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MODELLING STOCK RETURNS VOLATILITY AND ASYMMETRIC NEWS EFFECT: A GLOBAL PERSPECTIVE

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ABSTRACT

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This paper modelled stock returns volatility using daily S&P Global 1200 index from 1st September, 2010 to 30th September, 2020. The S&P 1200 represents a free-float weighted stock market index of global equities covering seven (7) regional stock market indices and approximately 70% of the global market capitalization, hence was used to compute global stock returns. The data analysis was carried out with Generalized Autoregressive Conditional Heteroskedasticity (GARCH) techniques. Of the variant GARCH models specified in this study, the symmetric GARCH-M (1,1) and the asymmetric TGARCH (1,1) models were found suitable for the estimation. The findings from the GARCH-M and TGARCH models revealed explosive volatility persistence and strong asymmetric news effect in the global stock market, respectively. The implication of volatility persistence is that current volatility shocks influenced expected returns over a long period. The asymmetric news effect showed that negative news (bad news) spurred stock returns volatility than positive news (good news) especially in 2020 which was due to the COVID-19 crisis as shown by the plot of the conditional variance. These results were consistent with the empirical findings of a number of studies in emerging markets. Hence, the study concludes that the global stock market exhibited high volatility persistence and leverage effect during the sampled period.

Contribution/Originality: This study contributes to the literature by modelling global stock returns volatility and asymmetric news effect using a new stock index (S&P 1200 global index). The paper contributes the first logical analysis that volatility of S&P 1200 returns is explosive and largely influenced by news available in the global markets.

1. INTRODUCTION

In both developed and developing economies, the stock market is an integral component of the financial system that contributes immensely to capital formation, wealth creation and economic growth. Although it plays a prominent role in economic prosperity by deepening the financial system, problems occasioned by volatility of stock returns has immensely influenced the effective functioning of the global market. According to literature allied to stock markets, volatility is the level of uncertainty or risk associated with the value of financial assets (Engle & Patton, 2001). Periods of higher volatility connotes significant variation in the value of financial assets while lower volatility suggests that the value of financial assets does not dramatically change overtime (Banumathy & Azhagaiah, 2015). This volatility risk could cause financial shocks to investors, thus creating challenges of low capital investments in financial assets, vulnerability in market-making, loss of investors' confidence and fickle stock

prices and returns (Bello, 2020; Chiang & Doong, 2014; Wang & Yang, 2017). Consequently, in a highly volatile stock market, it is difficult for quoted companies to raise sufficient funds as rational investors prefer stocks with less volatile returns/prices unlike the risk takers (Onyele, Opara, & Ikwuagwu, 2017). Though, returns volatility in the stock market may not necessarily be destructive all the time, but volatility persistence in market returns, especially in developed markets will likely lead to a crash in the global financial market due to increasing financial integration (Onyele. & Ikwuagwu, 2020).

Volatility of stock returns is majorly triggered by investors' expectations and perceptions of daily information (news effect) in the market. When there is upsurge in returns volatility as a result of news effect, efficiency and liquidity is altered as market participants receive the news with different mindset (Ho & Hung, 2012). In reality, however, bad news will accelerate returns volatility more than good news which may be interpreted by investors as higher risk-return tradeoff (Jegadeevan, 2015). Since returns on financial assets is a function of the market risk, risk takers are expected to receive a rate of return that will compensate for the risk taken in making such long-term funds (such as, debentures, common share, bond and mortgage loan) available to economic units (Edem & Ogbonna, 2020). This explains the long age maxim of Efficient Market Hypothesis (EMH) that all available information is correctly reflected in stock prices and thus stock prices rapidly react to any novel information at the moment it reaches the market participants (Brealey & Meyers, 2003). This informational fundamental comprise changes to firms' operations, modifications in macroeconomic policies, twist in the level of investors' risk-return preference, financial integration, natural disaster, etc. (Onyele, Ikwuagwu, & Onyekachi-Onyele, 2020; Sansa, 2020).

Myriad of studies has indicated that stock markets at different time period exhibits volatility persistence, risk-return tradeoff or asymmetric news effects; hence, it can be said that no conclusive model can fit every stock market all the time. Notwithstanding, enormous studies has been done for developed stock markets such as the United States, United Kingdom, Japan, etc. while some other studies focused on emerging stock markets like China, India, etc. (see, (Banumathy & Azhagaiah, 2015; Caporale, Karanasos, Yfanti, & Kartsaklas, 2019; Khedhiri, 2008; Lai, Cheong, & Lee, 2019; Wei, 2009)). In the developing markets of Africa, there have been research efforts towards modelling volatility of stock market returns and asymmetries in Nigeria, South Africa, Kenya, Morocco, Egypt, etc. (Bello, 2020; Jebari & Hakmaoui, 2017; Kuhe, 2018; Ndei, Muchina, & Wawure, 2019). These empirical studies, though with varying findings, used country specific market indices (such as, the Dow Jones, S&P 500, FTSE 100, Nikkei index, NIFTY index, NSE index, etc.) but the current study confirmed the stylized facts using the S&P global 1200 index that represents a free-float weighted stock market index of global equities covering seven (7) regional stock market indices and approximately 70% of the global market capitalization. In view of this research gap, the main goal of this paper is to model stock returns volatility and asymmetric news effects in the global stock market using the S&P Global 1200 index.

