FORECASTING OF NIGERIA MANUFACTURING SECTOR GROWTH RATES USING ARIMA MODEL

Jonathan O. ONIORE[1], Uju R. EZENEKWE[2], Uche C.C NWOGWUGWU[3]

Abstract

The objective of this study is to identify a good forecasting model that can predict Nigeria's future manufacturing sector growth rate and to ascertain whether policy makers could maintain a steady and sustainable growth rate in the manufacturing sector. The study employed Autoregressive Integrated Moving Average (ARIMA) on annual data from 1970 to 2014 on manufacturing production index (MPI) as a measure of manufacturing sector growth rate. The ARIMA model selected is the Autoregressive (AR) [ARIMA (1, 0, 0)]. That is, the $AR_{(1)}$ model was selected as the most appropriate for forecasting model for manufacturing sector growth rates in Nigeria. The forecasted values of manufacturing sector growth for 2015, 2016, 2017, 2018, 2019 and 2020 using Dynamic Forecast were 72.1%, 75.6%, 75.9%, 76.4%, 76.8% and 77.2% respectively. The major finding of this study is that Nigeria's manufacturing sector future growth rate is moving gradually with an average annual projected growth of approximately 90.8 %. The projected rate showed that Nigeria needs to double her efforts in order to fructify its vision of becoming twenty largest economies in the world by 2020 and the 12th largest economy by 2050.

Keywords: *Economic Growth; Manufacturing; Forecasting; ARIMA; Nigeria*
JEL Classification: *O4; L60; C53; N37*

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[1] *Department of Economics, Faculty of Humanities, Social and Management Sciences, Bingham University, Karu, Nigeria*

[2] *Department of Economics, Faculty of Social Sciences, Nnamdi Azikiwe University, Awka, Nigeria; e-mail: jonathanoniore@gmail.com*

[3] *Department of Economics, Faculty of Social Sciences, Nnamdi Azikiwe University, Awka, Nigeria; e-mail: jonathanoniore@gmail.com*

1. Introduction

The Nigerian economy aspires to become one of the twenty largest economies in the world by 2020 and the 12th largest economy by 2050. Indeed, it is the aim of Vision 20:2020 to transform the Nigerian economy into one of the largest in the world within the shortest possible time as well as achieving a sound, stable and globally competitive economy, with GDP of not less than $900 billion USD and a per capita income of $4,000 per annum (CBN, 2009). One of the surest ways to achieve the afore-stated goals is to pursue a rapid and sustainable economic growth and development via industrialization. In the light of the great expectation from industrialization, manufacturing has been mostly favoured in the blueprint of various industrial policies that have been put in place so far in Nigeria. The manufacturing sector according to Egbon (1995) is the most favoured sector in the Nigerian economy, especially as the main instrument of rapid growth, structural change and self-sufficiency and that industrial policies are geared towards improving the economic performance of individual agents, firms and industries on the supply side of the economy. However, in the face of these policies, the performance of the manufacturing sector has not been impressive.

For example, the Nigerian manufacturing industry grew quite rapidly during the 1974-'80 period that coincided with the country's oil boom. During this period, manufacturing value added recorded an annual average growth rate of about 12 percent. At the end of the oil boom, however, the sharp fall in domestic demand (resulting from a sharp decline in aggregate income) and drastic reduction in the country's import capacity had a direct and significant impact on the manufacturing sector. One indicator of this effect is the rapid decline of capacity utilization of the manufacturing sector from a peak of 76.6 percent in 1975 to 43.8 percent in 1989. The utilization capacity of the manufacturing industry further dwindled in the 1990s and ranged between 40.3 per cent and 34.6 per cent; while 36.1 and 54.8 percent were recorded in 2000 and 2005, respectively. The improved performance in the manufacturing sector during these periods was attributed to a number of factors, which included the relative macroeconomic stability and the regular supply of petroleum products. The capacity utilization of the manufacturing industry further dwindled to 53.3 percent in 2006. A brief spike in manufacturing capacity utilization was observed in 2010 as the utilization capacity increased to 56.79 percent before peaking at 60.3% in 2014. The improved performance of this sector during this period could be linked to the improved availability of inputs as a result of increased inflow of foreign exchange. In addition, the share of manufacturing in the economy's aggregate output remains stuck at the very low levels. For example, the manufacturing industry share in gross domestic product, which stood at 7.2 percent in 1970 fell to 5.2 per cent in 1975 before rising gradually to 11.2 percent in 1982. Following the depressing state of the economy in the 1980s, manufacturing share in

