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# ASSESSING STOCK MARKET VOLATILITY USING GARCH MODELS: EVIDENCE FROM SOUTH AFRICA AND INDIA STOCK MARKETS

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## ABSTRACT

*Volatility is a statistical measure of the dispersion of returns for a given security or market index. Volatility can either be measured by using the standard deviation or variance between returns from that same security or market index. Commonly, the higher the volatility, the riskier the security.A variable in option pricing formulas showing the extent to which the return of the underlying asset will fluctuate between now and the option's expiration. Volatility, as expressed as a percentage coefficient within option-pricing formulas, arises from daily trading activities. How volatility is measured will affect the value of the coefficient used.In other words, volatility refers to the amount of uncertainty or risk about the size of changes in a security's value. A higher volatility means that a security's value can potentially be spread out over a larger range of values. This means that the price of the security can change dramatically over a short time period in either direction. A lower volatility means that a security's value does not fluctuate dramatically, but changes in value at a steady pace over a period of time.*

**Key words :** Financial Market, ARCH, GARCH Model

## Introduction

Financial markets exhibit dramatic movements, and stock prices may appear too volatile to be justified by changes in fundamentals. Such observable facts have been under scrutiny over the years and are still being studied vigorously (LeRoy and Porter, 1981; Shiller, 1981; Zhong et al., 2003).

Volatility as a phenomenon as well as a concept remains central to modern financial markets and academic research. The link between volatility and risk has been to some extent elusive, but stock market volatility is not necessarily a bad thing. In fact, fundamentally justified volatility can form the basis for efficient price discovery. In this context volatility dependence that implies predictability is welcomed by traders and medium-term investors. The importance of volatility is widespread in the area of financial economics. Equilibrium prices, obtained from asset pricing models, are affected by changes in volatility, investment management lies upon the mean-variance theory, while derivatives valuation hinges upon reliable volatility forecasts. Portfolio managers, risk arbitrageurs, and corporate treasurers closely watch volatility trends, as changes in prices could have a major impact on their investment and risk management decisions.

Volatility may be defined as the degree to which asset prices tend to fluctuate. Volatility is the variability or randomness of asset prices. Volatility is often described as the rate and magnitude of changes in prices and in finance often referred to as risk. The Nobel laureate Merton Miller writes “by volatility public seems to mean days when large market movements, particularly down moves, occur. These precipitous market wide price drops cannot always be traced to a specific news event. Nor should this lack of smoking gun be seen as in any way anomalous in market for assets like common stock whose value depends on subjective judgment about cash flow and resale prices in highly uncertain future.(LeRoy and Porter, 1981; Shiller, 1981; Zhong et al., 2003).In this particular study a comparative analysis will be carried out on two stock exchanges, namely: The NSE(National Stock exchange) and JSE(Johannesburg Stock exchange) of India and South Africa respectively, the aim is to give an overview as to how volatility experience internationally effects the degree of volatility in local markets .

In the African context stock markets are at most volatile due to various factors such as political instability, corruption and lack of capital as most stock exchanges are still in their infancy stages and usually underdeveloped, as a result this study focuses on the JSE stock exchange which is notably the largest stock exchange on the African continent.Similarly in the Indian context the study emphasizes on the largest stock exchange in the country the NSE as this will enhance the accuracy of the data. Since the seminal works by Bollerslev (1986) and Engle (1982), traditional time series tools such as autoregressive moving average (ARMA) models for the conditional mean have been extended to essentially analogous models for conditional variance that model persistence in volatility shocks. The autoregressive conditional heteroskedasticity (ARCH) family of models are now commonly used to capture the volatility dynamics of financial time series. This class includes the ARCH and GARCH models of Bollerslev (1986) and Engle (1982) as well as their various nonlinear generalizations such as Glosten et al.'s (1993) threshold GARCH model, Higgins and Bera's (1992) nonlinear GARCH models, Nelson's (1991) EGARCH model, Sentana's (1995) quadratic GARCH model, and Zakoian's (1994) threshold ARCH model. For a survey of ARCH models, see Bera and Higgins (1993) and Bollerslev et al. (1992 & 1994).

## Data and Methodology

This study examines Africa's largest stock market Johannesburg stock market along with the Indian stock market. The sample usedin this study consists of weekly national indexes representing market weighed price averages retrievedfrom the Johannesburg Stock Exchange and the Indian National stock exchange. The national indices are constructed using the same pattern and adjusted by the same formulas, making this two comparable to one another. Each of the country indexes broadly represents stock composition in different countries.

