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MODELING SOUTH AFRICAN STOCK MARKET VOLATILITY USING UNIVARIATE SYMMETRIC AND ASYMMETRIC GARCH MODELS

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ABSTRACT

Contemporary empirical literature is rich in studies that have modelled and forecasted the nature and behavior of volatility of equity returns in both emerging and advanced stock markets. Modelling and estimating volatility is crucial in dynamic risk management, equity valuation and portfolio diversification. However, South African financial markets have not received ample attention in this regard. It is against this backdrop that we sought to determine the nature and behavior of volatility inherent in the South African stock market. Furthermore, we examined the effect of the 2014 global oil crisis on the volatility spillover in this market. The FTSE/JSE Top 40 index of the Johannesburg Stock Exchange has been selected as the study sample. Sample data for the period spans from October 14, 2009 to December 31, 2019, wherein the crisis period is from March 03, 2014 to February 27, 2015. Conditional volatility has been modelled and estimated using GARCH (1.1), GARCH-M (1.1), TGARCH (1.1) and EGARCH (1.1). The log likelihood, Akaike Information Criterion and Bayesian Information Criterion have been followed for model selection. The results showed that the EGARCH model is the most suitable for predicting the behavior of equity returns including for the global oil crisis period.

Keywords: Modeling, Volatility, Equity Returns, Global Oil Crisis, FTSE/JSE Top 40 Index.

JEL Classification Codes: C01, C13, C52, C53, C87.

INTRODUCTION

Investigating the nature and behavior of volatility exhibited by equity returns is of wider interest for researchers, market analysts, risk assessors and portfolio managers. Financial management and investment decisions rely on modelling and estimating equity returns volatility as it aids in asset pricing strategies, risk management and portfolio optimisation (Abdalla & Winker, 2012). In an efficient stock market, fluctuations in equity return are used to estimate and predict the value of potential market and financial risk. Practically, investment decisions and portfolio allocation are invariably futuristic, implying that the expected risks and expected returns must be accurately forecasted. By forecasting equity return volatility inherent on the FTSE/JSE Top 40 index, we establish an important relationship between current values and their expected future values. Moreover, econometric based quantitative estimation used in this study provides evidence-based knowledge to investors and financial managers with valuable and near accurate forecast of future market trends and cycles. In addition, modelling volatility by taking the influence of the global oil crisis into account serves to accurately unearth how South African markets are influenced by global oil prices spill over effects.

There have been widespread studies in different financial markets that have documented the properties of equity return volatility. These properties include; volatility clustering, information symmetry, leverage effects and leptokurtosis. Volatility clustering implies that enormous price movements are synonymously ensured by enormous price movements, either positive or negative, and small price movements are synonymously ensured by small price movements. This phenomenon was earlier documented in literature by (Fama, 1965; Chou, 1988; Schwert, 1989; Baillie, Chung, & Tieslau, 1996). Information symmetry refers to the postulation that positive and negative past information (news/shocks) inflict similar impact on volatility. Numerous studies have observed this symmetric impact on volatility. These include; (Butterworth, 2000; Srinivasan, 2013; Atoi, 2014; Gurgul & Machno, 2015; Singh & Tripathi, 2016). First documented by Black (1976), leverage effects imply that a decrease in equity returns is superseded by a surge in volatility that is more substantial in comparison to the volatility prompted by an increase in equity returns. This is also referred to as information asymmetry. This feature is noted in the work of (Enders, 2008; Emenike, 2010; Kosapattarapim, Lin, & McCrae, 2012; Emenike & Enock, 2020). Mandelbrot (1963) and Fama (1965) observed that equity returns have a tendency to be leptokurtic. This means that they are not normally distributed but rather show fat tails. Al Freedi, Shamiri, & Isa (2012) have provided evidence to this regard. Determining pattens of volatility is crucial as is it indicative of financial risks that have an adverse impact on the portfolio assets and wealth of investors. Thus, financial proofing these risk forces their holders to part with high-risk premium indemnity to offset the potential of losses, a situation that results in an increase in the cost of capital.

