THE INTERDEPENDENCE BETWEEN THE SPOT AND INDEX FUTURES MARKETS IN INDIA: AN EMPIRICAL ANALYSIS

BY
VARADI VIJAY KUMAR
(04SEPH05)

UNDER THE SUPERVISION OF
DR. B. NAGARJUNA

TO BE SUBMITTED FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY IN ECONOMICS

DEPARTMENT OF ECONOMICS
SCHOOL OF SOCIAL SCIENCES
UNIVERSITY OF HYDERABAD

HYDERABAD-500 046
SEPTEMBER 2009

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To God And My Beloved Parents…

DECLARATION

I hereby declare that the work embodied in this dissertation entitled ***"The Interdependence between the Spot and Index Futures Markets in India: An empirical analysis"***carried out under the supervision of Dr. B. Nagarjuna is an original work of mine and has not been submitted for the award of any research degree or diploma of any university.

Place : Hyderabad **Signature of the Candidate**

Date : (VIJAY KUMAR VARADI)

DEPARTMENT OF ECONOMICS
School of social sciences
University of Hyderabad
Hyderabad-500046

Certificate

This is to certify that **Mr. V. Vijay Kumar** has carried out the research embodied in the present dissertation entitled ***"The Interdependence between the Spot and Index Futures Markets in India: An empirical analysis"*** for the full period prescribed under PhD ordinances of the University of Hyderabad.

This dissertation is an independent work and does not constitute part of any material submitted for any research degree or diploma here or elsewhere.

(DR. B. NAGARJUNA)
Supervisor

Dean
School of Social Sciences

Head
Department of Economics

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CHAPTER I

INTRODUCTION

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1.1 INTRODUCTION:

Indian capital markets have witnessed a radical transformation over just one decade. There is hardly any country in the world which has witnessed such massive changes in its capital market during such a short period[i]. During the early part of the 1990s, the ranking of the Indian capital market with reference to the standard global indices relating to efficiency, safety, market integrity, etc, was not at all laudatory. With reference to the risk indices, in particular, the Indian capital market was regarded as one of the worst as it figured almost at the bottom of the league. The same was the case in regard to its efficiency levels in trading and settlement systems. Strangely, neither state nor people involved in capital markets appeared to be bothered about the dismal state of our capital markets. As we are all accustomed to find India figuring in the bottom league in regard to so many other indicators of development viz., per capita income, nutritional standards, and health amenities to its citizens, literacy levels, etc, capital market bottom doesn't seem to be worried much.

It was all the past now, the same cannot be said about the current state of the Indian capital markets. From the standpoint of both adoption to sophisticated technology tools in trading and settlement mechanisms and regarding to strategy implementation for the efficiency of capital markets, not only presently India ranked in the top league but also considered to be way ahead of many developed country capital markets. Even at the risk of being, it would affirm that the National Stock Exchange of India Ltd. (NSE) has been largely responsible for significantly upgrading the Indian capital markets to the best global standards. It is also agreeable with the proposition that the government and the

Securities and Exchange Board of India (SEBI) have also played a very crucial role in this transformation process. But there is a limit to what can be achieved merely through official interventions or directives. It may be recalled that the government was seriously try to bring about several desirable reforms in the capital markets in response to the recommendations of the 1985 G S Patel Committee report. But it was not possible to make much progress in the desired direction as the stock exchange community was not receptive even to a marginal set of reforms. What is even stranger was that, the powerful broker community started talking about their fundamental rights to do business as they thought fit, although that may not always have been in the interests of the markets and the investor community.

NSE happens to be the first truly de-mutualised stock exchange of the world; it has almost fully resolved the conflict of interest issues that arise when brokers are in control of the boards of the stock exchanges. NSE represents a basic paradigm shift as the ownership and management of the exchange have been fully separated from the trading rights. NSE is owned by a set of premier financial institutions/banks and is managed by professionals who do not trade directly or indirectly on the exchange. NSE is the only stock exchange in the country which decided not to seek exemption from corporate tax, where all other stock exchanges in the country routinely enjoy the benefit. In addition, NSE has been paying sizeable corporate taxes every year, right from the first year of its operation.

NSE believes in the philosophy of a fully competitive system insofar as its trading membership is concerned. There are no entry or exit barriers in regard to NSE membership. Since NSE does not limit arbitrarily as to how many members it will admit in any of its trading segments, any eligible corporate or non-corporate entity can aspire to become a trading member by paying the required security deposits and meeting other normal membership requirements. Similarly, its members are also to free to exit later if they find that they have other more profitable business opportunities; such exiting members can seek a refund of all the membership deposits kept with NSE once they meet the dues of the exchange and their clients.

NSE thus incorporates today the features of (a) the big board of NYSE dealing mainly in very large stocks that are widely known across the length and breadth of a vast country like ours, (b) a nationwide presence of trading terminals on the pattern of NASDAQ, (c) a computerized order-driven trading system of the type found on the Paris bourse or in Vancouver, which is free from the manipulative behavior of the market makers or specialists, and (d) a settlement guarantee system akin to the Chicago's futures exchanges.

In terms of the number of number of transactions, NSE is today the third largest exchange in the world, next only to NASDAQ and NYSE. How did NSE come to occupy this position within a decade? It has also been able to establish another major landmark. It is the first stock exchange in the world to cross the turnover of an already well entrenched stock exchange in its own country, viz, BSE, in a very short period of one year. It is worth noting in this context that the initial run for the NSE was not at all that smooth. During the first few months of its existence, its trading turnover was quite modest, often less than Rs 10 crore a day. It appears that the investors as also our members were testing our systems and our management capabilities. When they saw that all the settlements were being completed absolutely on time without any hitches they started developing confidence in us. As our rules and regulations were absolutely transparent and once investors started seeing prices and quantities in different stocks on a real time basis at all places where our terminals were located, they came to recognize a major difference between NSE and all other exchanges. As NSE volumes started growing, the prices reflected on its screen became a benchmark for all other exchanges including BSE. It did not require much time for NSE to establish its leadership in the market. Another interesting thing that is worth noting is the composition of its investor class when it emerged as the largest stock exchange of the country. At that time more than 90 per cent of the value of trading was accounted for by non-institutional or retail investors. Strangely, even most of the promoters of NSE were not trading on NSE. That is why we consider that institutional investors are less market savvy and laggards as compared to retail investors. Although the institutional investors' holdings have grown quite rapidly during the last decade the retail investors continue to be the backbone of our equity markets. Given the fact that NSE enjoys the maximum trust of the retail investor community, it will continue to grow both in terms of trading volumes as also in terms of market share.

NSE commenced trading in index futures on June 12, 2000. The index futures contracts are based on the popular market benchmark S&P CNX Nifty index, which is a diversified of 23 sectors representing the Indian Economy (see Appendix I for S&P CNX Nifty Index Constitutes). NSE defines the characteristics of the futures contract such as the underlying index, market lot, and the maturity date of the contract. The futures contracts are available for trading from introduction to the expiry date. Contract Specifications and Trading Parameters (see Appendix II).

Futures market may influence Spot prices if they have an effect on the behavior of investors. Since futures markets allow investors to hedge price risk, the existence of futures may affect an investor's decision of in which to invest, how much to invest and what investment strategies to use. In addition, the future prices may contain information about anticipated demand that can feed back into investment decisions.

As Cox (1976) argues that futures trading can be alter the available information and thus spot market volatility for two reasons: First, futures attract additional traders to a market. Second, as transactions costs in the futures market are lower than with reference to spot market, new information may be transmitted to the futures market more quickly. Now, the question is how the rate of information flow related to spot price volatility. This issue addressed by Ross (1989). Thus, if the derivative trading increases the flow of information, then in the absence of arbitrage opportunity, the volatility of the spot price must change.

Thenmozhi M (2002) studies the impact of the introduction of index futures on underlying index volatility in the Indian markets. Robet W Faff and Micheal D Mckenzie Icle (2003) investigated the impact of the introduction of stock index futures trading on the daily returns. Nagaraj K S and Kotha Kiran Kumar (2004) studies of Index futures trading on spot market volatility of Nifty and found that the relation between futures trading activity and spot volatility strengthened, implying that the market has become more efficient in assimilating the information into its prices and M Thenmozhi and M Sony Thomas (2004) analyzed the relationship between stock index futures and corresponding stock market volatility and concluded that the reduction of volatility in the underlying stock market and increased market efficiency. And for the further (see BS Bodla and Kiran Jindal, 2006).

If the information simultaneously flows in both the spot and futures market, then there will be contemporaneous co-movement of prices in those markets and there will be no lead-lag relationship among them. But, if the information flows faster in a specific market (i.e., spot/futures), then there will be a lead-lag relationship and the market incorporating the information faster is said to lead the other market.

The dependence on expectations makes the values inherently volatile Keynes "A conventional valuation which is established as the outcome of the mass psychology of a large number of ignorant individuals is liable to change violently as the result of a sudden fluctuation of opinion due to factors which do not really make much difference to the positive yield; since there will be no strong roots of conviction to hold it steady. In abnormal times in particular…. The market will be subject to waves of optimistic and pessimistic sentiment, which are unreasoning and yet in a sense legitimate where no solid basis exists for a reasonable calculation".

If markets are complete and perfect, derivative and underlying spot prices must reflect information simultaneously; otherwise, difference in prices would induce arbitrage opportunity. In practice, when institutional characteristics and transaction cost are taken into consideration, one market may lead the others without implying arbitrage opportunity. To the extent that the futures are able to reduce the transaction cost, their introduction should be expected to increase the flow of information into the market.

In India, derivatives mainly introduced with view to increase liquidity which may in turn curb the increasing volatility of the asset prices in financial markets and to introduce sophisticated risk management tools leading to higher liquidity by reducing risk and transaction costs as compared to individual financial assets. Though the onset of derivative trading has significantly altered the movement of stock prices in Indian spot market, it is yet to be proved whether the derivative products has served the purpose as claimed by the Indian regulators. In an efficient capital market where all available information is fully and instantaneously utilized to determine the market price of securities, prices in the futures and spot market should move simultaneously without any delay. However, due to market frictions such as transaction cost, capital market microstructure effects etc., significant lead-lag relationship between the two markets has been observed.

Ah-Boon Sim et al (1997), motivation for lead-lag relationship 1) discover market co-movements, 2) price leadership effects and 3) volatility spillovers across markets. The explanation for the relationship between sport and futures markets can be attributes to the price maintenance of the cost-of-carry relation for any pair of continuous trading and efficient futures and stock markets. Departures from the cost-of-carry relation are found in earlier studies, and it is conjectured that these deviations may represent significant evidence that suggest futures markets vehicles for price discovery within the corresponding stock markets. One primary reason for this is that futures markets tend to have fewer trading rendering futures markets potentially more informational efficiently than their underlying primary markets.

In this juncture, with the inception of Indian Derivative market the following needs to be answered:

1.2. DIFFERENT RESEARCH QUESTIONS RESEARCH QUESTIONS:

1. How does the information affect the link between spot and futures markets?
2. How do the adjustment patterns of prices to new information vary between the spot and futures markets?
3. How futures (spot) prices tend to influence spot (futures) prices?
4. Is this relationship unidirectional/bi-directional?
5. How these lead-lag relationship patterns change different conditions? i.e., How these two markets becomes higher or lower depending upon
    a. Relative intensity of trading in the two markets
    b. The extent of market wide movement
6. In presence of (non-trading/non-synchronous trading problem) infrequent data and missing observations how can it be resolve it?
7. In the problems of seasonality?
8. Is there any effect of speculation, hedging, arbitrage trading in these markets i.e., lead-lag relationship?

1.3. NEED FOR THE PRESENT STUDY:

The current study assume a high note because all other earlier studies were in the context of developed market and of the existence most of them have less volumes regarding to index futures trading compared to a emerging market like us. In addition, there is lack of comprehensive studies which addressed above research questions raised in detail with respect to the growing popularity of derivative segement in India. As of now, studies (Thenmozhi 2002; Anand Babu 2004; Kedarninath Mukharjee et.al 2007; Bhaskar Sinha 2007) that look at lead-lag relation between spot and index futures markets, employ daily and monthly data, except Kedarninath Mukharjee, and hence not able to capture intra-day dynamics that die out on a daily basis. Further, these studies employ granger causality type of techniques and hence not able to address volatility spillover between the markets.

1.4. OBJECTIVES OF THE STUDY:

Therefore, to answer the above raised research questions, the present study has been contemplated with the following specific objectives:

I. To investigate the lead lag relationship between the spot and futures market in India, both in terms of return and volatility
    a. To discover market co-movements
    b. To explain price leadership effects
    c. Volatility spillovers across markets

II. To incorporate price co-integration relationship between spot and futures markets in the lead lag relationship analysis.

The present study seeks to contribute to the existing knowledge base and literature by not only examining the actual lead-lag relationship among the Indian spot and futures market in terms of return and volatility, and also in terms co-integration effect.

1.5. GAPS IN THE INDIAN STUDIES:

1. In a perfectly frictionless market, return would disappear immediately after the announcements. However, with market frictions, profit opportunities can persist. Hence, comparison of the persistence of return opportunities in the spot and futures markets may provide information about the level of frictions in the two markets.
2. In the study of the lead-lag relationships between the time varying volatility spillover of the markets should control for the intraday seasonality of the volatility and also investigate the lead-lag relationships between the spot and futures markets.
3. The Efficiency Market Hypothesis (EMH) implies that mis-pricing, and associated with arbitrage opportunities, between related markets would be rapidly eliminated, and that can be tested. There are some (theoretical) conjectures whether trading on the basis of news should appear first in a derivative, or its associated spot market i.e, the lead-lag relationship; and there are a variety of arguments, on either side, about whether existence of derivatives, especially futures markets increases or decreases, volatility in the associated spot market.

4. Data considered in the previous studies either monthly or daily data. In order to analyze information flows between markets on short time intervals, high frequency data are required. The use of high frequency data and the choice for a small unit time interval to measure these lead-lag relation comes at the cost of some or many missing observations, causing traditional estimators to either under or overestimate covariance's and correlations.

1.6. LIMITATIONS OF THE STUDY:

In order to examine the interdependence between spot and futures markets, we have used only the data from 1st January, 2001 to 31st November, 2005. We are unable to access further recent data for the analysis. And we also not included trade volume, Number of traders and other dimensions of Market microstructure.

1.7. DATA SOURCES:

The basic data proposed to be used in this study consist of intraday price histories from January 2001 to November 2005 for the nearby contract of nifty index futures, nifty spot index. The required intra-day data will be obtained from NSE Research Initiative and then we construct 5-minute, one-minute, ten-minute and one hour (logarithmic) return series for both Nifty spot and futures indices.

1.8. CHAPTERIZATION OF THE STUDY:

This study discuss introduction, problem of the study in the first chapter and second chapter follows the review of literature, third chapter discussed methodology which we follow for the analysis, and fourth chapter includes data, results and inferences were drawn out of the used models of various methodologies and finally the fifth chapter discussed conclusions and recommendations for the future research and practitioners.

[i] World stock exchanges report (2005).

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CHAPTER - II

REVIEW OF LITERATURE

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2.5 IN INDIAN CONTEXT
2.6 RESEARCH GAPS IN INDIAN STUDIES

2.1. INTRODUCTION:

Both futures prices and cash index prices reflect the aggregate values of underlying stocks. Futures and cash prices will differ, however, because of differences in carrying costs. But if interest rates and dividend yields were non-stochastic, contemporaneous price changes in the two markets would be perfectly correlated and no lead-lag relation would exist between them. Various frictions, however, may cause one market to react faster to information than the other, so that the lead-lag relation is observed. The lead-lag relation between futures and cash index prices may be attributed to infrequent trading of stocks within the index. Since component stocks may not be traded in the last instant of each time interval, observed index values, which are the averages of the last transaction prices of component stocks, cannot update actual developments in the stock market and lag behind “true” index values. If futures prices reflect information instantaneously, cash index prices will lag behind futures prices.

The first stock index futures contract introduced in the world was the Value line contract, introduced by the Kansas City Board of Trade (KCBT) in 1982 in the USA. Since then we have seen numerous markets all over the world launching new derivative contracts every year. Recently, research work has focused on the causal relationship between the cash and futures markets returns.

Several studies have examined the temporal relationship between futures and cash returns. Most of the empirical evidences support the lead effect more than the lag effect and have concluded that there is a significant lead-lag relationship among the spot and the futures market, and also provide the possible explanation for this relationship.

2.2 THEORETICAL BACKGROUND:

Theoretically the temporal relationship between the price of an index futures contract and the price of the underlying index is given by the condition of net cost-of-carry model: According to Stoll and Whaley (1990), the theoretical relationship between the price of an index futures contract and the price level of the underlying index is

$$F_t = S_t e^{[(r-d)(T-t)]} \qquad (1)$$

The market force driving the cost-of-carry relation (1) is never ending search for a 'free-lunch'. When the futures price is above the level implied by the RHS of (1), a riskless arbitrage profit equal to the difference between the futures price and the index price plus the cost of carry, a long arbitrage profit of $F_t - S_t e^{[(r-d)(T-t)]}$ can be earned by selling the futures contract and buying the stock index portfolio, financing the stock purchase with riskless barrowings.