The rest of the paper is organized as follows; Section 2 presents the literature review on issues concerning the modelling of stock market returns volatility. Sections 3 captures the model, data and methodology used for the estimation while section 4 presents the results and discussions. The conclusions of the study are documented in section 5.

2. LITERATURE REVIEW

2.1. Stylized Facts

There are quite a number of stylized facts regarding volatility of stock market returns that has been confirmed by prior studies. Consequently, a good volatility model should reflect these stylized facts to a large extent. Features of stock returns series such as volatility clustering, volatility persistence, risk-return tradeoff and asymmetric news effect (leverage effect) has been confirmed in several empirical works. These stylized facts have been discussed below as follows:

a) Non-Normal Distribution:

Distribution of stock returns as well as other financial time series are not normal or exhibits fatter tails also referred to as excess kurtosis (Fama, 1995; Mandelbrot, 1963). Hence, stock returns series are usually leptokurtic with fourth moment above 3. This stylized fact is common and it has been confirmed by many empirical studies.

b) Volatility Clustering

Volatility clustering is a situation where small and large values (of either signs) in the return series is likely to occur in clusters, that is, small moves being accompanied by large changes (Fama, 1995; Mandelbrot, 1963). This implies that volatility could be time-varying, that is, excessive volatility comes and goes over a period of time (Aroui, Lahiani, Lévy, & Nguyen, 2012; Cong, 2017).

c) Volatility Persistence:

Stock returns volatility is highly persistent or has long memory if it is characterized by insignificant autocorrelations of absolute or squared returns (Owidi & Mugo-Waweru, 2016). Persistence in volatility of stock returns series majorly affect future market volatility under influence of shocks. The implication of such volatility persistence is that today's volatility shocks will affect the expectation of volatility over many periods in the future. Hence, volatility persistence is sequentially beneficial in forecasting future stock returns.

d) Returns Are Mean Reverting:

A mean-reverting volatility is interpreted to imply a level of normal volatility to which volatility will eventually return. Long-run predictions of volatility would often converge to this same level of normal volatility, not minding when the predictions were made (Engle & Patton, 2001). Though, many studies opined that mean-reversion is a feature of volatility, they might be differences on the level of normal volatility and whether it is constant over all the time (Bello, 2020; Owidi & Mugo-Waweru, 2016).

e) Asymmetric News Effect:

One of the assumptions of volatility models is that the conditional variance of financial assets is influenced symmetrically by negative and positive innovation. For example, the GARCH (1,1) model permits the variance to be influenced by the square of the lagged innovation only, totally ignoring the effect of positive or negative innovation. Regarding stock returns, it is particularly said that positive and negative shocks/news would affect volatility (Wei, 2009). Sometimes, asymmetry is likened to a leverage effect and a risk premium (risk-return tradeoff) at other times (Engle & Patton, 2001). Here, news of higher volatility lowers demand for a particular stock due to risk aversion, which is accompanied by the increased volatility as predicted by the news.

2.2. Theoretical Underpinning

Theoretically, studies on stock returns volatility are often anchored on the Efficient Market Hypothesis (EMH) which was developed by Fama (1970). The EMH explains why stock prices is seen to follow a random walk. According to Fama (1970) an efficient market is one in which all available information are reflected in the stock prices. According to the EMH, the intrinsic value of shares and other financial assets is defined by the future discounted value of cash flows accruing to investors (Fauzel & Fauzel, 2016). Hence, if the stock market is efficient, all available information must be reflected in stock prices. This is needful for the assessment of a firm's performance in the future, therefore the intrinsic and market value of a share should be equal (Dukes, Bowlin, & MacDonald, 1987; Lo & MacKinlay, 1988). Hence, an information that may alter firm's profitability in the future must be reflected in the share price immediately, else any delay in information diffusion to price would lead to irrationality as availability of some information could be exploited to predict or forecast profitability (Bohl & Henke, 2003;

Fama, 1991). As such, in an efficient market, it is assumed that changes in share prices are unpredictable since there is random arrival of information. Using Equation 1 the random walk model is specified as follows:

$$P_{t+1} = P_t + \varepsilon_{t+1} \quad (1)$$

Where,

P_{t+1} = share price at time $t + 1$.

P_t = share price at time t .

ε_{t+1} = random error with zero mean and finite variance.

Equation 1 shows that share price at time $t + 1$ is equivalent to its price at time t in addition to a specific value

that depends on arrival of unpredictable new information between t and $t + 1$. In other words,

$\varepsilon_{t+1} = P_{t+1} - P_t$ does not depend on previous price changes.

