SIMULATION STUDY ON THE COMPARISON OF ERROR CORRECTION MODEL AND AUTOREGRESSIVE DISTRIBUTED LAG MODEL FOR NON-NORMALLY DISTRIBUTED DATA

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ABSTRACT

This study investigates simulation study of the comparison between Error Correction Model (ECM) and Autoregressive Distributed Lag (ARDL) Model on non-normally distributed data. The study utilized both simulated data with 5000 iterations and the real life data of inflation rate and unemployment rate in Nigeria from a period of 1981 to 2016. The Augmented-Dickey Fuller (ADF) test revealed that inflation and unemployment are stationary at first difference while cointegration test and bound testing revealed an existence of long run relationship between the macroeconomic variables. The Root Mean Square Error (RMSE) of the simulated data of the two models were compared and the normality test (Jarque-Bera test) shows that the variables are non-normally distributed. The study revealed that the ARDL model outperforms the ECM model for both the real life data and simulated data and that there is evidence of both short and long run relationship between inflation rate and unemployment rate in Nigeria. It also revealed that there is causality relationship between inflation rate and unemployment. The study therefore recommended based on the findings that the Central Bank of Nigeria should pursue monetary policy that is consistent with the maintenance of a realistic and stable inflation rate in order to reduce the unemployment rate in Nigeria and the government should formulate adequate economic policies to stimulates and sustain the economic growth. In addition, the inflation rate should adequately check to achieve viable economy.

Keywords: ECM, ARDL, Cointegration, Simulation, Macroeconomic Variables

INTRODUCTION

As often acclaimed and attested to by many scholars, most economic variables are always not stationary at first level, but they become stationary at first difference. In such circumstances, models that are capable of taking care of the error correction mechanism are use in the analysis. Error Correction Models (ECMs) belong to a class of multiple time series models mainly used for data whose underlying variables possess long-run stochastic trend, known as the cointegration. ECMs also, are theoretically-driven techniques useful for estimating and evaluating both the short-term and the long-term relationships (effects) of one-time series on another series. The term error-correction mirrors the fact that the last-periods deviation from a long-run equilibrium, that influences its short-run dynamics. So, ECMs estimate the speed at which a variable (dependent) returns to equilibrium after a change has occurred in other variables (Iqbal & Uddin, 2013). ECMs are an appropriate modeling to use when the macroeconomic variables are cointegrated and useful when desiring the long-run forecast. Modeling time series and keeping their long-run information intact is mainly done through cointegration. Cointeegration entails the co-movement among variables under consideration (Zhao, et al, 2020). Cointegration test examines how multiple time series that are distinctively non-stationary, drifting extensively away from equilibrium is combined in such a way that the equilibrium forces ensure they are not pulled or drifted too far apart. This means that, cointegration is stationary linearly combination of variables which are individually non-stationary but become integrated to an order, I(1). Therefore, two or more non stationary series are said to be cointegrated if the linear combination of the two or more non stationary series is stationary (Emeka & Uko, 2016).

Autoregressive Distributed Lag (ARDL) model or bound test on the other hand investigates the short term and the long term association between time series data and also investigated the cointegration relationship among the macroeconomic variables. It investigates how variables selected for investigation are bound together in long run. It uses the long term equilibrium correction to reconcile or correct the short term dynamics (Zhao, et al, 2020, Acha, 2019). ARDL model has been used by Adenomon (2017), Adenomon and Ojo (2019), Amaluha and Acha (2018), Acha (2019) etc to elucidate vital information about the economy trajectory of a nation.

While there are many articles on the analysis of macroeconomic variables using either ARDL model or ECM model, the comparison of the performance of ARDL and ECM models on macroeconomic variables has not received much empirical scrutiny. In view of these, the research seek to compare the performance of ARDL model and ECM model on both real life data and simulated data.

