IMPACT OF SINGLE STOCK FUTURES TRADING ON STOCK MARKET VOLATILITY

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DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Research Proposal contains no material previously published or written by another person except where due reference is made in the Research Proposal itself.

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ABSTRACT

This paper analyses the impact of trading single stock futures on stock market volatility. Specifically, it investigates the effect of trading single stock futures on individual stock return volatility. In addition, it aims to identify any presence of volatility feedback which is an asymmetric effect. This is based on an EGARCH model. The paper uses India stock market data on stocks from the information technology, banking, oil and gas and the consumer sectors. Eight stocks are chosen as result of ranking the stocks with single stock futures contracts based on market capitalization. First, the stocks are tested for ARCH effects which results into dropping the ITC stock. Individual EGARCH models are run followed by an extraction of the conditional volatility values. A regression is ran based on the stock returns against a dummy variable representing pre/post futures trading and the conditional volatility values. Subsequently, diagnostics tests are run for each of the EGARCH models. WIPRO displays the most conclusive results as a result of passing the model diagnostic test while the stock with the most inconclusive results was Tata Motors. Based on these results, it is evident that some of the stock returns volatility was affected by futures trading while for other stocks, there was an insignificant effect or no effect.

CHAPTER 1

1.0 INTRODUCTION

1.1 Background

1.1.1 Definition of Key Concepts

A derivative is a financial contract whose price is based on the price of an underlying instrument (Hull, 2009). Derivatives have become increasingly important in the finance world. Forwards, futures and option contracts are the three main derivative contracts that are currently trading in exchanges around the world.

A forward contract is an agreement between two parties, one to buy and another to sell an underlying asset for a certain price and at a certain future time. On the contrary, a futures contract is an agreement between two parties, one to buy and another to sell a fixed quantity of a certain commodity or financial instrument, at an agreed price, on or before a delivery date. This contract is standardized according to the quality, quantity, time and place of delivery for the commodity traded. There are various types of futures contracts and these contracts are differentiated by their underlying instruments. These futures contracts include equity index futures, single stock futures and commodity futures on commodities such as special metals, natural resources or agricultural products.

A single stock futures contract is a derivatives contracts whose underlying is an individual stock. It is an agreement between two parties, one to buy and another to sell a fixed quantity and grade of a stock at an agreed upon price on a specific date in the future (Hull, 2009).

1.1.2 History and Global Trends in Futures Trading

Futures trading began in the United States as a contract on commodities. The United States was an agrarian economy around the 17th century and many farmers required protection on price risk of their commodities. Forward contracts were already in existence but these were less standardized contracts. In this regard, futures contracts were introduced as a more standardized contract that ensured the protection of futures traders. There are currently around 86 futures exchanges across the world with the leading exchanges in the United States and Asia.[1] In Africa alone, there is only one exchange that trades on derivatives which is the Johannesburg Securities Exchange (JSE) with

[1] https://fimag.fia.org/articles/2014-fia-annual-global-futures-and-options-volume-gains-north-america-and-europe-offset

other countries such as Kenya and Nigeria preparing to launch their derivatives market. Futures trading is continuing to grow and to adapt to the needs of the evolving financial world.

Currently, there exists a global futures trading association known as the Futures Industry Association (FIA). FIA was first started in the United States as an Association of Commodity Exchange for firms. The association has grown to include different futures exchanges in the world. This is an indication that the futures markets in the world are evolving and there is need for an association to support the market, enhance integrity in the financial system and most of all to ensure the smooth running of futures trading.

1.1.3 Uses of Futures Contracts

The uses of futures contracts fall into two categories: futures contracts are used for hedging and for speculation purposes. Hedging is an activity that protects financial market investors against price risk, that is, against the risk of adverse movements in prices of commodities or financial securities. Hedging also protects commercial traders who are sensitive to demand and supply, firms and individuals involved in the cash trade of business. Futures markets provide an opportunity for the hedgers to establish a price for the product in advance of delivery thus protecting the hedger against a change in price during delivery. In spite of this, during most times in futures hedging activities, very few hedgers take delivery or very few futures contracts are actually delivered.

Speculation involves the use of futures contracts for risk taking. The main motive in this purpose is profit making. Speculation provides the assumption of risk by these speculators and also provides liquidity for producers of different commodities. For example, farmers need protection against price risk, speculators can assume this risk through speculation and in turn ensure liquidity in the agricultural commodities market. There are two types of speculators; large speculators such as fund managers and small speculators such as individual investors (Kline, 2001). Other activities in the futures market that may also be considered forms of speculation include arbitrage, price discovery and position taking.

In order for futures trading to be successful it has to take place in an active futures market and information must be widely available in this market in order for trade not to fail. Futures trading has proven not to be very successful in futures markets with very stringent government controls (Kumar B. , 2009). A successful futures market also requires that there exists real economic risks that producers and users need to manage. In this case, little or no volatility in the price of the underlying instrument of the contract means that for futures traders, there is little or no incentive to trade risk (speculation) or manage risk (hedging).

1.1.4 Developments in Futures Trading

A review by the FIA in 2014 states that trading in equity index futures and options showed an increase during the year 2014, but this was not so in 2015 as trading in these contracts surged.[2] The increase in trading was based on the number of contracts that were traded in the different futures exchanges in the world. As of March 2015, the highest traded futures by contract was the individual equity futures contracts. India was not only the country with the exchange that traded the most equity futures contracts but also the country that traded the most single stock futures contracts (Acworth, 2016).

As evidenced by the high growth rates from the year 2014 at 13.5%, it is viable to say that the futures market is continuing to grow.[3] Due to the development of derivatives markets and particularly futures trading, there is plenty of research on derivatives trading. Research on futures trading and stock market volatility has focused on index and commodity futures, hence currently, there is little focus on single stock futures trading and its impact on the volatility of the stock market. The focus has been on equity indices because they capture wide market forces and are more liquid compared to single stock futures. Despite this, they may not be best when it comes to identifying origins of certain issues such as volatility. This is because indices are themselves not traded (Chapman & Hall , 2009).

1.1.5 Volatility of Stock Returns

Stock prices are lognormally distributed and they follow a random walk. It is ultimately not possible to predict stock prices with certainty and this is because they are volatile as they change over time. Stock price volatility is a measure of uncertainty about the returns provided by the stock and is typically between 15% and 60 % (Hull, 2009). Volatility is mainly reflected by the standard deviation of the stock returns. There are many causes of volatility and one of them is new information in the market, for example, new information in the futures market may either increase

[2] https://fia.org/articles/2015-fia-annual-futures-and-options-volume-survey-asia-takes-lead

[3] http://marketvoicemag.org/?q=content/2015-annual-survey-global-derivatives-volume

or decrease volatility of the underlying spot market. Volatility to some extent is caused by trading of securities in the financial markets.

There are several features of volatility of stock returns and these include; the volatility of returns are mean reverting that is the volatility is always pulled back to a long term mean; they exhibit volatility clustering, that is large changes (small changes) is returns are followed by large changes (small changes) in returns; volatilities within and across stocks also tend to move together; serial correlations of returns are negatively correlated to volatility of returns; stocks with high variance (which is also a representation of volatility) tend to have higher returns; macroeconomic uncertainty causes volatility and lastly the leverage effect that is, changes in stock prices tend to be negatively related to changes in volatility (Chapman & Hall , 2009).

Stock returns are more volatile during exchange trading hours than during non-trading hours. This is because, during trading hours, analysts have an incentive for searching for private information, traders have time to act on both public and private information and in turn there is trading noise in the market. According to French and Richard (1986), stock return volatility may be as a result of, arrival of public and private information into the market, as well as trading activities. Investors may not be able to predict stock prices, but using futures contracts, it is possible for them to hedge their investments in these stocks or to speculate the movement of prices in the stocks and in turn earn profits. These trading activities may affect the volatility of the underlying instruments of futures. This volatility may have a secondary effect on investors' returns who invest in traditional asset classes such as stocks or any other assets that are an underlying of futures contracts.

Due to this, volatility of stock returns is an important aspect to investors because volatility is what generates the market returns that investors experience. Volatility may also determine the choice of stocks that investors or portfolio managers choose for investment due to its negative relationship with stock prices. Hence, if stock price changes are negatively related to volatility changes, investors who seek high returns for high taking high risks may choose not to invest in certain stocks due to their low prices as a result of increased volatility. This paves the way for researchers to understand how equity futures trading affects the volatility of the return of the underlying.