Contemporary volatility modelling and estimation is based on an autoregressive conditional heteroscedastic (ARCH) process that was pioneered by Engle (1982). This process was further broadened to a generalised autoregressive conditional heteroskedastic (GARCH) formulation by Bollerslev (1986). Although these two earlier models successfully capture stylised facts exhibited by financial markets data series that comprises of volatility clustering, information symmetry and leptokurtosis, they are unable to account for leverage effects and fat tails. Hence to overcome this shortcoming, several better sophisticated models that observe non-linearity were developed. Nelson (1991) extended the traditional GARCH formulation into an exponential generalized autoregressive conditional heteroskedasticity (EGARCH). Similarly, Zakoian (1994) also refined the GARCH model to form the threshold autoregressive conditional heteroskedasticity (TGARCH), which is much the same as the GJR-GARCH technique advanced by Glosten, Jagannathan, and Runkle (1993). Asymmetric volatility models recognise the different impact that desirable (bad) and undesirable (good) news has on conditional volatility. Bad information shocks tend to stimulate greater volatility in comparison to good information shocks.

The focal intention of the present work is to primarily capture and estimate the properties of equity return volatility inherent in the FTSE/JSE Top 40 Index. It further determines how the global oil crisis of 2014 affected equity return volatility for the concerned period. Sample data for the futures index series and cash market index series has been used for the period October 14, 2009 to December 31, 2019. The global oil crisis period under observation, spans from March 03, 2014 to February 27, 2015. A basket of symmetric and asymmetric GARCH models is harnessed for analysing the returns of the two concerned index series. By doing so, our research contributes and augments current literature two ways. Firstly, the study is distinguishable from prior research with particular regard to the dataset sampled, theoretical composition and methodological approach. Secondly, we have observed a recent global oil crisis (2014) that has not been assessed in previously, which enables this study to furnish fresh and unique insights on volatility behaviour. Our findings are financial decision-making oriented as they assist relevant stakeholders in capital allocation and portfolio selection.

The ensuring part of this work is arranged in this manner: Section 2 brings forth a summary of the reviewed academic literature. Section 3 presents the research methodology. Section 4 contains the results of the descriptive statistics and econometrics analysis. Section 5 contains the eventual concluding inferences.

REVIEW OF LITERATURE

Pioneering studies by Fama (1965) and Black (1976) were the first to uncover volatility clustering, fat tails (leptokurtosis), and leverage effects features in equity returns. Engle (1982) developed the autoregressive conditional heteroskedasticity (ARCH) model to capture and estimate volatility of the conditional variance by allowing it to depend on its error term and the linear combination of the squared previous error terms. This model was further enhanced by Bollerslev (1986) who instituted the generalised autoregressive conditional heteroskedasticity (GARCH) process which allowed the conditional variance to be modelled formulated on its lagged values and squared lagged error term values. The traditional symmetric GARCH model has received considerable attention in literature. Hsieh (1989) and Taylor (1994) in their empirical work, considered this model to effectively capture the essential characteristics exhibited by financial and econometric time series, for-instance, volatility clustering, heteroskedasticity, information symmetry and leptokurtosis. Similar findings were also observed by (Bandivadekar & Ghosh, 2003; Brook & Burke 2003; Ryoo & Smith, 2004; Pok & Poshakwale, 2004; De Beer, 2008; Mangani, 2008; Olowe, 2009; Dawson & Staikouras, 2009; Sehgal, Rajput & Dua, 2012; Matanovic & Wagner, 2012; Babikir, Gupta, Mwabutwa, & Owusu-Sekyere, 2012; Fong & Han, 2015; Yao, 2016). However, the major drawback of this model is its inability to model and estimate extreme observations and skewness in equity return series, a drawback that Emenike (2010) recorded. This shortcoming stimulated the interest of researchers to study the properties of equity return volatility by utilising asymmetric models that capture asymmetric tendencies.

Asymmetric GARCH models were developed to negate the assumption of normal distribution that is held by the GARCH (1. 1) and its related symmetric counterparts. Mandelbolt (1963) argued that extreme observations are prevalent in the variables of financial markets data series for the assumption of normal distribution to bear. As a result, the exponential autoregressive conditional heteroskedastic model (EGARCH) was expanded by Nelson (1991), to capture these extreme events. A similar model by Zakoian (1994), the threshold GARCH was also proposed. This model is identical to the GJR-GARCH except that the latter specifies conditional standard deviation rather than conditional variance. The effectiveness of these models to effectively capture the properties of time series has been substantiated by (Aggarwal, Inclan, & Leal, 1999; Alberg, Shalit, & Yosef, 2008; Onwukwe, Bassey, & Isaac, 2011) in their empirical studies.