MATERIALS AND METHODS

ECM and ARDL Models

The two main models whose performances are under investigation in this research work are ECM and ARDL models. In an attempt to investigate both the short term and long run performance of these models under the simulated and non-normally distributed data, we employ the theory of unit root test, followed by co-integration test, Autoregressive Distribution Lag Model and Error Correction Model. The entry point is to test for the stationarity in the macroeconomic variables after which the normality test (Jarque Bera Test) and the existence of co-integration among the selected variables is also investigated. If co-integration of order one exist, it will lead to the estimation the models. These estimation procedures will be carried out with the aid of E-View statistical software.

Unit Root Test

Unit root test is useful in determining the order of integration or stationarity of variables. Divers methods suh as Augumented Dickey-Fuller test (ADF) and Phillips-Perron test (PP), KPSS test etc are the commonly used method of testing for stationarity of a given series. But for this study, we employ the Augmented Dickey-Fuller (ADF) unit root test because of its robustness and compatibility with macroeconomic data (Adenomon, 2017). The ADF test is based on testing the hypothesis that series contains unit root against the series is stationary under the statistical assumption that errors are white noise (Zhao, et al, 2020). If a series is stationary, then it is integrated of order zero; $I(0)$. On the other hand, if the series is not stationary, it is integrated of order 1 ie I(1). In general, if a time series is $I(d)$, after several differencing d, we obtain a $I(0)$. ADF test is an offshoot of Dickey-Fuller test proposed in 1979.

Bounds Test for Cointegration

Bounds test is another way of testing for cointegration and causality in an ARDL model. It was developed by Pesaran *et al.* (2001) and is applicable irrespective of the order of integration of the underlying variables (whether regressors are $I(0)$, $I(1)$ or otherwise).

The model for the bound test of cointegration for the macroeconomic variables where INF is the inflation rate, UER is the unemployment rate, ε is the error term and t is the time is:

$$\Delta \mathrm{INF}_t = \alpha_0 + \alpha_1 \mathrm{INF}_{t-1} + \alpha_2 \mathrm{UER}_{t-1} + \varepsilon \tag{2}$$

The Granger Causality Test

Granger causality test also known as prima facia causality test is the standard statistical method use in determining whether one variable is useful or otherwise in predicting another variable. Granger causality test includes; estimating the given VAR model, checking the significance of the coefficients and applying the variable deletion tests in the lagged terms of the equations. The variable deletion tests helps to conclude the direction of causality (Emeka & Uko, 2016).

Stationarity and cointegration test results also determine the application of Granger-causality test. If INF is the inflation rate and UER is the unemployment rate, the standard Granger-causality test will be carried out be estimating the following:

$$\mathrm{UER}_t = \delta_0 + \sum_{i=1}^{n} \beta_{1i}\, \mathrm{IFR}_{t-1} + \sum_{i=1}^{n} \beta_{2i}\, UER_{t-1} + \varepsilon_t \tag{3}$$

$$\mathrm{IFR}_t = \delta_0 + \sum_{i=1}^{n} \beta_{3i}\, \mathrm{IFR}_{t-1} + \sum_{i=1}^{n} \beta_{4i}\, UER_{t-1} + \varepsilon_t \tag{4}$$

Where t denotes time, ε is a white noise error and δo is the growth rate of UER and IFR.

If INF is the inflation rate and UER is the unemployment rate are not-stationay and integrated at order 1, but they are not cointegrated, the Granger-causality test will be carried out with the forward difference series of the variables:

$$\Delta \mathrm{UER}_t = \delta_0 + \sum_{i=1}^{n} \beta_{1i} \Delta\, \mathrm{IFR}_{t-1} + \sum_{i=1}^{n} \beta_{2i}\, \Delta UER_{t-1} + \varepsilon_t \tag{5}$$

$$\Delta \mathrm{IFR}_t = \delta_0 + \sum_{i=1}^{n} \beta_{3i} \Delta\, \mathrm{IFR}_{t-1} + \sum_{i=1}^{n} \beta_{4i}\, \Delta UER_{t-1} + \varepsilon_t \tag{6}$$

Error Correction Model (ECM)

When the set of variables are having one or more cointegrating vectors, the suitable estimation technique is the Error Correction Model (ECM) that adjusts both short run changes in the variables and deviations to equilibrium. ECM becomes the appropriate modeling approach when the variables are cointegrated. It is also necessary and useful when the long-run relationship among the variables is desired.