1.2 Problem Statement

The impact of derivatives trading on the spot market has been conflicting among different empirical studies and due to this, there is no formal conclusion on the same. Thus, there is currently no theoretical standing on the impact of all derivatives trading on the spot market of the underlying. It is not generally stated whether derivatives trading should stabilize or destabilize their underlying instrument and this leaves more room for study.

Empirical studies such as (McKenzie, Brailsford, & Faff, 2001) also show that volatility on stock returns is not symmetric. Volatility feedback has been put forward as a justification of volatility asymmetries which are present in a time series of stock returns. The volatility feedback hypothesis shows that the causality runs from volatility to stock prices such that they have a negative relationship.

Owing to this, the research seeks to determine the impact of single stock futures trading in the stock returns volatility and to determine whether there is any volatility feedback on the stock prices which may be as a result of asymmetries. Thus the study will also test the relationship between changes in volatility and stock prices.

1.3 Research Questions

This study seeks to answer the following questions:

1. Does single stock futures trading have an effect on the volatility of stock returns?
2. Does a change in stock return volatility due to futures trading change the stock price?

1.4 Justification

Individual share futures are traded in many modern financial markets and analyzing them brings more insight into the financial markets. Derivatives trading is being introduced in Kenya with single stock, index and currency futures as the first products. Therefore the effect of these new instruments on the spot market volatility is important to portfolio managers, arbitrageurs and risk managers as they make their day to day decisions. The study may also interest policy makers and regulators of the capital markets who may want to determine the rules that they should put in place on futures trading.

CHAPTER 2

2.0 LITERATURE REVIEW

Futures trading has been introduced in various countries at different times. The discussion on whether general futures trading impacts the volatility of the underlying instrument has been inconclusive. As a result of this, several researchers have researched on stock futures trading extensively and have also made different conclusions on its impact on the volatility of stock market.

This section reviews various literature on stock index futures, single stock futures, futures trading activity and how they affect the volatility of the underlying. Beyond this, it includes a review on the importance of studying asymmetries in volatility and how they affect stock prices.

2.1 Stock Market Volatility and Equity Futures Trading

Equity Futures Trading was first introduced into the markets in the early 1980's. (Edwards, 1988) Studied the equity futures market a few years after its introduction in the United States. Just then, it had been signed out as a possible cause of market volatility that was being experienced in the U.S equities markets. This study was aimed at identifying the effect of index futures trading on the underlying instrument which was the S&P 500 index. The author's intention was to determine the long term perspective of trading of equity futures on volatility of the underlying equity instrument because many previous researchers had focused on the short term perspective. According to the evidence from the tests carried out, volatility was lower. This author concluded that introduction of index futures trading did not exhibit an increase in volatility.

2.2 Futures Trading and Volatility in Various Countries

Research has also been focused on specific countries' futures markets. These countries include Australia, India and China.

(McKenzie, Brailsford, & Faff, 2001) not only researched on single stock futures trading and stock return volatility on 10 Australian stocks with futures, but also determined whether there were any changes in the systematic risk of the stocks._The researchers studied the unconditional variance, the change in systematic risk, conditional variance and any change in asymmetries in volatility. Using the test of significance on all these parameters, they were able to determine the effects as a result of individual futures trading. The results were as follows; there was a decline in unconditional volatility, conditional variance underwent a formal change when the futures contracts were introduced, the asymmetry for some stocks changed but with lack of clarity on whether there was an increase or decrease and this was due to sign reversals.

(KoustubhKanti & Ajay, 2011) based their study on the Indian derivative market, focusing on 15 individual stocks with futures contracts. The authors also followed the same approach as Gulen and Mayhew (2000) by studying volatility pre introduction and post introduction of futures trading. The main issue that differentiated this study from McKenzie et al. (2001) was that they wanted to determine whether the derivatives effect, if confirmed, is immediate or delayed. They came to a conclusion that out of these fifteen stocks that were tested, only eight were experiencing changes in their volatility pattern after the implementation of derivatives. Thus the current volatility of the eight stocks could be well analysed by the help of past return volatility.

(Xie & Huang, 2014) investigated the impact of index futures trading on the volatility of the spot market in China. In China, the equity futures markets was introduced in 2010. This was a long time coming because investors had been awaiting the arrival of instruments for short selling and thus were flooding the equities markets after its arrival. The authors studied the first stock index futures that was launched in China, that is, China Securities Index (CSI) 300 index futures. They found that introduction of CSI 300 index futures did not have an impact on the magnitude of the spot price volatility.

2.3 Stock Market Volatility, Trade Volume and Open Interest

Researchers have identified different future trading activities that may affect the volatility of the stock market. These activities include open interest as well as the volumes of trade of futures contracts. Futures trading activity varies throughout the lifecycle of the futures contract.

(Bessembinder & Seguin, 1992) stated that there are systematic increases in the futures trading activity as the futures contract nears expiration. They examined whether greater futures trading activity is associated with greater equity volatility and also focused on the general lifecycle of the futures contract. They use daily data from the S&P 500 index and to estimate the effects of each of these components, they use the ARIMA method. Conclusions were based on the estimated coefficients as follows; higher volatility is associated with large trading volumes even though the estimated co-efficient on the expected component is significant. On the other hand the estimated coefficient on the unexpected component is larger and this implies that surprises in the spot trading volume are more important in explaining equity market volatility. In the case of open interest, the authors concluded that equity volatility declines as a function of open interest in the equity future market.

Gulen and Mayhew (2000) studied a set of 25 countries, with stock indices data for a period of 18 years. This allowed an analysis of the stock market's volatility before and after the introduction of equity-index futures. They tested the change in the volatility using the ARIMA model and decomposed the time series which is comparable to Bessembinder and Seguin (1992). The results from the study indicated that market volatility was positively related to the unexpected components thus reflecting the positive effect on volume. The findings on open interest were different from those of Bessembinder and Seguin (1992) as they concluded that open interest was not positively related to equity market volatility. On the other hand, market volatility was negatively related to the expected component and this suggested an underlying stabilizing influence.

Both of these studies conclude that indeed futures trading activity does have an effect on equity market volatility; in the case of futures trading volumes, both studies conclude that the effect on the spot market volatility is mostly in regards to the unexpected components but differ in relation to open interest.

(Shastri, Thirumalai, & Zutter, 2008) focused their study on information revelation in the futures market due to single stock futures trading with a purpose to analyse whether and to what extent price discovery about the underlying stocks occurs in the market for single stock futures. Using 137 single stock futures contracts listed on the NYSE and NASDAQ exchanges and a methodology that required them to replicate the pricing equation of (Hasbrouck, 1995), they find that price discovery in the markets actually decreases because there was more information that was being shared in the financial markets. For that reason, the informative nature and the quality of the underlying market improved after the introduction of single stock futures trading. With this, they concluded that, indeed futures trading contributed to the price discovery in the underlying market.

(Kumar B. , 2009) studied spot market volatility in relation to commodity futures in India, an emerging commodities market but which is generally thin in terms of volume, number of derivatives products and participation. Kumar B. (2009) investigated the contemporaneous and dynamic relationship between spot market volatility in commodity markets and futures trading activity using an augmented GARCH model for the volatility and a Vector Autoregressive specifications for the dynamic relationship. Comparable to Bessembinder and Seguin (1992) and Gulen and Mayhew (2000) studies on equity markets, the researcher found that for agricultural commodities, unexpected volume is positively related to spot market volatility. On the other hand, the results on the effect of open interest on the volatility of the spot market is insignificant in most of the commodities.

2.4 Stock Market Volatility and Activities of Futures Markets Players

Researchers have also reflected in their papers that futures market traders such as arbitrageurs, speculators, informed and uninformed investors may influence the futures trading activity and in turn affect the volatility of the underlying spot market.

(Cox, 1976) discussed these different investors in his paper as he related how spot prices of the underlying of futures contracts behave depending on the information in the market. Cox (1976) mentions that futures trading may de-stabilize the spot market volatility and this is because uninformed traders may take advantage of the low transaction costs by shifting from spot market trading to futures market trading. Due to this shift, these traders decrease market depth and destabilize the futures market in turn increasing stock market volatility.

French and Roll (1986) examined three hypotheses that they believed were the general causes of changes in stock return variances in trading and non-trading hours of the exchange. One of these hypotheses is that high trading volatility is caused by the "trading noise" that occurs during trading. They concluded that there were low variances of stock returns during trading hours in an exchange and this was because all the different futures trading participants tend to act on information that comes into the market during trading hours.

