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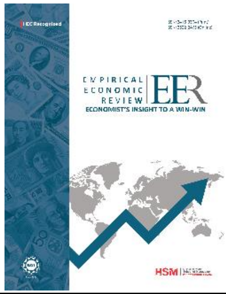

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Modelling the Volatility of Sub-Indices Returns of Nigerian Stock Exchange Using GARCH Model

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Abstract

The current study examined the weekly returns of six sub-indices of the Nigerian stock exchange including banking, consumer goods, insurance, oil/gas, pension, and industrial goods indices from September 02, 2020 to February 28, 2022**.** The returns were stationary at level and not normally distributed. Ljung-Box-Q statistics and Ljung-Box square statistics (Q^2) for the transformed power of 0.75., 0.5, and 0.25 and lags 20, 12, and 6 indicated the existence of conditional heteroscedasticity in all indices returns. The results revealed that the APARCH model measured volatility more persistently than the GARCH model and leverage effects were present in the returns of all the six indices. To conclude, the APARCH model was determined as the best model for estimation and forecasting purposes for all the indexes. Incorporating the effect of negative shocks was also found to be crucial when formulating and implementing stabilization policy in the stock market.

Keywords**:** Stock Returns volatility, Sub-Indices, Nigerian Stock Exchange, GARCH model

Introduction

Stock price provides information about the health of a business entity or a particular sector of an economy and, by extension, the health of the nation's economy in which these entities operate. The price of equity provides a prospective investor with a guide regarding which stocks to invest in and where not to invest. Also, the stock market is an avenue for investing in publicly quoted companies to co-own businesses that ordinarily might never be ventured into individually. It also provides investors with opportunities to grow their wealth without going through the hustle of managing a business themselves, as well as to possess diversified financial holdings and as a hedge against risk. The stock market provides income and employment to the individual participant. It

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also allows the government to benefit in terms of tax revenue from capital gain taxes payable to the government.

The volatility of stock prices has been linked to the economy's performance at large. Stock price volatility tends to transmit from one sector of the economy to another, resulting in investors searching for a safe haven and the diversification of portfolio to insulate themselves from negative asset price volatility and to maximize their returns when there is positive price movement in stocks. Nigeria is a mono-economy and oil price changes profoundly affect the stock price. Also, the stock market is an avenue in which surplus funds are moved from saver-lender to borrower-spender with a shortage of funds (Mishkin, 2000).

Extensive research has been conducted on the correlation between exchange rate volatility and stock market volatility. Additionally, studies have analyzed the impact of macroeconomic variables on stock market volatility and the influence of oil price volatility on stock market performance. Moreover, a comparative analysis of volatility has been conducted in the currency market and stock market in Nigeria. However, research on sectoral stock price volatility and its transmission from one sector of the economy to another is scarce, if not, totally non-existent. For instance, comparative study of the sub-indices of Nigerian stock exchange and volatility transmission from consumer goods index to industrial goods index, banking index, pension index, oil/gas index vice versa (to mention but a few) are hard to come by in economics literature available on Nigerian financial market. This research aims to address one of these gaps by comparatively analyzing volatility persistency and leverage effect of six sub-indices, namely consumer goods, banking, insurance, pension, oil/gas, and industrial goods indices of the Nigerian stock exchange.

A key measure of market risk is the volatility of stock prices. This aids in determining the degree of risk connected to certain equities or with the market as a whole for investors and financial institutions. Therefore, in order to make wise financial decisions, one must comprehend volatility. Furthermore, the current study advances the creation of investing techniques. Policymakers use stock price volatility to design and modify economic policies. Investors may modify their portfolios depending on the predictions of future volatility. During times of heightened volatility, investors may adopt risk-averse tactics or they may seek larger returns in turbulent markets. For central banks and regulatory agencies, understanding how monetary and fiscal policies affect market volatility and stability is crucial in the process of formulating and implementing financial sector policies.

The current paper is structured as follows. Introduction is followed by literature review. Section III dwells on the method employed for the study. Section IV presents the data and discusses the results. Finally, Section V concludes the paper.

Literature Review

Abraham (2016) investigated the impact of oil prices on the Nigerian stock market, as well as the countercyclical effects of exchange rate using daily data for the crude oil price, exchange rate, and all share indexes from 2008 to 2009 and 2012 to 2015. The study employed the auto-regressive distributive lag method and found that increased oil prices positively impact the stock market. On the contrary, a decrease in oil price is a drag on it. While, exchange rate depreciation is a countervailing measure during a negative growth period or decline in oil price.

Abdullahi (2020) examined the effect of volatility persistent in stock market performance in Nigeria. The study used ARCH and GARCH models to analyze weekly data from January 8th, 2010 to October 26th, 2018. According to the study, Nigeria's stock market saw considerable and enduring volatility over the time period under consideration. Ghufran et al. (2016) found that the persistence of stock market volatility is directly linked to inflation and interest rate volatility, while Ariwa et al. (2017) linked the Nigerian stock market volatility persistence to news, unstable stock prices, liquidity shortage, and low level of confidence exerted by investors.

Kandora and Hamdi (2016) examined volatility persistence and leverage effect of Sudan’s principal stock market index using monthly data for the period January 1999 to December 2013. They used asymmetric and symmetric GARCH models to the model exchange stylized fact, such as volatility clustering and leverage effect. They found that stock returns volatility is very persistent (explosive) and the leverage effect exists. Moreover, the asymmetric model is the best-fitted model as compared to the symmetric model.

Lim and Sek (2014) investigated the causal relationship between stock returns and exchange rate volatility in /emerging Asian nations. A bidirectional causation was discovered between stock returns and exchange rate volatility in Thailand, Indonesia, and Korea. Lawal and Ijirshar (2013) conducted a research investigating the link between exchange rate volatility and performance of Nigerian stock market. The findings revealed a causal relationship, where exchange rate volatility influences the stock market. This suggests that when there is a higher level of volatility in the currency market, it has a negative effect on the equities market performance. Adebayo and Harold (2016) analyzed the impact of global shocks on exchange rate volatility between Russian Ruble and US Dollar. The researchers used exchange rate spanning the period January 1994 to December 2013. They also employed asymmetric and symmetric GARCH models and observed that exchange rate volatility does not respond asymmetrically to global shock. Hence, no evidence of leverage effect was found in the returns of exchange rate. They also found that symmetric model is the best fit for a non-normal distribution. Ahmad (2020) analyzed Naira exchange rate volatility against US Dollar pass through to Nigerian stock market. The study used monthly data from January 2004 to January 2018. It employed asymmetric and symmetric GARCH models to model volatility in both markets. The study found that stock market volatility is mean-reverting in GARCH in mean model. In contrast, volatility was non-mean-reverting in asymmetric GARCH (1,1) model and leverage effects existed in asymmetric model. The post-analysis diagnostic test showed that all models completely took out the ARCH effect in the returns.