In order to elucidate the relationship among the macroeconomic variables selected in this research work, we adopt the Error Correction Model (ECM) which is an offshoot of the Vector autoregressive (VAR) Model. In most cases, the co-integration of the VAR Model is often represented by Error Correction Model (ECM). Using the variables of interest in this study, we have

$$\mathrm{InIFR}_t = \alpha_0 + \sum_{i=1}^{n} \beta_2\, \Delta \mathrm{InUER}_t + \sum_{i=1}^{n} \beta_2\, ECT_{t-1} + \varepsilon_{1t} \tag{7}$$

$$\text{InUER}_t = \delta_0 + \sum_{i=1}^{n} \beta_1 \Delta\text{InIFR}_t + \sum_{i=1}^{n} \beta_3 ECT_{t-1} + \varepsilon_{2t} \quad (8)$$

Where INF is inflation rate and UER is unemployment rate, α_0 , ω_0, δ_0, *and* μ_0 are the vectors of regressors that a the macroeconomic variables, ECT_{t-1}'s are the lagged stationary residuals from the co-integration equations and $\varepsilon's$ are the stochastic regression residuals and t is the time.

Autoregressive Distributed Lag (ARDL) Model

The autoregressive distributed lag model of order p and q, ARDL (p,q), is defined for a scalar variable y_t as

$$y_t = \sum_{i=1}^{p} \delta_i y_{t-1} + \sum_{i=0}^{q} \tau_i x_{t-1} + \varepsilon_t \quad (10)$$

where ε_t is a scalar zero mean error term (known also as white noise) and x_t is a K-dimensional column vector process. The coefficients δ_i are scalars while τ_i are row vectors. The autoregressive distributed lag (ARDL) Model, ARDL (1,1) Model is considered as:

$$y_t = \mu + \alpha_1 y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + \varepsilon_t \quad (11)$$

Where y_t and x_t are stationary variables and ε_t is the white noise.

Hence, in a general standard ARDL(p, $q_1, q_2, \ldots, q_k$) model:

$A(L)y_t = \mu + B_1(L)\, x_{1t} + B_2(L)\, x_{2t} + \ldots + B_k(L)\, x_{kt} + \varepsilon_t$ (Amaluha,and Acha., (2018).

The ARDL model used in this research work may be expressed as:

$\text{INF}_t = F(UER_t, \varepsilon_t)$

Where INF is the inflation rate and UER is the unemployment rate, ε is the error term and t is the time. The ARDL framework pertaining to the macroeconomic variables use in this research is:

$$\Delta\text{InIFR}_t = \alpha_0 + \sum_{i=1}^{n} \beta_1 \Delta\text{InIFR}_{t-1} + \sum_{i=0}^{n} \beta_3 \Delta\text{InEUR}_{t-1} + \varphi_1 \text{InIFR}_{t-1} + \varphi_3 \text{InEUR}_{t-1} + \varepsilon_t \quad (12)$$

Where the parameter φ_i $\forall$ i = 1, 2, …, n is the corresponding long run multiplier, β_i for i=1, 2, …, n are the short run dynamic coefficient of the Autoregressive Distributed Lag (ARDL) Model, ε is serially uncorrelated disturbance with mean zero and constant variance and Δ is the first difference operator.

Simulated Techniques and Procedures

In most cases, simulation studies are done to examine the optimal performance of statistical procedures, or to compare and contrast the performance of two or more different statistical procedures for the same problem. Also, it is used when the observable data (macroeconomic variables) are not readily available to mimic (Adenomon, 2017). The simulation done in this research was repeated five thousand times. The real life data use in the analysis was source from the statistical bulletin of the Central Bank of Nigeria. The data were analyzed using the E-View statistical software where the simulation was done using the R statistical software. The period of study is from 1981 to 2016.the data source are the annual inflation rate and unemployment rate. These were analyzed using the two models under investigation. The Root Mean Square Error (RMSE) of the simulated data was also compared

Forecast Assessment

The Root Mean Square Error (RMSE) was the forecast estimate/criterion used and it is given as;

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - y_j\right)^2}{n}} \qquad (13)$$

Where y_i is the macroeconomic time series data (Onwukwe and Nwafor, 2014). It is a forecast with smaller values that gives a better analysis and forecasting performance.

