel predictive models (PDPM) are specified. Multiple linear regression models using crop production as the dependent variable and five development indicators (area planted, fertilizer usage, employment in crop farming, farmgate prices and cost of seeds/seedlings) as the predictor variables are specified as shown below;

$$\mathrm{Y}_l = \alpha + \beta_1 X_{1l} + \beta_2 X_{2l} + \cdots + \beta_{\mathrm{p}} X_{pl} + \varepsilon_l \quad (13)$$

$$\mathrm{Y}_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + \cdots + \beta_{\mathrm{p}} X_{pit} + \mu_i + \lambda_t + v_{it} \quad (14)$$

$$\mathrm{Y}_{it} = \alpha + Y_{i(t-j)} + \beta_1 X_{1it} + \beta_2 X_{2it} + \cdots + \beta_{\mathrm{p}} X_{pit} + +\mu_i + \lambda_t + v_{it} \quad (15)$$

where (13) is a pooled regression model, (14) is a static model and (15) is a dynamic model and j is an integer, representing lag, $i = 1, 2, \ldots, n$; $t = 1, 2, \ldots, T$ and $l = 1, 2, \ldots, nT$; $n = 37$ is the number of cross-sections, $T = 10$ is the number of periods (years) and $nT = 370$ is the total number of observations or cases.

Y_l = Crop production for observation l

Y_{it} = Crop production for state i and year t

$Y_{i(t-j)}$ = Crop production for state i and year $t-j$

X_{1it} = Area planted for state i and year t

X_{2it} = Fertilizer usage in state i and year t

X_{3it} = Employment in crop farming in state i and year t

X_{4it} = Farmgate Prices in state i and year t

X_{5it} = Cost of seeds/seedlings in state i and year t

β_i = Unknown Parameter i to be estimated

μ_i= Cross country fixed effect (the states in Nigeria)

λ_t= Period fixed effect (the years)

v_{it}=Idiosyncratic error term

III. Empirical Results and Discussion of Findings

3.1 Exploratory Data Analysis (EDA)

In this section, we explore the data by showing some hidden features within the dataset. Tables 1 and 2 and Figures 1 and 2 are used to explain in descriptive capacity some features of the dataset. Also, time plot in the appendix 1 to 7 depict the pattern of movement of the panel data and the time series data. The mean, median, standard deviation, maximum, minimum, kurtosis, skewness and other descriptive measures are used to explain the dataset.

Table 1: Descriptive Statistics

	PRODUCTION	AREA	FERTILIZER	EMPLOYMENT	PRICE	COST
Mean	3055.613	641.1475	2508.710	1562.321	155.2039	3947.743
Median	2181.490	501.1450	1916.636	1248.350	150.3676	1937.445
Maximum	13688.21	2576.780	10721.90	8731.892	269.4383	20847.96

Minimum	92.52000	31.07000	0.000000	32.00000	72.76000	82.03000
Std. Dev.	2850.251	495.7357	2130.103	1304.665	39.68566	4367.267
Skewness	1.264425	1.800555	1.042525	2.517594	0.510019	1.214090
Kurtosis	4.141248	6.493740	3.592575	10.77448	2.938432	3.737247
Sum	1130577.0	237224.6	928222.5	578058.9	57425.45	1460665.0

Table 1 shows the descriptive statistics of selected crops used as proxy to agricultural production in Nigeria for 8 years from 2006 to 2015. The table shows that on the average, crop production for the period under review is 3,055,613 metric tons with standard deviation of 2,850.251. The average land area for the production of these selected crops is 61,147.1 hectares with standard deviation of 495.7357. The average fertilizers used for the production of the selected crops for the period under review is 2,508.710 metric tons with standard deviation of 2,130.103. The average employment in crop production of the selected crops for the period under review is 1,562,321 persons with standard deviation of 1304.665. The average farmgate price in crop production of the selected crops for the period under review is ₦155.20 with standard deviation of 39.69. Finally, the average cost of seeds/seedlings of the selected crops for the period under review is ₦3,947.74 million with standard deviation of 4367.27. In summary, the total food production in Nigeria for the period under review is 1,130,577,000 metric tons.

Table 2: States Codes and Average Agricultural Production ('000 Metric Tons) by States

Code	State	Prod.	Code	State	Prod.	Code	State	Prod.	Code	State	Prod.
1	Abia	1781	11	Ebonyi	2874	21	Kebbi	302	31	Plateau	2007
2	Adamawa	760	12	Edo	1463	22	Kogi	6024	32	Rivers	3171
3	Akwa-Ibom	3106	13	Ekiti	3823	23	Kwara	1791	33	Sokoto	434
4	Anambra	3299	14	Enugu	8365	24	Lagos	699	34	Taraba	7975
5	Bauchi	688	15	Gombe	593	25	Nasarawa	4146	35	Yobe	504
6	Bayelsa	404	16	Imo	4926	26	Niger	6657	36	Zamfara	718
7	Benue	10331	17	Jigawa	284	27	Ogun	2264	37	FCT Abuja	184
8	Borno	2087	18	Kaduna	9274	28	Ondo	5365			
9	Cross River	6234	19	Kano	1041	29	Osun	1352			
10	Delta	3540	20	Katsina	1307	30	Oyo	5205			

Table 2 shows the code of each state for the 36 states and the Federal Capital Territory (FCT) Abuja. Abia is coded 01, Adamawa as 02 in that order to Zamfara as 36 and FCT Abuja is 37. The table shows that Benue State has the highest average food production in Nigeria for the period under review with an average production level of *10,331,000* metric tons, followed by Kaduna State with a production figure of *9,274,000* metric tons. Third largest crop production in Nigeria is Enugu State with a production figure of *8,365,000* metric tons and the forth is Taraba State with a production figure of *7,975,000* metric tons.

