

## RELATIONSHIP EXISTING AMONG NIGERIA URBAN AND RURAL CONSUMER PRICE INDEX (CPI)

Udegbunam Edwin CHINONSO, Onu Inyanda JUSTICE

Department of Agricultural Economics and Extension, Modibbo Adama University of Technology, P.M.B. 2076, Yola, Nigeria, Phone; +2348037858314,+2348036050936, edwinudegbunam@gmail.com, justiceonu@yahoo.co.uk

**Corresponding author:** edwinudegbunam@gmail.com

### Abstract

*This is time series analysis of Nigeria urban CPI and rural CPI to find out whether there exist relationship among urban and rural areas inflation. The CPI uses data from survey of consumption pattern of households to produce a timely and precise average price change for the consumption sector of any economy like the Nigerian economy. A total of 180 samples were used from monthly urban and rural CPI data from January 2001 to December 2015. Johansen Cointegration Test and Granger Causality Test were carried on, Vector Autoregression VAR model constructed to find out that there exist relationship among Nigeria Urban and Rural All item Consumer Price Index (NURACPI). Finally, impulse response function was used to check the response of urban (rural) CPI to the impulse of rural (urban) CPI and they were positive. This study finds out that there is high inflation rural area of Nigeria than urban area, the possible causes of it and how they affected each other.*

**Key words:** consumer price index (CPI), Nigeria urban and rural all item consumer price index (NURACPI), impulse response, time series

### INTRODUCTION

The consumer price index (CPI) is a measure that examines the weighted average of prices of a basket of consumer goods and services, such food, energy, education, transportation, medical care etc. It is a measure of changes in the purchasing power of a currency and the rate of inflation. It expresses the current prices of a basket of goods and services in terms of prices during the same period in a previous year, to show the effect of inflation on purchasing power. It has been the best known lagging indicator. The CPI market basket is developed from detailed expenditure of information provided by families and individuals on what they actually bought. The CPI reflects spending pattern for urban and rural population, it is frequently called a cost-of-living index but it differs in several important ways from a complete cost-of-living measure. A cost-of-living index is a conceptual measurement goal and not a straight forward alternative to CPI. Several works have investigated the relative accuracy of alternative inflation forecasting models [11], in their study of the best models to use in

forecasting inflation rates in Nigeria identified areas of future research on inflation dynamics to include re-identifying ARIMA models, specifying and estimating VAR models and estimating a P-Star model, amongst others that can be used to forecast inflation with minimum mean square error.

China monthly CPI data recorded from 2001 to 2010 was analyze using impulse response function to explain the relationship that exist between China urban and rural area and forecasted on the CPI [2]. He constructed a Vector autoregression (VAR) model and carry on Granger causality test. Hylleberg-Engle-Granger-Yoo (HEGY) test was used to examine whether there are seasonal unit roots. Decomposition of inflation and its volatility and according to the traditional quantity theory of money, the rate of inflation is decomposed into three components: the rate of change in the money supply, plus the rate of change in the velocity of circulation, minus the rate of change in real output [10]. They derived a generalization of this decomposition by postulating that the rate of change of money supply, velocity, and output follow diffusion equations. Using stochastic calculus

techniques, two expressions are obtained decomposing inflation and its volatility as a sum of several economically important terms. Two sets of U.S. data are used to illustrate these decompositions with actual numbers.

