S L U J S T
Sule Lamido University Journal of Science & Technology Vol. 6 No. 1&2 [March, 2023], pp. 8-20
https://doi.org/10.56471/slujst.v6i.286
Online ISSN: 2736-0903
Print ISSN: 2736-089X
www.slujst.edu.ng

Modelling of Post-COVID-19 Food Production Index in Nigeria using Box-Jenkins Methodology

Mohammed Kabir Garba[1*], Saheed Busayo Akanni[2], Kola Yusuff Kareem[3], Ahmed Ayobami Yusuf[4], Saheed Olalekan Jabaru[5], John Seyi Abolarin[6], Femi Emmanuel Amoyedo[7] and Samuel Oluwaseun Ekundayo[8]
[1,2,4,7]Department of Statistics, University of Ilorin, Ilorin, Nigeria
[3]Department of Agricultural & Biosystems Engineering, University of Ilorin, Ilorin, Nigeria
[5]Department of Physical Sciences (Statistics Option), Al-Hikmah University, Ilorin, Nigeria
[6]Department of Civil Engineering, University of Ilorin, Ilorin, Nigeria
[8]Department of Finance, University of Ilorin, Ilorin, Nigeria
garbamk@gmail.com[1*]

[*]Corresponding Author

Abstract

Before the COVID-19 pandemic, global food security has been known to be a major threat for developed and developing countries of the world. However, during the COVID-19 pandemic, global food security was expected to be at a very high risk due to lockdown across the globe. Consequently, the developing countries, most especially, were expected to experience food shortage challenges. One important way to measure the amount of food production of any country in the world is through the use of a macroeconomic variable known as Food Production Index (FPI). Therefore, this study seeks to examine the post-COVID-19 behavior of the Nigeria's FPI using the Box-Jenkins methodology for modeling univariate time series. A low-frequency time series datasets over 56 years spanning from 1961 to 2016 on Nigerian FPI was extracted from World Bank repository. Pre-tests results from the unit root analyses, correlogram and selection criteria techniques showed that the FPI is a differenced stationary series of order one {I(1)}and that ARIMA (2, 1, 2) model best fitted the series. Besides, diagnostic checking of the fitted model confirmed that the error was white noise and forecast of 8 years (2017 to 2024) was made. Findings from the study revealed that the future values of the FPI are erratic and expected to fluctuate (i.e., rise and fall) within the predicted periods. Conclusively, the fourteen years out sample forecast of FPI for the periods 2017 to 2030 indicates that the gains of FPI in recent years is currently being affected by the current COVID-19 pandemic. The study recommends that concerted efforts to achieve optimal FPI must be focused on the improvement of inter-regional trade which will result in shorter food chains, and thereby creating more market for farmers and enhancing accessibility to both inputs and outputs.

Keywords: *Food Production Index; Correlogram; Selection Criteria; ARIMA; COVID-19; Nigeria.*

1. Introduction

Global food security will remain a worldwide concern for the next 50 years and beyond (Rosegrant and Cline; 2003). With the occurrence of the Coronavirus disease in 2019, it became imperative to address possible global food scarcity as a result of high records of perishability of products, poor patronage by customers, poor market access, trade embargo, borders closures, quarantines and unwillingness of state farmers to plant in in due season. Consequently, proper and regular assessment of Food Production Index (FPI) is crucial to food security and economic growth of any nation that is currently experiencing the devastating effect of the pandemic.

According to World Health Organization (2019), COVID-19 refers to an infectious disease caused by the SARS-COV-2 virus. Historically, the novel human COVID-19 emanated from Wuhan, China in 2019 where the first case was reported. Afterward, it spread globally and became the fifth documented pandemic after the 1918 flu

Online ISSN: 2736-0903
Print ISSN: 2736-089X
www.slujst.edu.ng

pandemic (News Medical Life Sciences, 2019). Statistics shown that over 1.6 million cases have been recorded with a fatality rate of 6.19% as at 11 April 2020 (WHO, 2019). The COVID-19 pandemic shocked the world as it overwhelmed the health systems of even high-income countries (Amzat et al., 2020). However, Nigeria recorded an imported case from Italy on February 27, 2020 (Adegboye et al., 2020; Ibrahim et al., 2020). Laborde et al. (2020) noted that COVID-19 threatened access to food mainly through losses of income and assets that prejudiced ability to buy food.

The index number of food production compares a volume of agricultural production (of basically crops that contain nutrients) in a given year with the base period. In other words, food production index covers food crops that are considered edible and that contain nutrients excluding edible coffee and tea which have no nutritional value (World Bank Repository, 2018). If there is access to enough food at all times, then there is food security (Kent, 1995). Otherwise, there is food insecurity. One of the factors that affects food security is the failure of developing countries to harness the potentials inherent in the agricultural sector. For instance, agriculture used to be the mainstay of the Nigerian economy before oil was discovered in 1956. In fact, agriculture was the major source of Nigeria's foreign exchange earnings through the exportation of cash crops such as rubber from Delta State in South-South region; groundnut, hide and skin produced by the Northern region; cocoa and coffee from the Western region; and palm oil and kernels from the Eastern region of the country (Okotie, 2018). Evidently, every part of Nigeria is blessed with certain natural resources or the others. Unfortunately, statistics showed that agriculture contributions to the Nigerian Gross Domestic Product (GDP) have reduced drastically from 54.8% to 24.6% from 1965 to 2000 (Yahya, 2008).

The rate of growth of Nigeria's food production is 2.5% per annum in recent years, while food demand has been growing at the rate of more than 3.5% per annum due to high rate of population growth of 2.83% (Kolawole and Ojo; 2007). The obvious disparity between the rate of food production and demand for food has ignited a food demand-supply gap leading to an increasing resort to food importation with its negative consequences (Ojo, 2004). Therefore, achieving food security in Nigeria requires the right mix in terms of policy and its implementation such that youth are motivated to engage in agriculture, especially during post-COVID-19 era.