The research uses the National Stock Exchange Composite Index from the Indian Stock Exchange; one of the largest in Asia by market capitalization. The India index is the most used weighed composite index that reflects the performance of the Indian Stock exchange.

In South Africa, we use the FTSE/JSEAlbi index a market capitalization weighted index composed of 99percent of the total free float market capitalization of all listed companies on the Johannesburg Stock Exchange (Bloomberg, 2018).

The data we analyze in this paper are monthly-observed indexes for the stock markets in South Africa (JSE) and India. The data span is about 4 months, with the first observation being the month of July 2016 and the last observation being April 2018.

**The model**

The ARCH and GARCH models are the most popular instruments for measuring volatility dynamics in financial time series. The GARCH model makes a current conditional variance dependent on lags of its previous variance. Nevertheless, one of the limitations is that it enforces symmetric responses of volatility to both negative and positive volatility market shocks (Bollerslev et al., 2017).

**GARCH (1.1) Model**

**Definition**

Consider a return time series rt=μ+εt, where μ is the expected return and εt is a zero-mean white noise. Despite of being serially uncorrelated, the series εt does not need to be serially independent. For instance, it can present conditional heteroskedasticity. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model assumes a specific parametric form for this conditional heteroskedasticity. More specifically, we say that εt~GARCH if we can write εt=σtzt, where zt is standard Gaussian and:

σ2t=ω+αε2t−1+βσ2t−1

**Estimation**

V-Lab estimates all the parameters (μ, ω, α, β) simultaneously, by maximizing the log likelihood. The assumption that zt is Gaussian does not imply the returns are Gaussian. Even though their conditional distribution is Gaussian, it can be proved that their unconditional distribution presents excess kurtosis (fat tails). In fact, assuming that the conditional distribution is Gaussian is not as restrictive as it seems: even if the true distribution is different, the so-called Quasi-Maximum Likelihood (QML) estimator is still consistent, under fairly mild regularity conditions.

Besides leptokurtic returns, the GARCH model captures other stylized facts in financial time series, like volatility clustering. The volatility is more likely to be high at time t if it was also high at time t−1. Another way of seeing this is noting that a shock at time t−1 also impacts the variance at time t. However, if $\alpha+\beta<1$, the volatility itself is mean reverting, and it fluctuates around $\sigma$, the square root of the unconditional variance:$\sigma2 \coloneqq Var (rt) = \omega 1-\alpha-\beta$

Usual restrictions on the parameters are $\omega$, $\alpha$, $\beta>0$ though it is possible to have $\omega=0$ and $\alpha+\beta=1$. The conditional variance is then an integrated process (shocks to the variance are persistent), hence the model is called IGARCH (Integrated GARCH). This is the model Risk Metrics uses to compute Value-at-Risk (VaR).

**Prediction**

Let rt be the last observation in the sample, and let $\omega\hat{}$, $\alpha\hat{}$ and $\beta\hat{}$ be the QML estimators of the parameters $\omega$, $\alpha$ and $\beta$, respectively. The GARCH model implies that the forecast of the conditional variance at time T+h is:

$\sigma\hat{}2T+h=\omega\hat{}+(\alpha\hat{}+\beta\hat{})\sigma\hat{}2T+h-1$

And so, by applying the above formula iteratively, we can forecast the conditional variance for any horizon h. Then, the forecast of the compound volatility at time T+h is

$\sigma\hat{}T+1: T+h=\sum i=1h\sigma\hat{}2T+i$−−−−−−√

Notice that, for large h, this forecast of the compound volatility converges to:

$H\sqrt{}\omega\hat{}1-\alpha\hat{}-\beta\hat{}$−−−−−−−−√scaling over the forecast horizon with the well-known square-root law, times the estimate of the unconditional volatility implied by the GARCH model.

GARCH (p, q)

The specific model just described can be generalized to account for more lags in the conditional variance. A GARCH (p, q) model assumes that:

$\sigma2t=\omega+\sum i=1q\alpha i\varepsilon 2t-i+\sum j=1p\beta j\sigma 2t-j$

The best model (p and q) can be chosen, for instance, by Bayesian Information Criterion (BIC), also known as Schwarz Information Criterion (SIC), or by Akaike Information Criterion (AIC). The former tends to be more parsimonious than the latter. V-Lab uses p=1 and q=1 though, because this is usually the option that best fits financial time series.