There are three levels of efficient markets among which is the weak-form efficiency whereby the information content of interest is historical prices (Fama, 1970). The weak form efficiency suggests that current stock prices reflect all information of previous prices and that investors cannot apply technical analysis of any form in their investment decisions (to determined undervalued or overvalued stocks) but can research firm's financial statements to boost their chances of gaining returns higher than that of the market. On the other hand, the semi-strong form is hinged on the notion that investors cannot use either fundamental or technical analysis to obtain higher returns in the market since all publicly available information is used in the computation of current stock prices and that only information that is not available to the public (private information) can aid investors boost their returns above that of the market. The advocates of the strong form version states that all available information (both public and non-public) is completely reflected in the current stock prices, that is, there is no type of information that can make an investor make returns higher than the market, not even insider knowledge give investors a predictive edge over the entire market. The building block of this study is the weak form of market efficiency.

2.3. Empirical Review

On the empirical sphere, studies on stock returns volatility dates back to the 1980s but the empirical studies have improved in recent times. The first reason adduced to this development is the fact that different data on stock market indices has been computed globally. Availability of these data has empowered researchers to conduct studies on stock returns volatility in less developed, emerging and developed countries across the world. The second reason for the current development in the literature is associated with advancement in econometric estimation methods as captured by various GARCH models applied in the literature. The econometric estimation models are built on the weak-form EMH, showing evidence of volatility persistence and asymmetric volatility/news or leverage effect. Notable among earlier studies are Bollerslev, Chou, and Kroner (1992); Bollerslev (1986); Ding, Granger, and Engle (1993); Engle (1982) who confirmed presence of volatility in financial times series. On the other hand, recent empirical studies on the subject emerged with different results due to time period, methodology and geography covered by the various studies. The gap identified in the empirical literature is that none of the prior empirical works had investigated stock returns volatility and asymmetric news effect using return series from S&P Global 1200 index (see components of S&P Global Index in Table 1 in section 3).

Most recently, Bello (2020) used GARCH(1,1) and daily data from 2008-2018 to analyze stock returns volatility and found high volatility persistence in the Nigerian Stock Market. In another study, Musa, Adamu, and Dauran (2020) applied PGARCH and revealed that volatility persistence in the Nigerian Stock Market reduced significantly after unexpected shocks between 1987 and 2019. In Southern Asia, Iqbal, Saeed, and Shah (2020) used GARCH(1,1) model to analyze daily returns series from 2007 to 2019 and found explosive volatility of stock returns. Also, using daily data from 1999 to 2016, Edem and Ogbonna (2020) showed evidence of returns volatility persistence and asymmetric news effect in the Nigerian Stock Market. In Malaysia, Lai et al. (2019) used daily time series data spanning from 1996 to 2016 with GARCH (1,1) model to show that stock returns of oil & gas sector were most volatile. In Kenya, Ndei et al. (2019) analyzed the Nairobi Stock Market from 2010 to 2017 using GARCH(1,1) and TGARCH(1,1) and revealed persistent returns volatility, leverage effects, and absence of risk-return trade-off. Using daily time series from 1997 to 2018, Caporale et al. (2019) showed that volatility persistence in the Korean stock market was driven by buy and sell trades depending on the type of investor trading and phase of business cycle. In a comparative analysis of America, Europe, Far East, BRICS stock markets from 1997 to 2008, Tsuji (2018) found evidence of persistent asymmetric volatility in all the markets. On the other hand, using the GARCH (1,1) model and daily return series from 1997 to 2008, De Gaetano (2018) found that returns in the BRICS market was time varying. In a study of emerging markets, Abdennadher and Hallara (2018) applied GARCH(1,1) on daily time series spanning from 2005 to 2015 and found that returns volatility varied with structural changes. Kuhe (2018) observed high volatility persistence in stock returns in the Nigeria Stock Market from 1999 to 2017. Using Frictionally Integrated EGARCH model, Jebari and Hakmaoui (2017) reported strong volatility persistence in the Moroccan stock market from 1993 to 2017.

In other studies, Wang and Yang (2017) observed that long-term returns volatility in the Shanghai Stock Exchange, China was driven by negative returns. Using TGARCH, Aguda (2016); Owidi and Mugo-Waweru (2016); Ndwiga and Muriu (2016) showed that stock returns volatility decreased with asymmetric effects in Nigeria and Kenya respectively. Ahmad, Ahmed, Vveinhardt, and Streimikiene (2016); Babikir, Gupta, and Owusu-Sekyere (2010) and Babikir et al. (2010) found that the Asian and South African markets exhibited volatility persistence of returns. Again, using the Symmetric GARCH (1,1) model, Adewale, Olufemi, and Oseko (2016) found high volatility persistence with no leverage effect in Nigeria. Banumathy and Azhagaiah (2015); Jegageevan (2015); Sethapramote and Prukumpai (2012) and Khedhiri (2008) found that stock returns volatility was driven by bad news in India, Sri Lanka, Thailand and UAE, respectively. Using Bivariate GARCH, Wang, Huang, and Padmanabhan (2015) found volatility persistence of stock returns in the United States. Bentes and Da Cruz (2010) analyzed the G7 markets using GARCH, IGARCH and FIGARCH and found persistent stock returns volatility in Germany, Italy and France, but less returns volatility in Japan. Comparing African markets, Alagidede and Panagiotidis (2009) found evidence of leverage effects. Chiang and Doong (2001) revealed that bad news was responsible for volatility persistence in most Asian markets. Berument and Kiyamaz (2001) found that highest and lowest stock returns volatility in the United States was observed on Wednesday and Monday, respectively. In Japan, Bekaert and Wu (2000) indicated that returns volatility persistence and feedback at firm level is driven by strong asymmetries in the conditional covariances.