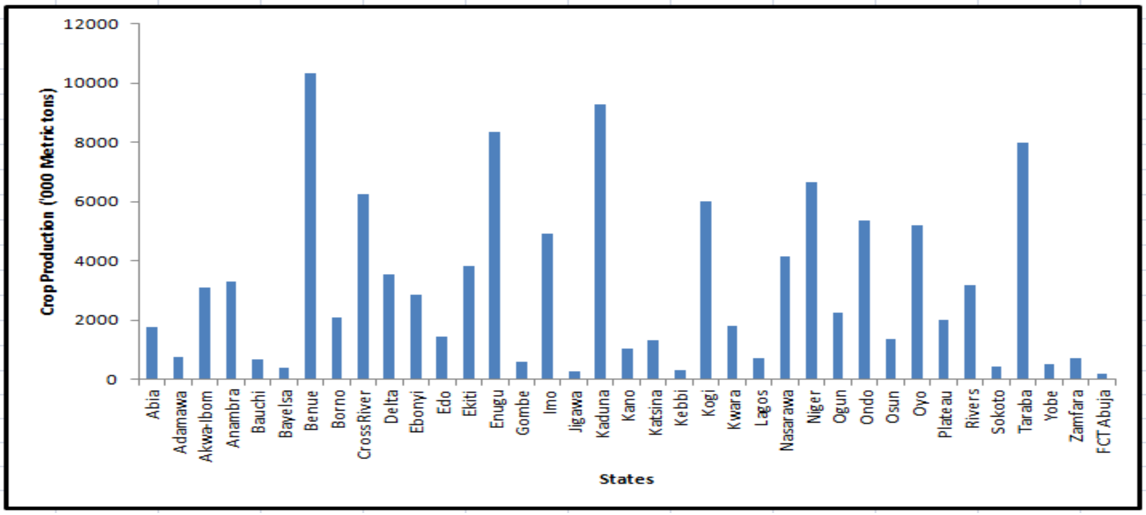

Figure 1: Bar Plot of Crop Production by the 36 States in Nigeria including FCT Abuja

Furthermore, other states with high production figures are Niger, Cross River, Kogi, Ondo, Oyo and Imo in that order with average production figure of *6,657,000; 6,234,000; 6,024,000; 5,365,000; 5,205,000* and *4,926,000* respectively. The state with the least crop production is FCT Abuja, followed by Jigawa and Kebbi with average crop production of *184,000; 284,000* and *302,000* respectively. The average crop production for each state is better depicted and explained as shown in Figure 1.

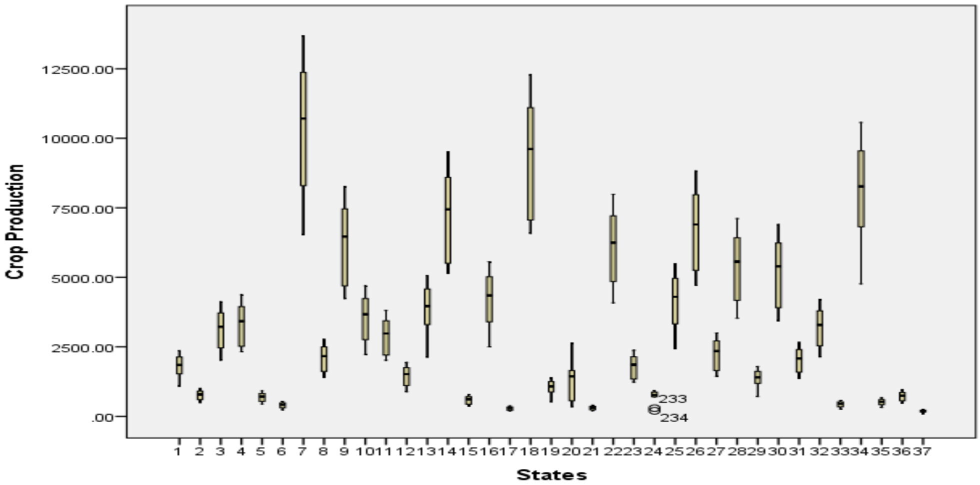

Figure 2: Box Plot of Crop Production by the 36 States in Nigeria including FCT Abuja

Figure 2 depicts the box plot, displaying the maximum, 3rd quartile, median, 1st quartile and minimum crop production for each states in Nigeria. Figure 2 shows that the minimum crop production in Benue State is higher than the maximum crop production in 28 states of the federation.

3.2 Panel Regression Analysis

In this section, we explore the different methods of analyzing panel data, we compared the result obtained from panel pooled regression models, static panel data models and dynamic panel data models using the best estimation techniques available for each. All the analyses in this section are run on Eviews 7. Only the best of all the models are compared in this analysis.

Tables 3 shows the estimates from panel pooled regression models. It shows that for ordinary panel least squares (PLS) model, only the coefficient of employment in crop farming (β_3) is not significant while all other coefficients are significant at 5% level. Here the constant is negative meaning that all the coefficients can never be zero., even if all coefficients are zero, size of land area used for crop production can never be zero. So, the coefficient cannot be interpreted alone. All the variables for this model have positive relationship with the level of crop production while only fertilizer used for crop production (β_2) has negative relationship with crop production. For the Censored Normal method, the results of the parameters estimates are the same with that of PLS only that their p-values are different. They have better p-values than PLS since their p-values are smaller (approaches zero) than those of PLS.