With regards to speculators, Newbery (1987) embarked in determining whether speculators on futures markets stabilize or destabilize spot prices of the underlying instruments using a futures commodities market. This was due to the fact that, in the 17th century there were a few technological advances in communication and computing which had led to the rapid growth in futures markets. Speculators assume price risk in the expectation of making high profits and they affect stability by offering price insurance which in turn reduces the price risk. Newbery (1987) concluded that these risky activities tend to reduce price instability if the risky activities do not increase price risk.

(Bailey, 2005) stated that informed and uninformed investors are both public investors, but informed investors have good knowledge about the financial markets while the uninformed do not. As a result of these, uninformed investors bring in “trading noise” into the market.

Arbitrageurs also affect the stability of the spot market underlying the futures contract. (Kumar B. , 2009) stated that because there are arbitrageurs in the futures market, the effect of arbitrage activities may also affect the spot market of the underlying thus destabilizing the spot market through high volatility.

2.5 Volatility Models

2.5.1 A Simple Volatility Model

Edwards (1988) examined the impact on volatility pre and post introduction of futures trading using a simple method which was a computation of cash market volatility as variance of close-to-close percentage daily return changes. The year 1986 and 1987 exhibited a sharp rise in stock market volatility which was attributed to intraday price movements. The volatility was examined using two alternative estimators:

The Parkinson which is a high-low variance estimator as shown by equation (2.1):

$$ln\, H_t/L_t \qquad (2.1)$$

The intraday price range estimator, a more intuitive measure of volatility as shown by equation (2.2):

$$ln2\sqrt{ln(H_t) - ln(L_T)} \qquad (2.2)$$

2.5.2 Extension of the Pure GARCH

Bessembinder and Seguin (1992) used a more sophisticated approach by generating an extension of a pure GARCH model which accommodated effects of persistence of volatility shocks (asymmetries). This model involved iterating two equations:

An equation that estimates daily returns:

$$R_t = \delta + \sum_{j=1}^{n} \gamma_j R_{t-j} + \sum_{i=1}^{4} \rho_i d_i + \sum_{j-1}^{n} \pi_j \hat{\sigma}_{t-j} + U_t \qquad (2.3)$$

An augmented equation that estimates the conditional return standard deviation:

$$\hat{\sigma}_t = \alpha + \sum_{i=1}^{4} \eta_i d_i + \sum_{j=1}^{n} \beta_j \hat{\sigma}_{t-j} + \sum_{j=1}^{n} \omega_j U_{t-j} + \varepsilon_t \qquad (2.4)$$

Where R_t the return is on day t, U_t is the residual form, $\hat{\sigma}_t \equiv |U_t|\sqrt{\pi/2}$ is the estimated conditional return standard deviation on day t. The 4 dummy variables represented the days of the week because S&P 500 daily prices were used and iterated these two equations.

2.5.3 GJR GARCH

Gulen and Mayhew (2000) aimed at improving on previous methodologies. They used a GJR-GARCH and interacted it with a multiplicative dummy to estimate the impact of futures introduction on volatility of the equity markets. This allowed them to obtain reliable estimates.

The conditional volatility equation takes the form:

$$h_t = \alpha_0 + \alpha_1 h_{t-1} + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 max(0, -\varepsilon_{t-1})^2 \qquad (2.4)$$

The interaction of the above equation with a multiplicative dummy is as follows:

$$h_t = (1 + \alpha_m D_t)[\alpha_o + \alpha_1 h_{t-1} + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 max(0, -\varepsilon_{t-1})^2] \qquad (2.5)$$

2.5.4 *Threshold ARCH*

Mckenzie et al. (2001) estimated the effect on stock market volatility using the threshold ARCH model estimates the conditional standard deviation and does not limit estimations unlike the pure GARCH model. They were able to show any asymmetry changes by constructing two equations as follows

The first was a mean regression equation presented by equation (2.6) below:

$$R_{it} = \phi_0 + \phi_1 D_1 + \phi_2 R_{mt} + \phi_3 D_1 R_{mt} + \varepsilon_t \qquad (2.6)$$

Where the dependent variable is the market return to test for change in systematic risk, dummy variables which represented pre and post introduction of futures trading on the stock.

Equation (2.7), a modification of the GARCH along the lines of a TARCH model is:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 D_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \beta_2 D_1 h_{t-1} + \gamma_1 D_1 + \gamma_2 D_2 \varepsilon_{t-1}^2 \qquad (2.7)$$

Where they introduced dummy variables in the conditional variance equation as follows: the first dummy was similar to the one in the first equation while the second (third) took a value of unity if the error is negative pre (post) introduction of futures trading on stocks and zero otherwise.

2.5.5 Combination of ARCH and GARCH

KoustubhKanti and Ajaya (2011) combined GARCH and ARCH models. The equation captured allowed persistence of volatility. By generating test statistics using the ARCH-LM, they observed that all the stocks in the pre and post derivatives period had ARCH effects implying that previous period error terms had an influence on current return distributions. They incorporated the ARCH term in the GARCH model and estimated, thus the GARCH estimates showed the part of the conditional variances that was carried over to the present. In order to determine persistence, they took the sum of the ARCH and GARCH coefficient. To show the short term dynamics of volatility, a large ARCH error coefficient meant that the volatility reacted intensely to market movements and a large GARCH error coefficient indicated that shocks to conditional variance took a long time to die out. But, if the ARCH coefficient was higher than the GARCH coefficient, the volatility was said to be 'spikier'. They concluded that current volatility was best explained by past volatility that tends to persist over time.

2.6 Incorporation of Asymmetries into Volatility Models

As seen above, some researchers, have studied volatility using the original GARCH (1, 1) model which suggests that volatility responds symmetrically to both positive and negative shocks. But, this may not be the case as negative or positive shocks (such as introduction of a new trading instrument in the financial market) may cause volatility to respond asymmetrically. Asymmetries in volatility may cause a leverage effect or volatility feedback (Brooks, 2014). The following literature describes studies that have been carried out to understand these two concepts.

(Haugen, Talmar, Torous, & N., 1990) directly estimated the reaction of the level of stock prices and an investors expected return to changes in volatility. They examined price level adjustments to the volatility shifts and the magnitude of realized returns in periods subsequent to the price adjustment. Wichern, Miller and Hsu (1976) derived a formula where they assume that variance changes occur at infrequent time points and this makes it possible to identify points of variance change statistically. Haugen et al. (1990) divided the data from the Dow Jones Industrial Average into consecutive blocks and use the above methodology to generate a sequence of ratios of variances. Their conclusion was that increases in volatility are associated with significant subsequent declines in stock prices and increase in realized future returns, while a decrease in volatility is associated with a significant subsequent rise in stock prices and lower realized future events.

(Campbell & Hentschell, 1992) examined the asymmetric effects of volatility. They stated that volatility feedback effect has the potential to explain some stylized facts of stock returns for example skewness and excess kurtosis. They began by stating that large pieces of news tend to be followed by large pieces of news and this news increases future expected volatility. This increases the required rate of return on the stock and lowers the stock price which in turn dampens the positive impact of news. With log returns data from NYSE and American Stock Exchange, they used a GARCH M to allow for the volatility feedback effect. The volatility feedback in the model was in terms of "no news is good news" in extreme cases where there is no news in the market. This model also gives the feature that volatility feedback is important when the volatility is high than when it is low. They found that large pieces of news have a negative effect which is converse for small pieces of news. Campbell and Henstchel (1992) concluded that much of the variance of underlying stocks was due to other changes in expected excess returns.

2.7 Conclusion

This literature has highlighted the different aspects that may cause volatility in the underlying market to change as a result of futures trading. A wide array of country studies also provides an understanding of derivatives trading and volatility in different countries.

Futures trading activity varies in different countries due to the depth of the market and how advanced the market is. Futures market traders take the opportunities that the futures markets offer. Regardless of this, derivative instruments in general are versatile, hence these traders may cause problems in the markets as opposed to taking advantage of it. It is important that the traders are monitored and regulated by the relevant authority in order to prevent their activities from leading to market disasters. Nonetheless, these regulations should not be stringent as it would cause the activities in the futures market not to run smoothly.

Volatility can be modelled using different processes as found fit by a researcher as seen from the literature. Extensions of the pure GARCH model in the different studies allowed for response of volatility to any asymmetries unlike the ARCH model which only focuses on symmetric responses of volatility. Regardless of the presence of models such as the E GARCH, some of the extensions captured in these studies of futures markets are the GJR GARCH and the Threshold GARCH. The simpler model used by Edwards (1988) did incorporate the heteroskedastic nature of volatility as seen presently in many asset returns trends and consequently are not suggested models.