GDP fell and remained in the range of between 7.8 percent and 8.4 percent. With the fluctuating growth in manufacturing production since 1992, the contribution of the sector to the GDP fell from 8.3 to 3.4 percent between 1993 and 2001. Between 2002 and 2007, manufacturing share in the GDP witnessed only a marginal increase of 3.0 percent. A decline was again recorded in 2008 and 2009 but recorded a consistently upward trend of 7% in 2010 to 10 percent in 2014 and marginal rate of 9.5% in 2017 (ERGP,2017). These provided strong indices that manufacturing industry in Nigeria has been dwindling, hence the need for the present study to forecast manufacturing sector growth rates in Nigeria.

Forecasting or projecting into the future will give a clearer picture of how the state of the economy is likely to perform and also inform policy makers on whether they are progressing or not and how they need to fine-tune their efforts, the quantum of resources to be mobilized and allocated efficiently and whether they can sustain a steady and increasing manufacturing sector growth. Sustained growth in the manufacturing sector will guarantee the country's vision of becoming one of the twenty largest economies in the world by 2020 and the 12th largest economy by 2050.

2. Materials and Methods

The study depended on secondary data that were obtained from the Central Bank of Nigeria (CBN) Annual Report and Statement of Accounts. It covers the period from 1970 to 2014.

The study made use of ARIMA model. The ARIMA model combines both the moving average (MA) and the autoregressive (AR) models. Initially, these models were analyzed by Yule-Walker. However, a systematic approach that synchronizes both approaches for identifying, estimating and forecasting the models was advanced by Box and Jenkins (1976). The Box-Jenkins methodology begins with an ARMA (p,q) model which combines both the AR and MA models as follows:

$$Y_t = \gamma \chi_t + e_t \tag{1}$$

$$e_t = \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j}^{q} \beta_j \varepsilon_{t-j} + \mu_t \tag{2}$$

Where, χ_t represents the explanatory variables, e_t is the disturbance term. In equation (2), y_{t-i} are AR terms of order p, ε_{t-j} are MA terms of order q and μ_t is a white-noise innovation term. In case of a non-stationary data, the series is differenced (integrated) such: $\Delta^d Y_t = (1-B)^d y_t$, (d is the number of times a series is differenced to become stationary; I=d) then the ARMA (p, q) model becomes ARIMA (p,d,q) models (Auto-regressive Integrated Moving Average of order p, q). The Box – Jenkins model building techniques consist of the following four steps:

1. Preliminary Transformation: if the data display characteristics violating the stationarity assumption, then it may be necessary to make a transformation so as to produce a series compatible with the assumption of stationarity. After appropriate transformation, if the sample autocorrelation function appears to be non-stationary, differencing may be carried out.

2. Identification: if $\{yt\}$ is the stationary series obtained in step 1, the problem at the identification stage is to find the most satisfactory ARIMA (p,q) model to represent $\{yt\}$. Box – Jenkins (1976) determined the integer parameters (p,q) that governs the underlying process $\{yt\}$ by examining the autocorrelations function (ACF) and partial autocorrelations (PACF) of the stationary series, $\{yt\}$. This step is not without some difficulties and involves a lot of subjectivity; hence it is useful to entertain more than one structure for further analysis. Salau (1998) stated that this decision can be justified on the ground that the objective of the identification phase is not to rigidly select a single correct model but to narrow down the choice of possible models that will then be subjected to further examination.

