

Full Length Research Paper

Can Cameroon become an emerging economy by the year 2035? Projections from univariate time series analysis

Louis Sevitenyi Nkwatoh

Department of Economics, Yobe State University, Nigeria.

Received 12 August, 2016; Accepted 19 September, 2016

Cameroon is among the African countries aspiring to become an emerging economy by the year 2035. Therefore, projecting into the future by policy makers in order to know the right course of action is imperative. The objective of this study is to identify a good forecasting model that can predict Cameroon's future economic growth rate and to ascertain whether policy makers could maintain a steady and sustainable growth rate that will fructify its vision of becoming an emerging economy by 2035. The study employed ARIMA and ARIMA/GARCH models on quarterly data from 1994q1 to 2014q4 on economic growth rate extracted from World Bank Development Indicators. Among the different models used, the mixed ARIMA(0,1,3)/E-GARCH(1,2) model was selected on the basis of the root mean squared error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE) and the Theil's inequality coefficient (U-STATISTICS) criteria. The major finding of this study is that Cameroon's future growth rate is slow and not sustainable with an average annual projected growth of approximately 6.099 %, unlike China that maintained a steady growth rate till it transcended into an emerging economy. The projected rate compared to China's growth rates, shows that Cameroon needs to double her efforts in order to fructify its vision of becoming an emerging economy by the year 2035.

Key words: Emerging economy, economic growth rate, ARIMA/GARCH models.

INTRODUCTION

Most African countries want to become key decision makers in the world's economic arena by swinging their economic pendulum towards an emerging economy. In this light, careful planning, strategies and transformation agenda that will diversify their economies, improve private sector development, and above all increase the rate of competitiveness are gradually being implemented.

Therefore, warning signals on the behaviour of future macroeconomic variables are necessary for policy makers to plan, strategize and take necessary measures ahead of time in order to circumvent economic downturns and brighten opportunities for sustained development. Cameroon is one among the many visionary African countries that wants to impose her position in the top 20

E-mail: sevinkwatoh@gmail.com. Tel: +2348062218765.

JEL: E24, C22, C53

Authors agree that this article remain permanently open access under the terms of the [Creative Commons Attribution License 4.0 International License](https://creativecommons.org/licenses/by/4.0/)

leading economies of the world by the year 2035. To fructify its vision, the government has prioritized five areas of development: (i) infrastructure development in energy; (ii) telecoms and transport; (iii) development of the rural and mining sectors; (iv) improvement in human resources through health, education, and training; (v) greater regional integration and export diversification; and financial sector deepening and strengthening (Cameroon, 2009). It is expected that all these will be achievable through a robust industrialization strategy, greater national integration and the advancement of democracy, private-sector promotion strategy, good governance and management strategy with blueprint for a resource allocation strategy, a strategy for sub- regional and international integration, a strategy for partnership and development assistance, and a development funding strategy (Cameroon, 2009).

However, the aspirations of becoming an emerging economy seem to be fading gradually, simply because the government does not want to relinquish its centrally planned economic structure to a decentralized system that fully integrates the private sector. The emergence of China began with a transition from a centrally planned economy to a socialist market economy initiated by the then Vice Premier of China Deng Xiaoping (Barth et al., 2009). Also, the country is saddled with a high rate of corruption, severe insurgency that is diverting attention and resources and a despondent democratic society. Freedom House Assessment (2014) shows that the regime is authoritarian and restrains the political rights and civil liberty of its citizens (Freedom House, 2014).

Though Cameroon's growth indicator exhibited a positive upward trend within the last five years, that is, approximately 3.27, 4.14, 4.49, 5.56 and 5.89% in 2010, 2011, 2012, 2013 and 2014 respectively (World Development Index, 2015), the process is still very slow and not promising. World Bank Development Index (2015) shows that China grew at an approximate rate of 7.81, 8.17, 9.02, 10.75% and 15.21% in 1980, 1981, 1982, 1983 and 1984 respectively just immediately after the transition process was initiated in 1979.

However, since the government is determined and is effortlessly strategizing towards an emerging economy by the year 2035 despite its socio-politico economic upheavals, it needs to gauge the tempo of its future economic growth. 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 economic growth that will guarantee the country's emergence by the year 2035.

Therefore, the rationale for this study is to identify a forecasting model that can project Cameroon's future growth rates that will eventually guide policy makers to carefully strategise ahead of time, thereby, fructifying its

vision of an emerging Cameroon in 2035.

THEORETICAL/EMPIRICAL LITERATURE

Theoretical literature

Historical patterns in time series data can be generated with the use of forecasting models predicated on mathematical formulae. Time series data by their nature, display a pattern such that their successive observations are dependent or correlated. The principal aim of modelling is to capture this underlying phenomenon using the observed time series in order to predict the likely realization of future values (Nkwatoh, 2012).

Early traditional forecasting models range from; the Naïve model to the Moving Averages and Exponential Smoothing models and to the Holt's and Winter's models. Nasir et al. (2008) note that though the applicability of the naïve method is simple and can be used for relatively short time series, yet the model is highly sensitive to changes in actual values such that a sudden drop or sharp increase in the series will affect the forecast. Furthermore, fitting this model type will result in the loss of the first two observations in the series, just like the moving averages method which gives equal weighting to each and every observation, with the average value being over dominated by extreme values (Yule, 1926; Pardhan, 2012). The major advantage of the exponential smoothing method among others is that, it embodies the advantages of weighted moving averages since current observations are assigned larger weights and also, it reacts more quickly to changes in data patterns than the moving averages (Pardhan, 2012). However, the main difficulty encountered when using this method resides in the determination of the size of a smoothing coefficient (α) (Nasir et al., 2008).

The Holt's method is highly adaptable for data with small local trend with no seasonal patterns while the Winter's method suitably works for data that has both seasonal and a trend factor alongside a random pattern (see, Eviews-2). However, it poses the same problem of choosing α just like with exponential smoothing.