Colavecchio and Michael (2008) used the GARCH approach to assess the transmission of volatility between the Renminbi forward market and seven Asia Pacific nations for the period spanning January 1998 to January 2005. The Renminbi forward significantly impacted Asian currency markets during the said period, though the impact differed across nations. Wei (2008) used multivariate GARCH to analyze the relationship between USD/RMB exchange rate and Chinese stock markets. The research identified a negative relationship between unexpected fluctuations in the USD/RMB rate and the performance of China's stock markets. It indicated that unanticipated shocks had a detrimental impact on China’s stock markets. Agya (2017) analyzed the impact of exchange rate on Nigerian stock market for the period May 31, 2002 to November 1, 2016. The research used the bivariate GARCH technique and found that historical returns had a considerable influence on present returns in both markets, with a greater effect on the exchange rate. Furthermore, there was a transmission of feedback volatility in both markets, as well as a one-way transfer of shocks from the stock market to the currency rate. Additionally, the impact of leverage was seen in both markets.

Zhao (2010) used the GARCH model to examine the correlation between the real exchange rate of the Renminbi (RMB) and the price of Chinese equities for the monthly data spanning January 1991 to June 2009. The study revealed a bilateral transmission of volatility between China's stock prices and real exchange rate, with past stock market innovations exerting a greater influence on future foreign currency market volatility. In addition, Yau and Nieh (2009) examined the nexus between stock prices in Taiwan and the exchange rate between Japanese Yen and Taiwanese dollar. They found evidence of asymmetrical causal links. Bahmani-Oskooee and Sohrabian (1992) found evidence of a two-way relationship between stock prices and the effective dollar exchange rate in India. In a similar manner, Apte (2002) used the E-GARCH model to study the nexus between stock market and currency market volatility in India. The study also included the presence of asymmetric effects inside and across markets. The results revealed a significant association between volatility and spillover from stock market to exchange rate market. Manasseh et al. (2019) investigated the nexus between stock prices and currency rate by using a VAR-GARCH model. They analyzed monthly data from January 2000 to October 2014. The findings indicated that there was a transfer of impact between stock and exchange markets. Moreover, there was a feedback transmission of volatility between stock prices and exchange rate. Caporale et al. (2014) examined the nexus between stock market values and exchange rates in six advanced economies, namely Canada, Japan, the US, the UK, the euro area, and Switzerland. The study covered the period 2007-2010. It used the bivariate GARCH-BEKK methodology. The findings indicated one-way spillover effects from stock returns to exchange rates in the UK and from exchange rates to Canada stock returns, and two-way spillover effects in Switzerland and the EU region.

Methodology

This study used the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model established by Bollerslev (1986), as well as the Generalized Power Autoregressive Conditional

Heteroscedasticity (PARCH) model developed by Ding et al. (1993). The second model has the benefit of specifying the asymmetric impact of shocks on conditional volatility. Additionally, it allows for the estimation of standard deviation, rather than imposing restrictions akin to other asymmetric models.

Model Specification

We begin with a standard GARCH (m,n) model specified below:

$$\sigma_t^2 = \varpi + \sum_{i=1}^{m} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{n} \beta_j \sigma_{t-j}^2 \qquad 1$$

where m ≥ 0, n > 0, ϖ >0, α_i ≥0, β_j ≥ 0, i =1,…, m, j=1,…,n.

Equation (1) is the GARCH (*m*,*n*) model, where p and q refer to the square of the error term and the conditional variance lagged terms, respectively. This shows that conditional variance is explained by previous shocks (ARCH term) and previous variances (GARCH term). The GARCH impact denotes $\sum_{i=1}^{m} \alpha_i \varepsilon_{t-i}^2$ the ARCH, GARCH impact $\sum_{j=1}^{n} \beta_j \sigma_{t-j}^2$.

The APARCH (m,n) model is stated as follows:

$$\sigma_t^\delta = \varpi + \sum_{i=1}^{m} \alpha_i (|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i})^\delta + \sum_{j=1}^{n} \beta_j \sigma_{t-j}^2 \qquad 2$$

where δ > 0, $|\gamma_i| \leq 0$ for i=,…,r, γ_i > 0 for all I>r, and r ≤ m if $\gamma \neq 0$. Hence, the effect of shock is not asymmetric.

The exponent term δ in equation (2) above allows to capture the actual underlying volatility distribution. Also, in modelling the financial data normality assumption, restricting δ to either equation (1) or equation (2) is not realistic owing to significant skewness and kurtosis, as opined by Longmore and Robinson (2004). Hence, δ is allowed to estimate a free parameter, thereby removing the arbitral restriction.

Data Description

The data collected for this study covered the period extending from 2nd September 2020 to 28th February 2022. Data was collected from the banking, insurance, pension, consumer goods, oil/gas, and industrial goods indices (which are weekly sectoral stock price indices, sourced from the Nigerian stock exchange, weekly stock market report via http://www.http://www.nse.com.ng).

Since continuously compounded returns have appealing statistical features and benefits over simple net returns, they were utilized in this study. These included the inclusion of an unlimited number of periods. It indicates that compounding frequency is irrelevant, thus makes it simple to evaluate returns on various assets and on the basis of the symmetry of continuous compounding. Continuous compounding is also time additive, which indicates that returns are the sum of the logarithm and it is imperative to avoid negative returns.

The returns are defined as follows: $r_t = \text{Ln}(R_{t/}/R_{t-1}) \text{ X } 100$.

Results and Discussion

Table 1 shows the descriptive statistics of the banking, consumer goods, insurance, oil/gas, pension, and industrial goods indices. It depicts that the oil/gas index has the highest mean value, while the banking and consumer goods indices have the lowest mean values, all indices have zero (0) median values. The oil/gas index has the maximum value (0.74), while the consumer goods index has the lowest maximum value (0.29). Furthermore, the banking index has the highest minimum rate (-0.228), while the oil/gas index has the lowest minimum rate (-0.547). The standard deviation, the measure of volatility, shows that the oil/gas index is the most volatile, while the consumer goods index is the least volatile. The skewness of the indices shows that all indices are positively skewed, except for the industrial goods index which is negatively skewed. The value of kurtosis is much higher than the recommended 3 for a normal distribution for all indices, which is against normal distribution (0 skewness for normal distribution), a sign of asymmetric distribution. The greater kurtosis value indicates that the series is leptokurtic, indicative of fat tails. The value of skewness suggests a non-normal distribution, showing the benefits of trading the stocks that make up these indexes. The J-B also tests lend the non-normality distribution further support, with a probability of (0.000) for all indices. Moreover, the Ljung Box Q statistics show serial correlation (autocorrelation) in the return of the indices for the considered lags of 1, 5, and 10 and remain significant at 5%.