In the literature, the relevant published works on food related issues and COVID-19 pandemic are mostly reviewed studies, cross-sectional studies or structural equation modelling approach. For the review parts, Bai et al. (2022) compared monthly retail food prices in up to 181 countries from January 2019 to June 2021 tested for differences over time. They discovered that average prices rose significantly, especially for more nutritious food groups in countries with higher COVID-19 case counts. However, Ali and Khan (2020) examined the impact of COVID-19 lockdown on wholesale prices of the agricultural commodities particularly fruits and vegetables in the Union Territory of Jammu and Kashmir, India using a comparative analysis technique. They found that perishable fresh fruits and vegetables with high water content faced significant decline in wholesale prices during the lockdown while other perishable fruits and vegetables realized a gain in the average wholesale prices. Furthermore, Chitrakar et al. (2021) investigated the improvement strategies of food supply chain through novel food processing technologies during COVID-19 pandemic. They noticed that these technologies would make food processing activities smarter, which would ultimately help to run the food supply-chain (FSC) smoothly during COVID-19 pandemic. Based on demand and supply of food items, Prajapati (2020) studied the COVID-19, food security and agricultural development in Asia. He stressed that the smooth supply of food at the national and global level depend on the normalcy of supply-chain whereas for the demand for food, consumption will occur through income, which directly related to employment. He also found that both supply-chain and employment are negatively affected due to the lockdown policy adopted by many Asian counties to control the spread of the virus. Moreover, Pu and Zhong (2020) investigated the impact of COVID-19 on agricultural production in China followed by government responses to alleviate the negative effects. Their results showed that unreasonable restrictions would block the outflow channels of agricultural products, hinder necessary production inputs, destroy production cycles, and finally undermine production capacity. Also, Guiné et al. (2022) examined consumers' trends and the consumption of foods obtained through organic farming in Portugal and Turkey using a tree classification technique. They discovered that the consumption patterns are relatively similar in both countries, with many respondents consuming organic foods, especially vegetables and fruits, mostly two or three meals per week. Mishra and Rampal (2020) focused their research on COVID-19 pandemic and

Online ISSN: 2736-0903
Print ISSN: 2736-089X
www.slujst.edu.ng

insecurity in India. Their findings highlighted the need for the Indian government to carefully combine governmental and non-governmental interventions in reducing India's food insecurity and hunger rates despite the COVID-19 related slowdown.

Other works that utilized survey studies are those of Campbell (2021) and Mthembu et al. (2022). In his survey study, Campbell (2021) examined the impact of COVID-19 on Local Government Stakeholders' perspectives on local food production in the United States. His results revealed that Local Government Stakeholders' have generally positive attitudes and perceptions of benefits of Local Food Production. Mthembu et al. (2022) employed survey techniques to investigate the effects of COVID-19 pandemic on agricultural food production among smallholder farmers in Northern Drakensberg areas of Bergville, South Africa. They demonstrated that COVID-19 lockdowns accompanied by movement restrictions negatively impacted food production of staple crops (maize, dry beans, soybeans) despite suitable rainfalls during COVID-19 periods. Similarly, Aghaei et al. (2021) studied the role of COVID-19 virus pandemic on marketing innovations and social responsibility of food companies in Tehran using structural equation modelling techniques. They found out that food companies need to increase marketing innovations and social responsibility behaviors to improve activities and strategies for the success of companies and attract customers in critical illness conditions. Akanni and Adeniyi (2020) used ARIMA (1, 1, 1) model to show that cereals production in Nigeria will continue to increase for the foreseeable future.

Based on the foregoing relevant literature, it was observed that no previous study has forecasted the amount of food production (FPI) in developing and developed countries, especially Nigeria. As a result**,** this study aimed to model and forecast post-COVID -19 Food Production Index (FPI) in Nigeria using techniques developed by Box and Jenkins in 1976.

2. Materials and Methods

In this study, an annual time series data on Food Production Index (FPI) in Nigeria from 1961 to 2016 was extracted from the repository of World Bank via their website *http://data.worldbank.org*. Box-Jenkins methodology technically known as ARIMA modeling developed by Box and Jenkins (1976) was employed to analyze the FPI in Nigeria. An ARIMA model is an algebraic statement showing how a time-series variable is related to its own past values (Pankratz, 1983). According to Box and Jenkins (1976), the practical four-stage procedures for finding a good model are: identification, estimation, diagnostic checking and forecasting. Moreover, the ARIMA (p, d, q) models a non-stationary time series variable by applying finite differencing of the data points. The general form of the ARIMA (p, d, q) model is given by equation (1):

$$Y_t = \mu + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} + \varepsilon_t \qquad (1)$$

where: Y_t = Y at current time t, Y_{t-1} = Y at immediate past period t-1, Y_{t-2} = Y at past period t-2, Y_{t-p} = Y at past period t-p, ε_t= Random shock at period t, e_{t-1}= Random shock at immediate past period t-1, e_{t-q}= Random shock at period t-q. μ, $\emptyset_p$ and θ_q are parameters to be estimated.

According to (Hipel and McLeod, 1994; Lombardo and Flaherty, 2000), the mathematical formulation of equation (1) using lag polynomial is of the form specified by equation (2).

$$\phi(L)(1-L)^d Y_t = \theta(L)\varepsilon_t \qquad (2)$$

where $\phi(L)$ and $\theta(L)$ give the set of autoregressive and moving average parameters and ε_t still remains the white noise.

To investigate the stationarity of the ARIMA (p, d, q) process, all the roots of $\phi(L)$, characteristic equation must lie outside the unit circle.

Online ISSN: 2736-0903
Print ISSN: 2736-089X
www.slujst.edu.ng

Equation 2 can also be expressed as equation (3):

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)(1-L)^d Y_t = \left(1+\sum_{i=1}^{p}\theta_j L^j\right)\varepsilon_t \quad (3)$$

where p, d and q are integers greater than or equal to zero and refer to the order of the Autoregressive (AR), Integrated (I) and Moving Average (MA) parts of the model respectively. The integer "d" indicates the level of differencing.

