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Univariate Volatility Modeling Of Stock Returns on the Nigerian Stock Exchange Using Garch Models

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ABSTRACT
This study investigates the behaviour of stock returns volatility (conditional variance) and asymmetry effects of the Nigerian Stock Exchange (NSE) using GARCH (I, I) and EGARCH models. Monthly All Share Price Indices (APSI) of the NSE from January 1985 to December 2017 provided the empirical sample for investigation. We performed the serial correlation and ARCH-Effects tests. The preliminary analyses suggest that ASPI exhibit volatility judging by the serial correlation and heteroskedasticity tests. Thus, in modeling ASPI, this inherent statistical feature must be accounted for. In essence, the appropriate modeling framework is the univariate volatility modeling. The key results are as follows: the GARCH models are sufficiently capable of capturing the dynamics of the financial time series particularly with respect to volatility clustering, the leptokurtic characteristic of the distribution of the monthly return series and the leverage effects. The leverage effect is captured by the EGARCH. Secondly, there is evidence of the existence of positive interactions between the expected risk and the expected return for all markets as predicted in the investment theory. The findings of this study can be used by investors to make investment decision and manage risk. The results are in tune with international evidence of financial data exhibiting the phenomenon of volatility clustering, fat-tailed distribution. However, it suggests no asymmetry effects and the persistence of stock return volatility in the Nigerian Stock Exchange (NSE).
Keywords: Heteroskedasticity, EGARCH, Ljung-Box Q test, serial correlation, ARCH-Effects.

INTRODUCTION

Volatility is a measure of dispersion of a security's returns from its mean or the average return. Generally, higher standard deviation means high uncertainty/unpredictability about the future returns of the security and therefore greater risk in the value of the investment. Lower volatility means that the value of a financial security changes at a steady pace over a period of time in either direction. Changes in the price of a security in itself may not be bad but the extent of the variability of its price changes makes investors planning uncertain and difficult. High fluctuations in security prices influence the investors' decision making with regards to the type of investment to be undertaken. Excess volatility in markets makes it difficult for companies to raise funds in the capital markets; create uncertainty about security prices; loss of investor confidence and sometimes lead to crashes or crisis. If there is high volatility in a stock market, the investors should be compensated in the form of higher risk premium. If investors are risk averse, theory predicts a positive relationship should exist between stock return and volatility (Leon, 2007). Therefore, accurate estimation of volatility is pivotal to risk management, and of critical importance to the valuation of derivative products such as options (Hull, 2012) and foreign exchange rates.

Time-varying volatility is pervasive in financial time series, so much so that it is difficult to find an asset return series which does *not* exhibit time-varying volatility. A number of explanations have been proffered to explain this phenomenon, although treated individually, none have been completely satisfactory.

• ***News Announcements*:** The arrival of unanticipated news (or "news surprises") forces agents to update beliefs. These new beliefs trigger portfolio rebalancing and high periods of volatility correspond to agents dynamically solving for new asset prices. While certain classes of assets have been shown to react to surprises, in particular government bonds and foreign exchange, many appear to be unaffected by even large surprises. Additionally, news-induced periods of high volatility are generally short and the apparent resolution of uncertainty is far too quick to explain the time-variation of volatility seen in asset prices.

• ***Leverage*:** When firms are financed using both debt and equity, only equity will reflect the volatility of the firm's cash flows. However, as the price of equity falls, a smaller quantity must reflect the same volatility of the firm's cash flows and so negative returns should lead to increases in equity volatility. The leverage effect is pervasive in equity returns, especially in broad equity indices, although alone it is insufficient to explain the time variation of volatility.

• ***Volatility Feedback*:** Volatility feedback is motivated by a model where the volatility of an asset is priced. When the price of an asset falls, the volatility must increase to reflect the increased expected return (in the future) of this asset, and an increase in volatility requires an even lower price to generate a sufficient return to compensate an investor for holding a volatile asset. There is evidence that this explanation is empirically supported although it cannot explain the totality of the time-variation of volatility.

• ***Illiquidity*:** Short run spells of illiquidity may produce time varying volatility even when shocks are i.i.d. Intuitively, if the market is oversold (bought), a small negative (positive) shock will cause a small decrease (increase) in demand. However, since there are few participants willing to buy (sell), this shock has a large effect on prices. Liquidity runs tend to last from 20 minutes to a few days and cannot explain the long cycles in present volatility.

• ***State Uncertainty*:** Asset prices are important instruments that allow agents to express beliefs about the state of the economy. When the state is uncertain, slight changes in beliefs may cause large shifts in portfolio holdings which in turn feedback into beliefs about the state. This feedback loop can generate time-varying volatility and should have the largest effect when the economy is transitioning between periods of growth and contraction. The actual cause of the time-variation in volatility is likely a combination of these and some not present.

