Volatility, Hedging Effectiveness and Price Discovery – An Empirical Analysis of Nifty Futures

A Thesis Submitted during 2013 to the University of Hyderabad in Partial Fulfilment of the Award of a Ph.D. Degree in Economics

By

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CERTIFICATE

This is to certify that the thesis entitled "**Volatility, Hedging Effectiveness and Price Discovery – An Empirical Analysis of Nifty Futures"** submitted by Sibani Prasad Sarangi bearing Redg. No. 04SEPH01 in partial fulfilment of the requirements for the award of Doctor of Philosophy in Economics is a bonafide work carried out by him under my supervision and guidance.

The thesis has not been submitted previously in part or in full to this or any other university or institution for the award of any degree or diploma.

Prof. Naresh Kumar Sharma

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DECLARATION

I, Sibani Prasad Sarangi, hereby declare that the thesis entitled "**Volatility, Hedging Effectiveness and Price Discovery – An Empirical Analysis of Nifty Futures**" submitted by me under the guidance and supervision of Prof. Naresh Kumar Sharma is a bonafide research work. I also declare that it has not been submitted previously in part or in full to this university or any other university or institution for the award of any degree or diploma.

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Sibani……

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List of Abbreviations

ACF	Auto Correlation Function
ADF	Augmented Dicky-Fuller
AIC	Akaike Information Criterion
ARCH	Auto Regressive Conditional Heteroskedasticity
ARIMA	Auto Regressive Integrated Moving Average
ARMA	Auto Regressive Moving Average
BHEL	Bharat Heavy Electricals Limited
BIS	Bank of International Settlement
BPCL	Bharat Petroleum Corporation Ltd
BSE	Bombay Stock Exchange
BVAR	Bivariate Vector AutoRegressive
CBOT	Chicago Board of Trade
CCE	Cross Correlation Function
CLRM	Classical Linear Regression Model
CME	Chicago Mercantile Exchange
CRISIL	Credit Rating Information Service of India
DCE	Dalian Commodity Exchange
DJIA	Dow Jones Industrial Average
EGARCH	Exponential Generalized Autoregressive Conditional Hetroscedasticit
F&O	Futures and Options
FIA	Future Industry Association
FII	Foreign Institutional Investors
FTSE	Futures Trading Stock Exchange
GARCH	Generalised Autoregressive Conditional Hetroscedasticity
GDP	Gross Domestic Product
GKV	Garman-Klass Volatility
GNMA	Government National Mortgage Association
GOI	Government of India
HDFC	Housing Development Finance Corporation Ltd
HE	Hedging Effectiveness
HINDLEVER	Hindustan Lever Ltd.
HKFE	Hong Kong Futures Exchange Ltd

HR	Hedge Ratio
ICA	Indian Contract Act
IMF	International Monetary Fund
IMM	International Monetary Market
IRS	Interst Rate Swap
ISDA	International Swap and Derivative Association,INC
ISE	International Security Exchange
ITC	Indian Tobacco Companies
JPC	Joint Parliamentary Committee
KCBT	Kansas City Board Trade
KSE	Korean Stock Exchange
LB	Ljung-Box
LEAS	Long-term Equity Anticipation Security
LIFEE	London International Financial Futures and Option Exchange
LM	Largange Multiplier
LME	London Metal Exchange
M&M	Mahindra and Mahinadra Limited
MAE	Mean Absolute Error
MAIC	Multivariate Akaike Information Criteria
MAPE	Mean Absolute Percentage Error
MCX	Multi Commodity Exchange
MDE	Mexican Derivative Exchange
MGARCH	Multi-variate Multivariate Generalised Autoregressive Conditional Hetroscedasticity
MTM	Marking to Market
MVHR	Minimum Variance Hedge Ratio
NASDAQ	National Association of Securities Dealers Automated Quotations
NEAT F & O	NSE Electronic Automated Trading on Futures and Options
NSA	Nikkei Stock Exchange
NSCCL	National Securities Clearing Corporation Limited
NSE	National Stock Exchange
NSEIL	National Stock Exchange of India Limited
NYME	New York Mercantile Exchange

NYSE	New York Stock Exchange
OLS	Ordinary Least Square
OSE	Osaka Security Exchange
OTC	Over-The-Counter
PP	Phillips-Perron
PSE	Philadelphia Stock Exchange
RACR	Random Co-efficient Auto Regression
RBI	Reserve Bank of India
RMSE	Root Mean Square Error
S & P	Standard and Poor's
SBI	State bank of India
SC	Schwarz's criteria
SCRA	Security Contracts Regulation Act
SEBI	Security and Exchange Board of India
SFE	Sydney Futures Exchange
SIME	Singapore International Monetary Exchange
TSE	Tokyo Stock Exchange
VAR	Vector Auto Regression
VECM	Vector Error Correction Model

CHAPTER-I

Problem-Setting

I.1 Statement of the Problem

Capital market reforms in India were an integral part of the financial sector reform which was initiated in September 1992, based on the recommendations of the *Narasimham Committee*[1]. These reforms were aimed at enhancing competition, transparency and efficiency of the Indian financial market and various financial institutions. Over the years, the Indian capital market has evolved into a dynamic segment of the Indian financial system.

Increased volatility in asset prices in financial markets, increased integration of national financial markets with international markets and improvement in communication facilities necessitated the introduction of derivatives trading in India. Derivatives trading were introduced on the recommendations of the *L.C. Gupta Committee Report*[2]. Derivatives in India were introduced in June 2000[3] with the introduction of stock index futures in the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE). This was followed by the introduction of index options (June 2001), stock options (July 2001) and stock futures (November 2001). The volume of derivatives markets, especially for futures and options on the National Stock Exchange, witnessed a tremendous increase and recently the turnover is much higher than that of the cash market.

Derivatives are financial instruments whose values are derived from the price of an underlying item. The underlying item can be equity, index, foreign exchange, commodity or any other asset. Derivatives include futures, forwards, options and swaps; and these can be combined with each other or with traditional securities and loan to create hybrid instruments. Equity derivatives in India started as part of a capital market instrument to hedge price risk resulting from the greater financial integration between markets. Derivative products such as

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[1] This was a nine-memher committee under the Chairmanship of Shri. Narasimham, appointed by the Government of India, on August 14, 1991, for making recommendations to improve the operational efficiency of the financial system.

[2] L.C. Gupta Committee was appointed by the Securities and Exchange Board of India (SEBI) in November 1996 with an objective to develop appropriate regulatory framework for derivatives trading in India.

[3] As a part of capital market reforms, derivatives were introduced in a phased manner (Appendix 3. 1). This was based on the recommendation of the LC Gupta Committee.

futures and option have become important instruments for price discovery, portfolio diversification and risk hedging in the Indian stock market in recent years.

One of the important issues which require attention is the impact of the introduction of derivatives on spot market volatility because volatility continues to be one of the key areas of financial market research for academicians, policy makers and investors. The impact of futures and options on the underlying index volatility is an important empirical question. A number of studies have been carried out on this subject across the countries. In general, two types of arguments prevail in the existing literature. One school of thought argues that derivatives trading increases stock market volatility due to a high degree of leverage and hence, destabilizes the market (Cox, 1976; Figlewski, 1981; Stein, 1987). Further, the futures market is likely to attract informed traders, due to the low transaction costs involved, to take positions in the market. The lower level of information on derivatives trade with respect to cash market trade is likely to increase asset market volatility. On the other hand, another school of thought claims that the futures market plays an important role of price discovery and has a beneficial effect on the underlying cash market. Kumar et *al.* (1995) argued that derivatives trading helps in price discovery, improves market depth, enhances market efficiency and reduces asymmetry of information in the spot market. This gives rise to the controversy among the researchers, academicians and investors on the effect of derivatives on the underlying market volatility.

With respect to futures trading, most of the studies are related to index futures due to lack of trading in single-stock futures. Studies by Edwards (1988) on the Value-line Index, Chan Chan K.C and Karolyi (1991) on the Nikkei 225 Index, Lee and Ohk (1992) on the Australian All Ordinaries Index, Darrat and Rahman (1995) and Kumar Shastri (1995) on the S&P 500 Index found no significant changes in the volatility of the spot market. On the other side, studies by Lockwood and Linn (1990) on the DJIA Index, Brorsen (1991) on the S&P 500 Index found increase in the volatility of the spot market. A study by Gulen and Mayhew (2000), based on 25 countries, found an increase in volatility for the S&P 500 and Nikkei 225 indices, and other indices showed no significant change in volatility. Similarly, Ibrahim et *al.* (1999) and Oliveira and Armada (2001) did not find any significant change in the spot market volatility of Malaysia and Portuguese stock markets, respectively. Similarly, Butterworth (2000) found no significant change in the volatility of the FTSE-250 Index after the onset of futures trading. Some studies show a decrease in the volatility of the underlying market.

These studies include Bessembinder and Seguin (1992) on the S&P 500 Index, Pierluigi and Laura (2002) on the Italian Stock Market. Antoniou and Holmes (1995) found that the introduction of stock index futures caused an increase in spot market volatility in the short run but no significant change in volatility in the long run.

Few studies have been carried out to detect spot market volatility in the Indian context. One of the earlier studies by Thenmozhi (2002) showed a decline in volatility of the spot market. Similar results were obtained by Gupta and Kumar (2002) and Raju and Karande (2003). On the other hand, Shenbagaram (2003) did not find any significant change in spot market volatility. Nath (2003) showed that the volatility of the Nifty stock futures declined, except for some stocks, after the introduction of futures. It was further found that cash market volatility reduced after the introduction of the derivative market. It was also noted that changes in the market microstructure and robust risk management practices were also responsible for the reduction in volatility.

The aforementioned studies provide mixed evidence on the effect of futures and options on the volatility of the underlying market across the countries. The results vary, depending on the indices and the methodology used. Most of the studies pertained to developed countries such as the US, the UK or Japan. Only a few studies have been conducted in the Indian context. This study thus seeks to make good of this deficiency by examining the behaviour of the spot market and by measuring the market volatility before and after the introduction of futures and options.

It is well known that derivatives were introduced against the fluctuations in asset prices in stock markets; it serves as a risk-management tool or hedging device. In this regard, another important issue is: to what extent derivatives (futures and options) have been able to reduce risk as a risk-management tool?

By their very nature, financial markets are marked by a very high degree of volatility. Through the use of derivatives products, it is possible to partially or fully transfer price risks by locking-in assets prices. There are many techniques available for reducing and managing the risk: the simplest and perhaps the most widely used is hedging with futures contract. The most important function of the futures market is to hedge the risk of the investor and the motive behind hedging is to control the risk of the adverse price changes. Individuals, investors and financial institutions have used hedging extensively as a risk-management tool.

A hedge is achieved by taking opposite positions in spot and futures market simultaneously, so that any loss sustained from an adverse price movement in one market should, to some extent, be offset by a favourable price movement in the other.

Markowitz (1959) measured the hedging effectiveness as the reduction in standard deviation of portfolio returns associated with a hedge. Ederington (1979) following the work of Johnson (1960) and Stein (1961), measured hedging effectiveness as the percent reduction in variability. Howard and D'Antoni (1984) defined hedging effectiveness as the ratio of the excess return per unit of risk of the optimal portfolio of the spot commodity and futures instrument to the excess return per unit of the risk of the portfolio containing the spot position alone. Hsin et.al (1994) measured hedging effectiveness by the differences of the certainty equivalent returns between the hedged position and the spot position. Figleswki (1984) observed that presence of unsystematic risk in the hedging portfolio damages the hedging effectiveness of the futures because unsystematic risk in the hedging portfolio increases the basis risk. Markowitz (1952) observed that risk and return are positively related, which means that reduction in portfolio variance results in decline in mean portfolio returns. Further, Markowitz (1952) stated that an optimal portfolio is one which reduces portfolio variance to the maximum extent with decline in portfolio returns. Figlewski (1984) studied the hedging effectiveness of US stock index futures contracts and observed that basis risk increases as the duration of the hedging horizon decreases. Malliaris and Urrutia (1991) also found that hedging effectiveness changes with the length of hedging horizon. Robert J Myers (1991) estimated the optimal hedge ratio for storage of wheat in the US by employing moving sample variances and covariance and GARCH techniques, and found that the GARCH model provides superior hedging performance than either constant hedge ratios model or the moving sample variances and covariance models. Holmes (1995) investigated the ex-ante hedging effectiveness of UK index futures contracts and suggested that the introduction of the FTSE-100 futures has given portfolio manager a valuable instrument to avoid risk. Butterworth and Holmes (2000) further examined the ex-ante hedging effectiveness of the FTSE-100 and FTSE mid 250 index futures contracts for a range of portfolios. They found that: the FTSE contracts have been seen to provide the most effective hedge for portfolios dominated by large-capitalization stocks, and the mid-250 contracts that provide the most effective hedge for stocks dominated by low capitalization stocks. Park and Switzer (1995) examined the hedging effectiveness for three types of stock index futures, i.e., the S&P 500, MMI futures and Toronto 35 index futures. The empirical results show that the bivarate GARCH estimation improves the hedging performance over the conventional constant (OLS) hedging strategy. Brooks, Henry & Persand (2002) considered the impact of asymmetry on the time-varying hedgers for financial futures by using various multivariate GARCH, specification and other simpler techniques. They found that asymmetric models, which allow positive and negative price innovations, affect volatility forecasts differently, and saw yield improvements in forecast accuracy in sample, but not in out of sample.

The above literature is based on the hedging effectiveness of the futures market for different countries of the world. It shows how the futures market is able to reduce the risk of the spot market. Most of the studies relate to the developed countries; and in India as it was introduced recently, there is a lack of systematic studies on the hedging effectiveness of the futures market. This present study will provide background for the hedge ratio estimation in India. Earlier studies estimate the hedging effectiveness by using monthly, daily and hourly data and use the techniques like GARCH, *Bivariate* Vector Autoregressive Model (BVAR), ECM etc for the estimation. The results show that in most cases, these techniques provide better results than the conventional methods, and in some of the cases the traditional method outperforms the modern techniques. Finally, the above-discussed literature shows that futures market is efficient in reducing the risk of the investor in most of the developed countries.

The relationship between stock and index futures market and stock index market has been the subject of numerous empirical studies. A large part of them concentrate on examining an opportunity for index arbitrage. From a theoretical point of view, existence of an arbitrage strategy violates assumptions of the efficiency of the market. In turn, brokerage houses, mutual funds, large investors seek profits from the spread between prices on the spot and futures markets. Therefore, for practitioners, the analysis of the magnitude and frequency of mismatching of these prices is a subject of vital interest.

In a competitive market, if two assets are equivalent from the point view of risk and return, they should sell at the same price. If the price of the same asset is different in two markets, there will be operators who will buy in the market where the asset sells cheap and sell in the market where it is costly. This activity is termed as arbitrage and it involves simultaneous purchase and sale of the same or essentially similar security in two different markets for advantageously different prices (Sharpe and Alexander 1990). The buying cheap and selling expensive continues until prices in the two markets reach equilibrium. Theoretical arbitrage requires no capital, entails no risk and appears to be an easy way of earning profits. However, real-world arbitrage calls for large outlay of capital, entails some risk and is a lot more complex than textbook definition suggests. A major weak link in India's financial sector today is inadequate knowledge about arbitrage. This explains the low levels of financial capital deployed in it. Several studies examine temporal relationships between futures and cash index returns using a Granger (1969) and Sim (1972) causality specifications for the intra-day observed time series. The studies by Finnerty and Park (1987), Kawaller et. al (1987), Harris (1989), Stoll and Whaley (1990) Chan (1992) and Huang and Stoll (1994) suggest that the futures returns lead the cash returns and that this effect is stronger when there are more stocks included in the index. For the S&P 500 and MMI futures this lead varies from five minutes to 45 minutes (Stoll and Whaley, 1990, Kawaller et al. 1987) but the relationship is not completely unidirectional. Balck (1976) was the first one to suggest that the higher leverage available in the options market might induce informed traders to transact in options rather than in stocks.

Another important aspect in this context is to measure the overall informational efficiency in futures markets. Apart from these, other relevant issues are the impact of derivatives on macroeconomic variables, money transmission mechanisms: what is the appropriate regulatory structure for derivatives markets? How does the presence of price limits on the equity spot market impact options and futures indices and options on individual stocks? How do we optimize arbitrage for index futures and index options etc? In this context, the present study tries to focus on some of these issues related to financial derivatives.

I.2. Objectives of the Study

The Indian capital market has undergone remarkable changes since 1991. The prime motive for this change was to check the shortcomings of capital market viz. long delays, lack of transparency in procedures and vulnerability to price rigging and insider trading. One of the contributions made by regulators, in this regard, with a view to meet international standards is the introduction of derivatives in the Indian capital market with the main objective of providing risk management and efficient market to the investors. Since then it has opened a large field of work for academicians, policymakers and investors to understand the effect of derivatives on the financial market. Based on the literature in the first section, the broad objectives of the study are:

1. To examine the impact of introduction of futures on underlying spot market volatility
2. To measure the nature and structure of volatility after the introduction of futures trading
3. To evaluate the existence of a causal relationship between spot and futures prices
4. To examine whether the establishment of Indian stock index futures market effectively serves the price discovery function
5. To measure the hedge ratio and hedging effectiveness of the futures market.

I.3. Data Sources

All the required data for the study has been obtained from the National Stock Exchange (NSE) website.

For the first and second objective, the daily closing returns of the S&P CNX Nifty spot index and Nifty Junior index and 15 individual stocks have been considered for the analysis. The study considers daily data from January 1, 1997 to March 31, 2012. The introduction of S&P CNX Nifty futures index commenced from June 12, 2000. Thus, the proxy for futures index has been used to allow comparison of pre-futures and post-futures periods. After excluding non-trading days, the daily data series consists of 3,807 observations. Out of these observations, 857 and 2,950 observations are related periods prior to the introduction of futures and post-futures, respectively.

In order to examine the third and fourth objective, daily closing prices of the Nifty index futures for the near month have been taken from June 12, 2000 to March 31, 2011. Similarly, for the 15 individual stocks cash and futures prices have been taken from November 09, 2001 to March 31, 2012.

For the last objective, the main data for the study are the daily closing values of the S&P CNX Nifty index futures for near month contracts and spot Nifty index have been considered from June 12, 2000 to October 30, 2012. In-sample analysis is carried out for the period June 12, 2000 to March 2012 and remaining observations from April 1, 2012 to October 30, 2012 are used to evaluate the out-of-sample forecasting performance of the model.

The near month futures contracts have been considered for the whole analysis as they are heavily traded compared with the middle-month and far-month contracts.

The 15 individual scripts are as follows:

- ACC Ltd.
- Bharat Heavy Electricals Ltd.
- Bharat Petroleum Corporation Ltd.
- Cipla Ltd.
- Grasim Industries Ltd.
- Hindalco Industries Limited
- Mahindra & Mahindra Ltd.
- I T C Ltd.
- Infosys Technologies Ltd.
- Hindustan Lever Ltd.
- Housing Development Finance Corporation Ltd.
- Ranbaxy Laboratories Ltd.
- Reliance Industries Ltd.
- . State Bank of India
- Tata Power Co. Ltd

I.4 Methodology of the Study

The present study is based on the closing prices of the indices and stocks. The returns were calculated by using the following equation:

$$R_t = \text{Log}\ (P_t / P_{t-1}) \text{---} \ (1)$$

Where:

R_t is the returns on Nifty Index/ stock at time period t.

P_t is the price of Nifty Index/Stock on day t.

P_{t-1} is the price of Nifty Index/Stock on day t-1.

It is a well-accepted that many a financial time series contain a unit root, i.e., the series are non-stationary and it is generally acknowledged that stock index and stock index futures series might not be exceptions. Knowledge of non-stationarity in time series is significant in the modeling of economic relationships, because standard statistics assumes that stationarity may give invalid inferences in the presence of stochastic trends. In the case of non-stationary, Ordinary Least Square can produce spurious results. Therefore, prior to modeling any relationship, non-stationarity must be tested in order to eliminate the possibility of spurious regression. The present study uses the Augmented Dicky Fuller (ADF) test given by Dicky and Fuller (1979), and the Phillips-Perron (PP) tests given by Phillips (1987); PP tests differ from ADF tests with regard to the method they use to account for residual serial correlation by introducing a correction to the test statistics of an Augmented Dicky Fuller regression.

Model Design

In order to measure the optimal hedge ratio and its hedging effectiveness for both forecast in-sample and out-of-sample data with one-, five-, ten- and twenty-day time horizons, the present study employs various models: Ordinary Least Square (OLS), Vector Auto Regression (VAR), Vector Error Correction Model (VECM) and Time-Varying Multi-Variate GARCH (M-GARCH) models (i.e., VAR-GARCH and VEC-GARCH models).

Second, to estimate the objective pertaining to the impact of the introduction of futures trading on spot price volatility, the present study makes use of the Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) and Exponential GARCH models to capture the asymmetric features of data statistically. Asymmetry effect occurs when there is an unexpected drop in price, as a bad news increases volatility more than an unexpected increase in price because of a good news of similar magnitude. This model expresses the conditional variance of a given variable as a non-linear function of its own past values of standardized innovations (Drimbetas, et al, 2007).

In order to test the causality and price discovery functions of the futures market, the stationarity of the data series is tested with the help of Dickey Fuller (DF), Augmented Dickey Fuller (ADF) and Phillips Peron (PP) tests. After the stationarity, the Engel and Granger and Johansen's (1988) Vector Error Correction Model (VECM) is employed to investigate price discovery and the causal relationships between spot and futures prices. Further, to examine the forecasting ability of futures prices on spot prices, three forecasting techniques, namely Auto Regressive Integrated Moving Average (ARIMA), Vector Auto Regression (VAR) and Vector Error Correction (VEC) models, are employed to estimate out-of-sample data up to a 20 trading-day horizon. These forecasts are compared with the actual prices for forecast accuracies by using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE).

I.5. Justification of the Study

Financial market reforms in terms of introduction of derivatives trading in June 2000 was the hallmark of some of the major reform measures that had a direct bearing on the functioning of the capital market in India. Introduction of derivatives poses a number of issues for academicians, policymakers and investors for research. More or less, we have briefly discussed these issues in previous sections. In this context, the present study differs from earlier studies in the following aspects:

First, most of the studies pertain to developed country markets and a fewer number of studies exist in emerging economies such as India. Therefore, it is necessary to examine the economic functions of the futures market in the Indian context.

Second, given the volatile nature of the financial market, derivatives were introduced as risk-management tools. Thus, it is important to know to what extent derivatives have been able to reduce the risk, *i.e.*, hedging the risk. The effective use of index futures in hedging decisions has become the focus and centre of a debate and so are finding an optimal hedge ratio and the hedging effectiveness in empirical research by employing the Time-Varying Multivariate GARCH model. In this context, the present study measures the hedging effectiveness by employing various models: Ordinary Least Square Regression, Vector Auto Regression (VAR), Vector Error Correction Models (VECM) and Time-Varying Multivariate Generalized ARCH (M-GARCH).

Third, most of the earlier studies have focused on index futures and neglected the stock futures segment. Particularly in India, trading volumes in individual stock futures are increasing over time. Thus, the present study studies the impact of derivatives of all individual stocks on which futures have been introduced.

Fourth, price discovery is one of the important functions of the futures price. In this context, it is necessary to know whether the spot market or the futures market transforms information more efficiently. At the national level, most of the studies are based on stock index futures. The present study is based on the index as well as Individual stocks: price discovery and causality have been examined by employing Engel-Granger and Johansen's (1988) Vector Error Correction Model (VECM).

Fifth, on the subject of overall market efficiency and arbitrage opportunities, very few studies have been carried out. The results obtained from earlier studies are inconclusive in nature. Thus, the present study will provide some new light in this area. In brief, it is expected that the present study will be helpful for researchers, policymakers and academicians as it deals with most of the challenging issues that a country needs to address.

I.7. Chapter Outline

Against this backdrop, the present study is laid out into seven chapters. The present chapter introduces the research problem, justifies the study and gives a broad outline of the study. The second chapter provides some literature review relevant to the study and issues for discussions. The third chapter introduces the Indian derivatives market and provides the basics of the derivative markets. The fourth chapter deals with the impact of futures and options on spot market volatility and the nature and structure of spot market volatility after the derivatives introduction. The fifth chapter examines the causal relationship between spot and futures markets and the price discovery function of the futures market. The sixth chapter deals with the hedge ratio and hedging effectiveness of the futures market. The last chapter provides a summary and conclusions and the scope for further research.

CHAPTER II

Literature Review

2.1: Futures Trading and Volatility

The impact of futures and options on the underlying index and stock volatility is an empirical question. A number of studies have been carried out on the subject across the countries. In general, most of the studies supported two schools of thought to the empirical question. One school of thought argues that futures market increases the spot market volatility and destabilizes the market. Another school of thought argues that futures trading reduces the spot market volatility and thus stabilizes the spot market. Authors who report that inceptions of futures trading increases spot market volatility are Harris (1989), Brosen et. al (1991), Lee and Ohk (1992), Kumara et. al (1992) and Antoniou and Holmes (1995). These studies support the view that futures markets are likely to attract informed traders because of their high degree of leverage and advocate that derivatives support speculation. Let us deal with the literature in a more detailed manner.

Edward (1988) employed the variance ratio 'F' test to examine the impact of introduction of futures trading on the underlying stock market volatility. The data set consists of daily closing prices for the period of June 1973 to May 1987. He found that the introduction of futures trading has changed short-term volatility to some extent but not in the long run.

Harris (1989) examined the effect of S&P 500 futures index on its underlying market by comparing daily return and volatility. The data has been taken from 1975 to 1987 for S&P 500 and non-S&P 500 group of stocks, controlling for differences in firm attributes. The study has been analyzed by cross-sectional analysis of a variance regression model. It concluded that increase in volatility is a common phenomenon in different markets and index futures may not bear the sole responsibility. Further, the study mentioned other index-related instruments and developments, such as growth in index funds and increase in foreign ownership of equities as possible explanations of higher volatility of stock market.

Hodgson and Nicholas (1991) evaluated the effect of the introduction of All Ordinaries Share Index futures on the All Ordinaries Share Index in Australia by employing standard deviation of daily and weekly returns. The data are taken from the daily prices of the Australian equities spot market and obtained from the Sydney Stock Exchange for the period February 2, 1981 to June 30, 1987. The result showed that introduction of futures and options trading has not affected the long-term volatility.

Kamara (1997) investigated the impact of the introduction of Standard and Poor's 500 index futures contracts on the daily mean return seasonality of the US market index return. The data are collected between 1962 and 1993 from Datastream. He concluded that the daily seasonality effect in the S&P 500 declined significantly in the post-futures trading period. He also observed that the decline in daily seasonal is consistent with the fact that futures trading generally reduces the obstacle to arbitraging it, due to considerable reduction in transaction costs. A similar study in the Japanese market was done by Hiraki, Marberly and Taube (1998). In their study, they found that trading of the Nikkei 225 stock index futures had impacted on daily index return seasonality. Specifically, the Tuesday effect was found to disappear in the post trading period, while a Monday effect seemed to take its place. The author mentions that such effects are the results of heightened information flows which result from futures index trading.

Bessembiner and Seguin (1992) investigated the impact of volumes and open interest in futures trading on the volatility of the underlying market by employing Auto Regressive Integrated Moving Average (ARIMA). The dataset consisted of daily data from January 1987 to September 1989 of the S&P 500 index and index futures. He found that futures market is able to reduce the spot market volatility.

Jagadeesh and Subrahmanyam (1993) examined the effect of introduction of the S&P 500 index futures by comparing the spread of S&P 500 stocks with a random sample of non-S&P 500 stocks traded on the New York Stock Exchange (NYSE) before and after the introduction of futures. The study was analyzed using the pooled cross-sectional time-series regression equation. They found that average proportional spread has increased subsequent to the introduction of futures trading , and after controlling factors like price, return, variance and volume of trade, they still found higher spread during the post-futures period. The spread increased significantly in the S&P 500 sample and marginally in the non-S&P 500 sample after controlling for changes in price, return volatility and volume. They concluded that the introduction of index futures does not reduce spreads in the spot market.

Darrat and Rahman (1995) examined whether futures trading brought volatility into stock prices on the S&P 500 index and index futures by employing Granger-causality tests. The data set for the analysis was taken from 1982 to 1991. They further looked into the effect of macroeconomic factors such as inflation, term structure interest rates on stock returns volatility of the S&P 500. The study reached the conclusion that futures trading does not bring in any occasional and sudden extreme changes in stock prices, but term structure rates and over-the-counter indices are responsible for stock price volatility.

Antoniou and Holmes (1995) studied the impact of the introduction of futures on the FTSE 100 Index in the UK with the help of GARCH technique. The study also examined the relationship between information and spot market volatility. Daily data for the period of November 1980 to October 1991 were used. They found that the flow of information was faster to the spot market prior to the futures trading. Further, they found that the introduction of stock index futures caused an increase in spot market volatility in the short run while there was no significant change in volatility in the long run.

Board and Sutcliffe (1995) studied the impact of the introduction of futures on the FTSE 100 index by using hourly data from May 3, 1984 to June 30, 1991. It excluded the stock market crash of October 1987. They concluded that the relationship between stock market and index futures price volatility varies systematically with the length of time interval used to measure the volatility.

Gregory and Michael (1996) studied the effect of S&P 500 futures on the S&P 500 index volatility; further, with the use of EGARCH technique they studied different effects of good and bad news on spot market volatility. The correlation between the index and futures in the pre- and post-1987 crash was also seen. The study found that that bad news increases the volatility more than good news, and that the asymmetry in the volatility is much higher for the futures market. Furthermore, the correlation declined during the crash period for the indices. A similar study was done by Perieli and Koutomos (1997) on the S&P 500 index; they found that volatility of the spot market has reduced in the derivatives period.

Dennis and Sim (1999) studied the effect of individual stock futures on the underlying market by employing the EGARCH technique on the Sydney Futures Exchange. The volatility of the underlying shares in the cash market was looked into with the use of an exponential ARCH model. It was found that the future trading does not have much impact on the volatility of individual stocks.

Gulen and Mayhew (2000) made a more detailed study of the introduction of futures trading on the volatility of underlying spot market by including both developed as well as emerging markets of 25 countries. The data covers the period from January 1873 to December 1997, and taken from the Datastream world market index. They found an increase in volatility for the S&P 500 and Nikkei 225 indices while for other countries they found no significant change in volatility.

Broad, Sandmann and Surcliffe (2001) studied the impact of FTSE 100 index futures volumes on spot market volatility with the application of Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) model. Using data from January 1988 to December 1995, the study supported the view that futures trading does not destabilize the spot market.

Butterworth (2002) investigated the effect of futures trading on the FTSE-250 index with the help of symmetric and asymmetric GARCH methods. This study allowed for the possible existence of an asymmetric response of volatility to news, whereby a price fall results in greater volatility than does an equivalent price increase. It found no significant change in spot market volatility, but a significant change in the structure of spot market volatility. Specifically, there is evidence of more information flowing into the spot market following the onset of trading. This new information is assimilated into prices less rapidly than before the onset of trading, leading to an increase in the persistence of volatility.

Bae, et al. (2004) examined the effect of index futures trading on spot price volatility in Korea, and also studied the market efficiency of the underlying Korean Composite Stock Price Index (KOSPI) 200 stocks relative to the carefully matched non-KOSPI 200 stocks. They found both a decrease in spot market volatility and an increase in the efficiency of the futures market.

Drimbetas, et al. (2007) examined the impact of futures and options trading on the FTSE/ASE 20 index volatility by using data from August 1997 to April 2005. The study made use of the EGARH model to capture the asymmetry effect. The empirical results supported the hypothesis that the introduction of derivatives has stabilized the spot market by reducing the volatility and by increasing informational efficiency of the FTSE/ASE 20 index.

Bohl, Salm, and Wilfling (2011) investigated the impact of introducing index futures trading on the volatility of the underlying stock market. The study employed the Markov-switching-GARCH approach to endogenously identify distinct volatility regimes. The empirical evidence from the Poland market suggests that futures trading does not destabilize the spot market.

National Studies

In the Indian scenario, one of the earlier studies by Thenmozhi (2002) focused on the change in the volatility of the Nifty index after the introduction of Nifty futures. The main data for the study were the returns of the S&P CNX Nifty index futures and the spot Nifty index. Daily closing price returns of the NSE-50 index from June 15, 1998 to July 26, 2002 were considered for the study. This study employed the standard deviation and multiple regression models to measure the impact. The results showed that the inception of futures trading had reduced the volatility of spot index returns.

Raju and Karande (2003) studied price discovery and volatility in the context of introduction of Nifty futures on the NSE. Co-integration and GARCH techniques were used to study price discovery and volatility, respectively. The major findings were that the futures market responds to deviations from equilibrium; price discovery occurs in both the futures and the spot market. The results also showed that volatility in the spot market has come down after the introduction of stock index futures. Bandivadekar and Ghosh (2003) made a similar study on the NSE and BSE. They found that futures market plays a significant role for the change in volatility for the S&P CNX Nifty index, while market forces play an important role for the change in the volatility of the Sensex.

Nath (2003) studied the impact of derivatives on cash market volatility in case of India. In this paper, the volatility was measured using GARCH, IGARCH and standard deviation. This study took data from January 1999 to October 2003 of the S&P CNX Nifty and S&P CNX Junior Nifty, which are traded on the National Stock Exchange of India. In the case of stock market, volatility has come down after the introduction of derivatives market, except for a few individual stocks. Further, although the cash market volatility has also come down after the introduction of derivatives market, it could also be attributed to other reasons such as microstructure changes and robust risk-management practices.

Shenbagaraman (2002) examined the impact of futures and options trading on stock market volatility. He took daily closing prices from October 5, 1995 to December 31, 2002 for the CNX Nifty, and used the Generalized Auto-Regressive Conditional Heteroskedasticty (GARCH) model to measure the volatility. The results suggested that futures and options trading had not led to a change in the volatility of the underlying stock index, but the nature of the volatility seemed to have changed in post-futures. This paper also investigated whether greater futures trading activity was associated with greater spot market volatility. In this case, the author found no evidence of any link between the two.

Vipul (2006) studied how the volatility in the Indian stock market has changed after the introduction of derivatives. The study used the daily prices of six equity shares and the Nifty index for the period January 1, 2002 to June 9, 2004, and applied the GARCH (1, 1) model. It showed a reduction in volatility of the underlying shares with the trading of derivatives.

The various literature on the impact of introduction of futures and options trading on the underlying stock market volatility are inconclusive in nature. The results varied, depending on the nature of data and the methodology used. Most of the studies pertained to developed countries such as the US, the UK or Japan. Only a few studies have been conducted in the Indian context. This study thus seeks to make good of this deficiency by examining the behaviour of the spot market and by measuring the market volatility before and after the introduction of futures and options in Indian stock market.

2.2 Hedge Ratio and Hedging Effectiveness of the Futures Market

The basic motivation for hedging is to eliminate/reduce the variability of profits and firm value that arises from market changes. Hedge effectiveness becomes relevant only when there is a significant change in the value of the hedged item. A hedge is effective if price movements of the hedged item and the hedging derivative roughly offset each other. According to Pennings and Meulenberg (1997), a determinant in explaining the success of financial futures contracts is the hedging effectiveness of futures contracts. The detailed literature on the hedging effectiveness of the futures market is discussed below.

Ederington (1979), following the work of Johnson (1960) and Stein (1961), measured the hedging effectiveness as the percentage reduction in variability. He examined, a hedge is effective if the R-squared of the OLS regression explaining the data is high. The study found that the objective of hedging is to minimize the variance of a spot portfolio held by the investor. Therefore, the hedge ratio that generates the minimum portfolio variance should be the optimal hedge ratio, which is also known as the minimum variance hedge ratio.

Figlewski (1984) studied the hedging effectiveness of US stock index futures contracts and observed that basis risk increases as the duration of the hedging horizon decreases. Malliaris and Urrutia (1991) also found that hedging effectiveness changes with the length of the hedging horizon.

Holmes (1995) investigated the hedging effectiveness for the FTSE 100 stock index futures contracts by employing Ordinary Least Square (OLS). The database for measuring hedging effectiveness was taken from July 1984 to June 1992 for hedges of one- and two-week duration. He mentioned that earlier studies have examined this issue using ex-post-hedge ratios resulting in an overestimation of hedging performance. Thus, he utilized ex-ante-hedge ratios which were determined on the basis of historical information. He found that hedge ratios estimated over longer periods are shown to provide greater risk reduction than a short period. The study also shows that while hedge ratios vary through time, it is also possible to use this futures contract to achieve very substantial risk reduction as compared with an un-hedged position.

Butterworth and Holmes (2000) estimated the ex-ante hedging effectiveness of the FTSE-100 and FTSE-mid-250 index futures contracts for a range of portfolios traded in the UK for the period of February 1994 to December 1996. The hedge ratio was estimated on the Least Trimmed Square approach (LTS) and Minimum Variance Hedge Ratio (MVHR). The analysis explored that the FTSE-Mid-250 contract was shown to be an additional hedging instrument despite the relatively thin trading. The new contract is more effective for hedging Investment Trust Companies (ITCs) than the established FTSE-100 contract. They found that, the FTSE contracts have been seen to provide the most effective hedge for portfolios dominated by large-capitalization stocks, and the mid-250 contracts that provide the most effective hedge for stocks are dominated by low-capitalization stocks.

Park and Switzer (1995) examined the hedging effectiveness for three types of stock index futures, i.e., the S&P 500, MMI futures and Toronto 35 index futures. The empirical results show that the bivarate GARCH estimation improves the hedging performance over the conventional constant (OLS) hedging strategy. Similar studies were also conducted by Bera, Gracia and Roh (1997), using a bivariate GARCH model and a Random Coefficient Autoregressive (RCAR) model, to examine the hedging performance of spot and futures prices of corn and soybeans.

Chou, Denis and Lee (1996) investigated the hedging effectiveness of the Japan's NSA index and NSA index futures with different time intervals by using the conventional model and the Error Correction Mechanism (ECM). They found that the conventional hedge outperforms the error correction hedge over the in-sample period, but the error correction model outperforms the conventional model over the out-of-sample period.

Lypny and Powalla (1998) examined the hedging effectiveness of German stock index DAX futures using a bivariate GARCH (1,1) model and an error-correction of mean returns. The data set was provided by Deutsche Bank, Frankfurt, and consisted of weekly closing prices of Wednesday for the DAX index and its near-time delivery futures contract for the period of July 1991 to December 1994, for a total of 207 observations. Empirical results confirmed that the dynamic model is superior to models with constant hedges with or without error correction means. This is in accordance with Kroner and Sultan (1993). Kroner and Sultan (1993) argued that a bivariate error correction model with the GARCH error structure leads to more effective hedges than the conventional (OLS) method.

Kavussanos and Nomikos (2000) showed that a GARCH-X model outperforms all other hedges, while a constant hedge ratio provides greater variance reduction over the sample. However, out-of-sample results reported that the ECM-GARCH-X model outperforms alternative hedging strategies. Yang (2001) also showed that M-GARCH dynamic hedge ratios provide the greatest degree of variance reduction.

Brooks, Henry & Persand (2002) considered the impact of asymmetry on time-varying hedgers for financial futures by using various multivariate GARCH specifications and other simpler techniques on the FTSE-100 stock index and stock index futures contracts. They found that asymmetric models which allow positive and negative price innovations affect volatility forecasts differently – yield improvements in forecast accuracy are for in-sample, but not for out-of-sample. Further, he found that allowing for asymmetry leads to considerably reduced portfolio risk at the shortest forecasting horizons and modest benefits when the durations of the hedge are increased.

