Modelling Inflation Rate Volatility in Nigeria with Structural Breaks

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This study compares the performance of GARCH-Type models in modelling inflation volatility in Nigeria covering the period 1995M01 to 2016M10. In the paper, we provide two main innovations: (i) we analyze inflation rate of two pronounced consumer prices indices namely headline and core consumer price indices using the Augmented Dickey-Fuller break point test which allow for structural breaks in the data series; and (ii) the method is modified to include both symmetric and asymmetric volatility models. The empirical examination observes evidence of volatility persistence in the consumer price indices, but only headline is consistent with leverage effects. Thus, applying one-model-fits-all approach as well as discarding the role of structural breaks for inflation rate volatility in Nigeria will yield misleading and invalid policy prescriptions.

Key Words: Inflation rate, Volatility modelling, Leverage effects, Monetary Policy

JEL Classification: C22, E31

1.0 Introduction

Central Banks are charged among other functions with the responsibility of ensuring and maintaining price stability. With this, modelling the dynamics of inflation is increasingly gaining prominence both in theory and practice. This is underscored by the fact that incessant inflation rate fluctuations may: (i) add inefficiencies in the market; (ii) distort exchange rate balance; (iii) breed unforeseen redistribution of wealth and ultimately a reduction in overall economic growth and; (iv) cause higher risk premia, hedging costs (see for example, Pourgerami and Maskus, 1987; Judson and Orphanides, 1999; Kontonikas, 2004; Samimi and Shahryar, 2009; Eisenstat and Strachan, 2014). Thus, both the government and profit-maximizing investors are keenly interested in the dynamics of inflation rate to make policy/investment decisions. Therefore, a measure of volatility in inflation rate provides useful information both to the investors in terms of how to make investment decisions and relevant authorities in terms of how to formulate appropriate policies. A more serious concern however centres on how to model inflation rate when confronted with such volatility.

The concept of inflation rate volatility has been extensively dealt with in the literature.[1] Berument and Sahin (2010) point out that inflation level in an economy may not really be what matters strictly to macroeconomists, but its volatility. In the same vein, Salisu and Fasanya (2012) conclude that oil price variations result in a high gain or loss to investors in the oil market, other economic agents (including the government) are also not free from the good or unprecedented havoc caused by variability in inflation level. Other negative effects include its bad impacts on growth (see Friedman 1977), uneven redistribution of income and inducement of risks, among others. Carporale et al (2010), Elder (2004) and Rother (2004), among others also give evidential conclusion on this report. However, different dimensions witnessed in the various analyses have continued to create vacuum for further studies. Summarily, a major concern can be raised on the modelling of inflation rate volatility with structural breaks: Does one-model-fits-all syndrome applies to inflation rate volatility modelling? Most of the related studies tend to impose or presume a particular structure of volatility models to analyze inflation rate volatility. Often times, very little attention is paid to: (i) the use of appropriate model selection criteria including pre-tests as suggested by Engle (1982) to determine the choice of volatility model; (ii) the application of appropriate volatility models to evaluate the performance of the preferred model; and (iii) most importantly the synchronization of (i) and (ii) to validate the choice of the preferred model over other competing models. Thus, in most cases, there may be problem of under-fitting or over-fitting of model which may affect the outcome of the analyses.

This paper makes the following contribution to the literature: first, we add to the relatively low number of studies that have modeled inflation dynamics in Nigeria (see Feridun & Adebiyi, 2005; Kelikume & Salami, 2004; Oyediran, 2006; Olubusoye and Oyaromade, 2008; Omotosho & Dogunwa, 2012; Kelikume, 2013; Okafor & Shaibu, 2013; Omekara et al., 2013; Osarumwense & Waziri, 2013; Bawa et al., 2016 and Ekpenyong & Uduodu, 2016). Second, studies that have considered both the symmetric and asymmetric effect consider, at best, without considering the relevance of structural breaks in their modelling structure. Lastly, the scope (in terms of time coverage) covers period that has witnessed drastic changes in prices. Hence, this would further

[1] A brief review of some of these papers is provided in section 2.

bring out the beauty of the structural break in modelling inflation dynamics in Nigeria.