3. METHODOLOGY AND DATA

3.1. Methodology

The degree of volatility which is also termed “conditional variance of a financial asset” must be estimated in a model that best show its time varying conditional variance (Engle, 1982; Tsay, 2010). Financial time series depend on three basic factors, viz; their own previous values (that is, autoregressive), past information (that is, conditional) and exhibit non-constant variance (that is, heteroscedasticity) which forms the bedrock of the popular Autoregressive Conditional Heteroscedasticity (ARCH) model. Hence, the presence of these fundamental features

should be well captured in the proposed volatility model(s) to be adopted in a research study of this nature (Cont, 2005). Recent econometric techniques within the scope of GARCH family models provide the tool for solving this research problem.

In this paper, as originated by Bollerslev (1986) and applied in recent empirical studies Bello (2020); Ndei et al. (2019); Banumathy and Azhagaiah (2015); Jegageevan (2015) the GARCH model was adopted to unravel stock returns volatility from a global perspective. In the GARCH model, the conditional variance is a function of its previous own lags. Stock returns volatility is determined by the magnitude of coefficients α and β . If the addition of both parameters is equal to or approximately one (1), then volatility of the return series is said to be persistent and *vice versa*. In its simplest form, the symmetrical GARCH models (mean and variance equations) is specified as displayed in Equations 2 and 3:

$$\text{Mean equation: } r_t = \mu + \varepsilon_t \quad (2)$$

$$\text{Variance equation: } \sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (3)$$

Where,

$$\omega > 0, \alpha_1 \geq 0, \beta_1 \geq 0$$

r_t represents the stock market return at time t .

μ denote the average return of the market.

ε_t indicate the residual return.

In a GARCH model, the conditional variance equation is directly fitted into the mean equation, leading to the GARCH-M model (mean-reversion GARCH). Regarding the GARCH-M model, the coefficient λ in the mean equation represents the risk premium. If λ is positive, it indicates that there is positive relationship between stock return and its volatility, that is, an increase in mean return is determined by a rise in conditional variance as a proxy of higher risk. As a matter of fact, a positive and significant λ indicates presence of risk-return tradeoff or risk premium. In the GARCH-M model, stock return is dependent on its own volatility and as such a simple GARCH-M (1,1) model is specified as shown in Equations 4 and 5:

$$\text{Mean equation: } r_t = \mu + \lambda \sigma_t^2 + \varepsilon_t \quad (4)$$

$$\text{Variance equation: } \sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (5)$$

The shortcoming of symmetric GARCH models is that the conditional variance does not react asymmetrically to fluctuations in returns. As a result, a number of models known as asymmetric models such as EGARCH and TGARCH, amongst others, have been developed to deal with this issue. In consonance with Banumathy and Azhagaiah (2015) to ascertain the relationship between asymmetric volatility and stock returns, the Exponential GARCH (EGARCH) and the Threshold GARCH (TGARCH) models were applied. The EGARCH model is hinged on logarithmic expression of the conditional variability. With the EGARCH model, the presence of leverage effect can be tested (Nelson, 1991). The presence of leverage effect or asymmetry is tested based on the hypothesis that

$Y < 0$. The impact is said to be symmetric if $Y \neq 0$. The EGARCH model is expressed as shown in Equation 6 below:

$$\ln(\sigma_t^2) = \omega + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left\{ \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{\pi}{2}} \right\} - Y \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (6)$$

Where,

$\ln(\sigma_t^2)$ denote the log of the conditional variance.

Y represents the leverage term or asymmetry

With regards to the Threshold GARCH (TGARCH), in tandem with Zakoian (1994) the following Equation 7 was applied:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + Y d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (7)$$

Where,

Y is the asymmetry or leverage parameter. In the TGARCH model, good news ($\varepsilon_{t-1} > 0$) and bad news ($\varepsilon_{t-1} < 0$) on the conditional variance. Here, the impact of good news is α_i while the impact of bad news is $\alpha_i + Y_i$. As such, supposing Y is positive and significant, negative shocks would have a greater impact on σ_t^2 .

Prior to estimating the GARCH models, the distributional properties of the return series were considered. To specify the distributional properties of the daily return series of S&P Global 1200 index, the descriptive statistic was carried out. Also, to ensure that stock returns are stationary as one of the conditions required for the application of GARCH models, unit root tests were conducted using the Augmented Dickey-Fuller Test (ADF) and Phillips-Perron (PP) tests (Dickey & Fuller, 1979; Phillips & Perron, 1988).