Table 1
Descriptive Statistics and Autocorrelation of Indices

Indices / Stats.	Banking	Consumer Goods	Insurance	Oil/Gas	Pension	Industrial Goods
Mean	0.0014	0.0014	0.0028	0.0031	0.0023	0.0020
Med.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Max.	0.4020	0.2993	0.6721	0.7396	0.5318	0.4487
Min.	-0.2288	-0.3073	-0.5478	-0.5826	-0.3983	-0.5073
Std. Dev.	0.0856	0.0824	0.1654	0.2162	0.1249	0.1389
Skew.	1.4396	0.1272	0.3143	0.0955	0.7029	-0.4421
Kurt.	9.3606	9.1699	9.1124	5.3853	9.1039	6.6598
Jarq-Ber.	375.75 (0.0000)	293.93 (0.0000)	291.03 (0.0000)	44.14 (0.0000)	302.43 (0.0000)	109.27 (0.0000)
Obs.	185	185	185	185	185	185
Ljung Box Q Statistics						
Q(1)	0.788** (0.000)	12.703** (0.000)	21.896** (0.000)	26.512** (0.000)	18.030** (0.000)	25.686** (0.000)
Q(5)	14.214** (0.014)	18.589** (0.002)	25.219** (0.000)	43.000** (0.000)	23.359** (0.000)	31.951** (0.000)
Q(10)	17.926** (0.045)	21.854** (0.016)	31.274** (0.001)	65.503** (0.000)	32.694** (0.000)	34.593** (0.000)

Note. *p*-value in parentheses with ** denote 5% level.

The Q-Q plot displayed in Figures 1-6 for the returns of the indices for banking, consumer goods, insurance, pension, oil/gas, and industrial goods shows a striking divergence from the normality graphs.