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) etc. 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 (Nanda, 1988). Yule (1926) first introduced the autoregressive (AR) models, which was later complemented in 1937 by Slutsky with the introduction of Moving Averages (MA) models. Wold (1938) combined the two mathematical models commonly referred to as the ARMA model (*Autoregressive Moving Average*). He showed that ARMA processes could be used to model any stationary time series as long as the appropriate number of AR terms (p), and the appropriate number of MA terms (q), was correctly specified. This implies that any series (y_t) can be modelled as a linear combination of its previous time value and a finite number of its past errors. That is:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q} \dots \dots \dots \quad (1)$$

However, ARMA models could not be applied to real series until the mid 1960s when computing technology became available and economical (Makridakis and Hison, 1979). The use of ARMA models was made popular by Georg Box and Gvily Jenkins (1970), with the provision of guidelines for making the series stationary in both its mean and variance¹. Makridakis and Hison (1979) also suggest the use of the coefficients of the sample autocorrelation functions (ACF) and partial autocorrelation functions (PACF) for determining appropriate order of p and q (Nanda, 1988; Greene, 2003; Bourbonnais, 2004; Gujarati, 2004). Their approach to modelling ARIMA models otherwise known as the Box-Jenkins methodology has become highly applicable in recent times. The applicability of this methodology has permeated other areas of science chiefly because of the development of new statistical procedures accompanied by more powerful computers that can manage larger data sets with ease. The integrated component (I), gives the model leverage over non-stationary time series. This methodology is found in the empirical works of (Cooper, 1972; Nelson, 1972; Elliot, 1973), among others (Narasimham et al., 1974; McWhorter, 1975) etc and recently in the 2000s (Proietti, 2001; Mandal, 2005; Ghosh, 2008; Pei, 2008;

Wankhade et al., 2010; Ahmad and Latif, 2011; Lee et al, 2012) etc.

Just like other forecasting methods, the short comings of the Box-Jenkins' methodology are not farfetched. First, the interpretation of the autocorrelation functions (ACF and PACF)² is sometimes difficult and requires a lot of expertise. Second, ARIMA models are susceptible to outliers leading to false results. However, Javendani and Suhartono (2010) showed that, the exponential smoothing method can suitably replace the ARIMA model in this case, because it gives more weight to the most recent observation.

Empirical Literature

Modelling macroeconomic variables and projecting into the future, with the use of historical data from time series (univariate or multivariate time series) is not only a fascinating and academic exercise but also, it gives a bearing to policy makers' decision making-process. Modelling economic growth like any other macroeconomic variable has either been analyzed using the traditional moving averages method or the use of econometric models, often related to stationary time series, ranging from the simple ordinary least square technique, to the Autoregressive Integrated Moving Average (ARIMA) models and to the Generalised Autoregressive Conditional Heteroscedastic (GARCH) models (Elham, 2010; Assis et al., 2010).

Recently, the Box and Jenkins methodology has been extensively used, to project future macroeconomic variables including economic growth.

However, other econometric techniques have been used other than the ARIMA models proposed by Box and Jenkins. For instance, Gan and Wang (1993) used the Base Bayesian Vector Autoregressive (BVAR) model to project the economic growth of Singapore. Abeyasinghe (1998) employed an exponential nonlinear approach to predict Singapore's seasonal GDP. Hukkinen and Viren (1999) used a model based on the Keynesian theory to project 50 macroeconomic variables for Finland. Similarly, Jaafar (2006) and Nasir et al. (2008) have used methods other than ARIMA models. Other econometric models have proven their predictive power over ARIMA models.

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

²SACF and PACF can be used to determine order of stationarity of a time series. If the SACF of the time series values either cuts off or dies down fairly quickly, then the time series values should be considered stationary. On the other hand, if the SACF of the time series values either cuts off or dies down extremely slowly, then it should be considered non-stationary. Bowerman, O'Connell, and Koehler, 2005)

¹The constant mean and variance can be obtainable by removing the pattern caused by the time dependent autocorrelation.

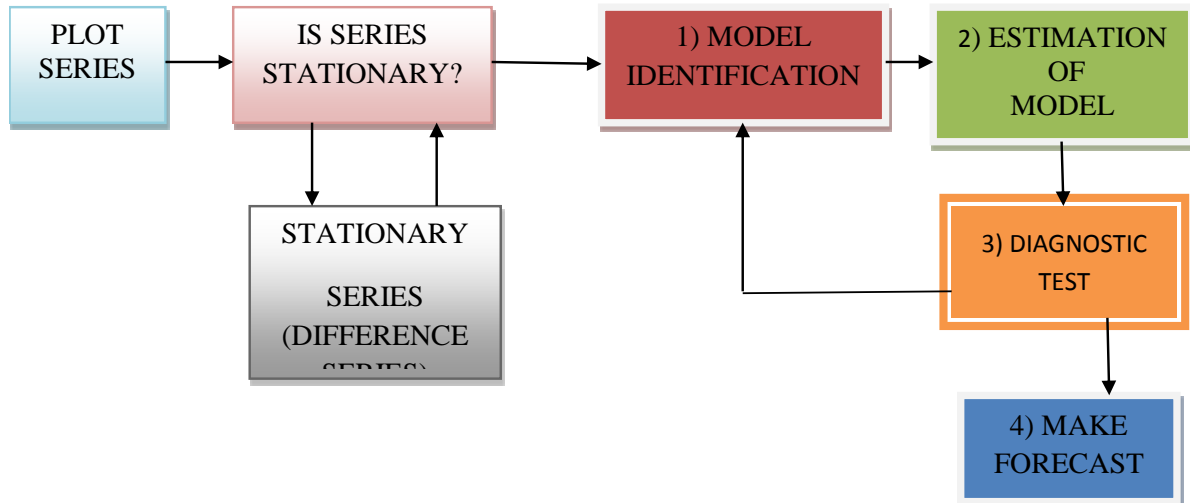


Figure 1. Box-Jenkins methodology.

other techniques used in their study. A more recent submission by Sarbijan (2014) shows that the Markov switching model could better forecast Iran's economic growth than ARIMA models. Gil-Alana (2001) showed that a Bloomfield exponential spectral model gave a feasible result, in lieu of ARMA models, for UK's unemployment rate while, Golan and Perloff (2002) concluded that nonparametric methods of forecasting unemployment rates in the U.S outperformed other models.