2.1 Identification of the Model

Prior to model identification, the FPI date has been subjected to the unit root analyses using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for appropriate determination of order of integration of the series. These tests developed in Dickey and Fuller (1979) and Phillips and Perron (1988) both test the null hypothesis of non-stationarity in the series. The test equation is given in equation (4)

$$\Delta Y_t = \beta_1 + \beta_2 t + \partial Y_{t-1} + u_t \quad (4)$$

where Y_t are random walks at current time period t, β_1= constant term, β_2= trend or time, $\partial = \rho - 1$, u_t= white noise error term, Y_t denotes the lagged one term of Y variable. If $\partial = 0$, then $\rho = 1$; which means a time series has a unit

Before an ARMA (p, q) may be estimated for a time series Y_t, the AR and MA orders **p** and **q** must be determined by visually inspecting the Sample Autocorrelation Function (SACF) and Sample Partial Autocorrelation Function (SPACF) for Y_t. The SAFC is used for detecting the order ***q*** of the MA term while the SPACF is used for detecting the order ***p*** of the AR term from the sample correlogram. By sample correlogram, we mean a plot of SACF$\hat{\rho}_k$ against the lags k (see Gujarati, 2009).

Mathematically, the Sample Autocorrelation Function (SAFC) $\hat{\rho}_k$at lag k is defined as:

$$\hat{\rho}_k = \frac{\hat{\gamma}_k}{\hat{\gamma}_0} \quad (5)$$

where: $\hat{\gamma}_k$ is the sample covariance at lag k and $\hat{\gamma}_0$ is the sample variance. In order to compute $\hat{\rho}_k$ in equation (4), the values of $\hat{\gamma}_k$ and $\hat{\gamma}_0$ is first computed from equations (5) and (6)

$$\hat{\gamma}_k = \frac{\sum(Y_t-\bar{Y})(Y_{t+K}-\bar{Y})}{n} \quad (6)$$

However, the specification of equation (7) below is done in accordance with Tsay and Tiao (1984)

$$\hat{\gamma}_0 = \frac{\sum(Y_t-\bar{Y})}{n} \quad (7)$$

where **n** is the sample size and $\bar{\mathbf{Y}}$ is the sample mean

Alternatively, statistical model selection criteria may be used. The idea is to fit all ARMA (p, q) models with orders $p \leq p_{max}$ and $q \leq q_{max}$ and choose the values of ***p*** and ***q*** which minimizes some model selection criteria. Based on Box and Jenkins (1976) methodology, model selection criteria for ARMA (p, q) model as given in equation (8)

$$MSC(p,q) = \ln\left(\sigma^2(p,q) + C_T.\varphi(p,q)\right) \quad (8)$$

Sule Lamido University Journal of Science & Technology Vol. 6 No. 1&2 [March, 2023], pp. 8-20
https://doi.org/10.56471/slujst.v6i.286
Online ISSN: 2736-0903
Print ISSN: 2736-089X
www.slujst.edu.ng

where $\sigma^2(p,q)$ is the maximum likelihood estimator (MLE) of $\mathrm{Var}(\varepsilon_t) = \sigma^2$ without a degree of freedom correction from the ARMA (p, q), C_T is a sequence indexed by the sample size T, $\varphi(p,q)$is a penalty function which penalizes large ARMA (p, q) models.

The two most common information criteria are the Akaike (AIC) and Schwarz-Bayesian (BIC) (Burnham and Anderson; 2004). The AIC and BIC are stated as equations (9) and (10)

$$\mathrm{AIC}(p) = n\ln\left(\frac{\hat{\sigma}^2_{\varepsilon_t}}{n}\right) + 2p \tag{9}$$

$$\mathrm{BIC}(p) = n\ln\left(\frac{\hat{\sigma}^2_{\varepsilon_t}}{n}\right) + p + p\ln(n) \tag{10}$$

Where **n** is the number of effective observations used to fit the model, **p** is the number of parameters in the model, $\boldsymbol{\hat{\sigma}^2_{\varepsilon_t}}$is sum of sample squared residuals.

Another selection criterion which is often cited but under-utilized is the Hannan–Quinn information criterion (HQC), according to Burnham and Anderson (2002). The HQC is of the form is given in equation (11)

$$\mathrm{HQC} = -2L_{max} + 2p\ln(\ln(n)) \tag{11}$$

where $\mathbf{L_{max}}$ is the log-likelihood, **p** is the number of parameters, and **n** is the number of observations.

3. Data Analysis and Results

In this section, we present the results of the analyses carried out on the Food Production Index (FPI) series using Gnu Regression, Econometrics and Time-Series Library (GRETL). Figure 1 (a and b) have the time series plot of the Nigerian FPI before and after first differencing.

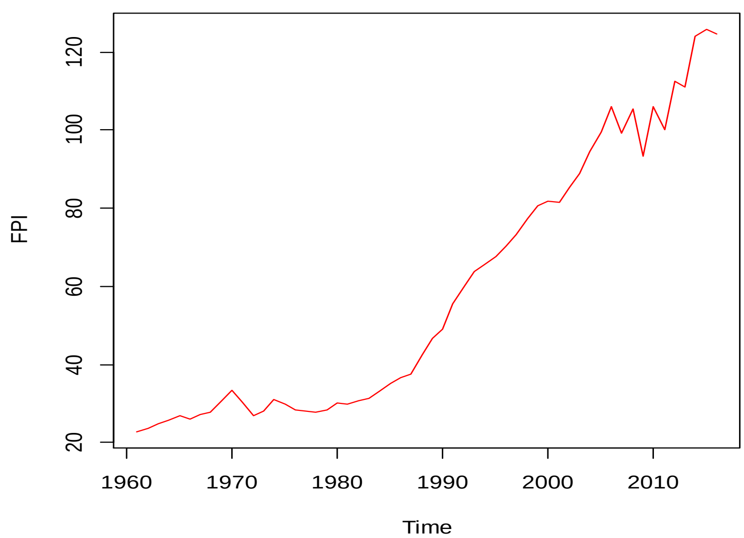

Figure 1a: Time series plot of Nigerian Food Production Index before differencing