Figure 1
Banking Index Q-Q Normality plot

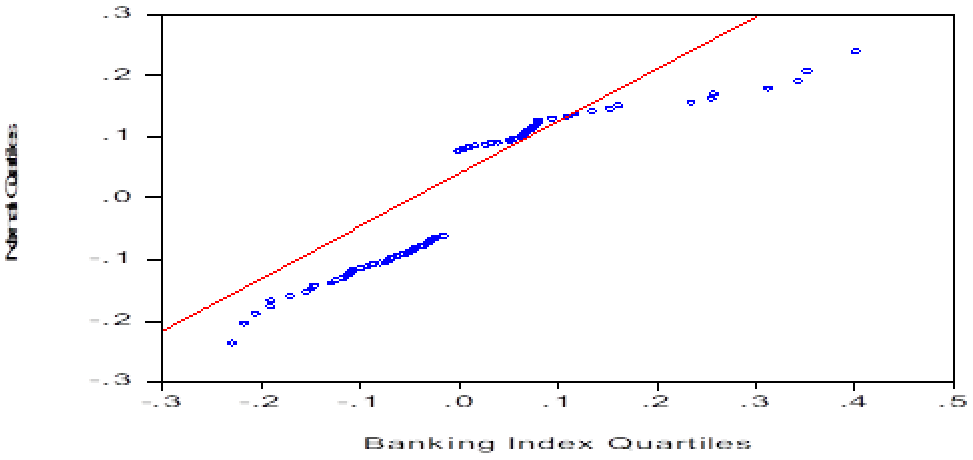


Figure 2
Consumer Goods Q-Q Normality plot

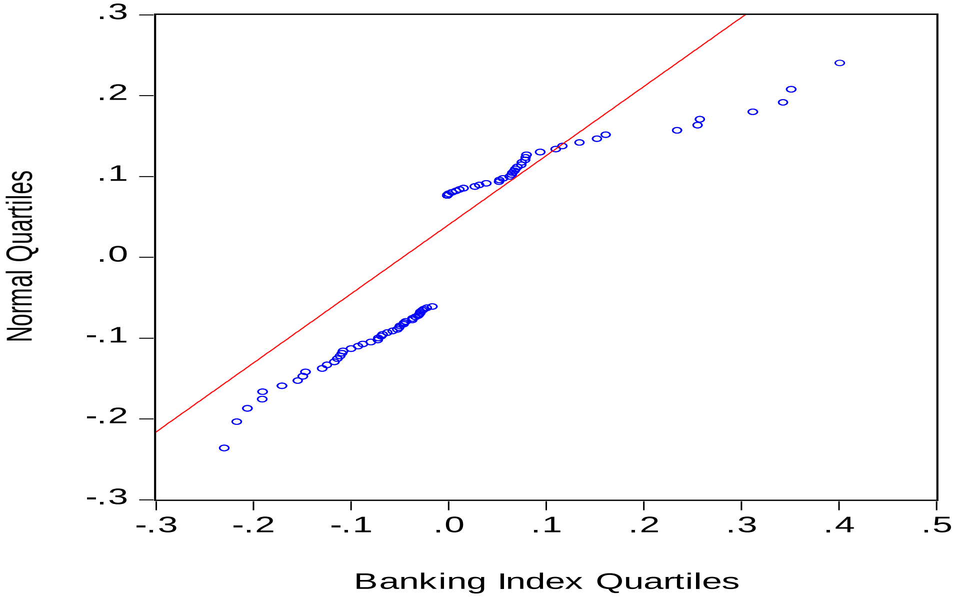


Figure 3
Insurance Index Q-q Normality Plot

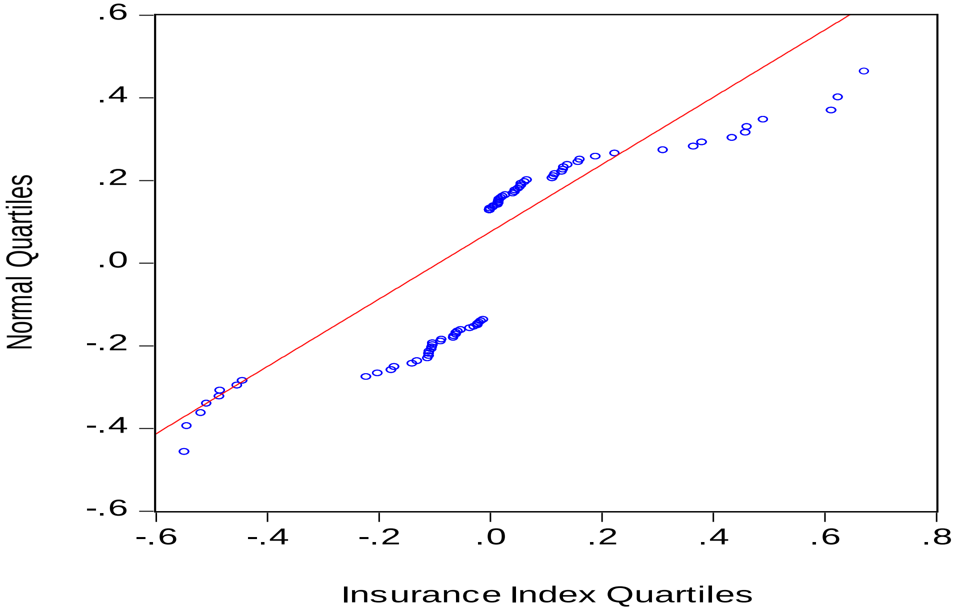


Figure 4
Oil/Gas Normality Plot

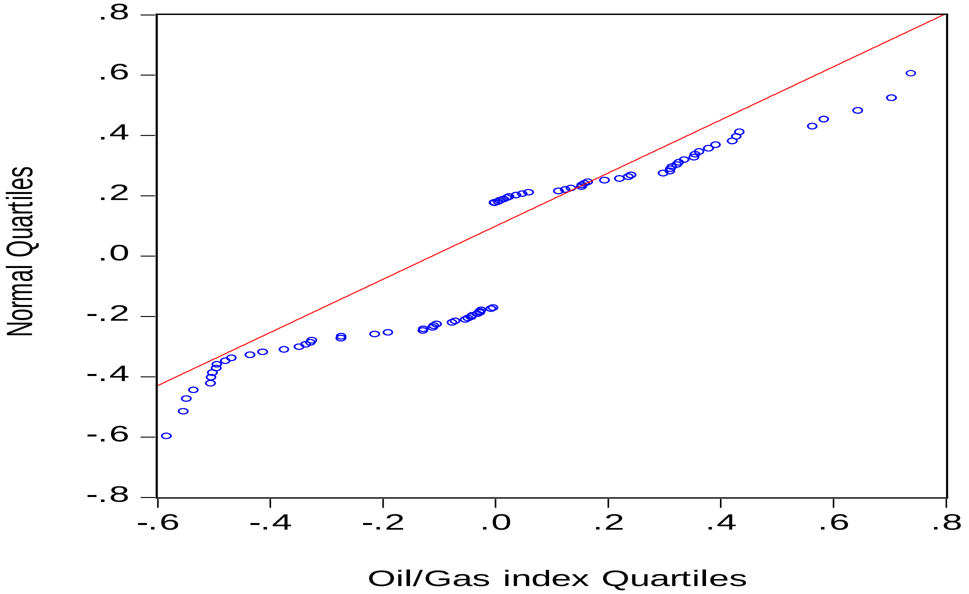


Figure 5
Pension Index Q-Q Normality Plot

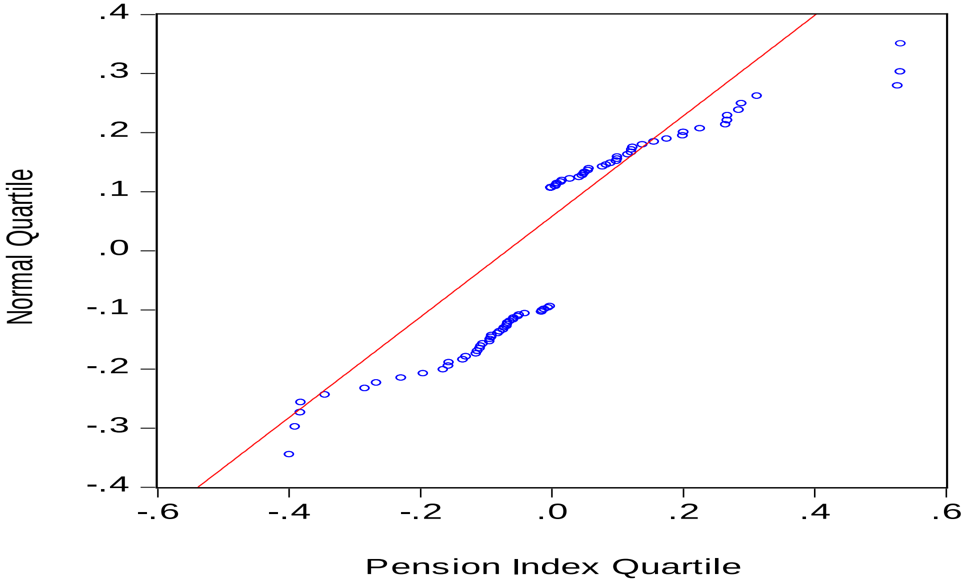
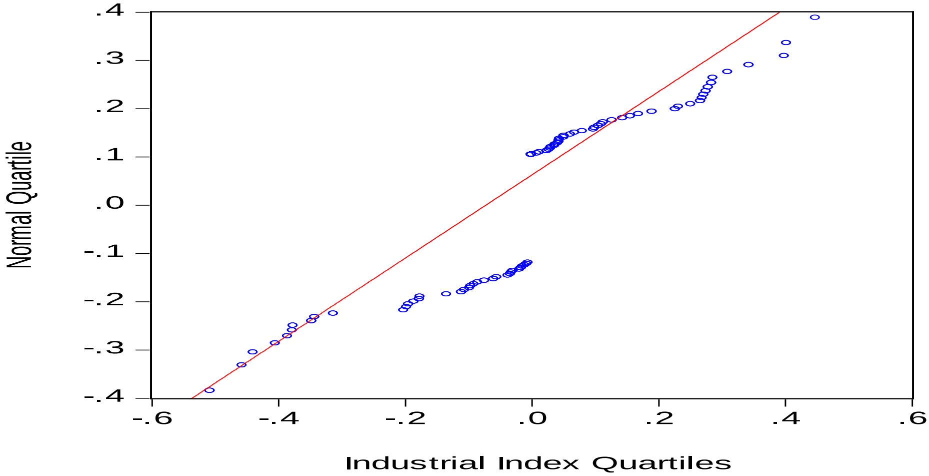


Figure 6

Industrial Goods Index Q-Q Normality Plot



The graph for volatility clustering, displayed in figures 1, 2, 3, 4, 5, and 6 below, unmistakably demonstrates the occurrence of volatility clustering, whereby a time of high instability is preceded by a time of high instability and a time of low instability is also preceded by a time of low instability. For all indices, the return tends to cluster around the mid-2021 surge.