Volatility clustering occurs when large stock price changes are followed by large price changes of both signs and small price changes are followed by periods of small price changes. Leptokurtosis means that the distribution of stock returns is not normal but exhibits fat-tails. In other words, leptokurtosis signifies high probability for extreme values than the normal law predicts in a series. Asymmetry, also known as leverage effects, means that a fall in return is followed by an increase in volatility greater than the volatility induced by an increase in returns. This implies that more prices wander far from the average trend in a crash than in a bubble because of higher perceived uncertainty (Fama, 1965; Black, 1976). These characteristics are perceived as indicating a rise in financial risk, which can adversely affect investor's assets and wealth. For instance, volatility clustering makes investors more averse to holding stocks due to uncertainty. Investors in turn demand a higher risk premium in order to insure against the increased uncertainty. A greater risk premium results in a higher cost of capital, which then leads to less private physical investment.

Modeling volatility is an important instrument in pricing equity, risk and portfolio management. Stock prices reflect all available information and the quicker they are in absorbing accurately new information, the more efficient is the stock market in allocating resources. Modeling volatility improves the usefulness of stock prices as a signal about the intrinsic value of securities, thereby making it easier for firms to raise funds in the market. Also, detection of stock returns volatility-trends would provide insight for designing investment strategies and for portfolio management. Our review indicates that the vast majority of the empirical work on the volatility of stock prices in the stock and foreign exchange markets has been done using data on developed markets like the US stock market and on exchange rates against the US dollar.

US markets are probably the deepest and most competitive financial markets in the world, so they provide a favourable testing ground for the efficient market hypothesis. However, financial sector development, recapitalization of the banking industry in July 2004 followed by the Insurance industry in September 2005 boosted the number of securities on the stock market; increased public awareness and confidence and shifted the financial system from bank-based to security market-based in Nigeria. The Increased trading activity on the stock market could have affected the volatility of the stock market. Hence, it has become imperative to understand the behaviour of stock returns volatility in the Nigerian Market. This interest in understanding the dynamics of volatility of returns on the stock market does not come as a surprise considering the rapid pace of development and change, this will be useful in the determination of the cost of capital and evaluation of asset allocation decisions.

This study contributes to the existing body of empirical literature in many ways. First, by estimating and analyzing stock return volatility focusing on the Nigerian market as an emerging economy. The major contribution of the application of the GARCH type models is that future directions in the volatility of financial time series may be predictable and hence the result is useful in making investment decisions. Secondly, this study makes a contribution by reinforcing empirical evidence of positive interaction between expected risk and expected return as predicted in financial theory. The application of GARCH to modeling the attitude of investors towards risk and expected returns is of great importance in financial application. Thirdly, this study also incorporates asymmetric effects of volatility which very often characterizes the dynamic behavior of financial time series data that has not been adequately explored for Nigeria in previous empirical studies.

For ease of understanding and analyses, the rest of this study is organized as follows: Following the introduction is section 2 which is theoretical framework and review of existing literature. Section 3 describes the methodology adopted for the study while the empirical results and analyses are presented in Section 4. Finally, in Section 5 is conclusion and recommendation.

Section 2: Literature Review

2.1: Theoretical Framework: Efficient Market Hypothesis (EMH)

The efficient market hypothesis is concerned with the behaviour of prices in asset markets. The term ‘efficient market’ was initially applied to the stock market, but the concept was soon generalized to other asset markets. The Efficient Market Hypothesis (EMH) is an application of ‘Rational Expectations Theory’ where people who enter the market, use all available & relevant information to make decisions. The only caveat is that information is costly and difficult to get. This Efficient Market Hypothesis implies that stock prices reflect all available and relevant information, so you can’t outguess the market or systemically beat the market. This means it is impossible for investors to either purchase undervalued stocks or sell stocks for inflated prices. When investors use all available information in forming expectations of future rates of return, the equilibrium price of the asset equals the optimal forecast of fundamental values based on the available information (i.e., the present value of expected future returns on the asset). There are three forms of market efficiency.

1. Weak-form efficiency

Future prices cannot be predicted by analyzing prices from the past meaning there are not meaningful patterns to gain from past performance. Future price movements are determined entirely by information not contained in the price series.

2. Semi-strong-form efficiency

In a semi-strong-form efficiency, share prices adjust to publicly available new information very rapidly and in an unbiased fashion, such that no excess returns can be earned by trading on that information.

3. Strong-form efficiency

In the strong-form market efficiency, the share prices reflect all information, public and private, and no one can earn excess returns.

Implications of the Efficient Market Hypothesis (EMH)

1. Any change in market price from one period ahead will be completely accounted for by new information on market fundamentals which arrives between time t and t + 1. If the predicted price based on publicly available information is different from the current price, there exists an arbitrage opportunity.