3.2. Description of Data

The daily time series data of S&P Global (SPG) 1200 index used for this study spanned from the trading days between 1st Sept., 2010 and 30th Sept., 2020. The SPG daily data was sourced from (<https://www.spglobal.com/spdji/en/indices/equity/sp-global-1200/#overview>). The SPG rate of returns series (R_SPG) within the sampled period was calculated as natural logarithm (ln) of the first difference associated with daily closing stock prices. The formula used for computing the R_SPG is as shown in Equation 8:

$$R_SPG_t = \ln \frac{P_t}{P_{t-1}} * 100 \quad (8)$$

Where,

R_SPG_t represent the logarithmic SPG daily returns for time t .

P_t denote the closing price at time t .

P_{t-1} shows the corresponding price in the period at time $t - 1$.

Table-1. Components of S&P Global 1200 index.

Country/Region	Index
United States	S&P 500
Hong Kong, Singapore, South Korea and Taiwan	S&P Asia 50
Australia	S&P/ASX 50
Eurozone, Denmark, Norway, Sweden, Switzerland and UK	S&P Europe 350
Brazil, Chile, Colombia, Mexico and Peru	S&P Latin America 40
Japan	S&P/TOPIX 150
Canada	S&P/TSX 60

As detailed in Table 1, the S&P Global (SPG) 1200 represents a weighted stock index of global equities covering thirty-one (31) countries, seven (7) regional stock markets and about 70% of global market capitalization, including all ten (10) Global Industry Classification Standard (GICS) sectors.

4. RESULTS AND DISCUSSIONS

The logarithmic of the S&P Global 1200 index from 1st Sept., 2010 to 30th Sept., 2020 have been plotted in Figure 1:

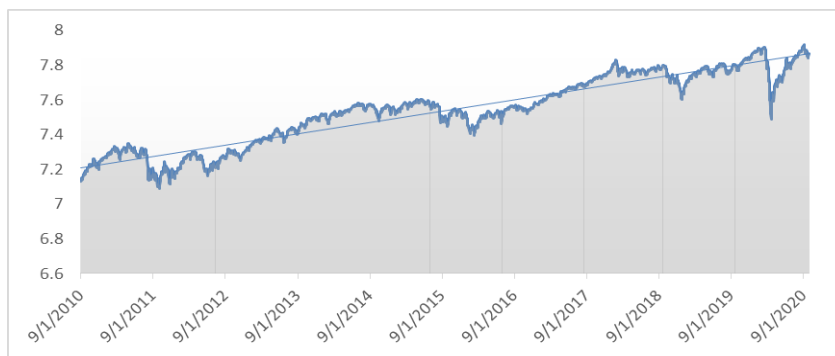


Figure-1. Trend of S&P Global 1200 index.

Having computed the daily SPG returns using Equation 8, Figure 2, shows evidence of volatility clustering for R-SPG over the sampled period (1st Sept., 2010 to 30th Sept., 2020) which is one of the stylized facts of financial time series. There was higher volatility clustering during the trading days in 2011 and 2020 due to the European and US debt crisis as well as the recent COVID-19 pandemic. On the other hand, the histogram captured by Figure 3 shows that the return series are not normally distributed based on Kurtosis ($19.35118 > 3$) and p-value (0.0000) of the Jarque-Bera test which rejects the normality distribution of the R_SPG series. The non-normal distribution of the R_SPG confirmed the stylized fact that distribution of financial returns series is largely leptokurtic.

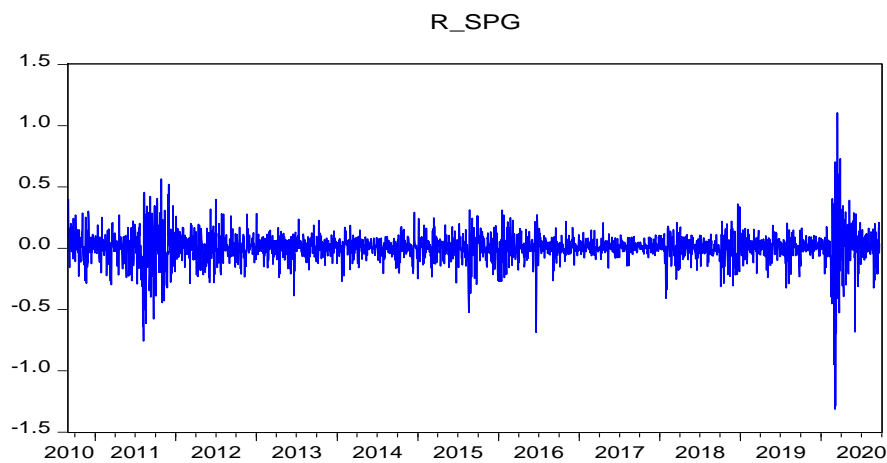


Figure-2. Time plot of daily R_SPG.