Time series plot in Figure 1a indicated that the FPI series displayed a pronounced upward trend albeit with fluctuations. This implies that the series would have to undergo a difference stationary process for it to become

Sule Lamido University Journal of Science & Technology Vol. 6 No. 1&2 [March, 2023], pp. 8-20
https://doi.org/10.56471/slujst.v6i.286
Online ISSN: 2736-0903
Print ISSN: 2736-089X
www.slujst.edu.ng

stationary. To properly determine the order of integration of the series **d**, unit root tests such as Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests were used to conduct individual unit root analyses on the series.

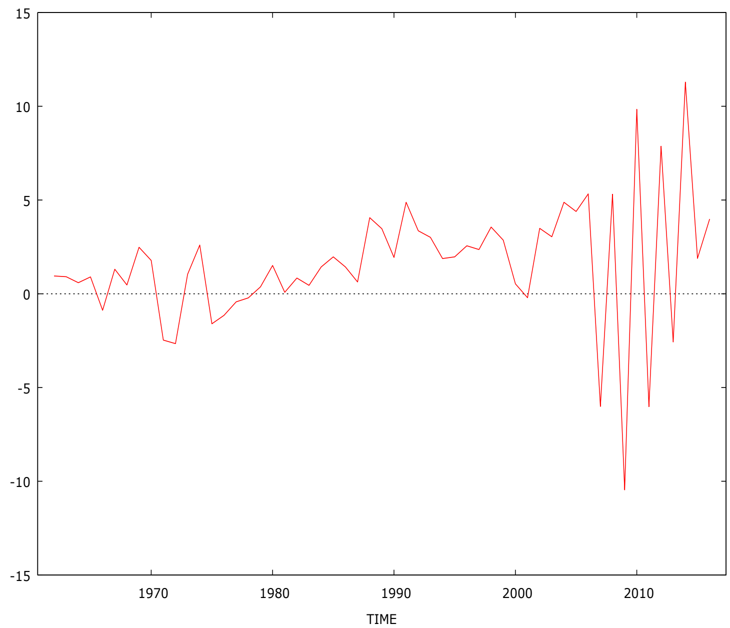

Figure 1b: Time series plot of Nigerian Food Production Index after first differencing

Visualizations from time series plot in Figure 1b revealed that the mean of the FPI series is now zero with invariant or constant variance. As a result, the series is suggested to be difference stationary series of order one {I(1)}. However, this suggestion of Figure 1b would be subjected to appropriate confirmation empirically using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Tables 1a and 1b presented the results of unit root tests conducted on the FPI series.

Table 1a: Results of Augmented Dickey-Fuller (ADF) Test on FPI

Test Variable		At level		
	t-stat	Critical values	p-value	Order of Integration
lnFPI	-2.243066	-3.500495	0.4563	None
Test Variable		After first difference		
	t-stat	CV at 5%	p-value	Order of Integration
FPI	-3.486205	-2.91765	0.0122	I(1)

Table 1b: Results of Phillips-Perron (PP) Test on FPI

Test Variable		At level		
	t-stat	Critical values	p-value	Order of Integration
FPI	4.814454	-1.946878	1	None
Test Variable		After 1st difference		
	t-stat	CV at 5%	p-value	Order of Integration
FPI	-10.58784	-2.916566	<0.00001***	I(1)

S L U J S T
Sule Lamido University Journal of Science & Technology Vol. 6 No. 1&2 [March, 2023], pp. 8-20
https://doi.org/10.56471/slujst.v6i.286
Online ISSN: 2736-0903
Print ISSN: 2736-089X
www.slujst.edu.ng

From Tables 1a and 1b, it can be deduced that both the ADF and PP tests jointly agreed that the FPI is not a level stationary series but a difference stationary series of order one {I(1)}. This is in agreement with Figures 1a and 1b which suggested that the FPI is not level stationary series {i.e., I(0)} but an I(1).