ARIMA models for forecasting the Irish inflation used two alternative approaches to identifying ARIMA models, namely, the Box-Jenkins approach and the objective penalty function methods [8]. The emphasis was on forecast performance, which suggests that ARIMA forecast outperformed the other approach. Two time-varying parameter models for Chilean inflation rates was carried out and the study discovered that ARIMA models outperformed the two other models considered in that paper for short-term out-of-sample forecasts. However, this superiority diminishes in longer forecasts [12]. Upon the discovering similar results confirmed that simple ARIMA models do well in predicting inflation rates [14]. An autoregressive model with a deterministically shifting intercept was introduced [3]. This implies that the model has a shifting mean and is thus non stationary but stationary around a nonlinear deterministic component. The shifting intercept is defined as a linear combination of logistic transition functions with time as the transition variables. The number of transition functions was determined by selecting the appropriate functions from a possibly large set of alternatives using a sequence of specification tests. This selection procedure is a modification of a similar technique developed for neural network modelling [20]. Analysis of Nigeria monthly CPI data using seasonal ARIMA model and a multiplicative seasonal autoregressive integrated moving average (ARIMA) model,  $(0, 1, 1) \times (0, 1, 1)^2$  [1]. While Nigeria All Item Consumer price Index from 1960 to 2008 was modelled using ARIMA model and Fourier Series Model [18]. He found the model well fitted using normal probability plot and quantile-quantile plot but when APE and RMSE values were used ARIMA (1,1,0) model outperformed the Fourier Series Model. Fourier Series model comprising the trends, seasonal and error component is fitted to Nigeria monthly CPI from 2003 to 2011 [15].

The model was used to forecast inflation rates for thirteen months. Also, Nigeria urban and rural monthly CPI was modeled and forecasted using Box-Jenkins Model  $(0, 1, 0) \times (0, 1, 13)$  [17]. This work sees the need to critically look at the relationship existing among urban area and rural area inflation and stands to provide answer to this question; Are there relationship existing between urban area inflation and rural area inflation?

The main objective of this study is to check whether there exist relationships among urban and rural area CPI. Other specific objectives of the study are as follows;

1. To run Johansen Cointegration Test on NURACPI and check whether there exist cointegration relationship among urban and rural CPI.
2. To run Granger Causality Test on NURACPI and check if urban CPI can play a role in determining rural CPI and vice versa.
3. To construct Vector Autoregression VAR Model on NURACPI and look at lag order criteria selection, lag exclusive, residual and residual normality, inverse root graph, exogeneity of NURACPI
4. To check Impulse Responses of NURACPI.

The investigation of the existence and timing of changes in U.S. inflation persistence was examined [7]. To do so, they developed an unobserved components model of inflation with Markov-switching parameters and measured persistence using impulse response functions based on the model. An important feature of their model is its allowance for multiple regime shifts in parameters related to the size and propagation of shocks. The urban and rural dwellers have different consumption habit because their surrounding and may affect the standards of consumption [2]. This work analyzed Nigeria urban and rural CPI and checked whether there exist relationships among them. It ran impulse response function thereby used urban (rural) CPI to predict rural (urban) CPI. Furthermore, vector autoregressive (VAR) model was constructed for more analysis and prediction of the existing relationship among urban CPI and rural CPI.

## MATERIALS AND METHODS

The study was conducted in Nigeria. Nigeria is located at the extreme inner corner of the Gulf of Guinea on the west coast of Africa, occupies an area of 923,768 sq. km (356,669 m<sup>2</sup>), extending 1,127 km (700 m) East-West and 1,046 km (650 m) North-South with total population of 184635279 people [18]. It has 36 states and FCT Abuja. Its currency is Naira. Consumer Price Index Data of urban and rural Nigeria All Items for the period of January 2001 to December 2015 were collected from National Bureau of Statistics publication as at March 2016 [13]. It is a monthly time series data. The total sample used was 180.

### *Johansen Cointegration Test*

VAR-based cointegration tests methodology was developed by Johansen (1991, 1995) using a Group object or an estimated VAR object [4][5]. The Johansen tests may be performed using a Group object or an estimated VAR object. The residual tests may be computed using a Group object or an Equation object estimated using nonstationary regression methods.

Let's look at a VAR of order ( $p$ ):

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + Bx_t + \varepsilon_t \quad (1)$$

where  $y_t$  is a  $-k$  vector of non-stationary I(1)

variables,  $x_t$  is a  $-$ vector of deterministic variables, and  $\varepsilon_t$  is a vector of innovations.