The utilisation of asymmetric GARCH models led to a plethora of research particularly in the developing financial markets and to a limited extent, developed ones. The majority of these studies involves comparing symmetric and asymmetric models to determine the model that is most suitable for capturing stylised facts of stock returns. These include; Gulen and Mayhew (2000) who modelled volatility of 25 countries, Neokosmidis (2009) in USA, Atoi (2014) in Nigeria, Abdalla & Winker (2012) in Egypt and Sudan, Alberg et al. (2008) in Israel, Lim, & Sek (2013) in Malaysia, Chong, Ahmad, & Abdullah (1999) in Singapore, Emenike & Aleke (2012) in Nigeria, Siopis & Lyroudi (2007) in Greece, Gunay, & Haque (2015) and Yilgor & Mebounou (2016) in Turkey. In the same regard, India's emerging financial markets have considerably attracted the interest of researchers that include; (Pandey, 2003; Mall, Pradhan, & Mishra, 2011; Goudarzi & Ramanarayanan, 2011; Sahu, 2012; Banumathy & Azhagaiah, 2015; Varughese & Mathew, 2017; Kumar & Biswal, 2019; Shanthi & Thamilselvan, 2019). Empirical findings from the above studies substantially validates asymmetric models as best suited for capturing and explaining extreme properties of equity return volatility.

Numerous studies have also been conducted in South Africa's stock markets to explore and determine the dynamic volatility behaviour using GARCH models. These studies include the works of; (Magweva, Munyimi, & Mbudaya, 2021; Mashamba & Magweva, 2019; Naik & Padhi 2015; Kgosietsile, 2015; Oberholzer & Venter, 2015; Masinga, 2015; Babikir et al., 2012; Samouilhan &

Shannon, 2008; De Beer, 2008; Mangani, 2008). Although the above studies presented empirical findings that provide a crucial understanding of volatility in the capital markets, only (Mashamba & Magweva, 2021; Oberholzer & Venter, 2015; Kgosietsile, 2015; Masinga, 2015) made an empirical attempt to model and estimate the price movements of FTSE/JSE Top 40 index. Other studies focused on different indices altogether, hence their findings do not address the objective we seek to achieve. A recent study by (Mashamba & Magweva, 2021) utilized a modified symmetric GARCH (1.1) model to analyze how index futures trading impacted volatility, from 03 June 2002 to 31 December 2014. Their research objective, methodology and sample period significantly differ from this present study. Similarly, the use of different spillover effects such as the global financial meltdown of 2007 used by Oberholzer & Venter (2015) in determining its impact on volatility, remarkably contradict our study as we consider a more recent event (i.e., global oil crisis, 2014) into account and different model specification. Similarly, Kgosietsile (2015) and Masinga (2015) utilized a different research methodology and other variables in the assessment of volatility, an approach that again is distinguishable from this study. As a result of these methodological differences and unfulfilled research gaps, we are motivated to further revisit their work by improving their findings and adding more recent evidence to related literature in South Africa.

On the basis of the findings documented in the empirical literature above, it is apparent that traditional symmetric GARCH models are useful in capturing and forecasting certain stylized facts of equity return volatility. However, their major drawback stems from their inability to capture leverage effects and fat tails. As a result, information asymmetry-oriented models namely EGARCH and TGARCH, were developed to capture and estimate asymmetric behavior of equity returns and these two models have been employed in this study along with a GARCH (1.1) in conjunction with GARCH-in-M (1.1).

RESEARCH METHODOLOGY

Data Source and Transformation

The present work is established on secondary data which has been obtained from the Johannesburg Stock Exchange (JSE). The index selected for the current research is FTSE/JSE 40 Top index which represents the Johannesburg Stock exchange. The data collected was in the form of daily closing prices from 14 October, 2009 to 31 December, 2019. The dataset consists of 2552 number of total observations during the study period. The daily returns have been calculated at first difference of the logarithm of FTSE/JSE 40 Top index of successive days. The calculation of daily returns is based on the given formula:

$$r_t = log[\frac{p_t}{p_{t-1}}]$$

Where, r_t represent the return on the current day which is the log of the division of latest day's price (p_t) by previous day's price (p_{t-1}).