For the Quantile Regression method using median (Q_2), all the coefficients are also significant except for that of employment in crop production, just like that of PLS. The coefficients have the same signs as that of PLS, thus having the same interpretation in terms of relationship. While for the Generalized Linear Model (GLM) method, the constant is positive and land area used for crop production, employment in crop production and cost of seed/seedlings are significantly positively related to level of crop production at 5% level of significance. While on the other hand, fertilizer used and farmgate price are negatively related to level of crop production, with farmgate price showing no significant relationship.

Table 3: Panel Pooled Regression Models Estimates

Models/Method	α	β_1	β_2	β_3	β_4	β_5	F-statistic
Panel Least Squares (PLS)	- 580.0151 (0.0050)	1.474172 (0.0000)	-0.133631 (0.0000)	***0.060825*** ***(***0.1834***)***	7.047454 (0.0000)	0.465300 (0.0000)	624.5872 (0.000000)
Censored Normal (TOBIT)	- 580.0151 (0.0044)	1.474172 (0.0000)	-0.133631 (0.0000)	***0.060825*** ***(***0.1790***)***	7.047454 (0.0000)	0.465300 (0.0000)	NA
Quantile Regression (Median)	- 603.7774 (0.0017)	1.220250 (0.0056)	-0.077892 (0.0041)	***0.003620*** ***(***0.9517***)***	6.552506 (0.0000)	0.506704 (0.0000)	NA
Generalized Linear Model (Normal with Log Link)	7.461624 (0.0000)	0.000198 (0.0011)	-0.0000326 (0.0014)	0.0000422 (0.0003)	***-0.000381*** ***(***0.5283***)***	0.000101 (0.0000)	NA

Among these four methods, the censored normal using TOBIT is the best method, followed by PLS, which was determined by their p-values.

Table 4: Static Panel Regression Models Estimates

Models/Methods	α	β₁	β₂	β₃	β₄	β₅	F-statistic
Panel EGLS (Cross-section Fixed)	323.3342 (0.0010)	2.847027 (0.0000)	-0.224254 (0.0000)	0.020779 (0.7824)	3.003874 (0.0001)	0.245919 (0.0000)	315.3642 (0.000000)
Panel Least Squares (Cross-section Fixed, Time Fixed)	-263.8362 (0.7415)	2.384164 (0.0000)	-0.240617 (0.0000)	0.151196 (0.0000)	6.698748 (0.2497)	0.283351 (0.0005)	265.3700 (0.000000)
Panel EGLS (Cross-section Fixed, Time Random)	-67.22354 (0.8359)	2.504261 (0.0000)	-0.253044 (0.0000)	0.135783 (0.0004)	5.594141 (0.0375)	0.271467 (0.0005)	307.9912 (0.000000)
Panel Least Squares (Time Fixed)	-1173.371 (0.0000)	1.337663 (0.0000)	-0.130333 (0.0000)	0.104710 (0.0000)	10.87854 (0.0000)	0.467693 (0.0000)	241.6426 (0.000000)
Panel EGLS (Cross-section Random, Time Fixed)	-980.2457 (0.0358)	2.092376 (0.0000)	-0.212558 (0.0001)	0.146626 (0.0319)	10.41476 (0.0008)	0.350098 (0.0000)	102.0480 (0.000000)

Table 4 shows the estimates from static panel regression models. In this analysis for all the static panel regression methods used, all the explanatory variables are positively related to level of crop production except for fertilizer usage, which has a negative relationship. All the constants are negative for all the models except for panel EGLS with fixed effect cross-section. So, judging the best model using the p-value, we selected panel least squares with fixed effect time as the best model, followed by Panel EGLS with random effect cross-section and fixed effect time.

Table 5 shows the estimates from dynamic panel regression models. In this analysis for all the dynamic panel regression methods used, all the explanatory variables are significantly positively related to the level of crop production at 5% level of significance, except for fertilizer usage, which has a significant negative relationship. All the coefficients of the lag dependent variables are positive for all the models. So, judging the best model using the p-value, we select Panel Generalized Method of Moments (GMM) with orthogonal cross-section and fixed effect time as the best model.

Table 5: Dynamic Panel Regression Models Estimates

Models/Methods	Y_{t-1}	β₁	β₂	β₃	β₄	β₅	J-statistic
Panel GMM (Cross-section Differenced, Time Fixed)	0.093898 (0.0000)	3.428114 (0.0000)	-1.913495 (0.0000)	0.701887 (0.0131)	23.27594 (0.0000)	0.149159 (0.0000)	28.24114
Panel GMM (Cross-section Orthogonal, Time Fixed)	0.092738 (0.0000)	3.424715 (0.0000)	-1.873721 (0.0000)	0.667389 (0.0010)	23.45327 (0.0000)	0.145018 (0.0000)	28.06216
Panel GMM (Cross-section Orthogonal)	0.092738 (0.0000)	3.424715 (0.0000)	-1.873721 (0.0000)	0.667389 (0.0010)	23.45327 (0.0000)	0.145018 (0.0000)	28.06216

Table 6 shows the model fit for panel pooled regression models. Judging the most adequate model using AIC, we selected PLS as the most adequate model because it has the smallest AIC of 16.51830. The smaller the AIC, the more adequate the model is. Also, PLS is also the best judging with SIC. Quantile regression using median does not have AIC and SIC but comparing PLS with it in terms of R^2, PLS has a better R^2 of about 89.6% compared to 69.5%. Thus, the most adequate model is PLS.