Figure 7

Volatility Clustering Consumer Goods Index Return

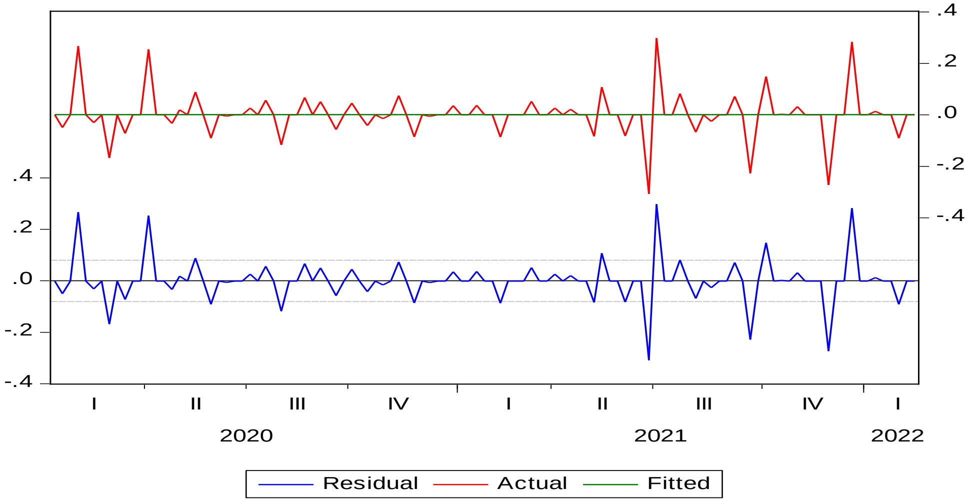


Figure 8

Volatility Clustering Insurance Index Return

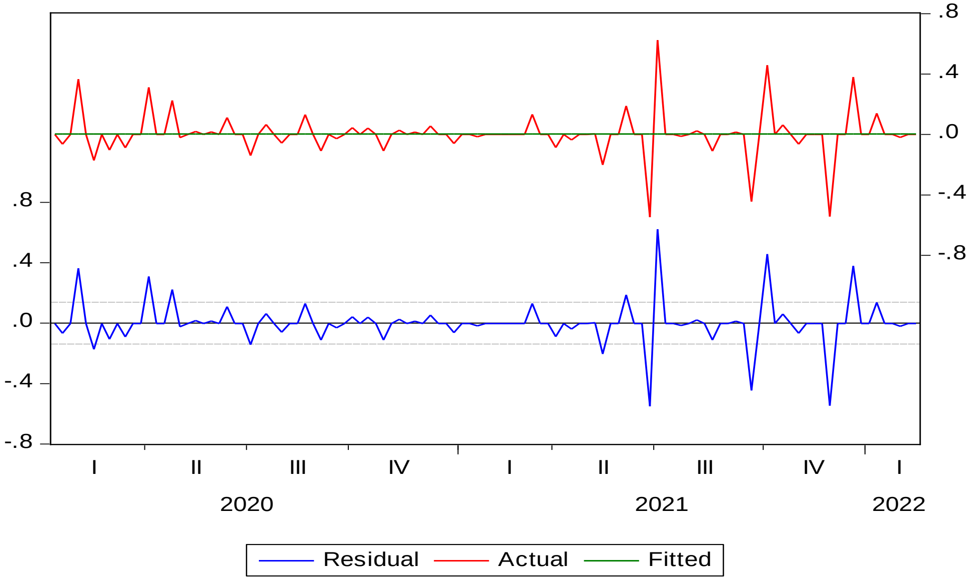


Figure 9

Volatility Clustering Pension Index Return

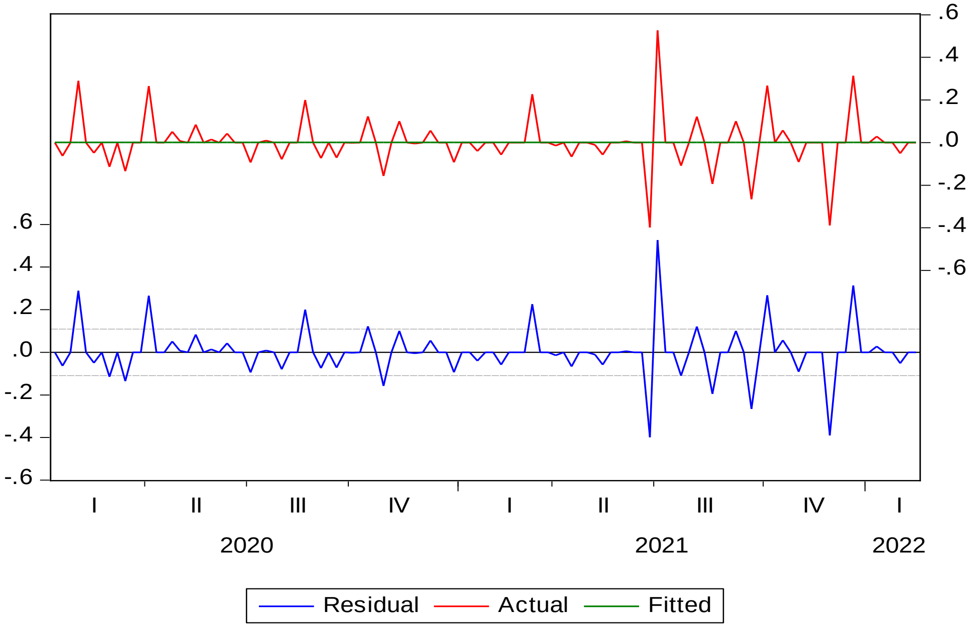


Figure 10
Volatility Clustering of Banking Index Return

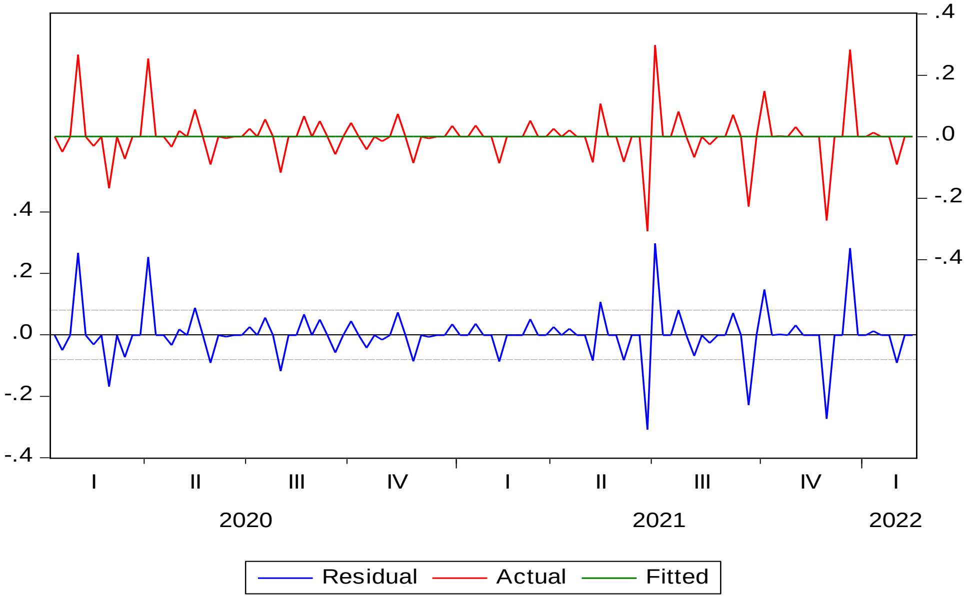


Figure 11
Volatility Clustering of Industrial Goods Indes Return

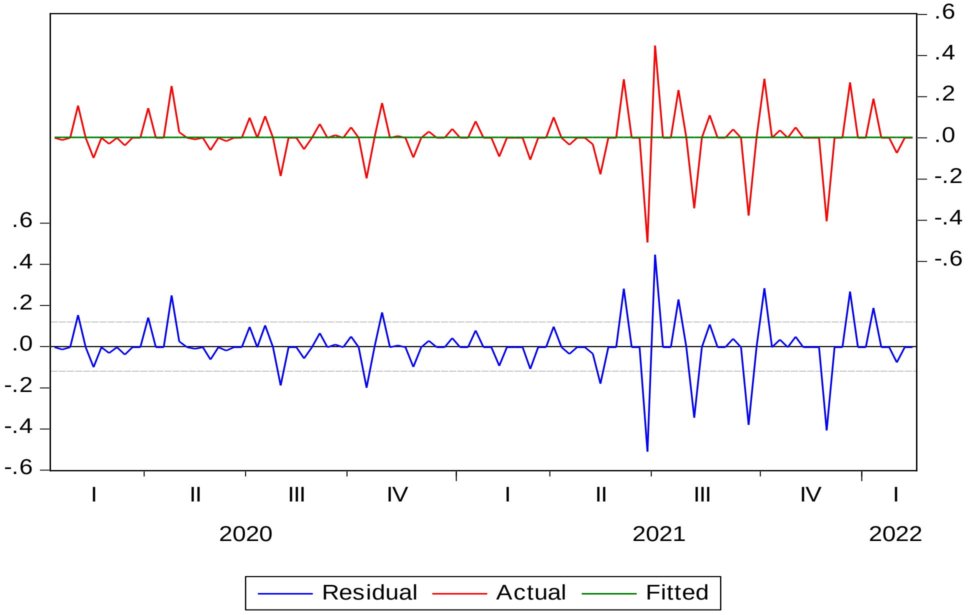
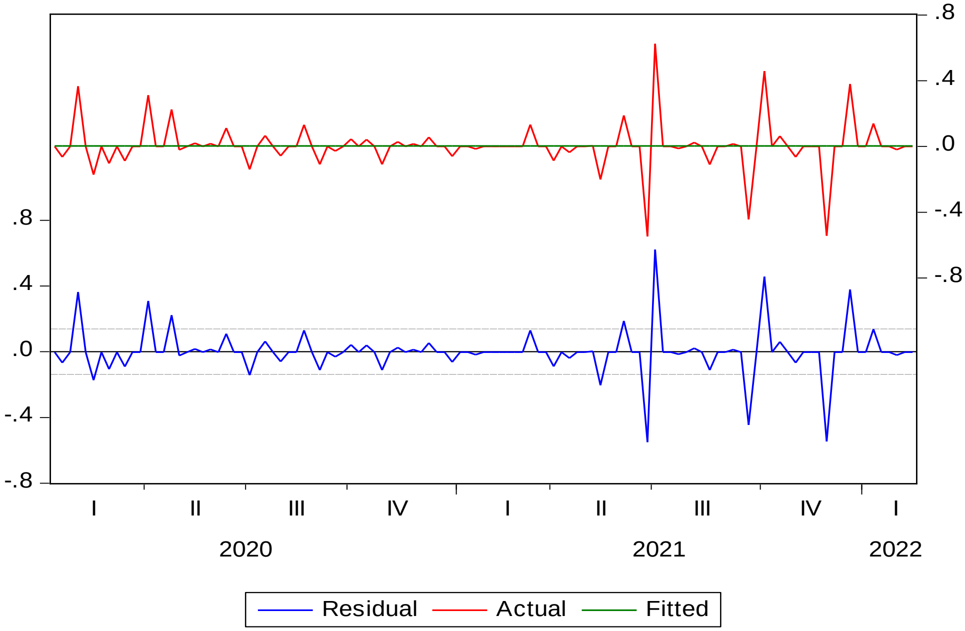


Figure 12

Volatility Clustering of Oil Index Return



The standard test for conditional homoscedasticity, which uses the autocorrelation of squared return series, remains ineffective given the non-normal distribution of these series. Mckenzie (1997) noted that volatility clustering is not just confined to the square of asset price returns. Volatility clustering often appears when an asset's price varies absolutely. As a result, by highlighting outliers in the returns, the introduction of power terms increases the relative duration of stability and instability.

Table 2 displays power transformed autocorrelation results using the powers of 0.75, 0.5, and 0.25. The autocorrelation of the power transformed returns of the banking, consumer goods, insurance, pension, oil/gas, and industrial goods indices was tested. The results indicate that the presence of conditional heteroscedasticity. Moreover, the Ljung-Box statistics for the 0.25, 0.5, and 0.75 powers for the return of the six indices were found to be significant at 5% significance level for all lags (6, 12, and 20) and powers.

Table 2

Transformed Autocorrelation for the Powers of 0. 25, 0.5, and 0.75