Empirical Tests

Unit Root Test

The existence of a unit root or stationarity within the financial market data series under observation has been inspected using the Augmented Dickey-Fuller (ADF) and Philips-Peron (PP) tests. Using data that is non-stationary results in misleading or spurious regressions which cannot be relied upon. Ruxanda and Botezatu (2008) documented that, evaluating financial time series variables characterised by non-stationarity, leads to unrealistic association between the returns.

Normality Test

The present study utilized the Jarque-Bera test to check for normality. It is important to check for normality as the validity of our regressions and t-tests are based on the assumption that data conforms to normal or Gaussian distribution. Any deviations from normality implies that the series is not normally distributed.

ARCH/GARCH Effect Test

Before applying ARCH/GARCH models, the existence of heteroscedasticity in the return residuals has been tested by applying the Lagrange Multiplier (LM) test suggested by Engle (1982). An absence of ARCH/GARCH effect means that the processes are not applicable for the data.

Modelling Volatility

This study employs an assortment of univariate GARCH models to capture and estimate the properties of volatility of the FTSE/JSE Top 40 equity returns. The financial econometric models have been specified to estimate and capture both symmetric and asymmetric features of the data set. Symmetric tendencies in the series have been observed using the GARCH (1.1) and GARCH-M (1.1). Similarly, information asymmetry has also been observed by using EGARCH (1.1) and TGARCH (1.1). A detailed breakdown of the models is given below:

Symmetric GARCH Models

The Generalized Autoregressive Conditional Heteroscedastic (GARCH) Model

The process and specification of the model relies on a linear function of previous squared values of residuals along with the lagged values of conditional variances. It is computed using the following equation:

$$\sigma^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 + \delta\, crisis \qquad (1)$$

Where α_0 is a constant term, and $\alpha_1, \alpha_2, \alpha_3, \ldots \alpha_n$ are the parameters or coefficients of the ARCH specifications. Similarly, $\beta_1, \beta_2, \beta_3 \ldots \beta_n$ are the parameters or coefficients of GARCH specifications. The p and q are the respective orders of the ARCH and GARCH process.
The GARCH equation can be simplified as follows;

$$\sigma^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \delta\, crisis \qquad (2)$$

The parameter constraints imposed on this model are:

$$a_0 + > 0,\ a_1 > 1,\ \beta > 0,\ (a_1 + \beta) < 1.$$

The Generalized Autoregressive Conditional Heteroscedastic-in-Mean (GARCH-M) Model

The specification process for this model was propounded by Engle et al. (1987). Modelling the properties of equity returns using this approach is ideal if the return on equity is dependent on volatility. The letter 'M' represents a mean which indicate the conditional mean representing a successive order relies on the inherent conditional variance. Hence, the current equity returns are predicted based on conditional volatility. The mean equation for GARCH-M is as follows:

Mean equation $$r_t = \mu + \lambda \sigma t_\tau^2 + \delta\, crisis + \varepsilon_t \qquad (3)$$

Variance equation $$\sigma^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \delta\, crisis \qquad (4)$$

Where λ given in the mean equation denote the parameter of the risk premium. Positive λ represents the direct relationship between returns and its volatility. Alternatively explained, a rise in the average equity returns is generated by a rise in conditional volatility. The variance equation is similar to the one mentioned above for the GARCH model.

Asymmetric GARCH Models

The Threshold Generalized Autoregressive Conditional Heteroscedastic (TGARCH) Model

Devised by Zakoian (1994), the model is used to estimate the leverage effects in conditional variance. It is almost identical to the GJR-GARCH model. The framework for conditional variance estimation is given below:

$$\sigma^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \gamma d_{t-1}\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + {}_{\delta}\, crisis \qquad (5)$$

Where γ in the variance equation is the parameter of leverage effect or information asymmetry. When asymmetric parameter is positive and significant, its effect on volatility is $\alpha_i + \gamma_i$ where $d_{t-1} = 1, \varepsilon_{t-1} < 0$, otherwise $d_{t-1} = 0$ where the effect on volatility is α_i. Positive leverage effect ($\varepsilon_{t-1} > 0$) in TGARCH indicates that the impact of negative information (bad news) on equity volatility surpasses that of positive information (good news).