Many studies have focused entirely on the ARIMA models to predict macroeconomic variables. Maity and Chatterjee (2012) showed that a simple tentative ARIMA (1, 2, 2) model was well fitted for projecting Indian's GDP growth rates. Similarly, Reynolds et al. (1995) and Reilly (1980) have also projected economic growth rates using ARIMA models.

The choice of the ARIMA models for forecasting other macroeconomic variables other than GDP can also be found in studies: Purna (2012) forecasting cement production output in India; Mordi et al. (2006) analyzing inflation rates in Nigeria; Fatimah and Roslan (1998) forecasting cocoa prices in Malaysia, Nkwatoh (2012) forecasting unemployment rates for Nigeria etc. Notably, Assis et al. (2010) observed that the research costs of ARIMA models is relatively low compared to other econometric models, and relatively more efficient in short term forecasting.

Recently, studies have captured the heteroskedastic property of time series by incorporating the Autoregressive Conditional Heteroscedastic (ARCH) model introduced by Engle (1982). However, the Generalized Autoregressive Conditional Heteroscedastic (GARCH) models have provided more parsimonious results than ARCH models. This is similar to situations where ARMA models have perform better than simple AR models

(Assis et al., 2010).

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 et al. (2006) showed that the ARIMA/GARCH model outperformed the Fractional Autoregressive Integrated Moving Average (FARIMA)³ for predicting telecommunication network. Assis et al (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 (Figure 1).

METHODOLOGY/FORECASTING MODELS

This work used GDP growth rates data from 1994 to 2015 obtained from World Bank Development Indicators Website 2015. The initial data was annual but later transformed into quarterly data using Eviews software. The rationale for splitting the data is because short term forecast is better than long term forecast. The starting date 1994 is considered because it is the period immediately after devaluation when Cameroon's growth rate assumed a continuous positive value. This study employed ARMA, and the mixed ARIMA/GARCH models with aim of identifying the best model suitable for predicting future growth rates for Cameroon.

ARIMA Models

The analysis of ARIMA models follows the Box-Jenkins methodology

³ For Fractional Autoregressive Integrated Moving Average model,(see, Green 2004, 647-648).

that 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 (1970). The Box-Jenkins methodology begins with an ARMA (p,q) model which combines both the AR and MA models as follows:

$$Y_t = \gamma x_t + e_t \dots \dots \dots (2)$$

$$e_t = \sum_{i=1}^p \alpha_i y_{t-i} + \sum_{j=1}^q \beta_j \varepsilon_{t-j} + \mu_t \dots \dots \dots (3)$$

Where, x_t represents the explanatory variables, e_t is the disturbance term. In equation (3), (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; l=d) then the ARMA (p,q) model becomes ARIMA(p,d,q) models (Auto- regressive Integrated Moving Average of order p,q).

Conceptual Framework for the Box-Jenkins Methodology

The process of Box-Jenkins ARIMA modeling requires four major steps: identification, estimation, diagnostic checking and forecasting.

1) The identification process starts by testing for the stationary properties of the series. This is done by analyzing the correlogram of the time series or carrying out a unit root test (Augmented Dickey Fuller Test and Phillips Perron test)⁴. After testing the stationary properties, it is essential to find the order of the ARIMA process. An autoregressive process AR (p) model has partial autocorrelations (PACF) that truncates at lag 'p' while its autocorrelation functions (ACF) dies off smoothly at a geometric rate. A moving average process MA (q) has an ACF that is truncated at lag 'q', while its partial autocorrelations (PACF) declines geometrically.

Alternative model selection criteria such as Akaike Information Criteria, Schwarz Bayesian Criteria⁵, Adjusted R², and Final Prediction Error can be used to verify the order (p,q).

2) After determining the order of p and q the specified regression model is estimated which entails a nonlinear iterative process of the parameters α_i and β_j . An optimization criterion like least error of sum of squares, maximum likelihood or maximum entropy is used. An initial estimate is usually used. Each iteration, is expected to be an improvement of the last one until the estimate converges to an optimal one (Etuk et al., 2012).

⁴ADF test: $\Delta X_t = a + bt + \rho X_{t-1} + \sum_{i=1}^k \Delta X_{t-i} + \mu_t$: ΔX_t is the first difference of the series X, k is the lag order, t is the time.

PP test: $\Delta X_t = a + bX_{t-1} + c(t + \frac{T}{2}) + \mu_t$; a, b, and c are the coefficients and T is the total number of observations. Therefore, the ADF and PP unit root tests posit a null hypothesis $\beta = 0$ versus an alternative hypothesis $\beta < 0$, where the ADF and PP statistics is compared with the observed Mackinnon critical values.

⁵ $AIC(p + d + q) = \ln \sigma_{p+d+q}^2 + 2(p + d + q)$ and $SIC(p + d + q) = \ln \sigma_{p+d+q}^2 + \frac{2(p + d + q)}{n}$

σ^2 is the maximum likelihood estimate of the residual variance when the model has k parameters. The optimum model corresponds to the minimum of the criteria within the explored range.

3) The fitted model is tested for goodness-of-fit. It can be tested using the above mentioned model selection criteria. Alternatively, the ACF and PACF obtained from the residual of the specified ARIMA model as well as the χ^2 and Ljung-Box Q statistics are diagnostic checking tools. If the residual is free from all classical assumption of the regression model and stationary then the model is correct (Purna, 2012).

4) The estimated ARIMA model is used to recursively forecast periods ahead.

Consider the general ARMA model:

$$y_t = \alpha + \varphi_1 y_{t-1} + \dots + \varphi_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \dots \dots \dots (4)$$

Then the forecasted ARIMA model:

$$\hat{y}_{t+1} = \hat{\alpha}_1 y_t + \hat{\alpha}_2 y_{t-1} + \hat{\theta}_1 \varepsilon_t + \hat{\theta}_2 \varepsilon_{t-1} + \hat{\delta} \dots \dots \dots (5)$$

Where a, is the intercept term, φ_i are the parameters of the autoregressive process, θ_j are the parameters of moving average process.