### *Vector autoregression*

Vector autoregression (VAR) models which were introduced into empirical economics by Sims (1980) provide a method to estimate dynamic relationships between economic variables and forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables [16]. We will use VAR models to analyze relevance between UCPI and RCPI. Vector autoregression is a statistical model used to represent the linear interdependencies among multiple time series. A VAR model describes the development of a set of  $n$  variables over the same sample period ( $t=1, \dots, T$ ) as a linear function of only their past evolution. The variables are collected in a

$n \times 1$  vector  $t y_t$ , which has as the  $i^{th}$  element  $y_{i,t}$ , the time  $t$  observation of variable  $y_i$ . A VAR( $p$ ) (the  $p$ -th order vector autoregression model), is

$$y_t = c + \Phi_1 y_{t-1} + \dots + \Phi_p y_{t-p} + \varepsilon_t \quad (2)$$

where  $c$  is a  $(n \times 1)$  vector of constants,  $\Phi$  is a  $(n \times n)$  coefficient matrix for every  $i=1, \dots, p$  and  $\varepsilon_t$  is a  $(n \times 1)$  vector of error terms satisfying

$$E\varepsilon_t = 0, E\varepsilon_t \varepsilon_\sigma = \Omega \text{ if } t = \sigma \text{ and } E\varepsilon_t \varepsilon_\sigma = 0 \text{ if } t \neq \sigma (\Omega \text{ is a } n \times n \text{ positive definite matrix}).$$

The  $l$ -periods back observation  $y_{t-l}$  is called the  $l$ -th lag of  $y$ . Thus, a  $p$ -th order VAR is also called a VAR with  $p$  lags. Or,

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + Bx_t + \varepsilon_t \quad (3)$$

where  $y_t$  is a  $-k$  vector of endogenous

variables,  $x_t$  is a  $d$  vector of exogenous variables,  $A_1, \dots, A_p$  and  $B$  are matrices of coefficients to be estimated, and  $\varepsilon_t$  is a vector of innovations that may be contemporaneously correlated but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables. Since only lagged values of the endogenous variables appear on the right-hand side of the equations, simultaneity is not an issue and OLS yields consistent estimates. Moreover, even though the innovations  $\varepsilon_t$  may be contemporaneously correlated, OLS is efficient and equivalent to GLS since all equations have identical regressors.

### *Granger Causality Test*

Based on the vector autoregression part, it is good to know how useful each variable is for forecasting the other one. That means to know whether rural (urban) part plays a role in predicting UCPI (RCPI) series, which is the primary objective of this research. Thus in this section, we will discuss the forecasting relation between RCPI and UCPI using Granger causality test proposed by Granger (1969) [6]. Granger causality is a statistical conception of causality that is based on the thought that the past cannot be caused by the present or future. It is decided by observing whether including the past values of a variable in the information set can improve the

forecast of another variable. Let  $x$  and  $y$  be stationary time series. To test the null hypothesis that  $x$  does not Granger-cause  $y$ , we should first find the proper lagged values of  $y$  to contain a univariate autoregression of  $y$ :

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + \dots + a_m y_{t-m} + \varepsilon_t \quad (4)$$

where  $\varepsilon$  is the disturbance.

Here  $y_{t-j}$  is reserved in the regression if and only if it has a significant  $t$ -statistic,  $m$  is the largest lag length for which the lagged dependent variable is significant.

Secondary, the autoregression is extended by including lagged values of  $x$ :

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + \dots + a_m y_{t-m} + \varepsilon_t \quad (5)$$

where  $\varepsilon$  is the residual.

In this regression, these entire  $x$  are individually significant according to their  $t$ -statistic, provided that they add explanatory power to the regression according to an  $F$ -test. In the above augmented regression item,  $p$  is the shortest and  $q$  is the longest, lag length for  $x$  is significant. The null hypothesis that  $x$  does not Granger-cause  $y$  is accepted if and only if no lagged values of  $x$  are retained in the regression, that is,  $b_p = b_{p-1} = \dots = b_q = 0$ .