The Exponential Generalized Autoregressive Conditional Heteroscedastic (EGARCH) Model

The aforementioned technique is a logarithmic expression of conditional variance. It captures the asymmetries in the positive and negative stock returns whilst constantly maintaining a positive variance. It is specified and computed as shown below:

$$\ln(\sigma^2) = \alpha_0 + \beta_1\ln(\sigma_{t-1}^2) + \alpha_1\left\{\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{\pi}{2}}\right\} - \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + {}_{\delta}\,\text{crisis} \qquad (6)$$

Where γ is an asymmetric parameter or coefficient of leverage effect in conditional variance. As it models the log of conditional variance, the given conditional variance effectively becomes positive supposing that the parameter is negative. In this process, negative the leverage effect indicates that the larger effects of negative information than the positive information.

Model Selection

Since several models have been employed to unearth the properties and nature of volatility in the stock returns, finding out best fitting model is imperative. In this regard, the most appropriate GARCH models for conditional volatility are chosen by utilizing the information criteria (Javed & Mantalos, 2013; Bonga, 2019). The best suited model is reached upon when the Akaike information criterion (AIC) and Schwartz information criterion (SIC) are minimum and log likelihood and r-square are maximum Dhingra, Gandhi, & Bulsara (2016). Hence, the best fitting model for FTSE/JSE Top 40 index has been selected using the same criteria.

RESULTS

Descriptive Statistics

In order to highlight the properties of the statistical distribution of the daily equity returns pertaining to the index prices of the considered sample period, the descriptive statistics have been presented in Table 1, below. It displays the values of the mean, standard deviation, skewness, kurtosis and Jarque-Bera. The skewness statistics is -0.13 which indicates the chances of earning higher than mean returns. Kurtosis is also greater than 3 indicating that the index series data has fat tails properties (leptokurtic) and is not in conformance with normal or Gaussian distribution. Furthermore, the Jarque-Bera statistics is significant at 1% level which confirms that skewness and kurtosis does not follow normal distribution.

Table 1. Descriptive Statistics for the Index Prices Returns

Particulars	Statistics
Mean	0.000132
Median	0.000285

Minimum	-0.017586
Maximum	0.020319
Std. Deviation	0.004507
Skewness	-0.135526
Kurtosis	4.314803
Jarque-Bera (*p*-value)	191.6315 (.0000)
Observations	2552

Test of Stationarity

The concept of stationarity refers to the property were the mean, variance and autocorrelation do not change in due course, but rather remain constant. To detect this property for the data of the present study, the Augmented Dickey-Fuller (ADF) and Phillip-Perron (PP) tests have been applied at both intercept and trend and intercept for critical values at one, 5% and 10% level of the significance (Dickey & Fuller, 1979; Phillip & Perron, 1988). The null hypothesis for stationarity defines data as having a unit root in its series. The findings of the unit root examination are presented in Table 2. The outcome of the test exhibits that either the ADF and PP alternative tests disavow the null hypothesis ultimately confirming the state of stationarity in the data set.

Table 2. Findings of the Stationarity Test

Values	ADF		PP	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-statistics	-38.16334	-38.17126	-52.78620	-52.83829
p-value	0.0000	0.0000	0.0001	0.0000
Critical Values				
1%	-3.432721	-3.961643	-3.432720	-3.961614
5%	-2.862473	-3.411570	-2.862473	-3.411569
10%	-2.567312	-3.127651	-2.567312	-3.127651

Figure 1 presents evidence of volatility clustering in Index prices during 2009 and 2019. The period of depressed volatility is succeeded by more depressed volatility periods and periods of soaring volatility is succeeded by more soaring volatility periods. The presence of volatility clustering is essential before specifying ARCH models. The present study has examined volatility clustering by performing ordinary least squares and then plotting the residuals to observe it. Furthermore, the presence of heteroscedasticity in the model reinforces the presence of volatility clustering. This fulfils the requisite conditions essential in the application of ARCH and GARCH models.