Addressing the highlighted concerns, this study looks into inflation volatilities of both core and headline, using monthly data from 1995 to 2016. Second, we modify the volatility models to account for structural breaks in the model as there appears to be evidence of some notable shifts in the series (see Figure 1). Not paying attention to these breaks may generate spurious results [see, inter alia, Salisu and Fasanya 2013; Salisu and Oloko, 2015]. In this study, the estimation procedure is carried out in three stages. First, we determine the statistical properties of CPI by carrying out some pre-tests. The Augmented Dickey-Fuller unit root test with breaks, in addition to other descriptive statistics, is explored to observe the behaviour of CPI and to reveal the inherent structural breaks. Volatility in CPI is captured with the help of the ARCH-LM (Autoregressive Conditional Heteroscedasticity-LanGragian Multiplier) test by Engle (1982). Second, we estimate both the symmetric and asymmetric models. The last stage considers necessary post-estimation evaluation with the use of ARCH-LM test for the validation of the volatility models.

The rest of this paper follows this pattern: Section II works on the exploration of necessary past studies; section III describes data and its statistical properties. In section IV, we develop the methodological framework and discuss the empirical results and section V gives the concluding remarks.

2.0 Literature Review

Empirical research on inflation volatility modelling especially across any policy period is limited. The situation is worse for the Nigerian economy. Majority of the available few studies have shown that inflation, with other financial time series exhibits tendencies of volatility and asymmetry (see Berument and Sahin, 2010; Omotosho and Dogunwa, 2012). Of the few numbers of studies that provide evidential reports on the analysis of inflation volatility determinants, Rother (2004) finds that fiscal policies importantly affect inflation volatility, and that the discretionary fiscal policies' volatility itself has positive impact on inflation volatility. Bowdler and Malik (2005) reveal that inflation volatility is reduced through openness. Also, Aisen and Veiga (2008) explain how inflation volatility highly responds to intense degree of political factors, such as political fragmentation and instability.

However, it has been discovered by past studies that inflation itself, induces inflation volatility. One of the earliest studies to discover this is the work of Friedman (1977). He asserts that changes in inflation leads to more uncertainty in future inflation. Further to this is the argument of Berument and Dincer (2005), Ball (1992) and Kontonikas (2004). Dmitriev and Kersting (2016) specially observe how inflation causes high inflation volatility in a situation where monetary policy is dominated by fiscal policy and the governmental deficit cannot be predicted.

The negative effects of inflation volatility are also available for review. As previously highlighted, inflation volatility is attached to uneven distribution of income, retarding economic growth, risk and inducement, among others. Friedman (1977) points out that the bad effect of inflation on growth is strictly necessitated by inflation volatility. Apergis (2004) discovers with support from the Friedman's hypothesis (1977), that inflation is significant to output growth. Arize et al (2005) argue that inflation volatility adversely affect real money demand of the eight less developed countries used in their study for both short and long run analysis.

Only very few studies accounted for the impact of structural changes in the economy caused by changes in policies, economic crises etcwhile modelling inflation volatility. Notable among the available studies is Berument and Sahin (2010). They discovered that season is present in the volatility of inflation. Also, Omotosho and Dogunwa (2012) confirm that headline and core inflation volatilities asymmetrically respond to shocks. Kelikume (2013) test the performance of P-star model predicting price movement in Nigeria using quarterly data over the period 1970 to 2011. The study obtained estimates of the price-gap, velocity-gap and output-gap model and concluded on the usefulness of the price-gap model in explaining and predicting inflation in Nigeria. In another study, Kelikume and Salami (2014) used a univariate model in the form of Autoregressive Integrated Moving Average model developed by Box and Jenkins and multivariate time series model in the form of Vector Autoregressive model to forecast inflation for Nigeria using monthly consumer price index over the period 2003 to 2012. Based on different diagnostic and evaluation criteria, it was observed that the VAR model performs better than the ARIMA model in forecasting inflation in Nigeria.

In the forecasting ability of Inflation models, Feridun and Adebiyi (2005) sought to establish whether monetary aggregates have useful information for forecasting inflation, other than that provided by inflation itself. In doing this, the study conducts forecasting experiments, using Mean Absolute Percentage Errors (MAPEs) and later evaluate whether each monetary variable improved the forecasts of a simple AR (1) model of inflation. The study found that the MAPEs for all the variables were less than that of the benchmark AR (1) model. In contrast to their findings, Omekara et al., (2013) considered the application of Periodogram and Fourier Series Analysis to model all-items monthly inflation rates in Nigeria from 2003 to 2011. Based on their analysis, it was found that inflation cycle within the period was fifty one (51) months, which coincided with the two administrations within the period. Further, appropriate significant Fourier series model comprising the trend, seasonal and error components is fitted to the data and this model is further used to make forecast of the inflation rates for thirteen months. These forecasts compare favourably with the actual values for the thirteen months. However, Ekpenyong and Udoudo (2016) considered the analyses and forecasting of the monthly All-items (Year-on-Year change) Inflation Rates in Nigeria and observed from their study that the Inflation rates of Nigeria are seasonal and follow a seasonal ARIMA Model.