ARCH/GARCH Model

The Autoregressive Conditional Heteroscedastic (ARCH) model was formulated by (Engle, 1982) and extended to the Generalised Autoregressive Conditional Heteroscedastic (GARCH) model by Bollerslev (1986). This approach requires a joint estimation of the mean and variance equations. The current conditional variance a time series depends on the past squared residuals of the process and on the past conditional variances.

A univariate regression with GARCH (p,q) effects in a polynomial form with a lag operator is represent as:

Mean Equation:

$$y_t = x_t \gamma + \varepsilon_t \dots \dots \dots (6)$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, \delta_t^2) \text{ and } \varepsilon_t = v_t \sqrt{\sigma_t^2}$$

Variance Equation:

$$\sigma_t^2 = \sigma + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \dots \dots \dots (7)$$

Where, p is the order of GARCH term and q is the order of ARCH term.

Whereas y_t is the endogenous variable and x_t exogenous, Ω_{t-1} is all collected messages up to t-1 period, and δ_t^2 is conditional variance which depends linearly on past squared-error terms and past variances. $\gamma_i \geq 0, \varphi_i \geq 0, \forall i$ are parameters to be estimated. $\alpha_i + \beta_i \leq 1$.

ARIMA/GARCH

A combination of the ARIMA (p,d,q) and the GARCH(p,q) are expressed as:

$$(\Delta y_t)^d = \sum_{i=1}^p \rho_i (\Delta y_{t-1})^d + \varepsilon_t + \sum_{j=1}^q \varphi_i \varepsilon_{t-j} \dots \dots \dots (8)$$

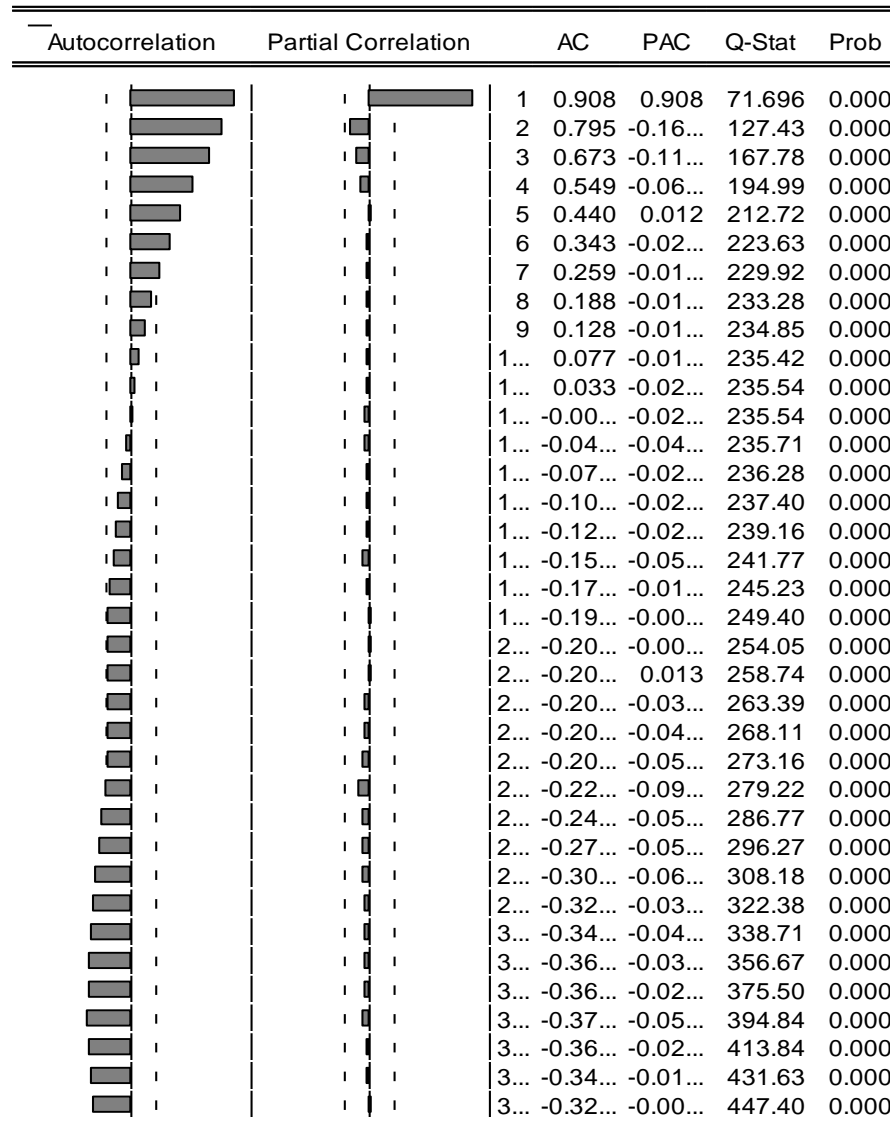


Figure 3. Correlogram of GDP growth rate series. Source: Eviews 9 Output.

Table 1. Quarterly seasonal coefficients.

Scaling factor	
1	0.999556
2	0.999051
3	1.000360
4	1.001034

Original series: GDP; Adjusted Series: GDPSA.

DGDPSA series. Only the first three spikes of the simple autocorrelation function (SACF) are significantly different from zero because they extend outside the band confidence interval while the remaining spikes die down slowly with the band up to the last lag. The spikes of

partial autocorrelation function (PACF) follow a sinusoidal pattern within the first nine lags and dies down slowly within the band confidence interval. It implies the anticipated model that can be used to project Cameroon's growth rate is a moving average model of order three

Table 2. Augmented Dickey–Fuller and Phillips-Perrons Tests for GDPSA at Levels (Eviews 9 Output)..

Null hypothesis: GDPSA has unit root		t-Statistic	Probability value
Augmented Dickey-Fuller test statistic		-1.243662	0.2980
Test critical values:	1% level	-4.072415	-
	5% level	-3.464865	-
	10% level	-3.158974	-
Phillips-Perron test statistics		-2.563179	0.0884
Test critical values:	1% level	-4.072415	-
	5% level	-3.464865	-
	10% level	-3.158974	-

Source: Eviews 9 Output

Table 3. Augmented Dickey–Fuller and Phillips-Perrons Tests for GDPSA at First Difference (Eviews 9 Output).