Table 6: Panel Pooled Regression Model Fit

Models/Methods	R^2	S.D. dependent var	S.E. of regression	Akaike info criterion (AIC)	Schwarz criterion (SIC)	Log likelihood
Panel Least Squares (PLS)	0.895610	2850.251	927.2020	16.51830	16.58177	-3049.886
Censored Normal (TOBIT)	NA	2850.251	932.0138	16.52371	16.59775	-3049.886
Quantile Regression (Median)	0.694901	2850.251	942.2808	NA	NA	NA
Generalized Linear Model (Normal with Log Link)	NA	2850.251	NA	17.26472	17.32818	-3187.973

Table 7 shows the model fit for static panel regression models. Judging the most adequate model using R^2, we selected PLS with fixed effect cross-section and fixed effect time as the most adequate model because it has the highest coefficient of determination (R^2) of 97.6% followed by Panel EGLS with fixed effect cross-section (97.5%). Table 8 shows the dynamic panel regression model fit. Panel Generalized Method of Moments (Cross-section Differenced, Time Fixed) has the smallest standard error of regression and smallest sum of squared residuals.

Table 9 shows the panel pooled regression model forecast fit. PLS has the least standard deviation, RMSE and Theil inequality while Quantile Regression (Median) has the least mean absolute error (MAE). For panel pooled regression model, PLS is the best model for forecasting crop production in Nigeria.

Table 7: Static Panel Regression Model Fit

Models/Methods	R^2	Adjusted R^2	S.E. of regression	Mean dependent var	S.D. dependent var	AIC
Panel EGLS (Cross-section Fixed)	0.975260	0.972168	490.8211	3459.237	2218.993	NA
Panel Least Squares (Cross-section Fixed, Time Fixed)	***0.976523***	***0.972843***	469.7065	3055.613	2850.251	***15.26946***
Panel EGLS (Cross-section Fixed, Time Random)	0.974683	0.971518	***469.1249***	3055.613	2779.743	NA
Panel Least Squares (Time Fixed)	0.905029	0.901284	895.5233	3055.613	2850.251	16.47239
Panel EGLS (Cross-section Random, Time Fixed)	0.800972	0.793123	475.4251	3055.613	***1045.265***	NA

Table 8: Dynamic Panel Regression Model Fit

Models/Methods	Mean dependent var	S.E. of regression	S.D. dependent var	Sum squared resid
Panel Generalized Method of Moments (Cross-section Differenced, Time Fixed)	219.2230	***570.4882***	***472.9034***	**94382473**
Panel Generalized Method of Moments (Cross-section Orthogonal, Time Fixed)	-602.5187	723.1942	760.6967	152000000
Panel Generalized Method of Moments (Cross-section Orthogonal)	-602.5187	723.1942	760.6967	152000000

Table 9: Panel Pooled Regression Models Forecast Fit and Standardized Residuals

Models/Methods	Jarque-Bera	Std. Dev.	RMSE	MAE	Theil Inequality Coefficient
Panel Least Squares (PLS)	29.05656 (0.000000)	***920.8987***	***919.6534***	668.7887	***0.111481***
Censored Normal (TOBIT)	35.89437 (0.000000)	924.6728	924.4261	676.1207	0.111963
Quantile Regression (Median)	31.41697 (0.000000)	934.5632	934.6095	***656.9453***	0.113123
Generalized Linear Model (Normal with Log Link)	67.54218 (0.000000)	NA	1335.602	1080.307	0.164228

Table 10 shows the static panel regression model forecast fit. Panel Least Squares (Cross-section Fixed, Time Fixed) has the least standard deviation, RMSE and Theil inequality while Panel EGLS (Cross-section Fixed, Time Random)has the least mean absolute error (MAE). For static panel regression model, Panel Least Squares (Cross-section Fixed, Time Fixed) is the best model for forecasting crop production in Nigeria.

Table 11 shows the dynamic panel regression model standardized residuals, Panel Generalized Method of Moments (Cross-section Differenced, Time Fixed) and Panel Generalized Method of Moments (Cross-section Differenced) have the least Jarque-Bera and standard deviation suggesting that they are the two best dynamic panel model for modeling crop production in Nigeria.

Table 12 shows that the standard error of regression is the criterion that is common to all the models and it is used in selecting the best-fitted model. The best model is the model with the smallest standard error of regression. The result in the table shows that static panel regression model (Panel EGLS with cross-section fixed, time random) is selected as the best model because it has the smallest standard error of regression.

Table 13 shows that the standard deviation is the criterion that is common to all the models for judging the best model and it is used in selecting the best forecast model. The best model is the model with the smallest standard deviation of error. The result in the table shows that static panel regression model (Panel Least Squares with cross-section fixed, time fixed) is selected as the best model because it has the smallest standard deviation of error.

Table 10: Static Panel Regression Models Forecast Fit and Standardized Residuals

Models/Methods	Jarque-Bera (P-value)	Std. Dev.	RMSE	MAE	Theil Inequality Coefficient
Panel EGLS (Cross-section Fixed)	15.91601 (0.000350)	462.7505	482.8315	328.2943	0.058062
Panel Least Squares (Cross-section Fixed, Time Fixed)	485.1042 (0.000000)	***436.7257***	***436.1351***	304.1536	***0.052363***
Panel EGLS (Cross-section Fixed, Time Random)	448.3040 (0.000000)	481.4378	436.9302	***301.6929***	0.052465
Panel Least Squares (Time Fixed)	21.51271 (0.000021)	878.3704	877.1830	643.2392	0.106212
Panel EGLS (Cross-section Random, Time Fixed)	40.88638 (0.0000000)	950.8655	440.5615	311.1330	0.052932

Table 11: Dynamic Panel Regression Models Standardized Residuals

Models/Methods	Jarque-Bera (P-value)	Std. Dev.
Panel Generalized Method of Moments (Cross-section Differenced, Time Fixed)	***283.4827*** (0.000000)	***565.1563***
Panel Generalized Method of Moments (Cross-section Orthogonal, Time Fixed)	7.753925 (0.020714)	707.8033
Panel Generalized Method of Moments (Cross-section Orthogonal)	7.753925 (0.020714)	707.8033