In conclusion, we identify the importance of determining any asymmetries in volatility that may cause changes not only in the required rate of return but also in the underlying stock price.

Therefore, over and above determining the impact of futures trading on volatility, it may be necessary to determine whether there is any volatility feedback with regards to the stock price as a result of any changes in volatility caused by trading futures using models such as E GARCH that capture asymmetries.

CHAPTER 3

3.0 METHODOLOGY

3.1 Research Design

The research design to be used in this paper is a causal design which is the measurement of an impact. The conclusion to this study will be based on whether there is any association between futures trading and volatility of a stock.

3.2 Population and Sample

The population to be used in this research is the data on stocks in the Indian stock market and these stocks have futures contracts that are trading on them. In the Indian futures market, there are currently 173 securities with futures contracts available on them. The sampling technique used to identify the stocks for this study is convenience sampling. This is because, the sample to be studied is selected from these futures based on the market capitalization of each of the stocks with futures trading on them. The following eight stocks with a high market capitalization are selected: HDFC Bank, ITC, Infosys, Reliance Industries, Tata Motors, State Bank of India, Hindustan Unilever, Housing Development Finance and Wipro. The study of these ten will be a representation of the remaining futures contracts.

3.3 Data Collection

Sources of Data

Weekly stock prices are obtained from the National Stock Exchange of India between the year 1994 and 2015.

3.4 Data Analysis

3.4.1 Testing for GARCH (P, Q) Effects

Firstly, it is important to test for GARCH (P, Q) effects on the specified returns data as this will ascertain whether to use the volatility class of models for the specified data. The Bollerslev (1986) test for GARCH effects is an appropriate test as it identifies whether the data is indeed heteroskedastic in nature, that is, if the error term has a non-constant variance. The test for GARCH effects requires the following:

To run a regression and obtain the residuals(u_t^2). For a bivariate model, the regression equation is as follows (3.2):

$$y_t = \beta_0 + \beta_1 x_1 + u_t \tag{3.2}$$

Where β_0 represents the constant term, β_1 the coefficient of the independent variable and x_1 as the independent variable. In this study x_1 will be a dummy variable representing the pre introduction and post introduction of futures trading. A dummy variable is a representation of a qualitative variable. This variable can take one or two alternatives and can be used to identify differences in these alternatives. The dummy variable D_1 is equal to 1 (0) post futures trading (pre futures trading). An auxiliary regression is obtained using the squared residuals:

$$u_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \cdots \alpha_m u_{t-m}^2 \tag{3.3}$$

Each coefficient in the above equation is a coefficient of the lagged residual term. Since a GARCH model is a combination of both an ARCH and a GARCH, the m represents the average of the lags for both these processes.

It is necessary to determine the lags that are to be used in GARCH model. There are specific descriptive statistic that are used in order to determine the hypothetical (P, Q) lags. These statistics are the Akaike Information Criterion (AIC), Schwartz Bayesian Criteria (SBC) and Hanna-Quin (HQ). These are the information criteria for model selection. They are stepwise selection criteria such that all possible alternatives of the lags on the variables are included in the regression. The most appropriate lag is chosen by carrying out several regressions. Following these regressions, the statistical properties are described. The model with the most appropriate lags is chosen by identifying the regression that has the lowest AIC, SBC or HQ.

A joint null hypothesis tests if the lags of the squared residuals have coefficient values that are not significantly different from 0.With only two variables in this case, a single hypothesis test is used. The hypothesis test is:

$H_0: \gamma_1 = 0$

$H_1: \gamma_1 \neq 0$

An LM test is used to conclude whether there are GARCH effects. In order to do so, an R^2 is obtained as this will enable one to define the value of test statistic as TR^2 (3.4).

$$TR^2 \sim \chi^2 \tag{3.4}$$

The T denotes the number of observations. If this test statistic is greater than the critical value from the chi-square distribution tables, the null hypothesis that states presence of no GARCH effects is rejected. This means that GARCH effects are present, hence a GARCH family model can be estimated.

3.4.2 Volatility Modelling

The GARCH family models were developed by Bollerslev and Taylor (1986) and are used in modelling volatility. This model is an extension of the ARCH model by Engle (1982) due to some of the limitations that were observed in the use of the former. These limitations are, the fact that there are non-negativity restrictions in the ARCH model. It is seen from the empirical evidence in literature that these constraints on the model were violated. There was also the fact that the model is not straight forward on the number of lags of squared residuals that were to be used in the variables.

The GARCH (P, Q) model is a model that allows the conditional variance to be dependent on previous lags and the equation given by Brooks (2014) is as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_1 u_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-1}^2 \qquad (3.5)$$

Equation (3.5) represents a GARCH (P, Q) model where the σ^2 represents the conditional variance. Using this model it is possible to interpret the current variance as a function of the long term averageα_0, past information about volatility during the previous period$\alpha_1 u_{t-1}^2$, and the variance during the previous period$\beta\sigma_1^2$.

Brooks (2014) mentions that, generally the GARCH (1, 1) is used to capture volatility clustering in data and thus rarely is any higher order of the model estimated for any financial study. But in this case, the applicable lags will be generated using the model selection criteria.

There have been some perceived limitations about this model. Despite its intention of improving the defects that have been mentioned, pure GARCH model does not correct for the non-negativity constraints as seen in the ARCH model. Thus, non-negativity may be violated in an estimated model and the only way to avoid this is by imposing artificial constraints on the coefficients in order to ensure that they remain positive. Furthermore, the GARCH model does not account for asymmetries as it assumes that volatility responds symmetrically to both positive and negative shocks.

This may not be the case as it has been argued that a negative shock to financial time series is likely to cause volatility to rise more than a positive shock. Consequently, this model also fails to account for the leverage effect as well as volatility feedback.

Due to these limitations, the pure GARCH model has been extended to other various types of models. The GARCH model has been extended to models that accommodate for the asymmetries that have been found to exist in financial time series. One of these models is the E GARCH model, still a family of GARCH but which caters for some of the restraints identified in the latter. This model was proposed by Nelson (1991) and it models volatility exponentially. E GARCH allows the conditional variance to be dependent on previous lags. It agrees to direct feedback between conditional mean and condition variance even if parameters are negative. The equation for the model is (3.6) as given by Brooks (2014):

$$ln\sigma_t^2 = \omega + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] + \beta_1 ln(\sigma_{t-1}^2) \qquad (3.6)$$

Parameter interpretation

The regression is in terms of the exponential of the pure GARCH model. The first part of equation (3.6), $\omega + \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}}$ represents the ARCH. This equation is made up of the constant term ω which measures the magnitude effect or the ARCH effect. The γ measures the asymmetry, that is the leverage effect or volatility feedback effect. If, the $\gamma = 0$ then the model is symmetric. The sign present on γ shows the direction in which the asymmetry effect will take on the dependent variable.

The second part $\beta_1 ln(\sigma_{t-1}^2)$ is the GARCH. β_1 Is the coefficient of the lagged variance of the residualσ_{t-1}^2.This coefficient measures persistence in volatility, that is, whether there is volatility clustering.

Using equation (3.6) will allow modelling of volatility without having to impose any non-negativity constraints due to the fact that $\ln \sigma_t^2$ allows for negativity of parameters as σ_t^2 will remain positive. This model also permits for asymmetries and therefore can be used to determine volatility feedback or leverage effect for example, if expected returns increase when stock prices volatility increases, then stock prices should fall due to this increase in volatility.

The model is ran for each of the stocks separately in order to determine both the asymmetry and the conditional variance series. By generating the conditional variance equation and interpreting the parameters akin to the parameter interpretation mentioned, it is possible to identify the change in conditional variance as well the asymmetry, in this case volatility feedback.

3.4.3 The effect of a change in Conditional Variance on Stock Returns

In order to determine further the effect of the change in volatility on stock returns, a series of conditional variance values for each of the EGARCH models is extracted. The stock returns are regressed on the dummy variable as well as the conditional variance series. The regression equation is represented as follows:

$$r = C + \beta_1 D_1 + \beta_2 \sigma_{t-1}^2 \tag{3.6}$$

Where R is the stock returns, D_1 is the dummy variable representing post futures and σ_{t-1}^2 is the conditional variance term.

Parameter Interpretation

The coefficient on the conditional variance term explains the changes on the stock returns as a result of a change in the conditional variance. On the contrary, the coefficient on the dummy variable represents the average change in the stock returns post introduction of futures contracts. This average change would be attributed to the change of returns as a result of conditional variance.

