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FORECASTING OF NIGERIA MANUFACTURING SECTOR GROWTH RATES USING ARIMA MODEL

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Abstract

The objective of this study is to identify a forecasting model that can predict Nigeria's future manufacturing sector growthrateand 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 AR1) model was selected as the most appropriate for forecasting model for manufacturing sector growth rates in Nigeria. The ARIMA model was selected on the basis of Autocorrelation (AC) and Partial Autocorrelation (PAC) Function and the inverse root of AR/MA polynomials for stability of the estimated model 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 government 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

JELCodes: *O4; L60; C53; N37*

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 (CBN, 2009). 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 US$900 billion 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 capacity utilization 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 capacity utilization 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 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, 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 (CBN Annual Report, Various Issues). 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. This precisely is the general thrust or focus of this research work. It is indeed to all intent and purpose, the overriding motivation for the study.

2. REVIEW OFRELATED LITERATURE

Samad, Ali & Hossain (2002) applied the Box-Jenkins (ARIMA) methodology to forecast wheat and wheat flour prices in Bangladesh. They concluded that the ARIMA forecasts were satisfactory during and beyond the estimation period and could be used for policy purposes as far as price forecasts of the commodities were concerned.

Valle (2002) used ARIMA and VAR models to forecast inflation in Guatemala. The results showed that ARIMA produced good results and the forecasts behaved according to the underlying assumptions of each model.

Katimon & Demun (2004) applied the ARIMA model to represent water use behaviour at the Universiti Teknologi Malaysia (UTM) campus. Using autocorrelation function (ACF), partial autocorrelation function (PACF), and Akaike's Information Criterion (AIC), they concluded that ARIMAmodel provides a reasonable forecasting tool for campus water use.

El-Mefleh & Shotar (2008) applied the Box-Jenkins (ARIMA) methodology to the Qatari economic data. They concluded that ARIMA models were modestly successful in ex-post forecasting for most of the key Qatari economic variables. The forecasting inaccuracy increased the farther away the forecast was from the used data, which is consistent with the expectation of ARIMAmodels.

Adebiyi, Adenuga, Abeng, Omamukue & Ononugo (2010) examined the different types of inflation forecasting models covering ARIMA, VAR, and VECM models. The empirical results from ARIMA showed that ARIMA models were modestly successful in explain inflation dynamics in Nigeria.

Baffigi, Golinelli and Parigi (2004), predicted the growth rate of GDP in Germany, France, Italy and Europe region using the Bridge Model (BM) and other basic models such as ARMA, VAR and a structural model. They concluded that the Bridge Model (BM) outperformed all other techniques used in their study.

A more recent submission by Sarbijan (2014) showed that the Markov switching model could better forecast Iran's economic growth than ARIMAmodels.

Gil-Alana (2001) showed that a Bloomfield exponential spectral model gave a feasible result, in lieu of ARMAmodels, for UK's unemployment rate.

Golan and Perloff (2002) concluded that nonparametric methods of forecasting unemployment rates in the U.S outperformed other models.

Floros (2005) compared the out-of-sample forecast accuracy for the United Kingdom unemployment rate and established that, though an MA(4) model performed well, the MA(4)-ARCH (1) model provided superior forecasts.

Zhou He and Sun (2006) showed that the ARIMA/GARCH model outperformed the

Fractional Autoregressive Integrated Moving Average (FARIMA) 3 for predicting telecommunication network.

Assis, Amran and Remali (2010) have also demonstrated the superiority of the mixed ARIMA/GARCH model over the exponential smoothing, ARIMA, and GARCH models in forecasting future prices of cocoa beans in Malaysia.

Similarly, Kamil and Noor (2006) concluded that the mix ARIMA/GARCH model outperformed the Autoregressive Conditional Heteroskedasticity (ARCH) model when used to forecast the price of raw palm oil in Malaysia.

3. Theoretical Framework and Methodology

The Box-Jenkins (1976) methodology refers to the set of procedure for identifying, fitting, and checking autoregressive integrated moving average (ARIMA) models with time series data (Hanke & Wichern, 2005; Roberts, 2006). Forecasts follow directly from the form of the fitted model. ARIMA methodology is not embedded within any underlying economic theory or structural relationship, and the forecasts from the models are based purely on the past behaviour and previous error terms of the series of interest (Hanke & Wichern, 2005; Roberts, 2006).

The Box-Jenkins (ARIMA) econometric modelling is a forecasting technique that completely ignores independent variables in making forecast. It takes into account historical data and decomposes it into *Autoregressive* (AR) process, where there is a memory of past events; an *Integrated* (I) process, which accounts for stabilizing or making the data stationary, making it easier to forecast; and a *Moving Average* (MA) of the forecast errors, such that the longer the historical data, the more accurate the forecasts will be, as it learns over time. ARIMA models therefore have three model parameters, one for the AR(p) process, one for the I(d) process, and one for the MA(q) process, all combined and interacting among each other and recomposed into the ARIMA (p,d,q) model. The ARIMA models are applicable only to a stationary data series, where the mean, the variance, and the autocorrelation function remain constant through time. The only kind of nonstationarity supported by ARIMAmodel is simple differencing of degree d. In practice, one or two levels of differencing are often enough to reduce a nonstationary time series to apparent stationarity (Hanke & Wichern, 2005; Roberts, 2006).