Choudhry (2003) investigated the hedging effectiveness of Australian, Hong Kong and Japanese stock futures markets by employing traditional hedge, minimum variance hedge and bi-variate GARCH models. The effectiveness of the hedge ratio was compared by investigating the out-of-sample performance of the three ratios. The whole sample consisted of weekly returns from January 1990 to December 1997. Two sets of futures indices based on two different expiration dates were taken for each country. He found that the time-varying GARCH hedge ratio outperforms the constant ratios in most of the cases.

Laws and Thompson (2002) studied the hedging effectiveness of FTSE-100 and FTSE-250 index futures traded on the LIFFE. The results showed that the Exponential-Weighted Moving Average (EWMA) method of estimating the hedge ratio is superior to the various historical methods used by them and the FTSE-250 index provides a better hedge than the FTSE-100 index.

Robert J Myers (1991) estimated the optimal hedge ratio for storage of wheat in the US by employing moving sample variances and covariance and GARCH techniques. He found that the GARCH model provides superior hedging performance than either the constant hedge ratio model or the moving sample variance and covariance models. However, the GARCH model performed only marginally better than a simple constant hedge ratio.

Yang (2001) reflected on the optimal of hedge ratios of the Australian market by using various econometric models such as OLS, the Bivariate Vector Autoregressive Model (BVAR), the Error Correction Mechanism (ECM) and the multivariate diagonal vec GARCH model. It reached the conclusion that in case of in-sample and out-of-sample forecasts, the M-GARCH dynamic hedge ratios provided the greatest degree of variance reduction but generated the smallest rate of return. Conventional regression model performed the worst in terms of reducing portfolios variance but yielded the highest rate of return. It implied that in selecting the most appropriate hedge ratio, the investor’s degree of risk aversion is important.

Floros and Vougas (2002) studied the hedging effectiveness of Greek Stock Index futures contracts on the FTSE/ASE 20 and FTSE/ASE Mid 40 by employing OLS, ECM and B-GARCH techniques. The purpose of this article was to examine whether ECM and BGARCH model provide better results than the conventional (OLS) regression in terms of hedging effectiveness and to investigate the hedging effectiveness in an out-of-sample performance using Greek financial debts. The OLS, ECM and BGARCH models showed that FTSE/ASE

20 indices produced the most effective hedges than the FTSE/ASE Mid 40. The hedge ratio obtained from the B-GARCH model showed a greater variance reduction. Thus, the B-GARCH model generates better results in terms of hedging effectiveness. Finally, the ECM appears to be superior to the OLS model because the root mean squared error of ECM is lower than that of OLS for both indices.

Miffre (2003) examined the hedge ratio estimation of the S&P 500 and the NYSE by using the conditional OLS hedge ratio. It modified the static OLS approach to incorporate conditioning information. He found that in case of in-sample and out-of-sample, the conditional OLS hedge ratio reduces the basis risk of an equity portfolio better than alternative conventionally used method in risk management.

Lasser (1987) investigated the hedging effectiveness of treasury bill and treasury bond futures contracts. He applied the MVHR on an ex-ante basis, and found that 'ex-ante hedges generated on the basis of a longer estimation period proved to be more effective hedges'. Furthermore, Benet (1990) investigated and analyzed risk reduction potential on an ex-ante basis with regard to foreign exchange futures contracts. He argued that there is a discrepancy between hedge ratios on an ex-post and an ex-ante basis, and therefore, his results reveal a more indicative measure of hedging effectiveness.

Chang and Shanker (1987) showed a new definition of hedging effectiveness following the model proposed by Howard and D'Antonio (1984, 1987). According to their analysis, Howard and D'Antonio's second order conditions do not have to be greater than zero. Also, Jong *et al.* (1997) applied three models to measure the effectiveness of currency futures: (1) the minimum-variance model of Ederington (1979), (2) the a-t model of Fishburn (1977) and (3) the Sharpe ratio model of Howard and D'Antonio (1984, 1987). Their results indicated that hedges are only effective for the minimum-variance and the a-t models. Brailsford, Corrigan and Heaney (2000) discussed several techniques of measures of hedging effectiveness using the Australian All Ordinaries share price index futures contract. Their results showed the impact from the selection of the measure of hedge effectiveness to the assessment of hedged portfolios.

Chou, Denis and Lee (1996) compared hedging performance using Japan's NSA and NSA index futures with different time intervals. They found that the conventional hedge outperforms the error-correction hedge over the in-sample period. However, the out-of-sample period evaluates better hedging strategies.

Hedging effectiveness has been widely investigated. Most studies focus on the ex-post hedging effectiveness of stock index futures contracts (Figlewski, 1984). Also, little attention has been given to the ex-ante hedging effectiveness (Malliaris and Urrutia, 1991; Benet, 1990; Holmes, 1995).

Malliaris and Urrutia (1991) evaluated the hedging effectiveness and non-stationarity of the hedge ratio. In order to measure the non-stationarity it is tested using the traditional methodology of Dickey and Fuller (1979, 1981) and the approach of Lo and Mackinlay (1988) which is known as the variance-ratio test. The data consisted of weekly closing prices of the S&P 500 index and the New York Stock Exchange from January 1, 1984 to December 27, 1988. The results indicated that the random walk hypothesis for two stock index futures: the S&P 500 index and the New York stock exchange. They found that the optimal hedges should be considered along with the dynamic hedging.

Lindahl, M. (1992) examined the stability of hedge ratios (HR) for the Major Market Index (MMI) and the S&P 500 stock index futures contracts with respect to hedge duration and time to contract expiration. Hedge durations of one, two, and four weeks were compared and these groups were further broken down by the number of weeks remaining until contract expiration. The hedge ratios were analyzed to see if they exhibited predictable trends, and statistical comparisons were made with the beta (or naïve or classic) hedge ratio. The study used the Major Market Index (MMI) data from August 1985 to August 1989 and also the S&P 500 data from 1983 to 1989. The results of this study showed that the minimum variance hedge ratios for the Major Market Index (MMI) and the S&P 500 stock index futures contracts increase significantly as hedge duration increases from one to four weeks. However, the duration effect is influenced by the fact that longer hedge durations are lifted closer to contract expiration.

Ghosh (1993) undertook a study on the optimal hedge ratio using stock index futures, incorporating non-stationarity, long-run equilibrium relationship and short-run dynamics. This study used the Cointegration method and the Error correction mechanism; further it was compared with the traditional regression result. The data was taken from January 2, 1990 to December 5, 1991. The study showed that hedge ratio estimated from VECM provides a better hedge than the traditional method. It was also found that the estimated error correction model incorporates both long-run equilibrium relationship as well as short-run dynamics.

Lien and Luo (1994) investigated multiple hedging decisions when conditional heteroscedasticity characterized the underlying spot and futures markets. They employed constant or error correction and Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) for estimating the hedge ratio. The sample period was from March 4, 1988 to December 27, 1988, consisting a total of 455 observations. The analysis found that the hedging performance of the GARCH model is not better than that of the constant or error correction hedges, and ex-post criteria are not favourable to the GARCH hedge at all.

Mcnew, K.P. and Fackler, P.L. (1994) examined an econometric methodology that facilitated statistical test of the hedge ratio by testing the hypothesis of a constant hedge ratio. There were three main features of this framework. First, it directly estimated the conditional hedge ratio as a function of information available to the firm. Second, it considered that the unhedged risk depends on observable information. Third, it utilized an iterative Generalized Least Squares (GLS) procedure, making it fairly simple to compute. The weekly data set was taken from February 1976 to August 1992 for the analysis. They found that this model is able to remove the apparent Auto Regressive Conditional Heteroscedasticity (ARCH) effect from the data. Furthermore, in contrast to the Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) approach, it provides a practical method for testing whether the constant hedge ratio is optimal and provides a direct estimate of the risk remaining in a portfolio that is hedged optimally.

Koutmos, G. and A. Pericli (1998) evaluated the hedging effectiveness of the dynamic model with the static regression model. An error correction bivariate GARCH-type model (EC-GARCH) was employed to estimate time-varying hedge ratios. The sample period was from January 5, 1985 to August 3, 1996 for a total of 545 observations. The empirical evidence found that dynamic hedge ratios are superior to static ones in terms of both total variance reduction and expected utility maximization.

Sim, A. and R. Zurbruegg (2001) examined the impact of the 1997 Asian Financial Market Crisis on the hedging effectiveness within the KOSPI 200 stock index and index futures markets. The paper investigated the inter-temporal relationship between the two markets to examine the characteristics of several minimum variance hedge ratios. It also examined the performances of alternative hedging strategies for dynamic portfolio management in the presence of cointegrated time-varying risks. The study utilized daily prices provided by the Korean Securities Exchange (KSE) quoted at 15:00 each day from May 14, 1996 to March 1999 for the South Korean Composite Stock Index 200 (KOSPI 200) and their corresponding index futures. The analysis employed an error-correction GARCH (ECGARCH) framework. They concluded that in the pre-crisis period both the markets showed a greater level of conditional volatility and hedge ratios significantly dropped after the crisis as general risk within the South Korean markets rose. Furthermore, it also showed that a cointegrating time-varying hedge ratio performs the best when compared with simple constant-hedge ratio strategies. The Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) model specifications do not incorporate all the information that can be relayed from past prices, and volatility (including the error-correction terms) was also found to be inferior in this model.

Cotter and Hanly (2006) investigated the hedging effectiveness of futures markets across seven international markets. The data set included prices of seven major indices for the period of January 1, 1998 to December 31, 2003. The methodology was based on an extensive set of performance-evaluation matrices. The performances of short and long hedgers were evaluated by traditional variance-based approaches along with modern techniques (including value at risk, conditional value at risk), and approaches based on downside risk. They showed that the matrices evaluation approach provides better hedging effectiveness over traditional methods.

Sung Yong Park and Sang Young Jei (2010) extended the Bollerslev's constant conditional correlation and Engle's Dynamic Conditional Correlation (DCC) Bivariate Generalized Autoregressive Conditional Heteroskedasticity (BGARCH) models. This study analyzed the behaviour of the optimal conditional hedge ratio based on two (BGARCH) models by: (i) adopting more flexible bivariate density functions such as a bivariate skewed-*t* density function; (ii) considering asymmetric individual conditional variance equations; and (iii) incorporating asymmetry in the conditional correlation equation for the DCC-based model. Hedging performance in terms of variance reduction, value at risk and the expected shortfall of the hedged portfolio were also conducted. Using daily data for the spot and futures returns of corn and soybean they found that asymmetric and flexible density specifications help increase the goodness-of-fit of the estimated models, but do not guarantee higher hedging performance. They also found that there is an inverse relationship between the variance of hedge ratios and the hedging effectiveness.

Juhl, Kawaller and Koch (2012) studied the hedging effectiveness by employing the simple regression and the Error Correction Model (ECM). They showed that when the prices of the hedged item and the hedging instrument are cointegrated, both the models provide same results in a long time interval, but in a short time interval, the ECM model provides better results than simple regression.

One of the earlier studies in the Indian context was done by Bhaduri and Sethu Durai (2007) who investigated the optimal hedge ratio and the hedging effectiveness of stock index futures by employing four competing models, *i.e.*, the simple Ordinary Least Square (OLS), the Vector Autoregression Model (VAR), the Vector Error Correction Model (VECM) and a class of multivariate Generalized Autoregressive Conditional Heteroscedastic model (GARCH). With the Multivariate GARCH model, they estimated the time-varying hedge ratio, whereas the other models tried to give single point estimates. Daily data of the NSE Stock Index Futures and the S&P CNX Nifty Index from September 4, 2000 to August 4, 2005, and for out-of-sample validation, daily data from August 5, 2005 to September 19, 2005 were considered for the analysis. The results concluded that the time-varying hedge ratio derived from the diagonal VEC-GARCH model gives a higher mean return than other counterparts. Overall, the variance reduction from the diagonal VEC-GARCH model indicated better performance only in long time horizons compared with the simple OLS method that scored well in short time horizons. The diagonal VEC-GARCH model imparted a slight edge over the OLS in the out-of-sample validation.

The issues that need to be addressed are: (1) As it was introduced recently in India, there is no systematic study on measuring the hedging effectiveness of the futures market. (2) Most of the studies pertain to developed country markets. (3) Earlier studies estimated the hedging effectiveness by using monthly, daily and hourly data and used the modern techniques such as GARCH, Bivariate Vector Autoregressive Model (BVAR) and ECM for the estimation. The results show that the modern techniques provide better results than the conventional methods, and in some cases the traditional methods outperform the modern techniques. In this context, the present study tries to explore all the possible solutions for the above-mentioned issues with regard to the hedging effectiveness of futures in an Indian market.

From the earlier studies on the hedging effectiveness of the futures market, it was concluded that the conventional regression approach to optimal hedge ratio estimation fails to take a proper account of all of the relevant conditioning information available to hedgers when they make hedging decisions, and that it implicitly assumes the covariance matrix of spot and futures prices and hence optimal hedge ratios remain constant over time (Myers, 1991), which was supported by Park and Switzer (1995), Lypny and Powalla (1998), Koutmos and Pericli (1998), Lien and Tse (1999), Floros and Vougas (2004), Bryant and Haigh (2005) and Bhaduri and Sethu Durai (2007). Also, the Vector Auto Regression and error correction models ignore the time-varying nature of hedge ratios. They concluded that the constant hedge ratio do not consider that joint distributions of the spot and futures vary over time, and that Multivariate GARCH (M-GARCH) provides a flexible and consistent framework for estimating time-varying hedge ratios by considering conditional variance and covariance of spot and futures returns.

2.3 Price Discovery in the Futures Market

Now, as far as the causal relationship between spot and futures markets is concerned, several studies have attempted to examine the lead-lag relationship between spot and futures markets both in terms of return and/or volatility, including: Ng. (1987); Kawaller, and Koch (1987); Harris (1989); Stoll & Whaley (1990); Chin, Chan and Karolyi (1991); Chan (1992); Abhyankar (1995); Shyy (1996); Iihara (1996); Pizzi (1998); De Jong (1998); Chatrath (1998); Min (1999); Tse (1999); Frino (2000); Thenmozhi (2002); Anand babu (2003); Simpson (2004). Almost all of these studies have concluded that there is a significant lead-lag relationship between spot and futures markets, and have tried providing possible explanations behind this relationship.

Kawaller, Koch and Koch (1987) investigated the causal relationship of S&P 500 futures and the S&P 500 index by employing Three-Stage Least Square (3SLS). The data set consisted of the intra-day data from 1984 to 1985. The results found that causality exits between two markets on a minute-to-minute basis throughout the day. Ghosh (1993) examined the causal relationship of the S&P 500 index futures and the spot index by cointegration forecasting techniques. The analysis found that one market price will help in forecasting the other price, and the error correction model forecasting provides better results than the conventional methods. A similar study was done by Mackinlay & Ramaswamy (1988) on the S&P 500 stock Index and Index futures by employing data for the period of September 1983 to June 1987. The analysis revealed that the futures market is more volatile than the spot market.

Khalid (1993) examined the impact of petroleum futures trading on the spot market of the New York Mercantile Exchange. The study employed an auto-regressive model and used the data set from January 1970 to July 1985. The results indicated that underlying market volatility increases with futures trading and there is increased flow of market information into the spot market with the advent of futures trading.

Harris (1989) studied the temporal relationship between the S&P 500 index and futures by employing correlation techniques and the weighted least square method. This study was based on the five-minute data during the October 1987 stock market cash period. The results found that the futures market of the S&P leads the cash market.

Stoll and Whaley (1990) empirically studied the intra-day relationship between the S&P 500 and the Major Market Index (MMI) futures by using data taken at a gap of five minutes. The study revealed that there is a strong evidence in favour of the futures market leading the spot market.

Kutner & Sweeney (1991) examined the causality tests between the S&P 500 cash and futures markets by using intra-day data. In order to overcome the problem of serial autocorrelation and to reduce raw returns to white noise process, Sims' test and Autoregressive Integrated Moving Average (ARIMA) techniques were used. The empirical results found that the futures market is leading the spot market in different market conditions.

A study by Chan, K. (1992) investigated the intra-day lead-lag relationship between returns of the Major Market Cash Index and returns of the Major Market Index futures and the S&P 500 futures. Autocorrelation, Cross Correlation and Bivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models were employed for examining the objective of the study. The data used in the study were for the period August 1, 1984 to December 31, 1984. Empirical results revealed a strong evidence of futures leading the cash index, and also a weak evidence that the cash index leads the futures using the correlation and regression technique.

Abhyankar (1995) investigated the lead-lag relationship by including the changes in transaction costs, in different periods of good, moderate and bad news associated with high and low trading volumes in the underlying equity markets. Autoregressive and Exponential GARCH models were applied to hourly data for the period 1986 to 1990 for the analysis. The author evaluated the lead-lag relationships for periods with different transaction costs, spot market volumes and volatility. The empirical results revealed that the futures' lead over the spot index reduced, when transaction costs for underlying asset fell. It was also observed that futures market leads spot market returns during periods of high volatility. But in the case of conditional volatility, he could not find any clear pattern of one market leading the other neither during the period of good or bad news nor during varying levels of market activity.

Brooks et al. (2001) analyzed the lead-lag relationship between the FTSE 100 stock index futures and the FTSE 100 index by employing cointegration and error correction models, as well as ARMA and Vector Autoregressive models. They employed observations (at a 10-minute gap) from June 1996 to 1997. The study found that futures lead the spot market, which was attributable to the faster flow of information into the futures market, mainly due to lower transaction costs.

Alphonse (2000) investigated price discovery in the French Stock Index futures and spot markets. The methodologies used to test the objective were the Error Correction Model (ECM) and the Vector Moving Average (VMA). In order to test the long-run relationship, the Johansen cointegration technique was used. The data set taken for the study consisted of the intra-day data from January 3, 1995 to March 31, 1995. The results suggested that price discovery happens in the futures market, and that the futures market leads the spot market most of the time. The ECM results revealed the existence of a long-run relationship between spot and futures prices.

Kavussanos, et. al (2003) investigated the casual relationship between futures and spot prices in the freight futures market by employing the Vector Error Correction Model (VECM) and the General Impulse Response (GIR). The study compared the forecasting performance of the VECM with that of the Vector Auto Regression (VAR), the Auto Regressive Integrated Moving Average (ARIMA) and the Random Walk (RW) models. The results found that futures prices tend to discover new information more rapidly than spot prices, and that information from futures prices could be used to generate more accurate forecasts of spot prices.

Chin (1991) examined the intra-day relationship between price changes and the volatility of price changes in the stock index and stock index futures markets. This study supported that the price innovations originated in one market, such as the cash (futures) market, can predict the futures volatility in the other, such as futures (cash) market. In other words, both cash and futures markets serve important roles in discovering the price.

Chan, K. (1992) investigated the intra-day lead-lag relationship between the returns of the Major Market Cash Index and the Major Market Index futures and the S&P 500 futures. The author examined two issues regarding the lead-lag relation between these markets. First, whether the lead-lag relationship is induced by the irregular trading of component stocks. Second, whether futures prices lead cash index prices in the case of non-sychronous trading. Correlation and regression techniques were employed for empirical analysis. This study considered two sample periods, i.e., August 1984 to June 1985, and January to September 1987 for examining the lead-lag relationship between futures and cash index prices. The infrequent trading of component stocks could cause a spurious lead-lag relationship between futures and cash index returns. Empirical results showed a strong evidence of futures leading the cash index, and also presented weak evidence that the cash index leads the futures. The results were robust even in 1987, when the cash market seemed to be faster in processing market-wide information. The results suggested that the futures leading cash index cannot be completely explained by non-sychronous trading.

Wahab, M. & Lashgari, M (1993) studied the causal linkage between the stock index and futures markets. The objective was examined by using daily closing data from January 4, 1988 to May 30, 1992, and with the help of cointegration techniques. The results indicated that the cash and futures markets are co-integrated. It also revealed that although feedback exists between cash and futures markets, the spot-to-futures lead appears to be more pronounced across days relative to the futures-to-spot lead. Also, the error correction specification achieved a significantly lower Mean Absolute Error (MAE) in most of the cases than the forecasting performance of a standard vector auto regression model.

Arshad, F.M. & Mohamed, Z (1994) examined the forward pricing efficiency of the Malaysian local crude palm oil (CPO) futures market. A regression test was conducted to examine the traditionally efficient market model (Hansen and Hodrick, 1980, Bilsen, 1981 and Birgman et al., 1983). The study compared the forecasting ability of futures prices on physical prices with four major forecasting techniques: univariate (Box-Jenkins), exponential smoothing, moving average and econometric modeling. The monthly data for crude palm oil (CPO) futures and spot prices were collected for the period of 1983 to 1992. The authors found that futures market does not exhibit a strong evidence of inefficiency and that it appears that the futures market is able to establish forward prices efficiently, particularly as the expiry date approaches.

Martikainen, T. and Puttonen, V. (1994) investigated the information flow from world stock markets to the thin Finnish stock index futures and cash markets. The authors also tested the causality between the index futures and stock returns in Finland. The causality tests of Engel and Granger (1987) and seemingly unrelated regression analysis (SUR) were employed for the empirical analysis. The daily closing prices at 3.30 p.m. were used (from the introduction of the Finnish stock index futures market on May 2, 1988 to the end of the March 1999). The analysis found that the Finnish futures and cash markets followed the behaviour of other stock markets of the world. The Finnish stock index futures returns showed significant causality with Finnish stock market returns.

Tse, Y. K. (1995) examined the lead-lag relationship between spot index and futures prices of the Nikkei stock average. This study investigated the interaction between the spot and futures series through the error correction model using daily data in the post-crash period. The error correction models are considered dependent on the postulated long-run equilibrium relationship. The analysis revealed that lagged changes in the futures price affect the short-term adjustment in the spot index, but not vice versa. Also, forecasting models for the spot index were constructed using the univariate time series approach and the vector autoregressive method. The analysis found that the error correction models outperformed the univariate time series model and the vector error regression (VAR) model for the post-sample forecasting comparison. The vector autoregressive methods performed better than the martingale model, while the univariate time series method showed the poorest forecasts.

Arshanapalli, B. and J. Doukesh (1997) illustrated the linkages between the S&P 500 index futures market and the underlying cash market before and after the October 1987 crash. The hypothesis was tested by employing cointegration and error correction models, using intra-day minute-by-minute data for the entire month of October 1987. The study found that the futures and stock markets are highly cointegrated except on the October 16 and 19. The results also revealed that the two markets converged immediately after the crash, and that the price discovery process originated in the futures market instead of the cash market.

Pizzi, et al. (1998) examined price discovery in the Standard and Poor’s 500 cash index and its three-month and six-month stock index futures using intra-day, minute-by-minute data.

Cointegration and error correction models were employed for examining the objectives. The data between January 1987 and March 1987 were considered. The results showed that both the three- and six-month futures markets lead the spot market by at least 20 minutes. The spot market leads the three-month futures by at least three minutes and six-month futures by at least four minutes.

James, (1993) studied the price discovery effect of the futures market on the cash market. The study employed Garbade and Silber model to understand the price discovery effect of the futures markets. It revealed that the existence of futures market is making cash market robust as it adds more efficiency, liquidity but lowers the long-term volatility in the spot market.

Booth, et al. (1999) examined the intra-day price discovery process among stock index, index futures and index options in Germany using the Deutscher Aktien Index (DAX) securities and intra-day transactions data from January 1992 to March 1994. A vector error correction (VEC) model was applied for examining the price discovery among the markets. The analysis revealed that price discovery happens in the futures market.

By using a specially designed correlation measure that takes into account the fact that high-frequency data are often observed at irregular intervals, De Jong (1998) confirmed that even in the presence of significant contemporaneous correlation among the spot, futures and the options market, the futures price changes lead both the changes in the cash index and index options by five to ten minutes. But, among the cash and the options markets, the relationships are largely symmetrical and neither market consistently leads the other.

Chatrath (1998) examined the intra-day behaviour of the spot and futures market following the release of information, and also investigated the role of such information in the volatility spillover among the two markets. The results suggested that one market leading to greater volatility in the other is partly driven by information, and therefore the leading role played by the futures market could be the result of new information getting reflected efficiently in the futures market.

Min (1999) investigated the possible lead-lag relationships in returns and volatility between cash and futures markets. The results suggested that unlike the lead-lag relationship in the returns of spot and futures markets, there is significant but time-dependent bidirectional causality between the markets, as far as the volatility interaction among the markets is concerned.

Frino (2000) examined the temporal relationship among the spot and the futures markets around the release of different types of information. He found that the lead of the futures market strengthens significantly around the release of macroeconomic information, while the leading role of the futures market weakens around stock-specific information release. Therefore, according to the study, the disintegration in the relationship between the two markets is mainly driven by noise associated with trading activity around the release of different types of information.

Bhattacharya, et al. (1986) investigated the causal impact of futures markets on the volatility in the cash market for Government National Mortgage Association (GNMA) securities by employing the Auto Regressive Integrated Moving Average (ARIMA) method and univariate models. They collected daily closing prices from December 1979 to December 1982 and concluded that futures market has some causal influence on cash market volatility based on the causality analysis.

Tang, et al. (1992) studied the lead lag relationship between the Hang Sang index futures and the Hang Sang spot index. The study period was divided into two sub-periods: the pre-crash period from May 6, 1986 to October 16, 1987 and the post-crash period from November 1, 1987 to February 28, 1989. The empirical results indicated that futures prices cause cash index prices to change during the pre-crash period. In the post-crash period, bi-directional causality existed between the two.

Turkington, J and D. Walse (1999) examined the causal relationship between Shares Prices Index (SPI) futures and the All-Ordinaries Index (AOI) in Australia, using the high frequency data. The authors estimated the lead-lag relationship between the SPI futures and the underlying spot index. The empirical analysis was evaluated by using the Cost-of-Carry model, the Auto Regressive Moving Average (ARMA), the bivariate Vector Error Correction (VEC) and Vector Auto Regression (VAR) models and impulse response functions. A sample of 12,597 pairs of observations was collected at five-minute intervals for the period from January 3, 1995 to December 21, 1995. The data series were obtained from the Sydney Futures Exchange (SFE) and the Securities Industry Research Centre of the Asia-specific (SIRCA). The study found that SPI futures and the spot AOI index are integrated. It showed a strong evidence of bi-directional causality (or feed back) between the two series. The impulse response functions also supported these results.

Lafuente, J.A. (2002) examined the lead-lag relationships between returns in the Spanish Ibex 35 spot and futures index using hourly data. The bivariate error correction GARCH model was employed for the analysis. The analysis showed a unidirectional causal relationship from futures to spot returns. The futures market performs its price discovery function, in the sense that new information transmits first into the futures market and subsequently to the spot market. A similar study by So, R. W. and Y. Tse (2004) was based on the Hang Seng index. The analysis revealed that the futures market contains most information and leads the spot market.

Hodgson, Masih A. and Masih R. (2003) studied the price-discovery function of the Australian stock index futures market and Individual stocks in different market conditions. Multivariate Cointegrated Vector Error Correction Modeling (VECM) and Variance Decomposition (VD) techniques were used. The sample for the data set consisted of observations with a gap of fifteen minutes, for the period of April 1, 1992 to March 30, 1993. The results indicated that in the short term, price discovery happens first in the futures market, and the futures market plays an important role in the transmission of price information. But for small stocks in a bull phase, the spot market plays an important role. In a bear phase, futures market influences the stock prices to a great extent.

Brandt, Kavajecz, and Underwood (2007) regression analysis utilized both futures and cash market prices and net order flow to determine where price discovery takes place as well as the forces at play that influence the location on the US Treasury cash market and futures market. The results revealed that the price discovery is influenced by environmental variables such as Repo financing rates and liquidity.

In the Indian context, Thenmozhi (2002) examined the lead-lag relationship between the Nifty stock index futures and stock index returns. The daily closing price returns of Nifty spot and futures index from June 15, 2000 to July 25, 2002 were used for the study. The lead-lag relationships between spot and index futures were estimated using simultaneous equation modeling, ordinary least squares and two-stage least squares regression. The lead-lag analysis showed that the futures market is faster than the spot market in disseminating information, and futures returns lead the spot index returns.

Raju and Karande (2003) examined the price discovery in the S&P CNX Nifty and its corresponding futures. Cointegration techniques and Error correction model were employed for examining the issue. Daily closing values of index futures and the BSE 100 index were taken for the period June 2000 to October 2002. All the required information was collected from the website of NSE. The analysis revealed that the futures market (and not the spot market) responds to the deviation from equilibrium, and price discovery occurs in the both the futures and the spot market.

Mukherjee and Mishra (2006) examined the lead-lag relationship in the Indian context. They have used intra-day data during April-September 2004. The study is based on the Nifty spot index and Nifty futures index. The results found a bi-directional relationship between the two markets and spot market leads the futures market. Similar study is done by Bhatia (2007) by employing Cointegration approach. The intra-day 5 minutes data has been taken from April 2005 to March 2006. He came to the conclusion that futures market leads the spot market by 10-25 minutes and price discovery happens in both the markets.

From the above literature, it is clear that price discovery explains the information dissemination from one market to the other. Most of the studies supported the hypothesis that the futures market leads the spot market most of the time [Kawaller (1987), Harris (1989), Stoll and Whaley (1990), Chan (1992), Alphonse (2000), Tenmozhi (2002) and Kavussanos (2003)]. Price discovery is expected to take place first in the futures market and then it is transmitted to the underlying cash market. The literature on the price discovery function of the futures market provides insightful knowledge and throws open the research gaps. The dominant issues are: (1) Most of the studies focused on the developed country markets. Hence, it provides issues to be studied in the context of developing countries such as India. (2) In the Indian context, most of the studies are based on index futures and less number of studies focused on the stock futures (3) Most of studies used Granger Causality, Engle-Granger's co-integration technique, for measuring the price discovery function, giving us justification to re-examine the same issues using more sophisticated and reliable techniques.

The whole literature is based on three aspects namely introduction futures trading on spot market volatility, hedge ratio and hedging effectiveness, and price discovery of the function futures market. Firstly, the literature on the issue of impact of introduction on the futures trading on the cash market volatility provides mixed results across the globe. Secondly, on the issue the nature and structure of volatility, it is found that some studies support that informational flow in the derivatives era has increased while some authors argued that due to low transaction cost it may lead to increase the spot market volatility. On the issue price discovery functions of the futures market, most of the studies are related to the developed countries and provides mixed results. Some studies found futures market play an important role in price discovery while others claim that there is no clear cut dominance of any one market. Form this one can conclude that the issues need to be examined in detail. Thus, the present study is based on the issues discussed in the literature.

2.4 Concluding Remarks

The above discussed literature is based on three aspects namely introduction futures trading on spot market volatility, hedge ratio and hedging effectiveness, and price discovery of the function futures market. Firstly, the literature on the issue of impact of introduction on the futures trading on the cash market volatility provides mixed results across the globe. Secondly, on the issue the nature and structure of volatility, it is found that some studies support that informational flow in the derivatives era has increased while some authors argued that due to low transaction cost it may lead to increase the spot market volatility. On the issue price discovery functions of the futures market, most of the studies are related to the developed countries and provides mixed results. Some studies found futures market play an important role in price discovery while others claim that there is no clear cut dominance of any one market. Form this one can conclude that the issues need to be examined in detail. Thus, the present study is based on the issues discussed in the literature.

Chapter III

Derivatives Market: Concepts, Mechanism and Trends

3.1 Introduction

The Indian capital market went through a major transformation and structural change during the process of liberalisation and globalisation. The aim of these reforms was to improve market efficiency, transparency, checking unfair trade practices and bringing the Indian capital market to the international level. A distinctive feature of the reforms of the 1990s had been the ascent of financial sector reforms. The creation and empowerment of Securities and Exchange Board of India (SEBI) helped providing higher-level accountability in the market. Establishment of the National Stock Exchange of India Limited (NSEIL), National Securities Clearing Corporations Limited (NSCCL) and National Securities Depositary have been instrumental in providing more transparency and safety to the financial system.

The first step towards the introduction of derivatives trading was the promulgation of Securities Laws (Amendment) Ordinance, 1995, which withdrew the prohibition on options in securities. The market for derivatives did not take off, as there was no regulatory framework to govern derivatives trading. The SEBI established a 24-member committee under the chairmanship of Dr. L.C. Gupta on November 18, 1996 to develop an appropriate regulatory framework for derivatives trading in India. The committee submitted its report on March 17, 1998, prescribing necessary pre-conditions for the introduction of derivatives trading in India. The committee recommended that derivatives should be declared as securities, so that it became easy to deal with derivatives. The SEBI also set up a group in June 1998 under the chairmanship of Prof. J. R. Verma to recommend the measures for risk containment in the derivatives market. The Securities Contracts (Regulations) Act (SCRA) was amended in December 1999 to include derivatives within the ambit of securities and regulations were developed for governing derivatives trading. Finally, derivatives trading commenced in India in June 2000 after the final approval of SEBI. Derivatives were introduced in India in a phased manner.

A derivative can be defined as a financial instrument whose value depends on the values of the underlying assets. The underlying asset can be an index, a stock, interest rate, currency, commodity etc. Apart from credit derivatives, electricity derivatives and weather derivatives have been introduced recently.

The International Monetary Fund (IMF) defines: "Financial derivatives are financial instruments that are linked to a specific financial instrument or indicator or commodity, and through which specific financial risk can be traded in their own right. The value of a financial derivative derives from the price of an underlying item, such as an asset or an index. Unlike debt securities, no principal is advanced to be repaid and no investment income accrues".[4]

In India, SCRA, 1956, and Securities Law (Second Amendment) Act (SLA), 1999, include 'derivatives' in the definition of 'securities'. The term derivative has been defined in SCRA as:

a) a security from a debt instrument, share, loan, whether secured or unsecured, risk instrument or contract for differences or any other form of security;
b) a contract which derives its value from the prices, or index of prices of underlying securities.

3.2 Derivatives Market: An Introduction

Derivatives Exchange

Traditionally, derivatives traders used what is known as the open outcry system. This involved traders physically meeting on the floor of the exchange, shouting and using a complicated set of hand signals to indicate the trades they would like to carry out. With the advancement of technology, the exchanges moved from the open outcry system to electronic trading.

The benefit of the derivatives exchange is that standardised contracts are viable having counter-party risk guarantee. The Chicago Board of Trade (CBOT) was the first exchange to offer trading in grain futures in the year 1848. In the year 1919, the Chicago Mercantile Exchange was established to trade in derivatives products. In recent times, both the exchanges joined hands to form CMEGROUP, the biggest derivatives exchange in the world. Apart from these two exchanges, futures exchanges exist all over the world.

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[4] IMF Committee on Balance of Payments Statistics, 1998

The Over-the-counter Market

This is a market where derivatives products are traded through telephonic conversations and computer-linked networks of dealers. The total turnover in this market is much higher than the turnover of exchange-traded derivatives.

Forward Contracts

It is a privately negotiated agreement between two parties to buy or sell an asset in the future for a certain price agreed today. Generally, the players in the forward contract are the financial institutions and their clients. A forward contract is traded over-the-counter and carries default risk as there is no counter-party guarantee. When one buys a forward contract, it means that he agrees to buy the underlying asset on a certain future date at a pre-determined price. Similarly, on the other side, another person having a short (sell) position in the forward market agrees to sell the product on a certain future date at a pre-determined price. Forward contracts are mostly used to hedge the exchange rate risk. The main disadvantage of the forward contract is that there is no counter-party guarantee, and that contracts are not standardised.

Futures Contract

Futures contracts are standardised contracts traded in the exchanges. It is an agreement between two parties to buy or sell an asset at a future date and at a pre-determined price. The most traded financial futures in the world market are stock indices, currencies and interest rates. Similarly, sugar, coffee, cocoa, live cattle, feeder cattle, lean hogs, crude oil and gasoil are the popular commodities traded in exchanges across the globe.

Options

Options are one of the important types of derivatives. As the name suggests, it gives the holder of the option the right but not the obligation to buy or sell an asset at a certain price on or before a specified date in the future. On the other side who is obliged to buy or sell the contract is known as the option writer. In order to buy the right, the option holder pays an upfront premium to the option writer as he is obliged to buy or sell the product if the option is exercised. Broadly, two types of options are available for trading, i.e., call option and put option. A call option gives the holder of the option the right to buy the underlying asset at a certain price on or before a certain future time. Similarly, put option gives the holder the right to sell the underlying asset at a certain price on or before a certain future time. Based on the maturity of the option, it can be classified as American option and European option. An American option can be exercised at any date prior to the expiry whereas a European option can only be exercised at the expiry date. The price in the contract is known as the exercise price or strike price; the date in the contract is known as the expiration date or maturity. Options are traded both at exchanges and over-the-counter markets.

Swaps

A swap is a derivative product where two parties make an agreement to exchange cash flows in the future. In the agreement, the date when the cash flows are to be exchanged and the procedure in which they are to be calculated have to be mentioned. The most-traded swaps are interest rate swaps and currency swaps. In the case of interest rate swap, one party agrees to pay cash flows equal to interest at a pre-determined fixed rate on a notional principal for a number of years and receives interest at a floating rate on the same notional principal for the same period of time.

Stock Index Futures

Stock index futures are those contracts whose underlying asset is the index. It presents the right and obligation to buy or sell a portfolio of stocks characterised by the index. Stock index futures are cash-settled and there is no delivery of the underlying stocks. The trading in stock index futures started on the Value line Index on the Kanas City of Board on February 24, 1982. This was followed by the Chicago Mercantile Exchange on the S&P 500 (April 1982), the NYSE Composite Index Futures Contract on the New York Futures Exchange (May 1982) and the Major Market Index (July 1984) and Dow Industrial Average (October 1997) on the Chicago Board of Trade. Stock index futures have a great impact on the world's equity market.

Divergence of Futures and Spot prices: The Basis

Basis refers to the difference between futures price and the spot price. If the futures price is above the spot price, the basis is said to be positive. It implies that futures prices provide an indication of the spot price in the future. Basis is different for each of the delivery month.

Generally, in a normal market economy, basis is positive and basis can be negative in an inverted market economy. When the futures price is below the expected future spot price, the situation is known as normal backwardation. When the futures price is above the expected future spot price, the situation is known as contango.

Daily Settlement and Margining System

In order to have a position in the futures market, the investor has to deposit money in the form of initial margin. In other words, initial margin is the amount of money the investor is required to deposit before taking a position in the market.

At the end of the each trading day, the margin account is adjusted to reflect the investor's gain or loss. This process is known as the marking to market the account.

The investor can take away any amount in the margin account in excess of the initial margin. To ensure that the balance in the margin account never becomes negative, a maintenance margin, which is somewhat lower than the initial margin, is set by the exchange. If the balance in the margin account falls below the maintenance margin, the investor receives a margin call and is required to deposit the differential amount to bring back the margin account to the initial margin level. The extra fund that must be deposited is known as variation margin.

3.3 Economic Functions of the Futures Market

Futures prices reflect the information about the future. This is known as the price discovery function of the futures market. By looking at the current futures price one can get an idea about the futures spot price and what supply and demand of a good in future can be expected.

The futures trading provides low-cost agreements to exchange money for goods at a future time. It will give leverage over the underlying or the cash market in taking positions.