3. Estimation of the model: This deal with estimation of the tentative ARIMA model identified in step 2. The estimation of the model parameters can be done by the conditional least squares and maximum likelihood.

4. Diagnostic checking: Having chosen a particular ARIMA model, and having estimated its parameters, the adequacy of the model is checked by analyzing the residuals. If the residuals are white noise; we accept the model, else we go to step 1 again and start over.

3. Results and Discussion

The ARIMA modelling strategy discussed under materials and methods is applied to analyze the data on manufacturing sector growth measured by manufacturing production index (MPI). The summary of the estimated ARMA model in equation 2 is presented in table 1. The ARIMA model selection was done using Eviews 9.5 econometric software. The ARIMA model selected is the Autoregressive (AR) [ARIMA (1, 0, 0)]. That is, the $AR_{(1)}$ model was selected as the most appropriate for forecasting model for manufacturing sector growth in Nigeria. The estimated $AR_{(1)}$ model is presented as follows:

Table 1: Estimated ARIMA (1, 0, 0)

Dependent Variable: LOG(MPI)				
Method: ARMA Generalized Least Squares				
Variable	Coefficient	Std. Error	t-Statistic	Prob
C	87.80755	46.60916	1.883912	0.0667
AR(1)	0.965106	0.055535	17.37848	0.0000
Inverted AR Roots	.97			

Source: Researcher's Computations (2017)

The above ARIMA cannot be interpreted as in OLS because the construction of ARIMA model is not based on any economic theory. It is often best not to ever interpret the individual parameter estimates, but rather to examine the plausibility of the model as a whole and to determine whether it describes the data well and produces accurate forecast (Brooks, 2008). The test of accuracy for the estimated model was conducted using the Autocorrelation (AC) and Partial Autocorrelation (PAC) Function and the inverse root of AR/MA polynomials for stability of the estimated model (see Brooks, 2008; Gujarati, 2009). The results of both tests are presented in Appendix I. The AC and PAC express a systematic strikes pattern and none of the AC and PAC is individually statistically significant. In other words, the correlograms of both autocorrelation and partial autocorrelation give the impression that the residuals estimated from table are purely random.

To support the conclusion from Autocorrelation (AC) and Partial Autocorrelation (PAC) Function, the test for stability or stationarity of the series using the inverse root of AR/MA polynomials for stability was employed. The result presented in Figure 1 in Appendix I showed that the series is stable. This is because the entire characteristic roots lies within the circle. From the Autocorrelation (AC) and Partial Autocorrelation (PAC) Function and inverse root of AR/MA polynomials for stability, there may not be any need to look for another ARIMA model. Therefore, the $AR_{(q)}$ model estimated in table 1 is reliable for forecasting manufacturing sector growth in Nigeria.

To obtain the forecast of LOG (MPI) level rather than its changes, we undo the first difference transformation that we had used to obtain the changes. This study employed the dynamic forecast to forecast manufacturing sector growth up to 2020.

$$AR(q): LOG(MPI) = 87.80755 + 0.9651060\, \varepsilon_{t-1} \quad (3)$$

The forecasted values of manufacturing sector growth for 2015, 2016, 2017, 2018,2019 and 2020 by Dynamic Forecast using Eviews 9.5 is given as 72.1%, 75.6%, 75.9%, 76.4%, 76.8% and 77.2% respectively. Taken the forecast into consideration (2015, 2016, 2017, 2018, 2019 and 2020) we can deduce that the MPI also increased gradually through the period that was considered. By implication, the null hypothesis of decreasing trend is rejected and the alternative of hypothesis of increasing trend accepted. In summary, the ARIMA model revealed that manufacturing production index (MPI) in Nigeria appear with increasing trend. This is an indication that the manufacturing sector still remains major source of hope for sustainable growth and development in Nigeria.