Indices Return / Ljung-Box $Q^{0.25}$ Stat.	Banking	Consumer Goods	Insurance	Oil/Gas	Pension	Industrial Goods
Box $Q^{0.25}(6)$	23.187** (0.001)	27.668** (0.000)	21.818** (0.001)	25.016** (0.000)	22.397** (0.001)	31.355** (0.000)
Box $Q^{0.25}(12)$	29.688** (0.003)	37.210** (0.000)	31.775** (0.001)	37.553** (0.000)	31.367** (0.002)	46.273** (0.000)
Box $Q^{0.25}(20)$	35.595** (0.017)	40.225** (0.005)	35.444** (0.018)	41.556** (0.003)	33.210** (0.032)	49.655** (0.000)
Ljung-Box Q0.5 statistics						
Box Q0.5(6)	15.772** (0.015)	18.178** (0.005)	12.875** (0.005)	22.670** (0.001)	15.520** (0.017)	23.616** (0.001)
Box $Q^{0.5}(12)$	22.096** (0.036)	26.710** (0.008)	19.965** (0.008)	33.224** (0.001)	21.518** (0.034)	37.228** (0.000)
Box $Q^{0.5}(20)$	27.285** (0.041)	29.629** (0.009)	23.606** (0.010)	37.182** (0.011)	24.487** (0.0041)	40.778** (0.004)
Ljung-Box Q0.75 statistic						
Box $Q^{0.75}(6)$	10.115** (0.020)	10.837** (0.004)	7.893** (0.002)	20.143** (0.003)	7.8932** (0.024)	17.554** (0.007)
Box Q0.75(12)	15.495** (0.015)	17.441** (0.004)	12.113** (0.037)	29.193** (0.004)	12.113** (0.033)	28.503** (0.005)
Box $Q^{0.75}(20)$	19.615** (0.042)	20.041** (0.005)	15.735** (0.033)	33.731** (0.028)	15.735** (0.0037)	32.040** (0.043)

Note. *p*-value in parentheses with ** denote 5% level

Table 3 presents the outcome of the stationarity test. The ADF and PP test results are compared to the critical values of 1%, 5%, and 10%. This comparison allows to determine whether all returns remain stationary at level, as seen in Table 3. The given values surpass their respective critical values at the given level, indicating that the returns are integrated of order zero (0).