RESULTS AND DISCUSSION

The results for the simulation carry out are presented in Table 1, while the analysis of the real life data are presented in Tables and Figures. From the simulated data, it was discovered that as sample size increases, the values of RMSE for both ECM and ARDL models decreases. In each iteration, the RMSE values under the ARDL model are smaller than that under the ECM model. This affirm and as also available in the literature that ARDL model is a better forecast model than the ECM model. Besides, the performance of the ECM in the simulated data and real life data are almost the same. This is in agreement with Safdar (2014) that says that the performance of simulated data and economic growth data in Pakistan are the same. It was also discovered from the simulated data that RMSE is the better model forecast assessment since it gives the lower value. This validates Onwukwe and Nwafor (2014), assertion that RMSE is the best model forecasting when selecting model for both simulation and real life data.

TABLE 1: Simulated data for Normal, Uniform and Exponential Distribution

	RMSE					
	Normal Distribution		**Uniform Distribution**		**Exponential Distribution**	
Sample Size	ECM	ARDL	ECM	ARDL	ECM	ARDL
100	1.316342	1.170683	0.380597	0.338895	1.298158	1.150886
200	1.190754	1.027741	0.344009	0.297613	1.185432	1.021145
300	1.122247	0.949097	0.324291	0.274512	1.118945	0.944470
400	1.082912	0.902219	0.312847	0.260641	1.078513	0.896860
500	1.056460	0.870140	0.305211	0.251397	1.052298	0.864431
1000	0.996842	0.796691	0.287693	0.229959	0.995793	0.795535
1500	0.974755	0.768527	0.281403	0.221832	0.974134	0.767684
2000	0.963597	0.754098	0.278264	0.217801	0.963172	0.753507
2500	0.956677	0.745358	0.276149	0.215078	0.956448	0.744577
3000	0.951543	0.738969	0.274806	0.213338	0.951753	0.739017
3500	0.948652	0.734970	0.273799	0.212089	0.948580	0.734503
4000	0.945621	0.730830	0.272991	0.211117	0.945876	0.731398
5000	0.9421166	0.726436	0.271975	0.209694	0.942240	0.726688

Figure 1 and 2 show the results of the normality test (Jarque-Bera Test) conducted on the macroeconomic variables selected for the study. The JB Test shows that both inflation rate and unemployment rate are non-normally distributed.

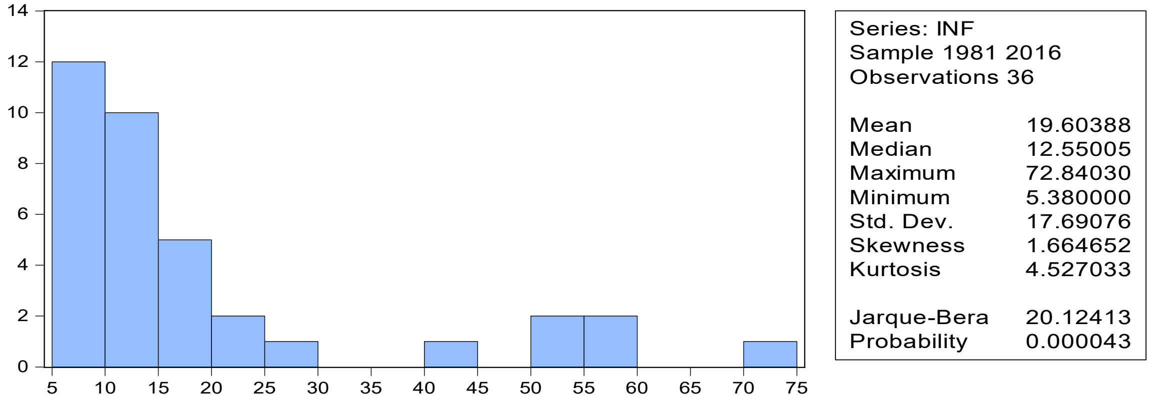

Figure 1: Normality Test (Jarque-Bera Test) for Inflation

JB Test having a value of 20.12413 indicating that the inflation rate is non-normally distributed.