This research wants to determine whether there exists granger causality between rural and urban CPI data. It is known that some urban wage earners come to the city, there may be more pressure on prices and high inflation than villages. This research is to know whether the inflation in city will influence that in the rural areas.

### Impulse Responses Function

A shock to the  $i$ -th variable not only directly affects the  $i$ -th variable but is also transmitted to all of the other endogenous variables through the dynamic (lag) structure of the VAR. The VAR models are usually emerged by impulse responses. Impulse response function (IRF) is widely used to reveal the dynamic relationship between macroeconomic variables within VAR models by tracing the effect of a one-time shock to one of the innovations on current and future values of the endogenous variables and describes the reaction of the system as a function of time or

possibly as a function of some other independent variable that parameterizes the dynamic behavior of the system. If the innovations are contemporaneously uncorrelated, interpretation of the impulse response is straightforward. The  $i$ -th innovation is simply a shock to the  $i$ -th endogenous variable. Innovations, however, are usually correlated, and may be viewed as having a common component which cannot be associated with a specific variable. In order to interpret the impulses, it is common to apply a transformation to the innovations so that they become uncorrelated. This study will use impulse response function to study the CPI whether it has feedback from urban (rural) area to rural (urban) district. A vector  $MA(\infty)$  representation was written as

$$y_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + \dots + \Psi_p \varepsilon_{t-p} \quad (6)$$

Thus, the matrix  $\Psi_s$  has the

interpretation  $\Psi_s = \frac{\partial y_{t+s}}{\partial \varepsilon_t}$ ; that is, the row  $i$ ,

column  $j$  element of  $\Psi_s$  identifies the consequences of a one unit increase in the  $j$ -th variable's innovation at date  $t$  ( $\varepsilon_{jt}$ ) for the value of the  $i$ -th variable at time  $t+s$  ( $y_{i,j+s}$ ), holding all other innovation at all dates

constants. The term  $\Psi_s = \frac{\partial y_{t+s}}{\partial \varepsilon_t}$ , as a function

of  $s$  is called the impulse response function which represents the response of  $y_{i,j+s}$  to a one time impulse in  $y_{jt}$  with all other variables dated  $t$  or earlier held constant.

$$\text{Or,} \quad v_t = p \varepsilon_t - (0, D) \quad (7)$$

where  $D$  is a diagonal covariance matrix. Several options for the choice of  $P$  will be given by EViews.

## RESULTS AND DISCUSSIONS

The present study is to research whether if they exist relationship between urban and rural inflation. The summary Statistics of these data are given in Table 1. The NURAICPI time series plot in Figure 1 indicates local trends from 2001 to 2015 and a general most likely linear upward trend from

2001 to 2015. The positive significant skewness of 0.329 for urban CPI and 0.417 for rural CPI suggest that NURAICPI is a normal distribution and right skewed. Kurtosis which measures the extent to which observations cluster around a central point has

the value of zero for a normal distribution. Negative kurtosis of -1.073 for UCPI and -1.117 for RCPI indicates that, relative to a normal distribution, the observations cluster less and have thicker tails.

Table 1. Summary of descriptive statistics of NURAICPI data

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
UCPI	180	94.290	42.5968	0.239	0.181	-1.073	0.360
RCPI	180	95.911	42.5544	0.417	0.181	-1.0117	0.360
Valid N (listwise)	180						

Source: Own calculation.

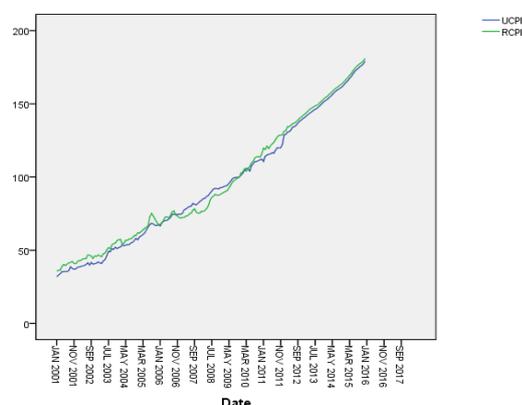


Fig. 1. Nigeria urban and rural inflation rate from 2001 to 2015.