Table 3

Stationary Test Results

Indices	Statistic	ADF Tabulated Value			Statistic	PP Tabulated Value L		
		1%	5%	10%		1%	5%	10%
Banking Index Return	-12.124** (0.0000)	-3.47	-2.877	-2.58	-34.631** (0.0001)	-3.47	-2.88	-2.58

Indices	Statistic	ADF Tabulated Value			Statistic	PP Tabulated Value L		
		1%	5%	10%		1%	5%	10%
Consumer Goods Index Return	-13.243** (0.0000)	-3.47	-2.877	-2.58	-33.063** (0.0001)	-3.47	-2.88	-2.58
Insurance Index Return	-14.218** (0.0000)	-3.47	-2.877	-2.58	-24.792** (0.0000)	-3.47	-2.88	-2.58
Oil/Gas Index Return	-12.463** (0.0001)	-3.47	-2.877	-2.58	-34.099** (0.0001)	-3.47	-2.88	-2.58
Pension Index Return	-11.474** (0.0000)	-3.47	-2.877	-2.58	-29.052** (0.0000)	-3.47	-2.88	-2.58
Industrial Goods Index Return	-9.889** (0.0000)	-3.47	-2.877	-2.58	-28.154** (0.0000)	-3.47	-2.88	-2.58

Note. *p*-value in parentheses with ** denote significance at 5 percent

In the GARCH model, as shown in Figure 10, the total of α and β is less than 1, suggesting that shocks to volatility gradually subside and the variance process reverts to its mean. In a nutshell, industrial index return volatility remains the most persistent, followed by the banking, pension, consumer goods, insurance, and oil/gas indices which has the least volatile return of the six indices analyzed during the study period.

Of all the indices, one would have anticipated the oil/gas index return to be the most volatile. The global supply chain disruption brought on by the COVID-19 lockdown and the gradual re-opening of the economy by industrial countries hardest hit by the outbreak of COVID-19 may be partially to blame for the fact that the industrial index return emerges as the most volatile, while the oil/gas index return remains the least volatile of all the indices.

The preliminary analysis displayed in Table 1 reveals that the returns of these indices are not normally distributed. So, in order to estimate the proposed models, student t distribution was used. As shown in Table 4 and statistically significant at 5%, the degree of freedom indicated by the V coefficient valuess validate student t rather than the normality assumption.

Table 4
GARCH Model Estimates for the Six Sub-Indices

	Banking	Consumer	Insurance	Oil/Gas	Pension	Industrial
Equation: Mean						
C	0.0000 (0.003)	0.0010 (0.009)	0.0000 (0.003)	0.0010 (0.005)	0.0020 (0.005)	0.0000 (0.000)
Equation: Variance						
ϖ	0.003 (0.007)	0.004 (0.000)	0.017 (0.064)	0.024 (0.108)	0.009 (0.002)	0.005 (0.010)
α	-0.049 (0.087)	-0.064 (0.014)	-0.066 (0.244)	-0.085 (0.387)	-0.062 (0.014)	-0.037 (0.067)
β	0.556 (0.440)	0.557 (0.026)	0.556 (0.327)	0.564 (0.362)	0.564 (0.084)	0.565 (0.274)
γ	-	-	-	-	-	-
δ	-	-	-	-	-	-
V	2.083** (0.161)	18.137** (14.509)	2.015** (0.056)	2.033** (0.157)	18.284** (10.398)	2.079** (0.160)
LL	282.417	208.709	218.634	104.439	131.661	201.188
Pers.	0.507	0.493	0.490	0.479	0.502	0.528
AIC	-2.999	-2.202	-2.309	-1.075	-1.369	-2.121
SC	-2.912	-2.115	-2.223	-0.988	-1.282	-2.034
HQC	-2.964	-2.167	-2.274	-1.039	-1.334	-2.086
N	186	186	186	186	186	186

Note. The standard errors are shown in parentheses. The notation ** displayed statistical significance at the 5%. The abbreviations LL, AIC, SC, HQC, and *N* stand for the maximum log-likelihood, Akaike Information criteria, Schwarz Criterion, Hannan-Quinn criteria, and total observations, respectively.

Table 5
APARCH Model Estimates for the Six Sub-Indices

	Banking	Consumer	Insurance	Oil/Gas	Pension	Industrial
Equation: Mean						
C	-0.0000 (0.003)	-0.0000 (0.002)	-0.0000 (0.003) -	0.000 (0.006)	0.0000 (0.004)	0.0000 (0.003)
Equation: Variance						
ϖ	0.005 (0.006)	0.005 (0.007)	0.019 (0.033)	0.032 (0.084)	0.015 (0.033)	0.014 (0.029)
α	-0.665	-0.550	-0.559	-0.998	-0.713	-0.668

	Banking	Consumer	Insurance	Oil/Gas	Pension	Industrial
	(0.069)	(0.051)	(0.100)	(0.252)	(0.197)	(0.122)
β	1.588 (0.323)	1.541 (0.391)	1.532 (0.280)	1.623 (0.607)	1.677 (0.621)	1.605 (0.706)
γ	0.287** (0.101)	0.180 (0.130)	-0.063 (0.153)	0.320** (0.138)	0.355** (0.105)	0.098* (0.010)*
δ	0.569 (0.239)	0.562 (0.222)	0.567 (0.252)	0.579 (0.207)	0.594 (0.227)	0.562 (0.232)
V	2.223** (0.154)	2.119** (0.157)	2.038** (0.079)	2.046** (0.159)	2.060** (0.147)	2.065** (0.157)
LL	281.162	312.388	217.936	107.127	222.025	201.869
Pers.	0.923	0.981	0.973	0.625	0.964	0.937
AIC	-2.964	-3.301	-2.280	-1.082	-2.325	-2.107
SC	-2.842	-3.179	-2.159	-0.961	-2.203	-1.985
HQC	-2.915	-3.252	-2.231	-1.033	-2.275	-2.057
N	186	186	186	186	186	186

Note. The standard errors are shown in parentheses. The notation ** displayed statistical significance at the 5%. The abbreviations LL, AIC, SC, HQC, and *N* stand for the maximum log-likelihood, Akaike Information criteria, Schwarz Criterion, Hannan-Quinn criteria, and total observations, respectively.

Table 5 demonstrates that the sum of α and β in the APARCH model suggests that the variance process exhibits mean reversion. This indicates that shocks to volatility quickly diminish, leading the variance process to rapidly return to its average level. The table shows that consumer goods have the highest level of return volatility, followed by insurance, pension, industrial goods, and banking, while oil/gas show the lowest level of volatility among the six indices analyzed during the study period.

The coefficient γ in Table 5, which indicates the presence of symmetry as well as leverage effects, has positive values and demonstrates statistical significance at 5% level. Based on the data, the null hypothesis that there is a leverage effect for these indices cannot be rejected. This implies that a negative shock to volatility has a stronger impact on volatility, as compared to a positive shock of the same magnitude.

Furthermore, due to the absence of a normal distribution in the returns, unlike the first inquiry shown in Table 1, student t-test was used to calculate the proposed models. The V coefficient values exhibit a statistically significant degree of freedom at 5% level across all indices returned, as seen in Table 5. This validates the use of the student t-test instead of relying on the assumption of normalcy.

Diagnostic Results

The diagnostic test results for the returns of the banking, consumer goods, insurance, oil/gas, pension, and industrial goods indexes are shown in Table 6. The Ljung-Box Q test results indicate that the autocorrelation of standardized residuals is statistically insignificant for all lags at 5% significance level. Thus, the null hypothesis stating that there is no autocorrelation in the standardized residuals cannot be rejected. With a significance level of 5%, the Ljung-Box Q2-statistics for all lags of squared standardized residuals are statistically insignificant. Thus, the null hypothesis stating the absence of autocorrelation in squared standardized residuals cannot be rejected either. Table 6 shows the results of the ARCH-LM test which indicate that the ARCH effect was either eliminated from the standardized residuals or it became undetectable. Furthermore, the Jarque-Bera statistics continue to indicate that the standardized residuals do not follow a normal distribution.