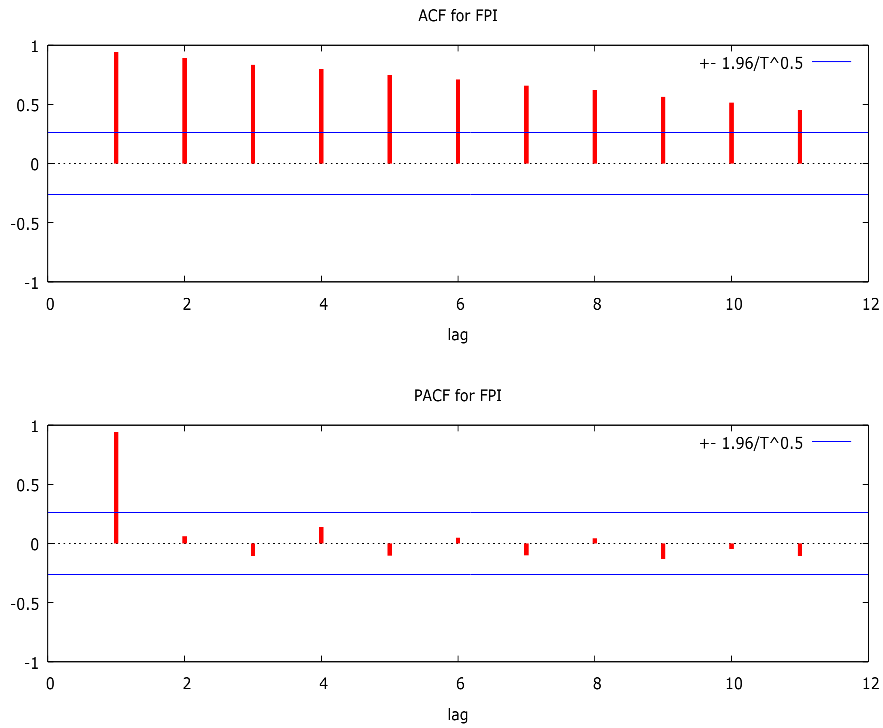

Figure 2a: ACF and PACF of the stationary FPI series at level form

Sequel to the ACF and PACF plots in Figure 2a, the spikes (vertical red lines) of the ACF plot are not statistically significant (that is, spikes are not within the 95% confidence bounds) at lags 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 and 11. Also, lag is also statistically significant since lag is not within the 95% confidence bounds. As a result, this is an indication the FPI series is not a level stationary series. The correlogram in this case is also in support of the time series plots of Figure 1a which suggested non-stationarity in the FPI series. Here, the correlogram of Figure 2a is interpreted for the purpose of stationarity.

Once the series has been rendered stationary, the ACF and PACF are examined to determine the type and order of the model (see Yaffee and McGee, 2000).

SLUJST
Sule Lamido University Journal of Science & Technology Vol. 6 No. 1&2 [March, 2023], pp. 8-20
https://doi.org/10.56471/slujst.v6i.286
Online ISSN: 2736-0903
Print ISSN: 2736-089X
www.slujst.edu.ng

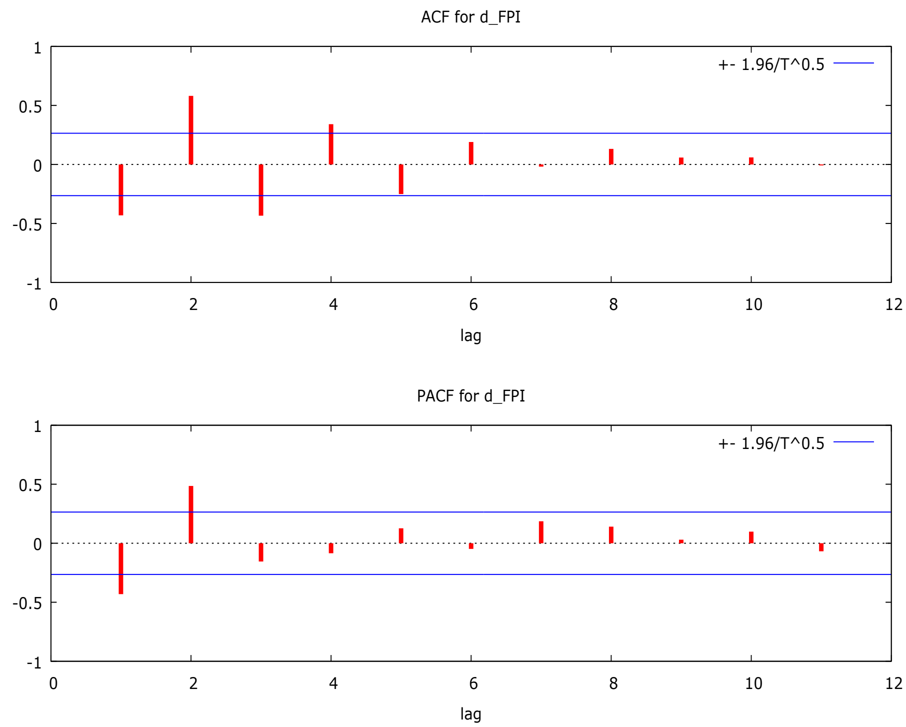

Figure 2b: ACF and PACF of the stationary FPI series after first difference

Figure 2b shows that the spikes of the ACF and PACF are decaying exponentially with the PACF having two significant spikes at lag 1 and lag 2 while the ACF has four significant spikes at lag 1, lag 2, lag 3 and lag 4. Hence, ARIMA (p, d, q) model with any possible order from **p** = 1, 2 of AR term and **q** = 1, 2, 3 and 4 of MA term is suggested to fit the data. Based on the results reported by the ACF and PACF, the values of order **p** and **q** are further examined using selection criteria AIC, BIC and HQC earlier described. The essence of this is to select the best model from all the possible fitted models. Table 2 presents the results of all the possible fitted models formed from orders **p** and **q** as well as results of the AIC, BIC and HQC.

Table 2: Possible Fitted ARIMA (p, d, q) Models

S/N	(p, d, q)	AIC	BIC	HQC
1	(1,1,1)	299.3074	307.3367	302.4124
2	(1,1,2)	293.0631	303.0998	296.9444
3	(1,1,3)	294.9618	307.0058	299.6193
4	(1,1,4)	296.2526	310.3040	301.6864
5	(2,1,1)	295.6903	305.7270	299.5716
6	**(2,1,2)**	**290.7165***	**302.7605***	**295.3740***
7	(2,1,3)	292.1424	306.1938	297.5762
8	(2,1,4)	298.4729	314.5315	304.6829

From Table 2, ARIMA (2, 1, 2) model has the least values of the AIC, BIC and HQC selection criteria. Hence, it is established as the best model for analyzing the FPI series. Having determined the best model, model estimation followed and the ensued estimates of the ARIMA (2, 1, 2) model are presented in Table 3.