On the other hand, when the futures price falls below the RHS of (1), a short arbitrage profit of $S_t e^{[(r-d)(T-t)]} - F_t$ it can be earned by buying the futures and selling the portfolio stocks, investing the proceeds of the sale of stock at the riskless rate of interest.

In perfectly efficient and continuous futures and stock market absent transaction cost, riskless arbitrage profit opportunities should not appear so the cost-of-carry relation (1) should be satisfied at every instant 't' during the futures contract life. In such is the case, the instantaneous rate of price appreciation in the stock index equal that not cost of carry of the stock portfolio plus the instantaneous relative price change of the futures contract i.e.,

$$R_{s,t} = (r - d) + R_{f,t} \qquad (2)$$

Where $R_{s,t} = Ln(S_t / S_{t-1})$, and $R_{f,t} = Ln(F_t / F_{t-1})$

Several implications follow from (2) under the assumptions that the short term interest rate and the dividend yield rate of the stock index are constant and that the index futures and stock markets are different and continuous. Here, the theory of the expected rate of price appreciation on the stock index portfolio $E(R_{s,t})$ equals to net cost of carry $(r - d)$ plus the expected rate of return on the futures contract $E(R_{f,t})$. The standard deviation of the rate of return on the futures contract equals the standard deviation of the rate of return of the underlying stock index. The contemporaneous rates of return on the futures contract and the underlying stock portfolio are perfectly positively correlated. The rates of return of the futures contract and of the underlying stock index portfolio are serially uncorrelated. The non-contemporaneous rates of return of the futures contract and the underlying stock portfolio are uncorrelated.

Naturally, all the above implications are based on the assumption that the cost-of-carry relation (1) holds at all points in time. It has been shown, however that (1) does not hold exactly; indeed one of the puzzles in stock index futures is the frequency with which deviations from (1) are observed.

Violations of the cost-of-carry relation may appear for a variety of reasons. Some are purely technical. An important one is the infrequent trading of stock with in the index.

Markets for individual stock are not perfectly continuous. Consequently, stock index prices, which are averages of the last transaction prices of component stocks, lag actual developments in the stock market Fisher (1966) describe it. Cohen, et.al (1986) gives a more general discussion of serial correlation of stock index returns in terms of delays in the price adjustment of securities. Lo and Mackinlay (1988) model the effects of infrequent trading on index returns under restrictive assumptions. Assuming that the index futures prices instantaneously reflect new information, observed futures returns should be expected to lead observed stock index returns because of infrequent trading, even through there is no economic significance to this behaviour whatsoever.

A second reason for violation of relation (1) is that transaction costs tend to induce noise in the relation (2). The prices used in the computations of returns are transaction prices, and these transaction prices tend to fluctuate randomly between bid and ask levels. The random price movement between bid and ask prices in successive transactions induces negative serial correlation in observed returns even though the true returns are serially independent.

At the individual security level, the negative serial correlation due to the bid/sk price effect is understandable, but the effect seems less likely when one considers a stock index portfolio for which movements between the bid and ask for some stocks could be offset by opposite movements from the ask to bid for other stocks; however, to the extent that the rates of return of the stocks in the index are positively correlated and/or that the index is narrowly based, negative serial correlation in individual stock return attributable to the bid/ask price effect also might appear in the stock index returns.

A third reason in violation of the cost of carry relation has to do with time delays in the computation and reporting of the stock index value. Once the transaction in the stock market takes place, the transaction information is entered into a computer and transmitted to the particular service that updates and transmits the index level. Three time delays therefore possible.

1. The delay in entering the stock transaction into the computer
2. The delay in computing and transmitting the new index value, and
3. The delay in recording stock index value at the futures exchange

Assuming that the new information arrives in the stock and futures markets simultaneously, such delays would tend to show the futures market returns leading stock index returns.

However, contrast to Brooks et. al (2001) Wahab and Lashgari (1993), observed that it is the economic incentives for the traders to use one market over the other, a lead-lag relation between prices in the two markets are likely.

There is an extensive amount of literature examining the impact of derivative trading on the return as well as on the volatility of underlying spot market, giving special emphasis on the lead-lag relationship between the spot and the derivatives, viz., futures and options market all over the world. Since the proposed study is exclusively concerned with the lead-lag relationship and their variation over time, the review of existing literature has been restricted only to that specific aspect. Introduction of stock index futures cause an increase in volatility in the short run while there is no significant change in volatility in the long-run (Edwards 1988).

2.3. VOLATILITY OF FUTURES AND SPOT MARKET:

Several studies have attempted to examine the behaviour of spot market volatility since the inception of futures trading. Edwards (1988) tries to gather evidence to verify the fact that stock index futures trading has established the spot market in the long run. Using variance ratio F tests from June 1973 to May 1987, Edwards concludes that the introduction of futures trading has not induced a change in the volatility in the long run. He observes that there is some evidence of futures-induced short-run volatility, particularly on futures contract expiration days, but this volatility does not appear to carry over to longer periods of time.

According to Lin et.al (1991) Stylized facts for volatility:

1. Volatility of stock prices is time varying
2. When volatility is high, the prices changes in major markets tend to become highly correlated;
3. Correlation in volatility and prices appear to be asymmetric in causality between the countries.

Harris (1989) observes increased volatility after the introduction of index futures by comparing daily return volatilities during the pre-futures (1975-1982) and post-futures (1982-1987) between S&P 500 and a non S&P 500 group of stocks controlling for differences in firm attributes (beta, price-level, size and trading frequency). He notes that increase in volatility is a common phenomenon in different markets and index futures by themselves may not bear the sole responsibility. He points out that other index-related instruments and developments such as growth in index funds and increase in foreign ownership of equity as possible explanations of higher volatility in stock markets.

Ross (1989) demonstrates that, under conditions of no arbitrage, variance of price change must be equal to the variance of information flow. This implies that the volatility of the asset price will increase as the rate of information flow increases. If this is not the case, arbitrage opportunities will be available. It follows, therefore, that if futures increase the flow of information, then in absence of arbitrage opportunities the volatility of the spot price must change.

Hodgson et. al., (1991) study the impact of All Ordinaries Share Index (AOI) futures on the Associated Australian Stock Exchanges over the All Ordinaries Share Index. The study spans for a period of six years from 1981 to 1987. Standard deviation of daily and weekly returns is estimated to measure the change in volatilities of the underlying index. The results indicate that the introduction of futures and options trading has not affected the long-term volatility, which reinforces the findings of the previous U.S. studies. However, there was a problem of confounding variables such as floating of Australian dollar in late 1983, deregulation of stock exchanges, foreign bank ownership and mutual fund investment rules during 1984.

Kalok Chan et.al. (1991) estimate the intraday relationship between returns and returns volatility in the stock index and stock index futures. The study covers both S&P500 and Major Market Index (MMI) futures. The intraday patterns of volatility are estimated using autocorrelation and cross correlation patterns of the intraday returns. Bi-variate GARCH model is used to estimate the volatility. Results indicate a strong inter-market dependence in the volatility of the cash and futures returns. It is also shown that the intraday volatility patterns that originate either in stock or futures market demonstrate predictability in the other market.

Bessembinder and Seguin (1992) examine whether greater futures trading activity (volume and open interest) is associated with greater equity volatility. Their findings are consistent with the theories predicting that active futures markets enhance the liquidity and depth of the equity markets. They provide additional evidence suggesting that active futures markets are associated with decreased rather than increased volatility.

Herbst et.al, (1992) examine the informational role of the end-of-day returns in the stock index futures for the period 1982 to 1988. Volatility is estimated from the standard deviation of the returns. It is shown that the end of day return volatility is positively correlated to the next day's spot returns.

Kamara et.al., (1992) observe the stability of S&P 500 index returns with the introduction of S&P 500 index futures. They also assess the change in the volatility of S&P 500 index due to the introduction of futures trading for the period 1976 to 1987. The changes in the volatilities are examined using parametric and nonparametric tests. The variance ratio F-tests used by Edwards (1988 a,b) are sensitive to the underlying assumption of normally distributed stock returns. Apart from F-tests, Kolmogorov-Smirnov two-sample test and Wilcoxon Rank sum test are used to find out if the dispersion is significantly high in the post-futures period. The results show that the daily returns volatility is higher in the post futures period while the monthly returns remain unchanged. They have concluded that increase in volatility of daily return in the post-futures period is necessarily not related to the inception of futures trading.

James. T.W., (1993) study the impact of price discovery by futures market on the cash market volatility. The study is conducted using Garbade and Silber model to estimate the price discovery function of the futures market. The results affirm that futures market is beneficial with respect to cash market as it offers better efficiency, liquidity and also lowers the long-term volatility of the spot market.

Jegadeesh and Subrahmanyam (1993) compare the spread in NYSE before and after the introduction of futures on S&P 500 index as volatility can also be measured in terms of individual stock bid-ask spread. They find that average spread has increased subsequent to the introduction of futures trading. When they repeat their test by controlling for factors like price, return variance, and volume of trade, they still find higher spreads during the post-futures period. They suggest that introduction of index futures did not reduce spreads in the spot market, and there is weak evidence that spreads might have increased in the post futures period.

Hong Choi et.al., (1994) examine the impact of futures trading on the volatility and liquidity (as measured by bid-ask spread) of the spot market. Intraday data of S&P 500 and Major Market Index is used for a period of one year. The results indicate that the average intraday day bid-ask spread in post Major Market Index futures has increased while there is no significant change in the volatility. The trading volume has registered a rise in both S&P 500 and Major Market Index. Information asymmetry also has posted an increase due the introduction of futures trading.

Hung-Gay Fung et.al, (1994) examine the dependency in intra-day (minute-to-minute) stock index futures for the period 1987 - 1988. The dependency of intraday futures price is estimated using various models such Auto Regressive Fractionally Integrated Moving Average, Re-scaled range test, Variance ratio test and Autocorrelation functions. It is shown that futures price do not appear to have long-term memory and that the price changes in futures market are not a random walk.

Darrat et.al, (1995) examines if futures trading activity has caused stock price volatility. The study is conducted on S&P 500 index futures for a period of 1982 - 1991. The study also examines the influence of macro-economic variables such as inflation, term structure rates on the volatility of the S&P 500 stock returns. Granger causality tests are applied to assess the impact on stock price volatility due to futures trading and other relevant macro-economic variables. The results indicate that the futures trading have not caused any jump volatility (occasional and sudden extreme changes in stock prices). Term structure rates and OTC index have caused the stock price volatility while, inflation and risk premium have not influenced the volatility of stock prices.

Antoniou and Holmes (1995) examined the relationship between information and volatility in FTSE-100 index in the U.K. using GARCH technique. Although they find that introduction of FTSE-100 index futures has changed volatility in the spot market, they attribute this to better and faster dissemination of information flow due to trading in stock index futures.

Gregory et. al, examine (1996) how volatility of S&P 500 index futures affects the S&P 500 index volatility. The study also examines the effect of good and bad news on the spot market volatility. The change in the correlation between the index and futures before and after October 1987 crash is also examined. Volatility is estimated by EGARCH model. It is shown that the bad news increases the volatility than the good news and the degree of asymmetry is much higher for the futures market. Butterworth investigates the effect of futures trading in the FTSE Mid 250 index on the underlying spot market using symmetric and asymmetric GARCH methods. The results reported for the Mid 250 index indicate that while the existence of futures trading had made little impact on the underlying level of volatility, as measured by the standard deviation, it has altered significantly the structure of the spot market volatility. The two most likely explanations for changes in volatility of stock returns are microeconomic and macroeconomic factors.

It is seen that the results on the effect of index futures on the underlying spot market volatility are mixed. One view is that derivative securities increase volatility in the spot market caused by more highly levered and speculative participants in the futures market. This is because futures markets result in uninformed (irrational) speculators trading in both futures and cash markets, shocking prices in search of short-term gains.

Hodgson and Nicholls (1991) quote that increased market volatility may increase real interest rates and the cost of capital, leading to a reduction in the value of investments and loss of confidence in the market. In turn, this can lead to a flow of capital away from equity markets. Secondly, with increased volatility, regulatory bodies may interfere in markets to enact further regulations. While these regulations are certainly costly, they may or may not reduce stock price volatility. However, another view is that derivative markets reduce spot volatility; by providing low cost-contingent strategies, enabling investors to minimize portfolio risk by transferring speculators from spot markets to futures markets. The low margins, low transaction costs and the standardized contracts and trading conditions attract risk-taking speculators to futures. Hence, futures have a stabilizing influence as it adds more informed traders to the cash market, making it more liquid and, therefore, less volatile. It is seen that increased spot volatility from futures markets may not be undesirable if induced by objective new information. In general, the quicker and more accurate prices reflect new information, the more efficient should be the allocation of resources.

It is seen from the literature that the volatility of the spot market is compared before and after introduction of futures and also tested for variations in volatility due to flow of market information. The impact of information content on the underlying markets is tested and is found to have strong correlation with the volatility of the underlying markets. Besides, standard deviations of daily returns, bid-ask spreads for all stocks, GARCH models have been used as a measure for volatility. A family of GARCH models has been used when the data spans over a long time period to accommodate heteroskedasticity in the returns. In the event of short run analysis of time series of data, standard deviation of daily returns have been used as a measure of volatility.

2.4. LEAD -LAG RELATION BETWEEN FUTURES AND SPOT MARKET:

The literature on the lead-lag relation between the index futures and the index indicate that futures market is the main source of market wide information and the futures lead the spot market. There is very little evidence of spot index leading the futures market. Most of the studies use simultaneous equation modeling solved by ordinary least squares method to examine the lead-lag relationship between the futures and the spot market.

The temporal relation between price movements of stock index futures and the underlying cash market reflects the flow of new information from one market to the other relatively, and discloses the inter-relations of the two markets. But if one market reacts faster to information, and the other market is slow to react, a lead lag relation is observed. Over the years there are a large number of studies that have empirically examined the temporal relationship between futures index and cash index.

As Ah-Boon Sim et al (1997), the motivation for lead-lag relationship 1) discover market co-movements, 2) price leadership effects and 3) volatility spillovers across markets. The explanation for the relationship between sport and futures markets can be attributes to the price maintenance of the cost-of-carry relation for any pair of continuous trading and efficient futures and stock markets. Departures from the cost-of-carry relation are found in earlier studies, and it is conjectured that these deviations may represent significant evidence that suggest futures markets vehicles for price discovery within the corresponding stock markets. One primary reason for this is that futures markets tend to have fewer trading rendering futures markets potentially more informational efficient than their underlying primary markets.

Investors prefer trading in the derivative markets rather than the stock markets, because of market frictions such as transaction costs, capital requirements. In futures markets, trading costs are generally lower than for the primary markets, and also they also tend to have more liquidity. These two factors play a vital role in enplaning the systematic evidence that futures markets tend to exhibit price leadership effects over stock markets.

Koch and Koch (1987, 1988) estimate the lead-lag relation between S&P 500 index futures and S&P 500 index. They probe the lead-lag effects using simultaneous equation model estimated by three stage least squares regression. Based on the minute-to-minute changes in both the index and the futures prices, a model was constructed to describe the dynamic intraday price relationship between the index and futures prices.

Finnerty and Park (1987) also discover a significant lead-lag relationship between futures and spot prices. Herbst, McCormak, and West (1987) too observe that the S&P 500 and Value Line futures lead the spot index between 0 to 16 minutes.

Ira Kawaller, et al. (1987) examined the leads and lags in S&P 500 index futures and cash trading. Their data consists of minute-to-minute prices of the S&P 500 cash and futures for all trading days in 1984 and 1985. The results report that the lead from S&P 500 futures to cash prices extends between 20 and 45 minutes, while the lead from cash to futures prices rarely extends beyond one minute.

Herbst, McCormak, and West (1987) investigated the lead and lag relationship between Value Line index and its futures, and for the S&P 500 index and the S&P 500 index futures. The study was first examined with the daily data and observed that there was a lead of less than a day between the futures market and the spot market. And to validate and refine their findings they have used the intraday data and found that the Value Line futures lead the spot index between zero and sixteen minutes, while the S&P 500 index futures tends to lead its underlying stock index between one and eight minutes.

Stoll and Whaley (1990) use ARIMA model and ordinary least squares to estimate the lead-lag between S&P 500 index futures, Major Market Index futures and the underlying spot market. The results indicate that S&P 500 and Major Market Index futures lead the cash market by 10 minutes and they attribute this to faster dissemination of information into futures market. The findings are consistent with the evidence gathered by Koch and Koch (1987), MacKinlay and Ramasamy (1988).