ATIONAL STOCK EXCHANGE CNX NIFTY INDEX GARCH VOLATILITY GRAPH

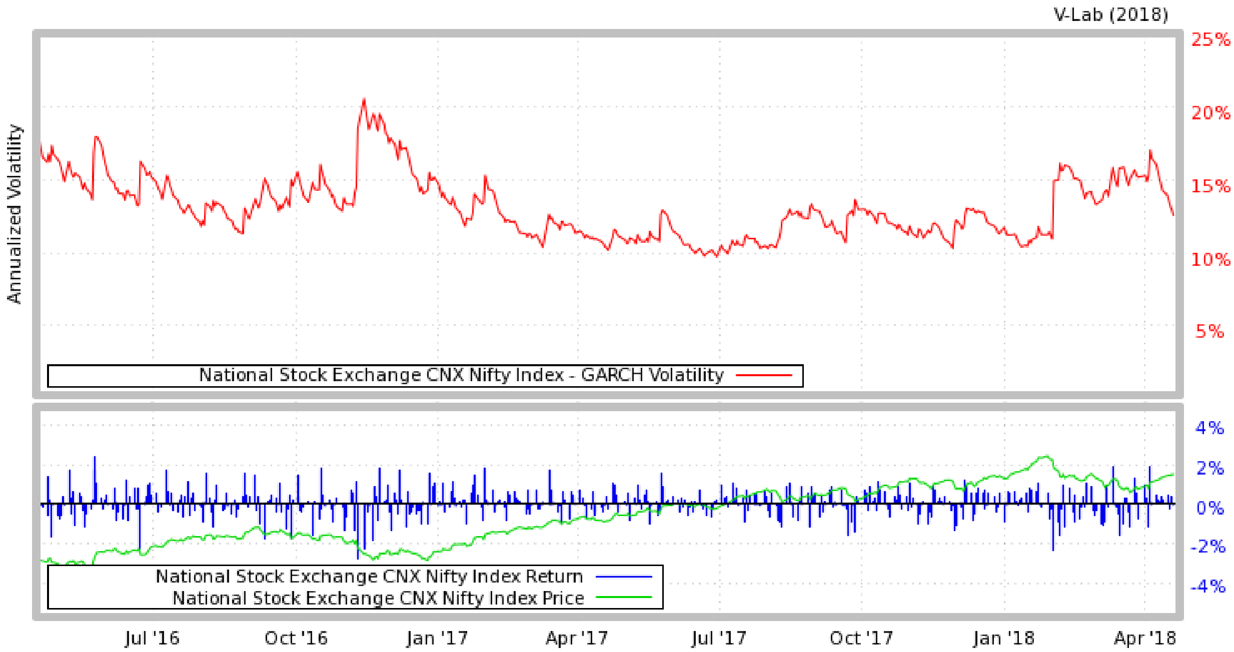


**Figure 1**: NSE CNX NIFTY

### Volatility Summary Table

| | | | | | |
|---|---|---|---|---|---|
| **Closing Price:** | ₹10,564.05 | **Return:** | -0.01% | **1 Week Pred:** | 12.86% |
| **Average Week Vol:** | 13.25% | **Average Month Vol:** | 14.88% | **1 Month Pred:** | 13.94% |
| **Min Vol:** | 9.74% | **Max Vol:** | 72.04% | **6 Months Pred:** | 18.57% |
| **Average Vol:** | 23.68% | **Vol of Vol:** | 23.36% | **1 Year Pred:** | 21.47% |

**Interpretation**: From the above line graph as well as the volatility summary table, it's clear that both stocks NSE CNX NIFTY INDEX RETURN and NSE CNX INDEX PRICE have shown both positive and negative stock movements between the periods of 2016 -2018, this could be attributed to likely causes such as a highly liquid stock market. Pricing of securities depends on volatility of each asset. An increase in stock market volatility brings a large change in stock prices. Investors interpret a raise in stock market volatility as an increase in the risk of equity investment as a result of this, they invest in a less risky asset... Changes in local or global economic and political environment influence the share price movements and show the state of stock market to the general public... Volatility is one of the best phenomenon without which stock markets will lose its charms. The volatility of the stock market is the tendency of the market fluctuation, which is indicated through it's the indices over a period of time. The higher the indices, the higher are the volatility. In fact, it is the ups and downs of the stock prices which add spice to the market behavior. The ups and downs of the stock market add spice to the market behavior, thus due this aforementioned factors volatility has been experienced, we also see negative prices around 2016 up until June 2017 when prices started picking up slightly ,this price fluctuations can be attributed to factors such as demonetization.