Source: Own calculation.

### Johansen Cointegration Test

Figure 1 shows that UCPI and RCPI plot have a similar trend. In regards to this, Urban and Rural CPI series can be cointegrated.

The cointegrating relationship can be interpreted as the long run equilibrium and is of great importance in economics.

If two series are individually integrated but some linear combination of them has a lower order of integration, then the series are said to be cointegrated.

The Johansen test which permits more than one lower order of integration, then the series are said to be cointegrated.

The Johansen test which permits more than one cointegrating relationship is a procedure for testing cointegration.

There are two types of Johansen test, either

with trace or with eigenvalue. Table 2 results reject the null hypothesis. This shows that UCPI series and RCPI series are stationary and have relationship of similar trend.

Table 2. Result of the Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical value	0.05 Prob.**
None *	0.060463	15.55550	15.49471	0.0490
At most 1 *	0.030310	5.140007	3.841466	0.0234

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level.

\* denotes rejection of the hypothesis at the 0.05 level

\*\*MacKinnon-Haug-Michelis (1999) p-values [9].

Source: Own calculation.

### Granger Causality Test

The p-value of UCPI and RCPI rejected the null hypothesis. This suggested that there exist granger causality between urban and rural area. The variation of UCPI may affect the variation of RCPI.

Table 3. Result of the Granger Causality Test of UCPI and RCPI

Null Hypothesis:	Obs	F-Stat	Prob.
RCPI does not Granger Cause UCPI	168	1.08809	0.3745
UCPI does not Granger Cause RCPI		1.84212	0.0467

### Lag Length Criteria

Table 4 result selected lag order 1, 2 and 9. Lag order 1 and 2 will be used.

Table 4. Result of the VAR Lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1316.661	NA	22529.78	15.69835	15.73554	15.71344
1	-491.7647	1620.332	1.284056	5.925771	6.037341*	5.971051*
2	-485.2858	12.57213	1.246751*	5.896260*	6.082210	5.971728
3	-484.0873	2.297303	1.289111	5.929610	6.189940	6.035265
4	-479.4914	8.699279	1.280138	5.922517	6.257227	6.058359
5	-478.3100	2.208032	1.324047	5.956072	6.365162	6.122101
6	-477.4019	1.675785	1.374026	5.992879	6.476350	6.189095
7	-475.2801	3.864732	1.405563	6.015239	6.573090	6.241642
8	-474.3023	1.757653	1.457691	6.051218	6.683449	6.307808
9	-466.8074	13.29447*	1.399062	6.009612	6.716223	6.296389
10	-464.0471	4.830586	1.420835	6.024370	6.805361	6.341334
11	-462.4388	2.776242	1.463087	6.052843	6.908214	6.399994
12	-461.8148	1.062317	1.524600	6.093033	7.022784	6.470371

\* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Source: Own calculation

### AR Roots Graph

Figure 2 shows that UCPI and RCPI series are stationary since all roots have absolute value less than one and lie inside the unit circle. Therefore influence of the shock for some variables may not decrease over time.

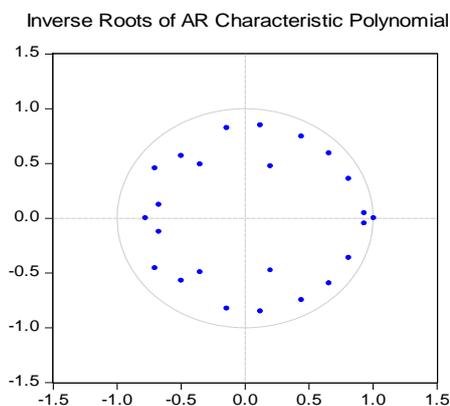


Fig. 2. VAR inverse root graph

Source: Own calculation

### Exogeneity Tests

The result of Chi-sq ( $\chi^2$ ) and Prob (p-value) statistics suggests that the series can be treated as exogenous variable.