To further support the results from the regression above, the P-Values of the sample coefficients are used to test for the significance of the coefficients. The null hypothesis to be tested is:

H_0= Not Significant

H_1= Significant

The level of significance to be used is 5%. If the P-Value ≥ α, we accept the null hypothesis while if P-Value α we reject the null hypothesis.

3.4.4 Diagnostic Tests

Diagnostic tests are carried out in order to determine if the models used, in this case the EGARCH models are the most appropriate for the data present. There are three diagnostic tests:

1. **No Serial Correlation**

Serial correlation is as a result of the error terms in different time periods being correlated. This is such that the errors terms in the present period are extended into the following period or the future. If found in model, Serial correlation has some consequences to the results of given by the model. One of the consequences is that it may affect the efficiency. Efficiency refers to when the model exhibits the last variance when compared to other models. Presence of serial correlation may show very small standard errors which may not be the case if there was no serial correlation.

This can be tested using the Q-Test which identifies statistical outliers. These statistical outliers are as result of constructing a correlogram. A hypothesis is generated where:

H_0 = No Serial Correlation

H_1 = Serial Correlation

The Q statistic from the test is calculated as:

$$Q_N \left|\frac{|X_a - X_b|}{R}\right| \tag{3.7}$$

Where Q_N is the Q statistic, X_a is the outlier, X_b is the data point closest to the outlier while R is the range of data points. A probability is generated from this statistic which is then compared to a 5% level of significance in order to accept or not to accept the null hypothesis.

2. **Normality Test**

The normality test is carried out in order to determine whether the data points follow a normal distribution and in turn should be estimated by the model in place. The hypothesis is:

H_0 = Normality

H_1 = Non- Normality

Normality can be tested using different tests depending on the number of observations present.

3. Test For Heteroscedasticity

This test is carried out in order to determine any presence of heteroscedasticity within the EGARCH model. The model is not expected to reveal any heteroscedasticity since this will have already been accounted for after the model is chosen and run.

The ARCH-LM is used to test for this. The test is comparable to the ARCH effects test previously mentioned. The hypothesis to be tested is:

H_o = No Heteroscedasticity

H_1 = Heteroskedasticity

The following tests are carried out after the models have been ran.

CHAPTER 4

4.0 RESULTS

4.1 Mean Equation

In order to run the EGARCH model, a mean equation is expressed as:

$$r = c + B_1 D_1 \qquad (3.8)$$

The r represents the stock returns and the c is a constant. The D_1 is a dummy variable that takes the value of 1 pre futures (1994-2002) and 0 post futures (2003-2015).

The variance equation is represented by equation (3.6). These equations are defined together in order to run the volatility model.

Below is a table that represents the values of the terms in the mean equation for each of the stocks.

Table 1: Mean Equation Coefficients

MEAN EQUATIONS				
	Constant	Dummy Coefficient		
HDFC BANK	0.00295	0.001181		
HINDUSTAN UNILEVER	0.001472	0.000526		
INFOSYS	0.009333	-0.006351		
ITC	-0.00137	0.004939		
RELIANCE	2.67E-05	0.002563		
SBI	2.61E-05	0.002353		
TATA MOTORS	-0.00267	0.006153		
WIPRO	0.00926	-0.007106		
NB: The mean equation is intended to be used inrunning the EGARCH Model				

4.1.1 Graph of Residuals Showing Volatility Clustering

Residual terms extracted from the mean equation as shown by equation (3.8) are graphed in order to ascertain any presence of volatility clustering. These graphs show the values of the residuals over the sample period of 1994 to 2015. These graphs justify the use of GARCH modelling if volatility clustering is present in the residual distribution.

The graphs of the residuals of these stocks behave differently. This is because of the effect that the introduction of single stock futures has had on these stocks. Other than the existence of volatility clustering, the conclusion on whether to run a GARCH model or not is further explained by ARCH effects.

All the graphs are similar for all the other stocks in that they show volatility clustering, that is, a period of low volatility is followed by low volatility while that of high volatility is followed by high volatility. In spite of this, the graphs also show how different stocks' volatility behave in terms of volatility before and after single stock future contracts are introduced.

Volatility clustering is present in the Infosys stock, but, the volatility is highest in 2001. It is possible to say that the introduction of single stock futures in 2003 decreased the volatility of Infosys. Periods of low volatility were followed by periods of low volatility throughout the period after 2003.

As for Tata Motors, low volatility was followed by low volatility between 1994 and 2002 which simply shows presence of volatility clustering. In face of this, in 2003 this stock appears to have high volatility in both directions (negative and positive). This is evidence that Tata Motors stock return may have been affected by the introduction of stock returns in 2003.

Similarly, the ITC stock may have been affected by the introduction of single stock futures underlying its stock. From the graph it is clear that in 2003, the stock return experienced high volatility such that stock returns went below 0. This was then also followed by a period of low volatility.

Accordingly, it is possible to detect that the introduction of single stock futures may have had an effect on these stock returns, in turn changing their volatilities from what was previously the norm. Aside from the change in volatility, it is also evident that after 2003, the stocks began adapting and in turn their returns experienced similar volatility movements to what they previously had before futures trading. The evidence lies on the graphs which show periods of high volatility in 2003, leading to positive and negative changes in stock returns. The periods of high volatility were then followed by periods of low volatility approximately between 2003 and 2008.In addition to this, volatility changes were mostly experienced during the first year of trading the single stock futures.

To further support this statement, an analysis of the EGARCH model is required.

Figure 1: Infosys

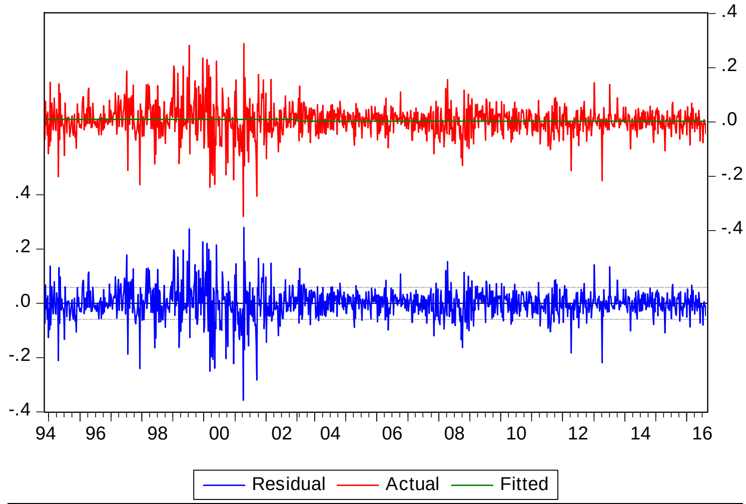


Figure 2: ITC

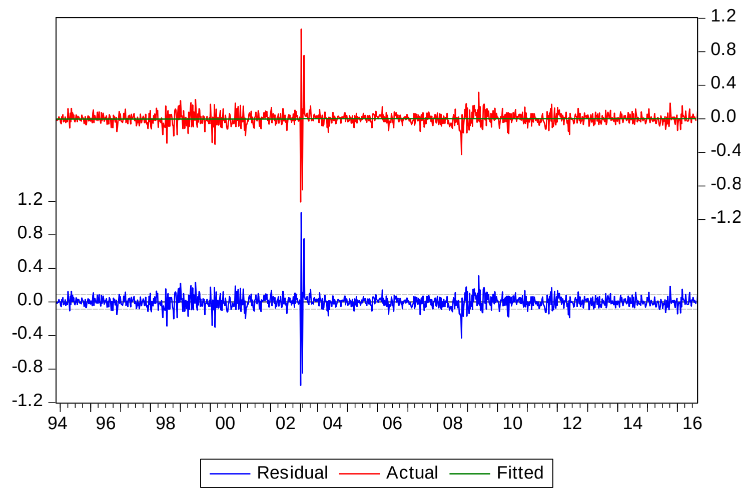
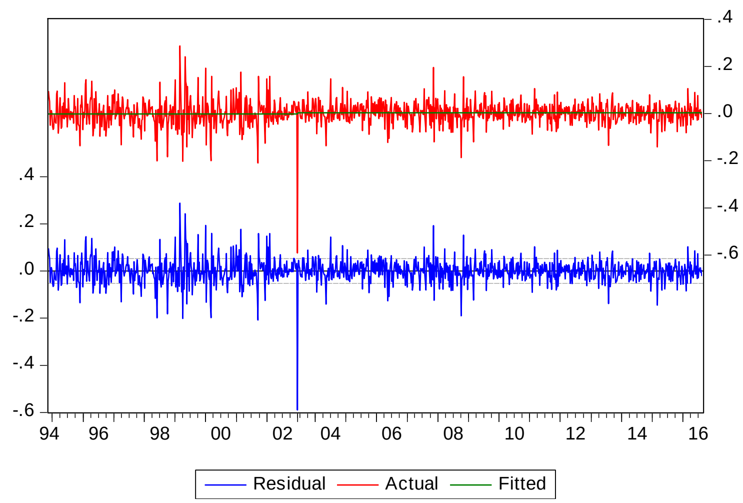


Figure 3: Tata Motors



4.2 Arch Effects Statistics

As previously mentioned, to test for ARCH effects, one is required to regress squared residuals against their lags. It is important to decide on the number of lags that are appropriate for the squared residuals. The lags are determined by comparing the Schwartz Criterion (SC), BIC and AIC values of models with different lags and picking the lag with the lowest SC. The main focus is on the SC since the BIC and the AIC tend to over-specify the model by making one to choose a high no. of lags when in essence, the lags should be fewer. In this case, 5 lags were applied in the regressions, the values of the SC were recorded, after which the lags with the lowest SC values were chosen.