However, the GARCH model and its extensions have been well recognized lately in analyzing volatility of financial time series. The limited studies that embraced GARCH models are based only on the analysis of headline inflation to determine its effect on other macroeconomic variables, while others only check for symmetric headline inflation volatility, neglecting the two sides of the asymmetric responses. Apergis (2004) employed GARCH model with panel data to reveal the positive relationship between inflation, output growth and volatility. Udoh and Egwaikhide (2008) applied the GARCH model also to analyze the effect of headline inflation volatility on foreign direct investment using annual data between 1970 and 2005. Arize and Malindretos (2000), on the other hand, used the ARCH model to establish that inflation volatility impacts short run and long run negative effect on real money demand. Berument and Sahin (2010) employed the

EGARCH model to judge seasonal effect on inflation volatility. They observe that the periods with set prices for coming year or at the start of the year or at the introduction of new products, raise inflation volatility. Omotosho and Dogunwa (2012) applied the trio of GARCH, EGARCH and TGARCH to assess Nigeria's inflation volatility for her core, headline and food consumer price index (CPI), using monthly data across the sampled period of 16years (1996-2011). Their results show those periods of food price shocks, conflicting fiscal and monetary policies and changes in government policies poorly impact inflation volatility. In a recent study by Bamanga et al., (2016), GARCH and EGARCH model was used to examine the relationship between inflation and inflation uncertainty in Nigeria using monthly inflation data spanning the period 1960:1 to 2014:07. Their study revealed inflation series display structural breaks, which was tested and found to be significant and was accounted for in the model. The EGARCH fitted the data better than the symmetric GARCH model.

Using bounds testing approach to cointegration, Bawa et al., (2016) examined the dynamics of inflationary process in Nigeria over the period 1981to 2015. Their results indicated that inflation exhibited a strong degree of inertia. The results also showed that past inflation and average rainfall appeared to have been the main determinants of inflationary process in Nigeria. They also found strong evidence of the importance of money supply in the inflation process, lending credence to the dominance of the monetarist proposition on inflation dynamics in Nigeria. Olubosuye and Oyaromade (2008) analysed the main sources of fluctuations in inflation in Nigeria through error correction framework, it was found that the CPI, expected inflation, petroleum prices and real exchange rate significantly propagate the dynamics of inflationary process in Nigeria.

As evidently discovered, poor attention has been directed to the issue of structural breaks in inflation volatility modelling. The scarcely available ones are made for other countries while little or no research is geared towards that for the Nigerian economy. This study, therefore, aims at contributing to knowledge in the following ways: (i) to the best of our knowledge, no study has been done for the Nigerian economy capturing structural breaks, therefore, to be the only or notable among the few studies (if there are) that have accounted for structural breaks in inflation volatility for Nigeria. (ii) to add to the scarce studies on inflation volatility with structural breaks world over.

3.0 Data and Statistical Properties

We make use of monthly Consumer Price Index (CPI) data of both headline and core obtained from the Central Bank of Nigeria (CBN) statistical bulletin over the period of January, 1995 to October, 2016. Headline CPI is the overall CPI aggregated for the relevant sectors of the economy. It is captured as "All items>monthly CPI", while the core CPI reflects the economy's CPI having adjusted for food CPI because the latter is prone to inflationary spikes. Core CPI is headlined by the CBN as "All items CPI less Farm Produce>monthly CPI". However, the pre-estimation analysis is carried out in three forms, with the first giving the descriptive statistics for the CPIs and their inflations, the second carries out the unit root test using the Augmented Dickey-Fuller (ADF) unit root test with breaks, and the third establishes the ARCH effect.