Table 12: Summary of Best Panel Models, Judging using S.E. of Regression Criterion

Models	S.E. of regression	Best Selected Model	Best of the Best
Pooled	927.2020	Panel Least Squares (PLS)	Static Panel EGLS (Cross-section Fixed, Time Random)
Static	***469.1249***	Panel EGLS (Cross-section Fixed, Time Random)	
Dynamic	*570.4882*	Panel Generalized Method of Moments (Cross-section Differenced, Time Fixed)	

Table 13: Summary of Best Panel Forecast Models, Judging using Standard Deviation Criterion

Models	Std. Deviation	Best Selected Model	Best of the Best
Pooled	*920.8987*	Panel Least Squares (PLS)	Panel Least Squares (Cross-section Fixed, Time Fixed)
Static	***436.7257***	Panel Least Squares (Cross-section Fixed, Time Fixed)	
Dynamic	*565.1563*	Panel Generalized Method of Moments (Cross-section Differenced, Time Fixed)	

Table 14: Static Panel Regression Best Models for Fit and Forecast

	From Parameter Estimate	Fit		Forecast			
Models/Methods	F-Statistic	R^2	S.E. of regression	Std. Dev.	RMSE	MAE	Theil Inequality Coefficient
Panel Least Squares (Cross-section Fixed, Time Fixed)	265.3700 (0.000000)	***0.976523***	469.7065	***436.7257***	***436.1351***	304.1536	***0.052363***
Panel EGLS (Cross-section Fixed, Time Random)	**307.9912** (0.000000)	0.974683	***469.1249***	481.4378	436.9302	***301.6929***	0.052465

Table 14 compares the best two static models selected as the best models for fit and forecast. The table shows that PLS (Cross-section Fixed, Time Fixed) has a better coefficient of determination (R^2), a better standard deviation, a better root mean square error and a better Theil inequality coefficient while Panel EGLS (Cross-section Fixed, Time Random) has a better F-statistic, a better standard error of regression and a better mean absolute error. So, judging the best model based on these seven criteria, we selected panel least squares with fixed effect cross-section and fixed effect period as the best model, followed by Panel EGLS with fixed effect cross-section and random effect period. We therefore suggest that these two models are the best models for modelling crop production in Nigeria.

Thus, static panel models are better than both pooled regression models and dynamic panel models. So, static panel models are best models in modelling crop production in Nigeria.

The first model is thus fitted as,

$$Y_{it} = -263.836 + 2.384X_{1it} - 0.241X_{2it} + 0.151X_{3it} + 6.699X_{4it} + 0.283X_{5it} + \mu_i + \lambda_t \quad (16)$$

The model shows that out of the total variation in crop production, 97.7% of it can be explained by the variations in area planted, fertilizer usage, employment in crop farming, farmgate prices and cost of seeds/seedlings while the remaining 2.3% can be explained by other factors not included in the model as shown in Table 4.

The second model is thus fitted as,

$$Y_{it} = -67.224 + 2.504X_{1it} - 0.253X_{2it} + 0.138X_{3it} + 5.594X_{4it} + 0.271X_{5it} + \mu_i + \lambda_t \quad (17)$$

The model shows that out of the total variation in crop production, 97.5% of it can be explained by the variations in area planted, fertilizer usage, employment in crop farming, farmgate prices and cost of seeds/seedlings while the remaining 2.5% can be explained by other factors not included in the model, as shown in Table 4.

The two models show that all the explanatory variables are positively related to level of crop production except for fertilizer usage, which has a negative relationship.

Table 15: Static Panel Models Cross-section Effects (μ_i)

i	States	Cross-section Fixed Effect (Model 1)	Cross-section Fixed Effect (Model 2)
1	Abia	-480.3652	-479.5012
2	Adamawa	-1021.897	-1050.145
3	Akwa-Ibom	-365.6993	-394.8620
4	Anambra	342.0426	352.4530
5	Bauchi	-1769.152	-1839.715
6	Bayelsa	-507.3229	-574.0676
7	Benue	1739.826	1806.622
8	Borno	-846.0411	-976.0125
9	Cross River	-105.4972	-39.81831
10	Delta	-155.6795	-60.34123
11	Ebonyi	-325.1386	-344.3966
12	Edo	-542.2882	-514.3331
13	Ekiti	1286.420	1286.868
14	Enugu	2343.684	2382.792
15	Gombe	-1187.614	-1258.344
16	Imo	282.7790	280.9436
17	Jigawa	-976.6902	-1000.703
18	Kaduna	815.3856	871.1549
19	Kano	-1382.143	-1373.536
20	Katsina	-537.4267	-548.6422
21	Kebbi	-762.3725	-775.0323
22	Kogi	2133.425	2167.550
23	Kwara	-106.0806	-92.49097
24	Lagos	-113.5260	-199.6777
25	Nasarawa	1419.782	1456.948
26	Niger	-358.2741	-339.2647
27	Ogun	268.9861	289.5328
28	Ondo	1917.001	1926.859
29	Osun	65.03346	45.34296
30	Oyo	443.6332	524.1260
31	Plateau	389.9361	442.2394
32	Rivers	33.94469	6.427464
33	Sokoto	231.4088	268.6109
34	Taraba	0.628953	4.003789
35	Yobe	154.5633	153.0689
36	Zamfara	-1295.404	-1381.625
37	FCT Abuja	-1029.867	-1023.035