Both UCPI and RCPI are independent variable having effect on the model but not affected by the model.

Table 5. Result of the VAR Granger Causality Test/ Exogeneity Tests

Dependent variable: UCPI			
Excluded	Chi-sq	Df	Prob.
RCPI	13.05707	12	0.3649
All	13.05707	12	0.3649
Dependent variable: RCPI			
Excluded	Chi-sq	Df	Prob.
UCPI	22.10540	12	0.0364
All	22.10540	12	0.0364

Source: Own calculation

### Lag Exclusion Test

The test of Table 6 suggests that jointly all four lags of all endogenous variables are statistically significant and there is no need of excluding any lag.

### Residual test

Figure 3 displays the matrix of pairwise cross-correlograms for the estimated residuals for the 12 lags.

### VAR Residual Normality Tests

The below table 7 reports the multivariate extensions of the Jarque-Bera residual normality test, which compares the third and fourth moments of the residuals to those from the normal distribution.

For the multivariate test, a factorization of the residuals that are orthogonal to each other was chosen. Therefore, the hypothesis that residuals are normally distributed is rejected.

Table 6. Result of Chi-squared test statistics for lag exclusion (Numbers in are p-values)

	UCPI	RCPI	Joint
Lag 1	112.7924 [ 0.000000]	166.7801 [ 0.000000]	251.3684 [ 0.000000]
Lag 2	0.915182 [ 0.632806]	0.555638 [ 0.757434]	1.649679 [ 0.799837]
Lag 3	2.737722 [ 0.254397]	2.357352 [ 0.307686]	3.969697 [ 0.410122]
Lag 4	1.786980 [ 0.409225]	0.206355 [ 0.901967]	2.281958 [ 0.684056]
Lag 5	0.395402 [ 0.820615]	2.203020 [ 0.332369]	2.259553 [ 0.688142]
Lag 6	0.138471 [ 0.933107]	1.678366 [ 0.432063]	1.735971 [ 0.784173]
Lag 7	0.232037 [ 0.890459]	3.958061 [ 0.138203]	4.245078 [ 0.373853]
Lag 8	1.760986 [ 0.414579]	3.124067 [ 0.209709]	6.823123 [ 0.145536]
Lag 9	1.864879 [ 0.393592]	4.092366 [ 0.129227]	6.262281 [ 0.180398]
Lag 10	0.264895 [ 0.875949]	0.315618 [ 0.854013]	0.467854 [ 0.976554]
Lag 11	0.461560 [ 0.793914]	0.038014 [ 0.981172]	0.588662 [ 0.964315]
Lag 12	0.455930 [ 0.796152]	0.438978 [ 0.802929]	1.064863 [ 0.899806]
Df	2	2	4

Source: Own calculation.

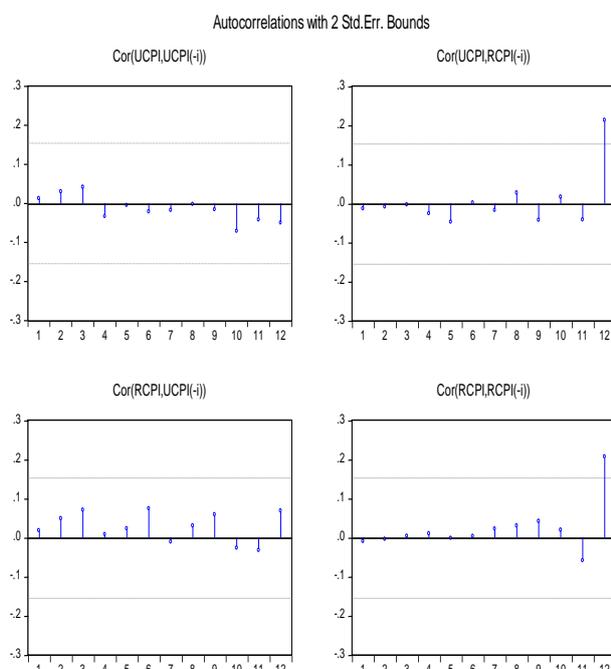


Fig. 3. Graphical result Residual Tests  
 Source: Own calculation

Table 7. Result of the VAR Residual Normality Tests.