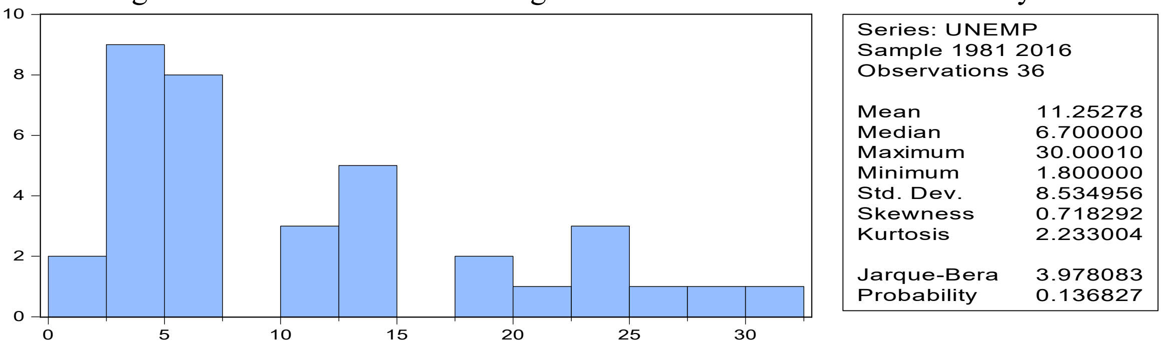

Figure 2: Normality Test (Jarque-Bera Test) for Unemployment

JB Test having a value of 3.978083 and kurtosis of 2.233004 indicating that the inflation rate is non-normally distributed. Therefore, Figure 1 and 2 shows that the data are non-normally distributed. Whereas, Figure 3 indicate the rate of inflation and unemployment.

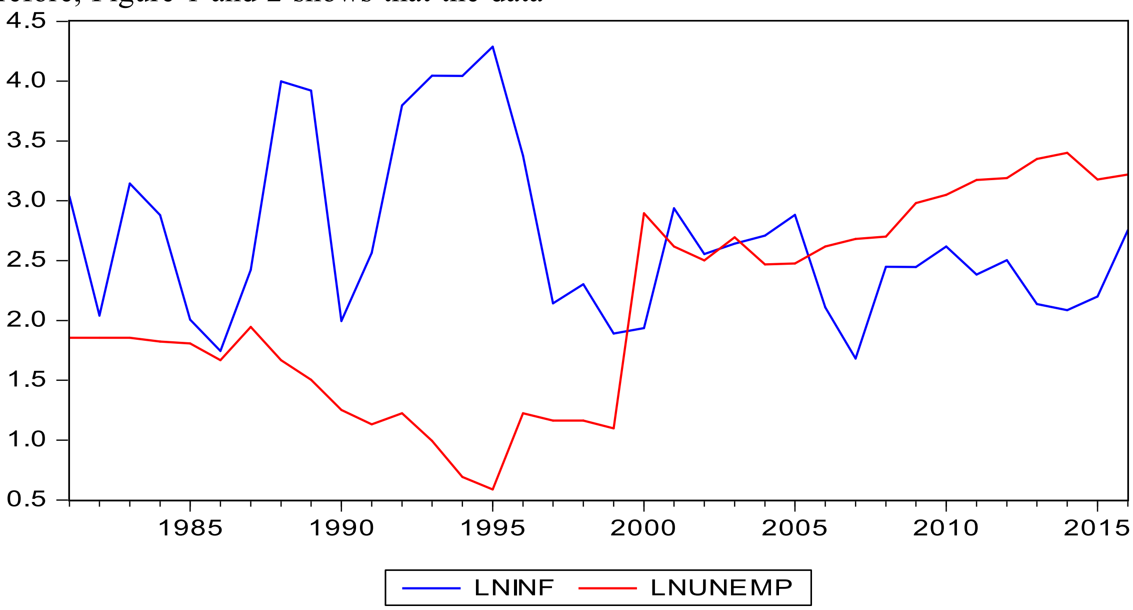

Figure 3: Time plot of inflation rate and unemployment rate.