Futures market will help the informed individual take positions on the information about the futures. This will lead to an efficient pricing in the cash market. It implies that prices will reflect more information, and therefore resources will be allotted in ways that are closer to optimal.

Futures market allows individuals to hedge against adverse price changes. Hedgers transfer the risk to speculators. Price volatility and uncertainty are major pre-conditions for a successful futures contract, attracting both speculators and hedgers.

3.4 Participants in the Derivatives Market

The participants of the derivative market can be broadly categorised as Hedgers, Speculators and Arbitrageurs.

Hedgers

Hedgers are those who want to use the derivative products to reduce their risk exposure due to unfavourable price movement in their portfolio. Hedgers can use the derivatives market to hedge the adverse price movement in a commodity, financial security and currency. If a hedger wants to hedge his position from a price decline, he can take a short position in the futures market to reduce the risk exposure.

Speculators

Speculators are those who speculate on the future movement of the prices and try to take advantage of those on the basis of their forecasting. Generally, traders speculate on the price movement based on the macroeconomic indicators; if their speculation is correct they can make a good amount of profit. These market players are willing to take risk in the market in order to make big profits based on their speculation.

Arbitrageurs

Arbitrageurs enter into two or more markets simultaneously and book the risk-free profit and play an important role in price discovery. If the price of the same product is different in two markets or exchanges, the arbitrageurs can buy in the lower-priced market and sell in the higher-priced market simultaneously. The opportunities for the arbitrageurs become wide after the derivatives trading as it provides more number of trading instruments for trading.

3.5 Mechanisms of the Futures Market

Trading Mechanism

Trading system is a process to regulate trading in the derivatives exchange. It is based on a set of rules or processes about order execution, order submission, setting up price information and order process. It also deals with the flow of orders and determines volume and price during transactions. In recent times, most of the exchanges are having the electronic trading system rather than the floor trading system. The trading system for the derivatives segment at the National Stock Exchange is called the NEAT-F&O trading system. It provides a fully automated trading environment for screen-based, floor-less trading on a nationwide basis and an online monitoring and surveillance mechanism. The system supports an order-driven market and provides complete transparency of trading operations.

Clearing and Settlement

Clearinghouse plays an important role in the futures market. It provides the guarantee to each party and acts as an intermediary in futures transactions. Clearinghouse is involved in the confirmation of trades of the traders and matches all buy and sell orders on a daily basis. After all the trades have been matched, the clearing house becomes the seller to all buyers and buyers to all the sellers. The clearinghouse keeps a track record of all the transactions in a day and calculates the net positions accordingly. In India, National Securities Clearing Corporation Limited (NSCCL) is the clearing and settlement agency for all deals executed on the Derivatives (Futures & Options) segment. NSCCL acts as a legal counter-party to all deals on NSE's F&O segment and guarantees settlement.

Regulations of the Derivatives Market

The most challenging task before the regulators is the regulation of the derivatives trading. The leveraged nature of the derivative products and recent crises in the financial market pose more challenges before the regulators for proper control of the derivatives market. Regulations for derivatives trading involve setting standards for contract design, margin requirement, reporting and record keeping, transparency, safeguard of investor funds, ensuring the financial integrity of the trading process, safeguard from market manipulations and ensuring proper risk management mechanism.

In this regard, the L.C. Gupta Committee report has laid down the regulatory framework for derivatives trading in India. SEBI has framed a regulatory framework for derivatives trading in India. The objective of the regulatory framework is to provide a transparent trading environment, market surveillance, safeguarding customer funds and ensuring financial integrity of the trading process. Some of the regulatory conditions are as follows:

- The derivatives exchange should have arrangements for dissemination of information about trades, quantities and quotes on a real-time basis through two information-vending networks, which are easily accessible to investors across the country.
- Derivatives trading has to be done through online screen-based trading and all the derivatives exchanges must have an online facility for market surveillance to monitor price quotes, volumes positions on a real-time basis.
- The clearinghouse should have capabilities to separate initial margins deposited by clearing members for trades on their own account and on account of their clients.
- The clearinghouse is to perform full novation. It means the clearing house is to interpose to every trade and should provide an unconditional guarantee for settlement of all trades.

Risk Management

Risk management plays an important role in any type of transactions. Derivatives products are traded by paying an upfront initial margin. In other words by paying a certain percentage of the asset one can have a position in the derivatives instruments. Thus, for any derivatives exchange, it is very important to have proper risk management mechanism. In India, National Securities Clearing Corporations Ltd (NSCCL) has taking care of the risk management system. They have developed a risk containment feature for the derivatives segment. The daily margining is decided by the volatility of the underlying asset. To calculate the daily volatility, Value-at-Risk methodology is used which is estimated through Standard Portfolio Analysis of Risk (SPAN). The SPAN calculated performance of bonds/margin requirement in different scenarios.

3.6 Theories of Hedging

Some of the economists like Keynes (1930), Kaldor (1939) in 1930s and early 1940s emphasised the futures market as a simple insurance for price risk. Some of the well accepted theories of hedging are the traditional theory of hedging, Hollbrook Working's Hypoethesis and The Portfolio theory of Hedging.

The Traditional Hedging Theory

The traditional theory of hedging is based on the one-to-one approach. This approach is also known as the theory of Normal Backwardation. According to this theory, the hedger has to take equal number opposite positions in the futures market to hedge the cash market positions. They argue that spot and futures prices move together, so the absolute value of the hedged position is less than the unhedged or cash market position. Thus the variance of the hedged item will be lower.

Hollbrook Working's Hypothesis

Hollbrook Working (1953) criticised the traditional concept of hedgers as pure risk minimisers and suggested the concept of expected profit maximization in hedging. According to him, hedgers are more concerned about the relative prices changes rather than absolute price changes. According to him hedgers act like speculators, but they hold position in both the markets. So they are concerned about relative price changes. Further, he pointed that hedging is done on the expectation that futures and spot price relationship will change. In other words, one can hedge his long position in the cash market when the price starts moving against him and won't hedge as long as it provides some return to him.

The Portfolio Theory of Hedging

In its simplest form, the portfolio theory of hedging begins with the assumption that hedged and unhedged inventory are two separate assets that a dealer in commodities could combine into a portfolio based on the riskiness of their returns. Unhedged inventory is simply a commodity in store, while hedged inventory is actually a package of two assets, a commodity in store and a short position in a futures market. Since the asset-hedged inventory embodies the sale of a future contract, the number of futures contracts sold depends on the proportion of the hedged inventory in the portfolio. The major postulate of the portfolio theory is that if there are assets with same returns, then people will prefer those assets where the risk is less. The application of portfolio theory allowed Johnson and Stein to explain why hedgers would hold both hedged and unhedged commodity stocks.

Following Johnson and Stein, this analysis is restricted to only one spot market commodity or security to derivation of the formula. Since spot market holdings are exogenous, any interest payments may also be viewed as predetermined and therefore irrelevant to the hedging decision. Suppose, U represents the return on an unhedged position,

$$E\,(U) = X_s E\,(P_s^2 - P_s^1) \quad (3.1)$$

$$Var\,(U) = X_s^2 \sigma_s^2 \quad (3.2)$$

Where P_s^2 and P_s^1 represent the spot prices in time period 2 and 1, respectively. Let H represents the return on a portfolio which includes both spot market holdings, X_s, and futures market holding, X_f.

$$E\,(H) = X_s\,E(P_s^2 - P_s^1) + X_f\,E(P_f^2 – P_f^1) – K(X_f) \quad (3.3)$$

$$Var\,(H) = X_s^2\,\sigma_s^2 + X_f^2\,\sigma_f^2 + 2\,X_s\,X_f\,\sigma_{sf} \quad (3.4)$$

Where, X_s and X_f represent spot and futures market holdings and P_f^2 and P_f^1 presents futures prices in period 2 and 1 respectively.

$K(X_f)$ are brokerage and other costs of engaging in futures transactions including the cost of providing margin.

σ_s^2, σ_f^2 and σ_{sf} represent the subjective variances and the covariance of the possible price changes from time 1 to time 2.

Let the returns of portfolio be represented by H and it is either completely or partially hedged. Then, there is no presumption as in traditional theory, that $X_f = - X_s$. Indeed cash and futures market holdings may even have same sign.

Let $b = -X_f / X_s$ represent the proportion of the spot position which is hedged. Since in a hedge X_s and X_f have opposite sign, b is usually positive.

$$Var\,(H) = X_s^2\,(\sigma_s^2 + b^2\sigma_f^2 - 2\,b\,\sigma_{sf}) \quad (5)$$

$$E\,(H) = X_s\,\{E(P_s^2 - P_s^1) - b\,E(P_f^2 – P_f^1)\} – K(X_s,b)$$

$$= X_s\,\{(1 – b)E(P_s^2 - P_s^1) + b\,E(P_s^2 – P_s^1) - bE(P_f^2 – P_f^1) – K(X_s,b) \quad (6)$$

Letting E (Δb) = E((P_f^2 - P_s^2) - (P_f^1 – P_s^1)) represent the expected change in the basis,

$$E(H) = X_s \{(1-b)\ E(S) – bE(\Delta B)\} - K(X_s,b) \tag{7}$$

Where E(S) = E(P_s^2 - P_s^1) is the expected price change on one unit of the spot commodity.

If the expected change in the basis is zero, then the expected gain or loss is reduced as b → 1. It is also obvious that expected changes in the basis may add to or subtract from the gain or loss which would have been expected on an unhedged portfolio {E(U) = X_s E(S)}.

Holding Xs constant, it would be considered the effect of a change in b with the proportion hedged on the expected return and variance of the portfolio R.

$$\frac{\partial Var(H)}{\partial b} = X_s^2\{2b\sigma_f^2 - 2\sigma_{sf}\} \tag{8}$$

So risk minimizing b, b*, is

$$b^* = \frac{\sigma_{sf}}{\sigma_f^2} \tag{9}$$

$$\frac{\partial E(H)}{\partial b} = -X_s\{E(\Delta B) + E(S)\} - \frac{\partial K(X_s, b)}{db} \tag{10}$$

Ederington's Hedging Theory

Ederington (1979) measured the hedging effectiveness as a percentage reduction in the variance as the effectiveness of hedging and it is presented below:-

$$HE = 1 - \frac{Var(R)}{Var(U)}$$

Where Var (H) denotes variance of the hedged portfolio and Var (U) refers to the variance of the unhedged portfolio .

3.7 Derivatives Trading at the National Stock Exchange of India

The future and options segment of the national exchange of India represents the derivatives trading at NSE. Currently, there are six indices and 144 securities where derivatives trading are allowed. The futures and options trading system provides a fully automated trading.

Business Growth of the Indian Derivatives Market Over the years

The growth in terms of volume has been seen very well in the National Stock Exchange's Derivative segment. The figures in Table 3.3 represent the turnover of the derivatives products by year. The total turnover in the year 2001-02 was Rs1,019,26 crore. It increased to Rs3,13,49,732 crore in the year 20011-2012. The average turnover was only 11 crore in its inception year, it went up to approximately Rs1,266,38 crore in the year 2012-13. The number of contracts traded over the years has also increased to a large extent which is presented in Table 3.4. The figures show, over the last decade, the growth of derivatives product in India. This may be due to the fact that after abolition of badla trading in India, people consider it as a substitute for the badla trading. From Figure 3.1 and 3,2, it is quite clear that the demand for different derivatives instruments is increasing rapidly. The average daily turnover of the NSE segment is presented in the figure 3.4. It indicates the daily average turnover has increased over the years.

The present study is based on Futures and Options (F&O) segment of the National Stock Exchange of India. The NSE F&O segment deals with the following products following products CNX Nifty Index, CNX IT Index, Bank Nifty, Nifty Midcap 50 Index, CNX PSE and Nifty Infrastructure. Currently futures contracts are available on 144 securities stipulated by Security and Exchange Board of India. These securities are traded in the capital segment of the exchange. The contract specification of NSE equity derivatives segment is presented in the Table 3.1. Similarly, the contract specifications of the S&P CNX Nifty is presented in the Table 3.2

3.8 Conclusions

This chapter provides an introduction to the derivatives market in India. It provides basic idea about the various derivatives instruments like forwards, futures, options and swaps. The number of derivatives products available for trading is increasing over the period. Further this chapter discuss various theories of hedging. This chapter will provide to understand the concepts, theories and economic functions of the derivatives market in India.

Table 3.1: Contract Specifications of NSE Equity Derivatives in India

Products	**Index futures**	**Index Options**	**Futures on Individual Securities**	**Option on Individual Securities**	**Long Term Index Option**
Underlying	CNX Nifty CNX IT Bank Nifty Nifty Midcap 50 CNX PSE CNX Infrastructure	CNX Nifty CNX IT Bank Nifty Nifty Midcap 50 CNX PSE CNX Infrastructure	144 Securities	144 Securities	Nifty
Instrument	FUTDIX	OPTIDX	FUSTSK	OPTSK	OPTIDX
Underlying Symbol	Symbol of underlying Index		Symbol of underlying Security	Symbol of underlying Security	NIFTY
Expiry Date	DD-MM-YYYY				
Option Type		CE/PE		CE/PE	
Strike Price		Strike Price		Strike Price	Strike Price
Trading Cycle	3 month trading cycle – the near month (one), the next month (two) and the far month (3)				Three quarterly expiry(March, June, Sept, Dec) and 8 haly yearly expiry
Expiry Day	Last Thursday of the expiry month. If the last Thursday is a trading holiday, then the expiry day is the previous trading day.				
Strike price Interval	Depending on underlying price			Depending on underlying Volatility	Depending on underlying price
Price Steps	Rs.0.05				
Price bands	Operating range of 10% of the base price	A contract specific price range based on its delta value is computed and updated on a daily basis	Operating range of 10% of the base price	A contract specific price range based on its delta value is computed and updated on a daily basis	A contract specific price range based on its delta value is computed and updated on a daily basis

Source: *The National Stock Exchange*

Notes: The S&P CNX Nifty is the market index for National Stock Exchange and consists of 50 stocks. It comprises of 22 sectors of the economy and has 1995 as the base year and 1000 as the base value.
The CNX IT is a 20-stock index covering the information technology sector, and was introduced on January, 1996, with base value of 100 with effect from May 28, 2004

The CNX Bank Nifty is a 12 stock index covering 79% of the market capitalisation of the banking sector, and was introduced on January 1, 2000 with base value of 1000.

The Nifty Midcap 50 index represents about 5.66% of the free float market capitalisation of the stocks listed on NSE as on March 28, 2013. It has a base date of Jan, 1, 2004 and a base value of 1000.

CNX PSE Index: It comprises 20 Public Sector Enterprises (PSE) stocks. It has a base date of Jan 1, 2004 and a base value of 1,000.

CNX Infrastructure: It comprising 25 infrastructure stocks with a base year of Jan, 1, 2004 and a base value of 1000.

Table 3.2: Contract Specification of S&P CNX NIFTY Index Futures

Underlying Instrument	S & P CNX Nifty
Exchange of Trading	National Stock Exchange
Security Depositor	Market Type: N Instrument Type: FUTIDX i.e. Index on futures
Contract Size	Permitted lot size is 200 and multiples thereof
Trading Cycle	3 month trading cycle - the near month (one), the next month (two) and the far month (three)
Expiry Date	Last Thursday of the expiry month. If the last Thursday is a trading holiday, then the expiry day is the previous trading day.
Price Steps	Rs.0.05
Price Bands	There are no day minimum/maximum price ranges applicable in the derivatives segment. However, in order to prevent erroneous order entry, operating ranges and day minimum/maximum ranges are kept as below: For Index Futures: at 10% of the base price For Futures on Individual Securities: at 10% of the base price For Index and Stock Options: A contract specific price range based on its delta value is computed and updated on a daily basis

Source: National Stock Exchange

Table 3.3 Turnovers of Derivatives at NSE (Year-wise)

Year	Total Turnover	Index Futures	Stock Futures	Index Options	Stock Options	Average Daily Turnover
2000-01	2365	2365	0	0	0	11
2001-02	101926	21483	51515	3765	25163	410
2002-03	439862	43952	286533	9246	100131	1752
2003-04	2130610	554446	1305939	52816	217207	8388
2004-05	2546982	772147	1484056	121943	168836	10107
2005-06	4824174	1513755	2791697	338469	180253	19220
2006-07	7356242	2539574	3830967	791906	193795	29543
2007-08	13090477.75	3820667.3	7548563.2	1362110.9	359136.55	52153.3
2008-09	11010482.2	3570111.4	3479642.1	3731501.8	229226.81	45310.63
2009-10	17663664.57	3934388.7	5195246.6	8027964.2	506065.18	72392.07
2010-11	29248221.09	4356754.5	5495756.7	18365366	1030344.21	115150.48
2011-12	31349731.74	3577998.4	4074670.7	22720032	977031.13	125902.54
2012-13	31533003.96	2527130.8	4223872	22781574	2000427.29	126638.57

Source: National Stock Exchange

Table: 3.4: Number of Contracts Traded at NSE (Year-wise) (Rs. Crore)

Year	Total Number of Contracts	Index Futures	Stock Futures	Index Option	Stock Options
2000-01	90580	90580	0	0	0
2001-02	4196873	1025588	1957856	175900	1037529
2002-03	16768909	2126763	10676843	442241	3523062
2003-04	56886776	17191668	32368842	1732414	5583071
2004-05	77017185	21635449	47043066	3293558	5045112
2005-06	157619271	58537886	80905493	12935116	5240776
2006-07	216883573	81487424	104955401	25157438	5283310
2007-08	425013200	156598579	203587952	55366038	9460631
2008-09	657390497	210428103	221577980	212088444	13295970
2009-10	679293922	178306889	145591240	341379523	14016270
2010-11	1034212062	165023653	186041459	650638557	32508393
2011-12	1205045464	146188740	158344617	864017736	36494371
2012-13	1131467418	96100385	147711691	820877149	66778193

Source: National Stock Exchange

Figure: 3.1: Business Growth of Derivatives Trading (Turnover)

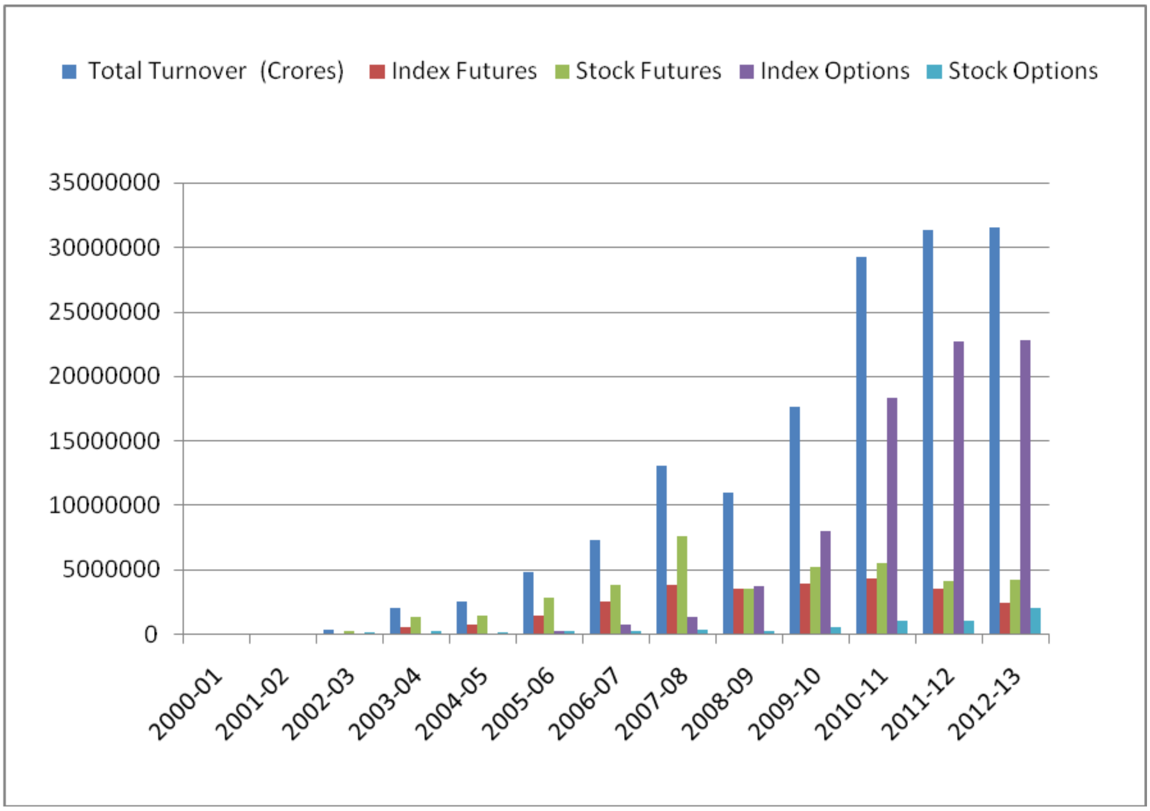


Figure: 3.2: Business Growth of Derivatives Trading (Number of Contracts)

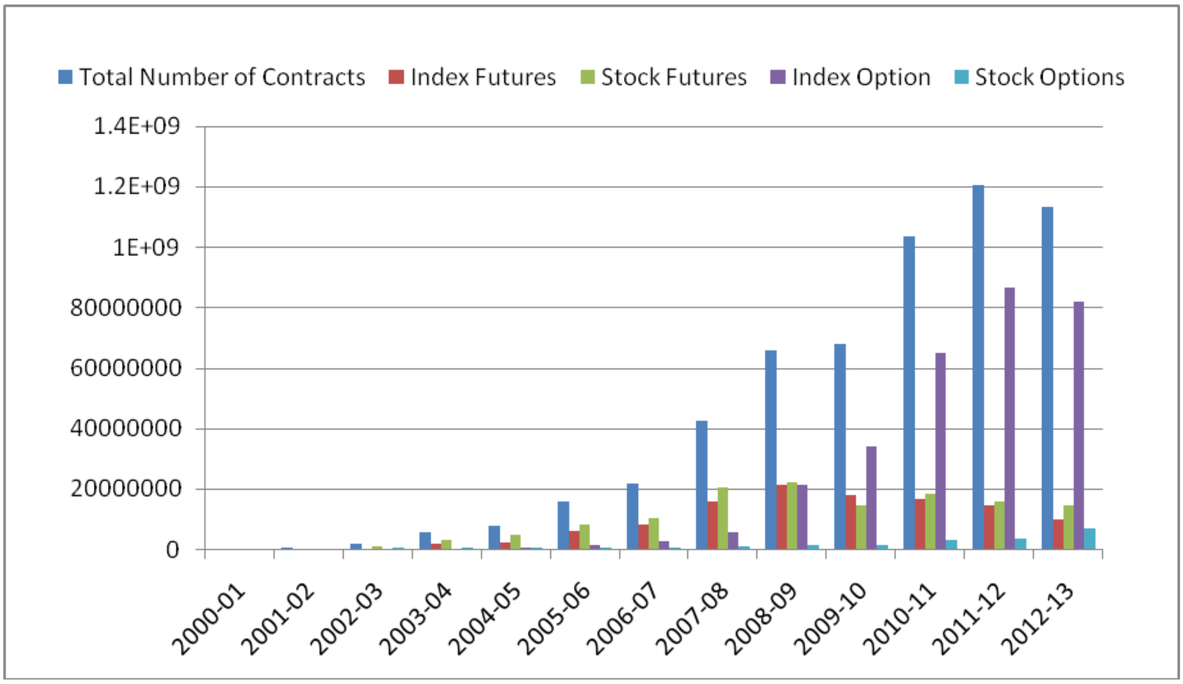
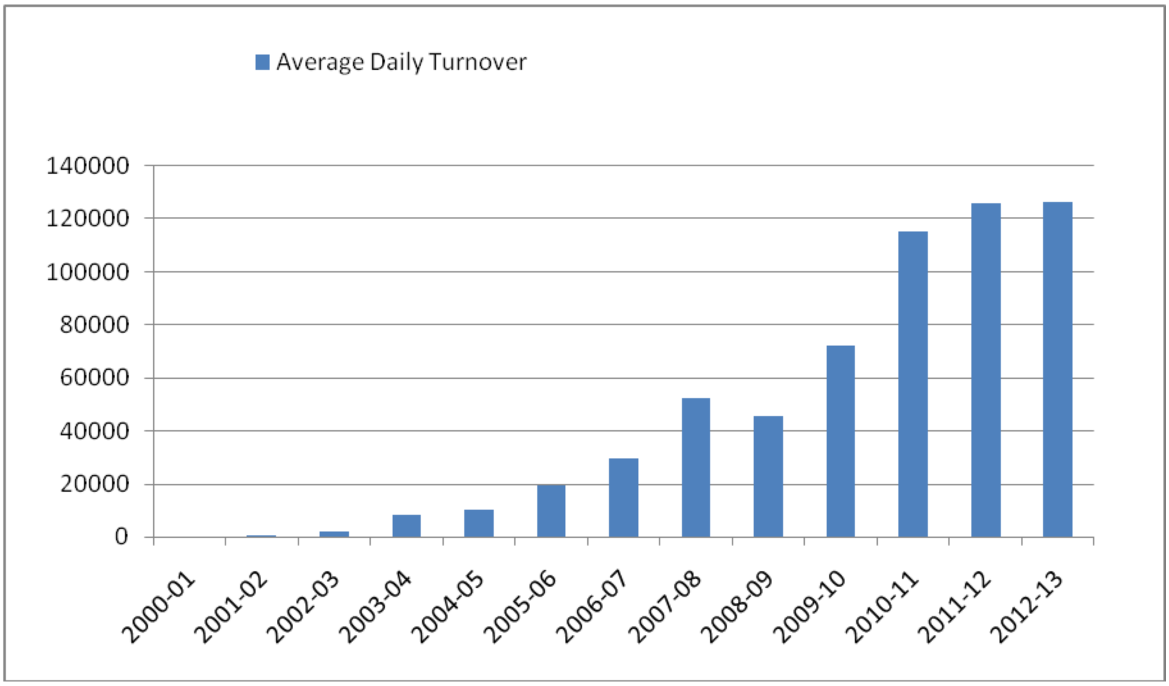


Figure: 3.3: Average daily Turnover of Derivatives Products (Year-wise)



Appendix 3.1

Chronology of Events leading to Derivatives Trading in India

- 1956: Enactment of the securities contracts (Regulation) Act which prohibited all options in securities.
- 1969: Issue of Notification which prohibited forward trading in securities.
- 1995: Promulgation of the Securities Laws (Amendment) Ordinance which withdrew prohibitions on options.
- 1996: Setting Up of L.C. Gupta Committee to develop regulatory framework for derivatives trading in India.
- 1998: Constitutions of J. R. Verma Group to develop measures for risk containment for derivatives.
- 1999: Enactment of the Securities Laws (Amendment) Act which defined derivatives as securities.
- 2000: Withdrawal of 1969 notification
- May 2000: SEBI granted approval to NSE and BSE to commence trading of derivatives
- .June 2000: Trading in Index futures commenced.
- June 2001: Trading in index options commenced. Ban on all deferral products imposed.
- July 2001: Trading in stock options commenced. Rolling settlement introduced for active derivatives.
- Nov 2001: Trading in stock futures commenced.

CHAPTER-IV

Introduction of Futures Trading on Spot Market Volatility

4.1 Introduction:

'Volatility' is an area of financial market research that continues to interest academicians, policy makers, investors and traders. Variation in the price of an asset during a specified period of time is termed as volatility. It is a measure of dispersion or variability from a central tendency. Volatility is associated with uncertainty and unpredictability, which results in risk. Derivatives products, such as futures, options and swaps, were introduced to limit the risk of a financial asset. The futures market has had a significant influence on the spot market. Black (1976a) was of the view that the most important benefit of opening a futures market is that it increases the flow of information. The futures market offers market participants quotes on futures as well as spot prices, providing information on future demand and supply in the stock market. Thus, opening of the futures market led to availability of more information to the investors. Stock markets normally exhibit high level of price volatility leading to unpredictable outcomes; hence, it is important to examine the dynamics of volatility. The introduction of derivatives opened new avenues for further research in the areas of volatility. Index futures, started from 12 June 2000, in India were intended to reduce the volatility of the underlying market.

4.2: Theoretical Motivation

The impact of derivatives on the underlying cash market volatility is an empirical question. A number of studies have been carried out on this subject across countries. Generally, two types of arguments prevail in the existing literature. One school of thought argued that derivatives trading increases spot market volatility due to high degree of leverage and hence, destabilizes the spot market. Further, futures market is likely to attract uniformed traders, due to low transaction costs involved, to take positions in the futures market. The relatively low level of information on derivatives trades with respect to cash market traders likely increases the asset volatility.

However, another school of thought claims that futures market plays an important role in price discovery and has a favourable effect on the underlying cash market. Kumar and Shastri (1995) argued that derivatives trading helps in price discovery, improves the market depth, enhances market efficiency and reduces information asymmetry in the spot market. This leads to a divide between researchers, academicians and investors on the effects of derivatives on the underlying market volatility. Some selected reviews related to equity futures and options are discussed in the following section.

With respect to futures trading, most of the studies are related to index futures due to lack of trading in single-stock futures. Studies by Edwards (1988) on the Value-line Index, Chan and Karloyi (1991) on the Nikkei 225 Index, Leela and Ohk (1992) on the Australian All Ordinaries Index, Darrat and Raman (1995) and Kamara Miller and (1992) on the S&P 500 Index found no significant changes in the volatility of the spot market. On the other side, studies by Lockwood and Linn (1990) on the DJIA Index and Brorson (1991) on the S&P 500 Index found increase in the volatility of the spot market. A study by Gulen and Mayhew (2000) was based on twenty-five countries. They found an increase in volatility for the S&P 500 and the Nikkei 225 indices, and other countries showed no significant change in volatility. Similarly, Ibrahim on the Malaysia stock market (1999), Bohl, Salm and Wilfling (2010) on the Polish Index futures market and Oliva and Armada (2001) on the Portuguese stock market did not find any significant change in the spot market volatility. Similarly, Butterworth (2000) found no significant change in the volatility of the FTSE-250 Index after the onset of futures trading. Board, Sandmann and Surcliffe (2001) showed that, contrary to regulatory concerns and the results of the other papers, contemporaneous information less futures market trading has no significant effect on the spot market volatility. Some of the studies showed a decrease in the volatility of the underlying market. These studies included Bessembinder and Seguin (1992) on the S&P 500 Index, Homes and Priestly (1998) on the DAX 100 and the Swiss MI Index, PierluiginBologana and Laura Cavallo (2002) on the Italian Stock Market. In the case of options, most of the studies were related to the individual stocks. They showed a decline in the volatility of the spot market (Conrad 1989), Elfakhani and Choudhury (1995). Antoniou and Holmes (1995) found that the introduction of stock index futures caused an increase in spot market volatility in the short run while there was no significant change in volatility in the long run. The daily seasonality effect in the S&P 500 declined significantly in the post-futures trading (Kamara, 1997). A similar study on the Japanese market was conducted by Hiraki, Marberly and Taube (1998) and they found that trading of the Nikkei 225 stock index futures had impacted daily index return seasonality.

A few studies were carried out by different academicians to detect the spot market volatility in case of India. One of the earlier studies by Thenmozhi (2002) showed a decline in volatility of the spot market by examining the S&P CNX Nifty Index. A similar result was obtained by O.P. Gupta (2002), Raju and Karnde (2003), while Shenbagaram (2003) did not find any significant change in the spot market volatility. The volatility of the Nifty stock futures has declined except for some stocks after the introduction of futures. Further, the cash market volatility has also come down after the introduction of the derivatives market, but there are other reasons like microstructure changes and robust risk management practices, which have been responsible for the reduction in the volatility. (G.C. Nath, 2003).

The above literature gives a mixed result about the effect of futures on the volatility of the underlying market across the countries. The results depend on the indices and methodology used in the study, because studies examining the same indices have arrived at different conclusions. Most of the studies are related to developed countries such as the US, the UK or Japan. But, a very few studies have been conducted in developing countries like India.

4.3: Objectives of the Study

Based on the earlier studies, the introduction of futures trading have raised several issues, which need to be discussed in detail. The present study is based on the following issues:

1. To examine the impact of introduction of futures and options on the underlying spot market volatility.
2. To measure the nature and structure of the volatility after the introduction of derivatives.

4.4 Methodology

Most of the time series data contain a unit root, i.e., the series are non-stationary. The non-stationary data might produce spurious regression, i.e., a regression equation with a high R^2, t-statistics that might appear to be significant, but the results are without any economic meaning (Granger and Newbold, 1974). Thus, the present chapter, firstly, estimates unit root test of the returns series by employing the Augmented-Dicky Fuller and Phillips-Parron test.

Financial research shows much evidence that stock returns data exhibit leptokurtosis, skewness, time-varying volatility, volatility clustering, leverage effect, which have been well documented. Authors like Mandelbrot (1963), Fama(1965) and Clark (1973) documented that the unconditional distribution of financial returns exhibits fat tails at the mean, indicating that return series does not follow normal distribution. In order to overcome the above problems, Engle (1982), for the first time, developed a systematic volatility model known as Autoregressive Conditional Heteroscedasticity (ARCH). This model does not assume variance of error to be constant and states that a shock of an asset return is serially uncorrelated but dependent, but dependence of the shock of an asset is a simple quadratic function of its lagged values. Thus, the present analysis is based on the ARCH/GARCH class of models.

In the ARCH model, the mean equation can be specified by an AR(p) process. The conditional mean equation can be written as:

$$y_t = \alpha + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n \quad \text{and } \mu_t \sim (N, 0, \sigma^t) \qquad (4.1)$$

y_t is the dependent variable varies over time and conditional variance of μ_t may be denoted as σ_t^2, which can be represented as:

$$\sigma_t^2 = \text{var}(\mu_t \mid \mu_{t-1}, \mu_{t-2}....) = E[(\mu_t - E(\mu_t)^2 \mid \mu_{t-1}, \mu_{t-2}....)] \qquad (4.2)$$

It is usually assumed that, $E(\mu_t) = 0$, so

$$\sigma_t^2 = \text{var}(\mu_t \mid \mu_{t-1}, \mu_{t-2}....) = E[(\mu_t{}^2 \mid \mu_{t-1}, \mu_{t-2}....)] \qquad (4.3)$$

The above equation implies that the conditional variance of a zero mean, normally distributed random variable μ_t is equal to the conditional expected value of the square of μ_t. In this model, the autocorrelation in volatility is modelled by allowing the conditional variance of the error term, σ_t^2 to depend immediately previous value of the squared error. This can be expressed as:

$$\sigma^2{}_t = \alpha_o + \alpha_1\, \mu_{t-1}^2 \qquad (4.4)$$

The above model is ARCH (1) and the conditional variance depends on the lagged values of the squared term obtained from the mean equation. An ARCH (p) process can be written as:

$$\sigma^2{}_{\mathrm{t}} = \alpha_{\mathrm{o}} + \sum_{t=1}^{p} \alpha_1 \mu_{t-1}^2 \qquad (4.5)$$

Generalized ARCH (GARCH) Model

In the ARCH model, it is difficult to decide the number of lags (q) of the squared residuals and the number of lags of the squared error that are required to capture all of the dependence in the conditional variance. In order to overcome these problems, Bollerslev (1986) developed the GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model. A stochastic process is called GARCH, if its time-varying conditional variance is heteroscedastic with both autoregression and moving average. In the GARCH model, the conditional variance depends not only on the squared residuals but also on its own past values. GARCH (1,1) model can represented as:

$$\sigma^2{}_{\mathrm{t}} = \alpha_{\mathrm{o}} + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 \qquad (4.6)$$

Where α_{o} is the intercept term, the ARCH term measures the information about volatility during previous period and is given by $\alpha_1 \varepsilon_{t-1}^2$. The forecast volatility from the previous period is called GARCH and is given by $\alpha_2 \sigma_{t-1}^2$. In other words, the coefficients of ARCH and GARCH show how volatility is affected by current and past information, respectively. The summation of ARCH and GARCH coefficients should be less than one to ensure covariance stationary of the conditional variance.

A generalized GARCH model may be specified as:

$$\sigma^2{}_{\mathrm{t}} = \alpha_{\mathrm{o}} + \sum_{t=1}^{p} \alpha_1 \varepsilon_{t-1}^2 + \sum_{t=1}^{q} \alpha_2 \sigma_{t-1}^2 + v_t \qquad (4.7)$$

Where p is the degree of ARCH, q is the degree of GARCH process and v_t is error term with white noise properties. The identification of GARCH is based on the same principle of ARMA method and the degree of p, q are identified by the help of an autocorrelation function and a partial autocorrelation function of the squared residual. The size of the parameters α_1 and α_2 determine the short run dynamics of the resulting volatility time series. Large coefficient α_2 shows the shocks to conditional variance take a long time to die out, so volatility is persistent. Large GARCH error coefficients indicate that volatility reacts quite intensely to market movements.

Following Bolonga and Cavallo (2002), a dummy variable is introduced in the variance equation which takes value zero for the pre-futures period and one for the post-futures period. Futures trading is introduced as a dummy variable in the equation. The coefficient of the dummy variable determines the direction and the magnitude of volatility after the introduction of derivatives. The sign and magnitude of dummy variable indicate changes in volatility of the spot market. A positive sign in the coefficient of dummy implies that volatility is increased and a negative sign indicates that volatility is decreased following the introduction of futures trading. The GARCH (1, 1) model can be specified as follows:

$$R_t = \beta_o + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_4 R_{t-4} + \varepsilon_t \qquad (4.8)$$

$$\varepsilon_t \mid \varepsilon_{t-1} \sim N(0, h_t) \qquad (4.9)$$

$$\sigma^2{}_t = \alpha_o + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 + \delta Dfutures + v_t \qquad (4.10)$$

Where R_t is the daily return on the S&P Nifty and R_{t-1} is the lagged Nifty return.

One of the objectives of this chapter is to address the issue whether the introduction of futures has been the only factor responsible for the change in volatility. To address the issue, following Pagan and Schwert (1990) and Ng (1993), the Nifty Junior Index is included in the mean equation to capture the market wide factors as a proxy variable and days in the variance equation to know the days of the week effect. Day-of-the-week effect means that on certain days in a week, mean return in the nifty is significantly positive or negative than average return in the Nifty for all other days. The GARCH (1, 1) model can specified as follows:

$$R_t = \beta_o + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_4 R_{t-4} + \beta_5 JuniorNifty + \varepsilon_t \qquad (4.11)$$

$$\varepsilon_t \mid \varepsilon_{t-1} \sim N(0, h_t)$$

$$\sigma^2{}_t = \alpha_o + \alpha_1\,\varepsilon_{t-1}^2 + \alpha_2\sigma_{t-1}^2 + \delta Df + \lambda_1 D_M + \lambda_2 D_{TU} + \lambda_3 D_W + \lambda_4 D_{TH} + \nu_t \qquad (4.12)$$

The Asymmetric GARCH Model

The GARCH model fails to take into account the asymmetric response of volatility as the conditional variance is modelled as a function of only magnitude and not a sign of the stock returns innovations. In order to capture the time-varying volatility, volatility clustering and asymmetric relationship, the Exponential Generalised Auto Regressive Conditional Heteroscedasticity (EGARCH) Model is employed to measure the impact of futures trading on price volatility in the underlying spot market. This model is proposed by Nelson (1991) to capture asymmetric features of data.

