Forecasting Unemployment Rates in Nigeria Using Univariate Time Series Models

Louis Sevitenyi Nkwatoh
Yobe State University, Nigeria
Email: Sevinkwatoh@Gmail.Com,
Tel: +2348062218765

Abstract

One of the major problems faced by policy makers is coping with the persistent increase in the level of unemployment in Nigeria. Thus projecting future unemployment rates is imperative to policy makers. The main objective of this paper is to search the best forecasting model among: the trend regression, autoregressive moving average (ARMA), autoregressive conditional heteroscedasticity (ARCH) and the generalized autoregressive conditional heteroscedasticity (GARCH) model that could give the best prediction of future unemployment rates in Nigeria. Applying quarterly data from 1976Q1 to 2011Q4 on unemployment rates, this study evaluated the forecasting performance of the four competing models using the forecast accuracy criteria such as the root mean squared error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE) and the Theil's inequality coefficient (U-STATISTICS). The results established that a positive and significant linear trend factor influenced the time series data. Furthermore, the Autocorrelation function (ACF) the Augmented Dickey-Fuller (ADF) and Phillips-Perron tests showed that the time series data was non stationary but was made stationary by differencing once. Among these models, the empirical study reveals that the mixed ARIMA/ARCH model could reasonably be used to forecast unemployment rates in Nigeria specifically in the short-run. Thus for policy implication an ARIMA (1,1,2)/ARCH (1) is relevant for decision making.

Keywords: *JEL: E24, C22, C53*

I. Introduction

Unemployment is one of the most challenging problems facing the governments of developing countries. In Nigeria, statistics show that, the level of unemployment is very high and most prevalent among the youths, who find it difficult to fulfill their aspirations, assume their economic independence thus failing to contribute gainfully to the economic development of the Country. The resultant effect of unemployment in Nigeria can be categorized into two. One, it increases the level of poverty in the country and two, it causes idleness among the youths, which makes them to engage into undesirable activities, thus wasting their talents, valuable skills energy and time.

A number of factors among others that have exacerbated the rise of unemployment in Nigeria are: One, structural factors which have to do with the mismatch between the nature of the educational system and the needs of the labor market, technical change and the use of capital intensive techniques of production, the skill mix of the labour force and available job opportunities. Two, Cyclical factors such as the insufficiency of aggregate local and foreign demand for goods and services. Three, institutional factors such as the move by the World Bank and IMF in the 1980s, ordering developing Countries to downsize their public sector and civil services (ILO Publication, 2005) and also, activities of labor unions and labor market regulations.

However, various administrative initiatives have been implemented to promote self-dependency and self-reliance that will gainfully generate self-employment, thus reducing the rate of unemployment. For instance, the introduction of vocational courses in the educational curriculum in 1997, the creation of the National Directorate of Employment in 1986 charged with the responsibility of promoting skills acquisition, the National Economic Empowerment and Development Strategies designed in 2004 with one of its doctrinal values geared towards fighting unemployment, coupled with election promises. Despite the above initiatives undertaken by the various regimes, reducing unemployment to a desirable minimum still remains elusive. For instance, Adebayo and Ogunrinola, (2006) and NBS (2010), cited in Ayoyinka and Oluranti (2011) confirmed that, the rate of open unemployment was 12% in March 2006; it rose to 19.7% in March 2009 while the rate of underemployment hovered around 19% in 1998 Among the youths in the 15-24 age cohort, the rate of unemployment is over 40% according to the 2010 edition of the Labour Force Sample Survey of the National Bureau of Statistics. Thus, signals of future unemployment rates are necessary for policy makers to plan and strategize before time in order to circumvent the persistent rise in unemployment levels in the Country. Consequently the main objective of this work is to identify the best forecasting model among others that can be used to model and forecast future unemployment rates in Nigeria.

2. Literature Review

Literature on macroeconomic modeling, and forecasting,with the use of historical data from time series (univariate or multivariate time series) is vast. Modeling unemployment rates like any other macroeconomic variable has been analyzed traditionally by building econometric models, often related to stationary time series, ranging from trend analysis, and exponential smoothening to the simple OLS technique including Autoregressive Integrated Moving Average(ARIMA) models and to the GeneralisedAutoregressive Conditional Heteroscedastic (GARCH) models (see, Elham et al, 2010; Assis et al, 2010).