Lo and MacKinlay (1990) examine the effects of non-synchronous trading on the cross-autocorrelation pattern. They show that the relative non-trading probabilities of security *i* and *j* are given by the ratio of the covariance of past returns of *j* to current returns of *i*, and the covariance of past returns of *i* to current returns of *j*. In other words, if security *i* has a higher non-trading probability than security *j*, security *i* lags security *j* more than it leads. This relation suggests that if the lag is only due to non-synchronous trading, futures returns will be dominant in leading returns of only those component stocks that have higher non-trading probabilities than futures. Lead-lag patterns may also depend on whether the information is market wide or firm specific.

Chan (1990) shows that even in the absence of transaction costs, a market-wide informed trader earns a higher profit by trading in futures contracts than by trading in individual securities. Therefore, if information acquisition is endogenous, futures traders have a higher incentive to collect market-wide information than do cash market traders. As the above discussion suggests, the futures market should reflect market-wide information more quickly than the cash market does. Thus, when there are more stocks moving together (because of market-wide information), futures prices should lead the cash index to a greater degree.

Subrahmanyam (1991) suggests that some informed traders are precluded from the cash and futures markets because of fixed costs of trading or budget constraints. Marketwide informed traders are discouraged from trading in individual securities because doing so requires a larger capital outlay than trading in futures contracts. Security-specific informed traders, on the other hand, do not trade index futures because the security-specific information is trivial in determining futures prices.

Schwarz et.al, (1991) examine the price leadership of index futures over the spot market and test the dynamic efficiency of index futures as a price discovery vehicle. However, they use Garbade & Silber model to quantify the price discovery function of the futures market. The study is done on the Major Market Index for the sample period 1985 to 1988. The results show that the spot and futures are integrated such that average mispricing leading to arbitrage is eliminated within one to seven days.

Schwarz and Laatsch (1991) examined a lead-lag study in relation to continued maturation of stock index cash and futures markets through testing of market efficiency of the price leadership. Major results does not indicate that neither of the two markets maintains price leadership at all times, nor does pricing efficiency increase monotonically in time. And that these markets attribute fluctuations both across periods and within a day. The supposition that the cash and futures markets follow maturation in efficiency that is monotonic appears to be unjustified.

Chan (1992) estimate the lead-lag relation between Major Market Index and Major Market Index futures under conditions of good and bad news, different trading intensities and under varying market wide movements. ARMA models are used as proposed by Stoll (1990). It is seen that the futures market leads the spot again attributed to faster information processing by the futures market. However, under bad news it is the cash index that leads over the futures market while, there is no effect on the lead-lag relation during different trading intensities. The findings are in line with the earlier studies of Koch and Koch (1987), Stoll and Whaley (1990).

Houthakkar (1992) argued that futures trading influences inter-temporal allocation of production and consumption decisions by holding inventories. Suppose that futures prices of distant deliveries are far higher than those of early deliveries. The relative difference between the futures and spot prices will trigger action with the postponement of current consumption and the subsequent change in spot prices arising from the change in demand in the spot market.

Similar studies postulating lead-lag relationship are also made in other countries. Following with this, Tang, Mak and Choi (1992) studied the causal relationship between stock index futures and cash index prices in Hong Kong, which revealed that futures prices cause cash index prices to change in the pre-crash period but not vice versa. In the post-crash period, they found that bi-directional causality existed between the two variables. Evidence from other markets also postulates a lead-lag relationship. Tse (1995) examined the lead-lag relationship between the spot index and futures price of the Nikkei Stock Average. Using daily data in the post-crash period, the interaction between the spot and futures series through the error correction model is investigated. It is found that lagged changes in the futures price affect the short-term adjustment in the spot index, but not vice versa.

Grunbichler, Longsatff, and Schwartz (1994) examine the lead lag relationship between intraday spot and futures prices for Germany. They find that futures prices lead spot prices by 20 minutes. Because stocks are floor traded – whereas futures contracts are screen traded – that screen trading accelerates the price discovery process.

Abhyankar (1995) investigates the lead-lag relationship between hourly returns in the FT-SE 100 stock index futures and the underlying cash index using hourly data for the period 1986 - 1990. They test the lead-lag relation for periods of differential transactional costs, good and bad news (measured by the size of returns), spot volume and spot volatility. The results revealed that when transaction costs for the underlying asset fell (post "big Bang"), the futures lead of the spot index reduced, implying that transaction cost differential is the major driver for the lead-lag relationship. It was found that the futures lead over spot was insensitive to variations is spot transaction volume. An AR (2) - EGARCH (1,1) model was then fitted to spot and futures returns to give a time series of estimated volatilities, and it was observed that during periods of high volatility, futures markets led spot market returns. Support is also found for the hypotheses that lower transactions and entry costs in the stock index futures market is one of the reasons why traders with market wide information prefer to use the futures markets. This causes the arbitrageurs to step in quickly to bring the cost-of-carry relationship into alignment. The author does not find a clear evidence of volatilities interdependence consistent with

Kawaller, Koch and Koch (1990) and Chan and Chung (1991) results for the U.S. However, lihara, Kato, and Tokunaga (1996) find that the Nikkei Stock Average (NSA) futures market leads the spot market both in terms of return and volatility. Frino and West (1999) made a similar study on Australian markets and found that futures returns lead the spot index returns by twenty to twenty five minutes.

Shyy, Vijayraghavan, and Scott-Quinn (1996) find the reverse causality from cash (CAC cash index) to futures (CAC futures contracts) for France. They conclude that the previous results – indicating futures market leading cash market – may be primarily due to market asynchronous trading and differences in trading mechanisms used in cash or futures markets.

Silvapulle and Moosa (1999) postulate various scenarios underlying the differential lead–lag relationship and Granger causality between spot and futures prices. The first line of argument predicts that futures prices lead spot prices when informed traders, hedgers and speculators react to new information by indulging in futures rather than spot transactions due to lower transaction costs, capital requirements and short-selling restrictions in the derivative markets. Since spot transactions require a greater deal of initial outlay and may take a longer time to implement, spot prices tend to react with a lag (see, Grossman and Miller, 1988; Miller, 1990).

There are some studies evidencing on bi-directional relationship between the stock index futures and the stock index. Wahab and Lashgari (1993) studied daily data from January 1988 to May 1992 using error correction methodology. Their results revealed bi-directional causality between spot and futures returns. Teppo et.al., (1995) study the two-way causality between the Finnish stock index futures and the stock index for a period of one year from 1989 - 1990. Granger Causality tests are applied on the daily returns due to non-availability of intra-day data. The results indicate that the futures market provides predictive information for both frequent and infrequently traded stocks while the reverse causality is found to be weak. Abhyankar (1998) revisited the relationship using 5-minute returns by regressing spot returns on lagged spot and futures returns, and futures returns on lagged spot and futures returns using EGARCH. It was found that the futures returns led the spot returns by 15 - 20 minutes.

Moosa and Al-Loughani (1995) in a theoretical model assert that futures prices are jointly determined by arbitrageurs' and speculators' demand for futures contracts. Arbitrageur demand depends on the difference between the arbitrage price as determined by the cost-of-carry model and the actual futures price. Speculator demand depends on the difference between the expected future spot price and actual futures prices. It is the futures price rather than the spot price that acts as a yardstick in both cases. The second line of argument predicts that spot prices lead to futures prices. For example, in a companion paper Moosa (1996) argued that a change in the spot price would trigger action from arbitrageurs and speculators leading to a subsequent change in futures prices. First, the index arbitrageurs will respond to the violation of the cost-of-carry condition by participating in the spot market. Second, speculators would react following the discrepancy between the current futures price and the expected spot price and to the discrepancy between the current futures prices and the expected futures prices. In both cases spot prices lead futures prices.

Chris et.al., (2001) estimate the lead-lag relation between the FTSE 100 stock index futures and the FTSE 100 index. Based on the results obtained, they develop a trading strategy based on the predictive abilities of the futures market. The study is conducted using Co-integration and Error Correction model, ARMA model and vector auto-regressive model. The results indicate that futures lead the spot market attributable to faster flow of information into futures market mainly due to lower transaction costs. It is shown that the error cointegration model predicts the correct direction of the spot returns 68.75% of the time. Ghosh (1993) also observed a similar lead-lag relationship for the U.S. market following the use of an error correction model.

Most of the studies have suggested that the leading role of the futures market varies from five to forty minutes, while the spot market rarely leads the futures market beyond one minute. While explaining the causes behind such relation, Kawaller et al. (1987) attribute the stronger leading role of the futures market to the infrequent trading of component stocks. Though, at the same time, Stoll & Whaley (1990), Chan (1992) etc. proved the existence of such relation even in case of highly traded stocks or after adjusting for infrequent trading of component stocks. Again, Chan (1992), Frino (2000), Simpson (2004) suggest that informed traders should trade in the futures market around the release of macroeconomic announcements; while, the leading role of futures market weakens through the discovery of stock specific information [Grunbicher, Longstaff and Schwartz (1994)]. Apart from this, while examining the volatility spillover, Abhyankar (1995), Tse (1999) and Min (1999) have documented that unlike a lead-lag relation, there is a bi-directional or contemporaneous relationship among the spot and the derivative markets, with bad news having a greater impact on volatility, and the relationship is entirely sample period dependent.

Several studies examine temporal relationships between futures and cash index returns using a Granger (1969) and Sims (1972) causality specification. The results frequently suggest that the futures returns lead the cash return. For the S&P500 and MMI futures this lead varies from five minutes (Stoll and Whaley, 1990) to 45 minutes (Kawaller et al., 1987) but the relationship is not completely unidirectional. The cash index may also affect the futures although this lead is almost always much shorter. Tang and Ho (1989) found a unidirectional causality running from Hang Seng index futures price changes to spot index price changes. Tang et al supported this in 1992, for the pre-crash period. However, they found a bi-directional causality in the post crash period. In an early study on the Korean market, Min and Najand (1999) found that the futures market leads the cash market by as long as 30 minutes, indicating that futures market reflects information more rapidly than the spot market. Similar results were obtained by Gwilym and Buckle (2001) for FTSE 100 stock index and its derivative contracts. The conclusion that the futures market serves as a price discovery vehicle for the stock prices and is thus the main source of market wide information is usually explained by transaction costs, restrictions on short sales in the cash market and the higher degree of leverage that can be attained by using futures. Since a trade in the futures markets requires little upfront cash (initial margin deposits are usually only a fraction of the stocks' market value) and can be effectuated immediately while purchasing the basket of stocks composing the index requires a greater initial investment and may take longer to implement, this preference for cost efficiency could cause the futures market to lead the spot market.

According to Schwarz and Laatsch (1991), futures markets are an important means of price discovery in spot markets. Powers (1970) argued that futures markets increase the overall market depth and informativeness. There are also several technical reasons why returns on a particular market may seem to lead returns on other markets. If futures markets instantaneously reflect new information and if the stocks within the index trade infrequently, observed futures returns would lead observed stock index returns. However, as Stoll and Whaley (1990) note, there is no economic significance to this behavior whatsoever.

Many researchers attribute the significant lead-lad relationship between the cash market and the futures market to the differences in market microstructure of the two markets. Grossman and Miller (1988) and Jong and Donders (1998), argue that lower transaction costs and greater liquidity in the futures market provides more immediacy to traders and hence traders will transact in the futures market first with the result that the futures market will lead the spot market. In an analysis of the lead-lag relation between the DAX Index and DAX Index futures contracts in Germany, Grunbichler et al. (1994) argue that screen based trading enhance price discovery by reducing costs of trading, reducing the time taken to execute orders and the time required to disseminate trade information. They found evidence to support their argument in the German screen- traded futures market, which according to their results leads the spot by twenty minutes.

Frino and West (1999) question the results of Grunbichler and found that returns on SPI futures led returns on the All Ordinaries Index by twenty to twenty five minutes even though the Australian equities market is screen-traded and futures market is floor traded.

Stoll and Whaley (1990), on the other hand, consider the impact that non-trading and bid-ask effects may have on the lead-lag relationship and find that even after adjustments for non-trading and bid-ask effects is made, the lead-lag relationship between the S&P 500 Index and the Index Futures market persists.

Kalok Chan (1992) investigated the lead-lag relation between intraday returns of the Major Market cash index and returns of the Major Market Index futures and S&P 500 futures for over two sample periods, August 1984 through June 1985 and January through September 1987. Empirical results confirm findings that there is strong evidence of futures leading the cash index and weak evidence that the cash index leads the futures. The asymmetric lead-lag relation holds between the futures and all component stocks, including those that trade in almost every five-minute interval. And evidence indicates that when more stocks move together the feedback from the futures market to the cash market is stronger. This suggests that the futures market is the main source of market-wide information.

Harris (1989) derives an estimator of the underlying index values using a simple one-factor representation of the value-generating process to estimate the nonsynchronous trading adjustment. Stoll and Whaley (1990) use an ARMA process to purge the effects of infrequent trading, and extract the return innovations to proxy for true index returns. However, these adjustments may not be adequate if the effects of nonsynchronous trading are changing.

In a recent paper Brooks et al. (1999) have examined the lead–lag relationship between a stock index and stock index future markets using daily data of the FTSE 100 index and index future contracts for the UK and for the S&P 500 index and index future contracts for the USA. Their empirical results based on the traditional Granger–Sims linear causality testing procedure reveal that future prices lead spot prices. They interpreted this result as an apparent contradiction of the theoretical prediction of the cost-of-carry model. In a recursive estimation approach based on cross-correlation and cross-bi-correlation using a window length of 35 observations, they found a weak bi-directional feedback relationship between spot and futures market only in a few occasions. They interpreted this result to be consistent with the prediction of the standard cost-of-carry model and market efficiency. The primary contention of this note is that the Brooks et al. (1999) results based on linear Granger causality tests exhibit overwhelming evidence of a contemporaneous relationship between spot and futures returns during the full sample period. This result of a contemporaneous relationship is consistent with the prediction of the cost-of-carry model. The resulting feedback relationship suggests that both spot and futures markets react simultaneously to new information and is consistent with the efficient market hypothesis.

Their results suggest that futures returns significantly lead cash index returns, although there is weak evidence that cash index returns have some predictive ability about futures returns. For instance, Kawaller, Koch, and Koch (1987) report that the lead from S&P 500 futures to cash prices extends between 20 and 45 minutes, while the lead from cash to futures prices rarely extends beyond one minute. Stoll and Whaley (1990) find that S&P 500 and Major Market Index (MMI) futures returns lead stock index returns by about five minutes on average, and occasionally by as long as 10 minutes or more, but the feedback from the cash market into the futures market is much shorter than that.

Most studies in this literature focus exclusively on the lead-lag relationship between returns in cash and derivative markets. Chan, Chan and Karolyi (1991) demonstrate that the interaction between cash and futures markets is more complicated than this. They use a bivariate GARCH framework to analyze more than five years of data from the S&P 500 cash and futures markets, and one year of data on the MMI. They find significant volatility feedback in both directions; that is, trading in either market affects the conditional volatility of subsequent innovations in the other market. This result suggests that we ought to broaden our view of information-based trading beyond the concept of price discovery alone. It also suggests that the other studies on lead-lag relationships, because they do not account for time varying volatility and cross-market volatility feedback, are misspecified. Research on lead-lag relationships in other international stock index futures markets corroborates the evidence found in the United States. For evidence from the Japanese market, see Tse (1995), Iihara, Kato and Tokunaga (1996), and Chung, Kang and Rhee (1996). For results on the FT-SE 100 market in the U.K., see Wahab and Lashgari (1993), and Abhyankar (1995, 1998). Other international evidence has been reported by Niemeyer (1994) for Sweden; Grunbichler, Longstaff and Schwartz (1994) for Germany; Martikainen, Perttunen and Puttonen (1995) for Finland; Shyy, Vijayraghavan and Scott-Quinn (1996) for France; De Jong and Donders (1997) for the Netherlands; Ferret and Page (1998) for South Africa; and Min and Najand (1999) for Korea.

2.5. IN INDIAN CONTEXT:

Thenmozi (2003), is to examine is there is any change in the volatility of nifty index due to the information of nifty futures whether movements in the futures price provide predictive information regarding subsequent movements in the index prices. If one market reacts faster to information, and the other market is slow to react, a lead-lag relation is observed. The lead-lag relation between price movement of stock index futures and the underlying cash market illustrates how fast one market reflects new information relative to the other, and how well the two markets are linked. Another view is that derivative markets reduce spot volatility, by providing low cost-contingent strategies, enabling investors to minimize portfolio risk by transferring speculators from spot markets to futures markets. The low margins, low transactions costs, and the standardized contracts and trading conditions attract risk-taking speculators to futures. Hence, futures have a stabilizing influence as it adds more unformatted traders to the cash market, making it more liquid an, therefore, less volatile. It is seen that increased spot volatility form futures markets may not be undesirable if induced by objective new information. In general, the quicker and more accurate prices reflect new information, the more efficient should be the allocation of resources.

Anand (2004), investigates temporal price relationship between the Nifty futures and S &P CNX Nifty Index of National Stock Exchange of India Ltd. (NSE) for the period June 2000 through 2003. The period of study is divided into three sub-periods based on the price series movement and growth of volume to observe the lead-lag relationship between the two markets. Empirical results confirm that there is strong evidence of Index futures market leading the underlying Nifty Index market, but not vice versa. It is found that, the lead-lag pattern between two markets is changing under different sub-period.