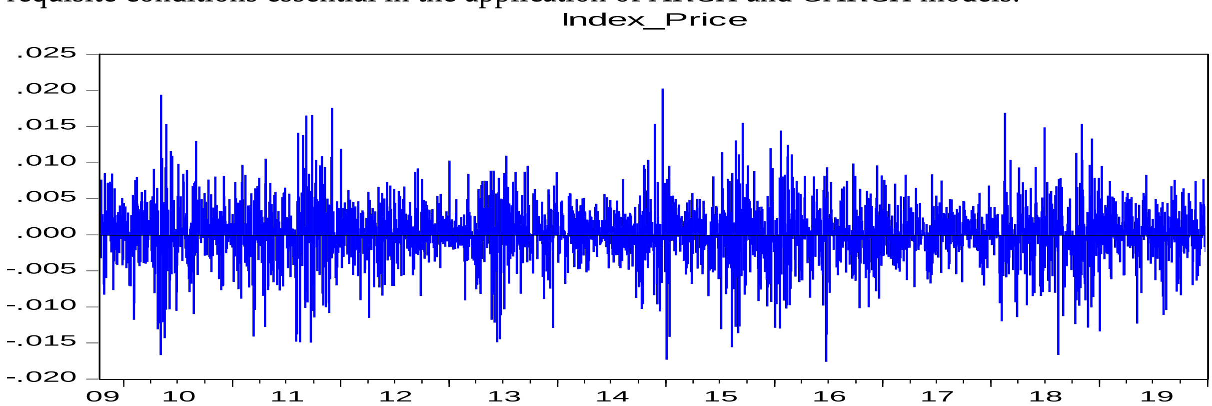

Figure 1. Volatility Clustering of Index Prices Daily Returns

In line with assessing heteroscedasticity, ARCH effect in the series and volatility clustering have been determined by visually depicting them using a graph. The results of the ARCH effect show the presence of heteroscedasticity in Index price daily returns [F (2, 2547) 39.91804, p-value < .0001]. It further asserts the appearance of volatility clustering within index price returns between 2009 and 2019. According to Naik and Padhi (2015), volatility clustering and ARCH effect are the essential conditions required for the application of ARCH and GARCH model. Therefore, the results of the ARCH effect confirm the fulfilment of essential assumptions required to estimate the GARCH models.

Table 3. Test of heteroscedasticity: ARCH Effect

F-statistic	39.91804	Prob. F(2, 2547)	0.0000
Obs*R-squared	77.50085	Prob. Chi-Square(2)	0.0000

Measurement of Volatility

After validating the availability of volatility clustering and ARCH effect within the data series, the next step is to ascertain a well-suited GARCH model for the present data series. In so doing, both the symmetric and asymmetric GARCH models are applied for daily index returns to understand the volatility in the returns of FTSE/JSE Top 40 index.

The volatility in daily returns is fitted with a GARCH (1.1) along with a GARCH-M (1.1) symmetric process. The results are presented in table 4. The results of GARCH (1.1) model in mean equation display that the respective coefficients of constant term and lagged index price returns are statistically significant at less than 1% significance level. The coefficient of the constant term shows that the current day returns of the index are significantly predicated by the average stock returns. Moreover, the lag of index prices returns indicate that the current day prices are predicted by the prices of the previous day. Hence, the information at two-lags influences the prices of the index prices today. Similarly, in the conditional variance equation of the GARCH (1.1) model, the ARCH term (α) for heteroscedasticity, GARCH term (β) for volatility are established to be statistically significant at less than 1% level of significance. The β coefficient is estimated to be substantial in comparison to the α coefficient which indicates that volatility within the series requires a protracted duration to eventually dissipate. The volatility in the present day is more sensitive to the returns of the previous days. Moreover, volatility is recorded to be persistent as the totality of α and β coefficients is 0.973, which is less than one. The sum of coefficients in close proximity to or near unity imply that the shock is bound to persist into the distant future. Moreover, the coefficient of the global crisis period is also recorded to be statistically significant at less than 5% level of significance which confirms the effect of crisis period on the volatility of the index prices daily returns. Furthermore, the ARCH-LM test has been employed to assess the existence of any ARCH effect still present within the residuals of the daily return dataset. The results of the ARCH-LM test accepts the given null hypothesis which posits that there is ‘no ARCH effect present’ within the series at more than 5% level of significance. The result of ARCH-LM test substantiates the non-availability of further ARCH effect that may have been contained within residuals of the index prices returns, a fact that proves that the variance equation is properly spelled out.