The Box and Jenkins methodology has been extensively used, to project future macroeconomic variables likewise unemployment rates. Ion and Andriana (2008) used an ARIMA (2,1,2) to forecast future unemployment rates in Romania. Power and Gasser (2012) established that an ARIMA (1,1,0) model gave a better forecast for unemployment rates in Canada, while Etuk, Uchendu and Uyodhu (2012) arrived at an ARIMA (1,2,1) model for Nigeria. The suitability of the ARIMA models for projecting macroeconomic variables can also be found in studies: Purna (2012), forecasting cement production output in India; Mordi et al (2006) that analyzed inflation rates in Nigeria; Fatimah and Roslan (1998) that forecasted cocoa prices in Malaysia etc. Assis et al, (2010) noted that, these models have the advantage of relatively low research costs when compared with other econometric models, as well as efficiency in short termforecasting.

Recently, studies have analyzed time series model with the incorporation the Autoregressive Conditional Heteroscedastic (ARCH) model introduced by Engle (1982). These models have been extended to the Generalized Autoregressive Conditional Heteroscedastic (GARCH) models leading to more parsimonious results than ARCH models. This is similar to situations where ARMA models are preferred AR models

(Assis et al, (2010). Comparing the out-of-sample forecasting accuracy for the United Kingdom unemployment rate, Floros (2005) established that, though an MA(4) model performed well, while both MA(1) and AR(4) proved to be the best forecasting models, the MA(4)-ARCH (1) model provided superior forecasts of unemployment rate in UK. Zhou et al. (2006) proposed a new telecommunication network prediction model based on non-linear time series ARIMA/GARCH. Their findings suggested that the ARIMA/GARCH model outperformed the Fractional Autoregressive Integrated Moving Average (FARIMA) model initially used, in terms of prediction accuracy. Assis et al, (2010) have also demonstrated that the mixed ARIMA/GARCH model outperformed the exponential smoothing,ARIMA, and GARCH models when used for forecasting future prices of cocoa beans in Malaysia. A similar conclusion has been reached by Kamil and Noor (2006) in their approach to forecast the price of Malaysian raw palm oil using the Autoregressive Conditional Heteroskedasticity (ARCH) model.

However, neither, the ARIMA models nor the ARCH/GARCH models have proven their suitability in some economies or when used to model some macroeconomic variables. Jaafar,(2006) established that the Holt's method with two parameters was suitable to forecast five major labour force indicators i.e. labour force, employed, unemployed, unemployment rate and underemployed in Malaysia. Nasir, Hwa and Huzaifah (2008) used different univariate modelling techniques: the naive with a trend model, average change model, double exponential smoothing and Holt's model, to forecast future unemployment rates in Malaysia. They used the smallest value of mean square error (MSE) to identify the most suitable model and evidently concluded that the Holt's model outperformed other techniques. However, the relative advantage of the Holt's Method Model over the others is that, recent observations are given relatively more weighting in forecasting than the older observations.

Gil-Alana (2001) showed that a Bloomfield exponential spectral model gave a feasible result, in lieu of ARMA models, when modelling UK's unemployment rate. Golan and Perloff (2002) concluded in their study that, the nonparametric method of forecasting unemployment rates in the U.S outperformed many other well-known models, even when these models use more information. They however attributed this result to the nonlinearity in the data generating process.

3. Methodology/Forecasting Models

This work employed unemployment rates data from 1976 to 2011 obtainable from quarterly abstracts and annual reports of the Central Bank of Nigeria. In this context unemployment rate is regarded as the percentage of the workforce that is jobless.

Forecasting implies what will happen to the desired event in future, which involves lots of uncertainties. It involves the process of studying and analysing the past and the present to have a saying over the future Purna (2012). The mode of analysis can either be judgmental which makes use of personal opinions (subjectivity) or building structural models which is a quite tasky. This study employed different econometric time series models like: Trend regression, ARMA, and the mixed ARIMA/GARCH models.

Trend Regression

Regression analysis was used to check if a trend factor exists in the time series data and if significantly induces changes in unemployment rates.