However, there is no evidence of lead-lag relation may be affected by trading activity in cash and futures markets. The feedback from the futures market to the cash market is because of high leverage, offsetting positions taken at lower transaction costs, standardized contracts, expected profits, etc., in the futures market trading. Generally it is found that futures market transmits information faster to cash market, because the futures market is faster than cash market in processing the information

Kedarinath Mukharjee (2006) used intraday (here minute-by-minute) data from April to September 2004, an effort has been made to investigate the possible lead-lag relationship, both in terms of return 25 and volatility, among the NIFTY spot index and index futures market in India and also to explore the possible changes (if any) in such relationship around the release of different types of information.

They found that though there is a strong contemporaneous and bi-directional relationship among the spot and futures market in India, the spot market has been found to play comparatively stronger leading role in disseminating information available to the market. Their results relating to the informational effect on the lead-lag relationship exhibit that the leading role of the futures market wouldn't strengthen even for major market-wide information releases.

Baskar Sinha et al (2007) studied the lead lag relationship between the spot and future market in the context of introduction of Nifty futures at the National Stock Exchange

(NSE) in June 2000. They have used the techniques of Co-integration and linear regression to find the existence of any such relation in the two markets during 1st April 2002 and 31st March 2005. They have found that the Nifty Futures market leads the nifty index cash market. At the same time a lead – lag relation has been traced for all the years under study individually. Their conclusions are the relationship among the Nifty index futures and cash market has changed considerably during the period under study

2.6. RESEARCH GAPS IN INDIAN STUDIES:

- None of the earlier studies used high frequency data
- Studies have used weekly and daily data which shows a null performance and could not able the desired relationship between spot and futures
- Studies have mainly focused on volatility rather than cost of carry relationship because with weekly and daily data many problems cannot be encountered as well, it could be smooth.
- To find the relationship between spot and futures markets it is important to consider many variables such as
    - Market imperfections such as transaction cost, asymmetric information and other market microstructure effects.

To attain the above given research gaps in Indian studies, we are considered and discussed in the next following chapters.

THE INTERDEPENDENCE BETWEEN THE SPOT AND INDEX FUTURES MARKETS: AN EMPIRICAL ANALYSIS IN INDIA

CHAPTER – III

REVIEW OF RESEARCH METHODOLOGY AND TECHNIQUES

CONTENTS:

3.1 INTRODUCTION
3.2 DICKEY-FULLER STATIONARITY TEST
3.2.1 STATIONARITY TESTS FOR ALL SERIES OF RETURNS
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3.8.1 THE VOLATILITY TRANSFERS

3.1. INTRODUCTION:

One of the economic functions of futures contracts is price discovery. Price discovery refers to the use of futures prices for pricing cash market transactions and its significance depends upon the close relationship between the prices of futures contracts and the underlying assets. The essence of the price discovery function of futures markets hinges on whether new information is reflected first in changes of futures prices or in changes of cash prices.

In other words, price discovery means whether price changes in futures markets lead price changes in cash markets more often than the reverse. If that is the case, there exists a lead-lag relationship between the two markets. Therefore, the futures prices may serve as the market's expectation of a subsequent delivery period cash price. The share of price discovery originating in the futures markets has important implications for hedgers and arbitrageurs who use these markets.

Two issues regarding the lead-lag relation between the two markets deserve examination. The first is whether the lead-lag relation is induced by the infrequent trading of component stocks. Many components of stocks on the spot index are not traded frequently enough to allow prices to update information quickly. When the lead-lag relation is analyzed based on intraday price change, the staleness of component stock prices can cause futures prices to appear to lead cash index prices. Thus, the evidence that futures prices lead the cash index may simply be due to infrequent trading of component stocks, not to a delay in the adjustment of cash index prices.

One of the important roles attributed to futures markets is that of ‘price discovery’; that is, the futures market reflects new information before the spot market. If new market information disseminates in the futures market before the stock market, then the introduction of a futures market increases the amount of information reflected in the spot price. This might be explained by the fact that trading futures has the advantages of a highly liquid market, low transaction costs, easily available short positions, low margins and rapid execution. Thus, informed traders may find they can act faster and at lower cost in the futures market than they can in the cash market, resulting in a lead-lag relationship between futures and spot prices.

Investigation of intraday lead-lag relationships typically involves high frequency data and observations on the three series are probably unequally spaced in time. In the literature this problem is dealt with in at least two different ways that both have serious shortcomings. One way is to choose a long unit time interval so that the number of missing observations is small. Especially when trading is not very frequent, in this procedure a lot of information is thrown away. Another solution is to impute zero returns for intervals in which no trading took place. This creates an error in the variables that will bias the covariance and correlation estimates towards zero. To avoid these problems we use an estimator developed by De Jong and Nijman (1997) that takes these characteristics of the data into account without introducing bias due to non-trading in many time intervals. The estimator that we propose is asymptotically unbiased under any pattern of observations. This method is more general than the specific models used by Cohen et al. (1993) or Lo and MacKinlay (1991), who rely on specific models for the transaction process. The only assumption we need is that the trading pattern is independent of the price process.

In most empirical studies the intraday lead-lag relation between different markets is examined by estimating a Granger-Sims causality regression where the returns in one market are explained by lagged, contemporaneous and lead returns in the other market (e.g. Kawaller et al., 1987; Chan. 1990; Stephan and Whaley, 1990; Stoll and Whaley, 1990; Chan et al., 1993).

The primary benefits futures markets provide to economic agents are price discovery and risk management through hedging. Since price discovery has been already defined above let’s look at risk management. Risk management refers to hedgers using futures contracts to control their spot price risk. The dual roles of price discovery and risk transfer provide benefits that cannot be offered in the spot market alone and are often presented as the justification for futures trading (see e.g. Garbade and Silber, 1983).

A considerable amount of empirical research has been directed towards examining the relationship between futures and the underlying spot prices in different commodity and financial futures markets. In particular, the focus of attention has been on the lead-lag relationship between futures returns and the underlying spot returns; for the futures prices to fulfil their price discovery role they must lead the underlying spot prices. Stoll and Whaley(1990) report the existence of a two-way feedback relationship between futures returns and stock index returns in the S&P-500 and the Major Market Index contracts with the lead from futures to spot being stronger. Similar conclusions are drawn by Wahab and Lashgari(1993) and Hung and Zhang (1995) in the examination of stock index futures (FTSE-100 and S&P-500) and interest rate futures, respectively. Finally, Tse (1995) finds that futures returns lead the spot price returns in the Nikkei Stock Index contract. Overall, the findings of these studies indicate that causality between spot and futures prices can run in one (futures to spot) or both (futures / spot feedback) directions, depending on the market under investigation, and in all the cases futures prices contribute to the discovery of new information regarding the future level of spot prices.

Under perfectly efficient markets, new information is impounded simultaneously into cash and futures markets. However, in reality, institutional factors such as liquidity, transaction costs, and other market restrictions may produce an empirical lead-lag relationship between price changes in the two markets. Futures markets could incorporate new information more quickly than do cash markets given their inherent leverage, low transaction costs, and lack of short-sale restrictions [Tse (1999)].

Several studies suggest that futures markets play a critical role in price discovery for the underlying spot market [Chatrath, Chaudhry, and Christie-David (1999), Lien and Tse 2000), and Yang, Bessler, and Leatham (2001)]. This price discovery function implies that prices in the futures and spot markets are systematically related in the short run and/or in the long run. In the co-integration jargon, the price discovery function implies the presence of an equilibrium relation binding the two prices together. If a departure from equilibrium occurs, prices in one or both markets should adjust to correct the disparity.

The relationship between stock index spot and futures markets is still attracting the attention of academics, practitioners and regulators due to both the considerable volume of trading in these contracts and their role during periods of turbulence in financial markets. An important aspect of this relationship is the nature of the lead-lag relationship in the returns between equivalent assets traded in different markets or the predictive power of price movements in one market for those in the other market.

One of the "*Economic*" functions of futures contracts is price discovery. Price discovery refers to the use of futures prices for pricing cash market transactions and its significance depends upon the above mentioned, close relationship between the prices of futures contracts and the underlying assets. The essence of the price discovery function of futures markets hinges on whether new information is reflected first in changes of futures prices or in changes of cash prices.

In perfectly frictionless and complete markets there would be complete simultaneity between the price movements of stocks or indices and derivative instruments such as options and futures. However, on small time intervals (high frequency) it is often noticed that some price series consistently lead other, closely related, prices. Such lead-lag relations indicate that one market processes new information faster than the other market(s). Due to arbitrage restrictions that link these markets, lead and lag correlation coefficients between price change series will generally be small although it is possible that one market consistently leads or lags the other(s).

Empirical research aimed at testing the lead–lag relationship between the index futures and the underlying spot market produced mixed results. Empirical evidence indicates that, (a) future prices tend to influence spot prices (see, Abhyankar, 1998 and a list of references therein), (b) spot prices tend to lead futures prices (Subrahmanyam, 1991;

Chan, 1992), and (c) a bi-directional feedback relationship exists between spot and futures prices (see, Abhyankar, 1998; Silvapulle and Moosa, 1999).

In the present chapter, we investigate the lead-lag relationship between the S&P CNX Nifty Spot Index and Index Futures contracts for India. Most tests of the lead-lag relationship make use of intra-daily data on stock index and stock index futures returns. One of the problems associated with tests of lead-lag relationships based on intra-daily data is the possible effect non-synchronous trading can have on the results. Indeed, the evidence suggests that it can have a substantive impact on observed return behaviour (Stoll and Whaley. 1990; Miller *et al.*, 1994).

The importance of this is that if factors such as non-trading are present then they may induce a spurious lead-lag relationship because in the case of non-trading the index will contain stale prices and thus the futures will appear to lead the spot for non other reason than the effect of stale prices on the index. Note also that technically, we can distinguish between non-trading and non-synchronous trading. Non-synchronous trading is the situation where securities trade at least once every time interval but not necessarily at the end of the interval, whereas non-trading is the situation where securities do not trade for several time intervals. However, since the effect of both of these is to induce autocorrelation in stock returns, we will use the two interchangeably here. It is therefore argued that a lead of the futures market over the cash market will be observed, even though there is no economic significance to this. A symptom of this infrequent trading effect is that intraday returns based on the reported index will exhibit significant positive autocorrelation (see Cohen *et al.*, 1986). A second problem with an index based on transaction prices is that these transaction prices tend to fluctuate randomly between bid and ask prices in successive transactions.

There are also several technical reasons why returns on a particular market may seem to lead returns on other markets. If futures markets instantaneously reflect new information and if the stocks within the index trade infrequently, observed futures returns will lead observed stock index returns. To solve the infrequent trading problem, Harris (1989) derives new estimators of the underlying value of a stock portfolio which abstract from non-synchronous trading problems by using the complete transaction history of all stocks in the portfolio. Stoll and Whaley (1990) adjust for the infrequent trading effect by using innovations from an ARMA process with constant parameters instead of raw returns. Chan (1992), however, shows that non-synchronous trading cannot completely explain the lead lag relations since even for stocks that are actively traded and have non-trading probabilities close to zero, the returns still lag the futures returns significantly.

In order to analyze information flows between markets on short time intervals, high frequency data are required. Typically, all transactions from some sample period are available for analysis. However, the statistical analysis of transactions data is often hampered by the fact that the clock time interval between such observations is varying. For some research questions, such as most microstructure issues, the differences in clock time interval are not very important and one relies on estimating models in transaction time. However, for the analysis of information flows between markets the clock time is of utmost importance. The usual approach to tackle the problem of irregularly spaced observations is to split the time axis in fixed length intervals of, say, 5 min and use the last observation recorded in that interval in the statistical analysis. This approach has an important drawback, however. If the intervals are small and trading is not very frequent, some intervals may contain no observation. This is referred to as the non-trading or non-synchronous trading problem. Another cause of missing observations are imperfections in data collection, e.g. errors on the data file, which sometimes cause a loss of observations. Lo and MacKinlay (1990a) demonstrated that non-trading or non-synchronous trading may lead to serial correlation in observed portfolio returns, even when the underlying true returns are serially uncorrelated. Moreover, there will be positive lead and lag covariance's between observed returns of assets whose true returns are only contemporaneously correlated.

Researchers have used five minute intervals, where few observations are missing. In this section, we also present results at the one minute interval, at which more intervals without trade occur in the futures market. Since the stock market index is adjusted every minute there are no missing data points on the index unless the frequency at which the data are analyzed is even higher than one minute.

Here, the trading day is divided into intervals of 5 min. The first prices to be observed in these intervals are then used to construct 5 min returns in both the cash index and futures markets. This creates some problems if there are no transactions in some interval. Usually, a zero return for these periods is imposed. Stoll and Whaley's empirical methodology is in two steps. First, they calculate the auto- and crosscorrelations of R^S and R^F. The S &P 500 cash index returns show strong positive serial correlation. The futures returns are almost serially uncorrelated. Individual stock returns tend to be negatively serially correlated due to the bid-ask bounce.

Most studies carried out so far implement the analysis separately, estimating volatilities from return innovations. Generally, studies concerning return interactions find that the futures market leads the spot market (Kawaller et al. 1987; Stoll and Whaley 1990; Wahab and Lasghari 1993; Pizzi et al. 1998, among many others). The fact that price discovery occurs more significantly in the futures market compared to the cash market can be attributed to two factors: a) the stocks in the index have no identical trading activity, so that the index does not immediately reflect all new information, and b) the futures contract allows for trading the market stock exchange portfolio with significantly lower transaction costs and with a short time requirement. Consequently, reactions in futures markets are faster, and movements in futures prices lead spot price fluctuations. On the other hand, there are numerous studies which analyse the causal relationship between spot and futures market volatilities (Kawaller et al. 1990; Chan et al. 1991; Chan and Chung 1993; Abhyankar 1995 and Min and Najand 1999, among others). Contrary to consistent empirical evidence on the causal relationship between spot and futures market returns, the findings on volatility relationships are not similar in all markets, but show a dependency on the sample period analyzed and the volatility measure considered.

The lead-lag relation between movements of spot and futures prices has been widely investigated with the methods used varying across studies. For example, Kawaller et al. (1987), Abhyankar (1998) and Tang et al. (1992) use modified/non-modified Granger causality tests. Whereas Wahab and Lashgari (1993), Fleming et al. (1996) and Pizzi et.

al. (1998) use co-integration and error correction models. However, irrespective of methodology, the results can be summarized concisely: market information tends to disseminate in futures prices prior to, and at greater speed than, in stock prices. Several studies examine temporal relationships between futures and cash index returns using a Granger (1969) and Sims (1972) causality specification for the intraday observed time series. See e.g. Finnerty and Park (1987), Ng (1987), Kawaller et al. (1987), Hams (1989), Stoll and Whaley (1990), Chan (1992) and Huang and Stoll (1994).

Three major approaches to the study of the price discovery of assets have been identified in the literature. The first approach focuses on the lead-lag relationship between the prices of national markets, or between different securities. For example, Eun and Shim (1989) studied the transmission of stock prices between different countries; Stoll and Whaley (1990) and Chan (1992) examined information transmission between the stock index and index futures markets. Harris, Mclnish, Shoesmith, and Wood (1995) investigated the transmission of price information about IBM in different stock exchanges.

The second approach involves examination of the role of volatility in the price discovery process. Volatility spillovers are important in the study of information transmission because volatility is also a source of information. Two seminal papers (French &: Roll, 1986; Ross, 1989) show that variance is an important source of information. French and Roll found that asset prices are much more volatile during exchange trading hours than at other times and that this divergence is caused by differences in the flow of information.

Ross proved that asset price volatility is related to the rate of information flow in competitive asset markets. Previous studies on volatility spillovers in different national stock markets include Hamao, Masulis, and Ng (1990), Susmel and Engle (1994), Lin, Engle, and Ito (1994), Karolyi (1995), Koutmos and Booth (1995), and Booth, Chowdhury, Martikainen, and Tse (1997).

The general conclusion is that volatility in one market will spill over to another market. In a study of volatility spillovers among similar assets, Chan, Chan, and Karolyi (1991), Kawaller, Koch, and Koch (1990), and Koutmos and Tucker (1996) considered information transmission between stock index and index futures markets. As with volatility spillovers among different national markets, empirical evidence indicates that the volatilities of similar assets affect one another.

Traditionally, commodity futures contracts are settled by physical delivery. A seller with an open position at contract expiration must make deliveries to liquidate the position. Similarly, a buyer must take deliveries to liquidate an open position held at the contract maturity. In spite of high transportation, inspection, and storage costs, this settlement specification was adopted to ensure the convergence between spot and futures prices at the contract expiration date. Moreover, to ensure the adequacy of the delivery mechanism (en route to reduce market manipulations such as corners and squeezes), most contracts allow the seller to choose among multiple deliverable grades and locations (at predetermined discounts and premiums). As a result, the futures price will converge to the cheapest deliverable grade. This creates additional uncertainty, the so-called delivery risk, which leads to a larger basis risk (Leuthold, 1992). The risk transferring and price discovery functions of a futures market are damaged.