Table 16: Static Panel Models Period Effects (λ_t)

t	Date	Cross-section Fixed Effect (Model 1)	Period Random Effect (Model 2)
1	2006	154.1982	105.3043
2	2007	-167.9587	-167.7734
3	2008	-212.6570	-204.0923
4	2009	-215.0155	-211.1235
5	2010	336.9999	279.2850
6	2011	365.0889	309.9242
7	2012	96.06310	81.79052
8	2013	-87.77416	-64.60997
9	2014	-112.1397	-59.33375
10	2015	-156.8051	-69.37109

Table 15 shows that Enugu State has the highest crop production followed by Benue State in Nigeria for the period under review for both models. Table 16 shows that 2011 is the best year for crop production in Nigeria, followed by 2010 for the period under review for both models. Example using the first model to forecast crop production for Enugu State, we have:

$$Y_{it} = -263.836 + 2.384X_{1it} - 0.241X_{2it} + 0.151X_{3it} + 6.699X_{4it} + 0.283X_{5it} + 2343.684 + \lambda_{2022} \quad (18)$$

The cross-section effect differentiates a state's crop production model from another state.

IV. Conclusion and Policy Implications

The results of the analysis lead to the following conclusion. There is an upward trend in crop production for all the 37 states and FCT as depicted in appendix 7. The static panel models are selected as best models in modelling crop production in Nigeria, especially using panel least squares with fixed effect cross-section and fixed effect period and Panel EGLS with fixed effect cross-section and random effect period. At least 97.5% of the variation in crop production can be explained by the variations in area planted, fertilizer usage, employment in crop farming, farmgate prices and cost of seeds/seedlings while the remaining 2.5% can be explained by other factors not included in the model. The area planted, employment in crop farming, farmgate prices and cost of seeds/seedlings are significantly positively related to the level of crop production in Nigeria except for fertilizer usage, which has a significant negative relationship. In addition, for the period under review, Enugu State followed by Benue State has the highest output in crop production in Nigeria and year 2011 followed by year 2010 recorded the highest output in crop production in Nigeria.

It is therefore recommend that static panel models should be adopted in modelling crop production in Nigeria since they performed better than both pooled regression models and dynamic panel models. So, static panel models are best models in modelling crop production in Nigeria. Government and all other stakeholders should provide more agricultural land for crop production, more employment in crop farming, consider farmgate prices and cost of seeds/seedlings as they all have significant positive effect on crop production. Fertilizer usage, if properly distributed among farmers and are well monitored can also increase crop production output but for this analysis, it does not have positive effect on crop production. Enugu and Benue states can still do better and all other states should be actively involved in crop production. Also, 2011 crop production level should be used as base to measure subsequent years crop production in Nigeria. If crop production level increases, then there will be no problem with food insecurity and the problem of malnutrition will be solved.

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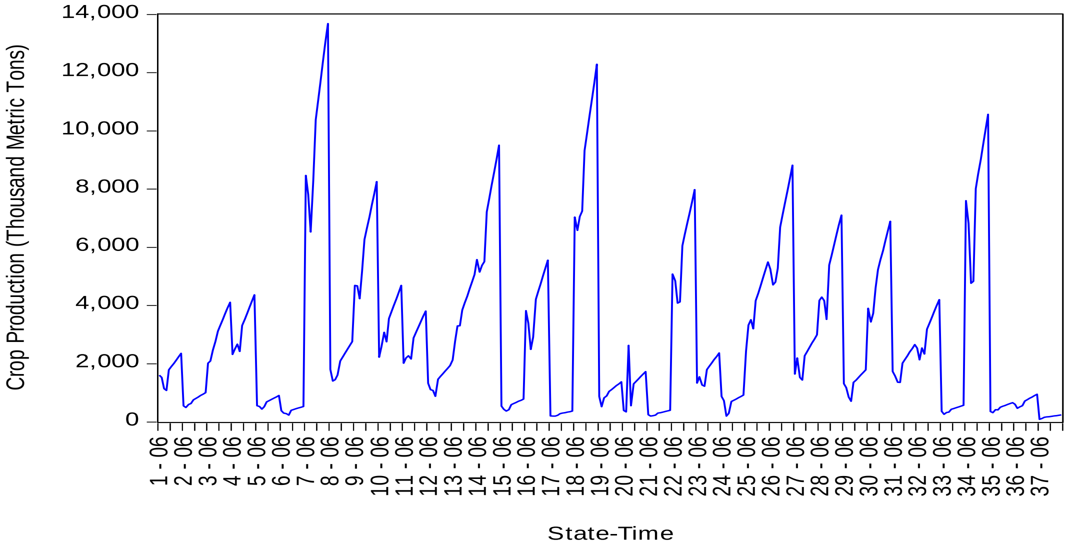
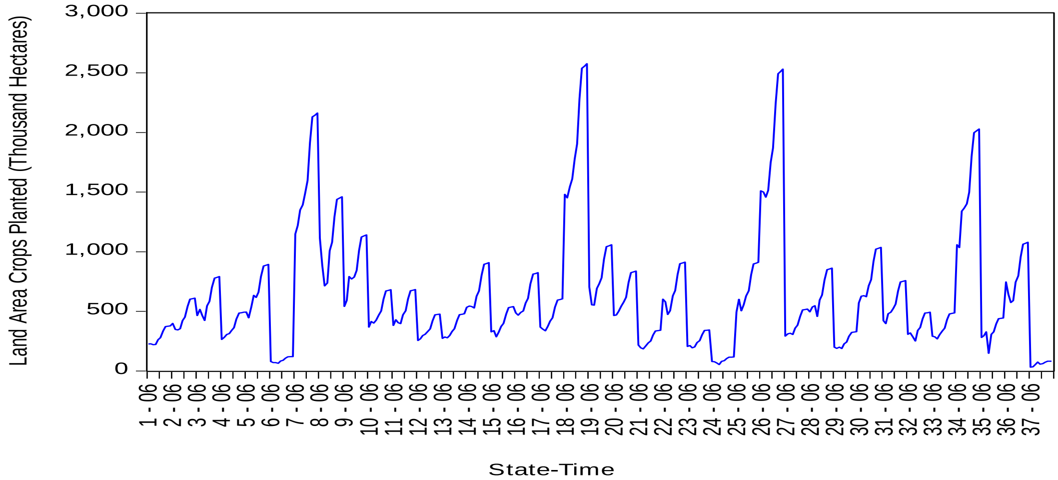
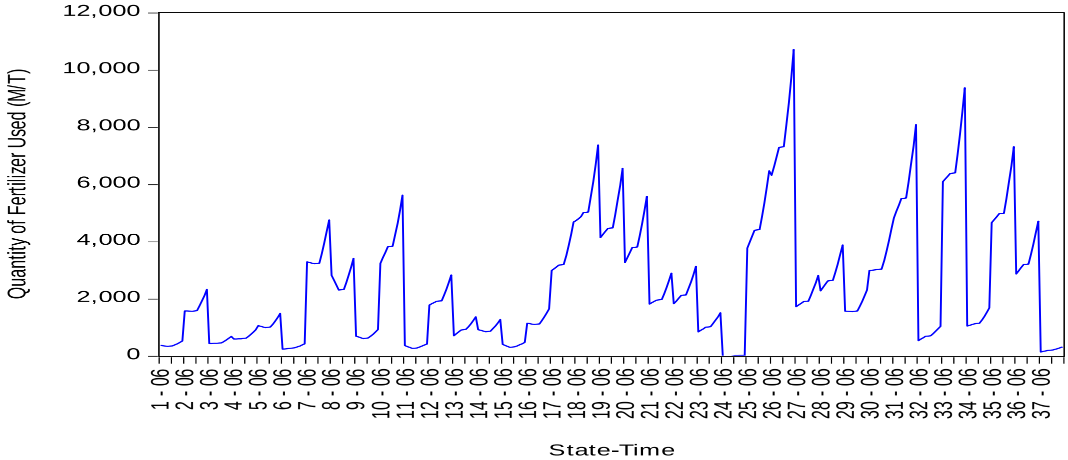
Appendix