Table 4. Symmetric GARCH (1.1) Models

Variable	GARCH (1.1)	GARCH-M (1.1)
	Coefficients	Coefficients
Mean		
C	0.000229***	-0.000432
Risk Premium	---	0.164372
Variance		
C	5.77E-07***	5.79E-07***

Α	0.080002***	0.079629***
Β	0.893468***	0.893534***
ϕ	-2.17E-07*	-2.00E-07
Log likelihood	10305.01	10306.63
Akaike info. criterion (AIC)	-8.072108	-8.072596
Schwarz info. criterion (SIC)	-8.067955	-8.058855
ARCH LM Test for heteroscedasticity		
Test Statistics	0.3719	0.4758
Prob. Chi-sqaure (2)	0.5418	0.4889
*Note: α = squared residual (RESID (-1) ^2); β = measure of volatility (GARCH (-1)); *p-value < .05; **p-value < .01; ***p-value < .001*		

In the GARCH-M (1.1) process, the influence of volatility on the expected return is estimated. The coefficient of conditional variance is incorporated into the mean equation. The ensuing outcome is shown in Table 4 displayed above. For the mean equation, the coefficient of constant terms has been established to be negative and statistically insignificant at 5% level of significance which shows that the average stock price does not predict the current day returns. The coefficient of index prices two-lag on the current day returns is found to be statistically substantial at less than 1% level of significance. In spite of that, the constant term is found to be insignificant which proves the existence of a normal return for the market. The coefficient of risk premium is discovered as positive and statistically significant at 5% level of significance. It implies that the volatility has a significant and positive impact on expected return which indicates that holding an asset in question will be risky. Within the variance equation of GARCH-M (1, 1) model, the coefficients of constant, ARCH and GARCH terms are determined to be statistically relevant below 1% significance level. The shocks are also recorded to be persistent for longer periods as the aggregate of α and β parameters which is 0.973 inches towards unity. The effect of the global oil crisis on conditional variance is found to be statistically insignificant. The results of ARCH-LM test are estimated to be statistically insignificant denoting the absence of any additional ARCH effect on the residuals in the index prices returns.

To understand the asymmetric tendencies in the series of index prices daily returns, asymmetric GARCH processes such as TGARCH (1.1) and EGARCH (1.1) are determined. The outcome from the asymmetric GARCH analysis is displayed in Table 5 given below. The results of mean equation in TGARCH (1.1) model unearth the constant term to be statistically insignificant and the coefficient of lag of index prices returns is estimated to be statistically significant at less than 1% level of significance. Moreover, a review of the conditional variance equation of TGARCH (1.1) model, presents a coefficient or constant ARCH and GARCH terms that are statistically significant at 1% level of significance. The duration of shocks that persist into future time periods is as also verified since α, β and λ ($\alpha + \beta + \lambda/2 < 1$) parameter is less than one. Moreover, the leverage effect is found to be positive and statistically significant at 1 percent level of significance. A positive leverage effect indicates that bad news or negative news has more influence on the returns of the index prices in comparison to positive shocks or good news. The TGARCH model also captures the significant impact of crisis on volatility of index prices at 5% level of significance. ARCH-LM test of TGARCH model for heteroscedasticity is insignificant, proving the absence of any additional ARCH effect in the series.