From table 1, variations in the trends of the two CPIs appear not to be significant across the sampled period. This is observed through the thin difference between the CPIs' maximum and minimum values. However, given a comparison, headline is more volatile than core as informed by their standard deviation values. Also, both CPIs appear to be rightward skewed because of their positive values while the kurtosis analyses show that the CPIs are platykurtic implying fat tails than the normally distributed series. Non-normality of the CPIs is similarly reviewed by the Jarque-Bera (JB) statistics. More so, both headline and core inflation rates are also rightward skewed and leptokurtic. On the other hand, both inflation rates are not normally distributed as shown by the JB test.

The dynamics of price levels is illustrated in Fig 1. Prices of goods and services are evidently seen to be increasing in both measurements (headline and core), confirming the proposition of the monetarist that price is sticky downwards, but their inflation rate trends suggest the probable existence of volatility clustering, that is, high volatility firstly occurred at the early periods followed by relatively low volatility at the latter periods. The evident spikes in both graphs show the unsteady patterns of inflation rates. Largely responsible for the upward spikes were fiscal expansion and monetary growth, while the downward spikes result from the government's strengthening of its stabilization measures through rugged monetary contraction, exchange rate stability and fiscal surplus, as response to the inflationary pressures of initial periods.

Table 1: Descriptive Statistics

Statistics	Headline		Core	
	CPI_t	π_t	CPI_t	π_t
Mean	80.49	1.0273	81.95	1.001
Median	70.18	0.8118	69.47	0.7726
Maximium	209.68	8.5564	205.86	13.2013
Minimum	15.02	-3.5718	14.75	-7.3492
Standard Deviation	52.15	1.6559	51.51	2.0111
Skewness	0.68	0.6407	0.6	0.7884
Kurtosis	2.32	5.7176	2.23	9.7087
Jarque-Bera	25.69	98.1722	2.25	516.4811
Observation	262	261	262	261

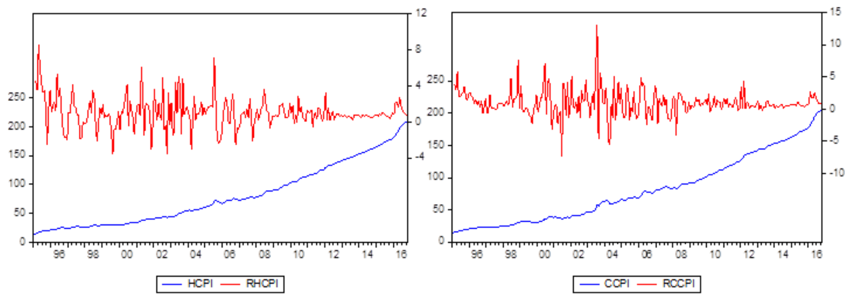

Figure 1: Combined graphs CPI and CPI returns (Headline and Core), Jan. 1995 to Oct. 2016

The result of the test statistics to test if ARCH effects are present in price changes is presented in Table 2. The test starts with a univariate model outlined as:

$$\pi_t = \alpha + \sum_{i=1}^{p} \beta_i \pi_{t-i} + \varepsilon_t \; ; \quad i = 1, \dots, p; \; t = 1, \dots, T; \; \varepsilon_t \sim \mathrm{IID}(0, \sigma^2) \; ; \; |\beta_i| < 1 \tag{1}$$

where π_t is the inflation rate, as it is shown to depend on past growth rate of price level (π_{t-i}) which captures the autoregressive components of inflation, α is the risk premium for investing in the long term securities, β_i represent the autoregressive parameters and ε_t is the error term and it measures the difference between the *ex-ante* and *ex post* rate of price returns. Inflation rate is therefore measured as:

$$\pi_t = [\Delta \log(CPI_t)] * 100 \quad (2)$$

where CPI_t represents Consumer Price Index and Δ is a difference operator of the first order.

However, the establishment of whether or not volatility exists in a series follows some three basic steps through the ARCH-LM test as proposed by Engle (1982): the foremost is the estimation of equation (1) by OLS to get the fitted residuals. Secondly, the square of the fitted residuals is regressed on constant and lagged values of the squared residuals, as presented in equation (3) below:

$$\hat{\varepsilon}_t^2 = \theta_0 + \theta_1 \hat{\varepsilon}_{t-1}^2 + \theta_2 \hat{\varepsilon}_{t-2}^2 + \cdots + \theta_k \hat{\varepsilon}_{t-k}^2 + \mu_t \quad (3)$$

The third step is the use of the ARCH-LM test to determine the presence of ARCH effect in the model. The ARCH-LM test has its null hypothesis as: $H_0: \theta_1 = \theta_2 = \cdots = \theta_k = 0$

Empirically, the F-test or Chi-square distributed ($\chi 2$) measured by the product of number of observations (n) and the coefficient of determination (R^2) obtained from the regressed equation (3) is used. The number of autoregressive terms in equation (3) is the degree of freedom (k).