Real Life Data Analysis

From Table 2 and 10 shows that there is relationship among the selected macroeconomic variables and that the influence of unemployment on inflation is significant and important in making inflation rate better with the use of its current rate to explain inflation and past rates of inflation are also important factors to be considered. The short term dynamics of the error correction model was observed to be equivalent with the result from the ARDL. Again the error correction model for the annual data indicates long run relationship exist between Inflation and unemployment rate. The ARDL models were found to be equivalent to the short term dynamics of the ECM, also the performance of the annual data gave a better and interpretable result.

Table 2: Descriptive Statistics

	LNINF	LNUNEMP
Mean	2.685463	2.103168
Median	2.529375	1.901105
Maximum	4.288270	3.401200
Minimum	1.682690	0.587790
Std. Dev.	0.720259	0.843132
Skewness	0.815099	-0.065551
Kurtosis	2.641843	1.707701
Jarque-Bera	4.178737	2.530838
Probability	0.123765	0.282121
Sum	96.67667	75.71405
Sum Sq. Dev.	18.15705	24.88051
Observations	36	36

Where,
LNINFL= Log of Inflation rate
LNUNEMP= Log of Unemployment
The mean values for Log of Inflation rate and Log of Unemployment are 2.685463 and 2.103168 respectively.
Precisely from the Table 3 below, Log of Inflation rate shows that it is stationary at first difference with its absolute ADF Test statistic of -6.434919 in which the p-value = 0.000 is less than 5% level of significance with it absolute value of -2.954021 and from Table 4, the Log of Unemployment rate shows that it is stationary at first difference with its absolute ADF Test statistic of -6.641959 which is greater than 5% level of significance with it absolute value of -2.951125. In summary, the ADF unit root test shows that all the variables are stationary at first difference.

Table 3: Augmented dickey-fuller test statistic for inflation

Null Hypothesis: D(LNINF) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.434919	0.0000
Test critical values:	1% level	-3.646342	
	5% level	-2.954021	
	10% level	-2.615817	

*MacKinnon (1996) one-sided p-values.

Table 4: Augmented dickey-fuller test statistic for unemployment

Null Hypothesis: D(LNUNEMP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.641959	0.0000
Test critical values:	1% level	-3.639407	
	5% level	-2.951125	
	10% level	-2.614300	

*MacKinnon (1996) one-sided p-values.

From Table 5, the race test indicates 1 cointegrating eqn(s) at the 0.05 level depict the long term relationship between the Inflation rate and Unemployment rate. Likewise, Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level. Hence, Johnson cointegration do provides the best evidence of existence of long term relationship between these variables.

Table 5: Cointegration Test

Date: 06/08/18 Time: 11:27
Sample (adjusted): 1983 2016
Included observations: 34 after adjustments
Trend assumption: Linear deterministic trend
Series: LNINF LNUNEMP
Lags interval (in first differences): 1 to 1
Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.494943	23.78641	15.49471	0.0023
At most 1	0.016381	0.561577	3.841466	0.4536

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.494943	23.22483	14.26460	0.0015
At most 1	0.016381	0.561577	3.841466	0.4536

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

From Table 6, contains the ECM and its coefficients as well as their t-statistic and p-value. ECM(-1) is the coefficient of the error correction model of Inflation Rate as the dependent variable while D(LNINF(-1)) and D(LNUNEMP(-1)) are short run coefficients.

ECM(-1) is the speed of adjustment towards long run equilibrium which is negative (-0.824620) and significant; meaning unemployment rate has long run equilibrium relationship with inflation rate and it returns to equilibrium at an approximately speed of 82.46% on the inflation rate.