Subsequently, the following hypothesis is tested in order to conclude whether or not there is presence of ARCH effects:

H_0 = No ARCH effects

H_1 = ARCH effects

After selecting the appropriate number of lags, the p-value as a result of running the models with these lags are obtained. They are compared to the 5% level of significance to decide whether to reject or not to reject the null hypothesis.

Table 2: SC Values for Arch Effects

ARCH EFFECTS LAGS								
	LAGS	1	2	3	4	5		P Values
HDFC	Schwartz Criterion	-7.23923	-7.23943	-7.23937	-7.23338	-7.23393		0
	Akaike Information Criterion	-7.24844	-7.25325	-7.25782	-7.25646	-7.26164		
NDUSTAN UNILIVI	Schwartz Criterion	-8.12976	-8.13145	-8.14664	-8.14352	-8.1369		0
	Akaike Information Criterion	-8.13876	-8.14495	-8.16466	-8.16607	-8.16398		
INFOSYS	Schwartz Criterion	-6.66808	-6.67296	-6.69846	-6.69363	-6.68701		0.2972
	Akaike Information Criterion	-6.67708	-6.68646	-6.71648	-6.71618	-6.71409		
ITC	Schwartz Criterion	-6.0332	-6.02607	-6.01886	-6.01196	-6.00531		0
	Akaike Information Criterion	-6.04219	-6.03958	-6.03688	-6.04503	-6.03239		
RELIANCE	Schwartz Criterion	-6.83521	-6.83167	-6.83078	-6.82375	-6.81779		0.0026
	Akaike Information Criterion	-6.84421	-6.84518	-6.8488	-6.8463	-6.84487		
SBI	Schwartz Criterion	-6.98269	-6.76451	-6.97014	-6.96535	-6.96725		0
	Akaike Information Criterion	-6.99169	-6.98996	-6.98816	-6.9879	-6.99432		
TATA MOTORS	Schwartz Criterion	-3.142	-3.15766	-3.21953	-3.27759	-3.32363		0
	Akaike Information Criterion	-3.15099	-3.17117	-3.23755	3.300138	-3.3507		
WIPRO	Schwartz Criterion	-4.69139	-4.70749	-4.71486	-4.70787	-4.70123		0
	Akaike Information Criterion	-4.70051	-4.72118	-4.73314	-4.70725	-4.72868		
NB:		Lowest SC						

Hindustan, Wipro and Infosys are seen to have ARCH effects with 3 lags; ITC, Reliance and SBI work well with 1 lag, while 5 lags and 2 lags are chosen for Tata Motors and HDFC respectively. In turn, regression equations with these lags are run so as to obtain P-Values for the hypothesis testing. The P-Values are as mentioned on the table above.

The P-Values on the all the stocks other than ITC are less than the 5% level of significance. Thus, the null hypothesis is rejected. On the other hand, for ITC we do not reject the null hypothesis and in turn this stock is seen to lack ARCH effects. With this information, it is possible to run an EGARCH model on the remaining stocks.

4.3 EGARCH Estimation Statistics

The Schwartz criterion is also used to decide on the number of lags to be used to run the EGARCH model. The smallest SC value was chosen for each of the stocks.

Table 3: EGARCH Model Lags

EGARCH MODEL LAGS						
	LAGS	1	2	3	4	5
HDFC BANK	Schwartz Criterion	-3.24604	-3.256126	-3.24975	-3.243649	-3.23734
HINDUSTAN UNILEVER	Schwartz Criterion	-3.4049	-3.401554	-3.395976	-3.377598	-3.393042
INFOSYS	Schwartz Criterion	-3.04864	-3.043361	-3.037482	-3.032562	-3.027843
RELIANCE	Schwartz Criterion	-3.0572	-3.052058	-3.046969	-3.04131	-3.036991
SBI	Schwartz Criterion	-2.79041	-2.840714	-2.83462	-2.830611	-2.812197
TATA MOTORS	Schwartz Criterion	-2.42339	-2.417755	-2.325438	-2.320283	-2.484065
WIPRO	Schwartz Criterion	-2.80078	-2.817223	-2.81593	-2.808824	-2.804792

For Hindustan, Infosys and Reliance, one lag is used whereas for ITC, SBI Wipro and HDFC two lags are used to run the EGARCH model. On the other hand an EGARCH model for Tata Motors stock returns worked best with 5 lags.

Following the above decision criteria, an EGARCH for each model is run in order to determine the asymmetry values which represent the volatility feedback.

Consequently, a test of significance is performed on the coefficients in order to determine whether indeed the asymmetry effect is significantly present. Table 4 represents the results from running the EGARCH model with the values of the coefficient of asymmetry and persistence displayed on the table.

Table 4: EGARCH Regression Coefficients

EGARCH COEFFICIENTS				
	Coeffi. Of Persistence	Coeff. of Asymmetry	P Value	Asymmetry
HDFC BANK	0.996583	-0.015642	0.1708	
HINDUSTAN UNILE	0.901314	-0.063136	0.0038	
INFOSYS	0.995878	0.007177	0.3211	
RELIANCE	0.90789	-0.090939	0	
SBI	-0.032651	-0.032651	0.0045	
TATA MOTORS	0.993776	-0.084205	0	
WIPRO	0.986598	-0.016738	0.1193	
		Presence of Asymmetry		
		Absence of Asymmetry		
NB: All P Values are 0. Therefore the coeffcients of persistence are all signifant				

Hindustan Uniliver, Reliance, SBI and Tata Motors display asymmetry because the p-values of the coefficients of asymmetry are significant at the 5% level of significance. Hence, these stocks display volatility feedback. Aside from this, HDFC Bank, Infosys and Wipro show absence of asymmetry. Accordingly, these stocks do not show signs of an asymmetric effect, in other words, they have no volatility feedback.

With regards to the persistence coefficient, each of the stocks displays volatility clustering and this supports volatility modelling using a GARCH model. Thus, these results are consistent with the graphs of residuals that also display volatility clustering.

Conditional volatility values are extracted for each stock, from the EGARCH model that has been run. These values are used in the regression of stock returns on the dummy variable and the conditional volatility values. This is done in order to understand whether the returns change as a result of a change in conditional volatility. The regression, through the dummy variable, also enables one to understand how the returns post futures change as a result of introduction of futures contracts.

Table 5: Volatility Regression Coefficients

CHANGE IN VOLATILITY								
	Constant	P Value	Dummy	P Value	Significance	Coeff. Of Conditional Volatility	P Value	Significance
HDFC BANK	0.00059	0.8726	0.001804	0.586		0.745514	0.3679	
HINDUSTAN UNILEVER	0.001377	0.7566	0.00053	0.8477		0.047442	0.9804	
INFOSYS	0.01576	0.0054	-0.010549	0.029		-1.125908	0.1875	
RELIANCE	-0.00362	0.3765	0.00348	0.328		1.012	0.231	
SBI	-0.00623	0.2955	0.002842	0.4364		1.711557	0.2312	
TATA MOTORS	0.007726	0.0974	0.003235	0.5401		-1.371399	0	
WIPRO	0.026317	0	-0.019884	0.0002		-1.689985	0	
					Significant			
					Not Significant			

The table above presents the values from the regression. A test of significance is important in order to back up the value of the coefficients from the regression. The constant term is interpreted as the value of the stocks' returns before single stock futures were traded in the market. The dummy coefficient added to the constant term represents the average value of returns after single stock futures were introduced into the market.