If the market is efficient, investors will rapidly bid on the stock so that the arbitrage opportunity will soon disappear.

2. The more efficient a market is, the more random the prices can be. There is no reason why asset prices cannot be extremely volatile. News may radically alter the investors' assessment of the future prospect of a corporation and its stock price.

3. Trading strategies (technical analysis) designed to beat the market cannot be successfully profitable. An investor cannot earn above-normal profits over an extended period of time. This follows from the fact that for the random walk model, the probability that the price of a stock will rise in value tomorrow is the same as the probability that the price will fall.

4. The dominant investment strategy is a very simple one: buy and hold a diversified portfolio of assets. A "buy and hold" strategy is the most sensible strategy for small investors.

Evidence in Favor of Efficient Market Hypothesis (EMH)

1. Compare the performances of some stocks recommended by investment advisers with a group of stocks chosen by throwing darts. They perform roughly equally.
2. Mutual funds do not perform better than the market on average either.
3. To test for the random walk hypothesis, researchers have used (1) past stock price data and (2) other publicly available data to see if stock prices are predictable. In general, these tests confirm that US stock market follow a random walk.
4. Tests on the performance of technical analysis by evaluating the profits following the timing of buying and selling suggest that technical analysis does not outperform the overall market.

Evidence against Efficient Market Hypothesis

1. Small-firm effect
2. January Effect
3. Market Overreaction: overshooting
4. Excessive Volatility: Volatility of security prices seems much too high to be justified by changes in market fundamentals.
5. Mean Reversion
6. New information is not always immediately incorporated into stock prices: in response to an unexpected profit announcement, the stock price may continue to rise or fall for some time.

Section 2.2: Stock Market Volatility

Stock market volatility refers to the potential for a given stock to experience a drastic decrease or increase in value within a predetermined period of time. Investors evaluate the volatility of stocks before making a decision to purchase a new stock offering, buy additional shares of stock already in the portfolio or sell stock currently in the possession of the investor. Recently, it has not been unusual to see the value of major stock indexes, such as S & P 500, NIKKEI, DOW JONES, KOSPI, FTSE and NSE-ASI change by as much as 3% in a single day. Unfortunately for many investors, the general direction of those changes has been downward. Stock market volatility tends to be persistent; that is, periods of high volatility as well as low volatility tend to last for months. In particular, periods of high volatility tend to occur when stock prices are falling during recessions. Stock market volatility is also positively related to volatility in economic variables, such as inflation, industrial production and debt levels in the corporate sector (Schwert, 1989). The persistence in volatility is not surprising: stock market volatility should depend on the overall health of the economy, and real economic variables themselves tend to display persistence. The persistence of stock market return volatility has two interesting implications. First, volatility is a proxy for investment risk. Persistence in volatility implies that the risk and return trade-off changes in a predictable way over the business cycle. Second, the persistence in volatility can be used to predict future economic variables. For example, Campbell, Lettau, Malkiel, and Xu (2001) show that stock market volatility helps to predict growth.

Volatility may impair the smooth functioning of the financial system and adversely affect economic performance (Mala and Reddy, 2007). Similarly, stock market volatility also has a number of negative implications. One of the ways in which it affects the economy is through its effect on consumer spending (Campbell, 1996; Starr-McCluer, 1998; Ludvigson and Steindel, 1999; and Poterba, 2000). The impact of stock market volatility on consumer spending is related via the wealth effect. Increased wealth will drive up consumer spending. Stock market volatility may also affect business investment (Zuliu, 1995) and economic growth directly (Levine and Zervos, 1996; Arestis, Demetriades and Luintel, 2001). A rise in stock market volatility can be interpreted as a rise in risk of equity investment and thus a shift of funds to less risky assets. This move could lead to a rise in cost of funds to firms and thus new firms might bear this effect as investors will turn to purchase of stock in larger well known firms. While there is a general consensus on what constitutes stock market volatility and, to a lesser extent, on how to measure it, there is far less agreement on the causes of changes in stock market volatility. Some economists see the causes of volatility in the arrival of new, unanticipated information that alters expected returns on a stock (Engle, 1982). Thus, changes in market volatility would merely reflect changes in the local or global economic environment. Others claim that volatility is caused mainly by changes in trading volume, practices or patterns, which in turn are driven by factors such as modifications in macroeconomic policies, shifts in investor tolerance of risk and increased uncertainty. The degree of stock market volatility can help forecasters predict the path of an economy's growth and the structure of volatility can imply that investors now need to hold more stocks in their portfolio to achieve diversification (Krainer, 2002).

It is found that the financial time series (particularly stock/index prices) often exhibit the phenomenon of volatility clustering (Stock and Watson, 2012) that is, the series exhibit sometimes high volatilities and sometimes low volatilities for an extended time periods. However, for a short period of time, there is a strong chance that a day of high volatility will be followed by another day of high volatility. In other words, if high volatility is observed yesterday, it is more likely that high volatility will also be observed today. This means that today's volatility is positively correlated with yesterday's volatility and thus we can estimate volatility conditionally on the past volatility.