The first studies to test the price transmission process have used mainly the regression analysis. However, if price series are not stationary, a phenomenon typical in financial markets, then standard statistical tests of parameter restrictions are not reliable (Elam and Dixon, 1988). Thus, for overcoming the problems of non-stationary price series and due to the fact that price discovery deals with short-run and long-run departures from a presumed equilibrium relation, the introduction of cointegration analysis with error correction models is fortuitous.

The lead-lag relation between price movements of stock index futures and the underlying cash market illustrates how fast one market reflects new information relative to the other, and how well the two markets are linked. In a perfectly frictionless world, price movements of the two markets are contemporaneously correlated and not cross-correlated. However, if one market reacts faster to information, and the other market is slow to react, a lead-lag relation is observed.

Several factors can influence how fast the cash and futures markets reflect information, and thus affect the lead-lag relation. One factor in short-sale constraints in the cash market, such as legal or contractual prohibitions of shorting by certain institutional investors and corporate insiders, the inability to borrow stock to short, and the "no short sale on a down-tick" rule. Diamond and Verrecchia (1987) show that prohibiting traders from shorting slows the adjustment of prices to private information, especially with respect to private bad news. Since there is no short-sale constraint in the futures market, futures prices are symmetric in reflecting private good news and bad news. Therefore, the lead-lag relation would not be the same under bearish and bullish markets, and futures prices should lead the cash index to a greater degree under bad news – if the short-sale constraints are binding. However, if the marginal arbitrageur has long positions in the stocks, and he is not constrained by short-sale restrictions, cash index prices should not lag futures to a greater degree under bad news.

Futures and cash markets contribute to the discovery of a unique and common unobservable price that is the efficient price. The contribution of each market to the price discovery depends, at least in part, on the microstructure of these markets, including the level of transparency, the liquidity supply mechanism, the rules governing the priority of orders, the constraints on short sales and the settlement mechanism.

The specific model used in this study is cointegration. This statistical concept introduced by Granger (1983), Granger and Weiss (1983) and Engle and Granger (1987) has received wide attention and is beginning to be applied to test the validity of various theories and models.

Cointegration is a property possessed by some non-stationary time series data. In this concept, two variables are co-integrated when a linear combination of the two is stationary, even though each variable is non-stationary. In particular, if we if consider two time series, X and Y that are non-stationary, conventionally one would expect that a linear combination of two the variables would also be non-stationary.

3.2. DICKEY-FULLER STATIONARITY TEST:

As was expected, the original series shown above (before we take returns) were not stationary with respect to the Dickey Fuller unit root test at a 1%, 5% or 10% probability level and not cointegrated, neither with an ADF test, nor with a Johansen test.

We observed the autocorrelations in all return series (one, five, ten and one hour) and we attempted to build ARMA models for the univariate cases.

In the Dickey-Fuller and the Augmented Dickey-Fuller test, the observed τ statistic, the t statistics for δ (the coefficient for the lagged variable in the level in the test equation), is compared with the critical value provided by Mc Kinnon(1991), who has provided response surface estimated (optimal design) of the crucial values of the Dickey-Fuller statistics. The Monte Carlo tables given by Dickey (1976) were adjusted slightly by Dickey and Fuller. If τ in absolute values is smaller than the critical values, then the series will not be stationary even after the trend has been removed. In this case, it will be necessary to work with first differences. If the first differences are stationary, the series is I(1), meaning integrated of order 1. The differenced series is then I(0).

The trend stationary process can be written:

$$y_t = \beta_1 + \beta_2 t + u_t , \qquad (1)$$

Where u_t is stationary with, for instance, a constant sample mean $\bar{u}$ equal to zero and a constant variance σ^2. In the difference stationary process (the random walk if α =0 or the random walk with rift if $\alpha \neq 0$), we have,

$$y_t - y_{t-1} = \alpha + u_t \qquad (2)$$

Where α is a constant.

3.2.1. STATIONARITY TESTS FOR ALL SERIES OF RETURNS:

We used the Augmented Dickey-Fuller test to check the stationarity of the all frequencies of returns series in differences of logarithms' over the period from 1st January, 2001 to 31st November, 2005. We used the test a first time with 4 lags because the returns show a significant autocorrelation of order 4 and because the AIC and SIC criteria indicate lower values for 3 lags than for 4 lags in the test equation.

3.3. CO-INTEGRATION TEST FOR THE RETURNS SERIES FOR ALL FREQUENCIES:

We will now investigate if the series in level are, if not stationary, perhaps co-integrated. We test the all returns series for cointegration with the Johansen cointegration test, using 6 lags of the differences of the residuals of the cointegration equation to account for autocorrelation. In both cases, the null hypothesis of no cointegration equation is not rejected at the 5% and at the 1% significance levels.

To computer the test statistics (Trace Statistic), we start from a VAR of order p:

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + C_t + \varepsilon_t \qquad (3)$$

Where y_t is a 2-dimesnion vector of non stationary, I(1) variables, C_t is a vector of constant terms and ε_t is a vector of innovations. One can write this VAR in the form similar to the ADF unit root test equation:

$$\Delta y_t = \Pi y_{y-1} + \sum_{i=1}^{p-1} \Gamma_i \Pi y_{y-i} + C_t + \varepsilon_t \qquad (4)$$

Where

$$\Pi = \sum_{i=1}^{p} A_i - I, \qquad \Gamma_i = -\sum_{j=i+1}^{p} A_j \qquad (4.1)$$

Where p-1 equal to 3, because this order of the process is selected by the AIC criterion in a test Vector Error Correction (VEC) model. It is also true that for this order, the first 3 autocorrelations are not significant in each of the residuals series of the two equations with respect to the Q statistics or to the t statistics. Further, we use the eigen values λ 's of the matrix Π to compute the trace statistic Q_r :

$$Q_r = -T \sum_{i=r+1}^{k} \log(1-\lambda_i) \qquad (5)$$

For r=0,1,……,k-1, where λ_i is the ith largest eigen values of the matrix Π. In our case, we take only one (the largest) value, because the first hypothesis (no cointegration equation) is not rejected. The alternative hypothesis is that the number of cointegration equations is equation to r (the number of endogenous variables have equal to 2)

3.4. VECTOR ERROR CORRECTION MODEL:

The finding that many time series may contain a unit root has spurred the development of the theory of non-stationary time series analysis. Engle and Granger (1987) pointed out that a linear combination of two or more non-stationary series may be stationary. If such a stationary, linear combination exists, then the non-stationary time series are said to be cointegrated. The stationary linear combination is called the co-integrating equation and may be interpreted as a long-run equilibrium relationship between the variables. Although the two series may be non stationary they may move closely together in the long run so that the difference between them is stationary. This section outlines the methodology of the Co-integration Analysis to study the relationship between Nifty spot index and Nifty futures index.

Two series St and Ft are said to be integrated of the order one, denoted by I(1), if they become stationary after first difference. If there are two such series which are I(1) integrated and their linear combination is stationary, then these two series are said to be cointegrated. This relationship is the long run equilibrium relationship between St and Ft.

A principal feature of cointegrated variables is that their time paths are influenced by the extent of any deviation from long-run equilibrium. If the system is to return to its long run equilibrium, the movement of at least one variable must respond to the magnitude of the disequilibrium. If cointegration exists between St and Ft, then Engle and Granger representation theorem suggests that there is a corresponding Error Correction Model (ECM). In an ECM, the short term dynamics of the variables in the system are influenced by the deviations from the equilibrium.

The present research, seeks to determine whether there exists an equilibrium relationship between Nifty spot index and Nifty futures index. Engle and Granger suggest a four step procedure to determine if the two variables are cointegrated. The first step in the analysis is to pre-test each variable to determine its order of integration, as cointegration necessitates that the two variables be integrated of the same order. Augmented Dickey-Fuller (ADF) test has been used to determine the order of integration. If the results in step one show that both the series are I(1) integrated then the next step is to establish the long run equilibrium relationship in the form

$$S_t = \beta_o + \beta_1 F_t + e_t \qquad (6)$$

Where S_t is the log of spot index price; F_t is the log of futures index prices at time t and e_t is the residual term. In order to determine if the variables are cointegrated we need to estimate the residual series from the above equation. The estimated residuals are denoted as (ê). Thus the ê series are the estimated values of the deviations from the long run relationship. If these deviations are found to be stationary, then the S_t and F_t series are cointegrated of the order (1,1). To test if the estimated residual series is stationary Engle-Granger test for co-integration was performed.

The third step is to determine the ECM from the saved residuals in the previous step.

$$\Delta S_t = \alpha_1 + \alpha_s \hat{e}_{t-1} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{s,t} \qquad (7.1)$$

$$\Delta F_t = \alpha_1 + \alpha_f \hat{e}_{t-1} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{f,t} \qquad (7.2)$$

In the above equations, ΔS_t and ΔF_t denote, respectively, the first differences in the log of spot and futures prices for one time period. $\hat{e}_{t-1}$ is the lagged error correction term from the co-integrating equation and $\varepsilon_{s,t}$ and $\varepsilon_{f,t}$ are the white noise disturbance terms.

The above equations describe the short-run as well as long-run dynamics of the equilibrium relationship between spot index and futures index. They provide information about the feedback interaction between the two variables.

In the equation ΔS_t has the interpretation that, change in S_t is due to both, short-run effects, From lagged futures and lagged spot variables and to the last period equilibrium error $\hat{e}_{t-1}$, which represents adjustment to the long-run equilibrium. The coefficient attached to the error correction term measures the single period response of changes in spot prices to departures from equilibrium. If this coefficient is small then spot prices have little tendency to adjust to correct a disequilibrium situation. Then most of the correction will happen in the other variable, in these case futures prices.

The last step involves testing the adequacy of the models by performing diagnostic checks to determine whether the residuals of the error correction equations approximate white noise. The reverse representation of Engle and Granger's Co-integration analysis along with the empirical findings has been given in the appendix. A pair wise Granger Causality test was done to establish the cause and effect relationship between spot index and futures index.

3.5. VAR MODELS:

VAR models are well known (see Sims (1980, p-16-20), Mills (1990, p.281), Luthepohl (1993, p.9), Hamilton (1994, p.291), Luthekpohl(1997), Franses (1998,p.201), Clements and Hendry (1998, P.19 and 123)

For the VAR(p)

$$x_t = A_0 + \sum_{j=1}^{p} A_j x_{t-j} + \varepsilon_t \qquad (8)$$

For the roots of the following polynomial in z

$$\left| I_n - \phi_1 z - \phi_2 z^2 - ..... - \phi_p z^p \right| = 0 \qquad (8.1)$$

(where ϕ_i are matrices and I_n is an identity matrix of dimension n) have to lied outside the unit circle (Hamilton (1994, p259 and 298)). Only when this condition is fulfilled will the process be covariance-stationary (Hamilton, 1994, p.259). Also important is that the variables are stationary, or, at least cointegrated (See Canova, 1995).

To get a good classical model diagnostic, the residuals of each equation should, in the case of constant variance, show a Gaussian distribution an no autocorrelations. The presence of autocorrelations in the residuals mostly signals the need for more lags in the VAR model. When the equations are estimated independently by recursion, and with the assumption that the covariance's of the residuals are zero or can be neglected, the cross correlations between the residuals of different equations $(Cor(\varepsilon_{it}, \varepsilon_{ji-k}))$ do not play a major role in recursive systems, even if with the previous assumption, they should be zero also.

Other important points in the diagnostic of the classical VAR model are that the variables are stationary, or at least pair wise co-integrated (canova, 1995), that the residuals of each equation are not auto- correlated and do not show a time varying variance, that the distribution is Gaussian, that the roots of the characteristic polynomial lie outside the unit circle, that the variance of each series of residuals is as small as possible, or, in other terms, that the determinant of the covariance matrix is as small as possible.

If $\hat{\Omega}$ is the covariance matrix of the residuals of the different equations of the VAR model, when estimated at the MLE of the parameters θ (assuming normal distribution, in which case the least sqares method is equivalent to the MLE), the maximized log likelihood function of the VAR system is:

$$Ln\,\mathrm{L}(\hat{\Omega},\theta) = -\frac{KT}{2}\ln 2\pi - \frac{T}{2}\ln\left|\hat{\Omega}\right| - \frac{1}{2}\sum_{t=1}^{T}\hat{\varepsilon}_t\hat{\Omega}^{-1}\hat{\varepsilon}_t\,, \qquad (9)$$

Or with diagonal matrix $\hat{\Omega}$:

$$Ln\,\mathrm{L}(\hat{\Omega},\theta) = -\frac{KT}{2}\ln 2\pi - \frac{T}{2}\ln\left|\hat{\Omega}\right| - TK/2, \qquad (9.1)$$

(Luthepohl, 1993, p.81, Hamilton, 1994, p-295-296), where:

$$\hat{\Omega} = (1/T)\sum_{t=1}^{T}\hat{\varepsilon}_t\hat{\varepsilon}_t^{\,1} \qquad (9.2)$$

I note that if the covariance's in the $\hat{\Omega}$ matrix are equal to zero, $\hat{\Omega}$ is diagonal, the determinant is equal to the product of the elements on the main diagonal.

The AIC criterion of the VAR system should be minimized (Mills, 1990, p.310, Luthepohl, 1993, p.129, Franses, 1998, p.202, Eviews, 1998)

$$\begin{aligned} AIC &= \ln\left|\hat{\Omega}\right| + \frac{2}{T}\text{(Number of parameters)} \\ &= \ln\left|\hat{\Omega}\right| + \frac{2mK^2}{T}\ \text{in the case without exogenous variables or} \\ &= \ln\left|\hat{\Omega}\right| + \frac{2(mK^2 + nEK)}{T}\ \text{in the case of n lagges values or the exogenous variables} \\ &\qquad\qquad\text{(including lag 0),} \end{aligned}$$

With

m = order of the model (number of lags for the endogenous variables)

K = number of endogenous variables = number of equations

n = number of lagged values of the exogenous variables

E = number of exogenous variables

T = number of observations

$$SIC = \ln\left|\hat{\Omega}\right| + \frac{\ln T}{T}\text{(Number of parameters)}$$
$$= \ln\left|\hat{\Omega}\right| + \frac{\ln T}{T}\left(mK^2 + nEK\right)$$

The test of Granger-causality is based on two regression models in the autoregressive distributed lag(ARDL) from (Green, 1987, p.714,782-786, Pindyck-Rubinfeld, 1998, p.243-244) for a pair of variables or on a VAR model (Hamilton, 1994, p.302). The forms of these regressions (or bivariate VAR models) are:

$$y_t = a_0 + a_1 y_{t-1} + ... + a_k y_{t-m} + b_1 x_{t-1} + ... + b_1 x_{t-m} \quad \text{and}$$
$$\mathrm{x_t} = a_0 + a_1 x_{t-1} + ... + a_k x_{t-m} + b_1 y_{t-1} + ... + b_1 y_{t-m} \qquad (10)$$

Where we use the Wald test (taking here the form of an $F_{q,n-k}$ test, with q equal to the number of restrictions and k the number of parameters – variables and constant, see Pindyck-Rubinfeld, 1998, p.128-130) to test the joint hypothesis:

$$b_1 = b_2 = ... = b_k = 0$$

for one of the two equations. The null hypothesis is that x does not Granger-cause y with the first regression, whereas in the second regression, the null is that y does not Granger-case x. We note however, that the validity of the F test depends on the normal distribution of the residuals. Here the residuals are not Gaussian (which is due to the non-Gaussian returns). We can replace the F test by a LR test (Pindyck-Rubinfeld, 1998, p.274 and 195) and achieve a similar results, but the assumption of Gaussian distribution is also made to compute the likelihood if we do not know the precise distribution.

In the case of the two series of returns of all frequencies (differences of logged data, i.,e stationary series) with 2 lags for both variables in the test regression, we note that the null hypothesis, the spot returns do not Granger-cause the futures returns, can be rejected. The value of the F statistics is just high enough to reject the null that spot does not Granger-cause the futures returns.

If we use the test in a multivariate framework (Hamilton, 1984, p.309), where 2 independent equations including the 2 lagged variables as regressors are estimated, we use a VAR(1) model for the two variables, because both the AIC and SIC are higher for VAR(2) model.