4. Conclusion

The manufacturing sector growth rates in Nigeria measured by manufacturing production index (MPI) have been shown to follow Autoregressive (AR) [ARIMA (1, 0, 0)]. That is, the $AR_{(1)}$ model was selected as the most appropriate for forecasting model for manufacturing sector growth in Nigeria. Also, the model has been used to make forecasts for future values, which appeared with increasing trend. The major finding of this study is that Nigeria's manufacturing sector future growth rate is moving gradually with an average annual projected growth of approximately 90.8 %. This is an indication that the manufacturing sector still remains major source of hope for sustainable growth.

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Appendix I: ARIMA MODEL Test Results

Dependent Variable: MPI
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 08/16/17 Time: 17:52
Sample: 1972 2014
Included observations: 43
Convergence achieved after 28 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

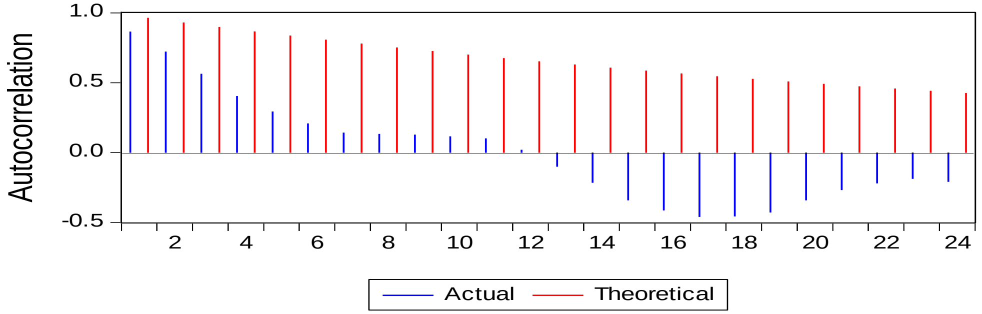
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	87.80755	46.60916	1.883912	0.0667
AR(1)	0.965106	0.055535	17.37848	0.0000

R-squared	0.845042	Mean dependent var	111.5647
Adjusted R-squared	0.841262	S.D. dependent var	37.95428
S.E. of regression	15.12172	Akaike info criterion	8.377859
Sum squared resid	9375.322	Schwarz criterion	8.459776
Log likelihood	-178.1240	Hannan-Quinn criter.	8.408068
F-statistic	223.5870	Durbin-Watson stat	1.751673
Prob(F-statistic)	0.000000		

Inverted AR Roots	.97

Forecasted Values

Period	Forecast
2015	**72.12789**
2016	**75.57034**
2017	**75.99735**
2018	**76.40945**
2019	**76.80718**
2020	**77.19103**



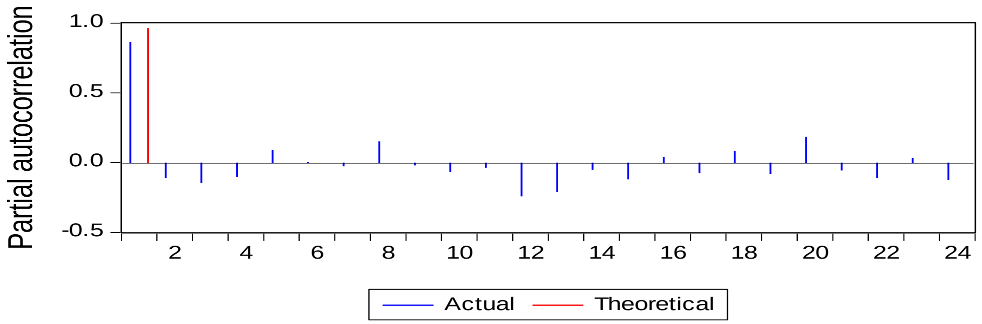


Figure 1: Inverse root of AR/MA polynomials for stability