The regression equation below was used to test for the existence of linear trend factors:

Where, Y_t is the time series data, *Trend* represents the linear trend factor, and are the coefficients ε_t is the error term with an assumption that it follows a of white noise *(WN)* process. The hypothesis of the above model is such that:

H_0: = 0 (No Trend factors exist)

H_1: ≠ 0 (Trend factors exist)

ARIMA Models

The analysis of ARIMA models follows the Box-Jenkins methodology that combines both the moving average (MA) and the autoregressive (AR) models. Initially, these models were analyzed by Yule-Walke. 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:

Where, x_t represents the explanatory variables, e_t is the disturbance term. In equation (21), (y_{t-i}) are AR terms of order p, are MA terms of order q and is a white-noise innovation term. In case of a non-stationary data, the series is differenced (integrated) such: , (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).

Box-Jenkins ARIMA modeling requires four 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).After testing the stationary properties, it is essential to find out highest 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 autocorrelation (ACF) that truncates at lag ‘q’, while its partial autocorrelations (PACF) declines geometrically.

Alternative model selection criteria such as Akaike Information Criteria, Schwarz Bayesian Criteria, Adjusted R^2, 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 and. 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).

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 $\chi 2$ 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:

Then the forecasted ARIMA model:

Where a, is the intercept term are the parameters of the autoregressive process, 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:

$\sim N(0,)$ and

Variance Equation:

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 is conditional variance which depends linearly on past squared-error terms and past variances. ,∀ are parameters to be estimated.≤ 1.

ARIMA/GARCH

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

4. Analysis of Results

This section began with the analysis of the effect of time on unemployment rate in Nigeria. The regression result reported below shows that the trend factor has a positive and significant influence on unemployment rate. That is, time induces a 64.9 percent increase in unemployment rate. This suggests that the total number of unemployed is more than double as years go by. This result is expected since the total number of graduates from tertiary institutions is on the increase every year and thus outweighs the absorptive capacity of the nation. The coefficient of determination (R^2) is quite high which indicates that, the variations in unemployment rate can adequately be explained by a linear trend. The Durbin-Watson value of 2.25 indicates the absence of serial correlation. The first order auto-regression AR(1) was used to correction for serial correlation. This is also called the Cochrane-Orcutt correction for serial correlation. Thus, the trend regression analysis can be used to forecast unemployment rates in Nigeria. Regression Results Showing Relationship Between Unemployment and Trend

UNEMPLOYMENT = -3.68268 + 0.6498*TREND + 0.79345*AR(1)

Std. Error	6.972	0.2927	6.354
t-Test	-0.528	2.220	6.354

$R^2 = 0.783$; DW = 2.25; F-Statistics = 57.77; p-Value = 0.000

ARIMA Model

The Box and Jenkins methodology was employed in view of obtaining a forecasting model for unemployment rate in Nigeria.The initial step in developing a Box-Jenkins model is to determine if the series is stationary or not. Three important approaches for investigating the stationary properties of a time series were employed: graphical analysis, the correlogram which analysis the simple autocorrelation function (ACF) and partial autocorrelation function (PACF) and the unit root test which makes use of the Augmented Dickey-Fuller test (ADF) and Phillips-Perron test (PP).