Sule Lamido University Journal of Science & Technology Vol. 6 No. 1&2 [March, 2023], pp. 8-20
https://doi.org/10.56471/slujst.v6i.286

Online ISSN: 2736-0903
Print ISSN: 2736-089X
www.slujst.edu.ng

Table 3: Estimates of AR and MA terms in ARIMA (2, 1, 2) model

Variables	Coefficient	SE	Z	p-value
Const	1.86367	0.410986	4.5346	<0.00001***
AR1	-1.5851	0.107429	-14.7549	<0.00001***
AR2	-0.753213	0.104005	-7.2421	<0.00001***
MA1	1.52896	0.0787744	19.4094	<0.00001***
MA2	1.0000	0.0903779	11.0647	<0.00001***

Specified equation (12) below is the estimated version of equation (1) which is also specified in accordance with Box and Jenkins (1976) methodology,

$$\mathrm{FPI}_t = 1.86367 - 1.5851\mathrm{FPI}_{t-1} - 0.753213\mathrm{FPI}_{t-2} + 1.52896\mathrm{e}_{t-1} + 1.0000\mathrm{e}_{t-2} + \varepsilon_t \qquad (12)$$

where: FPI_t= FPI at current time t (2016), FPI_{t-1} = FPI at immediate past period t-1 (2015), FPI_{t-2} = FPI at past two periods, ε_t= Random shock at period t.

3.1 Interpretation of the AR and MA Terms in Table 3

For the AR term, the results showed that two years past values t-2 (2014 and 2015) of FPI series is related to FPI in current time period t (2016) while for the MA term, random shocks in two years past values t-2 (2014 and 2015) are also related to FPI in current time period t (2016). This is evident from the p-values of their test statistic which are less than chosen level of significance ($\alpha = 0.05$). More so, the coefficients of AR1, AR2, MA1 and MA2 terms are statistically significant in that their respective p-values are lesser than the 5% chosen level of significance.

The Figure 3 below has Residual Correlogram of the fitted model ARIMA (2, 1, 2) which was used diagnostic measure to assess the suitability of the fitted model to the dataset. Therefore, it is noticeable from the Figure 3 that the spikes of the ACF and PACF of the residual correlogram are not statistically significant. This implies that ARIMA (2, 1, 2) model reasonably fits the Food Production Index (FPI) series under consideration

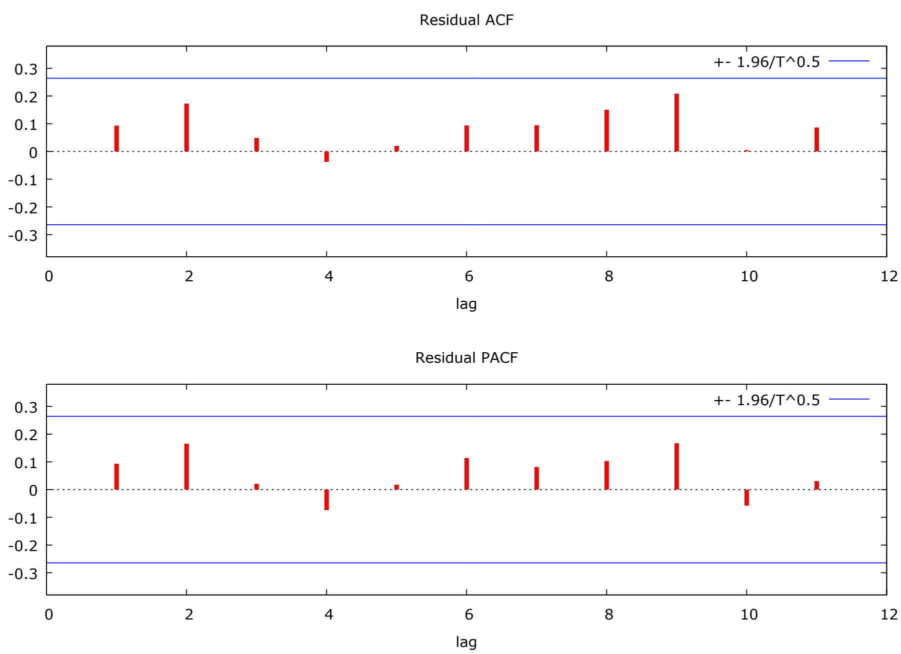

Figure 3: Residual Correlogram of the ARIMA (2, 1, 2) model

Having identified the correct model, estimated its parameters and carried out diagnostic check of the fitted the model, therefore it is imperative to forecast future values of FPI in Nigeria. This study adopts 8-year forecast periods to express sensitivity to political regimes in the country.

Table 4: Eight years forecast of FPI series

Year	Prediction	SE	Lo95	Hi95
2017	129.31	2.885	123.66	134.97
2018	126.28	3.968	118.5	134.06
2019	133.72	5.42	123.1	144.34
2020	130.43	5.879	118.91	141.95
2021	136.26	6.995	122.55	149.97
2022	135.72	7.415	121.19	150.25
2023	138.41	8.17	122.4	154.42
2024	140.77	8.667	123.79	157.76