Component	Skewness	Chi-sq	df	Prob.
1	0.512215	7.346203	1	0.0067
2	0.955832	25.58120	1	0.0000
Joint		32.92741	2	0.0000

Component	Kurtosis	Chi-sq	df	Prob.
1	6.256721	74.24360	1	0.0000
2	10.46572	390.1590	1	0.0000
Joint		464.4026	2	0.0000

Component	Jarque-Bera	df	Prob.
1	81.58981	2	0.0000
2	415.7402	2	0.0000
Joint	497.3300	4	0.0000

Source: Own calculation.

### Impulse Response

Figure 4 below shows that when the impulse is from rural, the response of urban is positive except in the last quarter of a year and highest effect emerges in the third month. Also, figure 5 below shows that when the impulse is from urban, the response of rural is positive with a smooth trend.

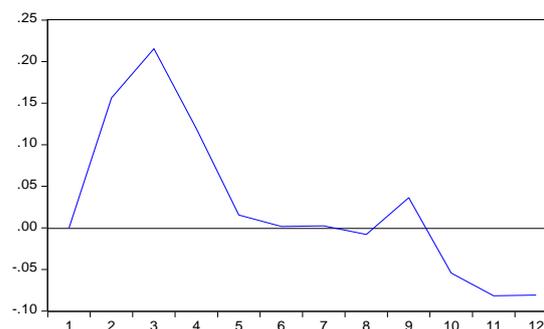


Fig. 4. Impulse Response from Rural to Urban  
 Source: Own calculation.

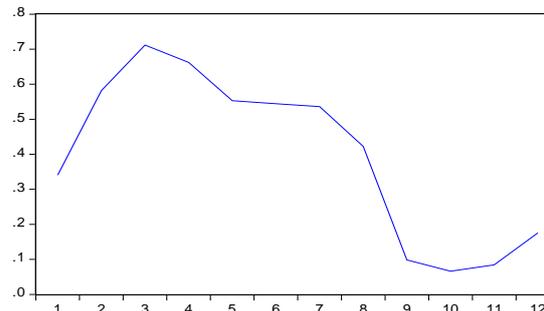


Fig. 5. Impulse Response from Urban to Rural  
 Source: Own calculation.

### CONCLUSIONS

The similar trend among urban and rural series while looking at the graph leads to running of Johansen Cointegration test which rejected the null hypothesis too like analysis of China urban and rural CPI data [2].

Granger Causality test, Vector autoregression and impulse response function all show urban inflation and rural inflation affect each other. Urban and rural dwellers have different consumption habits and most food products are produced in rural area while those in urban area bought from rural area [2]. The fluctuation in food prices may lead to variation of wages. In Nigeria urban CPI and rural CPI, figure 1 shows that there are high inflation in rural area. This seems unlikely, even the service inflation for rural not only food inflation is higher to urban inflation. The possible explanation to this is higher trade margins in supplying to rural, higher transportation cost in servicing rural etc. Also, there are periods where urban CPI is higher than rural CPI which explains the lower purchasing power and lower standard of living in the rural. Surprisingly the general higher rural inflation in Nigeria is actually worrisome.

Though, there is a contrarian view to this because we normally view inflation negatively. It can be viewed positively also to mean better prices and rural public. It can be viewed as increasing prosperity due to increase in prices of agricultural produce and are in a position to enhance the purchasing power of the urban, which can also be a sign of higher rural inflation. Service inflation for rural increasing can also be viewed as better nominal wages in rural areas. If wages go up, they tend to impact services sector. Therefore, it is difficult to explain whether it is due to higher prosperity or higher penalties the rural are forced with higher rural inflation. However, the overall inflation needs to get moderated to improve the standard of living in Nigeria.