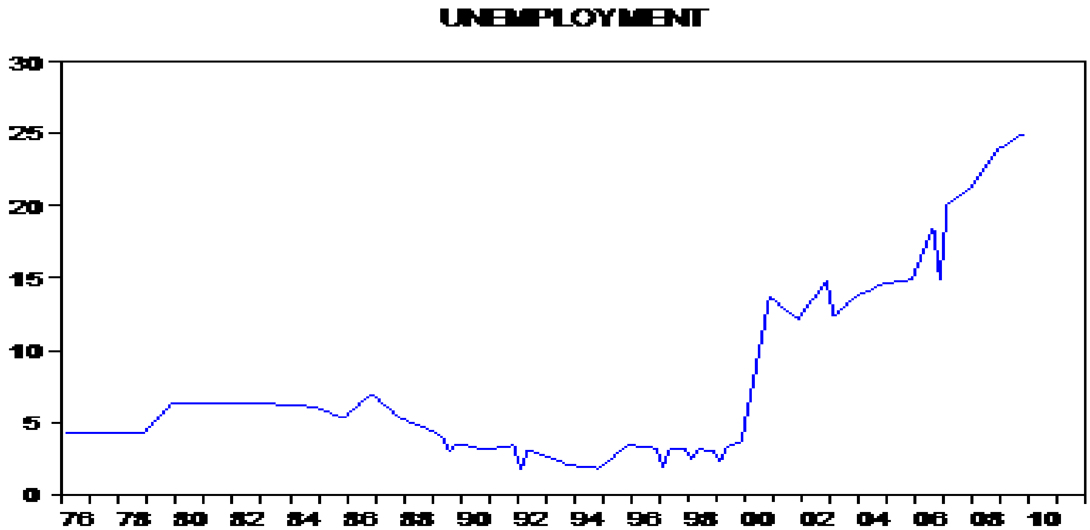

Figure 1: Time Series Plot of Unemployment Rates Series in Nigeria.

The graphical analysis in figure 1 above shows trendy movements; most especially upward trends from 2000 up to 2011. This suggests that the mean of the unemployment rate changes with time. Therefore, the unemployment rate series is non-stationary.

Figure 2 below, shows the correlogram of the unemployment rate series with a pattern of up to the 36th lag. The autocorrelation (ACF) starts with a high value and declines slowly, indicating that the series is non-stationary. Also the Q-statistic at lag 36has a probability value of 0.000 which is smaller than 0.05 thus not rejecting the null hypothesis that the unemployment rate series is non-stationary. Thus the series must be differenced for stationarity to occur.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|*******	.|*******	1	0.961	0.961	128.28	0.000
.|*******	.|. |	2	0.922	-0.005	247.42	0.000
.|******|	.|. |	3	0.881	-0.054	357.06	0.000
.|******|	.|. |	4	0.840	-0.032	457.33	0.000
.|******|	.|. |	5	0.797	-0.033	548.41	0.000
.|***** |	.|. |	6	0.757	0.000	631.07	0.000

.|*****		.|.		7	0.717	-0.009	705.88	0.000
.|*****		.|.		8	0.678	-0.014	773.32	0.000
.|*****		.|.		9	0.640	-0.022	833.77	0.000
.|****		.|.		10	0.602	-0.013	887.71	0.000
.|****		.|.		11	0.564	-0.020	935.52	0.000
.|****		.|.		12	0.528	-0.015	977.64	0.000
.|****		.|**		13	0.509	0.217	1017.2	0.000
.|***		*|.		14	0.478	-0.179	1052.4	0.000
.|***		.|.		15	0.451	0.014	1084.0	0.000
.|***		.|.		16	0.426	0.015	1112.4	0.000
.|***		.|.		17	0.406	0.049	1138.5	0.000
.|***		.|.		18	0.386	-0.022	1162.1	0.000
.|***		.|.		19	0.364	-0.036	1183.4	0.000
.|**		.|.		20	0.342	-0.019	1202.3	0.000
.|**		.|.		21	0.317	-0.062	1218.8	0.000
.|**		.|.		22	0.293	0.002	1232.9	0.000
.|**		.|.		23	0.268	-0.029	1244.9	0.000
.|**		.|.		24	0.244	-0.010	1254.8	0.000
.|**		.|.		25	0.219	0.036	1263.0	0.000
.|*		*|.		26	0.195	-0.107	1269.4	0.000
.|*		.|.		27	0.170	0.029	1274.4	0.000
.|*		.|.		28	0.146	-0.010	1278.1	0.000
.|*		*|.		29	0.111	-0.165	1280.3	0.000
.|*		.|.		30	0.077	-0.016	1281.3	0.000
.|.		.|.		31	0.046	0.010	1281.7	0.000
.|.		.|.		32	0.014	-0.029	1281.7	0.000
.|.		.|.		33	-0.016	-0.017	1281.8	0.000
.|.		.|.		34	-0.048	-0.048	1282.2	0.000
*|.		*|.		35	-0.081	-0.077	1283.4	0.000
*|.		*|.		36	-0.118	-0.070	1286.1	0.000

Figure 2: Correlogram of Unemployment Rate Series

The results of Augmented Dickey–Fuller (ADF) test and Phillips-Perrons (PP) test on unemployment rate series is presented on table 2 below. The t-statistic values for both ADF and PP tests are greater than their corresponding critical values; which reveals the fact that the null hypothesis of the presence of unit root in the series is not rejected. Hence the series is non stationary.