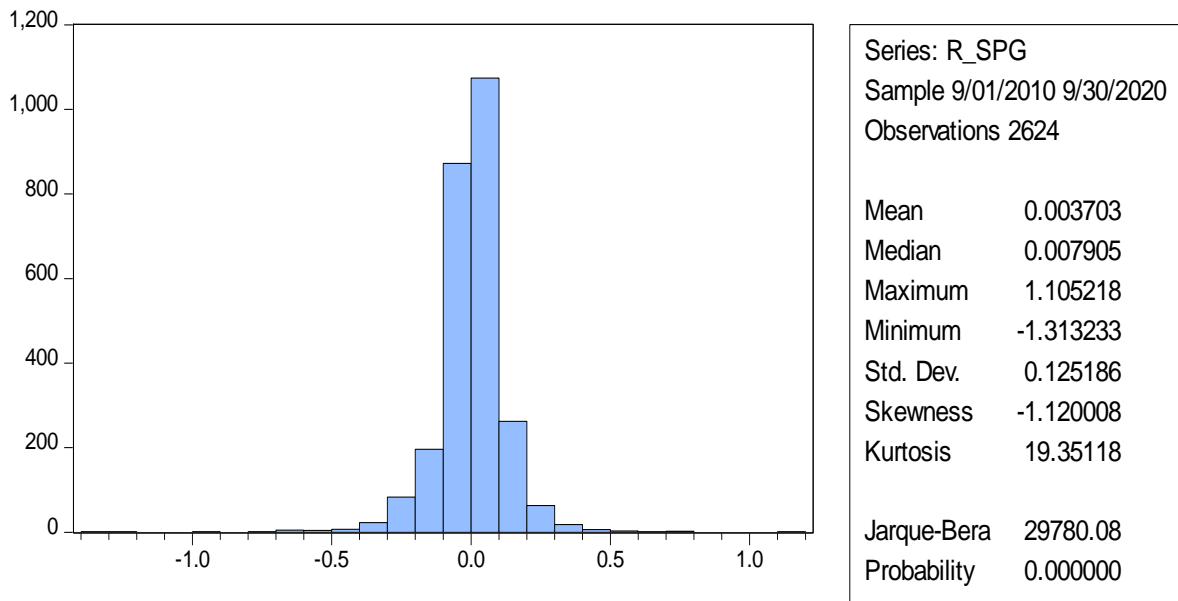


Figure-3. R_SPG normality testing.

Next, the study proceeded with the Augmented Dickey Fuller (ADF) and Philip-Perron (PP) unit root tests in order to investigate the level of stationarity of the R_SPG series. On the other hand, the presence of ARCH effect in the return series was confirmed by the ARCH-LM test. Details of the unit root and the ARCH-LM test results. As presented in Table 2 below, the R_SPG series has no unit root from the ADF and PP test approaches. The probability values of the ADF and PP t-Statistics are less than 0.05 which led to the conclusion that the R_SPG series for the sampled period is stationary, hence both the ADF and PP tests reject the hypothesis of non-stationarity of the R_SPG series at all levels of significance. On the other hand, the ARCH-LM test which was used to investigate the presence of ARCH effect on the returns series is highly significant since the p-value ($p < 0.05$), leading to the rejection of the null hypothesis of “no ARCH effect” in the residuals. Based on the outcome of these preliminary tests, the appropriateness of the GARCH family models was justified.

Table-2. Unit root test results.

		ADF @ Level		PP @ Level	
		t-Statistic	Prob.*	t-Statistic	Prob.*
Test statistic		-19.00810	0.0000	-50.50163	0.0001
Test critical values:	1% level	-3.432657		-3.432657	
	5% level	-2.862445		-2.862445	
	10% level	-2.567297		-2.567297	
ARCH-LM Test Statistics:					
F-statistic	290.1747		Prob. F(1,2620)		0.0000
Obs*R-squared	261.4407		Prob. Chi-Square(1)		0.0000

4.1. Estimation of GARCH Models

The best fit GARCH models are those with the highest Adjusted R-squared, lowest AIC and SIC, no serial correlation and heteroscedasticity in the residuals (Engle, 1982). Evidence of no serial correlation and heteroscedasticity is when the p-values of the Q-statistics and F-statistic are statistically insignificant. However, all the models passed the serial correlation and heteroscedasticity tests but varied slightly in other selection criteria such as the AIC and SIC, Log likelihood and coefficient of determination. Having, x-rayed the various GARCH models, the symmetric GARCH-M (1,1) and asymmetric TGARCH (1,1) models were selected.

The symmetric GARCH(1,1) and GARCH-M(1,1) are reported in Table 3:

Table-3. Estimated result of GARCH (1,1) and GARCH-M (1,1) models.