Null hypothesis: GDPSA has unit root		t-Statistic	Probability value
Augmented Dickey-Fuller test statistic		-3.50809	0.2980
Test critical values	1% level	-4.086877	-
	5% level	-3.471693	-
	10% level	-3.162948	-
Phillips-Perron test statistics		-4.239618	0.0061
Test critical values	1% level	-4.073859	-
	5% level	-3.465548	-
	10% level	-3.159372	-

[MA (3)]. Table 4 shows the estimated result of ARMA (0, 1, 3) inconformity with $p + q \leq 5$ criteria. The values of DW and R^2 are good and the values of the Akaike and Schwarz criteria are small. Also, all the coefficients of the model are statistical different from zero. Conclusively, the model is well fitted and can be used for projections. The correlogram in Figure 5 shows that none of the spikes extends out of the intervals and also, the Q-statistic has a critical probability value closer to 1 as we move downwards to the last lag. Thus, the residuals can be assimilated to a white noise.

However, the series exhibits a heteroskedastic property because the ARCH (1) test has a probably value of 0.000102 smaller than 0.05. Thus, to make the model void of heteroskedasticity, the series is modelled as ARIMA/ARCH or GARCH process.

Tables 5 and 6 show the results of the estimated ARIMA(0,1,3)/GARCH(1,2) and ARIMA(0,1,3)/E-GARCH (1,2) model. The models are more robust than the previous estimated ARIMA(0,1,3) model because the probability values of the ARCH tests are 0.99 and 0.104

greater than 0.05. Also, all the ARCH and GARCH effects are significant. Hence, Cameroon's growth rate can be forecasted using an ARIMA/GARCH mix model (Table 8).

Model selection criteria

The Root mean squared error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE) and Theil's inequality coefficient (U-Statistics)⁷ were used to determine the best forecasting model: The table below shows that, ARIMA(0,1,3)/E-GARCH (1,2) is the best

$$\begin{aligned}
 &^7 1. \quad RMS = \sqrt{\frac{ESS}{n}} \quad 2. \quad MAE = \sum_{t=1}^n |Y_t - \hat{Y}_t| \quad 3. \\
 &MAPE = \frac{\sum_{t=1}^n \frac{|Y_t - \hat{Y}_t|}{Y_t}}{n} \times 100\% \\
 &4. U - Statistics = \frac{RMSE}{\sqrt{\frac{\sum_{t=1}^n \hat{Y}_t^2 / n}{\sum_{t=1}^n Y_t^2 / n}}}
 \end{aligned}$$

NB: Y_t = The actual value at time t ; \hat{Y}_t = The forecast value at time t ;
 n = The number of observations; ESS = The error sum of square.

Sample: 1994:1 2014:4
 Included observations: 83

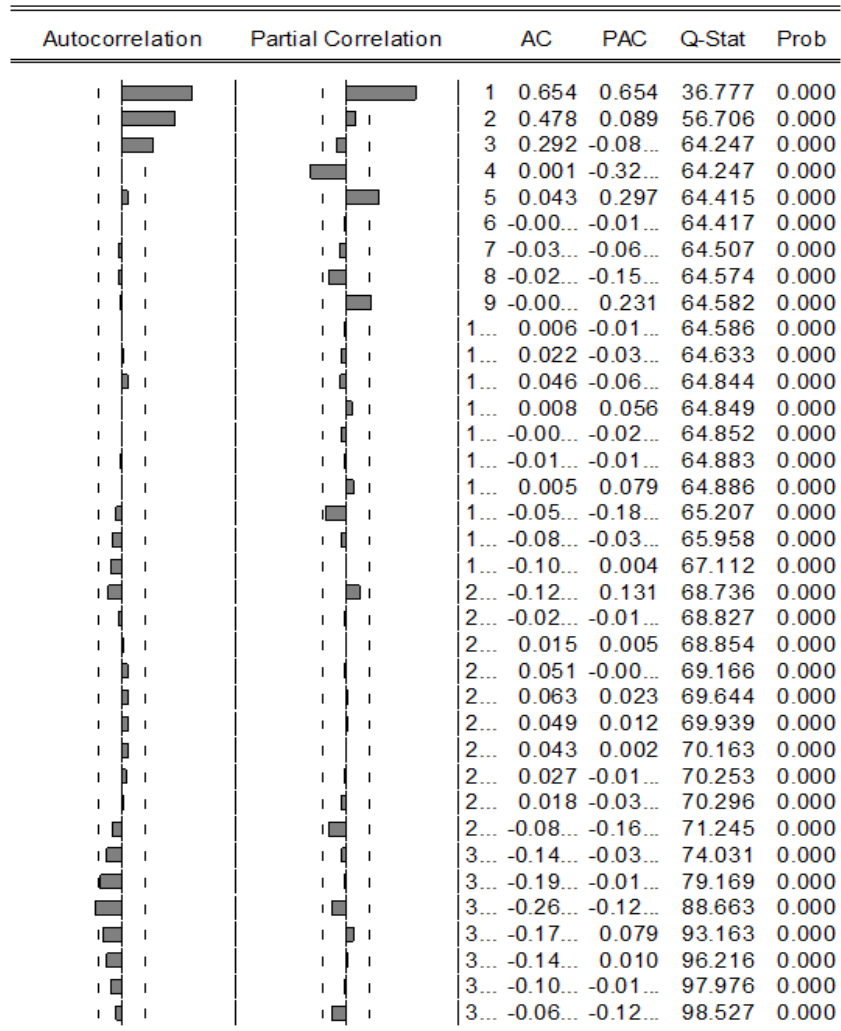


Figure 4. Correlogram of GDPSA after first difference (DGDPSA). Source: Eviews 9 Output.

Table 1. Estimated ARIMA (0,1,3).