Table 1: ADF and Phillip-Perron Test on Unemployment Series.

Augmented Dickey-Fuller test statistic

			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			0.021503	0.9962
Test critical values:	1% level		-4.027463	
	5% level		-3.443450	
	10% level		-3.146455	

Phillp-Peron test statistic

			t-Statistics	Prob.*	
Phillips-Perron test statistic			0.022666	0.9962	
Test critical values:	1% level		-4.027463		
	5% level		-3.443450		
	10% level		-3.146455		
**MacKinnon critical values for rejection of hypothesis of a unit root*.					

The results of the Augmented Dickey Fuller (ADF) test and Phillips Perron (PP) test presented in table 2 shows that the unemployment series is stationary since the t-statistic values for both ADF and PP tests are less than their corresponding critical values; which reveals the fact that the null hypothesis of the presence of unit root in the series is rejected.

Table 2: ADF and Phillip-Perrons Test on Unemployment Series.

Augmented Dickey-Fuller test statistic

			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-12.53010	0.0000
Test critical values:	1% level		-4.027959	
	5% level		-3.443704	
	10% level		-3.146604	

Phillps-Peron test statistic

			Adj. t-Stat	Prob.*	
Phillips-Perron test statistic			-12.49060	0.0000	
Test critical values:	1% level		-4.027959		
	5% level		-3.443704		
	10% level		-3.146604		
**MacKinnon critical values for rejection of hypothesis of a unit root.*					

The correlogram in figure 3 shows that the terms (spikes) of the ACF and PACF lie within the band confidence interval significantly equal to zero at 5 percent. Furthermore, the Q-statistic has a probability value of 0.953 greater than 0.05 critical value. Therefore the null hypothesis is accepted based on the coefficient of the correlogram, that the unemployment series is stationary at first difference.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.042	-0.042	0.2394	0.625
.|* |	.|* |	2	0.165	0.164	4.0372	0.133
.|. |	.|* |	3	0.062	0.077	4.5745	0.206
.|. |	.|. |	4	0.068	0.048	5.2196	0.266
.|. |	.|. |	5	-0.004	-0.022	5.2214	0.389
.|. |	.|. |	6	0.041	0.017	5.4675	0.485
.|. |	.|. |	7	0.054	0.055	5.8918	0.552
.|* |	.|* |	8	0.089	0.087	7.0491	0.531
.|. |	.|. |	9	-0.015	-0.028	7.0832	0.628
.|. |	.|. |	10	0.021	-0.021	7.1507	0.711
.|. |	.|. |	11	-0.004	-0.015	7.1531	0.787
*|. |	*|. |	12	-0.071	-0.080	7.9013	0.793
.|. |	.|. |	13	0.022	0.020	7.9721	0.845
.|. |	.|. |	14	0.019	0.040	8.0271	0.888
.|* |	.|* |	15	0.102	0.108	9.6389	0.842
*|. |	*|. |	16	-0.087	-0.092	10.815	0.821
.|. |	.|. |	17	0.054	0.006	11.265	0.842
.|. |	.|. |	18	0.042	0.064	11.540	0.870
.|. |	.|. |	19	0.005	0.016	11.543	0.904
.|* |	.|* |	20	0.140	0.155	14.715	0.792
.|. |	.|. |	21	0.007	-0.011	14.723	0.837
.|. |	.|. |	22	0.059	-0.005	15.289	0.850
.|. |	.|. |	23	0.011	-0.021	15.309	0.883
.|. |	.|. |	24	0.015	-0.001	15.348	0.910
.|. |	.|* |	25	0.073	0.076	16.253	0.907
.|. |	.|. |	26	0.060	0.065	16.864	0.913
.|. |	.|. |	27	0.029	0.013	17.010	0.931
.|* |	.|* |	28	0.171	0.105	22.046	0.779
.|. |	.|. |	29	-0.019	-0.029	22.110	0.816
.|. |	*|. |	30	-0.011	-0.073	22.132	0.849
.|* |	.|* |	31	0.127	0.153	24.994	0.768
.|. |	.|. |	32	-0.020	-0.005	25.065	0.803
.|. |	.|. |	33	0.026	-0.027	25.191	0.833
.|. |	.|. |	34	0.003	-0.026	25.193	0.863
.|. |	.|. |	35	0.065	-0.001	25.968	0.866
.|. |	.|. |	36	-0.011	0.014	25.993	0.891