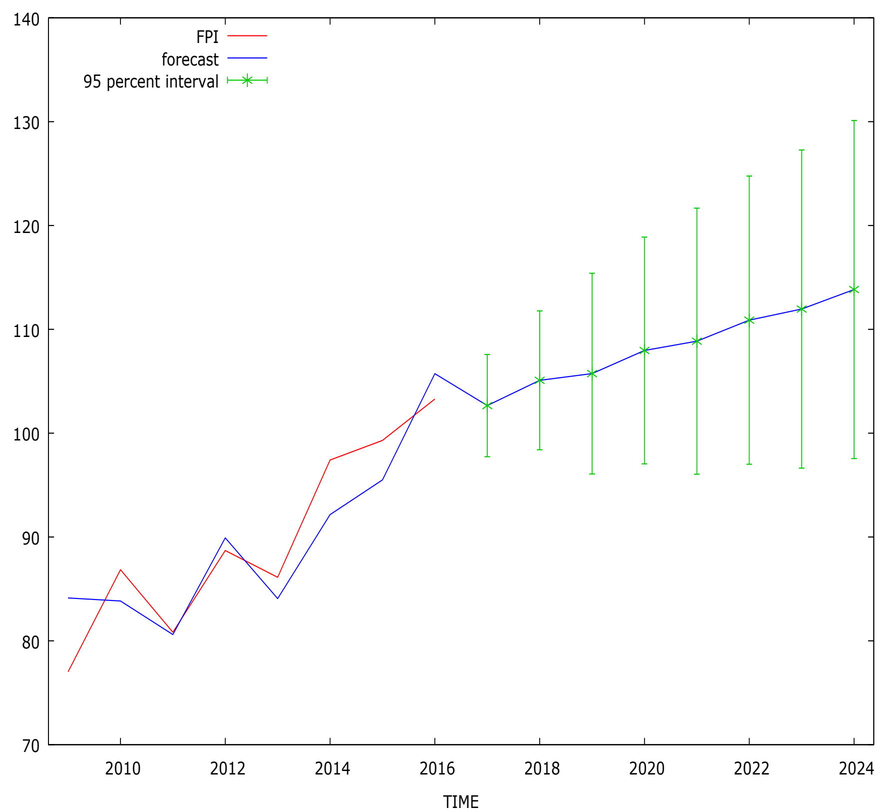

Figure 4: Plot for the forecasted model values superimposed on the original values

Results from Table 4 and Figure 4 showed that the value of the FPI fell by 2.34% between the periods 2017 and 2018. Although, there was a 5.56% rise between the periods 2018 and 2019. A 2.46% decline and 4.28% rise in the value FPI is expected between 2019 to 2020 periods and between 2020 and 2021 periods respectively. The value of the FPI is not only expected to fall by 0.4% between 2021 and 2022 periods. It is also predicted to rise again by 6.37% from 2022 through 2024 periods.

4. Discussion of Findings

In this study, we investigated the Food Production Index (FPI) of Nigeria using Box and Jenkins techniques otherwise known as ARIMA modeling. The analysis of the FPI series started by predetermining the stationarity status of the time series data using time series plots presented as Figures 1(a & b). Results from the Figures revealed that there is sufficient evidence that the series is non-stationary at level. In order to properly determine the order of integration (d) of the series, unit root analyses were further conducted using Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Results from the ADF and PP tests as reported in Tables 1(a & b) corroborated that truly the series was not stationary at level which was made stationary after first difference{I(1)}. Moreover, the four stages of the modeling as dictated by Box-Jenkins methodology were carefully carried out and were satisfied accordingly in this work. Results from the correlogram presented in Figure 2 and Table 2 jointly identified ARIMA (2, 1, 2) model as the best model for analyzing the data. The identified model was estimated and the results as reported in Table 3 showed that two years past values **t-2** (2014 and 2015) of FPI series is related to FPI in current time period **t** (2016) while for the MA term, random shocks in two years past values **t-2** (2014 and 2015) are also related to FPI series in current time period **t** (2016). Forbye, the estimated model was further diagnosed using the residual correlogram obtained from the model. Results of the diagnostic checking shown in Figure 3 revealed that the spikes of the ACF and PACF of the residual correlogram are not statistically significant which implies that ARIMA (2, 1, 2) model is a reasonable fit to the FPI series.

Finally, an out-sample forecast of eight years was made on FPI series from 2017 to 2024. Based on the forecast results presented in Table 4 and Figure 4, the value of Food Production Index (FPI) of Nigeria fell by 2.34% between the periods 2017 and 2018; however, there was a 5.56% rise between periods 2018 and 2019. However, a 2.46% decline in the value of FPI is expected between 2019 to 2020 periods. This is indicative of the current COVID-19 situation. This holds true as there is a consequential propensity toward global food insecurity at the moment. Disruptions in food supply chains of crops like vegetables and fruits have been recorded. Also, citizens are currently struggling to have the needed resources to buy the limited and dwindling food supply. As the pandemic abates, this in turn generates a decrease in food demand and prices will go down, thereby putting farmers and agricultural managers at the receiving end of low prices. Conversely, the study showed that a 4.28% rise in FPI value is expected between 2020 and 2021 periods respectively. This is representative of post COVID-19 agricultural production status. Although, at this point, there may still be traces of global recession, but the Nigerian agricultural sector is expected to invest a lot of resources to mitigate and compensate for the losses experienced during the 2019 to 2020 pandemic.

These resources may generate capacity for provision of seeds and planting materials to smallholders, animal feed to livestock breeders and aquaculture inputs in order to sustain agricultural food supply chains within and outside Nigeria. The value of the FPI is not only expected to fall by 0.4% between 2021 and 2022 periods, but it is also expected to rise again by 6.37% from 2022 through 2024 periods. Lastly, the eight years out sample forecast of FPI for the periods 2017 to 2024 indicates that the series has been greatly affected by the global pandemic that has ravaged the world.

5. Conclusion and Recommendations

This study contributes significantly to the existing literature on food related issues during COVID-19 pandemic in that it shed light on the post-pandemic values of the amount of production otherwise known as Food Production Index (FPI) in Nigeria. Based on the outcomes of the analysis and summary of findings, it is concluded that the eight years out sample forecast of food production index (FPI) for the periods 2017 to 2024 indicates that the gains of FPI in recent years is currently being affected by the current COVID-19 pandemic.

It is recommended that concerted efforts to achieve optimal FPI must be focused on the improvement of inter-regional trade. This will result in shorter food chains, thereby creating more markets for farmers and enhance

Online ISSN: 2736-0903
Print ISSN: 2736-089X
www.slujst.edu.ng

accessibility to both inputs; seeds, water and fertilizers, as well as outputs which is food produce for Nigerian populace, and if surplus is achieved, food exportation is recommended.

References

Adegboye, O. A., Adekunle, A. I., and Gayawan, E. (2020). Novel Coronavirus in Nigeria: Epidemiological analysis of the first 45 days of the pandemic. *medRxiv*, 2020-04.

Aghaei, M., GhasemianSahebi, A., and Kordheydari, R. (2021). The effect of COVID-19 on marketing innovations and corporate social responsibility (case study: active companies in food industry). *International Journal on Customer Relations*, *8*(2), 15-26.