From this information, the stocks with significant dummy coefficients are Infosys and Wipro while those with significant conditional volatility terms are Tata Motors and Wipro. The rest show evidence of being non-significant.

4.4 Diagnostic Tests

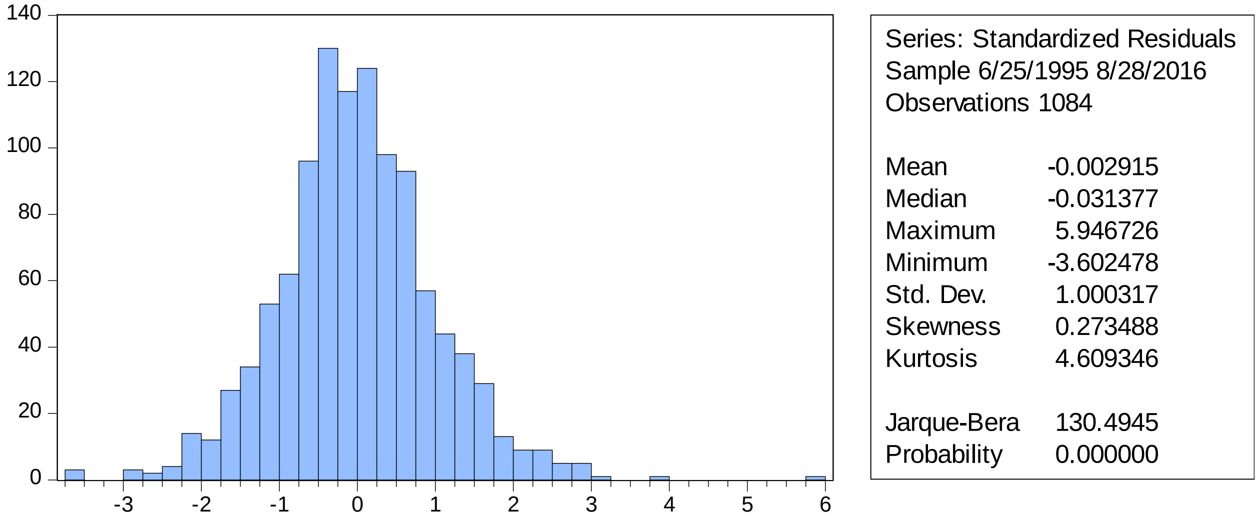
As previously mentioned, diagnostic tests on models assist in explaining the extent to which the models are the best bin explaining the data. The diagnostic tests are carried out for each stock.

4.4.1 Test for Normality

After running the test for normality for every individual stock, it yields the following graph which is in form of a histogram. The most important statistics from the data displayed is the Jarque-Bera Statistic a well as the probability.

Below is an illustration of the histogram that represents the normality test.

Figure 4: Histogram for Normality Test



The Jarque Bera statistics indicate normality or non-normality of data and probabilities for each of the individual stocks. All the stocks have a probability value of 0. In view of the p values being less than the 5% level of significance, the test shows that normal distribution may not be appropriate in the specification of the distribution assumption of the EGARCH model. Instead, a different distribution may be preferable.

4.4.2 Test for Heteroscedasticity

According to Table 7, all the stocks expect Tata Motors display no presence of heteroscedasticity as a result of the ARCH-LM test. Therefore the heteroscedasticity in the EGARCH models for these stocks has completely been eliminated.

Table 6: Test for Heteroscedasticity

ARCH_LM TEST					
	P Value				
HDFC BANK	0.7897				
HINDUSTAN UNILEVER	0.0809				
INFOSYS	0.3326				
RELIANCE	0.9645				No Arch Effects
SBI	0.7465				Arch Effects
TATA MOTORS	0				
WIPRO	0.9631				
NB: Null Hypothesis= No Arch Effects, Alternative Hypothesis= Arch Effects					

4.4.3 Test for No Serial Correlation

In order to actuate that neither of the stocks displays serial correlation, the focus is on the P-Values of the stocks as a result of running the No Serial Correlation test. Table 7 shows all the P-Values of each stock. It is evident that HDFC Bank, Wipro and Reliance, Serial Correlation is completely eliminated by using their specified EGARCH models. This is because, their P-Values are greater than the 5% level of significance which means that it is possible to accept the null hypothesis of no serial correlation. However, Hindustan Uniliver, Infosys and Tata Motors have their P-Values less than the 5% level of significance which leads to rejecting the null hypothesis of no serial correlations. In this case, these stocks exhibit the presence of serial correlation as a result of using their specific EGARCH models.

Table 7: Test for Serial Correlation

TEST FOR NO SERIAL CORRELATION						
HDFC BANK	**HINDUSTAN UNILEVER**	**INFOSYS**	**RELIANCE**	**SBI**	**TATA MO**	**WIPRO**
0.789	0.08	0.332	0.964	0.746	0	0.963
0.749	0.199	0.624	0.964	0.916	0	0.351
0.898	0.347	0.724	0.964	0.944	0	0.542
0.914	0.475	0.713	0.84	0.981	0	0.643
0.959	0.415	0.58	0.715	0.56	0	0.72
0.971	0.524	0.422	0.658	0.239	0	0.825
0.969	0.576	0.51	0.743	0.33	0	0.841
0.708	0.662	0.412	0.46	0.133	0	0.89
0.732	0.742	0.491	0.512	0.143	0	0.924
0.759	0.623	0.56	0.595	0.179	0	0.88
0.757	0.085	0.645	0.653	0.22	0	0.92
0.806	0.089	0.718	0.417	0.263	0	0.848
0.386	0.074	0	0.495	0.107	0	0.368
0.453	0.088	0	0.387	0.105	0	0.401
0.528	0.115	0	0.46	0.109	0	0.386
0.538	0.141	0	0.49	0.114	0	0.456
0.593	0.18	0	0.56	0.126	0	0.511
0.449	0.21	0	0.611	0.129	0	0.571
0.47	0.245	0	0.657	0.158	0	0.579
0.526	0.276	0	0.696	0.198	0	0.635
0.46	0.091	0	0.69	0.163	0	0.533
0.515	0.111	0	0.375	0.186	0	0.543
0.572	0.12	0	0.402	0.201	0	0.578
0.543	0.151	0	0.407	0.19	0	0.635
0.601	0.159	0	0.439	0.208	0	0.689
0.583	0.141	0	0.479	0.245	0	0.738
0.549	0.173	0	0.529	0.282	0	0.761
0.528	0.204	0	0.566	0.309	0	0.763
0.544	0.21	0	0.618	0.277	0	0.777
0.554	0.248	0	0.649	0.298	0	0.813
0.598	0.145	0	0.516	0.335	0	0.84
0.615	0.16	0	0.559	0.382	0	0.865
0.658	0.172	0	0.556	0.378	0	0.792
0.695	0.156	0	0.587	0.225	0	0.822
0.707	0.132	0	0.625	0.246	0	0.818
0.742	0.159	0	0.665	0.163	0	0.831
NB: These values represent the probability values of Q statistics. They are compared with the 5% level of significance.						

CHAPTER 5

5.0 ANALYSIS

5.1 HDFC Bank

The result on the P-Value, following an ARCH effects test entitles the running of the EGARCH model with 2 lags. This stock reveals no asymmetry on the variance equation. This means that volatility feedback is not present in the stock. This result is supported by the P-Value. Moreover, the question on whether introduction of single stock futures trading affects the volatility of stock returns is answered by how the volatility of the returns changes. Hence, the regression of the returns, the dummy variable and the conditional volatility values reveals that neither of the coefficients as a result of the regression are significant.

This may be evidence that the volatility if this stock may not have changed due to the introduction of single stock futures. Likewise, it may be a reason for the lack of volatility feedback on the stock. To further support this claims, the diagnostic tests display important characteristics of the models used for volatility. In terms of normality, tests reveal that the data may not have necessarily been normal. Changing the distribution of this data may have resulted to better results. Conversely, the remaining diagnostic tests show no serial correlation as well as no ARCH effects in the results.

5.2 Hindustan Unilever

The EGARCH model results reveal presence of asymmetry which means that volatility feedback exists in this stock. Thus, there is a negative correlation between the returns of the stock and the volatility of returns. This is such that, as volatility increases, returns on the stock decrease which is followed by a decrease on the prices. The results show a -0.063136 decline in returns as a result of the increase in conditional volatility. This also shows that stock prices and volatility on the stock are negatively related, which represents volatility feedback.