The asymmetry effect occurs when a bad news increases volatility more than that of a good news of similar magnitude. This model expresses the conditional variance of a given variable as a non-linear function of its own past values of standardized innovations. An EGARCH process is represented as:

$$R_t = \beta_o + \beta_1 R_{t-1} + \varepsilon_t \qquad (4.13)$$

$$\ln(\sigma^2{}_t) = \alpha_o + \alpha_1 \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \omega \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \qquad (4.14)$$

Here $\sigma^2{}_t$ is the conditional volatility, α_o is the long-term volatility, the coefficient γ measures the asymmetric relationship between news and volatility. If γ is not equal to zero then there is asymmetric impact on volatility. Leverage effect implies γ<1. A negative γ implies negative news increases volatility more than positive news. The lager coefficient of α_j implies higher degree of persistence in the volatility and α_j<1.

To address the impact of futures on spot market volatility, the model extends the conditional variance equation to include a dummy variable taking the value of zero for pre-futures and one for post-futures period. Further, the model also includes dummy variables for testing the day-of-the-week effect in the variance equations. It is necessary to remove market-wide influences on spot price changes by incorporating a proxy variable in the mean equation and have a proxy which is not associated with a futures contract. Therefore, to capture market-wide influences on price volatility, the index on Junior Nifty has been used. Thus, the equation (8) and (9) can be written as:

$$R_t = \beta_o + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_4 R_{t-4} + \beta_5 JuniorNifty + \varepsilon_t \qquad (4.15)$$

$$\ln(\sigma^2_t) = \alpha_o + \alpha_1 \ln(\sigma^2_{t-1}) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma^2_{t-1}}} + \omega \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma^2_{t-1}}} - \sqrt{\frac{2}{\pi}} \right] + \psi F_f + + \lambda_1 D_M + \lambda_2 D_{TU} + \lambda_3 D_W + \lambda_4 D_{TH} \qquad (4.16)$$

The estimation of the above mentioned equation is based on the following:

- σ^2_{t-1}: Estimation of the variance of the previous time period.
- $\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|$: Information concerning the volatility of the previous time period.
- $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$: Information concerning the leverage (γ_k >0) and the asymmetry ($\gamma_k \neq 0$).
- α,, γ, ω, ψ and λ are parameters.
- D_M, D_{TU}, D_W, D_{TH}: dummy variables for checking the day-of-the-week effect in the variance equations.
- R_t^{Junior} : is a proxy variable to capture "market-wide" volatility that is volatility unrelated to the onset of trading in futures contracts on the spot asset under investigation.
- ε_t : are the innovations distributions as a generalised error distribution (GED) which was assumed by Nelson, 1991.
- F_f: is the dummy variable that measures the introduction of futures. The dummy variable F takes zero value for the pre-futures period and one for the post-futures period.

Further, the study examined the impact of futures trading at the firm level on 15 individual stocks by employing EGARCH model. The following equations are used to estimate EGARCH (1,1) for the individual stocks.

$$R_t = \beta_o + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_4 Nifty + \varepsilon_t \quad (4.17)$$

$$\ln(\sigma^2_t) = \alpha_o + \alpha_1 \ln(\sigma^2_{t-1}) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma^2_{t-1}}} + \omega \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma^2_{t-1}}} - \sqrt{\frac{2}{\pi}} \right] + \psi F_f \quad (4.18)$$

Where, the Nifty spot index is used as proxy variable to control the market-wide factors for the individual stocks.

4.5 Empirical Results

The present study begins the empirical analysis by investigating the descriptive statistics of The Nifty spot index and The Junior Nifty Index. The mean daily percentage return on the Nifty Spot Index is 0.047% with a standard deviation of 1.75%. Similarly, the daily mean return of the Nifty Junior Index is 0.061 with a standard deviation of 2.1%. The standard deviation shows that the Nifty Junior Index is more volatile than the Nifty index. The negative value of skewness and kurtosis of more than 3 indicates that raw continuous compound percentage return series is not normally distributed but it is negatively skewed and leptokurtic. The non-normality can also be confirmed by the Jarque-Bera test where the null hypothesis is that the given series is normally distributed. Here the JB statistics is highly significant, hence rejects the null hypothesis. The non-normality also can be seen from Figures 4.1 and 4.2, where the volatility is relatively high and regions where the volatility is relatively low. In other words, high volatility is followed by higher volatility and low volatility is followed by lower volatility over time.

Table 4.1: Descriptive Statistics Spot Returns

Statistics	Nifty	Junior Nifty
Observations	3708	3708
Mean	0.0469	0.0613
Median	0.1152	0.1676
Maximum	16.3343	13.8253
Minimum	-16.9533	-20.0675
Standard Deviation	1.7541	2.0125
Skewness	-0.5208	-0.8116
Kurtosis	12.4270	11.3513
Jarque-Bera (Probability)	13897.85	11182.70
Obs*R^2 (ARCH-LM Test)	92.6402	254.4555

Figure 4.1: Nifty Spot Returns

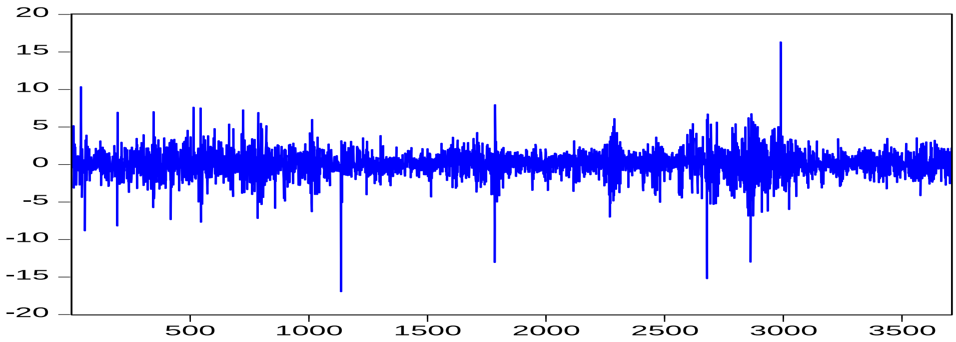
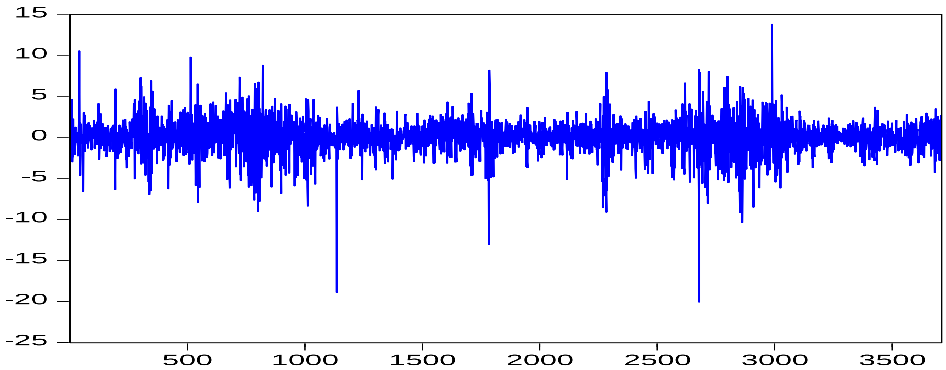


Figure 4.2: Nifty Junior Index Returns



The economic literature in the recent past has experienced an explosion of unit roots for stationarity of time series data as the choices of techniques and procedures for further analysis and modeling of series depend on their order of integration. Hence, without taking into account the presence of unit root in the variables, the analysis may produce spurious results. Therefore, Augmented Dicky-Fuller and Philips-Perron unit root tests are employed to test the integration of each variable. The ADF unit root test is sensitive towards the lag length included in the regression equation. Hence, the lag length is chosen on Akaike Information Criterion (AIC). All the return series are stationary at their level and they are significant at one percent level. Also, in Table 4.2, the hypothesis of a unit root in the return series of the Nifty spot index return is strongly rejected by the Augmented Dickey-Fuller (ADF) and Phillips and Perron (PP) tests. Therefore, returns follow a stationary process even though they fail to be normally distributed because of the presence of first and second moment dependencies.

Table 4.2: Unit Root tests for Nifty spot Returns

	ADF Test Statistics			Philips-Perron Test		
Variables	Without intercept	With intercept	With intercept and trend	Without intercept	With intercept	With intercept and trend
S&P CNX Nifty	-58.594*	-58.627*	-58.619*	-58.5655*	-58.591*	-58.599*
Nifty Junior	-54.452*	-54.491*	-54.485*	-54.426*	-54.470*	-54.464*

Before applying ARCH/GARCH class of models, it is necessary to check for possible presence of ARCH effects in the data. The ARCH effect signifies the temporal dependence in second moments; the approach is to check for the dependence in the squared innovations or residual from a model. Engle (1982) has proposed the ARCH-LM (Lagrange-Multiplier) test. If the squared residuals at time t are predicated by its past values, then the presence of ARCH effect is established. The results are presented in the Table 4.3.

Furthermore, the Engel (1982) ARCH-LM test results indicated that there are ARCH effects on the data at all frequencies, indicating Nifty return data is time varying. In summary, the Nifty spot index return series seems best described by an unconditional leptokurtic distribution and possesses significant conditional heteroscedasticity. Hence, ARCH/GARCH models should be used to capture all the stylized facts.

Table4.3: The Results of ARCH LM TEST

ARCH LM TEST		
Coefficients	Nifty Index	Nifty Junior Index
Intercept	2.5876* (14.7835)	2.9542* (13.9567)
Squared Residuals	0.1581* (9.7449)	0.2620* (16.5247)
F-Statistics	94.9641* 0.0000	273.067* 0.0000
Obs*R Square	92.6402* 0.0000	254.4555* 0.0000

Note: * Indicates 1% level of significance, Figures in ( ) presents t-statistics

4.5.1 Estimates of GARCH (1,1)

Table 4.4 presents the results of change in volatility for the Nifty spot index after the introduction of Nifty futures. The coefficient of futures dummy is -0.1578 and significant at 1%. As the coefficient of the dummy variable is negative, it implies that volatility of the S&P Nifty has declined after the introduction of futures trading. This results support the hypothesis that introduction of futures has reduced the volatility of nifty to some extent.

Table 4.4: The Impact of Futures on the Spot Market Volatility (GARCH 1, 1)

$$R_t = \beta_o + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_4 R_{t-4} + \varepsilon_t$$

$$\sigma^2{}_t = \alpha_o + \alpha_1 \varepsilon^2_{t-1} + \alpha_2 \sigma^2_{t-1} + \delta Dfutures + v_t$$

Mean Equation			
Parameters	Coefficients	t-statistics	P Values
Constant	0.12626*	4.9720	0.0000
Niftyt-1	0.07032*	3.5621	0.0004
Nifty-2	-0.0183	-1.007	0.3139
Nifty-3	-0.00004	-0.0025	0.9980
Nifty-4	0.031***	1.8030	0.0714
Variance Equation			
Constant	0.3558*	10.3958	0.0000
ARCH(1)	0.1246*	18.6613	0.0000
GARCH(1)	0.8019*	72.5892	0.0000
Futures Dummy	-0.1578*	-6.4328	0.0000

Note: * Denotes 1% level of significance, ** denotes 5% level of significance and *** denotes 10% level of significance.

Table 4.5: The Impact of Futures after Controlling Market-wide Factors GARCH (1,1)

$$R_t = \beta_o + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_4 R_{t-4} + \beta_5 JuniorNifty + \varepsilon_t$$

$$\sigma^2{}_t = \alpha_o + \alpha_1 \varepsilon^2_{t-1} + \alpha_2 \sigma^2_{t-1} + \delta Dfutures + v_t$$

Mean Equation			
Parameters	Coefficients	t-statistics	P Values
Constant	0.0015	0.1173	0.9066
Niftyt-1	-0.0382*	-4.8713	0.0000
Nifty-2	-0.0155**	-2.0097	0.0445
Nifty-3	-0.0092	-1.1683	0.2427
Nifty-4	0.0205*	3.3765	0.0007
Nifty Junior	0.7736*	177.3416	0.0000

Variance Equation			
Constant	0.0290*	5.7729	0.0000
ARCH(1)	0.0668*	10.3550	0.0000
GARCH(1)	0.9096*	100.6555	0.0000
Futures Dummy	-0.0137*	-4.1890	0.0000

Note: * Denotes 1% level of significance, ** denotes 5% level of significance and *** denotes 10% level of significance.

Table 4.5 Presents the GARCH (1,1) results after the inclusion of Junior Nifty Index. The results suggest that market-wide factors represented by the Nifty Junior are found to be significant in explaining the Nifty index. The coefficient of the dummy variable is negative and significant, suggesting that volatility has been reduced after the introduction of futures. The results of the day-of-the-week are presented in Table 4. It is found that a Monday effect is significantly present in case of Nifty futures, indicating higher volatility on these days than other days. One possible explanation for this finding is that investors operating in this market act cautious on these days.

Table 4.6: The Impact of Futures on Spot Market Volatility (Day-of-the week effect)

$$R_t = \beta_o + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_4 R_{t-4} + \beta_5 JuniorNifty + \varepsilon_t$$

$$\sigma^2{}_t = \alpha_o + \alpha_1 \varepsilon^2_{t-1} + \alpha_2 \sigma^2_{t-1} + \delta Df$$
$$+ \lambda_1 D_M + \lambda_2 D_{TU} + \lambda_3 D_W + \lambda_4 D_{TH} + v_t$$

Mean Equation			
Parameters	Coefficients	Significance	P Values
Constant	0.0025	0.1956	0.8449
Niftyt-1	-0.0392*	-4.9817	0.0000
Nifty-2	-0.0156**	-2.0249	0.0429
Nifty-3	-0.0091	-1.1495	0.2503
Nifty-4	0.0205*	3.3692	0.0008
Nifty Junior	0.7743*	172.5838	0.0000
Variance Equation			
Constant	-0.0339	-1.1409	0.2539
ARCH(1)	0.0656*	9.7541	0.0000
GARCH(1)	0.9104*	94.9720	0.0000
Futures Dummy	-0.0141*	-4.2241	0.0000
Monday	0.1259*	2.6266	0.0086
Tuesday	0.0296	0.7352	0.4622
Wednesday	0.0726***	1.6719	0.0945
Thursday	0.0899***	1.6771	0.0935

Note: * Denotes 1% level of significance, ** denotes 5% level of significance and *** denotes 10% level of significance.

4.5.2 Estimates of EGARCH (1, 1)

Further, the study employed the EGARCH model as it captures time-varying volatility, volatility clustering and asymmetric relationship between news and volatility in a more developed way than GARCH (1, 1). The results are presented in Table 4.7. The coefficient of the dummy variable is negative, indicating that volatility has been reduced after the introduction of futures. The asymmetry coefficient for the Nifty is -0.1567 and significant at 1% level, indicating that volatility increases when the stock price decreases. Thus, it shows the presence of leverage effect in the return series. Further, the persistence coefficient is 0.91, indicating that the response function of volatility to shocks decay at a lower rate. The estimated γ_1 indicates that the Nifty spot index exhibits statistically significant asymmetric effect at 1% level. This result indicates a size effect of news which is stronger for bad news than for good news. Black (1976) first examined this issue and suspected that asymmetry could arise due to the increase in the leverage that occurs when the market value of enterprises declines.

The results of Table 4.8 show the impact of introduction of futures after controlling the market-wide factors. The coefficient of the dummy variable is -0.045 with a t-value of -7.3581, indicating that volatility has declined after the introduction of futures trading. The persistence coefficient indicates that the response function of volatility to shocks decline at a slower rate. The coefficient for the return of the Nifty junior is significantly greater than zero, indicating that it captures market-wide volatility. The estimated γ_1 indicates that the Nifty spot index exhibits statistically significant asymmetric effect at 1%.

The leverage effect is present in the data but it is not significant. The results of the day-of-the week estimated from EGARCH model is shown in Table 4.9. It is found that the Monday and Friday effects have higher significance levels than other days. The days-of the-week effect is very helpful for developing profitable trading strategies. The results show that day-of-the-week is present in case of the Nifty index futures, exhibiting strong day-of-the-week effects even after accounting for conditional market risks. The results indicate that variation in the returns across different days of the week is significant. On Mondays and Fridays, futures prices show very high impact on the underlying market. Thus, investors and traders could buy the stocks on days with abnormally low returns and sell stocks on days with abnormally high returns. The day-of-the-week refers to the tendency of stocks to exhibit relatively large returns on these days compared with other days. During these days, investors can earn a good amount of profit by taking positions at different extreme levels.

Table 4.7: The Impact of Futures on Spot Market Volatility from EGARCH (1, 1)

$$R_t = \beta_o + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_4 R_{t-4} + \varepsilon_t$$

$$\ln(\sigma^2{}_t) = \alpha_o + \alpha_1 \ln(\sigma^2_{t-1}) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma^2_{t-1}}} + \omega\left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma^2_{t-1}}} - \sqrt{\frac{2}{\pi}}\right] + \psi F_f$$

Mean Equation			
Symbols	Coefficients	Significance	P Values
β_o	0.0863*	3.8050	0.0001
β_1	0.0661*	3.7631	0.0002
β_2	-0.0177	-1.0916	0.2750
β_3	0.0179	1.1953	0.2320
β_4	0.0152**	2.0355	0.0418
Variance Equation			
α_o	-0.0304*	-3.6071	0.0003
α_1	0.1823*	17.7247	0.0000
γ	-0.1567*	-19.3724	0.0000
ω	0.9189*	146.1188	0.0000
ψ	-0.0458*	-7.3581	0.0000

Note: * Denotes 1% level of significance, ** denotes 5% level of significance and *** denotes 10% level of significance.

Table 4.8: The Impact of Futures on Spot Market Volatility after Controlling Market-wide Factors from EGARCH (1, 1)

$$R_t = \beta_o + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_4 R_{t-4} + \beta_5 JuniorNifty + \varepsilon_t$$

$$\ln(\sigma^2_t) = \alpha_o + \alpha_1 \ln(\sigma^2_{t-1}) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma^2_{t-1}}} + \omega\left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma^2_{t-1}}} - \sqrt{\frac{2}{\pi}}\right] + \psi F_f$$

Mean Equation			
Symbols	Coefficients	Significance	P Values
β_o	0.0030	0.2376	0.8121
β_1	-0.0392*	-5.2246	0.0000
β_2	-0.0152**	-2.0308	0.0423
β_3	-0.0093	-1.2027	0.2291
β_4	0.0208*	3.4343	0.0006
β_5	0.7755*	168.9047	0.0000
Variance Equation			
α_o	-0.1096*	-11.9159	0.0003
α_1	0.1460*	12.3737	0.0000
γ	0.0034	0.5731	0.0000
ω	0.9765*	242.8061	0.0000
ψ	-0.0160*	-4.0290	0.0001

Note: * Denotes 1% level of significance, ** denotes 5% level of significance and *** denotes 10% level of significance.

Table 4.9: The Impact of Futures on Spot Market Volatility after Controlling Market-wide Factors and Day-of-the-week effect from EGARCH (1, 1)

$$R_t = \beta_o + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_4 R_{t-4} + \beta_5 JuniorNifty + \varepsilon_t$$

$$\ln(\sigma^2_t) = \alpha_o + \alpha_1 \ln(\sigma^2_{t-1}) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma^2_{t-1}}} + \omega\left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma^2_{t-1}}} - \sqrt{\frac{2}{\pi}}\right] + \psi F_f + $$
$$+ \lambda_1 D_M + \lambda_2 D_{TU} + \lambda_3 D_W + \lambda_4 D_{TH}$$

Mean Equation			
Symbols	Coefficients	Significance	P Values
β_o	0.0031	0.2478	0.8043
β_1	-0.0395*	-5.2157	0.0000
β_2	-0.0151**	-2.0074	0.0447
β_3	-0.0091	-1.1707	0.2417
β_4	0.0206*	3.3987	0.0007
β_5	0.7758*	166.5091	0.0000

Variance Equation			
α_o	-0.1833*	-3.1930	0.0014
α_1	0.1428*	11.4369	0.0000
γ	0.0023	0.3713	0.7104
ω	0.9771*	237.35	0.0000
ψ	-0.0157*	-3.9782	0.0001
λ_1	0.1791***	1.9139	0.0556
λ_2	0.0167	0.2180	0.8274
λ_3	0.0687	0.8692	0.3847
λ_4	0.1167	1.1639	0.2444

Note: * Denotes 1% level of significance, ** denotes 5% level of significance and *** denotes 10% level of significance.

4.5.3 The Impact of News Flow on Spot Market

Table 4.10: Pre-futures results

Mean Equation			
Parameters	Coefficients	Significance	P Values
Constant	0.0921	1.3363	0.1814
Niftyt-1	0.0432	1.0446	0.2962
Nifty -2	-0.0075	-0.1961	0.8445
Nifty -3	0.0184	0.4600	0.6455
Nifty-4	-0.0021	-0.0580	0.9537
Nifty-5	-0.0625***	1.7200	-0.0854
Variance Equation			
Constant	0.4963*	3.2810	0.0010
ARCH	0.0688*	4.5131	0.0000
GARCH	0.7976*	16.8121	0.0000

Note: * Denotes 1% level of significance, ** denotes 5% level of significance and *** denotes 10% level of significance.

Table 4.11: Post-futures Results

Mean Equation			
Parameters	Coefficients	t-statistics	P Values
Constant	0.1486*	5.1175	0.0000
Niftyt-1	0.0782*	3.4439	0.0006
Nifty -2	-0.0277	-1.3146	0.1886
Nifty -3	-0.0109	-0.6158	0.5380
Nifty-4	0.0396**	2.0164	0.0438
Nifty-5	-0.0401***	-1.8916	0.0585
Variance Equation			
Constant	0.2073*	13.0357	0.0000
ARCH	0.1465*	15.9954	0.0000
GARCH	0.7833*	55.8406	0.0000

Note: *, ** and *** Denotes 1%, 5% and 10% level of significance respectively

To address the issue whether there has been any change in the information flow after the introduction of futures trading, the present study applies GARCH (1, 1) to estimate it. The results are reported in Tables 4.10 and 4.11. The ARCH and GARCH coefficients for the pre-futures are 0.0688 and 0.7976, respectively, implying that returns volatility was more determined by the GARCH effect. The coefficients or ARCH and GARCH in the post-futures are 0.14 and 0.78, respectively. It indicates that the impact of recent news flow has remained the same, while the recent information flow has been improved after the introduction of futures.

4.6: Empirical Analysis on Individual Stock Futures

This section examines the impact of spot market volatility on 15 individual stocks after the introduction of futures on the same stocks. The analysis begins with descriptive statistics of the individual stocks and is reported in Table 4.12. The dataset has taken into account stock splits, rights issues and bonus announcements. The stocks selected show a positive mean return. The skewness and kurtosis show that the stocks' returns series are not normal. Non-normality can also be shown by taking the Jarque-Bera test. The J-B test is highly significant for all the stocks and rejects the null hypotheses that the given series are normally distributed.

Table 4.12: Descriptive Statistics for Individual Stocks

Statistics	**Mean**	**Max**	**Min**	**SD**	**Skewnes**	**Kurtosis**	**JB**
ACC	0.00061	0.14342	-0.1741	0.02718	-0.1476	5.8573	1308.594
BHEL	0.00065	0.1660	-0.2343	0.02848	-0.0502	6.3843	1817.972
BPCL	0.00041	0.16403	-0.2251	0.02905	0.0694	6.1773	1604.064
CIPLA	0.00080	0.10218	-0.1546	0.02344	-0.0237	6.4857	1927.202
GRASIM	0.00048	0.15439	-0.2320	0.02615	-0.0923	7.5735	3322.536
HDFC	0.000890	0.20272	-0.1450	0.02514	0.3075	7.3009	2993.45
HINDALCO	0.00017	0.16756	-0.1917	0.02748	-0.1118	6.5989	2062.034
HINDLEVER	0.00042	0.11269	-0.1634	0.02093	0.0966	6.1863	1616.022
INFOSYS	0.00143	0.67321	-0.6995	0.0326	-0.5511	108.78	177495
ITC	0.00074	0.10966	-0.1089	0.0221	-0.0493	6.2847	1712.546

M&M	0.00056	0.21499	-0.1699	0.0292	0.0259	6.5445	1992.861
RANBAXY	0.00044	0.19248	-0.1990	0.0257	-0.1317	8.4139	4659.239
RELIANCE	0.00068	0.19366	-0.2915	0.0252	-0.3653	11.698	12084.38
SBIN	0.00056	0.18254	-0.1537	0.0256	0.0053	5.7985	1242.007
TATAPOWER	0.00053	0.20883	-0.2279	0.0273	-0.0294	8.6557	5073.177

The unit root test statistics for the individual stocks are reported in Table 4.13. The returns series for all the stocks are stationarity at 1% level, indicating all the return series are stationary at its level.

Table 4.13: Unit Root Test for Individual Stocks

	ADF Test Statistics			**Philips-Perron Test**		
Variables	**Without intercept**	**With intercept**	**With intercept and trend**	**Without intercept**	**With intercept**	**With intercept and trend**
ACC	-59.0157	-59.0375	-59.0328	-59.0178	-59.0330	-59.0276
BHEL	-45.4697	-45.4972	-45.4912	-58.1433	-58.1598	-58.1519
BPCL	-58.0494	-58.0529	-58.0457	-57.9922	-57.9939	-57.9864
CIPLA	-57.1153	-57.1715	-57.1854	-56.9601	-57.0107	-57.0235
GRASIM	-32.6857	-32.6857	-32.6852	-56.4893	-56.4897	-56.4839
HDFC	-29.4703	-29.4703	-29.4667	-59.9448	-60.4567	-60.4478
HINDALCO	-56.0800	-56.074	-56.0677	-56.0134	-56.0007	-56.0078
HINDLEVER	-60.2363	-60.2463	-60.2528	-60.9218	-61.0480	-61.0455
INFOSYS	-65.6893	-65.8152	-65.9007	-65.8224	-66.2792	-66.0725
ITC	-60.3246	-60.3844	-60.3765	-60.9673	-60.9673	-60.9582
M&M	-54.1148	54.1256	-54.1353	-53.8624	-53.8587	-53.8611
RANBAXY	-56.7638	-56.7712	-56.7713	-56.8032	-56.8085	-56.8098
RELIANCE	-58.6968	-58.7315	-58.7349	-58.6506	-58.7216	-58.7000
SBIN	-56.9345	-56.9473	-56.9529	-56.8986	-56.9068	-56.9011
TATAPOWER	-45.1641	-45.1834	-45.1797	-57.6425	-57.6565	-57.6503

Note: The coefficients of ADF and PP tests are significant at 1% level

Before estimating the GARCH-type models, it is essential to compute the Engle (1982) test for ARCH effects to make sure that this class of model is appropriate for the data. For all the stocks under investigation, the ARCH effects were found to be significant. Thus, it is appropriate now to use ARCH/GARCH technique for the data set on individual stocks. The results for the ARCH LM test are reported in Table 4.14.

Table 4.14: ARCH LM TEST Results for Stocks

Parameters	OBS*R-Squared	F-Statistics
Stocks		
ACC	276.9918*	99.4790
BHEL	292.6261*	105.5620
BPCL	166.3593*	57.9288
CIPLA	232.3158*	82.3901
GRASIM	184.0233*	64.3924
HDFC	224.2190*	79.3387
HINDALCO	439.7967*	165.5949
HINDLEVER	246.3269*	87.7032
INFOSYS	1243.205*	615.014
ITC	240.7975*	85.6015
M&M	287.3000*	103.4837
RANBAXY	318.3483*	115.6888
RELIANCE	101.3064*	34.6564
SBIN	274.9157*	98.6753
TATAPOWER	651.1316*	261.6066

Note: * Denotes 1% level of significance, ** denotes 5% level of significance and *** denotes 10% level of significance.

Table 4.15: Estimates for Individual Stock Volatility from EGARCH (1, 1) Mean Equation

$$R_t = \beta_o + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_4 Nifty + \varepsilon_t$$

$$\ln(\sigma^2{}_t) = \alpha_o + \alpha_1 \ln(\sigma^2_{t-1}) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma^2_{t-1}}} + \omega\left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma^2_{t-1}}} - \sqrt{\frac{2}{\pi}}\right] + \psi F_f$$

Mean Equation					
Coefficients	β_o	β_1	β_2	β_3	β_4
ACC	0.00029 (1.0437)	0.0027*** (0.1709)	-0.0240 (-1.4838)	-0.0179 (-1.0644)	0.9147* (56.1040)
BHEL	-0.00009 (-0.3382)	0.0387** (2.3853)	-0.0239 (-1.4043)	-0.0180 (-1.0541)	0.0024* (71.5308)
BPCL	0.00018 (0.4230)	0.0247*** (1.6074)	0.0007 (0.0446)	0.0130 (0.7979)	0.0621* (2.7417)
CIPLA	0.00022 (0.7793)	0.0556* (3.2905)	0.0238 (1.3551)	-0.0248 (-1.4355)	0.5975* (39.6286)
GRASIM	0.00063** (2.3382)	0.0297*** (1.7551)	-0.0361** (-2.0428)	-0.0011 (-0.0655)	0.0050 (0.2896)
HDFC	0.00064* (2.2398)	-0.0629* (-3.5905)	-0.0576* (-3.4967)	-0.049* (-2.8347)	-0.4076* (-13.8507)
HINDALCO	-0.00007 (-0.2343)	0.0383** (2.3174)	-0.0042 (-0.2536)	-0.039** (-2.3472)	0.8826* (49.1097)
HINDLEVER	0.0001 (0.5432)	0.0357* (2.2030)	-0.0194 (-1.1594)	-0.0166 (-0.9477)	0.6387* (53.3874)
INFOSYS	0.0014* (5.1342)	0.0902* (4.4596)	-0.0429** (-2.4381)	-0.0589* (-4.082)	0.9027* (135.20)
ITC	0.0004** (2.0506)	0.0195 (1.2398)	-0.0450* (-2.7799)	-0.0271 (-1.6237)	0.6497* (45.1269)
M&M	0.0004 (1.4056)	0.0489* (3.2685)	-0.0382* (-2.5084)	0.0009 (0.0554)	0.9984* (57.4686)
RANBAXY	0.00001 (0.0518)	0.0755* (5.1714)	-0.0095 (-0.5982)	0.0092 (0.5662)	0.5920* (38.3496)
RELIANCE	0.0002 (1.3422)	0.0111 (0.6157)	0.0028 (0.1673)	-0.0106 (-0.6772)	1.0796* (131.0588)
SBIN	0.00008 (0.3088)	0.0340** (2.1400)	0.0109 (0.6723)	-0.0056 (-0.3504)	1.0914* (87.1914)
TATAPOWER	0.00008 (0.3497)	0.0146 (0.8848)	-0.0488* (-2.8606)	-0.0629* (-3.6840)	0.8917* (56.9828)

Note: *, ** and *** Denotes 1%, 5% and 10% level of significance respectively and . Figures in the parenthesis represent t-statistics

The results estimated from EGARCH (1, 1) for the individual stocks of the mean equation and variance equation are shown in Table. 4.15 and 4.16, respectively. The coefficient of dummy variable is negative for all the stocks, indicating that volatility has been declining after the introduction of futures on individual stocks. But, the absolute values are very low, which suggests to the fact that though there is decline in volatility but the magnitude is very low for the respective individual stock. The coefficient of dummies is found to be significant at 1% level for the stocks: ACC, BHEL, Cipla, Grasim, Hindalco, Hindustan Unilever, ITC, Mahindra and Mahindra, Reliance, State Bank of India and Tata Power. The asymmetric parameter for most of the stocks is significant, implying leverage effect in volatility. The persistence coefficient as indicated by β shows higher degree of persistence in the volatility. The asymmetry coefficient for most of the stocks except for Infosys, State Bank of India, Reliance Industries and Tata Power found to be negative. It implies that the negative news increases the volatility more than the positive news.

Table 4.16: Estimates for Individual Stock Volatility from EGARCH (1, 1)

Variance Equation					
Coefficients	α_o	α_1	γ	ω	ψ
ACC	-0.3970* (-9.3690)	0.1520* (12.6492)	-0.0068 (-0.9907)	0.9607* (189.40)	-0.0448* (-6.2561)
BHEL	-0.4418* (-8.3050)	0.1695* (12.9067)	-0.0044 (-0.4805)	0.9559* (143.84)	-0.0548* (-8.6124)
BPCL	-0.1908* (-8.9965)	0.1098* (14.3796)	-0.0247* (-5.4382)	0.9844* (366.54)	-0.004** -1.8579
CIPLA	-0.9817* (-9.5995)	0.2106* (14.0207)	0.0179*** (1.9160)	0.8889* (69.35)	-0.0690* (-5.5829)
GRASIM	-0.4352* (-11.470)	0.2001* (16.3059)	-0.0291* (-4.8904)	0.9607* (215.48)	-0.0332* (-6.015)
HDFC	-0.4076* (-13.850)	0.208183* (19.4439)	-0.015** (-1.9790)	0.9649* (277.37)	-0.0206* (-5.3404)
HINDALCO	-0.3841* (-8.7232)	0.1573* (13.4680)	0.0044 (0.6024)	0.9641* (191.55)	-0.0151* (-4.4878)
HINDLEVER	-0.6840* (-9.2569)	0.1896* (13.1771)	-0.0033 (-0.3744)	0.9320* (107.18)	-0.0181* (-3.1420)
INFOSYS	-2.1962* (-21.245)	0.7192* (55.6312)	0.1250* (9.0117)	0.7581* (54.23)	-0.2474* (-5.3254)
ITC	-0.4743* (10.1878)	0.1707* (13.2006)	-0.0048 (-0.6572)	0.9543* (177.29)	-0.0388* (-7.2763)
M&M	-0.1685* (8.5155)	0.0967* (12.5894)	0.011*** (1.7035)	0.9862* (409.66)	-0.0155* (-5.5681)
RANBAXY	-0.1747* (-9.9334)	0.1237* (13.9512)	-0.0263* (-4.9167)	0.9890* (563.50)	-0.0025 (-1.2019)
RELIANCE	-1.9569* (-17.085)	0.4184* (31.0185)	0.0638* (5.6234)	0.7941* (57.79)	-0.1325* (-9.7548)
SBIN	-0.4447* (-9.1114)	0.1462* (12.525)	0.0249* (3.1492)	0.9576* (175.19)	-0.0151* (-4.0727)
TATAPOWER	-0.4252* (-11.852)	0.2140* (18.2992)	0.0190* (2.502)	0.9641* (227.027)	-0.0268* (-5.2350)

Note: *,**and *** Denotes 1%, 5% and 10% level of significance respectively, Figures in () represent t-value

To address the nature and structure of the volatility after the introduction of futures, the whole period is divided into pre-futures and post-futures and the GARCH (1, 1) technique has estimated separately for each sub-sample. The coefficient of ARCH typically interpreted as news (shock) coefficient that measures the impact of recent news on volatility. Similarly, the GARCH coefficient is known as the persistent coefficient and measures the impact of past volatility on current volatility. The results are reported in Table 4.17. In the case of ACC, BHEL, BPCL, HDFC, Hindalco, M&M, Ranbaxy, SBIN, the GARCH coefficient shows an increase while the ARCH coefficient decreases in the post-futures scenario. Higher values of GARCH in the post-futures period indicate that the impact of past volatility on current volatility has increased after the post-futures period. Similarly, the impact of recent news has declined in the post-futures period as indicted by the lower value of ARCH coefficients. For CIPLA, Grasim, Infosys, ITC and Reliance, there is increase in flow of recent news to the spot market and decline in the effect of old news after the introduction of futures. The ARCH and GARCH coefficients have increased in the case of Tata Power.

Table 4.17: Volatility Before and After the Introduction of Futures

Parameters	**Pre-futures**			**Post-futures**		
Stocks	**Constant**	**ARCH**	**GARCH**	**Constant**	**ARCH**	**GARCH**
ACC	0.0001 (4.1607)	0.1513 (5.9614)	0.7343 (17.1084)	0.00001 (6.4526)	0.1020 (11.670)	0.8669 (74.515)
BHEL	0.0002 (3.8241)	0.1257 (4.3465)	0.6873 (10.1956)	0.00001 (6.7756)	0.1097 (14.92)	0.8681 (94.110)
BPCL	0.00001 (3.2194)	0.0774 (6.5655)	0.9125 (77.8613)	0.00002 (4.7752)	0.0421 (11.77)	0.9430 (172.10)
CIPLA	0.00002 (4.4150)	0.0895 (6.5188)	0.8838 (56.3047)	0.00006 (8.578)	0.1321 (11.096)	0.7107 (25.304)
GRASIM	0.000003 (2.8783)	0.0414 (5.1067)	0.9559 (115.016)	0.00005 (10.745)	0.1574 (18.836)	0.8062 (86.978)
HDFC	0.00008 (6.9350)	0.1475 (8.3786)	0.7394 (26.2444)	0.00001 (5.7345)	0.0871 (9.7124)	0.8914 (83.374)
HINDALCO	0.0001 (6.2383)	0.1696 5.5612	0.6111 (11.1159)	0.00009 (6.2250)	0.0914 (10.8226)	0.9002 (104.07)
HINDLEVER	0.00003 (6.4808)	0.1149 7.1285	0.8229 (47.302)	0.00005 (6.146)	0.1395 (7.995)	0.6907 (16.738)
INFOSYS	0.000134 (5.043)	0.1862 (5.972)	0.7236 (19.256)	0.00009 (13.090)	0.5153 (42.395)	0.4781 (27.758)
ITC	0.00003 (4.053)	0.0703 (5.367)	0.8875 942.931)	0.00001 (8.1572)	0.1101 (10.958)	0.8370 (63.973)
M&M	0.00014 (4.0521)	0.1361 (4.676)	0.7396 (14.1646)	0.00001 (5.6457)	0.0787 (10.407)	0.8986 (99.309)

RANBAXY	0.000002 (3.0837)	0.1209 (9.3258)	0.8897 (92.3674)	0.00005 (8.0530)	0.1047 (11.275)	0.8586 (76.127)
RELIANCE	0.0001 (5.518)	0.1756 (7.036)	0.7000 (18.198)	0.00005 (9.748)	0.2454 (27.022)	0.6743 (43.201)
SBIN	0.00005 (4.6918)	0.1092 (5.8837)	0.8284 (35.8676)	0.00003 (6.0556)	0.0783 (10.195)	0.9043 (103.71)
TATAPOWER	0.00007 (4.384)	0.1007 (6.7499)	0.8180 (29.8574)	0.00001 (6.0798)	0.1221 (14.00)	0.8652 (103.21)

Note: The ARCH and GARCH coefficients are significant at one percent level. Figures in () represent t-value

4.7 Conclusions

The present chapter examined the impact of introduction of futures on the underlying on S&P CNX Nifty Index and Individual stocks traded on the Nifty index by using symmetric GARCH and asymmetric GARCH approaches. The results show that spot market volatility has reduced after the introduction of futures both on indices as well as individual stocks. The GARCH (1,1) model shows the presence of GARCH effects controlling for the day-of-the-week effect and domestic market factors. After controlling the market-wide factors, the volatility of the spot market gets reduced, implying that the reduction of volatility is mainly due to introduction futures trading. The asymmetric EGARCH model also shows that volatility has declined after the introduction of futures trading. The results of EGRACH model for individual stocks show significant decline in volatility after the introduction of futures on the stocks.