## REFERENCES

- [1]Etuk. E. H., 2012, Predicting inflation Rates of Nigeria using A Seasonal Box-Jenkins Model. *Journal of Statistical and Econometric Methods*, Vol 1, no. 3, 2012, 27-37. ISSN: 2241-0384 (print), 2241-0376 (online), Scienpress Ltd. [2012].
- [2]Fei Sun, 2012, Analysis to China's Urban and Rural CPI Data. Master Thesis in statistics Department of Statistics Uppsala University, Sweden.
- [3]González, A., Teräsvirta, T., 2008, Modelling Autoregressive Processes with a Shifting Mean, *Studies in*

*Nonlinear Dynamics & Econometrics*: Vol. 12: No. 1, Article 1.

- [4]Johansen, S., 1991, Estimation and hypothesis testing of cointegrating vectors in Gaussian vector autoregressive models, *Econometrica* 59: 1551–1580.
- [5]Johansen, S., 1995, *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*. Oxford University Press, New York.
- [6]Granger, C. W. J., 1969, Investigating Causal Relationships by Econometric Models and Cross-Spectral Methods. *Econometrica* 37:424-38.
- [7]Kang, H. K., Kim, C. J., Morley, J., 2009, Changes in U.S. Inflation Persistence, *Studies in Nonlinear Dynamics & Econometrics*: Vol. 13: No. 4, Article 1.
- [8]Kenny, G., Meyler, A., Quinn, T., 1998, Forecasting Irish Inflation using ARIMA models, Central Bank of Ireland Technical Paper 3/RT/98.
- [9]MacKinnon, J. G., Haug, A. A., Michelis, L., 1999, "Numerical distribution functions of likelihood ratio tests for cointegration," *Journal of Applied Econometrics*, 14, 563–577.
- [10]Malliaris, A. G., Malliaris, M. E., 1995, Decomposition of inflation and its volatility: A stochastic approach. *Review of Quantitative Finance and Accounting* 5(1), 93 – 103.
- [11]Mordi, C.N.O, Essien, E.A, Adenuga, A.O, Omanukwe, P.N, Ononugbo, M.C, Oguntade, A.A, Abeng, M.O, Ajao, O.M., 2007, The Dynamics of Inflation in Nigeria: Main Report. Occasional Paper No. 2. Research and Statistics Department. Central Bank of Nigeria, Abuja.
- [12]Nadal-De Simone, F., 2000, Forecasting Inflation in Chile Using State-Space and Regime-Switching Models (October 2000). IMF Working Paper, Vol. pp. 1-55., Available at SSRN: <http://ssrn.com/abstract=880176>.
- [13]NBS, 2016, National Bureau of Statistics March 2016 Report: Consumer Price Index Pp.19-27.
- [14]Stockton, D., Glassman, J., 1987, An Evaluation of the Forecast Performance of Alternative Models of Inflation. *Review of Economics and Statistics*, 69(1), 108 - 117.
- [15]Omekara, C.O, Ekpenyong, E. J., Ekerete M. P., 2013, Modeling Nigerian Inflation Rates Using Periodogram and Fourier Series Analysis. *CBN Journal of Applied Statistics* Vol 4 No. 2. [December, 2013].
- [16]Sims, C. A., 1980, *Macroeconomics and Reality*, *Econometrica*. 48, pp. 1-48.
- [17]Udegbonam, C. E., Onu J.I., 2016, Modeling Nigeria Urban and Rural Inflation Using Box-Jenkins Model, MSc. non thesis seminar, Modibbo Adama University of Technology Yola, Nigeria, 2016.
- [18]Umanah, E. E., 2010, Time Series Modeling of All Items Consumer Price Index in Nigeria. MSc. thesis, Department of Statistics University of Nigeria, Nsukka.
- [19]UN, 2016, United Nations Department of Economic and Social Affairs: Population Division. <http://www.infoplease.com/atlas/country/nigeria.html>
- [20]White, H., 2006, Approximate Nonlinear Forecasting Methods, Elsevier, 460 – 512, *Handbook of Economics Forecasting*.