Parameters	GARCH-M (1,1)	GARCH-M (1,1)
Mean Equation:		
μ (mean return)	0.007780 {0.0000}***	0.006100 {0.0028}***
κ (risk premium)	--	0.245237 {0.2066}
Variance Equation:		
ω (constant)	0.000367 {0.0000}***	0.000368 {0.0000}***
α (ARCH effect)	0.187895 {0.0000}***	0.187645 {0.0000}***
β (GARCH effect)	0.796539 {0.0000}***	0.796632 {0.0000}***
$\alpha + \beta$ (persistence coefficient)	0.984434	0.984277
Log likelihood	2429.474	2430.389
AIC	-1.848627	-1.848562
SIC	-1.837433	-1.835130
Adjusted R-squared	-0.008763	-0.016122
Residual Diagnostics:		
Serial correlation (Q-statistic probabilities)	Q > 0.05 (No autocorrelation)	Q > 0.05 (No autocorrelation)
Heteroscedasticity:		
F-statistic	0.612562 {0.4339}	0.534893 {0.4646}

Note: ** and *** indicate rejection of the null hypothesis @ 5%, and 1 % levels of significance, respectively. Figures in parenthesis { } are the probability values.

From Table 3, though the SIC and AIC associated with the GARCH (1,1) and GARCH-M (1,1) varied slightly, the Adjusted R-squared (-0.016122) of the latter is greater than that of the former in absolute value. Hence the GARCH-M was accepted as the best fit model for the symmetric GARCH. It can be seen that the sum of ARCH and GARCH coefficients (α and β) of the GARCH-M (1,1) model is 0.984442. This indicates that volatility of the R_SPG series was highly persistent. It then suggests that the R_SPG for the sampled period is mean reverting. This finding is in line with those of Bello (2020); Jebari and Hakmaoui (2017); Wang and Yang (2017); Ahmad et al. (2016); Wang et al. (2015); Banumathy and Azhagaiah (2015) that stock markets of Nigeria, Morocco, China, Asian countries, United States and India exhibited high volatility persistence. Also, Ndei et al. (2019); Caporale et al. (2019); Aguda (2016); Berument and Kiyamaz (2001) are of the view that stock returns volatility is persistent but varied with time, business cycle, etc. On the other hand, the estimated coefficient of the risk premium (κ) in the mean equation is positive and statistically insignificant which indicates that volatility has no significant impact on expected returns of the global stock market which indicates lack of risk-return trade-off. This means that higher market risk arising from the conditional variance (volatility) did not necessarily trigger higher returns in the global market. In consonance with Ndei et al. (2019); Banumathy and Azhagaiah (2015) this implies that investors were not compensated for taking additional investment risks, but contrary to Ndwiga and Muriu (2016); Alagidede and Panagiotidis (2009) who found significant and positive risk premium in Kenya and selected African countries respectively.

The plot of the conditional variance presented in Figure 4 below depicts that volatility of R_SPG was high within the trading days in late-2011 and early 2012 probably due to the US and European debt crisis. There was also increased volatility in the trading days within the third quarter of 2015 and decreased towards the end of the fourth quarter of the same year. Volatility increased and dropped within the trading days in the second quarter of 2016. R_SPG volatility was also evident in the trading days of the first and fourth quarters of 2018 probably due to

the US/China trade war (see, Wang, Yao, and Bonne (2020)). Again, the R_SPG experienced explosive volatility during the trading days in the first and second quarters of 2020 which later trended downwards towards the trading days in the third quarter due to the COVID-19 pandemic and the lockdown restrictions. However, the downward trending variance curve during the trading days in the third quarter of 2020 is due to the easing of COVID-19 lockdown restrictions across the world.