Table 2: ARCH test

Dependent Variable: Inflation rate (πt)												
Model	z=1				z=5				Z=10			
	F-test		nR^2		F-test		nR^2		F-test		nR^2	
	HCPI	CCPI	HCPI	a	HCPI	CCPI	HCPI	CCPI	HCPI	CCPI	HCPI	CCPI
P=1	1.37	34.69**	1.37	30.81**	4.26*	7.10*	20.09*	31.82*	2.98*	4.53*	2.73*	39.30*
P=2	12.97*	20.16*	12.44*	18.84*	4.33*	4.38*	20.40*	20.61*	2.49*	3.55*	23.56*	32.30*
P=3	4.39**	20.05*	4.35**	18.73*	2.98*	4.00*	14.39**	18.94*	1.82***	3.43*	17.76***	31.35*

Table 3: Augmented Dickey -Fuller unit root test with breaks

Inflation rate		**Level**		
		M1	M2	M3
HCPI		-12.1224	-12.3232	-12.4918
Break date		(1996, M09)	(1996, M10)	(1996, M12)
CCPI		-15.7269	-15.2238	-16.7789
Break date		(2003, M07)	(1996, M09)	(2003, M07)

As clearly seen in table 2, except for the lag 1 of ARCH (1) process, there is a certainty of ARCH effects, determined through the strong significance of the test statistics across varying lags at majorly 1%. The reason for the insignificance of the ARCH effect for the first order and at one lag could result from the fact that changes in price level may not be that frequent and evidently seen following a short period. This is in line with what was obtainable under the descriptive statistics in Table 1 where we discovered a relatively small movement in the price indices.

The result of the unit root test is presented in Table 3. The Augmented Dickey-Fuller unit root test with break is used, and it accounts for just one structural break in the series. For the three models respectively accounting for intercept, trends, trend and intercept in both headline and core inflation rates, we resoundingly reject the null hypothesis and conclude that both inflation types are stationary at level. Conventionally, the break date of the Model 3 (M_3) is considered because the model has the highest absolute test statistic value for the two cases of inflation. The break for the headline inflation occurs in December, 1996 while core inflation has its break date in July, 2003.

4.0 Volatility Models and Empirical Analysis

In this section, we explore necessary volatility models for the variables under consideration and compare their performances. SIC, AIC and HQC are our major model selection criteria to know which model is the fittest, while varying post-estimation analyses are also included for the validation of the volatility models. As aforementioned, one resounding contribution of this study is the addition of structural break date in the study relating to inflation volatility from the outline of "Augmented Dickey-Fuller unit root test with breaks", capturing both symmetric volatility models [(GARCH, (1,1) and GARCH-Mean (1,1)] and asymmetric volatility models [EGARCH (1,1) and TGARCH (1,1)]. This way of estimation is fantastic, as it aids the achievement of good analysis of how the conditional heteroscedasticity of inflation varies with time, as well as observed the mean reverting characteristics of the variance. The GARCH (1,1) model has its mean equation defined as:

$$\pi_t = \alpha + \beta\pi_{t-1} + \delta B_{1,t} + \varepsilon_t \qquad (4)$$

where $B_{i,t}=1$ if $t \geq B$ and 0 otherwise; B represents the break dates as shown in Table 3 with a coefficient term $\delta\ that$ characterizes the break period. Given that $\varepsilon_t = \sigma_t e_t$ and $e_t \sim (0,1)$, then, the equation for the variance of the GARCH (1,1) model is described as:

$$\sigma_t^2 = \xi + \theta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2\ ;\ \xi > 0, \theta \geq 0, \lambda \geq 0 \qquad (5)$$

With equation (5), presence of volatility in the series will make the variance to be large and vice-versa. The ARCH effect is denoted by θ and the GARCH effect by λ. The sums of the coefficients for the ARCH and GARCH effects must be less than one (i.e. $\theta + \lambda < 1$), which is required to have a mean reverting variance process. The constant term of the variance equation is captured by ξ. In exploring the trend of behaviour of inflation, the GARCH-M model sufficiently analyses the conditional variance effect (or conditional standard deviation) and this is explained by $\emptyset$ in equation 6. The GARCH-M allows the conditional mean to depend on its own conditional variance. Hence, the GARCH-M is obtained from the modification of the mean equation of GARCH (1,1) as thus:

$$\pi_t = \gamma + \phi\sigma_t^2 + \beta\pi_{t-1} + \delta B_1 + \varepsilon_t \qquad (6)$$

The asymmetric GARCH models are also estimated to examine the probable existence of leverage effects. Evidently, the Exponential GARCH model (EGARCH model) and the Threshold GARCH (TGARCH) model have become prominent in this regard.