Further, this chapter examined the flow of information by employing GARCH (1, 1) model in pre- and post-futures scenarios. In the case Nifty index, the flow of recent news has increased to a great extent and flow of recent past news declined to some extent. The individual stocks ACC, BHEL, BPCL, HDFC, Hindalco, M&M, Ranbaxy, SBIN show an increase in past information and decline in current information flow post-futures scenario. In the case of CIPLA, Grasim, Infosys, ITC and Reliance stocks, there is an increase in the flow of recent news to the spot market and decline of the effect of old news in the post-derivatives period. To conclude, the volatility of the Nifty index and stocks have declined in the post-derivatives scenario and the nature and structure of the volatility in terms of the flow of information have also changed to a great extent.

The results indicate that variation in the returns across different days of the week is significant. On Mondays and Fridays, futures prices are showing very high impact on the underlying market. Thus, investors and traders could buy the stocks on days with abnormally low returns and sell the stocks on days with abnormally high returns. The day-of-the-week refers to the tendency of stocks to exhibit relatively large returns on these days as compared with other days. During these days, investors can earn a good amount of profit by taking positions at different extreme levels.

CHAPTER-V

Price Discovery in the Futures Market

5.1 Introduction

The essence of the price discovery functions depends on whether new information is reflected first in the futures markets or cash markets. Price discovery is the process whereby market participants attempt to find an equilibrium price. Price discovery describes how the information is transmitted into the prices across markets. Both markets contribute to the discovery of a unique and common unobservable price, which is the efficient price. The dynamic relationship between spot and futures price received much attention from academicians, regulators and practitioners. A well-developed and efficient financial market always fully reflects available information (Fama, 1970). Price discovery or transmission of information into prices is one of the important economic functions provided by the organised futures markets (Garbade and Silber (1979, 1983), Harris et al (1995), Hasbrouck (1995) and Abhyankar (1998). Price discovery implies that the futures market can be used for the pricing in the spot market (Working, 1948: Wiese, 1978). The ideal price discovery works when prices fairly reflect the supply and demand of all participants in the market. In a perfectly efficient market, there is no scope for arbitrage opportunity as price adjusts fully to incoming information.

The relationship between movements in prices of futures contracts and their underlying assets has been the subject of a significant amount of research. Many studies found that futures prices lead spot prices, where futures markets play an important role in the discovery process by disseminating new information faster than cash markets [Kawaller (1987), Harris (1989), Stoll and Whaley (1990), Chan (1992), Teppo (1995), Arshanpalli and Doukesh (1997), Alphones (2000), Lafuente (2002), Tenmozhi (2002), Kavussanos (2003), So and Tse (2004), and Bhatia (2007)]. Kavussanos and Nomikos (2003) defined that the lower cost of transaction in the futures markets may be the reason why futures markets seem to be informally more efficient than their corresponding spot markets. Studies like Wahab and Lashgari (1993), Pizzi et al(1998), Lien(2001), chen et al (2002), Lin et al (2002), Lin et al (2003), Mukherjee and Mishra (2006) and Thomas (2006) have found that spot markets disseminate price information to futures markets. Some studies found that the bi-directional causality exits between both the markets and price discovery takes place in both the cash and the futures market (Chan, 1991; Tang et al, 1992; Gorden et al, 1992; Turkingston and Walse, 1999; Zou and Pinfold, 2001; and Raju and Karande, 2003). Abhyankar (1995) studies on the FTSE-100 index and index futures found that the futures market lead the cash by an hour on an average. Stoll and Whaley (1990) studied on the S&P 500 index and MMI contracts and found that the futures market leads the cash with a lead time of five minutes.

In the Indian context, a few studies that have been carried out on it produced mixed results. Thenmozi (2002) and Raju and Karnade (2003) found a bi-directional causality between cash and futures markets. Thomas and Karnade (2002) and Sahadevan (2002) examined the price discovery in the commodities futures market.

With a brief introduction and identification of issues, this chapter is structured as follows. The section 5.2 provides a brief introduction to the theoretical relationship between cash and futures prices. The sections 5.3 and 5.4 discuss the data and methodology used in the study. The section 5.5 presents the empirical works and the last section concludes the chapter.

5.2 Theoretical Framework

The theoretical relationship between futures prices and spot prices can be described in terms of the Cost-of-Carry model and the Expectations model.

5.2.1 *The Cost-of-Carry Model*

The cost-of-carry model says that futures prices depend on the cash price of the asset and the cost of storing the underlying asset from the present to the delivery date of the futures contract.

The theoretical relationship between futures and spot prices can be explained by the Cost-Of-Carry model which can be defined as:

$$F_t = S_t e^{rT} \qquad (5.1)$$

Where, F_t = the futures price at time t,

S_t = the spot price at time t,

r = holding cost, and

T = time till expiration

If F >Se^{rT} or F <Se^{rT}, then arbitrage opportunities exist between the futures and the spot market. Arbitrageurs can take simultaneous positions in the underlying market and futures market, and hence lock the profit. When F >Se^{rT}, a long arbitrage profit can be earned by selling the futures contract, buying the spot index portfolio and financing the stock purchase with riskless borrowings. On the other hand, when F <Se^{rT}, a short profit can be earned by buying the futures and selling the portfolio of spots, investing the proceeds of the sale of stock at the riskless rate of interest (Stoll and Whaley, 1990).

5.2.2 *The Expectations Model*

In this model, the theoretical price relationship between two markets can be obtained by considering the relationship between risk and expected return in the economy. In general, the higher the risk of an investment, the higher will be the expected return. According to the Capital Asset Price Model, there are two types of risks: systematic and non-systematic. The non-systematic risk should not be important to an investor. It can be eliminated by holding a well-diversified portfolio. The systematic risk cannot be diversified away. An investor generally requires a higher expected return than the risk-free interest rate for bearing positive amounts of systematic risk. Also, an investor is prepared to accept a lower expected return than the risk-free interest rate when the systematic risk in an investment is negative. Let us consider a speculator who takes a long futures position in the hope that the spot price of the asset will be above the futures price at maturity. Suppose, that the speculator puts the present value of the futures price into a risk-free investment while simultaneously taking a long futures position. The proceeds of the risk-free investment are used to buy the asset on the delivery date. The asset is then immediately sold for its market price. The cash flows to the speculator are:

Time 0: $- F_0e^{-rT}$

Time T: $+ S_T$

Where, S_T is the price of the asset at time T. The present value of this investment is:

$$-F_0e^{-rT}+E(S_T)e^{-kT}$$

where, k is the discount rate appropriate for the investment and E denotes the expected value. Let us assume that all investment opportunities in securities markets have zero net present value:

$$-F_0e^{-rT}+E(S_T)e^{-kT}=0$$

$$Or\ F_0=E\ (S_T)\ e^{(r-k)\ T} \qquad (5.2)$$

The value of k depends on the systematic risk of the investment. If S_T is uncorrelated with the level of the stock market, the investment has zero systematic risk. In this case, k = r, and equation (2) that $F_0 = E\ (S_T)$. If S_T is positively correlated with the stock market as whole, the investment has positive systematic risk. In this case $k > r$ and the equation (2) shows that $F_0 < E\ (S_T)$. Finally, if S_T is negatively correlated with the stock market, the investment has negative systematic risk. In this case $k < r$, and equation (2) shows that $F_0 > E\ (S_T)$ (Hull, 2004).

5.3 Objectives of the Study

The objective of this chapter is to examine the price relationship between cash and futures markets and provide a comprehensive analysis of the Indian derivatives market. Specifically, the objectives of the study are:

a. To examine the existence of any causality between spot and futures market.
b. To know whether Indian stock index futures market effectively serves the price discovery function.

5.4 Data and Methodology

All the required data for the study have been taken from the National Stock Exchange (NSE) website. The main data set for the study consists of the daily closing values of the S&P CNX Nifty index futures and spot Nifty index, for the period from June 12, 2000 to April 30, 2012 for near-month futures contracts as the near-month futures contracts are the most liquid contracts in comparison with other contracts. In-sample analysis is carried out for the period of June 12, 2000 to March 31, 2012 and the remaining observations are considered to evaluate the out-of-sample forecasting performance of the model. Similarly, for the 15 stocks, the data set has been taken from November 9, 2001 to March 31, 2012. The futures trading in the stocks started on November 9, 2001. The study has taken *St* and *Ft* as logged spot and futures prices respectively.

First, stationarity[5] of the data series is tested with the help of Dicky Fuller (DF), Augmented Dicky Fuller (ADF) and Phillips Person Tests. After checking for the unit root in the data, Engle-Ganger co-integration approach followed by an error correction model are applied to capture both the long-run and short-run dynamics of spot and futures prices.

5.4.1 The Engle and Granger Cointegration Test

Cointegration is based on the long-term relationship between variables. Engle and Granger (1987) introduced the concept of cointegration approach where two variables move together, having a long-run equilibrium relationship, although individually they are non-satationary series. If two variables are integrated of order I(d) then any linear combination of the two series could be I(0), *i.e.*, the variables are cointegrated of order d-b. Further, Engle and Granger (1987) mentioned that if two series are cointegrated then they move together over time and their differences will be stationarity. Their long-run relationship is the equilibrium to which the system converges over time, and the disturbance term can be constructed as the disequilibrium error or the distance that the system is away from equilibrium.

Once the two variables are integrated of the same order, the next step is to estimate the parameters of co-integrating regression using the following equation.

$$Y_t = \alpha + \beta X_t + \mu_t \tag{5.3}$$

Where Y_t and X_t are integrated of order 1, *i.e.*, I (1). In order to find if X_t and Y_t are actually co-integrated, the OLS residual are obtained and tested for stationarity. If the residual series is stationarity then Y and X are cointegrated.

Engle and Granger (1987) have shown that if Y and X are both I(1), an error correction model exists. The following equations provide error correction framework for the above co-integrated equation.

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[5] For a detailed discussion on DF, ADF and PP test refer to Appendix 5.1

$$\Delta Y_t = \theta_1 + \sum_{i=1}^{m} \alpha_{1i} \Delta Y_{t-1} + \sum_{i=1}^{m} \beta_{1i} \Delta X_{t-1} + \psi_1 \mu_{t-1} + \varepsilon_{1t}$$

5.4

$$\Delta X_t = \theta_2 + \sum_{i=1}^{m} \alpha_{2i} \Delta Y_{t-1} + \sum_{i=1}^{m} \beta_{2i} \Delta X_{t-1} + \psi_2 \mu_{t-1} + \varepsilon_{2t}$$

5.5

Where μ_{t-1} the error is lagged one period and is derived from the cointegrating regression. In the above error correction model, the coefficient of one period lagged error term indicates the long-run deviations from the equilibrium point. ψ is the adjustment factor.

5.4.2 Johansen's Vector Error Correction Model (VECM)

Johansen (1988)'s Vector Error Correction Model (VECM) was employed to investigate the relationship between spot and futures prices. Johansen's maximum likelihood procedure provides a unified framework for estimating and testing the co-integration relationships in a vector error correction mechanism, which incorporates different short-term and long-term relationships in a dynamic system. In order to estimate the Johansen's Vector Error Correction Model (VECM) the following procedure is followed:

First, in order to know whether the data series are I (0) or I(1) process, it is necessary to test for unit root. The stationarity of the data is examined by Augmented Dicky Fuller (ADF) and Phillips Person (PP) tests.

Second, after confirming that the series are integrated in an identical order, the following equation of Johansen's Maximum Likelihood co-integrated test is applied to find out the long-run relationship between spot and futures prices.

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i X_{t-i} + \Pi X_{t-1} + \varepsilon_t \qquad 5.6$$

Where

$$\varepsilon_t = \begin{pmatrix} \varepsilon_{S,,t} \\ \varepsilon_{F,t} \end{pmatrix} \approx N(0, \Sigma),$$

$$\Pi = \left(\sum_{i=1}^{p} \beta_i \right) - I_g \text{ and } \Gamma = \left(\sum_{j=1}^{i} \beta_j \right) - I_g$$

Where $X_t = (S_t\ F_t)'$ is the vector of spot and futures prices, each being I (1) such that the first differenced series are I (0); Δ denotes the first difference operator; Γ and Π are 2×2 coefficient matrices measuring the short-and long-run adjustment coefficients.

Third, the lag length is selected on the basis of multivariate generalisations of Akaike's Information (AIC) and Schwarz's criteria.

Fourth, in order to identify the cointegration between the two variables, the likelihood tests are employed. Likelihood ratio tests are employed to identify the co-integration between the two series. The Trace test λ_{trace} is employed to test whether the number of cointegrating vectors is zero or one, and the Trace max test λ_{max} is employed to find out whether a single co-integrating equation is sufficient or if two are required. In Johansen's approach, the two test statistics for co-integration estimations are as follows; and r is the rank of the co-integrating vector.

$$\lambda_{Trace}(r) = -T \sum_{i=r+1}^{n} \ln\left(1 - \hat{\lambda}_i\right) \qquad 5.7$$

$$\lambda_{Max}(r, r+1) = -T \ln\left(1 - \hat{\lambda}_{r+1}\right) \qquad 5.8$$

Where, n is the number of separate series to be examined, T is the number of usable observations and ($\hat{\lambda}_i$) are the estimate design values (also called characteristic roots) obtained from the (i+1) × (i+1) 'co-integrating matrix.'

The first test statistic (λ_{trace}) measures whether the number of distinct co-integrating vectors is less than or equal to r. It involves a null hypothesis of no co-integrating vectors. If the null hypothesis is not rejected, it would mean that there are no co-integrating vectors. However, if null hypothesis of no co integrating vector is rejected, there is one or more co-integrating vector. The second test statistic (λ_{max}) measures the null that the number of co-integrating vectors is r against r+1.

Johansen and Jesuleus (1990) provide the critical values of these statistics. The rank of Π may be tested using the λ_{max} and λ_{trace}. If rank (Π) =1, then there is single co-integrating vector and Π can be factored as Π=αβ′, where α and β are 2×1 vectors. Using this factorization, β represents the vector of cointegrating parameters and α is the vector of error correction coefficients measuring the speed of convergence to the long-run steady state.

Lastly, using the methodology proposed by Granger (1986), it can be stated that if spot and futures prices are co-integrated, then causality exits at least in one direction. In order to test the causality, vector error correction model (VECM) is estimated for above cointegrating equation of the following form.

$$\Delta S_t = a_{S,0} + \sum_{i=1}^{p-1} a_{S,i}\Delta S_{t-i} + \sum_{i=1}^{p-1} b_{S,i}\Delta F_{t-i} + \alpha_S Z_{t-1} + \varepsilon_{S,t} \qquad 5.9$$

$$\Delta F_t = a_{F,0} + \sum_{i=1}^{p-1} a_{F,i}\Delta S_{t-i} + \sum_{i=1}^{p-1} b_{F,i}\Delta F_{t-i} + \alpha_F Z_{t-1} + \varepsilon_{F,t} \qquad 5.10$$

Where $a_{S,0}$ and $a_{F,0}$,are intercept terms, $a_{S,i}$,$b_{S,i}$, $a_{F,i}$, $b_{F,i}$ are the short-run coefficients and Z_{t-1} is the error correction term from equation.

The causality from the spot to futures exists if some of the coefficients $a_{S,i}$ are non-zero and/or the corresponding error correction coefficient is significant. Similarly, the causality from futures to spot exists if some of the coefficients $b_{F,i}$ are non-zero and/or the error correction term of the futures is significant. The reaction of the spot index and futures prices to the disequilibrium errors are captured by the coefficient of the error term or the speed of adjustment coefficient.

The Vector Error Correction Model (VECM) technique provides a framework for valid inference in the presence of I (1) variable. Moreover, the Johansen (1988) procedure provides more efficient estimates of the co-integrating relationship than the Engel and Granger (1987) estimator (Gonzalo, 1994). Also, Johansen (1988) tests are shown to be fairly robust to presence of non-normality (Cheung and Lai, 1993) and heteroscedasticity disturbances (Lee and Tse, 1996). Along with it, the Granger-causality test is applied on return series to test the consistency of the results.

5.4.3 Forecasting Models

Futures contract prices provide an indication towards the forecast spot prices. Forecasting of the futures prices may provide an indication of the extent futures prices guide the spot prices. Thus, the present chapter employs Auto Regressive Integrated Moving Average (ARIMA), Vector Auto Regression (VAR) and Vector Error Correction (VECM) models to compare the forecasting ability of the futures prices. Further, the study measures the forecast performance.

The Vector Error Correction Model

The forecasting equation of the Vector Error Correction Model (VECM) for the spot and futures return prices can be expressed as:

$$\Delta S_t = a_{S,0} + \sum_{i=1}^{p-1} a_{S,i}\Delta S_{t-i} + \sum_{i=1}^{p-1} b_{S,i}\Delta F_{t-i} + \alpha_S Z_{t-1} + \varepsilon_{S,t} \qquad 5.11$$

where Z_{t-1} is the error correction term.

The VAR Model

An unrestricted vector auto regression model (VAR) is also estimated for the spot and futures prices. Additionally, the purpose is to consider the explanatory and forecasting power of the cointegrating term in the VECM. The equation of the VAR which has the spot return as dependent variables may be expressed as:

$$\Delta S_t = \theta_{S,0} + \sum_{i=1}^{p-1} \theta_{S,i}\Delta S_{t-i} + \sum_{i=1}^{p-1} \phi_{S,i}\Delta F_{t-i} + \nu_{S,t} \qquad 5.12$$

The Akaike's information criteria (AIC) and Schwarz's criteria (SC) is employed to determine the appropriate number of lags (Brooks, et al., 2001).

The ARIMA Model

Lastly, an ARIMA model is used for the forecasting comparisons (with S_t as the dependent variable since prediction of the spot series is the modeling motivation). An ARIMA (*p, d, q*) model is a univariate time series modeling technique, where *p* denotes the number of autoregressive terms, d the number of integrated order and *q* the number of moving average terms which is based on Box-Jenkins methodology (Box-Jenkins, 1970). The ARIMA model may be expressed as:

$$S_t = \alpha_{S,0} + \sum_{i=1}^{p-1} \alpha_{S,i} S_{t-i} + \sum_{i=1}^{q-1} \beta_{S,i} \upsilon_{t-i} + \upsilon_{S,t} \quad 5.13$$

Again the Akaike's information criteria (AIC) and Schwarz's criteria (SC) are utilized for selecting lags of the model.

Further, the study employs Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) to measure the forecast performance[6].

5.5 Empirical Results and Discussions

In order to test the cointegration of the series, the first requirement is that the series must be non-stationarity at level. To test the non-stationarity of the data, the Dickey and Fuller (1979), Augmented Dickey Fuller and Phillips and Perron (1988) tests have been performed for the series in log form. The results of unit root test of Nifty Index and Nifty futures are shown in Table 5.1. The results indicate that both the Nifty and the Nifty Futures index are non-stationarity at their levels and stationarity at their first difference, and confirm that the variables are I(1). The results further imply that there could be existence of a long-run relationship between spot and futures prices.

Table 5.1: Unit Root Test Results

Constraint	**DF**		**ADF**		**PP**	
	Levels	**Difference**	**Levels**	**Difference**	**Levels**	**Difference**
Logged Spot price						
Intercept	0.4514	-8.2345*	-0.6113	-50.3559*	-0.5742	-50.3072*
Intercept and Trend	-1.4957	-48.4153*	-2.2658	-50.3485*	-2.2019	-50.2997*
Logged Futures price						
Intercept	0.4857	-846049*	-0.5688	-52.8616*	-0.5749	-52.8494*
Intercept and Trend	-1.4482	-8.3105*	-2.2618	-52.8560*	-2.2679	-52.8416*

Note: * Indicates 1% level of Significance.

[6] For derivation of RMSE, MAE and MAPE (Appendix 5.2)

Johansen's cointegration test (1988) has also been performed for Nifty Index spot and Nifty futures prices for the number of cointegrating vectors. The results are presented in Table 5.2. The results of the test statistics for $r \leq 1$ are greater than critical values at 1% level, indicating that the null of zero cointegrating vectors are rejected at 1% level. So, the spot and futures prices are integrated of order one at its level. The lag length selected for Johansen's cointegration test is 3, which satisfies the Akaike's Information Criteria (AIC) and Schwarz Information Criteria (SC)·

Table 5.2: Co-integration Tests of Johansen

Null Hypothesis	Alternative Hypothesis			5 % critical value
λ_{trace} tests		Eigen value	(λ_{trace}) Stat.	
$r = 0*$	$r > 0$	0.043698	120.3646	15.49471
$r \leq 1$	$r > 1$	0.0000314	0.081535	3.841466
$\lambda_{\max}$ test		Eigen value	$\lambda_{\max}$ Stat.	
$r = 0*$	$r = 1$	0.150111	438.3975	14.26460
$r = 1$	$r = 2$	0.0000214	0.057884	3.841466

Johansen's λ_{max} and λ_{trace} statistics reveal that the Nifty Index and Nifty futures prices stand in a long-run relationship with each other, as the null of no cointegration is rejected in both the cases. As pointed by Granger (1988), if two prices are co-integrated, then causality must exist in one direction.

Thus, a vector error correction model (VECM) is applied for showing short-run dynamics. The results obtained from the VECM are reported in Table 5.3. The results indicate that 18% of the adjustment is achieved in the spot market and 31% of the disequilibrium error is corrected in the futures market. This indicates that the futures price series *Ft* have a greater speed of adjustment to the previous period's deviation from long-run equilibrium than the spot price series. The coefficients of $a_{S,i}$, $b_{F,i}$ and error correction term suggest that there exists a bi-directional causality between two markets but the price discovery happens in the spot market as indicated by the lagged coefficients of the spot prices.

Table 5.3: Results for the Vector Error Correction Model

$$\Delta S_t = a_{S,0} + \sum_{i=1}^{p-1} a_{S,i} \Delta S_{t-i} + \sum_{i=1}^{p-1} b_{S,i} \Delta F_{t-i} + \alpha_S Z_{t-1} + \varepsilon_{S,t}$$

$$\Delta F_t = a_{F,0} + \sum_{i=1}^{p-1} a_{F,i} \Delta S_{t-i} + \sum_{i=1}^{p-1} b_{F,i} \Delta F_{t-i} + \alpha_F Z_{t-1} + \varepsilon_{F,t}$$

Parameters	ΔS_t	**t-statistics**	ΔF_t	**t-statistics**
α_i i=s,f	0.000406	1.3417	0.000407	1.27568
ΔS_{t-1}	-0.036030	-0.2778	0.2301***	1.6847
ΔS_{t-2}	-0.0775	-0.5894	0.1050	0.7582
ΔS_{t-3}	-0.1606	-1.2321	-0.0396	-0.2884
ΔS_{t-4}	0.0696	0.5368	0.1708	1.2509
ΔS_{t-5}	0.1092	0.8549	0.2267***	1.6849
ΔS_{t-6}	-0.1469	-1.1652	-0.0886	-0.6676
ΔS_{t-7}	-0.1605	-1.3016	-0.0369	-0.2843
ΔS_{t-8}	-0.0335	-0.2791	-0.0042	-0.0336
ΔF_{t-1}	0.1144	0.9182	-0.1756	-1.3384
ΔF_{t-2}	0.0343	0.2697	-0.1370	-1.0216
ΔF_{t-3}	0.1591	1.2619	0.0417	0.3140
ΔF_{t-4}	-0.0426	-0.3401	-0.1424	-1.0788
ΔF_{t-5}	-0.1155	-0.9367	-0.2293***	-1.7651
ΔF_{t-6}	0.0941	0.7739	0.0365	0.2857
ΔF_{t-7}	0.1713	1.4411	0.0551	0.4406
ΔF_{t-8}	0.0716	0.6208	0.0415	0.3419
Z_{t-1}	-0.1877**	2.2768	-0.3127*	-3.6007

Note: * Denotes 1% level of significance, ** denotes 5% level of significance and *** denotes 10% level of significance.

The results of forecasting are reported in Table 5.4. The best forecasting model would be the one that produces the lowest RMSE, MAE, MAPE statistics. The results illustrate that VAR and VECM models perform reasonably well as compared with the ARIMA model. In case of fifteen- and twenty-day forecasting horizons, the VAR model performs better than ARIMA and VECM as indicated by the lowest values of MAE and MAPE. The overall results suggest that the VECM forecasting model outperforms ARIMA and VAR models. From the above results, it can be interpreted that forecasting accuracy can be improved by using the causal relationship between the spot and futures markets rather than simply using information contained in the univariate spot prices.

Table 5.4: Forecasting Results

Horizon	Methods	ARIMA	VAR	VECM
1	RMSE	0.0331	0.0155	0.0153
	MAE	0.0341	0.0155	0.0154
	MAPE	1.5888	0.1288	0.1049
2	RMSE	0.0249	0.0110	0.0108
	MAE	0.0225	0.0081	0.0077
	MAPE	5.3695	0.2008	0.2109
3	RMSE	0.0206	0.0091	0.0089
	MAE	0.0171	0.0064	0.0060
	MAPE	3.0707	0.0702	0.1580
4	RMSE	0.0179	0.0079	0.0077
	MAE	0.0131	0.0050	0.0047
	MAPE	2.1355	0.1985	0.2034
5	RMSE	0.0206	0.0078	0.0076
	MAE	0.0163	0.0054	0.0052
	MAPE	2.9227	0.0201	0.0100
10	RMSE	0.0222	0.0122	0.0122
	MAE	0.0164	0.0091	0.0090
	MAPE	1.0785	0.0177	0.0669
15	RMSE	0.0187	0.0112	0.0111
	MAE	0.0138	0.0083	0.0083
	MAPE	1.6088	0.0225	0.0454
20	RMSE	0.0175	0.0116	0.0116
	MAE	0.0133	0.0091	0.0091
	MAPE	0.7131	0.0072	0.0137

5.5.1 Stock Futures Analysis

The results of ADF unit root tests for stock futures and spot prices at level and first difference are presented in Table 5.5. The log stock price is non-stationarity at level and stationarity at the first difference. Thus, it fulfills the requirement for the co-integration test. The ADF test confirms that the stocks are non-stationarity in their level, but stationarity at the first difference. It indicates that the two series are I (1).

The long-run relationship between stock futures and spot prices is estimated using Engle-Grange cointegration test and the error correction model is also provided to understand the short-run dynamics.

As the two series are integrated of order one, Engle-Granger and Johansen VECM can be used to test the co-integration between the two variables. In order to test the Engle-Granger co-integration test the following procedure has been followed It is necessary to check whether two variables are co-integrated. If the error terms are stationarity, then the two variables are cointegrated. First, therefore, the long-run cointegrating equations are estimated using OLS.

Second, after estimating the OLS regression of the two variables, the residuals are generated to test the stationarity of the series. In order to test the unit root, ADF test is employed and the results are presented in Table: 5.6. The results obtained from the unit root test for stationarity shows that the null hypothesis of unit root are rejected at 1% level of significance for all the stocks under investigation. It implies that long-run relationship exists between the spot and futures prices for all the stocks.

5.5.2 VECM Analysis for Stock Futures

The unit root results show that both futures and cash prices are non-stationarity at levels but stationarity at first difference, and it shows that both markets may have strong co-integration relationship over the long-run. The same has been confirmed using Johanson's co-integration tests. The two statistics ($\lambda_{\max}$ and (λ_{trace}) generated from the test are presented in Table 5.8, which indicate strong evidence that futures and cash markets are equilibrium in the long run. Existence of co-integration suggests that both the markets may be in disequilibrium in the short run but such deviations are corrected by the arbitrage process (Vipul, 2005). Thus, the existence of a long-run relationship between two markets has implications for the traders in the futures market. In order to check whether short-run disequilibrium exists, granger causality and Vector Autoregression (VAR) based on VECM have been applied.

The residual unit root test establishes a long-run relationship between spot and futures prices. Thus VECM model is employed to estimate the short-run disequilibrium. The results are presented in Table 5.7. The reaction of the spot stock prices and futures prices to the disequilibrium errors are captured by the coefficient of the error term or the speed of adjustment coefficient. Further, in all the cases, the speed of adjustment is higher in case of spot prices as compared with the futures prices. The coefficients of ΔF_{t-i} are significant in most of the spot price equations and the coefficients of ΔS_{t-i} are not significant in most of the futures prices equations. Hence it can be said that futures prices are causing spot prices and not vice-versa. Therefore, there is only one directional causality from futures to spot prices.

Granger causality tests are conducted using index returns and stock returns, and the results are presented in Table 5.9. Different lags are used for different stocks based on the lag length criteria. The results show mixed evidence of the response of one return series to the lagged returns of other series. There is unidirectional causality from Nifty index to nifty futures and reveal that there is causality from spot market to futures market. This result is consistent with the results obtained from vector error correction mechanism. *GRASIM, Mahindra and Mahindra, Ranbaxy and Housing Development Finance Corporation Ltd* observe bilateral causality whereas *ACC, Bharat Heavy Electricals Limited, Bharat Petroleum Corporation Ltd. Cipla Ltd., Hindalco Industries Limited, Hindustan Lever Ltd. Infosys Technologies, ITC, Reliance, State Bank of India and Tata Power* observe uni-directional causality. The uni-directional causality is from futures to spot indicating that strong lead lag relationship exists between the two markets. In the case of stocks, the causality from futures to spot market is quite visible for the stocks included in the sample size, and for the index, the causality is from spot to futures.

5.6 Conclusions

Price discovery serves an important function of the futures market. Thus, the present chapter examined price discovery and causality of the S&P CNX nifty index futures individual stocks futures listed on the nifty index. The unit root tests for index futures and stock futures reveal that both futures and spot prices are co-integrated indicating possibility of long-run relationship between the variables. The cointegration of the variables was again conformed from the stationarity of the residuals generated from estimation of both the series. To check whether short-run disequilibrium exists, Granger causality and Vector Autoregression (VAR) based on VECM have been applied. The results of the S&P Nifty futures reveal that causality exists from spot market to futures market and price discovery happens in both the market in the case of nifty index. These results are consistent with previous results. The forecasting results show that the VECM model provides better results than ARIMA and VAR models. The implication of the forecasting results is that, forecast accuracy can be further improved by making use of the long-term relationship between the spot and futures markets in an error correction model rather than using ARIMA and VAR models, which by definition will lose any long-term properties of the data.

The analyses of price discovery and causality are extended to some selected stocks. VECM and Engel Granger models provide mixed results. There is unidirectional causality for the scrips *ACC, Bharat Heavy Electricals Limited, Bharat Petroleum Corporation Ltd. Hindustan Lever Ltd., Housing Development Finance Corporation Ltd, Infosys Technologies, ITC, Reliance, State Bank of India and Tata Power.* The uni-directional causality is from futures to spot indicating that strong causality relationship exists between the two markets. Scrips *Cipla Ltd., Hindalco Industries Limited, Mahindra and Mahindra and Ranbaxy, observe a bidirectional causality.* The feedback relationship exists in case of index futures and some of the stock futures, and at the same time for some stocks both-way causation takes place. Thus, it can be concluded that both spot and futures prices have an important role to play in price discovery.

Table 5.5: Unit Root Test for Individual Scripts (ADF Test)

Series	Level			Difference		
	Intercept	Intercept and Trend	None	Intercept	Intercept and Trend	None
ACC Spot	-1.1697	-1.5795	1.6226	-46.7029	-46.6970	-46.6529
ACC Futures	-1.1787	-1.6115	1.5826	-47.0793	-47.0732	-47.0312
BHEL	-1.8611	-1.2463	1.6506	-35.9003	-35.9380	-35.8279
BHEL Futures	-1.8559	-1.2464	1.6525	-36.1607	-36.1979	-36.0885
BPCL Spot	-2.5437	-3.3141	0.8398	-47.1252	-47.1177	-47.117
BPCL Futures	-2.5600	-3.3424	0.8276	-46.5680	-46.5609	-46.560
CIPLA Spot	-2.0733	-2.1886	-0.7871	-47.2080	-47.2082	-47.2116
CIPLA Futures	-2.0765	-2.1945	-0.7891	-47.1699	-47.1699	-47.1736
GRASIM Spot	-1.8422	-1.2415	1.7573	-46.3274	-46.3541	-46.2644
GRASIM Futures	-1.8288	-1.2668	1.7146	-46.6423	-46.6678	-46.5815
HDFC Spot	-1.6525	-1.6108	-0.142	-49.168	-49.1701	49.1793
HDFC Futures	-1.6395	-1.6015	-0.149	-49.1000	-49.1011	-49.1105
Hindalco Spot	-1.4294	-1.8866	-0.654	-47.6875	-47.6785	-47.6942
Hindalco Futures	-1.4278	-1.9016	-0.6476	-47.7761	-47.7671	-47.7671
Hindlever Spot	-1.7773	-3.0682	0.2143	-48.0355	-48.0359	-48.0440
Hindlever Futures	-1.7466	-3.0244	0.2210	-48.3079	-48.3086	-48.3163
ITC Spot	-1.7312	-2.5158	-0.6790	-47.7501	-47.7400	-47.7562
ITC Futures	-1.7565	-2.5472	-0.6772	-48.2814	-48.2712	-48.2876
INFY Spot	-2.4232	-2.6162	-0.0678	-48.4388	-48.4313	-48.4491
INFY Futures	-2.4018	-2.5907	-0.0660	-48.3548	-48.3473	-48.3650
Mahindra Spot	-2.0860	-1.9792	0.9446	-45.1184	-45.1325	-45.0981
Mahindra Futures	-2.0788	-1.9761	0.9413	-45.1902	-45.2039	-45.1702
Ranbaxy Spot	-1.5885	-2.0076	-0.4231	46.46403	-46.4541	-46.4724
Ranbaxy Futures	-1.6117	-2.0417	-0.4269	-46.8785	-46.8685	-46.8869
Reliance Spot	-1.6001	-1.1563	0.8336	-47.2601	-47.2753	-47.2504
Reliance Futures	-1.6003	-1.1547	0.8252	-47.7098	-47.7256	-47.7001
SBI Spot	-1.2369	-2.8862	1.9091	-45.2046	-45.1992	-45.1261
SBI Futures	-1.2140	-2.7512	1.9963	-46.2583	-46.2529	-46.1812
Tata Power Spot	-1.0783	-2.1524	1.7391	-36.009	-36.0062	-35.9391
Tata Power Futures	-1.0861	-2.1797	1.7170	36.2146	-36.2110	-36.1458

Note: The ADF test for stocks are significant at 1% level in first difference

Table 5.6: OLS Results and Unit Root Test Results from Residuals

Scrips	Constant	Slope	R^2	ADF
ACC	-0.01141* (-3.43)	1.0017* (1884.88)	0.9992	-25.058
BHEL	-0.0018* (-0.7172)	1.0001* (2890.32)	0.9996	-44.82
BPCL	0.0197* 2.6458	0.9966* (798.041)	0.9959	24.16
CIPLA	0.0021 (0.4803)	0.9993* (1710.80)	0.9991	-46.99
GRASIM	-0.0046 (-1.2260)	1.0004* (1934.82)	0.9993	-18.07
HDFC	0.0109* (2.7244)	0.9984* (1958.37)	0.9993	-36.30
HINDALCO	0.0252* (3.0629)	0.9961* (860.90)	0.9965	-44.43
HINDLEVER	0.0214* (3.37)	0.9960* (843.42)	0.9963	-23.73
INFOSYS	0.0066 (1.4914)	0.9991* (2085.24)	0.9994	-48.93
ITC	0.0071*** (1.9236)	0.9989* (2055.03)	0.9993	-41.45
M&M	0.0017 (0.6597)	0.9995* (2570.02)	0.9996	-29.79
RANBAXY	0.0205*** (1.7184)	0.9968* (590.67)	0.9926	-11.70
RELIANCE	0.0027 (0.7722)	0.9991* (1950.60)	0.9993	-48.24
SBIN	-0.0069** (-1.9927)	1.0006* (1983.80)	0.9993	-44.49
TATAPOWER	-0.0041 (-1.2806)	1.0005* (1962.79)	0.9993	-42.80

Notes: Figures in ( ) are t-statistics. The 1% critical Value for the ADF Statistics is -2.5658.

*,** and *** Indicate significance at 1%, 5% and 10% levels, respectively.

Table 5.7: Johansen's Co-integration Test Results

	Null/Alternative Hypothesis	Trace Statistic	Max-Eigen Statistics
ACC	r=0	128.78	127.68
ACC Futures	r ≤ 1	1.10	1.101
BHEL	r=0	252.14	247.35
BHEL Futures	r ≤ 1	4.78	4.789
BPCL Futures	r ≤ 1	6.01	6.010
CIPLA	r=0	247.01	246.11
CIPLA Futures	r ≤ 1	0.9057	0.9057
Grasim	r=0	211.81	207.76
Grasim Futures	r ≤ 1	4.05	4.052
HDFC	r=0	236.14	235.05
HDFC Futures	r ≤ 1	1.09	1.091
Hindalco	r=0	233.86	229.39
Hindalco futures	r ≤ 1	4.46	4.464
Hindlever	r=0	167.49	166.90
Hindlever futures	r ≤ 1	0.5860	0.5861
ITC	r=0	204.13	203.93
ITC futures	r ≤ 1	0.1949	0.194
Infosys	r=0	183.87	182.27
Infosys futures	r ≤ 1	1.59	1.599711
M&M	r=0	135.30	132.54
M&M Futures	r ≤ 1	2.75	2.75
Ranbaxy	r=0	127.12	118.62
Ranbaxy futures	r ≤ 1	8.49	8.49
Reliance	r=0	199.45	197.26
Reliance futures	r ≤ 1	2.19	2.196
SBI	r=0	192.74	189.83
SBI Futures	r ≤ 1	2.91	2.912
Tata Power	r=0	144.39	142.32
Tata Power futures	r ≤ 1	2.07	2.07

Table 5.8: Results for the Vector Error Correction Model

$$\Delta S_t = a_{S,0} + \sum_{i=1}^{p-1} a_{S,i}\Delta S_{t-i} + \sum_{i=1}^{p-1} b_{S,i}\Delta F_{t-i} + \alpha_S Z_{t-1} + \varepsilon_{S,t}$$

$$\Delta F_t = a_{F,0} + \sum_{i=1}^{p-1} a_{F,i}\Delta S_{t-i} + \sum_{i=1}^{p-1} b_{F,i}\Delta F_{t-i} + \alpha_F Z_{t-1} + \varepsilon_{F,t}$$

Variables	**ACC** ΔS_t	**ACC** ΔF_t	**BHEL** ΔS_t	**BHEL** ΔF_t	**BPCL** ΔS_t	**BPCL** ΔF_t
Z_{t-1}	-0.4109* (-9.6862)	0.0549 (0.8121)	-0.55* (-10.808)	0.2426* (3.3738)	-0.4650* (-10.899)	0.0540 (0.8810)
ΔS_{t-1}	-0.4060* (-9.3932)	-0.0674 (-0.9775)	-0.0678 (-1.3827)	-0.0220 (-0.3198)	-0.3196* (-7.5051)	0.0117 (0.1920)
ΔS_{t-2}	-0.3465* (-8.1632)	-0.0957 (-1.4123)	-0.1835* (-4.0271)	-0.121** (-1.994)	-0.2464* (-6.0284)	-0.0177 (-0.3015)
ΔS_{t-3}	-0.2824* (-6.8670)	-0.0918 (-1.3993)	-0.1041* (-2.4972)	-0.0434 (-0.7403)	-0.1340* (-3.4891)	0.0115 (0.2086)
ΔS_{t-4}	-0.1559* (-3.9712)	0.0228 (0.3649)	-0.1388* (-3.6900)	-0.09*** (-1.8347)	-0.082** (-2.3900)	0.0082 (0.1671)
ΔS_{t-5}	-0.1247* (-3.4523)	0.0084 (0.1465)	-0.1084* (3.3242)	-0.0541 (-1.1779)	-0.0393 (-1.3607)	0.0461 (1.1092)
ΔS_{t-6}	-0.0930* (-2.9022)	0.0363 (0.7098)	-0.0713* (-2.6095)	-0.0241 (-0.6269)	-0.0189 (-1.0726)	0.0134 (0.5282)
ΔS_{t-7}	-0.0280 (-1.0632)	0.0492 (1.1697)	-0.0006 (-0.0380)	0.0255 (1.0462)		
ΔS_{t-8}	-0.0173 (-1.1470)	0.0060 (0.2493)				
ΔF_{t-1}	0.5000* (11.6748)	0.0860 (1.2581)	0.3057* (6.1298)	0.2248* (3.2028)	0.4411* (10.3428)	0.0600 (0.9793)
ΔF_{t-2}	0.3553* (8.2982)	0.0495 (0.7254)	0.0522 (1.1093)	-0.0333 (-0.5036)	0.2552* (6.1204)	-0.0116 (-0.1946)
ΔF_{t-3}	0.3044* (7.2931)	0.0839 (1.2602)	0.1558* (3.5809)	0.102*** (1.6809)	0.2031* (5.1311)	0.0272 (0.4789)
ΔF_{t-4}	0.2546* (6.3377)	0.0635 (0.9907)	0.1004* (2.5334)	0.0531 (0.9516)	0.1051* (2.8676)	-0.0195 (-0.3715)
ΔF_{t-5}	0.1375* (3.6084)	-0.0141 (-0.2329)	0.1173* (3.3205)	0.0365 (0.7344)	0.0730** (2.2833)	-0.0329 (-0.7150)
ΔF_{t-6}	0.1039* (2.9900)	-0.0240 (-0.4326)	0.0769* (2.5909)	0.0023 (0.0552)	0.0235 (0.9393)	-0.0278 (-0.7737)
ΔF_{t-7}	0.0783* (2.5999)	-0.0137 (-0.28553)	0.0404 (1.6796)	0.0226 (0.6682)		
ΔF_{t-8}	0.0181 (0.7742)	-0.0165 (-0.4422)				
C	0.0005** (1.9445)	0.0007 (1.4071)	0.0008* (2.5098)	0.001** (2.0260)	0.0003 (1.020)	0.0004 0.92896

Note: Figures in ( ) are t-statistics.