Figure 3: Correlogram of unemployment rate after first Difference

After stationarising the data, an appropriate ARMA (p, q) process was identified using the correlogram. Different estimated models which fulfilled the criteria of *p* *q*   5 were considered and compared, and the same time models whose parameters were not significant at 5% confidence level were dropped from the model. The estimation technique began by modelling the conditional mean process by an autoregressive process AR(1) and the moving average MA(1)with a further analysis of the correlogram of the residuals. Based on the Akaike criterion and the Schwarz criterion, the ARIMA(1,1,2) model gave a better fit as shown below.

Table 3: Results of ARMA (1,1, 2) model: (d(Unemployment)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.967567	0.034250	-28.25026	0.0000
MA(2)	-0.906691	0.055668	-16.28735	0.0000
R-squared	0.526898	Mean dependent var		0.002256
Adjusted R-squared	0.523287	S.D. dependent var		1.217538
S.E. of regression	0.840642	Akaike info criterion		2.505621
Sum squared resid	92.57493	Schwarz criterion		2.549085
Log likelihood	-164.6238	Hannan-Quinn criter.		2.523284
Durbin-Watson stat	2.177254			

The regression result above indicates that the coefficients of the model are significant based on the t-statistic. The coefficient of determination (R^2) is 52.6 %. The DW and the F statistics show the model has a good fit.

Figure4 shows that the auto-correlation functions (ACF) of the residuals which can also be used to test fitness of the regression model. It is observed that none of the terms (none of spikes) is exterior to the confidence intervals and the Q-statistic has a critical probability close to 1. Thus, the residuals may be assimilated to a white noise process, which implies the model gives a better fit. Thus, it is reasonable enough to use an ARIMA model to forecast unemployment rates in Nigeria.

Table 5 below shows the Lagrange Multiplier (LM) test. The *p*-value indicates the presence of an ARCH effect. This test result give us a firsthand information that unemployment rates in Nigeria can be modelled using ARCH, GARCH and ARIMA/GARCH models based on the significance of the ARCH and GARCH term.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*|. |	*|. |	1	-0.095	-0.095	1.2224	
.|* |	.|* |	2	0.095	0.086	2.4478	
.|. |	.|. |	3	0.019	0.036	2.4959	0.114
.|. |	.|. |	4	-0.008	-0.011	2.5041	0.286
.|. |	.|. |	5	-0.050	-0.058	2.8528	0.415

.|. |	.|. |	6	-0.029	-0.038	2.9720	0.563
.|. |	.|. |	7	0.017	0.022	3.0128	0.698
.|. |	.|. |	8	0.030	0.044	3.1407	0.791
.|. |	.|. |	9	-0.056	-0.054	3.5971	0.825
.|. |	.|. |	10	-0.039	-0.063	3.8207	0.873
.|. |	.|. |	11	-0.042	-0.047	4.0751	0.906
*|. |	*|. |	12	-0.113	-0.109	5.9704	0.818
.|. |	.|. |	13	-0.016	-0.023	6.0099	0.873
.|. |	.|. |	14	-0.023	-0.009	6.0867	0.912
.|* |	.|* |	15	0.077	0.076	6.9945	0.902
*|. |	*|. |	16	-0.130	-0.127	9.5735	0.793
.|. |	.|. |	17	0.027	-0.023	9.6881	0.839
.|. |	.|. |	18	0.010	0.022	9.7044	0.882
.|. |	.|. |	19	-0.027	-0.015	9.8158	0.911
.|* |	.|* |	20	0.117	0.123	11.994	0.848
.|. |	.|. |	21	-0.024	-0.025	12.085	0.882
.|. |	.|. |	22	0.030	-0.022	12.235	0.908
.|. |	.|. |	23	-0.019	-0.038	12.292	0.931
.|. |	.|. |	24	-0.015	-0.018	12.329	0.950
.|. |	.|. |	25	0.051	0.059	12.759	0.957
.|. |	.|. |	26	0.037	0.057	12.994	0.966
.|. |	.|. |	27	0.005	0.007	12.999	0.977
.|* |	.|* |	28	0.149	0.107	16.784	0.915
.|. |	.|. |	29	-0.052	-0.033	17.259	0.925
.|. |	*|. |	30	-0.042	-0.070	17.574	0.936
.|* |	.|* |	31	0.111	0.156	19.737	0.901
.|. |	.|. |	32	-0.045	0.004	20.098	0.914
.|. |	.|. |	33	0.002	-0.016	20.099	0.934
.|. |	.|. |	34	-0.022	-0.022	20.183	0.948
.|. |	.|. |	35	0.040	0.001	20.479	0.956
.|. |	.|. |	36	-0.039	0.013	20.763	0.964