Volatility can either be historical volatility which is a measure based on past data, or implied volatility which is derived from the market price of a market traded derivative particularly an option. The historical volatility can be calculated in three ways namely; (a) Simple volatility, (b) Exponentially Weighted Moving Average (EWMA) and (c) GARCH. In this study, we will apply the most commonly used stochastic volatility model GARCH (1, 1) as it is theoretically superior to and more appealing than the other two approaches. Furthermore, GARCH is also used as a preferred method for finance professionals as it provides a more real life estimate while forecasting parameters such as volatility, prices and returns

2.3: Empirical Literature

Elsheikh and Zakaria (2011) used GARCH-type models that include both symmetric and asymmetric models to estimate volatility in the daily returns of the Khartoum (Sudan) Stock Exchange over the period January 2006 to November 2010. They found evidence that the GARCH models are fit to characterize the daily returns for the case of Sudan. With respect to risk-return relationship, this study found risk premium coefficient positive and statistically significant implying that increased risk leads to higher return as predicted in financial theory.

Goudarzi and Ramanarayan (2011) studied the effects of good news and bad news on volatility in the case of Indian stock markets (BS 500 stock index) using the asymmetric models of EGARCH and TGARCH. They found evidence of the existence of standard leverage effects showing that bad news in the Indian stock market increases volatility more than good news.

Guidi and Gupta (2012) applied the asymmetric PARCH (APARCH) model with two different error distributions (student-t and GED) to model and forecast the volatility of the ASEAN-five stock markets. The study also found existence of standard leverage effects in all five markets. As for the extent of asymmetric effects, the results show that the volatility of Indonesian stock market responded strongly to a negative shock with asymmetric measure of 3.930 followed by Thailand 3.483, Singapore 2.597, Malaysia 2.033 and the Philippines 1.804.

Islam (2013) applied the GARCH-type models including symmetric and asymmetric models to test their applicability in analyzing the stylized facts (e.g., volatility clustering, leptokurtosis and leverage effects) commonly observed in high frequency financial time series such as stock/stock indices for the cases of 4-asian stock indices (Malaysia, Singapore, Japan and Hong Kong). The study found strong evidence that the models can characterize the dynamics of daily stock returns in all four markets in the sample. With respect to the risk-return relationship, the study found positive correlation in all cases which is consistent with the financial theory.

Few studies have been done on stock market volatility in emerging markets like Nigeria. Leon (2007) investigated the relationship between expected stock market returns and volatility in the regional stock market of the West African Economic and Monetary Union called the BRVM. He used weekly data from January 4, 1999 to July 29, 2005. Results indicate that expected stock return has a positive but insignificant relationship with expected volatility. He also opined that volatility is higher during market booms than when the market declines.

In Nigeria, the few published studies on stock returns volatility include: Ogum, Beer and Nouyrigat (2005), Jayasuriya (2002), Okpara and Nwezeaku (2009). Jayasuriya (2002) used asymmetric GARCH to examine the effect of stock market liberalization on stock returns volatility of fifteen emerging markets including Nigeria, from December 1984 to March 2000. The study reported among others, that positive (negative) changes in prices were followed by negative (positive) changes indicating cyclical type behavior in stock price changes rather than volatility clustering in Nigeria. In contrast, Ogum, Beer and Nouyrigat (2005) investigated emerging market volatility using Nigeria and Kenya stock returns series. Results of the exponential GARCH (EGARCH) model indicate that asymmetric volatility found in the US and other developed markets were also present in the Nigerian Stock Exchange, but Kenya shows evidence of significant and positive asymmetric volatility, suggesting that positive shocks increase volatility more than negative shocks of equal magnitude. They also show that while the Nairobi Stock Exchange return series indicate negative and insignificant risk-premium parameters, the Nigerian Stock Exchange return exhibited a significant and positive time-varying risk premium. Their study also reported that the GARCH parameter (β) was statistically significant indicating volatility persistence in the two markets.

Okpara and Nwezeaku (2009) examined the effect of the idiosyncratic risk and beta risk on the returns of 41 randomly selected companies listed on the NSE from 1996 to 2005. They employed a two-step estimation procedure. Firstly, the time series procedure was used on the sample data to determine the beta and idiosyncratic risk for each company. Second, a cross-sectional estimation procedure was used employing EGARCH (1, 3) model to determine the impact of these risks on the stock market returns. Their results indicate, among others, that volatility clustering is not quite persistent but there exists asymmetric effect on the Nigerian Stock market. They concluded that unexpected drop in price (negative news) increases predictable volatility more than unexpected increase in price (positive news) of similar magnitude in Nigeria.