*,** and *** Indicates significance at 1%, 5% and 10% levels, respectively.

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Table 5.8: (continued)

Variables	CIPLA ΔS_t	CIPLA ΔF_t	GRASIM ΔS_t	GRASIM ΔF_t	HDFC ΔS_t	HDFC ΔF_t
Z_{t-1}	-0.5194* (-11.7478)	0.1583** (2.3005)	-0.4638* (-12.101)	0.0732 (1.0703)	-0.5663* (-12.159)	0.2070* (2.6284)
ΔS_{t-1}	-0.2759* (-6.4321)	-0.0806 (-1.2079)	-0.2730* (-7.1262)	0.0750 (1.0962)	-0.2657* (-5.924)	-0.2262* (-2.9825)
ΔS_{t-2}	-0.1970* (-4.8432)	-0.0823 (-1.2999)	-0.2822* (-7.7074)	0.0086 (0.1322)	-0.2417* (-5.7384)	-0.2002* (-2.8112)
ΔS_{t-3}	-0.1750* (-4.6865)	-0.0836 (-1.4391)	-0.1730* (-5.0668)	0.0337 (0.5528)	-0.1149* (-2.9251)	-0.1059 (-1.5938)
ΔS_{t-4}	-0.0561*** (-1.6984)	-0.0422 (-0.8210)	-0.0993* (-3.3049)	0.0737 (1.3734)	-0.0882* (-2.4467)	-0.1249** (-2.0495)
ΔS_{t-5}	-0.0533** (-1.9636)	-0.0402 (-0.9516)	-0.0205 (-0.8253)	0.0703 (1.5797)	-0.1269* (-4.0690)	-0.105** (-1.9922)
ΔS_{t-6}	-0.0220 (-1.4330)	0.0155 (0.6476)	-0.0080 (-0.6221)	0.0503** (2.1926)	-0.0626* (-2.5131)	-0.0556 (-1.3208)
ΔS_{t-7}					-0.0125 (-0.9425)	-0.0096 (-0.4267)
ΔF_{t-1}	0.4092* (9.4366)	0.1526 (1.2617)	0.4657* (12.1778)	0.0609 (0.8915)	0.3811* (8.3236)	0.2411* (3.1139)
ΔF_{t-2}	0.2350* (5.6239)	0.0703 (1.0820)	0.2377* (6.3032)	-0.0779 (-1.1569)	0.2536* (5.7871)	0.130*** (1.7610)
ΔF_{t-3}	0.1703* (4.3283)	0.0415 (0.6788)	0.2571* (7.1981)	0.0347 (0.5440)	0.2198* (5.3568)	0.1448** (2.0875)
ΔF_{t-4}	0.1512* (4.2515)	0.091 (1.6486)	0.1569* (4.7651)	-0.0118 (-0.2012)	0.0878** (2.2964)	0.0704 (1.0884)
ΔF_{t-5}	0.0362 (1.1725)	0.0075 (0.1578)	0.0857* (3.0342)	-0.0172 (-0.3409)	0.0689** (1.9810)	0.0188 (0.3195)
ΔF_{t-6}	0.0164 (0.6855)	-0.0465 (-1.2502)	0.0144 (0.6510)	-0.0527 (-1.3265)	0.1078* (3.6381)	0.0580 (1.1587)
ΔF_{t-7}					0.0432*** (1.8830)	0.01538 (0.3961)
Constant	0.00036 (1.4404)	0.00047 (1.2136)	0.00055** (2.2421)	0.00065 (1.4670)	0.00065** (2.3333)	0.00101** (2.0337)

Note: Figures in ( ) are t-statistics.

*,** and *** Indicates significance at 1%, 5% and 10% levels, respectively.

Table 5.8: (continued)

Variables	Hindalco ΔS_t	Hindalco ΔF_t	Hindlever ΔS_t	Hindlever ΔF_t	ITC ΔS_t	ITC ΔF_t
Z_{t-1}	-0.5725* (-13.620)	-0.0131 (-0.1708)	-0.3320* (-9.0349)	0.1509* (2.8122)	-0.3947* (-11.044)	0.1587* (2.9183)
ΔS_{t-1}	-0.2130* (-5.1748)	0.0164 (0.2192)	-0.3808* (-9.9835)	-0.0741 (-1.3307)	-0.2944* (-8.1316)	-0.121** (-2.2064)
ΔS_{t-2}	-0.1601* (-4.0791)	-0.0192 (-0.2693)	-0.2681* (-7.1198)	-0.1110** (-2.0188)	-0.2796* (-8.0920)	-0.106** (-2.0325)
ΔS_{t-3}	-0.1402* (-3.8020)	-0.0367 (-0.5458)	-0.2019* (-5.5813)	-0.1221** (-2.3108)	-0.1648* (-5.1064)	-0.0349 (-0.7122)
ΔS_{t-4}	-0.0456 (-1.3552)	0.0329 (0.5360)	-0.1388* (-4.077)	-0.0794 (-1.5968)	-0.0855* (-2.9891)	-0.0096 (-0.2218)
ΔS_{t-5}	-0.0066 (-0.2238)	0.0335 (0.6222)	-0.0995* (-3.1763)	-0.0738 (-1.6115)	-0.047** (-2.0426)	0.0296 (0.8329)
ΔS_{t-6}	-0.0097 (-0.4052)	0.0624 (1.4174)	-0.050*** (-1.8713)	-0.069*** (-1.777)	-0.033** (-2.2031)	-0.0172 (-0.7510)
ΔS_{t-7}	0.00087 (0.0705)	0.0131 0.5829	-0.0257 (-1.5939)	-0.0143 (-0.6081)		
ΔF_{t-1}	0.3748* (8.9359)	0.0517 (0.6761)	0.5685* (15.2963)	0.1193** (2.1974)	0.3840* (10.6865)	0.1156** (2.116)
ΔF_{t-2}	0.1998* (4.9180)	0.0090 (0.1224)	0.3321* (8.7494)	0.0843 (1.5215)	0.3141* (9.0011)	0.0754 (1.4201)
ΔF_{t-3}	0.1464* (3.7856)	-0.0039 (-0.0564)	0.2228* (6.0122)	0.0940*** (1.7359)	0.2457* (7.3621)	0.0478 (0.9419)
ΔF_{t-4}	0.1191* (3.2928)	0.0103 (0.1567)	0.1873* (5.2895)	0.0777 (1.5024)	0.1623* (5.2659)	0.0397 (0.8468)
ΔF_{t-5}	0.0296 (0.9063)	-0.0197 (-0.3304)	0.1260* (3.7956)	0.0488 (1.0078)	0.0827* (3.0658)	-0.0219 (-0.5342)
ΔF_{t-6}	-0.05*** (-0.1785)	-0.0699 (-1.3484)	0.0745** (2.4896)	0.0666 (1.5225)	0.0366*** (1.7051)	-0.0057 (-0.1768)
ΔF_{t-7}	-0.0007 (-0.0317)	-0.0137 (-0.3397)	0.0459*** (1.911)	0.0098 (0.2810)		
Constant	0.0001 (0.5962)	0.0002 (0.4154)	0.0001 (0.5829)	0.0002 (0.6792)	0.0005** (2.3559)	0.0008** (2.3113)

Note: Figures in ( ) are t-statistics.

*,** and *** Indicates significance at 1%, 5% and 10% levels, respectively.

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Table 5.8: (continued)

Variables	Infosys ΔS_t	Infosys ΔF_t	Mahindra ΔS_t	Mahindra ΔF_t	Ranbaxy ΔS_t	Ranbaxy ΔF_t
Z_{t-1}	-0.5671* (-8.5983)	0.1310 (1.5300)	-0.3039* (-7.3952)	0.1789* (2.8789)	-0.3145* (-11.390)	-0.097** (-2.0543)
ΔS_{t-1}	-0.2742* (-4.2824)	-0.0577 (-0.6938)	-0.4667* (-10.9615)	-0.2243* (-3.4838)	-0.2842* (-9.1797)	0.1719* (3.2400)
ΔS_{t-2}	-0.2689* (-4.4011)	-0.0243 (-0.3068)	-0.4485* (-10.6385)	-0.3020 (-4.7374)	-0.1877* (-6.0500)	0.1544* (2.9038)
ΔS_{t-3}	-0.2510* (-4.3484)	-0.0224 (-0.2993)	-0.2954* (-7.2064)	-0.1264** (-2.0393)	-0.081* (-2.6906)	0.1525* (2.9318)
ΔS_{t-4}	-0.1794* (-3.3412)	0.0074 (0.1063)	-0.2682* (-6.9003)	-0.1565* (-2.6636)	-0.069** (-2.3915)	0.1550* (3.0944)
ΔS_{t-5}	-0.1444* (-2.9747)	0.0024 (0.0388)	-0.2164* (-5.9611)	-0.1029** (-1.8754)	-0.04*** (-1.7519)	0.1388* (2.8986)
ΔS_{t-6}	-0.1438* (-3.4214)	-0.0267 (-0.4902)	-0.1532* (-4.7599)	-0.0738 (-1.5171)	0.0127 (0.4898)	0.1879* (4.2199)
ΔS_{t-7}	-0.0908* (-2.6707)	-0.0350 (-0.7924)	-0.0917* (-3.3875)	-0.0954** (-2.3291)	0.0125 (0.5509)	0.1656* (4.2282)
ΔS_{t-8}	-0.0207 (-0.9780)	-0.0143 (-0.5205)	-0.0401** (-2.4720)	-0.041*** (-1.6771)	0.0078 (0.6130)	0.036*** (1.6777)
ΔF_{t-1}	0.3982* (6.1424)	0.1172 (1.3918)	0.6328* (15.2986)	0.3094 (4.9468)	0.5499* (18.600)	-0.0812 (-1.6140)
ΔF_{t-2}	0.2434* (3.8970)	-0.0377 (-0.4651)	0.4316* (10.2560)	0.2334* (3.6679)	0.2343* (7.5075)	-0.1757* (-3.2846)
ΔF_{t-3}	0.2335* (3.9426)	-0.0247 (-0.3219)	0.4055* (9.8347)	0.2022* (3.2438)	0.1539* (4.9760)	-0.128** (-2.4244)
ΔF_{t-4}	0.2113* (3.8132)	0.0032 (0.0451)	0.2749* (6.8926)	0.1298** (2.1529)	0.0838* (2.788)	-0.1289* (-2.5029)
ΔF_{t-5}	0.1438* (2.8291)	(-0.0215) (-0.3264	0.2442* (6.4802)	0.099*** (1.7508)	0.0667** (2.3102)	-0.1488* (-3.0040)
ΔF_{t-6}	0.1074* (2.3961)	-0.0141 (-0.2421)	0.1765* (5.0659)	0.0571 (1.0841)	0.045*** (1.6455)	-0.1608* (-3.4120)
ΔF_{t-7}	0.1120* (2.9922)	0.0398 (0.8197)	0.1171* (3.8271)	0.0897** (1.9385)	-0.0189 (-0.7525)	-0.1760* (-4.0757)
ΔF_{t-8}	0.0698** (2.4653)	0.0560 (1.5229)	0.07* (2.8649)	0.0413 (1.1180)	-0.0168 (-0.7896)	-0.084** (-2.3002)
Constant	0.0006*** (1.8106)	0.00075 (1.7316)	0.00081** (2.3688)	0.0012** (2.4164)	0.000140 (0.4937)	0.0002 (0.4583)

Note: Figures in ( ) are t-statistics.

*,** and *** Indicates significance at 1%, 5% and 10% levels, respectively.

Table 5.8: (continued)

Variables	Reliance ΔS_t	Reliance ΔF_t	SBI ΔS_t	SBI ΔF_t	Tatapower ΔS_t	Tatapower ΔF_t
Z_{t-1}	-0.6446* (-11.659)	0.0531 (0.5533)	-0.5941* (-11.629)	-0.0519 (-0.6319)	-0.4166* (-9.7694)	0.0091 (0.1376)
ΔS_{t-1}	-0.2477* (-4.6553)	-0.0395 (-0.4272)	-0.2054* (-4.1098)	0.0834 (1.0377)	-0.3298* (-7.5703)	0.0202 (0.2993)
ΔS_{t-2}	-0.2402* (-4.7542)	-0.0726 (-0.8274)	-0.2128* (-4.4733)	0.0217 (0.2848)	-0.3333* (-7.8179)	-0.0270 (-0.4071)
ΔS_{t-3}	-0.2357* (-4.9654)	-0.0492 (-0.5968)	-0.1290* (-2.8750)	0.0654 (0.9070)	-0.2732* (-6.6310)	-0.0071 (-0.1110)
ΔS_{t-4}	-0.1706* (-3.8955)	0.0098 (0.1299)	-0.1043* (-2.500)	0.0395 (0.5901)	-0.1612* (-4.1006)	0.0408 (0.6686)
ΔS_{t-5}	-0.099* (-2.5574)	0.0630 (0.9304)	-0.0853** (-2.2434)	0.0904 (1.4787)	-0.1457* (-4.0415)	0.0221 (0.3949
ΔS_{t-6}	-0.0943* (-2.8254)	0.0691 (1.1918)	-0.0974* (-2.9337)	0.0810 (1.5175)	-0.0898* (-2.8172)	0.0550 (1.1092)
ΔS_{t-7}	-0.0849* (-3.2361)	0.0345 (0.7566)	-0.047*** (-1.7376)	0.0521 (1.1941)	-0.0326 (-1.2251)	0.0304 (0.7344)
ΔS_{t-8}	-0.0164 (-1.2145)	0.0051 (0.2461)	-0.0082 (-0.5395)	0.0038 (0.1556)	-0.0214 (-1.3727	0.0194 (0.8017)
ΔF_{t-1}	0.3246* (5.9405)	0.0657 (0.6925)	0.3352* (6.5730)	-0.0053 (-0.0657)	0.4846* (11.2166)	0.0504 (0.7501)
ΔF_{t-2}	0.2338* (4.4784)	0.0298 (0.3288)	0.1778* (3.6125)	-0.1001 (-1.2651)	0.2803* (6.4844)	-0.0816 (-1.2143)
ΔF_{t-3}	0.2180* (4.4170)	0.0173 (0.2026)	0.1820* (3.9164)	-0.0310 (-0.4150)	0.2870* (6.8339)	-0.0067 (-0.1029)
ΔF_{t-4}	0.2169* (4.6970)	0.0178 (0.2221)	(0.1105)* (2.5339)	-0.0639 (-0.9111)	0.2477* (6.1379)	0.0012 (0.0204)
ΔF_{t-5}	0.1441* (3.4061)	-0.0287 (-0.3911)	0.0766*** (1.8971)	-0.112*** (-1.7339)	0.1421* (3.7260)	-0.0365 (-0.6163)
ΔF_{t-6}	0.0750** (2.0118)	-0.0879 (-1.3568)	0.0621 (1.7059)	-0.1342** (-2.2921)	0.1228* (3.554)	-0.0443 (-0.8253)
ΔF_{t-7}	0.0743** (2.3732)	(-0.0541) (-0.9941)	0.0764** (2.4681)	-0.0499 (-1.0016)	0.0745* (2.5007)	-0.0199 (-0.4297)
ΔF_{t-8}	0.0709* (3.0558)	0.0417 (1.0338)	0.0328 (1.3748)	0.011665 (0.3039)	0.0161 (0.6855)	-0.0414 (-1.1276)
Constant	0.0005*** (1.8906)	0.00060 (1.2849)	0.00074* (2.42937)	0.00094** (1.9059)	0.0005*** (1.6850)	0.0007 (1.5212)

Note: Figures in ( ) are t-statistics.

*,** and *** Indicates 1%, 5% and 10% significance levels respectively.

Note: Trace test and Max-eigen value implies that one coinetgrating equations at both 1% and 5% levels.

For Null r = 0, critical value for trace test at 5% and 1% levels are15.49 and 20.05, respectively.

For null r ≤ 1, critical value for trace test at 5% and 1% levels are 3.84 and 6.65, respectively.

For Null r = 0, critical value for Max-Eigen test at 5% and 1% levels are 14.07 and 18.63, respectively.

For Null r ≤ 1, critical value for Max-Eigen test at 5% and 1% levels are 3.84 and 6.65, respectively.

Table 5.9: Granger-Causality Results

Null Hypothesis	F-Statistics	Probability
Nifty spot does not Granger Cause Nifty Futures	3.35992	0.0008
Nifty futures does not Granger Cause Nifty Spot	1.04167	0.4019
ACC futures does not Granger Cause ACC spot	438.376	0.0000
ACC spot does not Granger Cause ACCR futures	1.31180	0.2326
BHEL futures does not Granger Cause BHEL spot	325.435	0.0000
BHEL spot does not Granger Cause BHEL futures	5.75798	0.0000
BPCL futures does not Granger Cause BPCL spot	405.238	0.0000
BPCL Spot does not Granger Cause BPCL futures	0.90538	0.4899
CIPLA futures does not Granger Cause CIPLA spot	556.680	0.0000
CIPLA spot does not Granger Cause CIPLA futures	0.72637	0.6284
GRASIM futures does not Granger Cause GRASIM spot	819.416	0.0000
GRASIM spot does not Granger Cause GRASIM futures	3.25541	0.0034
HDFC futures does not Granger Cause HDFC spot	1780.91	0.0000
HDFC spot does not Granger Cause HDFC futures	2.23747	0.0169
HINDALCO spot does not Granger Cause HINDALCO futures	0.82278	0.5682
HINDALCO futures does not Granger Cause HINDALCO spot	763.365	0.0000
HINDLEVER futures does not Granger Cause HINDLEVER spot	873.360	0.0000
HINDLEVER spot does not Granger Cause HINDLEVER futures	2.17630	0.0888
INFOSYS spot does not Granger Cause INFOSYS futures	0.70702	0.6856
INFOSYS futures does not Granger Cause INFOSYS spot	239.631	0.0003
ITC futures does not Granger Cause ITC spot	441.476	0.0000
ITC spot does not Granger Cause ITC futures	0.96256	0.4491
MAHINDRA futures does not Granger Cause MAHINDRA spot	413.289	0.0000
MAHINDRA spot does not Granger Cause MAHINDRA futures	3.60305	0.0004
RANBAXY futures does not Granger Cause RANBAXY spot	547.353	0.0000
RANBAXY spot does not Granger Cause RANBAXY futures	2.97005	0.0026
RELIANCE futures does not Granger Cause RELAINCE spot	593.956	0.0000
RELAINCE spot does not Granger Cause RELIANCE futures	0.80375	0.5992
SBI futures does not Granger Cause SBI spot	428.041	0.0000
SBI spot does not Granger Cause SBI futures	0.85411	0.5549
TATA Power futures does not Granger Cause TATA power spot	397.688	0.0000
TATA power spot does not Granger Cause TATA power futures	0.65257	0.7337

Appendix 5.1

Unit Root Test Methods

The Dickey-Fuller (DF) Tests

In general, the procedure is to test whether the variable S_t in its levels from is stationary. The model can be given as follows:

$$S_t=\alpha_1 S_{t-1}+\varepsilon_t \qquad (1)$$

If the hypothesis of stationarity is rejected (i.e., α_1=1), the first difference of variable ΔS_t is formed and tested for stationarity. Dickey and Fuller (1979) actually consider three different regression equations that can be used to test for the presence of a unit root:

$$\Delta S_t = \gamma S_{t-1} + \varepsilon_t \qquad (2)$$

$$\Delta S_t = \alpha_0 + \gamma S_{t-1} + \varepsilon_t \qquad (3)$$

$$\Delta S_t = \alpha_0 + \gamma S_{t-1} + \alpha_2 t + \varepsilon_t \qquad (4)$$

Where $\gamma=1-\alpha_1$.

In the above models, the first is a pure random walk model, the second adds an intercept or drift (α_0) term, and the third includes both a drift and linear time trend (t).

In such case, if $\gamma = 0$, there is a unit root. If ΔS_t is stationary, this implies that St is I (1). Dickey-Fuller (1979) found in their Monte Carlo study that the critical values for γ =0, depend on the form of the regression and sample size. The statistics labeled (τ), (τ_μ) and (τ_τ) are the appropriate statistics to use for equations (2), (3), and (4) respectively.

Augmented Dickey Fuller (ADF) Tests

From the DF tests, it has been implicitly assumed that the estimated errors (i.e., ε_t) are statistically independent and homoscedastic. Heteroscedasticity does not affect a wide range of unit root test statistics. However, a problem will occur if the estimated residual ε_t is not free form autocorrelation since this invalidates the test. If the error term ϵ_t is autocorrelated, the models (2), (3) and (4) can be modified as follows:

$$\Delta S_t = \gamma S_{t-1} + \sum_{i=1}^{k} \beta_i \Delta S_{t-i} + \varepsilon_t \tag{5}$$

$$\Delta S_t = \alpha_0 + \gamma S_{t-1} + \sum_{i=1}^{k} \beta_i \Delta S_{t-i} + \varepsilon_t \tag{6}$$

$$\Delta S_t + \alpha_0 + \gamma S_{t-1} + \alpha_2 t + \sum_{i=1}^{k} \beta_i \Delta S_{t-i} + \varepsilon_t \tag{7}$$

In the above models (5), (6) and (7), it uses lagged difference term. The number of lags is being determined by minimum number of residuals free from autocorrelation. This could be tested for in the standard way such as Akaike's information criterion (AIC) and Schwartz Bayesians Criterion (SBC). The same (τ), (τ_μ) and (τ_τ) statistics are all used to test hypothesis $\gamma = 0$, i.e., there exists a unit root. Dickey and Fuller (1981) provide three additional F-statistics such as: Φ_1, Φ_2 and Φ_3 to test joint hypotheses on the coefficients. With equation (3) or (6), the null hypothesis $\gamma = a_0 = 0$ is tested by using the Φ_1 statistic. Including a time trend in the regression in the equation (4) or (7) is estimated with the joint hypothesis $a_0 = \gamma = a_2 = 0$ which is tested using the Φ_2 statistic. The joint hypothesis $\gamma = a_2 = 0$ is tested using the Φ_3 statistic.

Philips-Perron (PP) Tests

The Dickey-Fuller test assumes that the residuals are serially independent and homoscedastic. In employing this methodology, care must be taken to ensure that the residual terms are uncorrelated and homoscedastic. Phillips and Perron (1988) developed a generalisation of the Dickey-Fuller procedure that allows for fairly mild assumptions concerning the distribution of the errors. To briefly explain the procedure, the model can be written as:

$$S_t = \alpha_0^* + \alpha_1^* S_{t-1} + \mu_t \tag{8}$$

$$S_t = \tilde{\alpha}_0 + \tilde{\alpha}_1 S_{t-1} + \tilde{\alpha}_2 (t - T/2) + \mu_t \tag{9}$$

Where T=number of observations and the disturbance term $E\mu_t$=0, but there is no requirement that the disturbance term is serially uncorrelated or homogenous. Instead of the Dickey-Fuller assumptions of independence and homogeneity, the Phillips-Perron test allows the disturbances to be weakly dependent and heterogeneously distributed.

Phillips and Perron characterise the distributions and derive tests statistics that can be used to test hypotheses about the coefficients α_i^* and $\tilde{\alpha}_i$ under the null hypothesis. The data are generated by

$$S_t=S_{t-1}+\mu_t \quad (10)$$

The Phillips-Perron test statistics are modifications of the Dickey-Fuller t-statistics that take into account the less restrictive nature of the error process. The most useful of the test statistics are as follows:

$Z=(t\alpha_1^*)$: Used to test the hypothesis $\alpha_1^*=1$

$Z=(t\tilde{\alpha}_1)$: Used to test the hypothesis $\tilde{\alpha}_1=1$

$Z=(t\tilde{\alpha}_2)$: Used to test the hypothesis $\tilde{\alpha}_2=0$.

The critical values for the Phillips-Perron statistics are precisely those given for the Dickey-Fuller tests. For example, the critical values for z $(t\alpha^*_1)$ and z $(t\tilde{\alpha}_1)$ are those given in the Dickey-Fuller table under the heading (τ_μ) and (τ_τ) respectively

Appendix-5.2

Derivation of RMSE and MAE

The RMSE for the variable is given by

$$\text{RMSE} = [1/T\sum_{t=1}^{T}\left(P_t - A_t\right)^2]^{1/2} \qquad (1)$$

Where T is number of periods in the simulation, P is the predicted value and A is the actual value. It measures the deviation of the predicted value from its actual time path.

The MAE is defined as;

$$\text{MAE} = 1/T\sum_{t=1}^{T}\left(\left|\{P_t - A_t\}\right|\right) \qquad (2)$$

The MAPE is defined as;

$$\text{MAPE} = 1/T\sum_{t=1}^{T}\left(\left|\{P_t - A_t\}/A\right|\right) \qquad (3)$$

CHAPTER-VI

Hedge Ratio and Hedging Effectiveness of Stock Index Futures

6.1 Introduction

With the passage of time, innovations in financial markets have brought an increasing number of financial products, such as futures, options and swaps, to reduce the price risk of a portfolio. Hedging with futures is one of the simplest and most widely used instruments to reduce the risk of a portfolio. A hedge is done by taking opposite positions in spot and futures markets simultaneously. Thus any loss arising due to adverse price movements in one market could be offset to some extent from the gain in other market. The ratio of the number of units of a futures position that is taken relative to the number of units of a spot position is known as the “hedge ratio”. Since risk in this context is usually measured in terms of the volatility of portfolio returns, an intuitively plausible strategy could be to choose the hedge ratio that minimizes the variance of the returns of a portfolio containing spot and futures positions; this is known as the optimal hedge ratio.

After the index futures were launched, investors widened their investment range, providing a good risk-management strategy for a portfolio manager. Until 1982, it was difficult for the market participants to control the market risk to a greater extent. The innovations in the stock index futures contract enable them to manage market risk without changing their portfolios and widened the investment range, providing a good risk-management strategy for a portfolio manager. There has been much empirical research into the calculation of optimal hedge ratios (Cecchetti, Cumby and Figlewski 1988; Myers and Thompson 1989; Baillie and Myers 1991; kroner and Sultan 1991; Lien and Luo 1993; Lin, Najand and Yung 1994; Strong and Dickinson 1994; Park and Switzer 1995; Donald and Shrestha 2005; Juhl, Kawaller and Koch 2012).

Much of the research is based on index futures because of its liquidity, speed and lower transaction cost, which includes bid-ask spread, brokerage and commissions. Stock index futures are contracts where the underlying instrument is the index. It is an agreement between a buyer and a seller to buy or sell a specified quantity of security that matches the underlying index on a future date and for an agreed-upon price. They are traded on organized exchanges and feature highly standardized contract terms in all aspects except for the price. Therefore, their clearing and settlement are facilitated and can be guaranteed by the clearinghouse against defaults of market participants. Factors that influence hedge construction and its effectiveness include basis risk, hedging horizon and the correlation between changes in the futures price and the cash price.

The practical usage of "portfolio theory" to hedging has great importance for academicians and market participants. By viewing hedging as a simple application of the basic portfolio theory, Jhonson (1960) and Stein (1961) were able to integrate the risk avoidance of traditional theory and introduced the concept of "portfolio theory of hedging the cash position with futures". Edrington (1979) applied this concept in determining a risk-minimizing hedge ratio and derived a measure of hedging effectiveness. These have been followed by numerous studies, including Hill and Schneeweis (1981, 1982): Figlewski (1984, 1985); Witt, Schroeder, and Hayenga (1987); Myers and Thomson (1989); Castelino (1990a, 1990b, 1992); Myers(1991); and Viswanath and Chatterjee (1992).

6.2 Theoretical Motivations

A hedging strategy is measured by the extent to which it reduces risk and several techniques have been developed to find out the optimal hedge ratio (OHR). A number of researchers, academicians, policy makers and analysts have investigated the hedging effectiveness of the futures market by applying different theories and techniques. Early investigations into hedging include Working (1953), Johnson (1960), Stein (1961) and Ederington (1979). They postulate that the objective of hedging is to minimize the variance of spot portfolio held by an investor. Therefore, the hedge ratio that generates the minimum portfolio variance should be the optimal hedge ratio, which is also known as the minimum variance hedge ratio. A large body of research has developed the techniques of estimating and evaluating optimal hedging strategies[7].

Several approaches have been suggested as a way to minimize the risk of a cash position. One of the approaches is called the naive or one-to-one hedge, assumes that the correlation between the spot and the futures prices is perfect and sets the hedge ratio equal to one over the period of the hedge. The problem with this is it fails to recognize that the correlation

[7]For details see review related to the hedging effectiveness of futures market in chapter-II.

between spot and futures prices is less than perfect and it fails to consider the stochastic nature of futures and spot prices and the resulting time variation in the hedge ratio.

To overcome the problem of one-to-one hedge, static OLS hedge was developed. It accurately recognizes that the correlation between the futures and spot prices is less than perfect and estimates the hedge ratio as the OLS coefficient of a regression of spot return on futures return (Ederington, 1979; Figlewski, 1984). However, it imposes the restriction of a constant joint distribution of spot and futures price changes. Hence, it could lead to sub-optimal hedging decisions in periods of high basis volatility.

The naive and OLS approaches are static risk-management strategies which involve a one-time decision about the best hedge and do not require any adjustment of the hedge ratio once this decision is taken. Some of the studies have applied OLS regression for estimating hedge ratio and hedging effectiveness based on its mean variance. This has been criticized on these grounds (Ballie and Myers 1991; Park and Switzer, 1995): First, the estimation using OLS regression is based on the assumption of unconditional distribution of spot and futures prices, whereas the use of conditional distributions is more appropriate because hedging decision made by any hedger is based on all the information available at that time. Second, OLS model is based on the assumption that relationship between spot and futures prices is time invariant, but empirically it has been found that the joint distribution of spot and futures prices are time invariant (Mandelbort, 1963; Fama, 1965). Several studies also supported the view and came out with similar conclusions: Lypny and Powalla (1998), Koutmos and Pericli (1998), Lien and Tse (1999), Floros and Vougas (2004), Bryant and Haigh (2005) and Bhaduri and Sethu Durai (2007).

Developments in the financial time series techniques are able to consider the deficiencies of the conventional methods. In comparison with the traditional methods, the Vector Autoregression (VAR) technique takes into account the history of both spot and futures prices as conditional information, while the error correction mechanism adds the previous basis as a conditional variable and accounts for a long-term relationship between spot and futures price movements. The Multivariate Generalized Autoregressive Conditional Hetroscedasticity (M-GARCH, has been used to calculate the time-varying hedge ratio. M-GARCH estimates time-varying hedge ratio by considering the conditional variance and covariance of the spot and futures prices.

Some the studies whose hedge ratio is estimation is based on the family of GARCH models introduced by Engle (1982) and Bollerslev (1986) are follows: Baillie & Myers, 1991; Myers, 1991 on variety of commodities, Cecchetti, Cumby, &Figlewski, 1988 on treasury securities, Kroner & Sultan, 1991, 1993; Lin, Najand, & Yung, 1994; Gagnon, Lypny, & McCurdy, 1998 on foreign exchange instruments and Park & Switzer, 1995; Brooks, Henry, & Persand, 2002 on Stock Indices.

The empirical findings across markets seem to suggest that the best model for hedging may be country and market specific. Several studies found that M-GARCH model provides better hedging effectiveness over conventional models. The number of studies in the case of emerging economies like India is less, thus the present chapter will focus on the hedging function of the Indian derivative market. Since the introduction of futures markets, it is necessary to see the efficiency of these markets in managing risks through hedging. In this context, it is pertinent to measure optimum hedge ratio in order to control or reduce risk of stock market portfolios. Hence, comparisons of the effectiveness of hedge ratios estimated from the ordinary least square regression, vector auto regression (VAR) models, vector error correction models (VECM) and time varying multi-variate generalized ARCH (M-GARCH) models will throw much light on identifying the most suitable method for comparison of hedging effectiveness of futures market. Further, the study make an in-sample and out-of sample analysis for validating the results obtained through different techniques.

The rest of the chapter is structured as follows: after a brief introduction to the subject in section one, Section three presents the methodology and data of the study. Empirical results and discussions are presented in Section four and concluding remarks are presented in section five.

6.3 Objective of the Chapter

Hedging plays important functions of the futures market. Based on the above discussions, the present chapter focuses on the following objectives:

1. To measure the hedge ratio and hedging effectiveness of the futures market
2. To test whether the stock index futures market provides an effective instrument in reducing the risk of the spot market

6.4 Data and Methodology

The data samples used in this analysis is the daily closing prices of the S&P CNX Nifty index and daily closing prices of nearby contracts of Nifty futures. The S&P CNX Nifty is a value-weighted index consisting of 50 large capitalization stocks maintained by the National Stock Exchange. It encompasses the S&P CNX Nifty Index and the corresponding NSE Stock Index Futures prices on a daily basis for the period of 12 June 2000 to 30 October 2012, summing up to 3100 observations. Only the first 2,950 observations are employed in the empirical tests, leaving the last 254 observations starting from 1 April 2012 for an out-of-sample hedge ratio performance comparison. Further, the data set has been divided into periods of pre-Sub-prime crisis and post-Sub-prime crisis and a separate analysis has been done per each period. The pre-Sub-prime data has been taken from 12 June 2000 to 30 June 2007 and the post-Sub-prime period consists of data from July 2007 to March 2012.

6.4.1 Methodology

Earlier studies have applied several methodologies to estimate the hedge ratio and hedging effectiveness of the index futures market. Four models are commonly used: (1) the Ordinary Least Square (OLS), (2) the Vector Autoregressive Regression (VAR) model, (3) the Vector Error Correction model (VECM) and (4) the Multi-variate Generalised Autoregressive Conditional Hetroscedasticity model (M-GARCH). The first three models are based on the assumption that the joint distribution of spot and futures prices is time invariant and do not take into account the conditional co-variance structure of spot and futures prices, whereas the M-GARCH model takes into account the time-varying hedge ratio and time-varying conditional co-variance of spot and futures price.

The present study applies these four models, such as OLS, VAR, VECM and time-varying M-GARCH models to determine optimal hedge ratios. The performance of the hedge ratios is compared to assess whether the more advanced time-varying hedge ratios calculated from Bollerslev, Engle and Wooldridge's (1988) Multivariate-GARCH model can provide more efficiency than other constant hedge ratios from the regression model, the Bivariate VAR model and the Vector Error-Correction model. Further, the study focuses on four different models for estimating the hedge ratios and testing their effectiveness for both in-sample and out-samples data forecasts.

Model 1: The Conventional Regression Method

Ederington (1979) extended the foundation work of Johnson (1960) and Stein (1961, 1964) by focusing on the empirical estimation of optimal hedge ratio within the portfolio framework. Based on the principles of portfolio theory, Ederington (1979) and Figlewski (1989) formulated the hedgers' problems and derived ratios that minimize the variance of the hedged portfolio. This method requires estimating a hedge ratio by regression of change in spot prices on changes in futures prices. The conventional approach in estimating minimum-variance hedge ratio (MVHR) relies on the simple regression method.

Let *St* and *Ft* be logged spot and futures prices, respectively; the one period minimum variance constant hedge ratio can be estimated from the expression:

$$\Delta S_t = \alpha + \beta \Delta F_t + \varepsilon_t \qquad (6.1)$$

Where, ε_t is the error term from the OLS estimation, ΔSt and ΔFt are representing spot and futures price changes. β is the estimated optimal hedge ratio.

Model 2: The Bivariate VAR Model

The traditional approach suffers from a number of limitations. One of the weaknesses of the OLS model is represented by the fact that estimation of the minimum-variance hedge ratio could suffer from problems of serial correlation in OLS residual (Herbst et al, 1993). This model does not take into account the fact that movements in the spot and futures markets may influence the current price movement. The bivariate VAR model considers the limitations, where there are two variables, each of whose current value depends on a combination of previous value of both the variables. In other words, the bi-variate VAR model incorporates the history of both spot and futures prices as the conditional information. The bivariate model is described as follows:

$$\Delta S_t = \alpha_s + \sum_{i=1}^{n} \beta_{si} \Delta S_{t-i} + \sum_{i=1}^{n} \gamma_{si} \Delta F_{t-i} + \varepsilon_{st} \tag{6.2}$$

$$\Delta F_t = \alpha_f + \sum_{i=1}^{n} \beta_{fi} \Delta S_{t-i} + \sum_{i=1}^{n} \gamma_{fi} \Delta F_{t-i} + \varepsilon_{ft} \tag{6.3}$$

Where, $(\varepsilon_{st}, \varepsilon_{ft})$ are independently identically distributed (IID) random vectors. Let $var(\varepsilon_{st}) = \sigma_{ss}$, $var(\varepsilon_{ft}) = \sigma_{ff}$ and $cov(\varepsilon_{st}, \varepsilon_{ft}) = \sigma_{sf}$. The minimum-variance hedge ratio is $\sigma_{sf} / \sigma_{ff}$, which is called the VAR hedge ratio. The optimal lag length k that permits eliminating the serial correlation from the system equation is defined using the multivariate version of the Akaike's and Schwarz's Bayesian information criteria.