Dependent Variable: DGDPSA				
Method: ARMA Maximum Likelihood (OPG - BHH...)				
Date: 10/29/15 Time: 11:12				
Sample(adjusted): 1994:2 2014:4				
Included observations: 83 after adjusting endpoints				
Convergence achieved after 18 iterations				
Backcast: 1993:3 1994:1				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(1)	-0.846074	0.079490	-10.64381	0.0000
MA(2)	-0.756934	0.079598	-9.509519	0.0000
MA(3)	-0.837983	0.046018	-18.20977	0.0000
R-squared	0.704842		Mean dependent var	0.058445

Table 2. Cont'd.

Adjusted R-squared	0.697463	S.D. dependent var	0.269200
S.E. of regression	0.148069	Akaike info criterion	-0.946801
Sum squared resid	1.753954	Schwarz criterion	-0.859373
Log likelihood	42.29226	Durbin-Watson stat	2.164340
Inverted MA Roots	0.06 -0.93i	.06+0.93i	-0.96
ARCH Test:			
F-statistic	18.05054	Probability	0.000058
Obs*R-squared	15.09573	Probability	0.000102

Source: Eviews 9 Output.

Date: 10/29/15 Time: 11:52
 Sample: 1994:1 2014:4
 Included observations: 83
 Q-statistic probabilities adjusted for 3 ARMA terms

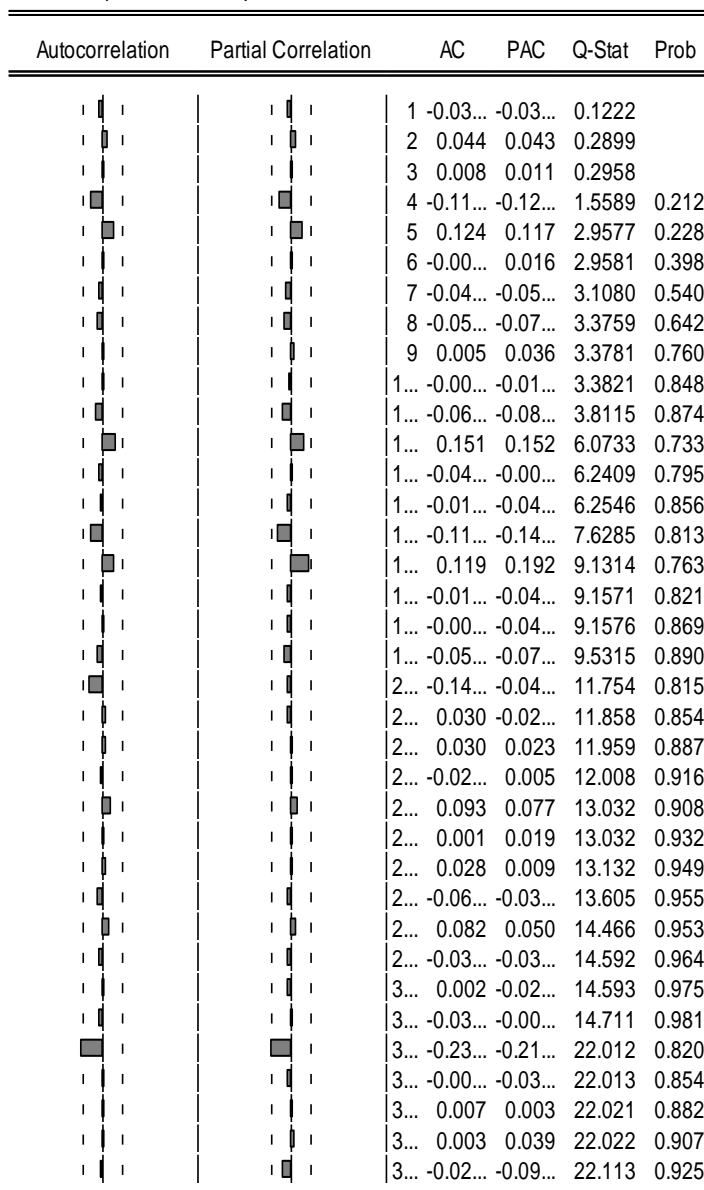


Figure 5. Correlogram of Residuals. Source: Eviews 9 Output.

Table 5. Estimated ARIMA (0,1,3)/GARCH(1,2).

Dependent Variable: DGDPSA				
MA backcast: 1993:3 1994:1, Variance backcast: ON				
	Coefficient	Std. Error	z-Statistic	Prob.
MA(1)	-0.778241	0.067371	-11.55153	0.0000
MA(2)	-0.663977	0.050183	-13.23123	0.0000
MA(3)	-0.818884	0.033676	-24.31626	0.0000
Variance Equation				
C	0.013918	0.006297	2.210291	0.0271
ARCH(1)	0.577803	0.167633	3.446824	0.0006
GARCH(1)	-0.508768	0.223608	-2.275267	0.0229
GARCH(2)	0.126521	0.083293	1.518985	0.1288
R-squared	0.699721	Mean dependent var		0.058445
Adjusted R-squared	0.676015	S.D. dependent var		0.269200
S.E. of regression	0.153228	Akaike info criterion		-1.154023
Sum squared resid	1.784383	Schwarz criterion		-0.950025
Log likelihood	54.89197	Durbin-Watson stat		2.028309
Inverted MA Roots	0.09+0.92i	.09 -.92i		-.97
ARCH Test:				
F-statistic	0.000127	Probability		0.991026
Obs*R-squared	0.000130	Probability		0.990886

Table 6. Estimated ARIMA (0,1,3)/E-GARCH(1,2).

Dependent variable: DGDPSA				
MA backcast: 1993:3 1994:1, Variance backcast: ON				
	Coefficient	Std. Error	z-Statistic	Prob.
MA(1)	-0.835273	0.067511	-12.37244	0.0000
MA(2)	-0.693393	0.056529	-12.26612	0.0000
MA(3)	-0.831580	0.033022	-25.18233	0.0000
Variance Equation				
C	0.028453	0.094023	0.302614	0.7622
RES /SQR[GARCH](1)	-0.235068	0.027465	-8.558732	0.0000
RES/SQR[GARCH](1)	-0.322097	0.047638	-6.761345	0.0000
EGARCH(1)	0.602136	0.066829	9.010119	0.0000
EGARCH(2)	0.356777	0.082554	4.321723	0.0000
R-squared	0.696909	Mean dependent var		0.058445
Adjusted R-squared	0.668621	S.D. dependent var		0.269200
S.E. of regression	0.154966	Akaike info criterion		-1.254413
Sum squared resid	1.801093	Schwarz criterion		-1.021272
Log likelihood	60.05814	Durbin-Watson stat		2.180181
Inverted MA Roots	.08+.91i	.08 -.91i		-.99
ARCH Test:				
F-statistic	2.659603	Probability		0.106857
Obs*R-squared	2.638380	Probability		0.104310

Source: Eviews 9 Output.