Based on author's reviews of empirical literature, it is obvious that the ARCH family of models has been used extensively in modeling volatility. While simple GARCH (I, I) is good enough to capture volatility clustering, it cannot capture fat-tails and asymmetry. Asymmetric model such as EGARCH, GJR-GARCH, were specifically developed to capture asymmetry. Also, while there is disagreement on volatility clustering in Nigeria, all agree that leverage effects exist.

SECTION 3: METHODOLOGY

3.1: Data and basic statistics:

The data used in this study is the monthly all price share index (ASPI) of the Nigerian Stock Exchange (NSE) over the period January 1985 to December 2017 totaling 396 observations. The data was sourced from the Central Bank of Nigeria (CBN) Statistical Bulletin of 2018.

The daily index returns are expressed in the continuously compounded returns calculated as:

$r_t = \ln (P_t / P_{t-1})$

where, P_t and P_{t-1} are the index prices on day t and t-1, respectively.

3.2: Descriptive Statistics

The statistics of interest here are Mean, Maximum, Minimum, Standard Deviation, Skewness, Kurtosis and Jarque-Bera Statistics.

Mean: It measures the average value of the series. It is obtained by adding up the values of the series in the current sample and dividing by the number of observations.

Max and Min: Are the maximum and minimum values of the series in the current sample.
Standard Deviation (Std. Dev.): This is a measure of dispersion or spread in the series. Thus, the higher (lower) the value, the higher (lower) the deviation of the series from its mean.
Skewness: It measures the asymmetry of the distribution of the series around its mean. A positive skewness means that the distribution has a long right tail and negative skewness implies that the distribution has a long left tail. The skewness of a normal distribution is zero.
Kurtosis: It measures the peakedness or flatness of the distribution of the series. For kurtosis, the normal distribution is 3, but if it exceeds this value, the distribution is assumed to be peaked (leptokurtic) relative to the normal, but if it is less than 3, the distribution is flat (platykurtic) relative to the normal.
Jarque-Bera: This is a test statistic for normal distribution. The null hypothesis for the test is that the series is normally distributed. Note that there are three conventional levels of statistical significance in econometrics namely 1% (0.01), 5% (0.05) and 10% (0.10). Therefore, if the computed probability value for the test is greater than 10% (0.10), we do not reject the null hypothesis otherwise, we reject it.
GARCH MODELS: GARCH is the extension of the Autoregressive Conditional Heteroskedasticity (ARCH) model. The ARCH and GARCH are said to be volatility clustering models and are importantly applied to measuring and forecasting the time-varying volatility of high frequency financial data like stock index returns (Stock and Watson, 2012). Since the introduction of the standard GARCH model and its large extension in literature, they have become very popular and most common predominantly in financial market research as they enable the financial analysts to estimate the variance of a series at a particular point in time more accurately. These models have been empirically applied to a large number of stock markets across the world including developed, emerging and developing countries and their applicability in capturing the dynamic characteristics of stock index returns has been demonstrated successful. Some of the studies who have applied the standard/basic GARCH models and its variations across different countries are Floros (2008), Elsheikh and Zakaria (2011), Shamiri and Isa (2009) and Islam (2013) etc. A large number of empirical studies also used the different extensions of the basic GARCH such as the Exponential GARCH (EGARCH) developed by Nelson (1991), the Threshold GARCH (TGARCH or ZGARCH) introduced by Zakoian (1994), the GJR-GARCH by Glosten *et al*. (1993), the Power GARCH (PGARCH) proposed by Ding *et al*. (1993) and so on. These models are called asymmetric GARCH models as they are capable of modeling asymmetric response and leverage effect.
GARCH (1, 1) model: In financial markets, volatility is known as a measure of uncertainty about the return provided by the stocks or stock indices. The volatility of many economic time series, especially financial time series changes over time. In some periods the monthly stock returns exhibit high volatility while in other periods they exhibit low volatility, a commonly observed phenomenon in financial time series which is referred to as volatility clustering. That is volatility comes in cluster. It is assumed that a day of high volatility most likely to be followed by another day of high volatility within each state or over a short period of time. As such, linear models which assume homoscedasticity (constant variance) are inappropriate to explain such unique behavior of financial time series data. It is thus preferable to use models that examine behavior of financial time series allowing the variance to depend upon its history. GARCH is one of the non-linear type models that can account for many of the dynamic characteristics such as volatility clustering, leptokurtosis, asymmetries and leverage effect associated in a financial time series (Bollerslev *et al.*, 1994). GARCH models are especially suitable for financial market data as the GARCH processes are 'fat-tailed' compared to the normal distribution. The GARCH (1, 1) model is defined as:

$$\sigma_t^2 = \gamma V_L + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{3.1}$$

where, V_L is the long-run average variance rate, γ is the weight assigned to the V_L, α is the weight assigned to u^2_{t-1} and β is the weight assigned to σ^2_{t-1}. Weights must be equal to unity as, $\gamma + \alpha + \beta = 1$. Equation 3.1 can be written by setting $\omega = \gamma V_L$ as:

$$\sigma_t^2 = \omega + \alpha u^2_{t-1} + \beta \sigma^2_{t-1}$$

Where:

$\omega > 0,\ \alpha,\ \beta \geq 0,\ \beta > \alpha$ Eq.3.2

A stable GARCH (1, 1) process requires $\alpha+\beta<1$. Once the parameters of the GARCH model are estimated, the long-term variance, V_L and γ can be calculated as ω/γ and $1-\alpha-\beta$, respectively. The GARCH (1, 1) model in equation 3.2 estimates the current volatility of assets returns based on a linear combination of the last period's squared returns and the last period's volatility. Since the GARCH model is no longer of the usual linear form, the parameters in GARCH (1, 1) model cannot be estimated by the usual OLS method. As such to estimate GARCH parameters, alternative technique is used. The most common method to estimate the GARCH parameter is to take the log likelihood which is the logarithm of the Maximum Likelihood (ML) method. ML employs trials and errors to determine the optimal values for the parameters that maximize the likelihood of the data occurring.

Exponential GARCH (EGARCH) model: The EGARCH model of Nelson (1991) explicitly allows for asymmetries in the relationship between return and volatility. It can account for the leverage effect feature of the financial time series. The conditional variance equation of Nelson's EGARCH model is expressed as:

$$\log(\sigma_t^2) = \omega + \alpha\left(\left|\frac{u_{t-1}}{\sigma_{t-1}}\right| - \mu\right) + \gamma\left(\frac{u_{t-1}}{\sigma_{t-1}}\right) + \beta \log(\sigma^2_{t-1})$$

Where:

$$\mu = E\left(\left|u_{t-1} / \sigma_{t-1}\right|\right)$$

In this model, the conditional variance is transformed into logarithmic form as opposed to the conditional variance implying that the leverage effect is exponential rather than quadratic. The logarithmic transformation also avoids complication of artificially imposing parameter restriction required to ensure non-negative conditional variance. The existence of asymmetric impact requires $\gamma\neq0$. γ is typically estimated to be less than zero so that for $\gamma<0$, negative shocks will have a larger impact on future volatility than positive shocks of the same magnitude. The process to be stable, it is still required that $|\beta|<1$.

SECTION 4: RESULTS, ANALYSES AND ESTIMATION

Table 4.1: Descriptive Statistics of ASPI return series

Mean	-	15544.65	Std.Dev.	-	15196.62
Median	-	1030.160	Skewness	-	0.862108
Maximum	-	65652.40	Kurtosis	-	2.92672
Minimum	-	111.3000	Jarque-Bera	-	45.78732
			Probability		-0.000000

Sample: January 1985- December 2017

Source: Author's Compilation from Eviews 9 Print out

Some highlights of the descriptive statistics

The maximum value of the return series in the current sample is while the minimum value is 111.3. The difference between max (65652.40) and min (111.3000) is very large. The standard deviation which is a measure of dispersion or spread in the series is 15196.62. This variation seems rather large indicating a high level of fluctuations of the monthly returns during the period under study. The skewness, which is a measure of asymmetry of the distribution of the series around its mean, is positively skewed (0.832106) suggesting the presence of a long right tail an indication of non-asymmetric returns The Kurtosis statistic that measures the peakedness or flatness of the distribution of each of the series is calculated at 2.926712 indicating the presence of a fat tail. As a rule, the kurtosis of the normal distribution is 3. If the kurtosis exceeds 3, the distribution is peaked (leptokurtic) relative to the normal; if the kurtosis is less than 3, the distribution is flat (platykurtic) relative to the normal. The Jarque-Bera statistic, which is a test statistic for testing whether the series is normally distributed; measuring the difference of the skewness and kurtosis of the series with those from the normal distribution; is reported at 45.78732 with a probability of 0.00000. Under the null hypothesis of a normal distribution, the Jarque-Bera statistic is distributed as with 2 degrees of freedom, the reported probability indicates that we reject the hypothesis of normal distribution at the 5% level significance level for this variable. The return series is non-normal. These findings appear to support the conventional theory of finance that the higher the risk, the higher the returns.

Formal Tests for Univariate Volatility Models

There are two prominent pre-tests for univariate volatility models.

Test 1: Serial Correlation test

The type of Serial correlation test conducted: Ljung-Box Q test. The null hypothesis for the test is that there is no evidence of serial correlation in the series. We are expected to reject the null hypothesis before modeling volatility and the null hypothesis is rejected if the probability value (PV) is less than 0.10/0.05/0.01; otherwise, you do not reject it.