Model 3: The Error Correction Model

The bivariate VAR model ignored the effect of co-integration of the two series. The presence or the absence of a cointegration relationship between the variables is an important investigation to conduct since standard inference procedures do not apply to regression where dependent variable and the regressors are integrated. Ghosh (1993), and kroner and Sultan (1993) have shown that the regression given by an equation like the standard VAR is misspecified when spot and future index prices are cointegrated because it ignores the error correction, excluding the impact of last period's equilibrium error. Ghosh (1993) and lien (1996) show that the existence of a cointegration relationship between spot and future markets will typically produce a downwardly biased hedge ratio if the error correction term is not considered in the estimated equation.

Further, they argue that if the two price series are found to be cointegrated, a VAR model should be estimated along with the error-correction term, which accounts for the long-run equilibrium between spot and futures price movements. Thus, a VAR model can be modified as:

$$\Delta S_t = \alpha_s + \sum_{i=1}^{n} \beta_{si} \Delta S_{t-i} + \sum_{i=1}^{n} \gamma_{si} \Delta F_{t-i} + \lambda_s Z_{t-1} + \varepsilon_{st} \tag{6.4}$$

$$\Delta F_t = \alpha_f + \sum_{i=1}^{n} \beta_{fi} \Delta S_{t-i} + \sum_{i=1}^{n} \gamma_{fi} \Delta F_{t-i} + \lambda_f Z_{t-1} + \varepsilon_{ft} \tag{6.5}$$

Where, $Z_{t-1}$is error correction term and λ_s, λ_f as speed adjustment parameters and measures how quickly each market reacts to the deviation from the long run equilibrium relationships. If this equilibrium is positive because the spot rate is too high in relation to the value of the futures prices, the error correction term should push down the spot price back to equilibrium and λ_s will have a negative value. At the same time, the error correction term should push up ΔF_t in the second equation, implying that however the two markets move following a long-run relationship, one market does all the readjustment; in other words, it is a market to follow the other. Same procedure of generating the residual series and the minimum variance hedge ratio can be calculated using VAR model.

Model 4: The Multivariate GARCH Model

Financial research shows much evidence that time series data of return possesses time-varying heteroscedastic volatility structure or ARCH effects (Bollerslev et al, 1992) and it leads the estimation of hedge ratio, and hedging effectiveness may turn out to be inappropriate. The earlier model which we already discussed has assumed that the residuals have constant variances and covariances. GARCH models assume that the conditional variance is affected by its own history and the history of the squared innovations. A usual way to capture the above stylized facts is to model the conditional variance of error term by using ARCH/GARCH class of models.

MGARCH model provides more precise estimates of the parameters because the model utilizes information in the entire variance covariance matrix of the errors (Conrad, Gultekin, and kaul, 1991). According to Engle and Kroner (1995), multivariate GARCH models allow the variance and covariance to depend on the information set in a vector ARMA model. This leads to the unbiased and more precise estimate of the parameters. The large literature on optimal hedging has been extensively used multivariate GARCH models to generate minimum variance hedge ratios. Those studies include Myers (1991), Park & Switzer (1995a, 1995b), Lypny&Powalla (1998), Koutmos&Pericli (1998), Lien &Tse (1999), Floros and Vougas (2004) and Cotter & Hanly (2006).

From hedging point of view, the multivariate GARCH models are suitable, because they can estimate jointly the conditional variances and covariances required for minimum-variance hedge ratio. Thus, the multivariate GARCH model is applied to calculate the dynamic hedge ratios that vary over time based on the conditional variance and covariance of the spot and futures prices. A standard M-GARCH (1, 1) model is specified as:

$$\begin{bmatrix} h_{ss} \\ h_{sf} \\ h_{ff} \end{bmatrix}_t = \begin{bmatrix} c_{ss} \\ c_{sf} \\ c_{ff} \end{bmatrix}_t + \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_s^2 \\ \varepsilon_s \varepsilon_f \\ \varepsilon_f^2 \end{bmatrix}_{t-1} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} \begin{bmatrix} h_{ss} \\ h_{sf} \\ h_{ff} \end{bmatrix}_{t-1} \quad (6.6)$$

Where, h_{ss}, h_{ff} are the conditional variance of the errors (ε_{st}, ε_{ft}) from the mean equations. The M-GARCH can be incoprtapted into bivariate VAR and VECM-VAR. As the model has large number of parameters to be estimated, Bollerslev, Engle and Wooldridge (1988) proposed a restricted version of the above model with αand βmatrixes having only diagonal elements which allow for a time-varying conditional variance. A diagonal restriction on the multivariate GARCH parameters matrices shows that each variance and covariance element depends only on its own past value and prediction errors. The diagonal representation of the conditional variance elements h_{ss} and h_{ff} and the covariance element h_{sf} can be specified as:

$$h_{ss,t} = c_{ss} + \alpha_{11}\varepsilon_{s,t-1}^2 + \beta_{11} h_{ss,t-1} \quad (6.7)$$

$$h_{sf,t} = c_{sf} + \alpha_{22}\varepsilon_{s,t-1}\varepsilon_{f,t-1} + \beta_{22} h_{sf,t-1} \quad (6.8)$$

$$h_{ff,t} = c_{ff} + \alpha_{33}\varepsilon_{f,t-1}^2 + \beta_{33} h_{ff,t-1} \quad (6.9)$$

In the above GARCH (1, 1) model, the diagonal VECH parameterization involves nine conditional variance parameters. To ensure a positive conditional variance, the values of c, α_{11}, α_{33}, β_{11} and β_{33} are restricted to zero or greater. The ARCH process in the residuals from the cash position is shown by the coefficient of $\varepsilon_{s,t-1}^2$ (α_{11}), while the coefficient $\varepsilon_{f,t-1}^2$ (α_{33}) presents the ARCH process in the futures equation residuals. The parameters α_{22} and β_{22} represent the conditional co-variance of residuals and GARCH parameters respectively, which account for conditional covariance between the cash and futures prices. Significant covariance parameters imply strong interaction between cash and futures prices. The time-varying hedge ratio has been estimated as the ratio between covariance of spot and futures prices with variance of futures price. So $h_{sf,t}/h_{ff,t}$ will be the time-varying hedge ratio and hence generates more realistic time-varying hedge.

6.5 Estimating Hedging Effectiveness

The models discussed above derived the hedge ratio by employing different econometric technique. The hedge ratio quantifies the appropriate hedge whereas the hedge effectiveness determines how effective the hedge will be or is likely to be. Estimation of hedge effectiveness is important in the sense that it measures the usefulness and success of the futures contract in risk reduction (Silber 1985, Pennings&Meulenberg 1997). Johnson (1960) defined the measure of the hedge effectiveness of the hedged position in terms of the reduction of the hedged position over the variance of the un-hedged position. The returns on the un-hedged and the hedged portfolios are simply expressed as:

$$R_{unhedged} = S_{t+1}-S_t \quad (6.10)$$

$$R_{hedged} = (S_{t+1}-S_t)-h^*(F_{t+1}-F_t) \quad (6.11)$$

Where, $R_{unhedged}$and $R_{hedged}$are returns on un-hedged portfolio and hedge portfolio, respectively. Ftand Stare logged futures and spot prices at time period *t*, respectively, and h* is optimal hedge ratio, and the return on the hedged portfolio is the difference between the return on holding the cash position and corresponding futures position. Similarly, the variance of the un-hedged and the hedged portfolios is expressed as:

$$Var_{unhedged} = \sigma_s^2 \quad (6.12)$$

$$Var_{hedged} = \sigma_s^2 + h^2\sigma_f^2 - 2h\sigma_{sf} \quad (6.13)$$

Where, $Var_{unhedged}$ and Var_{hedged} represent variance of un-hedged and hedged portfolios, respectively. σ_s, $\sigma_f$and σ_{sf} are standard deviations of spot and futures prices and covariance between them, respectively. The Hedging Effectiveness (HE) can be measured by the percentage reduction in the variance of a hedged portfolio as compared with the variance of an un-hedged portfolio (Ederington, 1979). The variance reduction can be calculated as:

$$HE = 1 - \left[\frac{Var_{HedgedPorfolio}}{Var_{UnhedgedPortfolio}}\right] \quad (6.14)$$

The hedging effectiveness gives the maximum possible variance reduction of the overall un-hedged spot position due to hedging. Assuming that a hedged position will always have a lower variance than an un-hedged position, the above formulation implies that the value of HE will be bounded by 1. It means the higher the value of HE, the better the hedging effectiveness.

6.6 Empirical Results and Discussions

6.6.1 Descriptive Statistics

The results of summary statistics of the Nifty index and Nifty futures index returns are presented in Table 6.1.The total data period of the descriptive statistics has been taken from June 12, 2000 to March 31, 2012. The mean returns of the nifty and nifty futures for the data period are 0.000441 and 0.000445, respectively, which are close to zero. The standard deviations of returns of nifty and nifty futures over the sample are 0.0164 and 0.0173, respectively. The standard deviation indicates that the volatility of the futures market is higher than its underlying cash market. The unconditional distributions of spot and futures returns are not normal, as shown by high skewness, high kurtosis and significant Jarque-Bera Statistics. Jarque-Bera test statistics appear to be significantly high (p value=0), implying that the returns are asymmetric and not normally distributed. Both return series show excess kurtosis, implying fatter tail than normal distributions and are skewed to the left. The result supports the observations of Fama (1965), Steven and Bear (1970) that fat tails are due to volatility clustering and asymmetry is due to asymmetric information and leverage effect. The descriptive statistics for pre-Sub-prime and post-Sub-prime crises also report similar results. The standard deviations of returns nifty and nifty futures for the post-Sub-prime sample are 0.01903 and 0.020 respectively, which indicate that futures is more volatile during the post-Sub-prime period in comparison with other periods.

Table 6.1: Summary Statistics for Nifty Spot Index and Futures Index

	Total Period		Pre-Sub-prime Crisis		Post-Sub-prime Crisis	
	Spot Price Return	Futures Price Return	Spot Price Return	Futures Price Return	Spot Price Return	Futures Price Return
Mean	0.000441	0.000445	0.00061	0.00061	0.00017	0.00018
Median	0.001221	0.00088	0.0016	0.00109	0.00046	0.00032
Maximum	0.1633	0.1619	0.0796	0.09593	0.1633	0.1619
Minimum	-0.1305	-0.1625	-0.1305	-0.1625	-0.1301	-0.1367
Std. Dev.	0.0164	0.0173	0.0144	0.01524	0.0190	0.0200
Skewness	-0.2826	-0.4506	-0.8760	-1.1187	0.1377	0.0272
Kurtosis	10.9044	11.8275	9.31134	13.5935	10.5582	9.7139
Jarque-Bera	7716.612	9675.01	3165.890	8650.616	2810.077	2214.539
Probability	0.0000	0.00000	0.0000	0.0000	0.0000	0.0000
Observations	2949	2749	1771	1771	1178	1178

After the model specification, the optimal lag length is selected by using two information criteria: the Akiake Information Criterion (AIC) and the Schwartz's Bayesian Information Criterion (SBC).

Figures 6.1 and 6.2 show the graphical presentation of the CNX nifty index and index futures from June 12, 2000 to March 31, 2013. The prices show an upward trend up to July 2007, shortly before the Sub-prime crisis. With the onset of the economic slowdown around the global market economies, the Indian stock market shows bearish trends for almost two years. During the Sub-prime crisis the Indian stock market fells sharply, as indicated by the data. The latter part of the graph again shows the recovery from the crisis period.

Figure 6.1: The Trend of Nifty and Nifty Futures

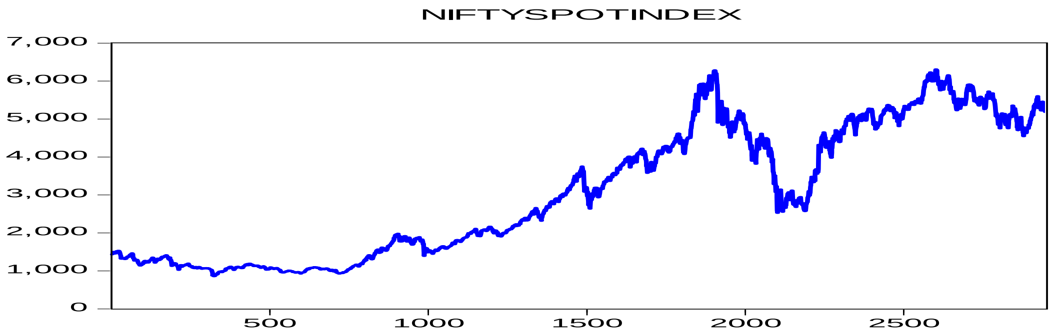
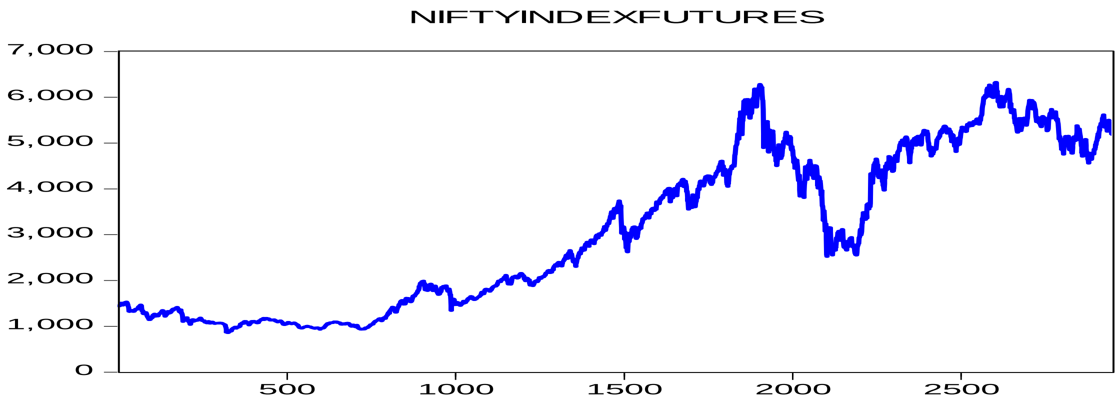


Figure 6.2: The Trend of Nifty Futures



The results of the unit root test for the logged spot S&P CNX Nifty index and logged futures of Nifty index with the levels and first difference are presented in Table 6.2. The results indicate that both the Nifty and Nifty Futures index in non-stationarity at their level and stationarity at their first difference, and confirm that the variables are I(1). The results further imply that there could be existence of long-run relationship between spot and futures prices.. The results of the cointegration test are presented in the Table 6.3. The trace and max-eigen value statistics suggest existence of one cointegrating vector and they are co-integrated in the long run.

Table 6.2: The Results of Unit Roots for Nifty Spot Index and Futures

Constraint	DF		ADF		PP	
	Levels	Difference	Levels	Difference	Levels	Difference
Logged Spot price						
Intercept	0.4514	-8.2345*	-0.6113	-50.3559*	-0.5742	-50.3072*
Intercept and Trend	-1.4957	-48.4153*	-2.2658	-50.3485*	-2.2019	-50.2997*
Logged Futures price						
Intercept	0.4857	-846049*	-0.5688	-52.8616*	-0.5749	-52.8494*
Intercept and Trend	-1.4482	-8.3105*	-2.2618	-52.8560*	-2.2679	-52.8416*

*Note: * denotes 1% level of significance*

Table 6.3: The Results of Cointegration

Null Hypothesis	Alternative Hypothesis			5 % critical value
λ_{trace} tests		Eigen value	(λ_{trace}) Stat.	
$r = 0*$	$r > 0$	0.043698	120.3646	15.49471
$r \leq 1$	$r > 1$	0.0000314	0.081535	3.841466
$\lambda_{\max}$ test		Eigen value	$\lambda_{\max}$ Stat.	
$r = 0*$	$r = 1$	0.150111	438.3975	14.26460
$r = 1$	$r = 2$	0.0000214	0.057884	3.841466

6.6.2 Hedge Ratio Estimation and Hedging Effectiveness

Ordinary Least Square Method

The results obtained by applying OLS regression equation to derive hedge ratio is presented in Table 6.4. The results show that the intercept is statistically insignificant, indicating that there is no linear trend in the data generation process. The slope of the regression equation gives the hedge ratio, and hedging effectiveness is ascertained by R^2. The hedge ratio obtained from OLS regression is 0.9462 and hedging effectiveness is 0.9682. Hedge ratio estimated from the OLS method provides approximately 96% variance reduction, which indicates that the hedge provided by these contracts is effective. Similarly, the hedge ratios for pre-Sub-prime and post-Sub-prime period are 0.93 and 0.95, respectively. The hedging effectiveness of pre-sub-prime and post-sub-prime as indicated by R square are 0.94 and 0.98, respectively. The hedge effectiveness in post-sample shows a greater reduction in variance. The overall results implies that despite of the limitations of the OLS model, it provides approximately 95 % variance reduction, which indicates that the hedge provides by the model is effective.

Table 6.4: The Results of the Regression Model

Parameters	Total Period	Pre subprime	Post subprime
Intercept	0.0005 (0.5533)	0.00004 (0.6739)	0.00001 (0.2604)
β	0.9462* (316.18)	0.9375* (185.31)	0.9536* (298.14)
R^2	0.9682	0.9464	0.9879

Note: * denotes 1% level of significance.

Figures in the parenthesis refer to the t-statistics.

Bivariate Vector Autoregressive (VAR) Model

In order to overcome the problems of the ordinary least square, the present study makes use of bivariate VAR. The Box-Jenkins methodology suggested to the buildup of the VAR for a time series requires identification of optimal lag selection, estimation of the model and diagnostic checking. The optimal number of lags is chosen by applying Akaike's Information Criteria (AIC) and Schwarz Bayesian Criterion (SBC) and the appropriate lag length of the bivariate VAR model is seven. The results of the bi-variate VAR is reported in Table 6.5.

Tests for autocorrelation are conducted to verify the persistence of this problem. The squared residuals of two series are displayed in Table 6.5. The LB Q-statistics at lag k tests the null hypothesis of absence of autocorrelation up to order k. The lag length chosen for LB Q-statistics is 30. The result indicates that there are low level of autocorrelation coefficients and high values of Q-statistics. Thus, the bi-variate VAR has adequately taken into account the serial correlation. The residuals of the bi-variate VAR and VECM estimates are extracted to estimate the hedge ratio and hedging effectiveness and the results are presented in Table 6.8. In Bivariate VAR model, $\mathrm{var}(\varepsilon_{st}) = \sigma_{ss}$=0.000268, $\mathrm{var}(\varepsilon_{ft}) = \sigma_{ff}$ =0.000298 and $\mathrm{cov}(\varepsilon_{st}, \varepsilon_{ft}) = \sigma_{sf}$ = 0.000279. The minimum-variance hedge ratio as per VAR model result is $\sigma_{sf} / \sigma_{ff}$ =0.9362 for the total period.

Table 6.5: Estimates of Bivariate Vector Autorgression (VAR) Model

$$\Delta S_t = \alpha_s + \sum_{i=1}^{n} \beta_{si}\, \Delta S_{t-i} + \sum_{i=1}^{n} \gamma_{si} \Delta F_{t-i} + \varepsilon_{st}$$

$$\Delta F_t = \alpha_f + \sum_{i=1}^{n} \beta_{fi}\, \Delta S_{t-i} + \sum_{i=1}^{n} \gamma_{fi}\, \Delta F_{t-i} + \varepsilon_{ft}$$

	Total period		Pre-subprime		Post-subprime	
Parameters	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t
α_i i=s,f	0.000428 (1.4133)	0.000424 (1.3286)	0.00055*** (1.6158)	0.000529 (1.4674)	0.000179 (0.3247)	0.000195 (0.3343)
ΔS_{t-1}	0.1114 (1.0113)	0.4688* (4.0352)	0.3147* (2.9023)	0.6417* (5.6045)	-0.5772** (-2.0081)	-0.1014 (-0.3343)
ΔS_{t-2}	0.0348 (0.3010)	0.2982** (2.4421)	-0.0026 (-0.0231)	0.2535** (2.1259)	0.0521 (0.1634)	0.3837 (1.1402)
ΔS_{t-3}	-0.0493 (-0.4180)	0.1400 (1.1257)	0.0282 (0.2454)	0.212*** (1.7504)	-0.2093 (-0.6364)	0.0104 (0.0301)
ΔS_{t-4}	0.1680 (1.4177)	0.3269* (2.6159)	0.2581** (2.2343)	0.4177* (3.4250)	-0.1895 (-0.5731)	-0.0169 (-0.0485)
ΔS_{t-5}	0.1942*** (1.6491)	0.3584* (2.8855)	0.1248 (1.0856)	0.2870** (2.3638)	0.2615 (0.7994)	0.4307 (1.2470)
ΔS_{t-6}	-0.0961 (-0.8300)	-0.0009 (-0.0077)	-0.0470 (-0.4175)	0.0657 (0.5524)	-0.2135 (-0.6735)	-0.1843 (-0.5509)
ΔS_{t-7}	-0.0611 (-0.5757)	0.0786 (0.7026)	-0.1824*** (-1.7297)	-0.0454 (-0.4080)	0.3175 (1.1850)	0.4367 (1.5436)
ΔF_{t-1}	-0.0318 (-0.3048)	-0.4135* (-3.7511)	-0.2065** (-2.008)	-0.5681 (-5.2327)	0.6065** (2.1271)	0.1203 (0.4185)
ΔF_{t-2}	-0.0791 (-0.7098)	-0.3305* (-2.8124)	-0.0921 (-0.8482)	-0.3291* (-2.8690)	-0.0372 (-0.1214)	-0.3636 (-1.1230)
ΔF_{t-3}	0.0474 (0.4186)	-0.1375 (-1.1513)	0.0038 (0.0350)	-0.1716 (-1.4760)	0.1800 (0.5678)	-0.0413 (-0.1235)
ΔF_{t-4}	-0.1396 (-1.2263)	-0.2967** (-2.4720)	-0.1835*** (-1.6597)	-0.3391* (-2.9060)	0.1697 0.53170	-0.0023 -0.0069
ΔF_{t-5}	-0.1996*** (-1.7639)	-0.3601* (-3.0181)	-0.0968 (-0.8802)	-0.2565** (-2.2089)	-0.2909 (-0.9209)	-0.4555 (-1.366)
ΔF_{t-6}	0.040411 (0.3634)	-0.0539 (-0.460)	0.0106 (0.0983)	-0.0933 (-0.8201)	0.1414 (0.4626)	0.1042 (0.3229)
ΔF_{t-7}	0.076491 (0.7500)	-0.0565 (-0.5257)	0.1610 (1.6002)	0.0343 (0.3230)	-0.2502 (-0.9649)	-0.3663 (-1.3381)
Residual Diagnosis						
LB Q (5)	350.54	405.14	568.93	406.51	97.942	117.28
LB Q (10)	581.05	592.59	633.41	481.78	176.04	209.36
LB Q (20)	758.91	760.56	700.95	525.56	244.15	293.00
LB Q (30)	839.75	832.76	713.59	532.28	279.48	335.82

Note:* denotes 1% level of significance, ** denotes 5% level of significance and *** denotes 10% level of significance. Figures in ( ) are t-statistics.

The Vector Error Correction Model

Further, the study employed VECM model to obtain the hedge ratio in the presence of longrun relationship between spot and futures prices. The results of the stationarity reveal that the spot and futures prices are non-stationarity and integrated of order one, suggesting the presence of a long-term relationship. The results of Johanssen and Juselius (1990) λ_{trace} and $\lambda_{\max}$ statistics shows that nifty spot index and nifty futures index returns are co-integrated in the long run in rank, r=1. Therefore, the Error Correction model is incorporated into the previous VAR model in the equation 6.3. The results are presented in Table 6.6.

The coefficient of the error correction terms reported to be significant implying that the long-run co-integrating relationship between spot and futures returns has been appropriately considered in the VECM model. The error correction term for the Nifty index is -0.187746 and for the Nifty futures index is -0.312731, implying that futures prices have a greater speed of adjustment than spot prices. This finding is consistent with the fact that on the delivery date of each contract, the futures price has to adjust itself to the prevailing spot price. Further, the results of pre- and post-Sub-prime period show that futures prices have a greater speed of adjustment than spot prices. However, the error-correction term is significant in both the equations and spot and futures price lags seem to be able to explain the current movements of both the prices except for the spot equation in the post-Sub-prime period.

Table 6.6: Estimates for the Vector Error Correction (VEC) Model

$$\Delta S_t = \alpha_s + \sum_{i=1}^{n} \beta_{si} \Delta S_{t-i} + \sum_{i=1}^{n} \gamma_{si} \Delta F_{t-i} + \lambda_s Z_{t-1} + \varepsilon_{st}$$

$$\Delta F_t = \alpha_f + \sum_{i=1}^{n} \beta_{fi} \Delta S_{t-i} + \sum_{i=1}^{n} \gamma_{fi} \Delta F_{t-i} + \lambda_f Z_{t-1} + \varepsilon_{ft}$$

	Total period		**Pre-subprime**		**Post-subprime**	
Parameters	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t
α_i i=s,f	0.000406 (1.3417)	0.00040 1.27568	0.00054 (1.5225)	0.00055 (1.6315)	0.00015 0.2685	0.0001 0.2662
ΔS_{t-1}	-0.036030 (-0.2778)	0.230*** (1.6847)	0.1871 (1.4699)	0.416* (3.1037)	-0.8572* (-2.5133)	-0.5043 (-1.4017)
ΔS_{t-2}	-0.0775 (-0.5894)	0.1050 (0.7582)	0.0554 (0.4147)	-0.1130 (-0.8912)	-0.2199 (-0.6201)	0.0045 (0.0122)
ΔS_{t-3}	-0.1606 (-1.2321)	-0.0396 (-0.2884)	0.0352 (0.2649)	-0.0777 (-0.6150)	-0.3859 (-1.0773)	(-0.2608) -0.69016
ΔS_{t-4}	0.0696 (0.5368)	0.1708 (1.2509)	0.2624** (1.9998)	0.1628 (1.3081)	-0.2684 (-0.7148)	(-0.3569) (-1.0025)
ΔS_{t-5}	0.1092 (0.8549)	0.226*** (1.6849)	0.1434 (1.1070)	0.0324 (0.2635)	0.1787 (0.4836)	(0.0793) (0.2266)
ΔS_{t-6}	-0.1469 (-1.1652)	-0.0886 (-0.6676)	-0.0672 (-0.5286)	-0.1356 (-1.1247)	-0.3996 (-1.1095)	-0.3688 (-1.0801)
ΔS_{t-7}	-0.1605 (-1.3016)	-0.0369 (-0.2843)	-0.1370 (-1.1180)	-0.261** (-2.2499)	0.1594 (0.4647)	0.0963 (0.2960)
ΔS_{t-8}	-0.0335 (-0.2791)	-0.0042 (-0.0336)	-0.1285 (-1.1294)	-0.1458 (-1.3500)	0.1956 (0.7181)	0.1702 (0.5924)
ΔF_{t-1}	0.1144 (0.9182)	-0.1756 (-1.3384)	-0.0803 (-0.6577)	-0.3445* (-2.6762)	0.5185 (1.4972)	0.8819* (2.6863)
ΔF_{t-2}	0.0343 (0.2697)	-0.1370 (-1.0216)	0.0170 (0.1392)	-0.1340 (-1.0365)	0.2349 (0.6417)	0.3615 (1.0416)
ΔF_{t-3}	0.1591 (1.2619)	0.0417 (0.3140)	0.1090 (0.8940)	0.0042 (0.0326)	0.2504 (0.6882)	0.3384 (0.9810)
ΔF_{t-4}	-0.0426 (-0.3401)	-0.1424 (-1.0788)	-0.0875 (-0.7302)	-0.1832 (-1.4503)	-0.2023 (-0.5652)	-0.1080 (-0.3182)
ΔF_{t-5}	-0.1155 (-0.9367)	-0.22*** (-1.7651)	-0.0053 (-0.0449)	-0.1138 (-0.9147)	0.3198 (0.9172)	0.2966 (0.8974)
ΔF_{t-6}	0.0941 (0.7739)	0.0365 (0.2857)	0.0976 (0.8438)	0.0367 (0.3010)	-0.0945 (-0.2850)	-0.0345 (-0.1097)
ΔF_{t-7}	0.1713 (1.4411)	0.0551 (0.4406)	0.2415** (2.1663)	0.1286 (1.0949)	-0.0825 (-0.2963)	0.1123 (-0.4253)
ΔF_{t-8}	0.0716 (0.6208)	0.0415 (0.3419)	0.1322 (1.2817)	0.10494 (0.9649)	-0.5043 (-1.4017)	-0.857* (-2.5133)
Z_{t-1}	-0.1877* (-2.2768)	-0.3127* (-3.6007)	-0.145*** (-1.7771)	-0.2754* (-3.1900)	-0.3390 (-1.5083)	-0.4920** (-2.0752)
Residual Diagnosis						
LB Q (5)	387.82	383.68	406.50	568.92	179.95	202.02
LB Q (10)	572.26	573.40	481.78	633.41	271.26	314.98
LB Q (20)	748.24	738.02	525.56	700.95	367.11	430.73

LB Q (30)	828.44	807.95	532.27	713.59	389.51	459.08

Note:* denotes 1% level of significance, ** denotes 5% level of significance and *** denotes 10% level of significance Figures in ( ) are t-statistics.

The minimum-variance hedge ratio as per VECM model result is $\sigma_{sf} / \sigma_{ff}$ =0.9360 is obtained in the same way as BVAR. The hedge ratios estimated from VAR for the pre- and post-Sub-prime period are 0.9251 and 0.9425, respectively. It may be because it takes into account the tighter long-run equilibrium relationship between spot and futures prices. The hedger ignorant of the co-integrating relationship between futures and spot prices is likely to take a smaller than optimal futures position. The hedge ratio and hedging effectiveness obtained by BVAR and VECM method is presented in the table 6.7. The results show that both the techniques were able to reduce a significant risk of the unhedged portfolio.

Table 6.7: Hedge Ratio and Hedging Effectiveness Estimation (BVAR and VECM)

Hedge Ratio and Hedging Effectiveness						
	Total period		**Pre-Sub-prime**		**Post-Sub-prime**	
	BVAR	**VECM**	**BVAR**	**VECM**	**BVAR**	**VECM**
$\text{Cov}(\varepsilon_{st}, \varepsilon_{ft}) = \sigma_{sf}$	0.000279	0.000278	0.000210	0.000209	0.000377	0.000378
$\text{Var}(\varepsilon_{st}) = \sigma_{ss}$	0.000268	0.000268	0.000204	0.000204	0.000359	0.00036
$\text{var}(\varepsilon_{ft}) = \sigma_{ff}$	0.000298	0.000297	0.000227	0.000226	0.000400	0.0004
Hedge Ratio (h)	0.9362	0.9360	0.9251	0.9347	0.9425	0.9437
Variance (H)	0.0000090	0.0000099	0.000006	0.000007	0.000011	0.000012
Variance (U)	0.000268	0.000268	0.000204	0.000204	0.000359	0.000509
HE	0.9558	0.9630	0.9669	0.9627	0.9681	0.9653

Figure 6.3: Residual series from Spot and Future equation in Bivariate VAR model

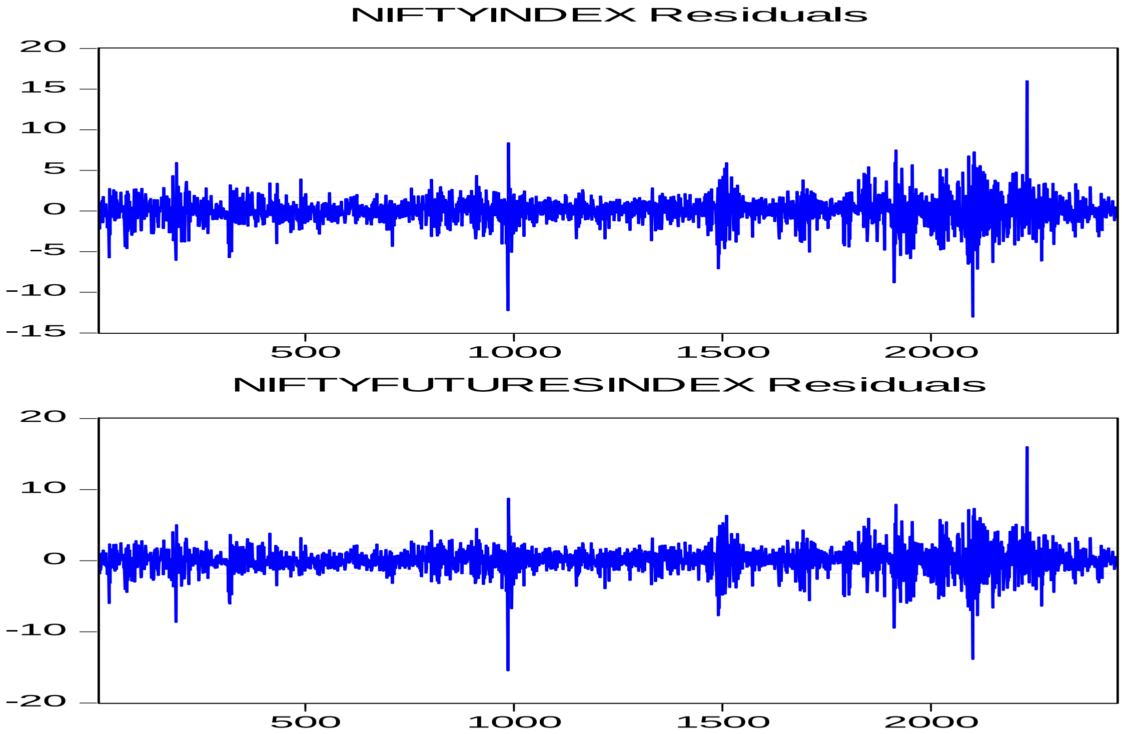
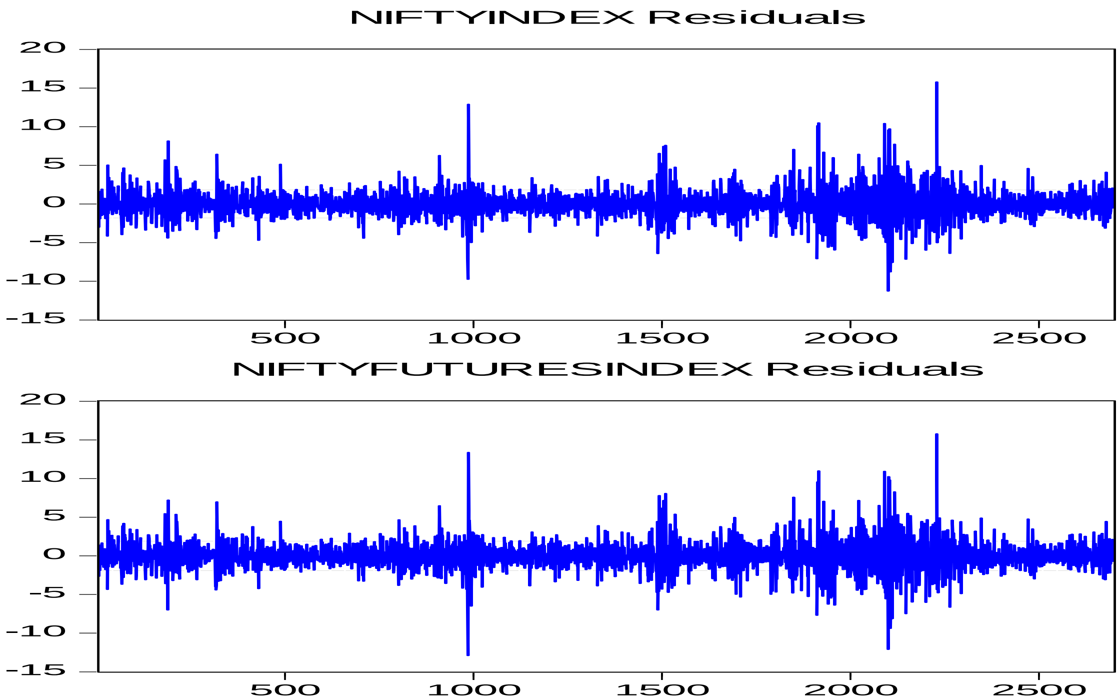


Figure- 6.4: Residual Series from Spot and Futures equation in VECM Model



The Multivariate GARCH Model

The plots of actual values of the residual of the VAR and VECM exhibit the volatility clustering as shown in Figures 6.3 and 6.4. They represent the variance of the series is changing over time and large changes to be followed by large changes and small changes to be followed by the small changes of either sign. These characteristics of the financial time series have been found by Mandelbrot (1963a, 1967), Klin (1977) and Engle (1982). It is an indication of the presence of an Autoregressive Conditional Heteroskedastic (ARCH) effect. The same has been proved by the squared residuals for a significant Q-statistics for a given lag. The results of squared residuals of both VAR and VECM have been presented in Table 6.5 and 6.6; they are highly significant, showing the presence of ARCH effect. Thus, the Multivariate GARCH model is required to tackle the problem of heteroskedasticity. In other words, a bivariate GARCH model is necessary to explicitly model the variance of the residuals of the error correction model.

The methods already discussed for the estimation of the optimal hedge ratio indicated the presence of heteroskedasticity in the VAR (with error-correction term). Therefore, it is necessary to estimate the conditional variance and covariance for calculating time-varying hedge ratios by employing the M-GARCH Model.

The results of the M-GARCH are divided into two sections: the bivariate vector autoregression (VAR) and vector error correction (VEC) multivariate GARCH model of Bollerslev, Engle and Wooldridge (1988). In particular, the mean equations (first moment) are modeled with bivariate vector autoregression (VAR) and vector error correction (VEC) models. In addition, time-varying variances and covariance are taken into account by modeling the second moment with VAR-GARCH and VEC-GARCH models.

The results of VAR-GARCH and VEC-GARCH are reported in Table 6.8 and 6.9 . The sum of the coefficients of VAR-GARCH is closer to 1, indicating the persistence of ARCH effects in the data sets. It implies that the current information remains important for forecasts of the conditional variance at all horizons. The parameter estimates are all positive definite and highly significant. Similar results have been found for VECM-GARCH.

Table 6.8: The Estimates of the VAR-GARCH Model

Variable	Total Period	Pre-Sub-prime	Post-Sub-prime
	Coefficients	**Coefficients**	**Coefficients**
c_{ss}	0.000007* (12.4011)	0.00001* (9.5007)	0.000006* (4.9171)
c_{sf}	0.000007* (11.7006)	0.000013* (9.7500)	0.000006* (5.0247)
c_{ff}	0.000007* (13.0359)	0.000013* (9.8369)	0.000006* (5.1239)
α_{11}	0.1086* (19.8795)	0.1299* (11.9282)	0.0817* (8.8386)
α_{22}	0.1061* (19.5487)	0.1224* (11.7685)	0.0807* (8.8271)
α_{33}	0.1060* (19.4903)	0.1224* (12.1127)	0.0801* (8.7621)
β_{11}	0.8622* (166.9145)	0.7973* (57.5299)	0.8979* (87.4323)
β_{22}	0.8646* (167.1609)	0.8051* (59.2075)	0.8993* (88.9634)
β_{33}	0.8653* (164.1226)	0.8070* (59.7166)	0.9005* (89.4162)

Note: This table reports the results estimated from VAR-GARCH model in equation. c_{ss}, c_{sf} and c_{ff} are constants. α_{11}, α_{22} and α_{33} are coefficients of the squared error terms respectively. β_{11}, β_{22} and β_{33} are coefficients of the conditional variances and covariance, respectively. :* denotes 1% level of significance, ** denotes 5% level of significance and *** denotes 10% level of significance and Figures in ( ) are t-statistics.