For the asymmetric volatility models considered in this study, the EGARCH is expressed as:

$$\ln(\sigma_t^2) = \psi + \varphi\left|\sqrt{\varepsilon_{t-1}^2 / \sigma_{t-1}^2}\right| + \omega\sqrt{\varepsilon_{t-1}^2 / \sigma_{t-1}^2} + \Omega\ln(\sigma_{t-1}^2) \qquad (7)$$

There is evidence of the asymmetric effect if $\omega < (>) 0$ and there is no asymmetric effect if $\omega = 0$. $\omega < 0$ means that volatility is increased by negative shocks more than positive shocks of the same magnitude. Essentially, the null hypothesis is $\omega = 0$ (i.e. there is no asymmetric effect and the testing is based on the t- statistic. The conditional variance in the EGARCH model is always positive with taking the natural log of the former. Thus, the non-negativity constraint imposed in the case of ARCH and GARCH models is not necessary (see Harris and Sollis, 2005).

The TGARCH (1,1) model, however, is an extension to equation (5). Dummy variable, D_{t-1}, is added;

$$\sigma_t^2 = \xi + \theta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \tau\varepsilon_{t-1}^2 D_{t-1} \qquad (8)$$

where positive shocks result as $D_{t-1}=1$ if $\varepsilon_{t-1}>0$ and otherwise as $D_{t-1}=0$. Therefore, there is evidence of asymmetric effect if $\tau < (>) 0$ which implies that positive (negative) shocks reduce the volatility of π_t by more than negative (positive) shocks of the same magnitude[2]. By implication, if $\tau < 0$, asymmetric effect is evident and therefore, means that positive shocks reduce the volatility of π_t more than negative shocks having the same magnitude and vice-versa. The Tables 4 and 5 present the results of the volatility models used.

Table 4: Empirical Results of Volatility Models with Structural Breaks for Headline Inflation

Variable	GARCH(1,1)	GARCH-M (1,1)	EGARCH (1,1)	TGARCH (1,1)
Mean Equation				
α	1.2762(2.2716)**	1.2260(2.7122)*	-0.0415(-0.2659)	1.3386(2.4023)**
β	0.3711(5.2695)*	0.3726(5.2738)*	0.3906(5.2232)*	0.3720(5.2070)*
δ	-0.7278 (-2.3113)**	-0.7948(-1.3609)	-0.6951(-1.6931)***	-0.7891(-1.4354)
δ	--------------------	-0.0415(-0.2659)	------------	
Variance Equation				
ξ	0.0078(2.2784)**	0.0075(1.6461)**	-0.1533(-6.1850)*	0.0080(2.4778)*
θ	0.0812(4.6215)*	0.0809(4.2810)*	-------	0.0965(3.0665)*
λ	0.9085(70.4880)*	0.9089(66.9614	-----	0.9071(69.3047)*
τ	-----------	-----------	-----------	-0.0291(-0.6201)
ϕ	-----------	-----------	0.2168(4.9696)*	----------
ω	-----------	-----------	0.1325(2.8183)*	----------
Ω	-----------	-----------	0.9686((121.2193)*	----------
Observation	260	260	260	260
Diagnostics				
AIC	3.3189	3.3095	3.3095	4.5057
SIC	3.401	3.4221	3.4054	4.5332
ARCH-LM test				
F-test	0.0852	0.111	0.1853	0.0927
nR^2	0.0859	0.118	0.1867	0.0934

Note: *, ** and *** respectively imply 1%, 5% and 10% significance level

[2] However, in some standard econometric packages like *GARCH* program and Eviews, the reverse is the case for the definition of D_{t-1}. That is, $D_{t-1} = 1$ if $\varepsilon_{t-j} < 0$ (negative shocks) and $D_{t-1} = 0$ otherwise. Thus, there is evidence of asymmetric effect if $\tau > (<)0$ which implies that negative (positive) shocks increase the volatility of π_t by more than positive (negative) shocks of the same magnitude.