Table 6
Diagnostic Test Results

	Q Quartile Statistics			Square Quartile Statistics			ARCH LM NML		
	(6)	(12)	(20)	(6)	(12)	(20)	F-Stat	NR^2	JB
GARCH									
Banking	1.138 (0.29)	18.80 (0.09)	30.06 (0.07)	1.715 (0.94)	4.37 (0.98)	7.895 (0.99)	0.065 (0.798)	0.066 (0.797)	521 (0.000)
Consumer	3.806 (0.07)	21.06 (0.07)	28.72 (0.09)	4.92 (0.55)	6.64 (0.88)	10.39 (0.96)	1.874 (0.173)	1.875 (0.171)	720 (0.000)
Insurance	1.472 (0.22)	1.171 (0.34)	1.90 (0.17)	8.73 (0.19)	11.40 (0.50)	22.73 (0.30)	0.152 (0.696)	0.154 (0.695)	540 (0.000)
Oil/Gas	22.124 (0.74)	22.62 (0.66)	21.87 (0.78)	7.24 (0.48)	5.99 (0.25)	20.17 (0.75)	0.710 (0.818)	0.712 (0.817)	653 (0.000)
Pension	19.78 (0.87)	29.25 (0.80)	35.70 (0.64)	6.23 (0.40)	7.24 (0.84)	11.38 (0.94)	0.504 (0.479)	0.508 (0.475)	6554 (0.000)
Industrial	28.89 (0.27)	30.95 (0.47)	34.40 (0.68)	4.88 (0.56)	7.97 (0.79)	9.99 (0.97)	1.915 (0.168)	1.916 (0.166)	484 (0.000)
APARCH									
Banking	10.13 (0.12)	13.60 (0.33)	21.61 (0.36)	0.45 (1.00)	0.98 (1.00)	1.63 (1.00)	0.115 (0.735)	0.116 (0.733)	6223 (0.000)

	Q Quartile Statistics			Square Quartile Statistics			ARCH LM NML		
	(6)	(12)	(20)	(6)	(12)	(20)	F-Stat	NR^2	JB
Consumer	8.048	11.01	13.52	0.27	0.42	0.65	0.160	0.162	33394
	(0.32)	(0.53)	(0.85)	(1.00)	(1.00)	(1.00)	(0.688)	(0.686)	(0.000)
Insurance	22.42	28.22	34.27	7.87	10.38	20.89	0.194	0.196	611
	(0.42)	(0.56)	(0.79)	(0.25)	(0.58)	(0.40)	(0.660)	(0.657)	(0.000)
Oil/Gas	20.70	22.36	27.46	0.13	0.38	0.29	0.882	0.807	74
	(0.36)	(0.45)	(0.64)	(1.00)	(1.00)	(1.00)	(0.716)	(0.718)	(0.000)
Pension	4.903	8.261	11.05	0.083	0.29	0.16	0.006	0.006	69206
	(0.56)	(0.76)	(0.94)	(1.00)	(1.00)	(1.00)	(0.937)	(0.936)	(0.000)
Industrial	21.75	22.07	23.84	1.02	1.48	2.04	0.725	0.730	7736
	(0.10)	(0.24)	(0.25)	(0.98)	(1.00)	(1.00)	(0.395)	(0.392)	(0.000)

Note. probability values in parentheses

The current investigation employed two models which are ranked in Table 7 based on the maximum log-likelihood ratio, Akaike information criterion, Schwartz information criterion, and Hannan-Quinn criterion. The best model, according to Table 7, is APARCH. With the exception of the consumer goods index return, where GARCH remains superior, APARCH model remains the best model for estimating and forecasting purposes for all indices' returns. As a result, it is concluded that APARCH is the optimal model for estimating and projecting returns of the indices.

Table 7

Models Ranking in Order of Maximum Log-likelihood, Akaike Information Criterion, Schwarz Information Criterion, and Hannan-Quinn Criterion

	SECTOR	LL	AIC	SC	HQC	Ranking
GARCH	Banking	282.417	-2.999	-2.912	-2.964	2nd
	Consumer	208.709	-2.202	-2.115	-2.167	
	Insurance	218.634	-2.309	-2.223	-2.274	
	Oil/Gas	104.439	-1.075	-0.988	-1.039	
	Pension	131.661	-1.369	-1.282	-1.334	
	Industrial	201.188	-2.121	-2.034	-2.086	
APARCH	Banking	281.162	-2.964	-2.842	-2.915	1st
	Consumer	312.388	-3.301	-3.179	-3.252	
	Insurance	217.936	-2.280	-2.159	-2.231	
	Oil/Gas	107.127	-1.082	-0.961	-1.033	
	Pension	222.025	-2.325	-2.203	-2.275	
	Industrial	201.869	-2.107	-1.985	-2.057	

Note. LL, AIC, SC, and HQC represent the maximal log-likelihood, Akaike Information criteria, Schwarz Criterion, and Hannan-Quinn criteria, respectively.

Conclusion

The current study examined the weekly returns of six sub-indexes of the Nigerian stock exchange including the banking, consumer goods, insurance, oil/gas, pension, and industrial goods indices, for the period extending from September 2, 2020 to February 28, 2022. These returns were not normally distributed and stationary at level. For lags of 6, 12, and 20, the Ljung-Box Q statistics and Ljung-Box Q2 statistics, calculated with power values of 0.25, 0.5, and 0.75, indicated the presence of conditional heteroscedasticity in all index returns.

In GARCH and APARCH models, the total of α and β was smaller than 1, suggesting that the variance process exhibits mean-reversion, whereas volatility shocks decay slowly in GARCH and rapidly in APARCH. Consequently, the variance process returns gradually to its average value in GARCH and rapidly in APARCH.

In sum, volatility was found to be more persistent in the APARCH model than GARCH model. Comparison between indices showed that volatility was more persistent in industrial goods, followed by banking, pension, consumer goods, insurance and oil/gas respectively in the GARCH model. While, volatility was found to be more persistent in consumer goods index, followed by insurance, pension, industrial goods, banking and oil/gas, respectively. Oil/gas was found to have the lowest volatility in both models.

The returns of all six indices exhibited asymmetric shocks to volatilities, wherein negative shocks of equal magnitude had a more pronounced impact on volatilities as compared to positive shocks. The standardized and squared standardized residuals exhibited no autocorrelation and the residuals showed no ARCH influence, as shown by the Ljung-Box Q test statistics for standardized residuals and the Ljung-Box Q2-statistics for squared standardized residuals. Based on the model ranking, the APARCH model was found to be the most efficient model for estimating and predicting all indices.

Limitations

Incorporating the effects of negative shocks is crucial when formulating and implementing stabilization policy in the stock market. However, the current study was limited by the use of weekly data which may hide some characteristics of the data, as compared to daily or higher frequency data.

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