Figure 4: The Correlogram of Residuals.

Table 4: ARCH LM Test on ARIMA (1,1,) Residuals.			
F-statistic	20.28684	Prob. F(2,129)	<0.01
Obs*R-squared	43.88374	Prob. Chi-Square(2)	<0.01

The regression result below shows that the coefficients of the model are significant as well the ARCH term. Therefore ARCH model can be a suitable model. This study rejected the GARCH model because all the different GARCH terms used in the different estimation models were insignificant

Table 5: Results of ARMA (1,1, 2)/ARCH(1) model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	-0.942958	0.006804	-138.5906	0.0000
MA(2)	-0.937420	0.009176	-102.1596	0.0000
	Variance Equation			
C	0.095794	0.009674	9.902176	0.0000
RESID(-1)^2	2.157868	0.332573	6.488409	0.0000
R-squared	0.517637	Mean dependent var		0.002256
Adjusted R-squared	0.513955	S.D. dependent var		1.217538
S.E. of regression	0.848830	Akaike info criterion		1.708744
Sum squared resid	94.38702	Schwarz criterion		1.795671
Log likelihood	-109.6314	Hannan-Quinn criter.		1.744068
Durbin-Watson stat	2.246583			

The results of LM test on table 5 indicate that the residuals do not show any ARCH effect which implies that the ARCH (1) model has adequately captured the persistence in volatility of the series. Hence, the ARIMA (1,1,2)/ARCH (1) model can reasonably be used to model and forecast unemployment rates in Nigeria.

Table 6: ARCH LM Test on ARCH(1)residuals.			
F-statistic	0.140101	Prob. F(1,130)	0.7088
Obs*R-squared	0.142103	Prob. Chi-Square(1)	0.7062

Model Selection Criteria

Four 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) were used to determine the best forecasting model from the three identified models that is the trend regression, ARIMA(1,1,2) and ARIMA (1,1,2)/ARCH (1) models. The table below shows that,from the three models considered, the ARIMA (1,1,2)/ARCH(1) gave the best forecasting model for unemployment rates in Nigeria.

Table 7: Model Selection Criteria……………………………………………..

Criteria	Trend	ARIMA (1,1,2)	ARIMA (1,1,2)/ARCH (1)
RMSE	14.51615	5.408114	5.321303
MPAE	276.9532	70.27601	70.25185
MAE	12.95547	3.988209	3.955172
U-Statistics	0.439882	0.314895	0.305862……..……

5. Conclusion

Projecting future unemployment rates like any other macroeconomic variable should be an important application to economists as well as policy makers. This paper investigated the different univariate time series models used for forecasting unemployment rates in Nigeria, namely trend regression analysis, ARIMA, GARCH, and the mixed ARIMA/GARCH models. Specifically, the forecasting techniques were compared based on the following criteria: Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percent Error (MAPE). Though all the models could be used for projection based on the significance of the parameters and the fitness of the models, the model selection criteria showed that the ARIMA/ARCH model outperformed the trend regression and the ARIMA models. Basically the results showed that unemployment rates in Nigeria could be modelled and predicted using an ARIMA (1,1,2)/ARCH(1) model. This results contradicts the findings of Etuk et al (2012) whose results showed that an ARIMA (1,2,1) could be used to forecast unemployment rates in Nigeria using monthly data from 1999 to 2008. This result is however possible since forecasting any macroeconomic variable may be affected by changes in time horizon (periods) as well as the sample size of the data.

A possible recommendation is that, since short-run projections are better, there should be continuous investigation of an appropriate model that could be used to project future unemployment rates. Further research on both simple and complex econometric techniques is imperative so that long-run unemployment rates could as well be projected.

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