As we have a big sample, the numerator and denominator of the t statistics are asymptotically respectively Gaussian and Chi-square, even though the residuals are not Gaussian (as the kurtosis is high). If a LR or an F test used to test the H_0 that one market is redundant (has no impact) in one equation, the result is extremely near from the result produce by the t statistics. Consequently, we use the t test for this causality test in a VAR(1) framework. We get the following results:

3.6. MULTIVARIATE GARCH MODELS:

In order to analyze information flows between markets on short time intervals, high frequency data are required. Typically, all transactions from some sample period are available for analysis. However, the statistical analysis of transactions data is often hampered by the fact that the clock time interval between such observations is varying. For some research questions, such as most microstructure issues, the differences in clock time interval are not very important and one relies on estimating models in transaction time. However, for the analysis of information flows between markets the clock time is of utmost importance. The usual approach to tackle the problem of irregularly spaced observations is to split the time axis in fixed length intervals of, say, 5 min and use the last observation recorded in that interval in the statistical analysis. This approach has an important drawback, however. If the intervals are small and trading is not very frequent, some intervals may contain no observation. This is referred to as the non-trading or non-synchronous trading problem. Another cause of missing observations are imperfections in data collection, e.g. errors on the data file, which sometimes cause a loss of observations. Lo and MacKinlay (1990a) demonstrated that non-trading or non-synchronous trading may lead to serial correlation in observed portfolio returns, even when the underlying true returns are serially uncorrelated. Moreover, there will be positive lead and lag covariances between observed returns of assets whose true returns are only contemporaneously correlated.

In this section we present an empirical application of the proposed estimator to the lead-lag relationship between the S&P 500 stock index and futures on this index. As stated in Section 1 this is a well-studied relationship, with the general conclusion that the futures market leads the cash market. Typically, researchers have used five minute intervals, where few observations are missing. In this section, we also present results at the one minute interval, at which more intervals without trade occur in the futures market. Since the stock market index is adjusted every minute there are no missing data points on the index unless the frequency at which the data are analyzed is even higher than one minute.
To study the Indian stock markets and its subsequent spillover or, in other words, the transfer of volatilities form one market to another, we use GARCH models to compute volatilities and VAR models for the returns of different markets and for the volatilities

(which may be expressed as squared returns). As mentioned by several authors (Engle, Ito and Lin (1990) and Booth, Chowdhury, Martikained and Tse(1997), these VAR models for the volatilities can show the nature of the change in volatility; authors refer to this situation when the impact of a shock coming from the same market is much bigger than the impact of shock transferred from other markets as a “heat wave”. When the impact of shock on one market are transferred from other markets, they call that a “meteor shower”.

The VAR models allows us to build impulse response functions which show, in the case of a meteor shower, how fast a shock on one market will affect other markets and how long the impact will last. In the heat wave case, the impulse response functions will show the impact of a shock on one market on the futures returns on volatilities. We also examine some univariate models for individual indices (ARMA or ARIMA), even though the explanatory power of autoregressive models for stock indices are very low.

Engle, Ito and Lin (1990) have estimated and tested meteor showers and heat waves for per-hour volatility of exchange rates in New York and Tokyo only. They also present a daily model` for the USD-Yen exchange rate on 4 markets (Pacific, Tokyo, Europe and New York) since September 1985 (p.534). They defined the Pacific market as the trade that happens after New York is closed and before Japan opens. For their data, they rejected the heave wave hypothesis (p.527).

In a heat wave, the conditional variance of the returns in one market depends only upon the past shocks in this market, Engle et al., (1990, P.533) noted positive and significant effects of yesterday’s change on today’s volatility as well as the possibility of a unit root in the variance process which says that these shocks last forever. In fact, they saw (p.533) that the sum of coefficients in the conditional variance equations is only slightly less than 1.0 and may reveal the integrated GARCH process described in Engle and Bollerslev (1986). The heat wave hypothesis is consistent with the view that major sources of disturbances are changes in country –specific fundamentals, and that one large shock increases the volatility in that country only. The large shocks can be due to new pieces of information (Engle, Ito,Lin (1990) and Engle and NG, in Engle (1993), for instance about a central bank like the FED raising or lowering the interest rates. The heat wave hypothesis is equivalent to a zero coefficient on the foreign market term.

For the meteor shower alternative, Engle et al (1990) used the per-hour squared change between the closing rate at the previous period and the opening rate at this period to measure the effect of the foreign volatility. The meteor shower can be illustrated for money supply announcements. When the money supply statistics are announced in New York at 4:10 pm on Thursdays, the differences in the traders' priors or beliefs increases the volatility. This process takes several hours. Ito and Roley (1987) showed evidence of the spillovers into the Pacific market after weekly money supply announcements, but they did not look at volatility spillovers. The meteor shower is equivalent to a zero coefficient on the domestic market term. Engle and Ng (1993) studies the impact of new on the volatility.

Booth , Chowdhury, Martikainen and Tse (1997) examined the intraday volatility for stock index futures for 3 markets: the United States, the United Kingdom and Japan. They used the high, low, opening and closing prices to compute an indicator for the 3 volatilties based on the price spreads between high and lower and between open and close. They then built a 3-dimensional VAR model for the volatilities which allowed them to check whether the changes in volatility were local or foreign in origin.

In this chapter, we will present the case of volatility spillover between Indian Stock markets i.e, spot index and Index futures price values. To study the interdependence, we will use a multivariate VAR(1)-GARCH(1,1) model, as the correlations are high for contemporary returns (lag 0) on financial markets, and we will concentrate on the BEKK methods.

The development of multivariate generalized autoregressive conditionally hetroscedastic (MGARCH) models from the original univariate specifications represented a major step forward in the modeling time series. MGARCH models permit time-varying conditional covariances as well as variances, and the former quantity can be of substantial practical use for both modeling and forecasting, especially in Finance. Brooks, Burke and Persand (2001) employed the FCP (1996) benchmark for evaluating the accuracy of the parameter estimates in the estimates in the context of univariate GARCH models and stressed the importance of the development of benchmarks for other non-linear models, including other in the GARCH class. However, there are currently no benchmarks yet development for multivariate GARCH models.

Several different multivariate GARCH model formulation have been proposed in the literature, and the most popular of these are the VECH, the diagonal VECH and the BEKK models. Each of these is discussed briefly in turn below; for a more detailed discussion, see Kroner and NG (1998).

Introducing some notation, let H_t denote a NxN conditional variance-covariance matrix, Ξ_i an Nx1 vector of innovations, Ψ_{i-1} represent the information set at time t-1, then the conditional variance-covariance equations of the unrestricted VECH model may be written

$$VECH(H_t) = C + AVECH(\Xi_{t-1}\Xi'_{t-1}) + BVECH(H_{t-1}),\ \Xi_i / \Psi_{i-1} \sim N(0, H_i) \qquad (11)$$

Where C is an (N(N+1)/2)x1 vector containing the intercepts in the conditional variance and covariance equations. A and B are (N(N+1)/2)x(N(N+1)/2) matrices containing the parameters on the lagged disturbance squares or cross-products and on the lagged variances or covariance's respectively. The term "VECH" arises from the use of the VECH(.) column-stacking operator applied to the upper triangle of the symmetric matrix. A potentially serious issue with the unrestricted VECH model described above is that it requires estimation of a large number of parameters. Even in the context of the trivariate system (N=3), an astonishing total of 78 parameters requires estimation in the variance and covariance equations. This over-parameterization led to the development of the simplified diagonal VECH model by Bollerslev, Engle and Wooldrige (1988), where the A and B matrices are forced to be diagonal, resulting in a reduction of the number of parameters in the variance and covariance equations to 18 for the trivariate case.

In order of an estimated multivariate GARCH model to be plausible, H_i is required to be positive definite for all values of the disturbances, but even checking this condition is a non-trivial issue for VECH or diagonal VECH models of moderate size or larger. To circumvent this problem, Engle and Kroner (1995) proposed a quadratic formulation for the parameters that ensured positive definiteness and this became know as the "BEKK" model.

Finally, an alternative specification proposed by Bollerslev (1990) was the constant correlation model. It does seem somewhat bizarre to allow the both the conditional variances and conditional covariance's to vary over the time but in a restricted way so that the conditional correlations are time-invariant; it is also not clear whether such an assumption of constant conditional correlations would be supported by the data in reality. Nonetheless, this model exists as an alternative specification that may be slightly easier to estimate than the less restrictive diagonal VECH.

In order to simplify matters as much as possible, we employ only the diagonal VECH representation, and we estimate only a bivariate system. This model is still probably more widely employed than the BRKK, and the parameters of the former model are more easily interpreted.

Although any set of data could potentially be used to compare the relative merits of the different time periods, we employ a data set i.e., S&P CNX Nifty index and its futures for the period of 1st January, 2001 to 30th November, 2005, with one minute, five minutes, ten minutes and one hour averages. Letting S_t and F_t denote the spot (i.e., cash index) and futures prices respectively, the return series are denoted by lower case letter and are calculated as $s_t = \log(S_t / S_{t-1}) * 100$ and $f_t = \log(F_t / F_{t-1}) * 100$ in the usual fashion.

The conditional mean equations for the model that we estimate can be written as

$$Y_i = M + \Xi_i \, , \; \Xi_i \sim N(0, H_i) \qquad (12)$$

Where $Y_i = \begin{bmatrix} s_t \\ f_t \end{bmatrix}$, M is a 2 x1 vector of intercepts in the conditional mean $\left(M = \begin{bmatrix} \mu_s \\ \mu_f \end{bmatrix} \right)$, and with the conditional variance-covariance equations being given by (1) using diagonal forms for A and B. The conditional variance-covariance matrix, H_t, will comprise the elements $h_{s,t}$ and $h_{f,t}$ on the leading diagonal and $h_{s,f,t}$ as both of the off-diagonal terms. For clarity, the conditional mean equations can be written out separately as

$$\begin{aligned} s_t &= \mu_s + \varepsilon_{s,t} \\ f_t &= \mu_f + \varepsilon_{f,t} \end{aligned} \qquad (13)$$

With the conditional variance and covariance equations as

$$\begin{aligned} h_{s,t} &= c_1 + a_1 \varepsilon_{s,t-1}^2 + b_1 h_{s,t-1} \\ h_{f,t} &= c_2 + a_2 \varepsilon_{s,t-1}^2 + b_2 h_{s,t-1} \\ h_{s,f,t} &= c_3 + a_3 \varepsilon_{s,t-1} \varepsilon_{f,t-1} + b_3 h_{s,f,t-1} \end{aligned} \qquad (14)$$

The purchase or sale of futures contracts provides a method for hedging exposures to movements in the price of the underlying asset. In the present context, estimating an optimal hedge ratio would be involve determining the optimal number of futures contracts that should be sold per holding of the spot asset. Many studies have compared the performance of time-varying hedge ratios estimated using multivariate GARCH models with those of naïve or time-invariant hedge rations estimated using OLS regressions. The majority of these studies have preferred the time-varying approach on the grounds that they provide slightly more accurate hedge ratio estimation leading to portfolio returns with lower variances. Given the coefficients and fitted values from the estimated model, it is possible to show that the optimal hedge ratio will be given by the negative of the ratio of the one-step ahead forecast of the covariance between the spot and futures returns to the one-step ahead forecast of the futures return variance:

$$\beta_{t-1}^{*} = -\frac{h_{s,f,t}}{h_{f,t}} \qquad (15)$$

When the hedge ratio is expressed in this way, the returns to the hedged portfolio can be written as

$$r_{p,t} = s_t + \beta_{t-1}^{*} f_t \qquad (16)$$

It is also possible to express the variance of the returns to the hedged portfolio as

$$\text{var}(r_{p,t}) = h_{s,t} + \beta_{t-1}^{*} h_{f,t} - 2\beta_{t-1}^{*} h_{s,f,t} \qquad (17).$$

And, the next chapter will discuss the results and draw inferences out of the sample period and for different time-periods such as one minute, five minutes, ten-minutes and one hour of the data considered.

3.7. A RESTRICTED VAR (1)-GARCH(1,1) FOR SPOT AND FUTURES RETURNS

Further, we use multivariate GARCH models, which often lead to significant autoregressive effects or significant coefficients for additional explaining variables, that can both not be observed without the GARCH specification and the use of a conditional standard deviation. These models are able:

1. To compute all the time dependent variances and covariances,
2. To show which covariances have significant coefficients in the corresponding variance equation.

A VAR(p) augmented with additional variables is written:

$$y_t = c + \sum_{i=1}^{L} \beta_i x_{t-i} + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t \qquad (18)$$

Where β_i is a matrix:

$$\beta = \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}, \text{ and}$$

- x variables are returns from 2 markets (spot and futures)
- y has 2 dimensions: spot and futures: $y_t = \begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix}$
- y_{t-i} are lagged endogenous variables (i.e., lags of spot and futures returns)
- ε_t is N(0,H_t), where H_t is in the simple multivariate normal case equal to $\sigma^2 I$. With a symmetric time varying covariance matrix, it becomes:

$$H_t = \begin{pmatrix} h_{11t} & h_{12t} \\ h_{21t} & h_{22t} \end{pmatrix}$$

We examine the case with L (the highest lag of the regressors in x) is equal to 1, and p equal to 1, such that we have 2 equations for spot and futures returns, with residuals ε_{1t} and ε_{2t}.

However, we can use a two dimension VAR(1)-GARCH(1,1) model in the BEKK (Baba *et al.*, 1987; Engle and Kroner, 1995) form to show the volatility transfers between Spot and Futures markets.

3.8. VAR(1)-GARCH(1,1) MODEL USING BEKK METHOD

THE MODEL

As mentioned by Isakov and Perignon (2000), Bollerslev et al (1998) have proposed a diagonal vector (dvec) model where the elements of the lower half H_t matrix are vectorized. The size of the matrices A and B was 3x3 for the 2 dimensional models, due to the coefficient for the covariance. They proposed to make the A and B matrices diagonal. This specification removes the potential interactions in the variances of two markets. On the other hands, the BEKK kind of multivariate GARCH models (Engle and Kroner, 1995) allows to keep these interactions. This is useful to how the volatility transfers from one market to another. Moreover, the BEKK kind of multivariate GARCH can be used association with a VAR specification, allowing a computation of VAR-coefficients that are efficient and consistent even in the residuals of the classical VAR do not present a Gaussian distribution and a constant variance.

We consider a VAR (1)-GARCH (1, 1) model in a BEKK form. The order one is chosen because the influence of on market on the other often lasts not more than one minute.

The mean equation is the following:

$$y_t = k + \beta y_{t-1} + \varepsilon_t \text{, for t=1,2……,T}$$

With $\varepsilon_t \sim N(0, H_t)$, where

$$H_t = C^{'}C + A_1^{'}(\varepsilon_{t-1}\varepsilon^{'}{}_{t-1})A_1 + B_1^{'}H_{t-1}B_1$$

where the matrices C, A_1, B_1 are of dimension dxd (C is higher triangular), with d equal to the number of equations. Because of paired matrices, symmetry and non negative definiteness of the conditional variance matrix H_t is assured (see Engle and Kroner, 1993, 1995).

In the case with 2 dimensions, we have

1) For the mean equation:

$$y_t = \begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix},\ \mathrm{k} = \begin{pmatrix} \mathrm{k}_1 \\ \mathrm{k}_2 \end{pmatrix},\ \beta = \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix},\ \varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

   where β is a 2x2 matrix of coefficients (not symmetric or diagonal), ε_t is a 2x1 vector of estimated residuals in the mean equation (1)

2) For the variance equation (2).

$$A_1 = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix},\ B_1 = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \text{ and } \mathrm{C} = \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix}$$

   we note that in this BEKK model, a_{12} and a_{21} are different from each other, as are b_{12} and b_{21}.

The variance system has 11 parameters for two equations. The parameters of the mean and the variance equation are estimated by maximum likelihood.

We estimate a series of bivariate models based on the equations above in order to show the links existing either between the spot and futures returns. If we develop the equations above, we find

$$\begin{aligned} y_{1t} &= \mathrm{k}_1 + \beta_{11} y_{1t-1} + \beta_{12} y_{2t-1} + \varepsilon_{1t} \\ y_{2t} &= \mathrm{k}_2 + \beta_{21} y_{2t-1} + \beta_{22} y_{2t-1} + \varepsilon_{2t} \end{aligned} \qquad (19)$$

We estimated the model above either for the spot or the futures index and one other market each time. The simultaneous estimation of the parameters in the mean and in the variance equation is reached by maximum likelihood.