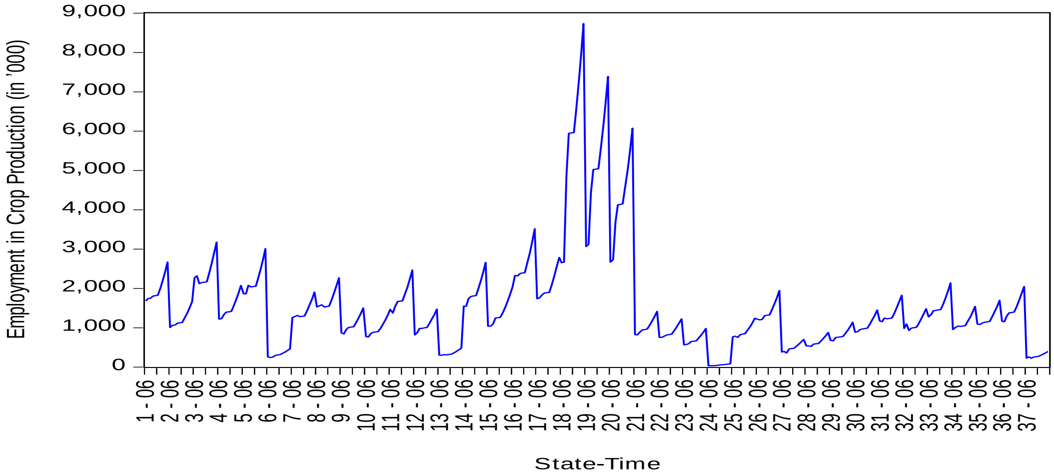
Appendix 1: Panel Time Plot of Crop Production (in '000 Metric Tons) for 37 States



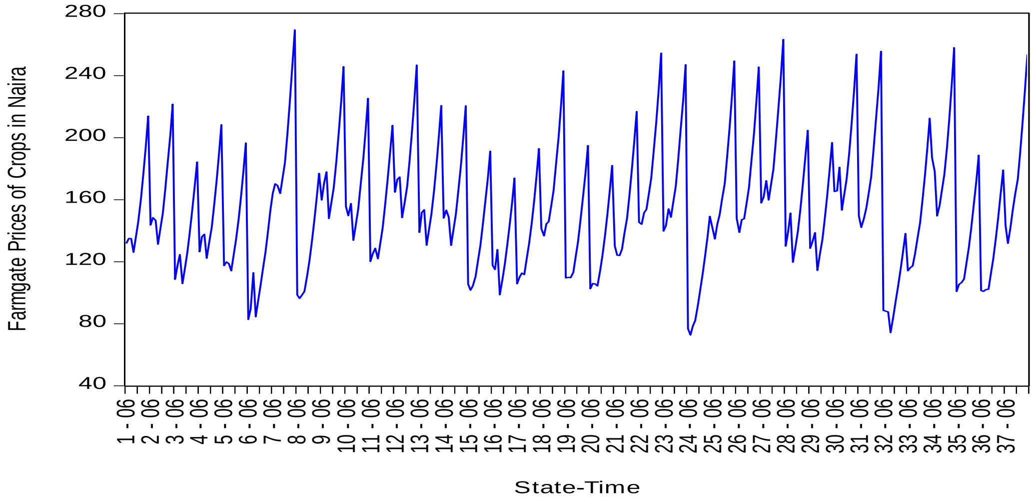
Appendix 2: Panel Time Plot of Land Area (in '000 Hectares) for 37 States