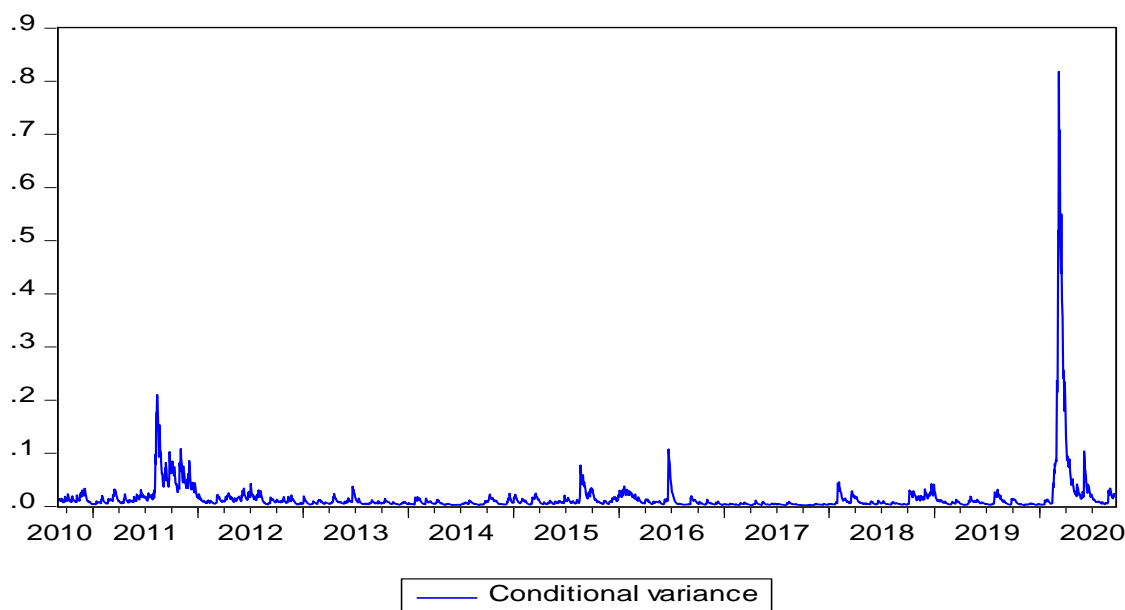


Figure-4. Conditional variance of the R_SPG series.

In a bid to capture the asymmetries in the R_SPG series, the EGARCH and TGARCH models were estimated as reported in Table 4.

Table-4. Estimated result of EGARCH (1,1) and TGARCH (1,1) Models.

Parameters	EGARCH (1,1)	TGARCH (1,1)
Mean Equation		
μ (mean return)	0.003613 {0.0180}**	0.004534 {0.0056}***
Variance Equation		
ω (constant)	-0.347425 {0.0000}***	0.000353 {0.0000}***
α (ARCH effect)	0.247916 {0.0000}***	0.075499 {0.0000}***
γ (asymmetric effect)	-0.129350 {0.0000}***	0.192600 {0.0000}***
β (GARCH effect)	0.965908 {0.0000}***	0.810012 {0.0000}***
$\alpha + \beta$ (persistence coefficient)	1.213824	0.985511
Log likelihood	2474.041	2459.418
AIC	-1.881846	-1.870696
SIC	-1.868414	-1.857264
Adjusted R-squared	-0.005529	-0.006363
Residual Diagnostics:		
Autocorrelation (Q-statistic probabilities)	Q > 0.05 (No autocorrelation)	Q > 0.05 (No autocorrelation)
Heteroscedasticity:		
F-statistic	0.037119 {0.8472}	0.831677 {0.3619}

Note: ** and *** indicate rejection of the null hypothesis @ 5%, and 1 % levels of significance, respectively. Figures in parenthesis { } are the probability values.

From Table 4 above, it can be seen that the TGARCH emerged with the lowest AIC and SIC as well as the highest Adjusted R-squared in absolute value. Hence, the TGARCH was chosen as the best fit model. Looking at the TGARCH estimates, the coefficients of α and β are statistically significant at 1% level. The sum of the ARCH (α) and GARCH (β) parameters is 0.985511 which is approximately unity (1), implying that conditional variance (volatility) was explosive. The leverage effect (γ) coefficient is positive and statistically significant at 1% level, which indicates that bad news or negative shocks exert greater influence on volatility of R_SPG than good news which provides evidence of leverage effect. This implies that the global stock market exhibited persistent returns volatility with leverage effects (asymmetric news effects). Studies such as Edem and Ogbonna (2020); Ndei et al. (2019); Tsuji (2018); Banumathy and Azhagaiah (2015); Jegageevan (2015) lend credence to the existence of volatility persistence and leverage effects in various stock markets, but Adewale et al. (2016) found no significant leverage effect in the Nigerian stock market.

5. CONCLUSION AND RECOMMENDATIONS

This study modelled stock returns volatility and asymmetric news effect in the global stock market over the period 1st Sept., 2010 to 30th Sept., 2020. The global stock market index was measured by the S&P Global 1200 (see description in Table 1). Generalized ARCH models such as GARCH (1,1), GARCH-M (1,1), EGARCH (1,1) and TGARCH (1,1) were estimated for the empirical investigation. However, the symmetric GARCH-M (1,1) and asymmetric TGARCH (1,1) best fit the estimation when compared to other variants of GARCH model. From the estimation results, it was found that volatility of R_SPG was highly persistent. Though, the estimation results of GARCH-M (1,1) showed that higher volatility did not result to higher R_SPG, implying lack of risk-return trade-off. On the other hand, the TGARCH (1,1) confirmed evidence of asymmetric volatility process in the global stock market, implying presence of leverage effect where bad news influenced R_SPG volatility more than good news. In summary, the empirical results significantly suggest that stock returns volatility in the global market persisted over a long period with no significant risk-return trade off, and that negative shocks or bad news exerted greater effect on global stock returns volatility than positive shocks or good news, especially in the trading days in 2020 which could be due to the COVID-19 crisis.

Based on the findings of this study, market regulators across the globe need to ensure market stability so as to accommodate diverse risk-classes of international investors by modelling and aligning trading rules and regulations of both developed and emerging stock markets since these markets are largely integrated. As the empirical results showed evidence of leverage effect in the global stock market, it is recommended that regulators avail reliable platforms for information flow through software application and other possible means to facilitate the ease of accessing market information which in turn drives investors investment decisions. Hence, market stability and better information dissemination will reduce the magnitude of stock returns volatility and improve transparency in the global stock market.

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