Table 4.2: Serial Correlation test result

Date: 12/18/18 Time: 11:05
Sample: 1 396
Included observations: 395
Q-statistic probabilities adjusted for 1 dynamic regressor

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|* |	.|* |	1	0.157	0.157	9.8698	0.002
.|** |	.|* |	2	0.222	0.202	29.569	0.000
.|** |	.|* |	3	0.228	0.180	50.339	0.000
.|. |	*|. |	4	0.019	-0.077	50.484	0.000
.|* |	.|. |	5	0.086	0.012	53.474	0.000
.|. |	.|. |	6	0.043	0.004	54.211	0.000
.|* |	.|* |	7	0.105	0.106	58.674	0.000
*|. |	*|. |	8	-0.103	-0.168	62.958	0.000
.|* |	.|* |	9	0.138	0.145	70.744	0.000
.|* |	.|* |	10	0.090	0.078	74.053	0.000
*|. |	*|. |	11	-0.121	-0.152	80.002	0.000
.|* |	.|. |	12	0.110	0.044	84.978	0.000

Source: EVIEWS 9 Printout

After considering different lag orders for robustness, we settled for 12. It is observed from table 4.2 that all the probability values are less than 0.01(1%) implying that the null hypothesis of no serial correlation is be rejected.

Test 2: Testing for heteroskedasticity (ARCH-effects): The linear structural model assumes that the variance of the errors is constant over time. But this assumption is not applicable for many financial data particularly stock prices or stock indices in which the errors exhibit time-varying heteroskedasticity. Before proceeding to applying GARCH models, it is necessary to ascertain the existence of ARCH effects in the residuals. To test for ARCH effects in the conditional variance of
u_t ($\sigma_t^2 = Var(u_t \Omega_{t-1})$)
where, Ω_{t-1} is the publicly available information at time t-1, we followed two steps: First we consider the AR(1) model for the returns series of each individual index as:

$$r_t = \beta_0 + \beta_1 r_{t-1} + u_t \tag{1}$$

and run the linear regression on it to obtain the residuals u_t. Secondly, we run a regression of squared OLS residuals (u_t^2) obtained from equation (1) on q lags of squared residuals to test for ARCH of order q. The ARCH (q) specification for σ_t^2 is denoted as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u^2_{t-1} + \alpha_2 u^2_{t-2} + \ldots\ldots\ldots\ldots + \alpha_q u^2_{t-q} \tag{2}$$

The null hypothesis of 'no ARCH effect':

$$H_0 : \alpha_1 = \alpha_2 = \ldots\ldots\ldots\ldots = \alpha_q = 0$$

is tested against the alternative hypothesis that,

$$H_1 : \alpha_1 \neq 0, \quad \alpha_2 \neq 0, \ldots\ldots\ldots \alpha_q \neq 0$$

If the value of the LM version of test statistic is greater than the critical value from the $\chi^2_{(q)}$ distribution, or the coefficient of the lagged term is statistically significant, then the null hypothesis is rejected that there is no ARCH effect in Eq. 1. The same conclusion can be achieved if the F-version of the test is considered. We carried out the test for a lag order of q = 3.The null hypothesis is rejected if the probability value (PV) is less than 0.10/0.05/0.01; otherwise, you do not reject it.
Second, perform the test on the regression output.

Table 4.3: Heteroskedasticity Test Result

Heteroskedasticity Test: ARCH

F-statistic	10.37455	Prob. F(12,346)	0.0000
Obs*R-squared	94.99274	Prob. Chi-Square(12)	0.0000

Source: EVIEWS 9 Printout

It is observed from table 4.3 above that the probability values for the test statistics (F test & Chi-Squared test) are less than 0.01 (1%) implying that the null hypothesis of no ARCH effects is rejected.

Summary of Preliminary Analyses

The preliminary analyses suggest that ASPI exhibit volatility judging by the serial correlation and heteroskedasticity tests. Thus, in modeling ASPI, this inherent statistical feature must be accounted for. In essence, the appropriate modeling framework is the univariate volatility modeling framework. The appropriate non-normal distribution is determined by SIC/AIC and the distribution with the least SIC/AIC value should be employed in the estimation process. Also, the series are non-normal implying that the assumption of normality is not valid and therefore, distributions like the student t distribution and Generalized Error Distribution (GED) may be considered.