Table 6: Short Run analysis using ECM

Dependent Variable: D(LNINF)
Method: Least Squares
Date: 06/08/18 Time: 11:31
Sample (adjusted): 1983 2016
Included observations: 34 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006850	0.099386	0.068926	0.9455
D(LNINF(-1))	0.445014	0.173080	2.571141	0.0153
D(LNUNEMP(-1))	0.165432	0.277059	0.597101	0.5549
ECM(-1)	-0.824620	0.194151	-4.247306	0.0002

R-squared	0.392691	Mean dependent var	0.020954
Adjusted R-squared	0.331960	S.D. dependent var	0.704656
S.E. of regression	0.575941	Akaike info criterion	1.844509
Sum squared resid	9.951248	Schwarz criterion	2.024080
Log likelihood	-27.35665	Hannan-Quinn criter.	1.905748
F-statistic	6.466080	Durbin-Watson stat	1.678600
Prob(F-statistic)	0.001656		

From Table 7, shows that the Coefficient of determination (R-squared) reveals that 45% variation in inflation rate can be explained jointly by five independent variables such as lag difference of log of Inflation Rate, difference of log of Unemployment Rate, lag difference of log of Unemployment Rate , log of Inflation Rate, and log of Unemployment Rate. The rest 55% variation in inflation Rate can be explained by residuals or other variables other than the five independent variables. From the table above, the Durbin–Watson test of 1.74 indicates the presences of autocorrelation. The table also that the constant variable has a positive relationship with inflation rate. It is that, if other variables that contribute to inflation rate are zero, there are other variables that can contribute 3.33% in a positive way to inflation rate.

However, the difference of log of Unemployment Rate has a negative relationship with inflation rate. A 10% increase in difference of log of Unemployment Rate will result to 51% increase in inflation rate. The lag difference of log of Unemployment Rate also has positive influence on inflation rate, when there is a 10% decrease in lag difference of log of unemployment rate, inflation rate will decrease by 6%. The P-value of 0.8492 indicating that lag difference of log of Unemployment rate is insignificant to inflation rate that it is one of the major contributors to inflation rate.

From the Table 8, the F-statistic= 10.88409; is greater than the Peasaran critical values with Lower bound=2.81 and upper bound =3.76 under 0.05 level of significant. This implies that there is evidence of long run relationship between inflation rate and unemployment rate.

Table 7: Standard ARDL(1,1)

Dependent Variable: D(LNINF)
Method: Least Squares
Date: 06/08/18 Time: 11:05
Sample (adjusted): 1983 2016
Included observations: 34 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.325506	0.786662	4.227365	0.0002
D(LNINF(-1))	0.470994	0.171538	2.745707	0.0104
D(LNUNEMP)	-0.511181	0.292419	-1.748109	0.0914
D(LNUNEMP(-1))	0.055111	0.287215	0.191879	0.8492
LNINF(-1)	-0.936922	0.201785	-4.643160	0.0001
LNUNEMP(-1)	-0.370657	0.153016	-2.422344	0.0221

R-squared	0.453868	Mean dependent var	0.020954
Adjusted R-squared	0.356345	S.D. dependent var	0.704656
S.E. of regression	0.565332	Akaike info criterion	1.855978
Sum squared resid	8.948806	Schwarz criterion	2.125336
Log likelihood	-25.55162	Hannan-Quinn criter.	1.947837
F-statistic	4.653938	Durbin-Watson stat	1.748759
Prob(F-statistic)	0.003234		

Table 8: Bound Testing

Wald Test:
Equation: Untitled

Test Statistic	Value	Df	Probability
F-statistic	10.88409	(2, 28)	0.0003
Chi-square	21.76818	2	0.0000

Null Hypothesis: C(5)=C(6)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(5)	-0.936922	0.201785
C(6)	-0.370657	0.153016

Restrictions are linear in coefficients.