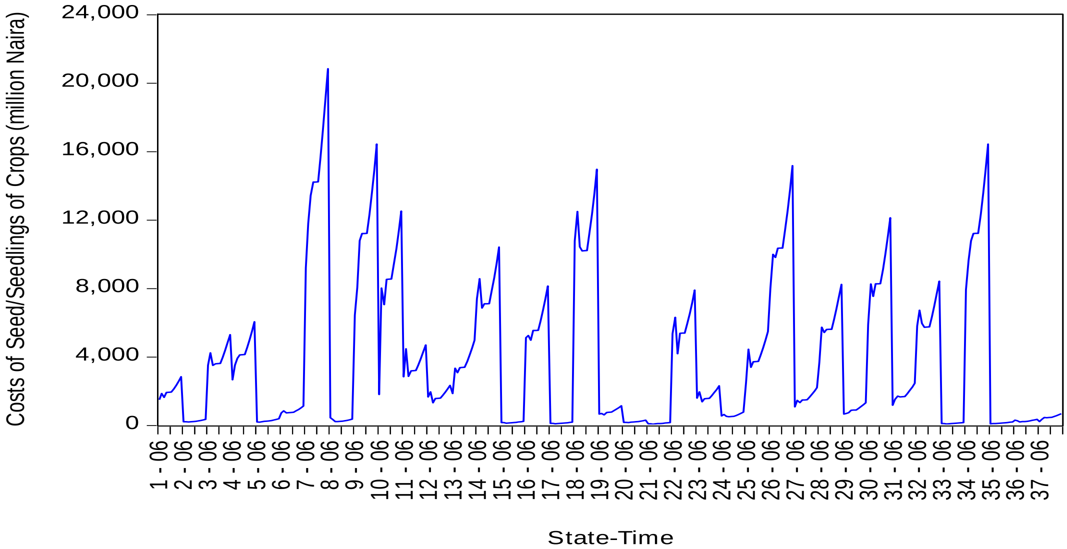
Appendix 3: Panel Time Plot of Fertilizer Used (in Metric Tons) for 37 States



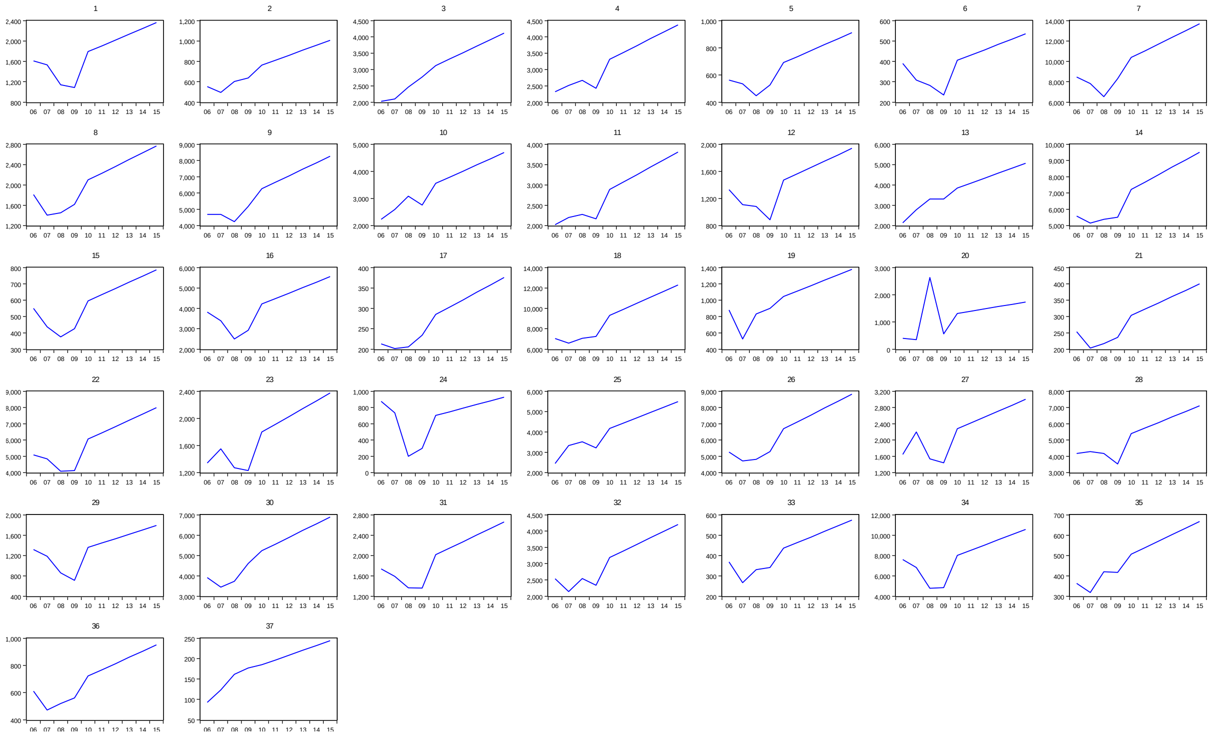
Appendix 4: Panel Time Plot of Employment in Crop Production (in '000) for 37 States



Appendix 5: Panel Time Plot of Farmgate Prices of Crops (in Niara) for 37 States



Appendix 6: Panel Time Plot of Costs of Seeds of Crops (in million Naira) for 37 States



Appendix 7: Panel Time Plot of Crop Production for each the 37 States in Nigeria

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