Table 7. Model selection criteria.

Criteria	ARIMA (0,1,3)	ARIMA (0,1,3)/GARCH(1,2)	ARIMA(0,1,3)/E-GARCH (1,2)
RMSE	0.145	0.146	0.147
MPAE	109.105	108.59	107.66
MAE	0.105	0.105	0.1044
U-Statistics	0.2897	0.2944	0.2938

Source: Eviews 9 Output.

Table 8. Projected quarterly growth rates (%) for Cameroon.

Year	ϵ_t	DGDPSA	GDPSA	Seasonal coefficients (SA)	Projected future values	China's annual growth rate	
						Year	Annual growth rate (%)
2014:q2	-0.0541					1982	9.02
2014:q3	-0.0683					1983	10.75
2014:q4	-0.0628		5.8662			1984	15.21
2015:q1		0.19944	6.06563	0.99956	6.06294	Source: WDI (2014)	
2015q2		0.00885	6.07449	0.99905	6.06871		
2015:q3		0.04501	6.11949	1.0031	6.13848		
2015:q4			6.11949	1.00103	6.12582		

Source: Author's Calculations Based on Estimated Results.

model for forecasting Cameroon's future economic growth rate. ARIMA (0,1,3) though is good, was rejected because it exhibited a heteroskedastic property (Table 7).

Projections based on ARIMA (0,1,3)/E-GARCH (1,2)

The study used the method employed earlier by Dobre and Alexandru (2008) adopted from Bourbonnais (2005:256). The itinerary for the projection based on the estimated results in Table 8 is as follows:

$$DGDPSA_t = (1 - 0.83527D - 0.693393D^2 - 0.83158D^3)\epsilon_t$$

$$DGDPSA_t = \epsilon_t - 0.83527\epsilon_{t-1} - 0.63393\epsilon_{t-2} - 0.83158\epsilon_{t-3}$$

The residual values for the last three quarters are:

$$\epsilon_{2014:4} = -0.0628; \epsilon_{2014:3} = -0.06830; \epsilon_{2014:2} = -0.05412.$$

The above result suggests that Cameroon's economic growth rate will increase approximately from 6.06% to 6.07% and to 6.13% in 2015 quarters 1, 2 and 3 respectively and will drop thereafter by 0.012% in quarter 4. This implies that Cameroon cannot sustain a steady growth path. On an average, Cameroon's annual growth rate will be approximately 6.099% everything being equal. The results show that the growth pace is still very slow as compared to China that maintained a steady and sustainable annual growth rate of 9.02 and 10.75% in

1982 and 1983 and jumped significantly to 15.21% in 1984 just immediately after the transition program to emergence was initiated. Therefore, policy makers in Cameroon need to double their efforts if they really want to fructify the vision of an emerging economy by the year 2035.

Conclusion

Cameroon is among the African countries aspiring to become an emergent economy by the year 2035. The fundamental objective of this study was to project Cameroon's future economic growth rate and to ascertain whether policy makers could maintain a steady and sustainable growth rate like China that transcended from a developing economy into an emerging economy. The study employed the ARIMA/GARCH models and concluded that the ARIMA (0,1,3)/E-GARCH(1,2) is the best model for projecting Cameroon's future growth rates and relevant for policy implication. This model is very appealing because the forecasted results are in conformity with the current annual growth rate of Cameroon as established by the government in December.

An important finding from this study is that Cameroon's growth pattern is slow and not sustainable. Therefore, Cameroon's policy makers need to double their efforts in order to become like China by the year 2035.

Conflict of Interests

The author has not declared any conflict of interests.