3.8.1. THE VOLATILITY TRANSFERS

TO explain the volatility transfers between markets in the framework a BEKK-kind of VAR(1)-GARCH(1,1) model for 2 variables, we consider the following variance equitation's:

$$h_{11t} = a_{11}(a_{11}\varepsilon_{1t-1}^2 + a_{21}\varepsilon_{1t-1}\varepsilon_{2t-1}) + a_{21}(a_{11}\varepsilon_{1t-1}\varepsilon_{2t-1} + a_{21}\varepsilon_{2t-1}^2) + b_{11}(b_{11}h_{11t-1} + b_{21}h_{21t-1}) + b_{21}(b_{21}h_{12t-1} + b_{21}h_{22t-1}) + c_{11}^2$$

$$h_{12t} = a_{12}(a_{11}\varepsilon_{1t-1}^2 + a_{21}\varepsilon_{1t-1}\varepsilon_{2t-1}) + a_{22}(a_{11}\varepsilon_{1t-1}\varepsilon_{2t-1} + a_{21}\varepsilon_{2t-1}^2) + b_{12}(b_{11}h_{11t-1} + b_{22}h_{21t-1}) + b_{22}(b_{12}h_{12t-1} + b_{21}h_{22t-1}) + c_{11}c_{12}$$

$$h_{21t} = a_{11}(a_{12}\varepsilon_{1t-1}^2 + a_{22}\varepsilon_{1t-1}\varepsilon_{2t-1}) + a_{21}(a_{12}\varepsilon_{1t-1}\varepsilon_{2t-1} + a_{22}\varepsilon_{2t-1}^2) + b_{11}(b_{12}h_{11t-1} + b_{22}h_{21t-1}) + b_{21}(b_{12}h_{12t-1} + b_{22}h_{22t-1}) + c_{11}c_{12}$$

$$h_{22t} = a_{12}(a_{12}\varepsilon_{1t-1}^2 + a_{22}\varepsilon_{1t-1}\varepsilon_{2t-1}) + a_{22}(a_{12}\varepsilon_{1t-1}\varepsilon_{2t-1} + a_{22}\varepsilon_{2t-1}^2) + b_{12}(b_{12}h_{11t-1} + b_{22}h_{21t-1}) + b_{22}(b_{12}h_{12t-1} + b_{22}h_{22t-1}) + c_{12}^2 + c_{22}^2$$

We are interested first of all in the impact of the squared residuals ε_{1t}^2 and ε_{2t}^2 on the 2 variances h_{11t} and h_{22t}, and the covariance. The volatility transfers are indicated in bold characters. Note that h_{12t} and h_{21t} are equal on the assumption that they were equal for the previous observation at time t-1 and so on until the beginning of the series. Using the BEKK modeling, we can show how far these squared residuals will lead to a strong change in h_{ijt}. We are aware that Isakov and Perignon (2000, p.133) wrote that, in their model, by using the Hadamard product in $B\Theta H_{t-1}$ instead of $B^{'}H_{t-1}B$, they constrain the volatility transmission mechanism. It is true that in this case, the only possible way for a market's volatility to influence another market's volatility is through shocks. However, it is not always sure that B will remain non negative definite or that H_t will have only positive elements on the main diagonal in all possible cases, in any possible situation. Further, the $B^{'}H_tB$ term in the BEKK model involves the presence of h_{11t-1} in the equation for h_{22t} and the presence of h_{22t-1} in the equation for h_{11t}. However, as h_{11t-1} and h_{22t-1} do not increase very fast, the main element of influence remains the squared residuals ε_{1t}^2 and ε_{2t}^2. The volatility spillover, the coefficient a_{21} will be relevant for measuring the effect of the spot markets volatility (h_{22t}) on futures markets volatility (h_{11t}). The coefficient a_{12} will be relevant for measuring the effect of futures market volatility on the spot market volatility. Moreover, the increase in volatility due to h_{t-1} take two steps: a shock happens in t-2, h_{t-1} increases at time t-1 only because of the shock in ε_{1t} or ε_{2t} at time t-2 and the increase in h_{t-1} will further increase h as late as in h_t. As we are interest in the mean impact of a shock after one period (independently from the shock that happened two periods before) and not only in the impact of one precise shock, ε_1 or ε_2 are the only important indicators for the volatility increase the next period.

THE INTERDEPENDENCE BETWEEN THE SPOT AND INDEX FUTURES MARKETS IN INDIA: AN EMPIRICAL ANALYSIS

CHAPTER – IV
RESULTS AND DISCUSSIONS

CONTENTS:

4.1 DATA
4.2 RESULTS DISCUSSION
4.3 CONCLUSIONS

4.1. DATA

The NSE provides a fully automated screen based trading system for Futures and Spot market transactions, on a nationwide basis . The beauty of NSE is supports an order driven market which provides complete transparency of trading operations & operates on strict price-time priority base. As mentioned earlier somewhere Derivatives trading on the NSE commenced with the S&P CNX Nifty Index futures on June 12, 2000 and now,NSE is the largest Derivatives exchange in India, in terms of volume and turnover. Currently, the Derivatives contracts have a maximum of 3-month expiration cycles. Three contracts are available for trading with 1-month, 2-months and 3-months expiry.

To examine the lead-lag relationship between the underlying spot market & the futures market, the basic data used in this study consists of intraday price histories, for the nearby contract of S&P CNX Nifty and S&P CNX Nifty futures. Nifty is a well diversified 50 stock index accounting for 22 sectors of the economy. It is used for a variety of purposes such as benchmarking fund portfolios, index based derivatives and index funds. I have used tick by tick transaction data, from the period of 1st January, 2001 to 30th November, 2005. The data is filtered by using simultaneous data for spot and futures prices, at one minute, five minutes, ten minutes and one hour intervals. Within an interval the first observed price has been recorded for Nifty Spot index and Nifty Futures index. For index futures, prices quoted for the near month contract have been used. As the near month contract approaches expiration date, price data was rolled over to the next month. To maintain uniformity, next month price quotes were used three days before the contract expires. Data relating to the spot as well as the futures market in India has been collected from the historical data CD-ROM's made available, by the National Stock Exchange. These CD's have high frequency tick by tick data and they keep records of every trade that takes place.

4.2 RESULTS DISCUSSION:

Here in, I need to mention that the development of high frequency data bases allows for empirical investigation of a wide range of issues in the financial markets includes methodological issues such as the treatment of time, the effects of intra-day seasonal, the effects of time-varying volatility and information content of various market data. The advent of high frequency data sets ends this disparity. In some markets, second by second data is now available, allowing virtually continuous observations of price.

In order to analyze information flows between markets on short time intervals, high frequency data are required. Typically, all transactions from some sample period are available for analysis. However, the statistical analysis of transactions data is often hampered by the fact that the clock time interval between such observations is varying. For some research questions, such as most microstructure issues, the differences in clock time interval are not very important and one relies on estimating models in transaction time. However, for the analysis of information flows between markets the clock time is of utmost importance. The usual approach to tackle the problem of irregularly spaced observations is to split the time axis in fixed length intervals of, say, 5 min and use the last observation recorded in that interval in the statistical analysis. This approach has an important drawback, however, if the intervals are small and trading is not very frequent, some intervals may contain no observation. This is referred to as the non-trading or non-synchronous trading problem. Another cause of missing observations is imperfections in data collection, e.g. errors on the data file, which sometimes cause a loss of observations. Lo and MacKinlay (1990a) demonstrated that non-trading or non-synchronous trading may lead to serial correlation in observed portfolio returns, even when the underlying true returns are serially uncorrelated. Moreover, there will be positive lead and lag co-variances between observed returns of assets whose true returns are only contemporaneously correlated.

In this section we present an empirical application of the proposed estimator to the lead-lag relationship between the S&P 500 stock index and futures on this index. It is a well-studied relationship, with the general conclusion that the futures market leads the cash market. Typically, researchers have used five minute intervals, where few observations are missing. In this section, we also present results at the one minute interval, at which more intervals without trade occur in the futures market. Since the stock market index is adjusted every minute there are no missing data points on the index unless the frequency at which the data are analyzed is even higher than one minute.

For a number of statistical reasons, it is preferable not to work directly with the price series, so that raw price series are usually converted into series of returns. Additionally, returns have the added benefit that they are unit free (Brooks 2002). For this analysis we have used return series i.e,

$$s_t = \ln(sprice_t / sprice_{t-1}) * 100$$
$$f_t = \ln(fprice_t / fprice_{t-1}) * 100$$

$$s_t = \log(sprice / lag(sprice) * 100$$
$$f_t = \log(fprice / lag(fprice) * 100$$

The data set consists of one minute (3,75,279 observations), five minutes (80,362 observations), ten minutes (41,627 observations) and one hour (8,624 observations) for both S&P CNX Nifty spot index and S&P CNX Nifty futures index for their period of 5 years i.e., from 1st January, 2001 to 31st November, 2005. In the figures 1-4 the shows the price series of all frequencies of spot and futures index are plotted with figures 5-8 residual price series. Figures A9-A12 shows the returns series of spot and futures are plotted. While scrutiny, the figures suggests that each of the series is non-stationary in price series, however, both the series appear to have a common stochastic trend and seem to be cointegrated. The Plot of the returns series values appears to be stationary suggestive of the series being integrated in I (1) form.

In Tables 1a and 2a provides some basic distributional characteristics of the spot and futures data – both raw and return series. All series show a high significance of skewness, excess kurtosis[1] and Jarque - Bera (JB) statitistics, implying non-normal distributions with fatter tails. The LB statistics for the standardized squared residuals shows a serial correlation of second moments between the spot and futures markets for all frequencies. Therefore, it is appropriate to apply a GARCH Model.

In tables 1b and 2b, provides the ADF test series for raw price & return series' for all the frequencies. The results shows that, Augmented Dickey-Fuller (ADF) tests for the existence of a unit root are strongly rejected for the spot and futures series, but cannot be rejected at raw levels.

Table1a:

Descriptive Statistics of raw Price series

	One Minute		**Five Minutes**		**Ten Minutes**		**One Hour**	
	SP	**FP**	**SP**	**FP**	**SP**	**FP**	**SP**	**FP**
Mean	7.255905	7.253662	7.2455	7.243228	7.244787	7.242491	7.242058	7.239763
Median	7.217241	7.217774	7.170584	7.171273	7.169273	7.17012	7.162392	7.162223
Maximum	7.910701	7.913027	7.910609	7.912661	7.910297	7.912661	7.909655	7.911947
Minimum	6.745827	6.747587	6.747515	6.754604	6.747515	6.754604	6.748785	6.758327
Std. Dev.	0.315522	0.314856	0.310416	0.309831	0.309231	0.308688	0.308427	0.3079

[1] Excess Kurtosis is referred as kurtosis to greater than 3

Skewness	0.286675	0.288651	0.364807	0.366754	0.374184	0.376093	0.390988	0.393012
Kurtosis	1.653033	1.655037	1.72741	1.728744	1.74323	1.744182	1.765176	1.766009
Jarque-Bera	33550.27	33537.01	7205.196	7212.912	3710.92	3716.708	767.6353	769.1771
Observations	375729	375729	80362	80362	41627	41627	8624	8624

Table 1b:
Test for non-stationarity on raw price series Augmented Dickey Fuller Test Statistic

	ADF Test statistic	
	spot price	futures price
One Minute	0.470371	0.562873
Five Minutes	0.522089	0.637610
Ten Minutes	0.268130	0.605766
One Hour	0.241351	0.296903

Table 2a: Descriptive Statistics of Returns Series

	One minute		**Five minutes**		**Ten minutes**		**One hour**	
	SRT	**FRT**	**FRT**	**SRT**	**FRT**	**SRT**	**FRT**	**SRT**
Mean	7.86E-05	0.0002	0.001011	0.00068	0.001965	0.001136	0.008895	0.006693
Median	0.000634	0	0.004356	0.005659	0.006522	0.007681	0.021329	0.024694
Maximum	4.050147	7.945603	9.914486	7.56528	9.914486	7.56528	12.09556	11.26581
Minimum	-10.413	-11.7748	-11.7748	-10.413	-11.7748	-10.413	-11.7748	-10.413
Std. Dev.	0.071084	0.22831	0.283612	0.181014	0.330537	0.247619	0.605009	0.541601
Skewness	-1.24517	-0.46034	-0.59271	-3.96772	-0.57416	-3.03383	-0.37141	-1.25852
Kurtosis	1666.867	96.46614	125.4049	298.7712	126.1544	167.5426	68.35651	59.81792
Jarque-Bera	4.34E+10	1.37E+08	50173880	2.93E+08	26308846	4.70E+07	1535081	1.16E+06
Observations	375729	375729	80362	80362	41627	41627	8624	8624

Table 2b:
Test for non-stationarity on returns series Augmented Dickey Fuller Test Statistic

	ADF	
	Srt	Frt
One Min	-244.30882**	-306.60631**
Five min	-105.35233**	-113.90730**
Ten Min	-79.39055**	-81.25405**
One Hour	-31.86826**	-33.36932**

Table 3a:
Correlations between the series of returns

Variable	One Minute		Five Minute		Ten Minute		One Hour	
	Srt	Frt	Srt	Frt	Srt	Frt	Srt	Frt
Srt	-	0.148069	-	0.408567	-	0.49515	0.10000	0.650259
Frt	0.148069	-	0.408567	-	0.49515	-	0.650259	-

Of course these correlations are unconditional.

Table 3a shows the correlations between the Spot and Futures returns for all intervals, and reveals that there is a positive correlation between spot and futures; but not auto correlated**.**

STATIONARITY TESTS FOR ALL RETURNS SERIES

Augmented Dickey-Fuller test[2] was used to check the stationarity of the all frequencies of returns series in differences of logarithms' over the period from 1st January, 2001 to 31st November, 2005. Since it has been observed from the autocorrelation of the return series' that the order is 'four', the ADF results are for fourth lag. It has been observed later from the AIC and SIC criteria indicated lower values for 3 lags than for 4 lags in the test equation.

COINTEGRATION TEST FOR ALL FREQUENCIES OF THE RETURNS SERIES:

We will now investigate if the series in level are, if not stationary, perhaps co-integrated. We test the all returns series for cointegration with the Johansen cointegration test, using 6 lags of the differences of the residuals of the cointegration equation to account for autocorrelation. In both cases, the null hypothesis of no cointegration equation is not rejected at the 5% and at the 1% significance levels.

To computer the test statistics (Trace Statistic), we start from a VAR of order p:

[2] Refer to Methodology chapter of ADF Tests

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + C_t + \varepsilon_t$$

Where y_t is a 2-dimesnion vector of non stationary, I(1) variables, C_t is a vector of constant terms and ε_t is a vector of innovations. One can write this VAR in the form similar to the ADF unit root test equation:

$$\Delta y_t = \Pi y_{y-1} + \sum_{i=1}^{p-1} \Gamma_i \Pi y_{y-i} + C_t + \varepsilon_t$$

Where

$$\Pi = \sum_{i=1}^{p} A_i - I, \qquad \Gamma_i = -\sum_{j=i+1}^{p} A_j$$

Where p-1 equal to 3, because this order of the process is selected by the AIC criterion in a test Vector Error Correction (VEC) model. It is also true that for this order, the first 3 autocorrelations are not significant in each of the residuals series of the two equations with respect to the Q statistics or to the t statistics. Further, we use the eigenvalues λ's of the matrix Π to compute the trace statistic Q_r:

$$Q_r = -T \sum_{i=r+1}^{k} \log(1 - \lambda_i)$$

For r=0,1,……,k-1, where λ_i is the i-th largest eigenvalues of the matrix Π. In our case, we take only one (the largest) value, because the first hypothesis (no cointegration equation) is not rejected. The alternative hypothesis is that the number of cointegration equations is equation to r (the number of endogenous variables, have equal to 2)

Table 3b: Cointegration test values for all frequencies (one min, five min, ten min and one hour returns series)

	Hypothesized number of CE	Eigenvalues of Π	Trace statistic	5% critical values	1% critical values
One minute	None At Most 1	0.338794 0.175803	228077.7 72644.65	15.41 3.76	20.04 6.65
Five minutes	None At Most 1	0.298239 0.154340	41930.30 13470.86		
Ten minutes	None At Most 1	0.285336 0.166054	21540.58 7554.97		
One Hour	None At Most 1	0.272053 0.135537	3992.092 1255.328		

In the table, the hypothesis that the number of co-integrating equations (CE) is equal is zero is test at the 5% and at 1% levels. These critical values are from Ostervaled-lenum (1992). The trace test statistic, which lied below the 2 critical values, indicates no cointegration at both 5% and 1% levels

Another cointegration test statistic now associated with the Johansen cointegration test procedure is the maximum eigenvalues test statistic. The hypothesis is are ‘r’ cointegration equations (here r=0) against the alternative that there are r+1 (here r+1=1). It also lead to the non rejection of the null hypothesis of 0 cointegration equations.

A VECTOR ERROR CORRECTION MODEL:

The finding that many time series may contain a unit root has spurred the development of the theory of non-stationary time series analysis. Engle and Granger (1987) pointed out that a linear combination of two or more non-stationary series may be stationary. If such a stationary, linear combination exists, then the non-stationary time series are said to be cointegrated. The stationary linear combination is called the co-integrating equation and may be interpreted as a long-run equilibrium relationship between the variables. Although the two series may be non stationary they may move closely together in the long run so that the difference between them is stationary. This section outlines the methodology of the Co-integration Analysis to study the relationship between Nifty spot index and Nifty futures index.

Two series St and Ft are said to be integrated of the order one, denoted by I(1), if they become stationary after first difference. If there are two such series which are I(1) integrated and their linear combination is stationary, then these two series are said to be cointegrated. This relationship is the long run equilibrium relationship between St and Ft.

A principal feature of cointegrated variables is that their time paths are influenced by the extent of any deviation from long-run equilibrium. If the system is to return to its long run equilibrium, the movement of at least one variable must respond to the magnitude of the disequilibrium. If cointegration exists between St and Ft, then Engle and Granger representation theorem suggests that there is a corresponding Error Correction Model (ECM). In an ECM, the short term dynamics of the variables in the system are influenced by the deviations from the equilibrium.