**FTSE/JSE AFRICA ALL SHARE INDEX GARCH VOLATILITY GRAPH**

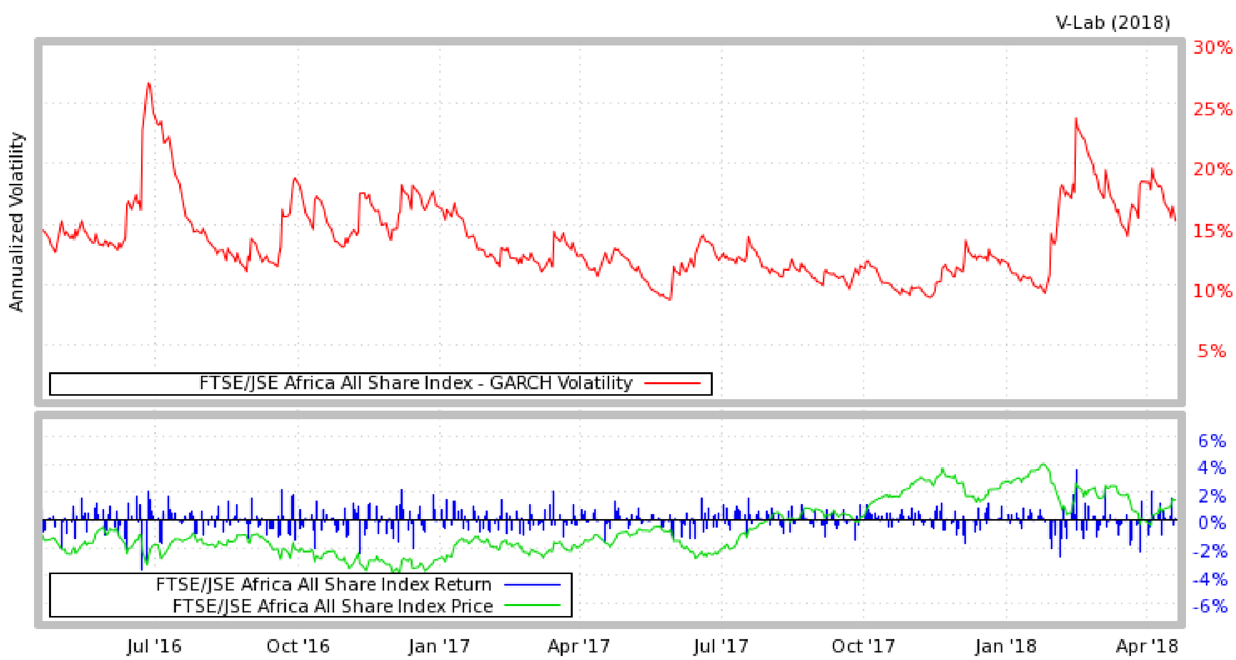


**Figure 2: FTSE/JSE AFRICA**

**Volatility Summary Table**

| | | | | | |
|---|---|---|---|---|---|
| **Closing Price:** | ZAR57,581.73 | **Return:** | 0.10% | **1 Week Pred:** | 15.39% |
| **Average Week Vol:** | 15.87% | **Average Month Vol:** | 17.27% | **1 Month Pred:** | 15.77% |
| **Min Vol:** | 7.67% | **Max Vol:** | 59.96% | **6 Months Pred:** | 17.43% |
| **Average Vol:** | 18.74% | **Vol of Vol:** | 19.33% | **1 Year Pred:** | 18.38% |

**Interpretation:** In the South African context the same period between 2016-208,similarly both negative and positive movements are observed in the stock movements, however the share index show both sharp rises as depicted around June 2016 ,with a slight fall thereafter, the year 2017 can be said to have been fairly constant, and 2018 is market by a rapid rise, this rise of 2018 can be associated to political reasons not to forget that there has been a transition of power as former president step down, the change in power brings about euphoria among investors especially when they have confidence in the new leadership, other factors can be attributed to economic crises which were caused as a result of corruption allegations against the former president and the Gupta brothers leading to a fall in many state owned enterprises and private firms respectively.

Furthermore if we analyse the volatility summary tables, the differences between JSE and CNX NIFTY are quite negligible on some parameters such as min volumes which is at 7.67% for JSE and 9.74% for CNX NIFTY respectively, as volume for JSE is at 59.96% and 72.04% for CNX NIFTY.

Some parameters however show big differences between the two stock markets, with JSE having a positive return of 0.10% whilst CNX NIFTY gives a negative return of –0.01% in the same period.

## Conclusion

This study focused on similarities and differences in volatility clustering in South African and Indian Stock market, with the help of the GARCH model, the study finds that the South African and Indian market exhibit negative similarities ,this could be due to less trading between the two economies.

The study however does not try to identify all the possible causes of this phenomenon between the two stock exchanges because the model used cannot fully capture the aspects of leverage and asymmetry in the stock markets.

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