REFERENCES

- Abeyasinghe T (1998). Forecasting Singapore's Quarterly GDP with Monthly External Trade. *Int. J. Forecasting* 14:505-513.
- Ahmad S, Latif H (2011). MP1 Competencies Analysis of Box-Jenkins Method in Forecasting Electricity Demand, Empowering Science, Technology and Innovation Towards a Better Tomorrow. UMTAS, pp. 201-204.
- Assis K, Amran A, Remali Y (2010). Forecasting Cocoa Beans Prices Using Univariate Time Series Models. *Int. Refereed Res. J.* 1:71-80.
- Baffigi A, Golinelli R, Parigi G (2004). Bridge Models Forecast the Euro Area GDP. *Int. J. Forecasting*, 20:447-460.
- Barth J, Caprio G, Phumiwasana T (2009). China's Emerging Financial Markets, The Milken Institute Series on Financial Innovation and Economic Growth 8:73-110.
- Bourbonnais R (2004). Manuel et exercices corrigés, 4^e édition Dunod, Paris.
- Bollerslev T (1986). Generalized Autoregressive Conditional Heteroskedasticity. *J. Econ.* 31(3):3 07-327.
- Box G, Jenkins G (1970). *Time Series Analysis: Forecasting and Control*. San Francisco: Holden-Day.
- Box G, Jenkins G (1976). *Time Series Analysis: Forecasting and Control*. 1st Edn., Holden-Day, San Francisco, , P 575.
- Cameroon (2009). Working paper. Yaounde: Ministry of the Economy, Planning and Regional Development.
- Dobre I, Alexandru A (2008). Modelling Unemployment Rate Using Box-Jenkins Methodology. *J. Appl. Quant. Method.* 3(2):156-166
- Engle F (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50(4):987-1008.
- Eilham K, Masoumeh Z, Ebrahim B (2010). Prediction of added value of agricultural subsectors using artificial neural networks: Box-Jenkins and Holt-Winters methods. *J. Dev. Agri. Econ.* 2(4):115-121.
- Etuk H, Uchendu B, Uyodhu V (2012). Arima Fit to Nigerian Unemployment Data. *Journal of Basic and Applied Scientific Research*, 2(6)5964-5970 ISSN, pp. 2090-4304.
- Freedom House (2014). <https://freedomhouse.org/report/freedom-world/freedom-world-2014>
- Floros C (2005). Forecasting the UK Unemployment Rate: Model Comparisons. *International Journal of Applied Econometrics and Quantitative Studies*.2-4:55-72.
- Gan W, Wong F (1993). A Bayesian Vector Autoregression Model for Forecasting Quarterly GDP: The Singapore Experience. *Singapore Economic Rev.* 38:15-34.
- Gil-Alana A (2001). A fractionally Integrated Exponential Model for UK Unemployment. *J. Forecasting* 20:329-340.
- Golan A, Perloff J (2002). Superior Forecasts of the U.S. Unemployment Rate Using a Nonparametric Method". UDARE Working Papers, P 956. <http://repositories.cdlib.org/are/ucb/956>
- Greene W (2003). *Econometric Analysis*. 3rd ed, Englewood Cliffs, N.J.: Prentice Hall.
- Ghosh S (2008). Univariate Time-Series Forecasting of Monthly Peak Demand of Electricity in Northern India. *Int. J. Indian Culture and Bus. Manage.* 1(4):466-474 .
- Gujarati D (2004). *Essentials of Econometrics*. 4th ed., McGraw-Hill, New York.
- Floros C (2005). Forecasting the UK Unemployment Rate: Model Comparisons. *Int. J. Appl. Econ. Quant. Stud.* 2-4:55-72.
- Hukkinen J, Viren M (1999). Assessing the Forecasting Performance of a Macroeconomic Model. *J. Policy Model.* 21:753-768.
- Javedani H, Suhartono L (2010). An Evaluation of Some Classical Methods for Forecasting Electricity Usage on Specific Problem. Proceedings of the Regional Conference on Statistical Sciences (RCSS'10), pp. 47-56.
- Kamil A, Noor A (2006). Time series modeling of Malaysian raw palm oil price: Autoregressive conditional heteroskedasticity (ARCH) model approach. *Discov. Math.* 28:19-32.
- Lee H, Rahman H, Suhartono L, Nor M, Kamisan M (2012). Seasonal ARIMA for Forecasting Air Pollution Index: A Case Study. *Am. J. Appl. Sci.* 9(4):570-578.
- Makridakis S, Andersen A, Carbone R, Fildes R, Hibon M, Lewandowski R, Newton J, Parzen E, Winkler R (1982). The Accuracy of Extrapolative (Time Series Methods): Results of a Forecasting Competition, *J. Forecasting* 1(2):111-153.
- Mandal B (2005). Forecasting Sugarcane Productions in India with ARIMA Model. www.interstat.statjournals.net
- Nasir M, Hwa K, Huzafah M (2006). An Initial Study on the Forecast Model for Unemployment Rate". Workshop Review of the Labour Force/Migration Survey, Putrajaya, Malaysia.
- Nelson D (1996). Conditional Heteroskedasticity in Asset Returns: A New Approach *Econometrica* 59(2):347-370
- Nkwatoh L (2012). Forecasting Unemployment Rates in Nigeria Using Univariate Time Series Models. *Int. J. Bus. Commun.* 1(12):33-46.
- Pardhan P (2012). Use of Univariate Time Series Models for Forecasting Cement Productions in India. *Int. Res. J. Financ. Econ.* 83:167-179.
- Pei L, Shih-Huang C, Hui-Hua Y, Ching-Tsung H, Mei-Rong T (2008). Application of Artificial Neural Network and SARIMA in Portland Cement Supply Chain to Forecast Demand. *Natural 179 International Research Journal of Finance and Economics - Issue 83* (2012). Fourth International Conference, 18- 20 Oct. 2008, 3:97-101.
- Purna C (2012). Use of Univariate Time Series Models for Forecasting Cement Productions in India. *Int. Res. J. Financ. Econ.* 83:167-179.
- Proietti T (2001). Forecasting the US Unemployment Rate. Working Paper, Dipartimento Di Scienze Statistiche, Università Di Udine, Udine, Italy.
- Purna C (2012). Use of Univariate Time Series Models for Forecasting Cement Productions in India. *Int. Res. J. Financ. Econ.* 83:167-179.
- Reilly D (1980). Experiences with an automatic Box-Jenkins modeling algorithm. *Time Series Analysis-Proceedings of Houston Meeting on Time Series Analysis*, Amsterdam: North-Holland publishing.
- Reynolds S, Mellichamp J, Smith R (1995). Box-Jenkins forecast model identification. *AI Expert*, pp.15-28.
- Sarbijan S (2014). A Comparison Study between Markov Switching Time Series Model and Arima Model for Forecasting Iran Economic Growth. *Int. J. Sci. Res. Knowled.* 2:058-065.
- Slutsky E (1937). The Summation of Random Causes as the Source of Cyclic Processes. *Econometrica*, 5:105-146.
- Syariza A, Noorhafiza M (2005). Comparison of time Series methods for electricity forecasting: A case study in Perlis. *ICOQSIA*, pp. 6-8 December, Penang, Malaysia.
- Taylor W (2008). A comparison of univariate time series methods for forecasting intraday arrivals at a call center. *Manage. Sci.* 54:253-265.
- Wankhade R, Mahalle S, Gajbiye S, Bodade V (2010). Use of the ARIMA Model for Forecasting Pigeon Pea Production in India. *Int. Rev. Bus. Financ.* 2(1):97-102
- World Development Indicator (2014). <http://data.worldbank.org/data-catalog/world-development-indicators>.
- Yule G (1926). Why Do We Sometimes Get Nonsense-Correlations between Time Series? A Study in Sampling and the Nature of Time Series. *J. Royal Stat. Soc.* 89:1-64.
- Zhou B, He D, Sun Z (2006). *Modeling and Simulation Tools for Emerging Telecommunication Networks*. Springer US: pp. 101-121.
- Zakion J (1996). Threshold Heteroskedastic models. Manuscript, CREST, INSEE, Paris.