From the Table 9, contains the ECM(-1), is negative and significant; meaning unemployment rate has long run equilibrium influence at an approximately speed of 93.77% on the inflation rate. Also, from table 4.9 shows that log of Unemployment Rate has a negative relationship on inflation rate. A 10% decrease in difference of log of unemployment rate will result to 6% decrease in inflation rate which means that log of unemployment Rate is a contributor to inflation rate. This agreed with Emeka and Uko (2016) which says that unemployment rate is one of the major contributors to inflation rate This shows and also confirm that there is a long run relationship between inflation rate and unemployment rate in Nigeria and agreed with Chamalwa and Bakari, (2016) that said that unemployment rate has long run equilibrium influence at an approximate speed of 82.46% on the inflation rate.

From Table 10, shows that there is causality relationship between the selected macroeconomic variables. It is found that unemployment rate and inflation rate in Nigeria has a bi-directional relationship. This agrees with Shittu, *et al.,* (2012) which says that there is bi-directional causality relationship between inflation rate and unemployment rate in Nigeria.

Table 9: ARDL(1,1) for Short Run Analysis

Dependent Variable: D(LNINF)
Method: Least Squares
Date: 06/08/18 Time: 11:36
Sample (adjusted): 1983 2016
Included observations: 34 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.029674	0.096696	0.306879	0.7611
D(LNINF(-1))	0.471892	0.167610	2.815422	0.0087
D(LNUNEMP)	-0.513096	0.284800	-1.801602	0.0820
D(LNUNEMP(-1))	0.058557	0.273742	0.213913	0.8321
ECM(-1)	-0.937792	0.197524	-4.747751	0.0001

R-squared	0.453821	Mean dependent var	0.020954
Adjusted R-squared	0.378486	S.D. dependent var	0.704656
S.E. of regression	0.555523	Akaike info criterion	1.797241
Sum squared resid	8.949583	Schwarz criterion	2.021706
Log likelihood	-25.55310	Hannan-Quinn criter.	1.873790
F-statistic	6.024035	Durbin-Watson stat	1.748776
Prob(F-statistic)	0.001178		

Table 10: Granger causality tests

Null hypothesis	**Obs.**	**F-Statistic**	**Probability**
ΔUNEMP does not Granger Cause ΔINF	(36)	14.7349	1.E-05 at 5%
ΔINF does not Granger Cause ΔUNEXP	(36)	5.7650	0.0031 at 5%

Finally, from figure 1 shows that both inflation and unemployment are on a steady increasing and agreed with Shittu, *et al.,* conclusion that if the Federal Government and its regulating agencies do not set up a mechanism that will stabilize the twin 'monsters' (inflation and unemployment), they will astronomically and at alarming rate in the nearby future. These 'monsters' will aggravate social economic hardship and societal instability.

CONCLUSION

In this study, we have presented the comparison of two models; ECM and ARDL models in the analysis of the interrelationship between inflation rate and unemployment rate in Nigeria using data obtained from the statistical bulletin of the Central Bank of Nigeria for the period from 1983 to 2016. The macroeconomic variables used in the study are chosen based on the fact that they are very important determinant of economic growth in Nigeria. In the simulated data, it was discovered that RMSE values of both ECM and ARDL models decreases as the sample size increases. The real life data was used to test the two models which shows that the chosen macroeconomic variables are integrated at order one. Furthermore, there is a bi-dimensional causality association between inflation rate and unemployment rate in Nigeria. The econometric estimations of the effects of unemployment rate on inflation rate in Nigeria suggests that there exist a long run association between inflation and unemployment in Nigeria. The findings show that deliberate effort by the federal government of Nigeria to reduce inflation rate in Nigeria economy through articulated policies will also reduce the unemployment rate since both variables co-exist and have long run relationship. In the analysis using ECM and ARDL Model Techniques reveals that the selected macroeconomic variables of the Nigeria economy are cointegrated in the long run horizon. The contribution of this empirical research work to knowledge in the field of econometrics is that ARDL model outperforms the ECM model for both in the real life data and the simulated data. Also, the government should make a stringent effort in stabilizing inflation to one-digit number. This will help to ameliorate the effects of other macroeconomic variables like unemployment rate in Nigeria.

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