Table 5: Empirical Results of Volatility Models with Structural Break for Core Inflation

Variable	GARCH (1,1)	GARCH-M(1,1)	EGARCH (1,1)	TGARCH (1,1)
Mean Equation				
α	0.5775(4.7188)*	0.3236(1.6676)***	0.7095(3.7614)*	0.5833(3.7934)*
β	0.2135(2.5722)**	0.1425(1.8803)***	0.1911(2.511)**	0.2198(2.5435)**
δ	0.0395 (2.2633)**	0.1428(1.9197) ***	-0.1474(-1.7767)***	0.0650(0.3784)
∅	--------------------	0.2266(1.9301)***	--------------------	--------------------
Variance Equation				
ξ	0.0692(3.9369)*	0.0652(5.4078)*	-0.3652(-7.4650)*	0.0607(3.6572)*
θ	0.4565(5.1918)*	0.4700(4.9568)*	-------	0.4696(4.7949)*
λ	0.6562(15.0825)*	0.6475(14.8631)*	-----	0.6958(15.717)*
τ	-----------	-----------	-----------	-0.1878(-1.5727)
ϕ	-----------	-----------	0.6470(7.7962)*	----------
ω	-----------	-----------	0.0537(0.9109)	----------
Ω	-----------	-----------	0.8969(58.6821)*	----------
Observation	260	260	260	260
Diagnostics				
AIC	4.7376	4.6886	4.7201	4.7202
SIC	4.765	4.7161	4.7426	4.7477
HQC	4.7486	4.6997	4.7302	4.7312
ARCH-LM test				
F- test	0.1097	0.1328	0.0035	0.1334
nR^2	0.1105	0.1338	0.0035	0.1344

Note: *, ** and *** respectively imply 1%, 5% and 10% significance level

The presented results in both tables show that the variance process has a slow mean reversion for all the symmetric and asymmetric models for both headline and core inflation. However, the core inflation reverts quicker than headline inflation as judged by the sum of ARCH and GARCH effects. For example, in the case of GARCH (1,1), the headline inflation gives a value of 0.91, core inflation reports 0.66. They are both closer to 1 and can be evidently seen to revert slowly, but the latter is quicker in reversion. This evidence of slow mean reverting process suggests strong persistence in inflation volatility for both types, although persistence degree differs. This analysis is in line with the outcome of the descriptive statistics in Table 2, which shows, as informed by their standard deviations, that headline CPI tends to embrace more volatility than core CPI.

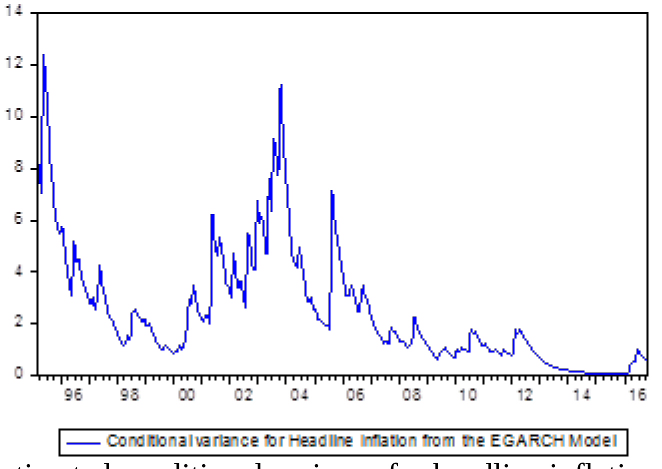

Figure 2: Estimated conditional variance for headline inflation from the EGARCH Model, Jan.1995 to Oct. 2016.