Estimation of GARCH (I, I) Model

Dependent Variable: ASP
Method: ML ARCH - Student's t distribution (BFGS / Marquardt steps)
Date: 12/18/18 Time: 11:40
Sample (adjusted): 2 396
Included observations: 395 after adjustments
Convergence achieved after 61 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.028507	0.497603	-2.066925	0.0387
ASP(-1)	1.023300	0.001534	666.9760	0.0000
	Variance Equation			
C	0.966481	1.234525	0.782877	0.4337
RESID(-1)^2	0.740822	0.139822	5.298306	0.0000
GARCH(-1)	0.591609	0.048179	12.27928	0.0000
T-DIST. DOF	5.097050	1.418130	3.594206	0.0003

R-squared	0.988205	Mean dependent var	15583.72
Adjusted R-squared	0.988175	S.D. dependent var	15195.96
S.E. of regression	1652.465	Akaike info criterion	14.13877
Sum squared resid	1.07E+09	Schwarz criterion	14.19921
Log likelihood	-2786.407	Hannan-Quinn criter.	14.16272
Durbin-Watson stat	1.579211		

Source: EVIEWS 9 Printout

The GARCH (, 1) model has a better fit than the best ARCH-type model [which is ARCH (4)] based on the SIC value (14.19921) and therefore was considered appropriate for modeling ASPI volatility. For the GARCH model, the effect of shocks to ASPI volatility is determined by summing both the ARCH and GARCH terms that are statistically significant [i.e. 1.023300 + 0.591609 = 1.614909]. Since the sum is more than 1.0, that means the shocks are more likely to have permanent effects on ASPI volatility. The result also suggests that shocks to ASPI volatility do not die out rapidly over time; rather, they tend to persist.

Estimation of EGARCH

Dependent Variable: ASP
Method: ML ARCH - Student's t distribution (BFGS / Marquardt steps)
Date: 12/18/18 Time: 11:52
Sample (adjusted): 2 396
Included observations: 395 after adjustments
Convergence achieved after 126 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.289948	0.394627	-3.268778	0.0011
ASP(-1)	1.025115	0.001750	585.8824	0.0000
	Variance Equation			
C(3)	-0.453854	0.090838	-4.996321	0.0000
C(4)	0.813102	0.103410	7.862926	0.0000
C(5)	-0.011717	0.054207	-0.216154	0.8289
C(6)	0.989823	0.006093	162.4540	0.0000
T-DIST. DOF	5.772920	1.900221	3.038026	0.0024

R-squared	0.988036	Mean dependent var	15583.72
Adjusted R-squared	0.988006	S.D. dependent var	15195.96
S.E. of regression	1664.237	Akaike info criterion	14.14904
Sum squared resid	1.09E+09	Schwarz criterion	14.21955
Log likelihood	-2787.436	Hannan-Quinn criter.	14.17698
Durbin-Watson stat	1.559790		

Source: EVIEWS 9 Printout

It can be observed that the GARCH (1, 1) model has a better fit than the EGARCH model judging by the SIC values (GARCH (I, I) =14.19921, EGARCH = 14.21955) and therefore EGARCH is not valid for the series under examination and therefore the interpretation is not of interest. However, the effect of shocks on ASPI volatility using the EGARCH model is determined by the coefficient of log (GARCH (-1)). There is persistence of shocks if the coefficient is greater than 0.5; otherwise, the shocks die out rapidly over time. The result above indicates that the shocks die out rapidly. Similarly, the effect is assumed to be permanent if the coefficient of log (GARCH (-1)) is not different from 1.0; otherwise, the effect is temporary. The result shows that the effect of shocks is temporary. Also, the asymmetry effect is captured with C (5). If the sign is negative and statistically significant, that means negative shocks reduce volatility than positive shocks. If the sign is positive, statistically significant, that means positive shocks give rise to higher volatility than negative shocks. The result suggests that the model is symmetric since the asymmetric effect is not statistically significant.

SECTION 5: CONCLUSION

The results of ARCH-LM test strongly reject the null hypothesis of ‘no ARCH effects’ in the residuals up to a lag of 12 as shown by the p-values which are highly significant for all cases. Similarly, Q-statistic test at a lag order of 12 rejects the null hypothesis of ‘no ARCH effects’ as the computed LB Q statistic exceeds the critical LB Q value from the chi-square distribution at 99% confidence level. This implies that the variances of the return series are non-constant over time and hence suitable for using GARCH models, a non-linear symmetric GARCH (1, I) and non-linear asymmetric model, the Exponential GARCH or EGARCH (1, 1). We empirically tested the applicability of these models in capturing volatility clustering, leptokurtosis and leverage effects mostly observed in high frequency financial time series such as the monthly stock index returns. The key results are as follows: the GARCH models are sufficiently capable of capturing the dynamics of the financial time series particularly with respect to volatility clustering, the leptokurtic characteristic of the distribution of the monthly return series and the leverage effects. The parameter estimates of GARCH (I, I) model (α1 and β1) suggest a high degree of persistence in the conditional volatility. The leverage effect is captured by the EGARCH. Secondly, there is evidence of the existence of positive interactions between the expected risk and the expected return for all markets as predicted in the investment theory. The findings of this study can be used by the investors to make investment decision and manage the risk.

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