Table 5. Asymmetric GARCH (1, 1) Models

Variable	TGARCH (1.1)	EGARCH (1.1)
	Coefficients	Coefficients
Mean		
C	4.63E-05	2.07E-05

Variance		
C	5.60E-07***	-0.380215***
α	-0.021026***	0.083949***
β	0.913632***	0.971075***
λ	0.160154***	-0.132208***
ϕ	-1.71E-07*	-0.011133*
Log Likelihood	10350.56	10357.81
Akaike Info. Criterion (AIC)	-8.107023	-8.112702
Schwarz Info. Criterion (SIC)	-8.093282	-8.098961
ARCH LM Test for heteroscedasticity		
Test Statistics	2.0721	0.5383
Prob. Chi-sqaure (2)	.1500	0.4630
Note: α = squared residual (RESID (-1) ^2); β = measure of volatility (GARCH (-1)); λ = Leverage Effect (RESID (-1) ^2(RESID (-1) <0); ϕ = Dummy Crisis; *p-value < .05; **p-value < .01; ***p-value < .001*		

Similarly, the results of EGARCH model for mean equation show that the constant term is statistically insignificant and the coefficient of past values of index prices returns are estimated to be statistically significant at 1% of significance. In conditional variance equation, the parameter estimates are found to be positive, except β coefficient, and statistically significant at 1 percent level of significance. The EGARCH (1.1) captures the leverage effect to be negative and statistically significant at 1% level of significance. This signals that bad information has a substantial influence on the index prices return than good information. The coefficient of the global oil crisis is recorded as negative and proved to be statistically significant at 5% significance level. The results of ARCH LM test portray the absence of additional ARCH effect in the index prices return series.

Hinging on the empirical outcome of symmetric processes, the GARCH (1.1) model predicts the effect of average equity returns on the current equity better than the GARCH-M (1.1) model. Moreover, this difference is also consistent in capturing the influence of the crisis period on the conditional volatility pertaining to index prices returns. As for measuring the persistence of shocks, the GARCH (1.1) model fits the index returns series better than the GARCH-M model. A positive and insignificant coefficient of conditional variance presented as risk premium in GARCH-M model denotes the inconsistencies between higher market risks and higher returns. Findings from asymmetric models show that both the TGARCH (1.1) and EGARCH (1.1) models are a good fit to the data. Both the models record a significant leverage effect and capture the impact of the global oil crisis period on volatility of stock returns. These findings support the conclusions of Kgosietsile (2015) and Masinga (2015) who also provided testimony of volatility clustering, fat tails, leverage effects on the FTSE/JSE Top 40 index. According to the log likelihood, AIC and SIC selection criteria, EGARCH (1.1) model is the best model for capturing the volatility in index prices returns as estimated log likelihood is highest and AIC and SIC are lowest for this model. The results in harmony with the outcome of Mukharjee, Sen, and Sarkar (2011) and Naik and Padhi (2015) who have also made model selection using information criteria provided above.

CONCLUSION

Capturing and forecasting the nature and behavior of volatility exhibited by equity returns has received wide attention from researchers, market analysts and risk and portfolio managers. This is because volatility properties provide a decision-making base for asset pricing strategies, risk management and portfolio optimisation. The present study modelled and estimated volatility in index prices daily returns and examined the impact of crude oil crisis of 2014 on index price volatility. The study used data from

FTSE/JSE Top 40 index ranging from October 14, 2009 to 31 December, 2019. The global oil crisis period for the current study has been considered from 03 March, 2014 to 27 February, 2015. The data has been pretested by confirming normality with Jarque-Berra, Unit Root tests using ADF and PP, visualizing volatility clustering and assessing heteroscedasticity using ARCH LM. The study employed both symmetric and asymmetric conditional volatility models, that is, GARCH (1.1), GARCH-M (1.1), TGARCH (1.1) and EGARCH (1.1). Empirical findings using symmetric models proved that the GARCH (1.1) model predicts the effect of average equity returns on the current equity better than the GARCH-M (1.1) model. Moreover, this difference has been consistent in capturing the impact of crisis period on the conditional volatility of the index prices returns. Furthermore, the GARCH (1.1) model fits the index returns series better in measuring the persistence of the shock as compared to the GARCH-M model. Evidence from asymmetric models substantiate that both the TGARCH and EGARCH models were better fit for the data as their corresponding leverage coefficient were recorded as positive and significant, and negative and significant respectively. However, based on information criterion and log likelihood estimates, EGARCH model has been determined to be the best suited for testing volatility in FTSE/JSE top 40 index. The result of ARCH-LM test confirmed the non-availability of any additional ARCH effect within the residuals of the series hence the variance equation has been well specified for the market.

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