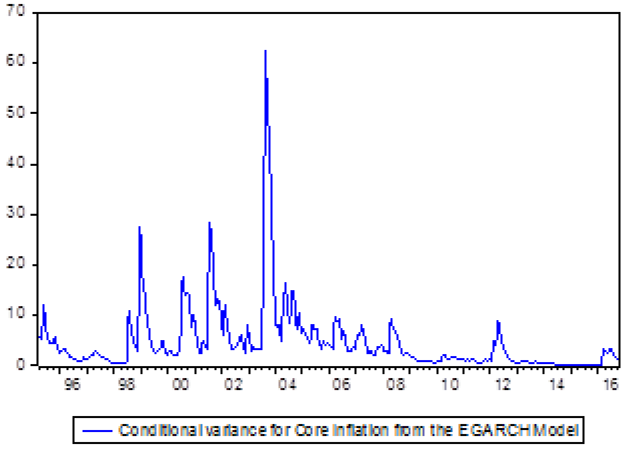

Figure 3: Estimated conditional variance for core inflation from the EGARCH Model, Jan.1995 to Oct. 2016

Comparatively, better fit is achieved by the GARCH (1, 1) model over the GARCH-M (1,1) model for the symmetric models, based on the AIC and SIC values. This is better revealed by the insignificance of the standard deviation coefficient of the inflation (i.e. ϕ) for the headline inflation, and although it is significant at 10% in the case of core, but the GARCH term (δ) is more resoundingly significant at 1%. This is consistent with the findings of Omotosho & Dogunwa (2012), and Kelikume & Salami (2013). Similarly, a better fit is also captured by the EGARCH (1,1) over the TGARCH (1,1) model for the asymmetric case. In all, the GARCH (1,1) model (i.e. the symmetric model) is less superior to the EGARCH (1,1) model (i.e. asymmetric model). This result is quite similar to results obtained in other studies for developing countries (see Kontonikas, 2004; Berument & Sahin, 2010; and Eisenstat & Strachan, 2014). The conditional variance graphs are also shown in Figs. 3 and 4 and they reveal some spikes revolving around the chosen break dates, and so, confirm the importance of capturing breaks in inflation volatility modelling.

Also, leverage effects are established by the results of the EGARCH model for headline inflation as it is shown to be significant at 1%, unlike the core inflation that shows no significance. It implies that positive shocks in headline inflation rates have larger impact on volatility than negative shocks of the same magnitude, as informed by the positive value of the coefficient measuring the leverage effects. In reality, it means that when good news occurs in relation to price changes, there is tendency of increasing volatility in inflation rate than bad news. Such effects are not found for core inflation because it embraces relative stability than headline inflation since it has been adjusted for food prices that are prone to inflationary trends. This result is in consonance with Bamanga et al., (2016), however, the study only observed this trend for general price level.

Confirming the above discussion on the evidence of volatility, we also carry out post-estimation diagnostic tests to further substantiate the reports of the pre-estimation test that reveals the existence of ARCH effects in the inflation rates. The ARCH test for post-estimation is done using both the F-test and chi-square distributed (nR^2) test. All the results obtained for the two inflation types for all the models are statistically insignificant at even the highest significance level of 10%. Hence, we do not reject the null hypothesis of no ARCH effects.

5.0 Conclusion

Inflation volatility is really a serious issue for economic concerns, due to its impending uncertainty or risks to concerned economic agents. To lenders, evidence of high inflation volatility is a discouragement. It also discourages savings as people would be afraid of reduction in the real value of their saved earnings, hence, investment is jeopardized and growth is aggregately retarded. Therefore, modelling inflation volatility for Nigeria has much policy importance, and this guides the motivation to carry out this study. Our major objective is to examine volatilities for both headline and core inflation types using monthly data from January, 1995 to October, 2016.

We use the augmented Dickey-Fuller Unit Root test with breaks to analyze the inflation types, and this technique allows for one break date in each of the variables. Headline inflation has such break in December, 1996 while it occurs for core inflation in July, 2003. Leverage effects are also found for headline inflation only; implying that concerned economic agents react to news in general price level, but such is not obtained for core inflation. This is probably due to the fact that core inflation is usually measured to adjust for food and energy prices that appear to have inflationary spikes. More specifically, we discover that good news in price changes has the tendency of increasing volatility than bad news. Also, we see that core inflation is more persistent in volatility than headline inflation. Comparing the volatility models, the symmetric models (GARCH and GARCH-M) prove to be less appropriate in modelling inflation volatility than asymmetric models (EGARCH and TGARCH). Categorically, EGARCH establishes the best fit, and therefore, is recommended to be given viable consideration for subsequent studies in this line. Generally, we strongly advise that structural breaks should not be left out in modelling inflation volatility in further researches. In connection with the findings, more realistic proactive measures may be required by the monetary policy authorities to promote price stability. The current design for ensuring price stability in Nigeria may have to be restructured to alter the existing trend. Finally, the concept using one particular model approach for modelling inflation rate volatility will yield misleading and invalid policy prescriptions.

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