Akanni, S. B. and Adeniyi, O. I (2020). On the forecast of cereals production in Nigeria. *Federal University Wukari Trends in Science and Technology Journal, FTSTJ-0216*

Ali, J., and Khan, W. (2020). Impact of COVID-19 pandemic on agricultural wholesale prices in India: A comparative analysis across the phases of the lockdown. *Journal of Public Affairs*, *20*(4), e2402.

Amzat, J., Aminu, K., Kolo, V. I., Akinyele, A. A., Ogundairo, J. A., and Danjibo, M. C. (2020). Coronavirus outbreak in Nigeria: Burden and socio-medical response during the first 100 days. *International Journal of Infectious Diseases*, *98*, 218-224.

Bai, Y., Costlow, L., Ebel, A., Laves, S., Ueda, Y., Volin, N., ... and Masters, W. A. (2022). Retail prices of nutritious food rose more in countries with higher COVID-19 case counts. *Nature Food*, *3*(5), 325-330.

Box, G. E. and Jenkins, G. M. (1976). Time series analysis, forecasting and control. San Francisco, Holden-Day Inc., USA.

Burnham, K. P., and Anderson, D. R. (2002). A practical information-theoretic approach. *Model selection and multimodel inference, 2nd ed. Springer, New York, 2*.

Burnham, K. P., and Anderson, D. R. (2004). Multimodel inference: understanding AIC and BIC in model selection. *Sociological methods & research*, *33*(2), 261-304.

Campbell, C. (2021). The impact of COVID-19 on local government stakeholders' perspectives on local food production. *Journal of Agriculture, Food Systems, and Community Development*, *10*(2), 71-88.

Chitrakar, B., Zhang, M., and Bhandari, B. (2021). Improvement strategies of food supply chain through novel food processing technologies during COVID-19 pandemic. *Food Control*, *125*, 108010.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*(366a), 427-431.

Ellis, F., and Sumberg, J. (1998). Food production, urban areas and policy responses. *World Development*, *26*(2), 213-225.

Guiné, R. P., Florença, S. G., Costa, D. T., Çelik, S., Ferreira, M., Cardoso, A. P., ... and Costa, C. A. (2022). Comparative Study about the Consumption of Organic Food Products on Samples of Portuguese and Turkish Consumers under the COVID-19 Pandemic Context. *Agronomy*, *12*(6), 1385.

Gujarati, D. N. and Porter, D. C. (2009). *Basic econometrics, 5th edition*. McGraw-Hill/Irwin, New York.

Hopfenberg, R. (2003). Human carrying capacity is determined by food availability. *Population and environment*, *25*(2), 109-117.

Ibrahim, R. R., and Oladipo, H. O. (2020). Forecasting the spread of COVID-19 in Nigeria using Box-Jenkins modeling procedure. *medRxiv*, 2020-05.

Kent, G. (1995). Aquaculture and food security. In *Proceedings of the PACON Conference on Sustainable Aquaculture* (Vol. 95, pp. 11-14).

Kolawale, O. and Ojo, S. O. (2007). Economic efficiency of small-scale food crop production in Nigeria. Journal For Social Sciences, 14(2): 123-130.

Laborde, D., Martin, W., Swinnen, J., and Vos, R. (2020). COVID-19 risks to global food security. *Science*, *369*(6503), 500-502.

Mishra, K., and Rampal, J. (2020). The COVID-19 pandemic and food insecurity: A viewpoint on India. *World Development*, *135*, 105068.

Mthembu, B. E., Mkhize, X., and Arthur, G. D. (2022). Effects of COVID-19 pandemic on agricultural food production among smallholder farmers in Northern Drakensberg areas of Bergville, South Africa. *Agronomy*, *12*(2), 531.

News Medical Life Sciences (2019). Coronavirus Disease (COVID-2019) pandemic history. Available online: https://www.news-medical.net/health/History-of-COVID-19.aspx, (accessed on 14th June, 2023).

Ojo, S.O. (2004). Improving labour productivity and technical efficiency in food crop production: A panacea for poverty reduction in Nigeria. *Food, Agriculture & Environment* Vol.2 (2):227-231.

Okotie, S. (2018). The Nigerian Economy Before the Discovery of Crude Oil. In *The Political Ecology of Oil and Gas Activities in the Nigerian Aquatic Ecosystem* (pp. 71-81). Academic Press.

Oriola, E. O. (2009). A framework for food security and poverty reduction in Nigeria. *European Journal of Social Sciences*, *8*(1), 132-139.

Pankratz, A (1983). Forecasting with Univariate Box-Jenkins: Concepts and Cases, John Wiley & Sons, Inc. New York.

Phillips, P. C., and Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2), 335-346.

Prajapati, H. R. (2020). COVID-19, Food Security and Agricultural Development in Asia. *Food Security and Agricultural Development in Asia (December 7, 2020)*.

Pu, M., and Zhong, Y. (2020). Rising concerns over agricultural production as COVID-19 spreads: Lessons from China. *Global food security*, *26*, 100409.

Rosegrant, M. W. and Cline, S. A. (2003). Global food security: challenges and policies. *Science*, *302*(5652), 1917-1919.

Tsay, R. S., & Tiao, G. C. (1984). Consistent estimates of autoregressive parameters and extended sample autocorrelation function for stationary and nonstationary ARMA models. *Journal of the American Statistical Association*, *79*(385), 84-96.

Yaffee, R. A. and McGee, M. (2000). *An introduction to time series analysis and forecasting: with applications of SAS® and SPSS®*. Elsevier.

Yahaya, O. Y (2008) A Geographical Analysis of Women Participation in Agriculture in Asa Local Government Area of Kwara State. A research Proposal presented at the Staff Seminar Series, Department of Geography, University of Ilorin, Nigeria.

World Bank Repository (2018). *Data on Food Production Index.* Retrieved from http://data.worldbank.org

World Health Organization. Coronavirus Disease (COVID-2019) Situation Reports. Available online:
https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports (accessed on 14th June, 2023).

.