On the contrary, neither the dummy variable coefficient nor the conditional variance coefficient in the regression were significant. When analysing the values of the coefficients, it is evident that the dummy coefficient only shows that return would change slightly, by 0.0053, due to introduction of single futures trading. Therefore, this slight change may not be as significant. But, as for the conditional volatility term, its effect on the change in the returns is notable. This begs the question of the appropriateness of the model in volatility modelling.

The diagnostic tests with reference to serial correlation shows that the model is good enough to measure volatility since it does not exist. The model also accounts for all heteroscedasticity within the data and therefore the diagnostic test for heteroscedasticity accepts the null hypothesis. These tests support that the model is a good fit for the data However, the same tests shows that normality does not exist in the model. This may be the cause of the insignificance of the coefficients.

Despite the fact that a few results such as the coefficients of the regressors do not support this, the stock may have been affected by the introduction of single stock futures. This is as a result of the dummy coefficient which is a reflection of the change of returns pre and post futures as well as the change in the conditional volatility term.

5.3 Infosys

Similar to the previous stocks, ARCH effects tested using 3 lags revealed presence of heteroscedasticity. The EGARCH model was run with 1 lag and it revealed no asymmetry. This is supported by the P-Value which shows that the coefficient of asymmetry is not significant. Hence, this stock does not show any volatility feedback present on it.

In terms of the regression, the dummy coefficient remains significant. The interpretation of the dummy coefficient is as follows: A constant term of 0.01576 represents the average return on the stock pre futures. This return decreased by the dummy coefficient value, 0.010549, to a value of 0.005211 post futures. This decrease cannot be related to the conditional volatility because the coefficient of conditional volatility is found not to be significant. In turn, the change in return may have been as a result of other factors other than volatility of the returns.

The support of this results is dependent on the diagnostic tests. Analogous to the previous stocks, the test for normality reveals that the data does not follow a normal distribution due to the P-Value of the Jarque-Bera. Otherwise, the other diagnostic tests support the model since they reveal that there is no serial correlation or heteroscedasticity.

5.4 ITC

Despite the fact that the graph of residuals reveals a decrease in the stocks volatility in 2003, volatility modelling cannot take place. Volatility modelling for this stock is dropped at the ARCH Effects level. This is because, the ARCH effects test hypothesis shows presence of homoscedasticity. This goes against the use of GARCH modelling and no conclusion can be made as to how introduction of single stock futures trading affected the stock.

5.5 Reliance

After modelling volatility using 1 lag, there is evidence of asymmetry. In turn volatility feedback exists in this stock. Accordingly, when conditional volatility increases by 1 unit, stock returns decrease by the value of the coefficient which in this case is 0.090939. As a result of this, prices are also expected to decrease due to their negative correlation with volatility. The coefficient of asymmetry is proven to be significant due to the P-Value.

Although the above is true, the regression reveals that neither of the coefficients is significant and with this it is not possible to show how the volatility of the returns actually changed even if it may have changed due to the presence of asymmetry effects.

Notwithstanding, none of the diagnostic tests other than the test for normality show that the model was inaccurate.

5.6 SBI

The EGARCH model is run with 1 lag and this reveals asymmetry. The volatility feedback in this stock is as follows: when the conditional volatility increases, the stock return decreases by -0.032651 as shown by the coefficient of the asymmetry. Consequently, if stock returns decreases, the prices of the stocks will decrease since volatility and prices have a negative relationship.

None of the coefficients of the regression model are significant. This information limits the possibility of making a conclusion with regards to the values by which the returns on the stock changed due to the introduction of single stock futures trading.

The impossibility of making a conclusion may be due to the fact that, the diagnostic tests revealed non-normality of the data as much as it showed that there was no serial correlation or heteroscedasticity. Thus, the conclusions made from the asymmetry term may be used to show the effect of introduction of single stock futures on stock returns.

5.7 Tata Motors

For this stock, the EGARCH model is run with 5 lagged independent variables. It discloses an asymmetric effect. The volatility feedback in this stock can be explained as: an increase in the conditional volatility results to a decrease in the stock returns by 0.05420 which also leads to a decrease in prices according to the definition of volatility feedback.

The dummy and conditional volatility coefficients are not significant and significant respectively. The coefficient of conditional volatility shows that returns change by -1.371399 as a result of the introduction of single stock futures trading. The dummy coefficient does not tell us much about the pre and post futures returns since it is not significant.

The above results may not support the ability of the model to explain the effects of introduction of futures trading. This is because the diagnostic test reveal the presence of non-normality, serial correlation as well as ARCH effects in the model.

This may not be a good model for the stock and changing this particular volatility model to another may give better results.

5.1.8 Wipro

The EGARCH model for this stock reveals no asymmetric effects and therefore a conclusion can be made that there exists no volatility feedback in this stock.

In terms of the regression, both the dummy coefficient and the conditional volatility coefficient are significant to explain the effect due to the introduction of futures contracts. The dummy variable reveals the average difference between the returns pre and post futures contracts. According to the results, the average of returns pre futures was 0.026317. Consequently, after the introduction of futures trading, the return decreased by 0.019884 to arrive at an average of 0.006433 post futures. This shows that the introduction of an underlying futures contract on the WIPRO stock led to a decrease in the stocks returns.

Further on, the coefficient on the volatility variable reveals that the returns actually decrease due to an increase in the volatility. From the results, the returns decrease by a value of 1.689985. This shows that futures trading resulted to a decrease in the returns due to a change in the volatility. The results above are ascertained by the diagnostic tests. Other than the test for normality, two thirds of the diagnostic tests showed that the model was appropriate in answering the research questions. On that account, for this stock, introduction of single stock futures contracts actually affected the returns on the stock.

CHAPTER 6

6.1 CONCLUSION

The intention of this research was to investigate the impact of single stock futures on stock market volatility with reference to stock returns. In addition to this, the research intended to identify any asymmetries with a focus on volatility feedback hypothesis.

Previous literature such as Bessembinder and Seguin (1992) as well as Gulen and Mayhew (2000) showed mixed conclusions on these issues while focusing on various features of derivative contracts such as volumes of trade as well as open interest and how they affect the volatility of returns. From the literature, limited research has been carried out specifically on single stock futures contract due to the fact that these contracts were not traded as often as other derivatives.

In light of this, the research uses EGARCH volatility modelling to acquire conditional volatility values that are used in a regression that determines the effect of introduction of single stock futures on the volatility of stock returns. The research also focuses on the asymmetry term of this volatility model which is a representation of whether volatility feedback exists or not. Data from eight Indian stocks, with the sample period between 1994 and 2015 is used for this study. Each stock reveals various results after running the model.

Out of the 8 stocks, only Wipro provided conclusive results in terms of answering the research question and this supported by the fact that its model passed the diagnostic tests. This stock had asymmetric effects on its conditional volatility which resulted to a change in the stock returns as per the data. On the other hand, Tata motors stock failed in answering the research questions due to its inability to pass the diagnostic tests.

With regards to the following stocks: HDFC Bank, Hindustan Unilever, Infosys, Reliance and SBI, their EGARCH models passed two out of the three diagnostic tests carried out on them. Moreover, the stocks also display mixed results in terms of the significance of the asymmetry coefficient and the conditional volatility coefficient. The ITC stock was eliminated from the analysis when it revealed that it had no ARCH effects which meant that EGARCH modelling was not appropriate for this stock. On that account, the remaining stocks exhibit inconclusive results with respect to answering the research questions.

From the stocks tested, it is not possible to make a general conclusion of the impact because each stock behaves differently. Even if some stocks displayed a change in the volatility, this change may have been due to reasons other than the introduction of single stock futures trading.

6.2 LIMITATIONS AND RECOMMENDATIONS

This research was limited to stocks in India. In addition few stocks were used due to the fact that there was no data on the stock prices pre futures, that is, between 1994 and 2002. This restricted my study in terms of exploring even more sectors whose stocks were closely related to those traded in Kenya.

In terms of the applicability of this study in the Kenyan context, few of the stocks used in the research reflect the types of stocks traded in the Kenyan stock market for example HDFC Bank and Tata Motors. Due to this it may be unwarranted to relate the results of this research to the Kenyan market when single stock futures are introduced.

The EGARCH model may have not been a good choice for each of the stocks due to the inability of some of the models to explain the impact of introducing futures trading into the market. This is evident from the results of the diagnostic tests of the model.

Further research can be carried out in other countries with data available as well as other with GARCH family models other than the EGARCH. Given that the results were inconclusive from the selected stocks, this study can be extended to single stock futures markets in other countries that are comparable to Kenya. Additionally, stocks related to those traded in the Kenyan stock market may be chosen.

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