Any forecasting technique that ignores independent variables also essentially ignores all potential underlying theories except those that hypothesize repeating

patterns in the variable under study. Since the advantages of developing theoretical underpinnings of a particular equation before estimating them have been emphasized in regression theory, why would we advocate ARIMA? The answer is that the use of ARIMA is appropriate when little or nothing is known about the dependent variable being forecasted or when all that is needed is one or two-period forecast (Hanke & Wichern, 2005; Roberts, 2006).

The Box-Jenkins methodology begins with an ARMA (p,q) model which combines both the AR and MA models as follows:

$$Y_t = \quad 1$$

$$e_t = \sum_{i=1}^{p} \quad \sum_{j} \quad t \qquad 2$$

Where, $_t$ represents the explanatory variables, e_t is the disturbance term. In equation (2), $y_{t\ i}$ are AR terms of order p, $_t$ is a white-noise innovation term. In case of a non-stationary data, the series is differenced (integrated) such that: $\quad = (1-B)^d y$ (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 foursteps:

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.

In recent years, forecasters have applied alternative approaches (Multiple Regression Models and the Box-Jenkins' Autoregressive Integrated Moving Average (ARIMA) Model) to forecast future values, owing to the fact that the traditional methods of forecasting are generally rigorous and time consuming, and also they require a laborious iterative approach.

The regression method has appeared in contemporary motivating literature: (Syariza and Noorhafiza, 2005; Taylor, 2008; Javadadi and Suhartono, 2010) etc. However, the major setback of the regression approach reposes on the severity of its underlying assumptions, thereby paving way for the Box-Jenkins methodology being extensively used in recent times (Floros, 2005; Kamil, and Noor, 2006; Purna, 2012). Two important assumptions of regression analysis that pose a threat to model building and forecasting are: independence of residuals (*No Autocorrelation*) and constant variance of residuals (*Homoscedasticity*). Violation of these two assumptions may make the regression estimates meaningless (Nanda, 1988; Greene, 2003; Bourbonnais, 2004 and Gujarati, 2004). Another key assumption of regression analysis is the independence of explanatory variables (*Multicollinearity*) and its violation which leads to a singular matrix (*Determinant Equals to Zero*) thus, making it impossible to obtain regression estimates.

For the sake of forecasting, the Box-Jenkins' method is considered to be superior as it directly takes into consideration the problem of autocorrelation. Hence, the study made use of ARIMA model. The ARIMA model combines both the moving average (MA) and the autoregressive (AR) models. ARIMA has the potential to provide short-term forecasts that are superior to more theoretically satisfying regression models. ARIMA modelling advocates that there is correlation between a time series data and its own lagged data.

Other econometric models have proven their predictive power over ARIMAmodels. Baffigi, Golinelli and Parigi (2004), predicted the growth rate of GDP in Germany,

Forecasted Values

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

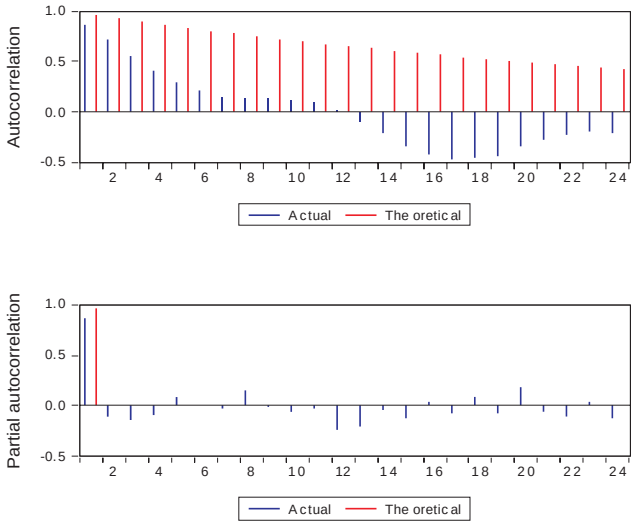
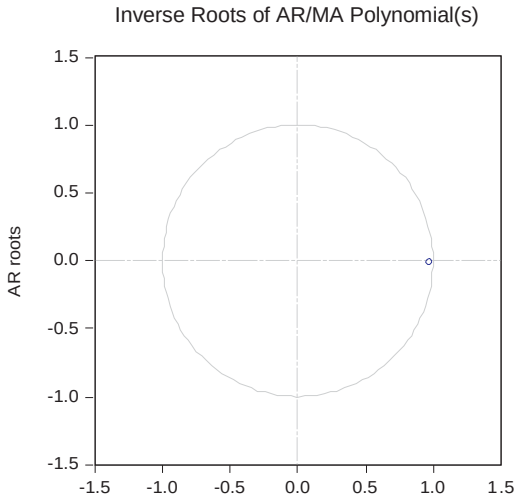
Figure 1: Inverse root of AR/MApolynomials for stability