Table 6.9: The Estimates of the VECM-GARCH Model

Variable	Total Period	Pre-Sub-prime	Post-Sub-prime
	Coefficients	Coefficients	Coefficients
c_{ss}	0.000005* (12.7582)	0.00001* (10.0735)	0.000007* (5.2242)
c_{sf}	0.000005* (12.3580)	0.00001* (10.078)	0.000006* (5.1160)
c_{ff}	0.000005* (11.7175)	0.00001* (9.9052)	0.000006* (4.9975)
α_{11}	0.0852* (19.2731)	0.1189* (12.9836)	0.0781* (8.7683)
α_{22}	0.0850* (18.9029)	0.1190* (12.5777)	0.0789* (8.8599)
α_{33}	0.0867* (18.7211)	0.1268* (12.6960)	0.0800* (8.8962)
β_{11}	0.8923* (194.1893)	0.8086* (63.9516)	0.9015* (89.2542)
β_{22}	0.8921* (193.6312)	0.8074* (64.0858)	0.9002* (88.8612)
β_{33}	0.8903* (188.2395)	0.7996* (62.6559)	0.8985* (87.3825)

Note: This table reports the results estimated from VECM-GARCH model in equation. c_{ss}, c_{sf} and c_{ff} are constants. α_{11}, α_{22} and α_{33} are coefficients of the squared error terms respectively. β_{11}, β_{22} and β_{33} are coefficients of the conditional variances and covariance, respectively. :* denotes 1% level of significance, ** denotes 5% level of significance and *** denotes 10% level of significance and Figures in ( ) are t-statistics.

6.6.3 Hedge Ratio and Hedging Effectiveness

In order to estimate the time-varying hedge ratio, the two conditional variance series are generated from the GARCH equation. The results of the VAR-GARCH and VECM-GARCH time-varying hedge ratios are presented for whole sample period as well as pre- and post-Sub-prime periods in the Table 6.10. The results of the dynamic hedge ratio estimated from the time-varying conditional variance and co-variances between spot and futures return range from a minimum 0.7054 to a maximum of 1.5139 for the total period in case of VAR-GARCH technique. The average hedge ratio estimated from VECM-GARCH is 0.7087 to 1.55 which is similar to the results of the VAR-GARCH technique. It implies that how the hedge ratio varies over period of time. Thus, it is very important to adjust to the hedge ratio based on the market conditions. Similar results have been found for the pre and post-Sub-prime period. A high Jarque-Bera suggests that the distribution of the hedge ratio is not normal.

To calculate the hedging effectiveness, the variance of hedged and unhedged portfolio is estimated. The results are reported in Table 6.11. The hedging effectiveness calculated from VAR-GARCH and VECM-GARCH is 0.9674 and 0.9708 respectively for the total period. The results imply that in the pre and post- sub-prime crises period the estimated hedge ratios are able to reduce the risk more than 95% of the unhedged portfolio as estimated by VAR-GARCH and VECM-GARCH. It can be concluded that time varying hedge ratios are able to provide a good hedging effectiveness in terms of variance reduction.

Table 6.10: Estimates from Time Varying Hedge Ratio

Time-Varying Hedge Ratio						
	Total Period		**Pre-subprime**		**Post-subprime**	
	VAR-GARCH	**VECM-GARCH**	**VAR-GARCH**	**VECM-GARCH**	**VAR-GARCH**	**VECM-GARCH**
Average Hedge Ratio	0.9264	0.9272	0.9401	0.9437	0.9099	0.9107
Minimum	0.7054	0.7087	0.6760	0.6797	0.7502	0.7410
Maximum	1.5139	1.5528	1.54855	1.5251	1.0851	1.0885
Jarque-Bera	3157.995	3431.778	784.9335	1158.469	13.7896	32.9609

Table 6.11: Hedging Effectiveness of M-GARCH Model

Hedging Effectiveness						
	Total Period		**Pre-subprime**		**Post-subprime**	
	VAR-GARCH	**VECM-GARCH**	**VAR-GARCH**	**VECM-GARCH**	**VAR-GARCH**	**VECM-GARCH**
Hedge Ratio	0.9264	0.9272	0.9401	0.9437	0.909904	0.9107
Variance (H)	0.000008	0.000007	0.000008	0.000008	0.000004	0.000004
Variance (U)	0.000268	0.000268	0.000205	0.000205	0.00036	0.000359
HE	0.9674	0.9708	0.9565	0.9566	0.9885	0.9886

Figures 6.5 to 6.10 depict time-varying hedge ratios for the three periods (full sample period, pre-Sub-prime period and post-Sub-prime period) calculated from time VAR-GARCH and VECM-GARCH models. As the figures show that how the hedge ratio changes over the period of time and exhibit fluctuations, this suggests that the hedgers are required to adjust their futures positions more often to cope up with the market dynamics.

Figure-6.5: Time-Varying Hedge Ratio – VAR-GARCH for Whole Sample

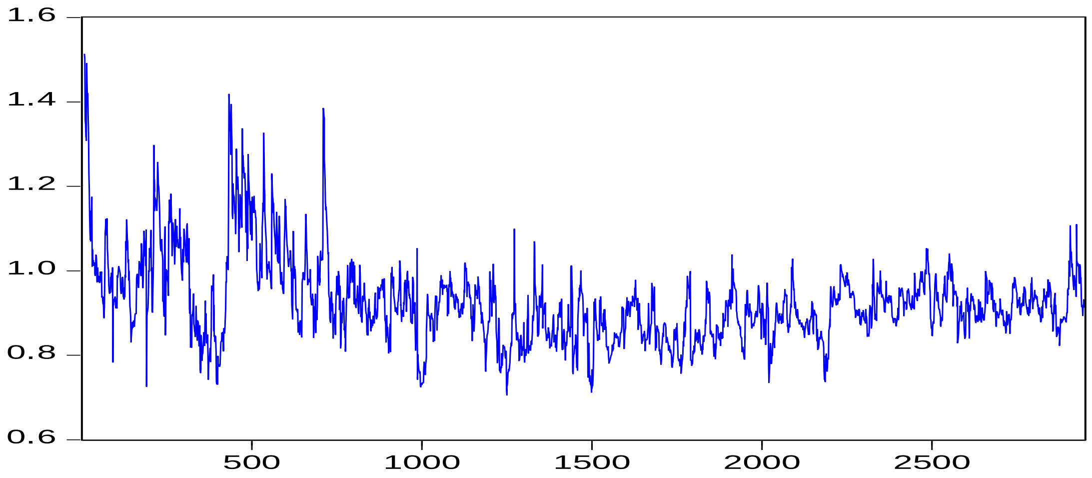


Figure 6.6: Time-Varying Hedge Ratio – VECM-GARCH for Whole Sample

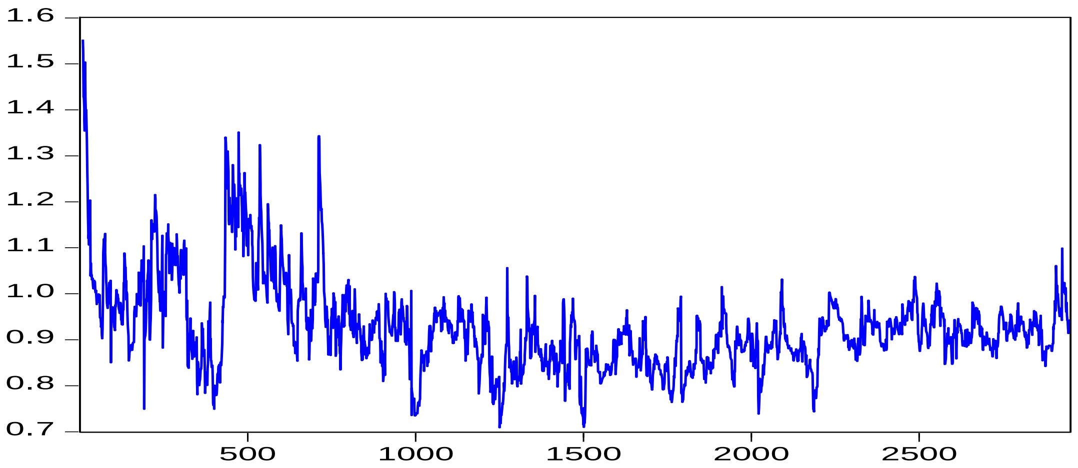


Figure 6.7: Time varying Hedge Ratio VAR-GARCH for Pre-Sub-prime Crisis

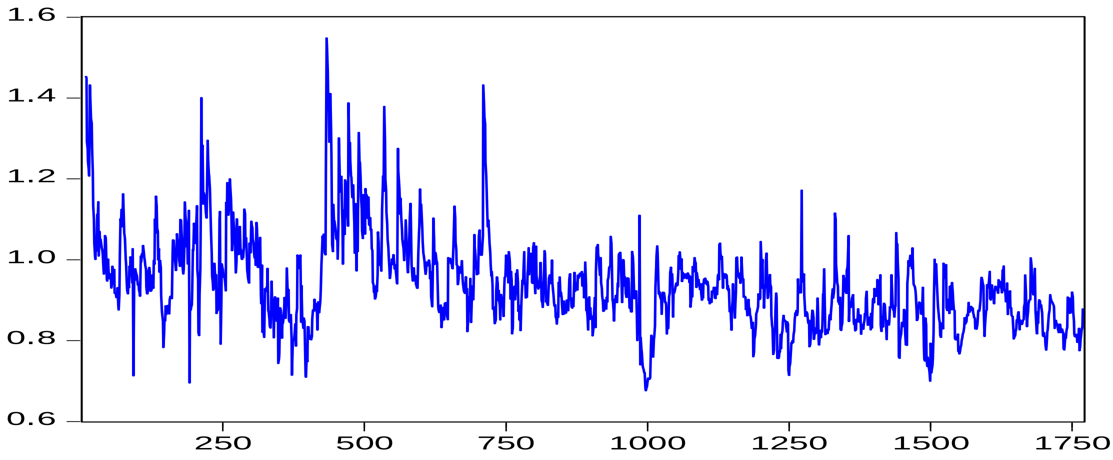


Figure 6.8: Time-Varying Hedge Ratio VECM-GARCH for Pre-Sub-prime Crisis

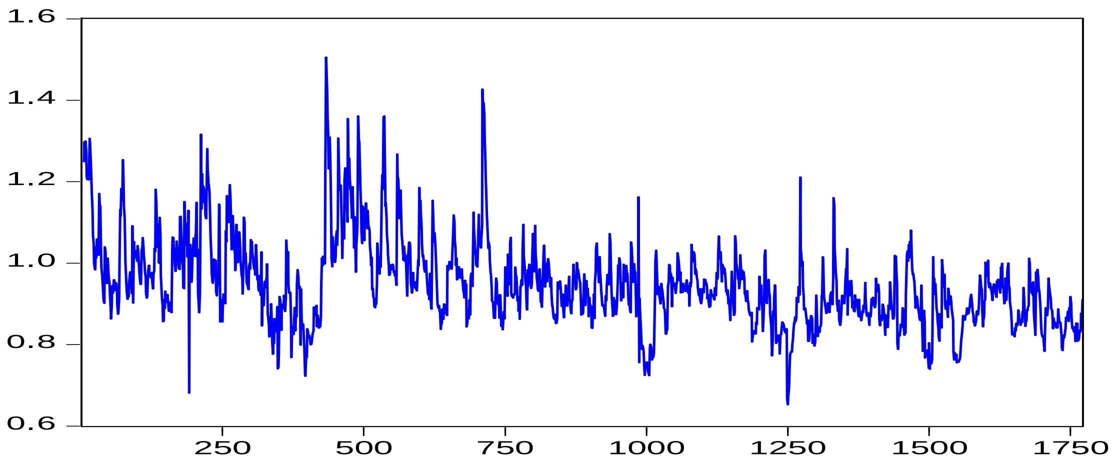


Figure 6.9: Time-Varying Hedge Ratio VAR-GARCH for Post-Sub-prime Crisis

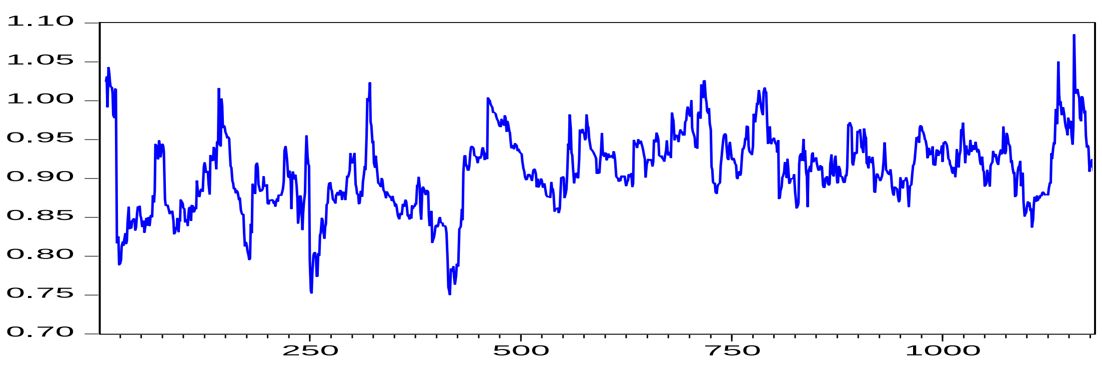
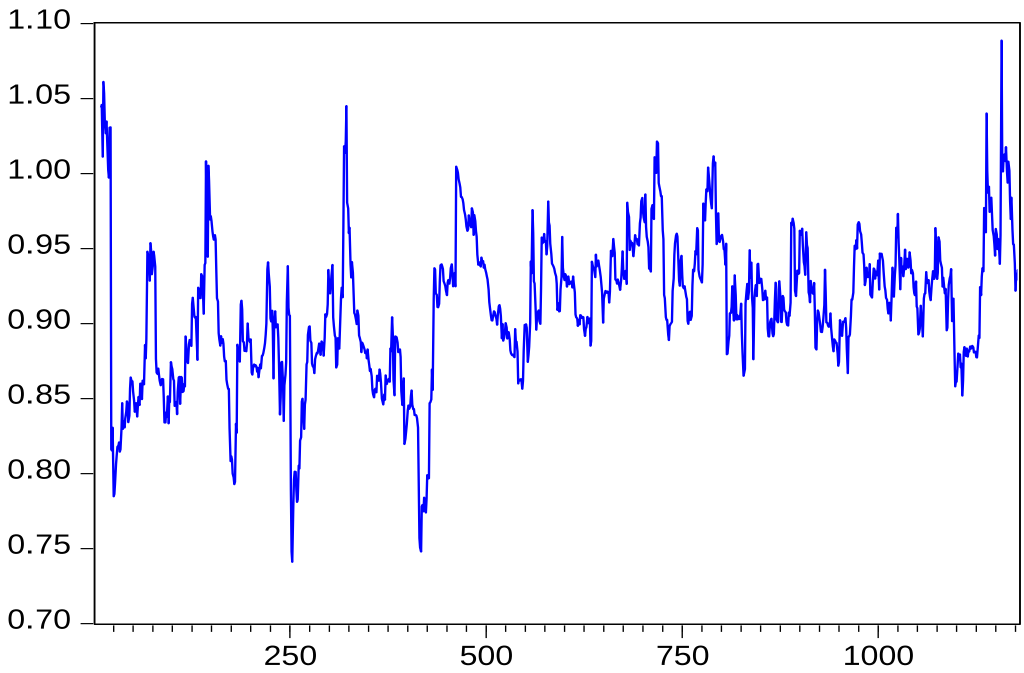


Figure 6.10 Time-Varying Hedge Ratio VECM-GARCH for Post-Sub-prime Crisis



The hedge ratios (HR) estimated from four different models are listed in Table 6.12. The results suggest that the hedge ratios estimated from different techniques provides a significant risk reduction.

Table 6.12: Hedge Ratios from different Models

	Total Period		Pre-subprime		Post-subprime	
Method	**HR**	**HE**	**HR**	**HE**	**HR**	**HE**
OLS	0.9462	0.9682	0.9375	0.9464	0.9536	0.9879
BVAR	0.9362	0.9558	0.9251	0.9669	0.9425	0.9681
VECM	0.9360	0.9630	0.9347	0.9627	0.9437	0.9653
VAR-GARCH	0.9264	0.9674	0.9401	0.9565	0.9099	0.9885
VECM-GARCH	0.9272	0.9708	0.9437	0.9566	0.9107	98.86

6.6.4 Hedging Effectiveness Comparison: In-Sample and Out-of-Sample

Further, in order to validate the hedge ratio and hedging effectiveness, we have estimated the in-sample and out-of-sample hedging performance for 1-, 5-, 10-, 15- and 20-day time horizons. The data set for in sample has been taken from June 12, 2000 to October 30, 2012 for estimating the optimal hedge ratio and its effectiveness. Similarly, an out-of-sample data set has been taken from April 1, 2012 to October 30, 2012. The comparison is based on the mean return of the hedged portfolio and variance reduction of the hedged portfolio. The mean return shows the return for the portfolio and variance is the risk reduced by using the optimal hedge ratio. The analysis is comparing the mean return and variance reduction of different competing strategies.

Table 6.13: The Results of in-Sample Comparison

Forecast Horizons	**Hedge Ratio**	**Mean Return**	**Variance Reduction**
One-Day			
OLS	0.9462	0.0023%	96.50
VAR	0.9362	0.0027%	96.52
VECM	0.9450	0.0023%	96.51
VAR-GARCH	0.9264	0.0031%	96.52
VECM-GARCH	0.9272	0.0031%	96.52
Five day			
OLS	0.9462	0.0024%	98.45
VAR	0.9362	0.0028%	98.40
VECM	0.9450	0.0024%	98.45
VAR-GARCH	0.9264	0.0032%	98.32
VECM-GARCH	0.9272	0.0032%	98.33
Ten Day			
OLS	0.9462	0.0024%	98.62
VAR	0.9362	0.0027%	98.56
VECM	0.9450	0.0024%	98.62
VAR-GARCH	0.9264	0.0032%	98.47
VECM-GARCH	0.9272	0.0031%	98.48
Fifteen Day			
OLS	0.9462	0.0022%	99.21
VAR	0.9362	0.0026%	99.14
VECM	0.9450	0.0023%	99.21
VAR-GARCH	0.9264	0.0031%	99.05
VECM-GARCH	0.9272	0.0030%	99.06

Twenty Day			
OLS	0.9462	0.0023%	99.33
VAR	0.9362	0.0027%	99.28
VECM	0.9450	0.0023%	99.35
VAR-GARCH	0.9264	0.0031%	99.18
VECM-GARCH	0.9272	0.0031%	99.19

Table 6.14: The Results of out-of-Sample Comparison

Forecast Horizons	Hedge Ratio	Mean Return	Variance Reduction
OLS	0.9462	0.0025%	95.37
VAR	0.9362	0.0029%	95.41
VECM	0.9450	0.0026%	95.38
VAR-GARCH	0.9264	0.0034%	95.42
VECM-GARCH	0.9272	0.0033%	95.43
Five day			
OLS	0.9462	0.0030%	97.34
VAR	0.9362	0.0036%	97.34
VECM	0.9450	0.0031%	97.35
VAR-GARCH	0.9264	0.0041%	97.32
VECM-GARCH	0.9272	0.040%	97.32
Ten Day			
OLS	0.9462	0.0021%	97.78
VAR	0.9362	0.0026%	97.76
VECM	0.9450	0.0021%	97.78
VAR-GARCH	0.9264	0.0032%	97.72
VECM-GARCH	0.9272	0.0031%	97.72
Fifteen Day			
OLS	0.9462	0.0027%	98.11
VAR	0.9362	0.0033%	98.09
VECM	0.9450	0.0028%	98.11
VAR-GARCH	0.9264	0.0040%	98.05
VECM-GARCH	0.9272	0.0039%	98.05
Twenty Day			
OLS	0.9462	0.0028%	98.20
VAR	0.9362	0.0037%	98.19
VECM	0.9450	0.0029%	98.20
VAR-GARCH	0.9264	0.0045%	98.16
VECM-GARCH	0.9272	0.0044%	98.17

Table 6.13 shows in-sample performance of mean return and percentage variance reduction for different hedge ratios. The results indicate that all the hedge ratios are able to reduce a significant risk in terms of variance reduction. The in-sample results imply that as the hedging horizon increases, the hedge becomes more effective. The variance reduction in the 15 day and 20 day time horizon provides slightly better hedging effectiveness over 1day, 5 day and 10 day time horizon. This implies that all the models offer similar hedging effectiveness. However, VAR-GARCH and VECM-GARCH models provide slightly better mean return than other models. The results of the out-of-sample analysis of the hedging performance are shown in Table 6.14. Similar result has been obtained for out-of-sample performance.

The results demonstrate that all hedging strategies enable achieving substantial risk reduction compared with the unhedged positions of the S&P CNX Nifty index. The results which report hedging effectiveness show that Multivariate GARCH performs better results in terms of risk reduction for all time horizons and a higher mean return than other methods. Under a risk-return trade-off basis, M-GARCH is found to be marginally better than other models, providing the greatest return and the lowest portfolio variance simultaneously. Overall, M-GARCH model provides better hedging strategies because they generate the greatest mean return and similar risk reduction when compared with other models and it takes into time varying component into account.

6.7 Conclusions

Hedging is considered one of the important tools in the futures market and is effective if the price movements of both the instruments (hedged and unhedged) approximately offset each other. The present chapter examined the hedge ratio and its effectiveness of the Nifty index future by using four competing models, OLS, VAR, VECM and M-GARCH. Further it also measured its effectiveness in both in-sample and out-of-sample datasets for different time horizons. The hedge ratio obtained from different methods has been compared under a variance reduction method All the models are able to offer a significant reduction in the portfolio variance reduction in comparison with the unhedged portfolio. Under a risk-return trade-off basis, M-GARCH is found to be marginally better than other models. The performances of the hedge ratios in the in-sample and out-of-sample forecasts have offered a similar picture. The overall results of in-sample and out-of-sample conclude that the time-varying GARCH method provides a better hedging effectiveness over all other models.

Chapter-VII

Summary and Conclusions

7.1 Rationale Approach of the study

Innovations in the Indian capital market have evolved it into a dynamic segment of the Indian financial system. A large number of reforms have taken place to enhance competition, transparency and efficiency in the capital market. These reforms have brought about a major transformation – through the introduction of electronic trading, derivatives trading and exchange-traded funds; abolition of *Badla* trading; and allowing foreign institutional investors to invest in India's capital market. Overall, capital market reforms in India have been an integral part of financial sector reforms, which were initiated in September 1992 based on the recommendations of the *Narasimham Committee on Financial System.*

Meanwhile, a series of reforms in the financial market between 1993 and 1996 paved the way for the development of exchange-traded derivatives market in India. Increased volatility in asset prices and greater integration of national financial markets with international markets necessitated the introduction of derivatives in India in June 2000, based on the recommendations of the *L.C. Gupta Committee report* of 1996. Over the years, derivatives market volumes, especially of futures and options, on the National Stock Exchange have seen significant growth, and currently the turnover is much higher than that in the cash market.

Derivatives refer to the financial instruments whose values are derived from the price of an underlying item. The underlying item could be equity, index, foreign exchange, commodity or any other asset. Derivatives instruments include futures, forwards, options and swaps – and these can also be combined with each other or with traditional securities to create hybrid instruments. In India, equity derivatives were introduced with an objective of hedging the price risk arising out of volatile capital market. In recent years, derivatives products such as futures and options have become important instruments of price discovery, portfolio diversification and risk hedging in the Indian stock market. The objective of this study is to improve the understanding and economic functions of the futures market in price discovery, volatility and hedging, and designing an appropriate framework for efficient derivatives market in India.

Derivative trading in India has thrown up new issues for researchers, policy makers, investors and traders. Understanding these issues and further investigation should lead to greater benefits for the various stakeholders of the financial market. The key issues are the following:

Given the volatile nature of the financial market, derivatives were introduced as risk-management tools. Thus, it is important to know to what extent derivatives have been able to reduce the risk, *i.e.*, hedging the risk. The activity of trading futures with the objective of reducing or controlling risk is called 'hedging' (Edward and Ma, 1992). The effective use of index futures in hedging decisions has become the focus and centre of debate, and so are finding an optimal hedge ratio and the hedging effectiveness in empirical research (Figlewski, 1985, Castenlino, 1992). Hedge ratio is usually defined as the proportion of a spot position that is covered with an opposite position in the futures market. The existing literature on the hedge ratio estimation is an inconclusive area in the sense that different models calculate different hedge ratios. In the literature of futures trading, it is still debatable as to how to calculate the hedge ratio. To measure the hedging effectiveness of the futures market, different models need to be applied in the Indian context and the findings should be subjected to various tests for checking their robustness.

Another important area in this subject pertains to the impact of introduction of derivatives on functioning of securities market. Some argued that the Indian market is not ready for highly leveraged products such as futures and options, as they could aggravate the spot market volatility, while others said that they could improve liquidity and market efficiency and thus should lead to volatility reduction. Earlier studies on the impact on spot market volatility show that the results are ambiguous. This issue has generated a huge debate- whether the introduction of futures has influenced spot market volatility. It has been more than a decade since the inception of the index futures in India. Thus, it is pertinent and useful to examine the influence of the futures market on the spot market, particularly after the former's tremendous growth over the past few years.

Price discovery, an important function of the derivatives market, is an important indicator of an efficient market. Price information of underlying asset values contributes to efficient allocation of resources in the economy. The process of transmission of information into prices is called price discovery. Thus, it is necessary to understand how price discovery takes place. There is always scope to investigate the "lead-lag" relationship between spot and futures prices. If the futures or spot price gives an indication of the other price, then one can be used for extracting price information of the other. If the inter-relationship is established, one can have an idea about the expected futures/spot price. This inter-relationship between the two should be tested for understanding the depth of this market.

The National Stock Exchange of India ranks first in the world in terms of contacts traded in single stock futures. Most of the countries in the world do not permit futures trading on individual stocks; in early 2003, trading in stock futures started in the US with the "physical settlement" system. The motive behind physical settlement is to reduce excessive speculation or unnecessary price volatility unrelated to real economic factors. However, the benefit of cash settlement is that it is easy to manage cash for settlement rather than securities, but the biggest disadvantage of it is that it gives rise to excessive speculation and unnecessary volatility in stock prices. In India, single stock futures and options were cash-settled. The L.C. Gupta committee report on derivatives also provides less preference to the futures on individual stocks. In this context, research on the behaviour of stocks for which derivatives are present may throw some light on this area.

The present study has tried to provide an understanding and functions of the futures market in India. The objectives of this study have been set as follows:

1. To examine the impact of introduction of futures on underlying spot market volatility;
2. To measure the nature and structure of volatility after the introduction of futures trading;
3. To investigate the existence of causal relationship between spot and futures prices;
4. To examine whether the establishment of Indian stock index futures market effectively serve the price discovery function;
5. To measure the hedge ratio and hedging effectiveness of the futures market;

For objectives 1 and 2, daily closing returns of the S&P CNX Nifty spot index and Nifty Junior index and 15 individual stocks have been used. The study uses daily data from 1 January 1997 to 30 October 2012. In order to examine objectives 3 and 4, daily closing prices of the Nifty index and Nifty index futures for the near-month have been taken from 12 June 2000 to 31 March 2012. Similarly, for the 15 individual stocks, cash and futures prices have been taken from 9 November 2001 to 31 March 2012. For the last objective, the main variables for the study are the daily closing values of the S&P CNX Nifty index futures for near-month contracts and spot Nifty index; and it covers data from 12 June 2000 to 30 October 2012.

7.2 Findings of the Study

With the above-mentioned objectives, the thesis consists of seven chapters. The first chapter introduces the concept of derivatives existing in the capital market of India. It provides a background to the issues in the derivatives market and explores the concept of price discovery, hedging and volatility of futures market; it also explores the problems associated with these. The objectives of the study, data sets and methodologies are also discussed in this chapter.

The second chapter provides a review of the earlier literature pertaining to this subject. The literature is based on price discovery, volatility and hedging effectiveness of the futures market across the globe. The chapter provides research gaps existing in the literature. The review on the impact of futures trading on the spot market volatility reveals that studies mostly focused on the well developed market and less on individual stocks. The findings on the issues are inconclusive in nature. Some studies support the hypothesis that derivatives stabilize the spot market volatility in the form of reduction of volatility in the post-derivatives era, whereas some authors argue that it has increased the volatility of the spot market. The hedge ratio estimation and hedging effectiveness review suggest that time-varying hedge ratios provide a better result in comparison with the OLS, VAR and VECM techniques. Further, some earlier studies provide an insight into how the futures and spot prices are related; and some of these [Kawaller (1987)**,** Harris (1989)**,** Stoll and Whaley (1990)**,** Chan (1992)**,** Alphonse (2000)**,** Tenmozhi (2002) and Kavussanos (2003)] support the hypothesis that futures market leads the spot market most of the time. From this literature review it can be concluded that most of the studies on various issues in the derivatives market are set against the backdrop of developed country markets and the results vary based on the indices used in these studies; also, very limited number of studies have been carried out for developing countries like India.

The third chapter gives an idea about the functioning of the derivatives market in India. First, it discusses the concept and types of derivatives instruments such as futures, forwards, options and swaps. Second, the mechanism of the futures market and different theories of hedging and pricing models are discussed in detail. Lastly, it provides a note on the history of derivatives trading India.

The fourth chapter first examines the impact of introduction of index futures and stock futures trading on the volatility of the underlying market, by employing GARCH (1,1) and EGARCH (1.1) models. Second, it considers the day-of-the-week effect (such as Monday, Tuesday, Wednesday, Thursday and Friday effect) and market-wide factors for measuring the volatility of the underlying market. Third, the changes in volatility and information efficiency are examined for both pre-and post-derivatives period by employing the GARCH (1,1) model.

The results of the nifty index show that volatility has been reduced after the introduction of futures market, after controlling market-wide factors. The results obtained from the EGARCH (1,1) model reveal the presence of asymmetry effect in the data. It means negative news increases the volatility more than positive news. It also shows that the day-of-the-week effect as Monday effect is found to be significant, indicating higher volatility on Monday and lower volatility on rest of the week days. Investors and traders can take advantage of this effect by using different strategies. The reasons for the significant Monday effect are due to the weekend effect and the release of overseas data mostly on Fridays. This could be the reason for the increase in volatility on Mondays in comparison with other days. The volatility arising from current news has increased, whereas the volatility arising from old news has declined after the introduction of futures trading. The results show that the day-of-the-week effect is present in the case of Nifty index futures, exhibiting strong day-of-the-week effects even after accounting for conditional market risks.

This study also investigates the impact of introduction of individual stock futures on the underlying market. The results show that spot market volatility has reduced after the introduction of futures on individual stocks, after controlling market-wide factors. The EGARCH (1,1) results on individual stocks show that the asymmetry coefficient is negative for all the stocks except for Infosys, State Bank of India and Tata power. It implies that except for these three stocks, negative news increases volatility more than positive news. The impact of current news has declined and the impact of past volatility on current volatility has increased for some stocks in the post-derivatives period. For Cipla, Grasim, Hindustan Unilever, Infosys and ITC, the volatility arising from the flow of recent news has increased, whereas the volatility arising from the old news has declined after the introduction of futures trading in the post-derivatives period. For the stocks of State Bank of India and Ranbaxy, both the ARCH and GARCH coefficients have increased in the post-derivatives period. The overall results suggest that the information flow has changed to a great extent in the post-derivatives era.

The fifth chapter examines price discovery, causality and forecasting at index and firm levels. The price discovery and causality have been examined by employing Engel-Granger and Johansen's (1988) Vector Error Correction Model (VECM). The results show that a long-run relationship exists between spot and futures prices at index and firm levels. The spot market leads the futures market at the index level and price discovery takes place in both the markets. One of the implications is that as long as one market leads the other market, the arbitrageur can make a good amount of money by entering both the markets. Further, ARIMA, VAR and VECM models have been employed to compare the forecasting ability of futures prices. These forecasts are compared with actual prices, with the use of standard statistical criteria of Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The results show that although all the models provide reasonably good results, VECM forecasts provide better results than ARIMA and VAR. The analysis on individual scripts shows unidirectional causality from futures to spot for some stocks and bi-directional causality for some other stocks. There is also lead-and-lag relationship between spot and futures prices in terms of causality. The results show that price discovery takes place in both the markets and there is no clear-cut dominance of any one market over the other.

The sixth chapter finds out the hedge ratios of the Indian stock market and the hedging effectiveness of the stock index futures by employing various econometric techniques. The hedge ratio is calculated by employing the Ordinary Least Square (OLS) regression model, the bi-variate Autoregressive Model (BVAR), the Vector Error Correction Mechanism (VECM) and the Multivariate GARCH models. After estimating the hedge ratio, hedging effectiveness from each strategy is estimated and compared to find out the model that provides better hedging effectiveness in terms of risk reduction. The hedge ratios obtained from different methods have been compared under a variance-reduction method. All the models are able to provide a significant reduction in the portfolio variance in comparison with the un-hedged portfolio. However, the performances of the hedge ratios with in-sample and out-of-sample show that the M-GARCH model provides higher mean returns than other models. Further, in order to validate the results, in-sample and out-of sample comparisons are made for 1, 5, 15, 20 time horizon. The in-sample and out-of-sample results provide better hedging effectiveness. Thus, the futures market is able to reduce a significant risk of the spot index.

7.3 Theoretical Implications and Policy Suggestions

The futures market serves as an effective risk-management tool in the case of S&P CNX Nifty index and index futures. It reduces risk exposure by permitting offsetting positions in the futures market. Thus, the futures market provides a risk reduction tool for the market participants. Before the introduction of futures, the available hedging instruments were few.

Markets are exposed to a variety of risks: commodity risk, interest rate risk and currency risk. Investors can use the optimum hedge ratio to minimize risk by holding a certain amount of futures contracts to hedge their exposure in the spot market. The hedge ratio obtained by employing different methodologies provides a better way to minimize the risk.

Information flow has significantly increased and volatility of the spot market has reduced at index and firm levels. Thus, the introduction of futures trading has improved the flow of information. This finding rejects the hypothesis that futures market destabilizes the spot market volatility.

In most developed markets, derivatives exchanges are different from exchanges for cash trading. The results of this study reveal that price discovery happens in both the markets, and there is no dominance of the futures market over the spot market. In this regard, this study suggests that there should be a separate exchange for derivatives trading. In the National Stock Exchange of India and the Bombay Stock Exchange, both these instruments are traded at one place. This could lead to irrational price movements due to the formation of a potential cartel among the significant players in the market. Therefore, the establishment of a separate exchange should be encouraged for the efficient functioning of the derivatives market. The L.C. Gupta Committee report also suggested for a separate exchange from the regulatory point of view.

7.4 Limitations and Scope for Further Studies

The present study is based on the equity derivative trading in the National Stock Exchange. Research may also be undertaken by using the Bombay Stock Exchange derivatives segment, although the liquidity for the latter is less than that in the National Stock Exchange.

Similar studies can be carried out for other Indices of the National Stock Exchange as well. The present study makes use of the daily data while the same can be investigated by using intra-day price data.

Research may also be carried out in the commodity and currency futures market, which requires utmost attention in these days because of the volatility nature of these products.

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GLOSSARY

Nifty:

A stock Price index in National Stock Exchange containing 50 highly traded Stocks

Hedging

It is an activity designed to reduce the risks imposed by other activities. The possible loss due to price movement on an asset can be mitigated by hedging, which involves selling the goods forward that is for delivery at an agreed price on future date or by selling in future market.

Derivative:

A financial asset such as futures and options contracts, the value of which is derived from the claim it makes against some underlying assets, such as a foreign currency, commodity, stock index.

Financial Derivatives:

If the underlying assets of derivatives are financial instruments like currency, share, price index, equity, then it is called financial derivatives.

Commodity Derivatives:

The underlying assets of the commodity derivatives are commodities.

Futures:

Future contracts are an agreement between two parties to buy or sell an asset at a certain time in the future at a certain price. Futures are standardized and exchange traded contracts.

Forwards:

A forward contract is customized contract between two entities, where settlement take place in future at to-days pre-agreed price.

Interest Rate futures:

An interest rate futures contracts is an agreement to buy or sell a standard quantity of specific interest bearing instruments, at a pre-determined futures date at a price agreed upon between the parties.

Index Futures:

Index futures are contracts whose underlying security is a stock market. By trading in index based futures, one buys or sells the entire stock market as a single entity.

Hedger:

An individual who hedges is called a hedger.

Treasury Bills:

The short term gilt edged securities sold at a discount from its face value to borrow funds.

Options:

An option is the right to buy or sell a particular asset for a limited time at a specified rate. These contracts give the buyers a right but not to impose obligation to buy or sell the specified asset a set price on or before a specified date.

Put Option:

The owner or the buyer of put option gets the right not an obligation to sell the underlying assets. Similarly the seller or a put option has only obligation but no right to buy the underlying asset.

Backwardation:

A consolidation in finance markets in which the forward or futures price is less than the spot price. Alternatively defined as a condition in which the fair forward or futures price is below the expected price.

Swaps:

A swap is a transaction in which two parties agreed to exchange a pre-determined series of payments over time. It is nothing but barter exchange of payments.

Interest Rate Swaps:

It is legal agreement between two counter parties involving the exchange of interest cash flows in the same currency or different currency. interest follows are calculated with reference to an agreed notional of principal.

Currency Swaps:

Currency swaps help to eliminate the difference between international capital markets. Currency swaps result in exchange of one currency for another.

Leverage:

The ability to control large monetary amounts of a financial instrument or commodity with a comparatively small amount of capital.

Long:

Long means purchasing a security , commodity or financial instruments in the belief that price will increase and it can at a higher price thus making a profit.

Short:

Short means selling a security, commodity or financial instruments in the belief that price will fall.

Long Hedging:

Long hedging occurs when the futures are purchased to hedge against increase the prices of the commodity to the acquired either in the spot or futures markets. it is also knows as buying hedge.

Shot Hedging:

The short hedging or selling hedge occurs when the futures are sold in order to hedge a decline in prices.

Bid Price:

The price at which a market offers to buy a currency, security, options or futures.

Clearing Houses:

The organization which registers, monitors, matches and guarantees trades on a futures or options markets, and carries out financial settlements transactions.

Cross Hedging:

The hedging with a future contracts of a different, but related, cash instrument.

DAX:

The German Stock Index on 30 blue-chip equities.

FTSE-100 Index:

Index of 100 major UK shares listed on London Stock Exchange. It was drawn up specially to be used for a futures contract and trade on LIFFE as a future and as European and American-style option.

Hedge:

A transaction in which an investor seeks to protect a position or anticipated positioning the spot market by using an opposition in the derivatives.

Marking to Market:

The process by which the daily price changes are reflected in payments by parties incurring losses to parties making profits. It is also knows as daily settlement.

Nikkei 225:

The Nikkei stock on 225 Japanese equities trade on the Tokyo Stock Exchange.

Spreads:

Options of futures transaction involving a long positioning one contract and short position in another similar contract.