The present research, seeks to determine whether there exists an equilibrium relationship between Nifty spot index and Nifty futures index. Engle and Granger suggest a four step procedure to determine if the two variables are cointegrated. The first step in the analysis is to pre-test each variable to determine its order of integration, as cointegration necessitates that the two variables be integrated of the same order. Augmented Dickey-Fuller (ADF) test has been used to determine the order of integration. If the results in step one show that both the series are I(1) integrated then the next step is to establish the long run equilibrium relationship in the form

$$S_t = \beta_o + \beta_1 F_t + e_t$$

Where S_t is the log of spot index price; F_t is the log of futures index prices at time t and e_t is the residual term. In order to determine if the variables are cointegrated we need to estimate the residual series from the above equation. The estimated residuals are denoted as (ê). Thus the ê series are the estimated values of the deviations from the long run relationship. If these deviations are found to be stationary, then the S_t and F_t series are cointegrated of the order (1,1). To test if the estimated residual series is stationary Engle-Granger test for co-integration was performed.

The third step is to determine the ECM from the saved residuals in the previous step.

$$\Delta \mathrm{S_t} = \alpha_1 + \alpha_s \hat{e}_{t-1} + lagged\left(\Delta S_t, \Delta F_t\right) + \varepsilon_{s,t}$$

$$\Delta \mathrm{F_t} = \alpha_1 + \alpha_f \hat{e}_{t-1} + lagged\left(\Delta S_t, \Delta F_t\right) + \varepsilon_{f,t}$$

In the above equations, ΔS_t and ΔF_t denote, respectively, the first differences in the log of spot and futures prices for one time period. $\hat{e}_{t-1}$ is the lagged error correction term from the co-integrating equation and $\varepsilon_{s,t}$ and $\varepsilon_{f,t}$ are the white noise disturbance terms.

The above equations describe the short-run as well as long-run dynamics of the equilibrium relationship between spot index and futures index. They provide information about the feedback interaction between the two variables.

In the equation ΔS_t has the interpretation that, change in S_t is due to both, short-run effects,

From lagged futures and lagged spot variables and to the last period equilibrium error $\hat{e}_{t-1}$, which represents adjustment to the long-run equilibrium. The coefficient attached to the error correction term measures the single period response of changes in spot prices to departures from equilibrium. If this coefficient is small then spot prices have little tendency to adjust to correct a disequilibrium situation. Then most of the correction will happen in the other variable, in these case futures prices.

The last step involves testing the adequacy of the models by performing diagnostic checks to determine whether the residuals of the error correction equations approximate white noise. The reverse representation of Engle and Granger's Co-integration analysis along with the empirical findings has been given in the appendix. A pair wise Granger Causality test was done to establish the cause and effect relationship between spot index and futures index.

Augmented Dickey-Fuller test was performed to substantiate finding from graphical analysis i.e., (Figures 1-4 and 9-12). The table 1b and 2b provides the results of ADF test. The test used return series of both spot index and index futures for all frequencies (One Min, Five Min, Ten Min and One hour). In both series, the null hypothesis is that the has unit root is rejected at (1% critical values) implying that Nifty spot index and Nifty index futures are I(1) integrated. One of the necessary conditions for any two series to be cointegrated is that they should be integrated of the same order. Both the series are I (1) integrated so, the long-run relationship between spot index and futures index can be tested.

A Simple regression with Nifty spot returns as the dependent variable and futures returns as the independent variables was done. The results of the regression are given in table 4a. The coefficients of futures returns for one minute (0.0461210290), five minutes (0.2607649262), ten minutes (0.3711354898) and one hour (0.5821088721) are highly significant. The probability of the variable being insignificant is zero, therefore, the null hypothesis that there is no relationship between nifty spot and nifty futures index is rejected.

Table 4a:
Test for cointegration and the fitted ECM for s_t

$$S_t = \beta_o + \beta_1 F_t + e_t$$

	Coefficient estimated	Coefficient value	t-ratio
One Min	β_0	0.0000694187	0.54499404
	β_1	0.0461010290	91.77303**

Five Min	β_0	0.0004165875	0.47447604
	β_1	0.2607649262	126.89406**
Ten Min	β_0	0.0004068425	0.38589
	β_1	0.3711354898	116.35854**
One Hour	β_0	0.0015153705	0.34196
	β_1	0.5821088721	79.47694**

** indicates at 1% level of significance

Residuals were estimated form the regression equation and Engle-Granger test was performed on the estimated results. Table 4b gives the results of the Engle-Granger test. Since the test statistic is lower than the critical values at 1% level of significance it shows that the residual variable is stationary. The Durbin Watson statistic for all frequencies (one min, five min, ten min and one hour) are close to 2 showing that there is no serial correlation in the residual variables. The results indicate that spot index and futures index are cointegrated and both the variables have a stable long-run equilibrium relationship.

Table 4b:
Engle-Granger Co-integration test statistics

	Engle-Granger Cointegration t-statistics
One Min	-245.51634**
Five min	-108.99759**
Ten Min	-82.95967**
One Hour	-34.87419**

If the spot index and the futures index are cointegrated in the long run, then according to Engle and Granger there exists a corresponding Error Correction Representation. The ECM describes the shot-run as well as the long-run dynamics of the two variables. To estimate, with the ECM equation, in which lagged estimated residuals ($\hat{e}_{t-1}$) from the cointegration equation and lagged changes in the spot and futures index have been included. Error correction equation is estimated by using Ordinary Least Squares, adding the lagged variables, one at a time, up to 6 lags. The results of the ECM are given in 5a and 5b for one minute, 6a and 6b for five minutes, 7a and 7b for ten minutes and 8a and 8b for one hour results.

The estimate of α_s for one minute (0.958959210) is very large and it is close to 1 at 1% significant level (table 5a). It implies that there is very high correction required in the spot index to adjust to the long term equilibrium values because most of the information gets absorbed in the first one minute. Since the coefficient α_s is positive whatever high correction takes place in the short-run in the spot index, is an upward adjustment. The lagged spot as well as lagged futures terms are highly significant up to 5 lags. This shows that the spot market reacts to lagged prices in the spot market as well as futures market. Last, five minutes information in the spot and futures index is relevant for short term correction in the spot market. The first 5 coefficients of lagged spot index and futures index are high. This shows that most of the correction in the spot market happens in the first 5 minutes. (Please see Figures 17 for Co-integration graph for one min, figure 18 for Auto correlations for both spot and futures returns and figure 19 for impulse responses for co-integration results)

Table 5a:
Error Correction Model for change in Nifty spot Index for one minute

ECM with change in spot index as the dependent variable

$$\Delta S_t = \alpha_1 + \alpha_s \hat{e}_{t-1} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{st}$$

Variable	Coefficient	Standard error	T-Stat	Significance
α_1	-0.000000479	0.000113786	-0.00421	0.99664309
α_s (ECM)	0.958959210	0.003642885	263.24169	0.00000000
D_SRT(1)	0.094845418	0.003317960	28.58546**	0.00000000
D_SRT(2)	0.097246416	0.002989178	32.53283	0.00000000
D_SRT(3)	0.069891969	0.002625866	26.61673	0.00000000
D_SRT(4)	0.040060450	0.002197056	18.23369	0.00000000
D_SRT(5)	0.016697767	0.001646810	10.13946	0.00000000
D_FRT(1)	-0.015509407	0.000539495	-28.74801	0.00000000
D_FRT(2)	0.005375326	0.000836406	6.42669	0.00000000

D_FRT(3)	0.012319732	0.000941125	13.09044	0.00000000
D_FRT(4)	0.011030957	0.000827092	13.33703	0.00000000
D_FRT(5)	0.005768677	0.000514013	11.22282	0.00000000

In table 5b the lagged residual term α_f is (0.614098900) which is also very high at 1% level significant. The futures index also has a very strong correction in the short term, to adjust to the long term equilibrium. Very high value of the correction term reinforces the fact that most of the price discovery happens in the first five minutes. The positive value of the correction term suggests that there is an upward correction in the futures index. In table 5b all coefficients of spot and futures are significant at 1% level. This shows that the futures index reacts to the immediately preceding spot index value. Only the first 1 minute spot market information is relevant for the futures index. Any information prior to that period has no relevance for the futures market. Also the futures market is influenced by its own market. It implies whatever information is available in the futures market is immediately absorbed in the current futures price and spot price. Lagged futures index has a impact on the current value of the futures index. All publicly available information is immediately reflected in the prevailing futures prices. Beyond one minute even the lagged spot index has a impact on the futures index.

Table 5b:
Error Correction Model for change in Nifty Futures Index for one minute

ECM with change in Futures index as the dependent variable

$$\Delta F_t = \alpha_1 + \alpha_f \hat{e}_{t-1} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{ft}$$

Variable	**Coefficient**	**Standard error**	**T-Stat**	**Significance**
α_2	-0.000001137	0.000354639	-0.00321	0.99744163
α_f (ECM)	0.614098900	0.011353806	54.08750	0.00000000
D_SRT(1)	0.954187289	0.010341111	92.27126	0.00000000
D_SRT(2)	0.915974720	0.009316391	98.31862	0.00000000
D_SRT(3)	0.695415123	0.008184056	84.97194	0.00000000
D_SRT(4)	0.398155418	0.006847581	58.14541	0.00000000
D_SRT(5)	0.123641124	0.005132624	24.08926	0.00000000

D_FRT(1)	-1.395945604	0.001681448	-830.20465	0.00000000
D_FRT(2)	-1.360726061	0.002606833	-521.98434	0.00000000
D_FRT(3)	-1.076733587	0.002933210	-367.08376	0.00000000
D_FRT(4)	-0.671635925	0.002577805	-260.54567	0.00000000
D_FRT(5)	-0.272843258	0.001602029	-170.31106	0.00000000

Table 5c:
Pair-wise Granger Causality Tests on Nifty Spot and futures index for one minute
Sample size: 375729 Lags:2

Null Hypothesis:	Obs	F-Statistic	Probability
FRT does not Granger Cause SRT	375727	1549.59	0.00000
SRT does not Granger Cause FRT		7461.41	0.00000

Granger Causality test was done to study the cause and effect relationship between spot index and futures index. Results of the same are given in table 5c. Here the null hypothesis that futures does not cause spot index is rejected and the second hypothesis that spot index do not cause futures index is also rejected. This means that futures index cause spot index and vice versa. Therefore there is a bidirectional relationship and both the variables are influencing each other.

The estimate of α_s for five minutes (1.295162552) is very large and it is at 1% significant level (table 6a). It implies that there is very high correction required in the spot index to adjust to the long term equilibrium values because most of the information gets absorbed in the first one minute. Since the coefficient α_s is positive whatever high correction takes place in the short-run in the spot index, is an upward adjustment. The lagged spot highly significant up to 3 coefficients as well as lagged futures terms are highly significant up to 5 lags. This shows that the spot market reacts to lagged prices in the spot market as well as futures market. Last, fifteen minutes information in the spot and futures index is relevant for short term correction in the spot market. The first 3 coefficients of lagged spot index and futures index are high. This shows that most of the correction in the spot market happens in the first 15 minutes. (Please see Figures 20 for Co-integration graph for five min, figure 21 for Auto correlations for both spot and futures returns and figure 22 for impulse responses for co-integration results)

Table 6a:
Error Correction Model for change in Nifty spot Index for five minutes

ECM with change in spot index as the dependent variable

$$\Delta S_t = \alpha_1 + \alpha_s \hat{e}_{t-1} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{st}$$

Variable	Coefficient	Standard error	T-Stat	Significance
α_1	-0.000010162	0.000630631	-0.01611	0.98714289
α_s (ECM)	1.295162552	0.011263561	114.98695	0.00000000
D_SRT(1)	0.138784721	0.010331278	13.43345	0.00000000
D_SRT(2)	0.049581059	0.009259504	5.35461	0.00000000
D_SRT(3)	0.024513556	0.007932619	3.09022*	0.00200075
D_SRT(4)	0.004641859	0.006172047	0.75208	0.45200659
D_SRT(5)	0.016833309	0.003921511	4.29256	0.00001768
D_FRT(1)	-0.235627324	0.003650263	-64.55078	0.00000000
D_FRT(2)	-0.160482491	0.004524948	-35.46615	0.00000000
D_FRT(3)	-0.090180011	0.004754458	-18.96746	0.00000000
D_FRT(4)	-0.042315492	0.004071214	-10.39383	0.00000000
D_FRT(5)	-0.015837767	0.002504968	-6.32254	0.00000000

In table 6b the lagged residual term α_f is (0.582192596) which is also very high at 1% level significant. The futures index also has a very strong correction in the short term, to adjust to the long term equilibrium. Very high value of the correction term reinforces the fact that most of the price discovery happens in the first five minutes. The positive value of the correction term suggests that there is an upward correction in the futures index. In table 6b all coefficients of spot and futures are significant at 1% level. This shows that the futures index reacts to the immediately preceding spot index value. Only the first 25 minute spot market information is relevant for the futures index. Any information prior to that period has no relevance for the futures market. Also the futures market is influenced by its own market negatively. It implies whatever information is available in the futures market has no impact on the current value of the futures index. Lagged futures index has an impact on the current value of the futures index. All publicly available information is immediately reflected in the prevailing futures prices. Beyond five minutes even the lagged spot index has an impact on the futures index.

Table 6b:
Error Correction Model for change in Nifty Futures Index for Five minutes

ECM with change in Futures index as the dependent variable

$$\Delta F_t = \alpha_1 + \alpha_f \hat{e}_{t-1} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{ft}$$

Variable	**Coefficient**	**Standard error**	**T-Stat**	**Significance**
α_2	-0.000007360	0.000985048	-0.00747	0.99403864
α_f (ECM)	0.582192596	0.017593724	33.09093	0.00000000
D_SRT(1)	0.763881511	0.016137494	47.33582	0.00000000
D_SRT(2)	0.718602924	0.014463379	49.68430	0.00000000
D_SRT(3)	0.549090723	0.012390779	44.31446	0.00000000
D_SRT(4)	0.311061714	0.009640760	32.26527	0.00000000
D_SRT(5)	0.123851735	0.006125414	20.21933	0.00000000
D_FRT(1)	-1.455515422	0.005701724	-255.27636	0.00000000
D_FRT(2)	-1.380969444	0.007067985	-195.38377	0.00000000
D_FRT(3)	-1.064390959	0.007426481	-143.32374	0.00000000
D_FRT(4)	-0.641620893	0.006359251	-100.89568	0.00000000
D_FRT(5)	-0.256667609	0.003912769	-65.59743	0.00000000

Table 6c:
Pair-wise Granger Causality Tests on Nifty Spot and futures index for Five minutes
Sample size: 80360 Lags:2

Null Hypothesis:	Obs	F-Statistic	Probability
FRT does not Granger Cause SRT	80360	464.449	3.E-201
SRT does not Granger Cause FRT		1805.37	0.00000

Granger Causality test was done to study the cause and effect relationship between spot index and futures index. Results of the same are given in table 6c. Here the null hypothesis that futures does not cause spot index is rejected and the second hypothesis that spot index do not cause futures index is also rejected. This means that futures index cause spot index and vice versa. Therefore there is a bidirectional relationship and both the variables are influencing each other.

Table 7a:
Error Correction Model for change in Nifty spot Index for Ten minutes

ECM with change in spot index as the dependent variable

$$\Delta S_t = \alpha_1 + \alpha_s \hat{e}_{t-1} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{st}$$

Variable	Coefficient	Standard error	T-Stat	Significance
α_1	-0.000030038	0.001196096	-0.02511	0.97996443
α_s (ECM)	1.499309188	0.017155733	87.39406	0.00000000
D_SRT(1)	0.308884247	0.015612869	19.78395	0.00000000
D_SRT(2)	0.227231907	0.013902157	16.34508	0.00000000
D_SRT(3)	0.190770033	0.011908617	16.01949	0.00000000
D_SRT(4)	0.093398138	0.009266590	10.07902	0.00000000
D_SRT(5)	0.039135766	0.005781109	6.76960	0.00000000
D_FRT(1)	-0.407494593	0.007130979	-57.14427	0.00000000
D_FRT(2)	-0.267516349	0.008069654	-33.15091	0.00000000
D_FRT(3)	-0.169895277	0.008086882	-21.00875	0.00000000
D_FRT(4)	-0.087166930	0.006859537	-12.70741	0.00000000
D_FRT(5)	-0.032673931	0.004240217	-7.70572	0.00000000

The estimate of α_s for ten minutes (1.499309188) is very large and it is at 1% significant level (table 7a). It implies that there is very high correction required in the spot index to adjust to the long term equilibrium values because most of the information gets absorbed in the first one minute. Since the coefficient α_s is positive whatever high correction takes place in the short-run in the spot index, is an upward adjustment. The lagged spot highly significant up to 3 coefficients as well as lagged futures terms are highly significant up to 5 lags. This shows that the spot market reacts to lagged prices in the spot market as well as futures market. Last, fifty minutes information in the spot and futures index is relevant for short term correction in the spot market. The first 5 coefficients of lagged spot index and futures index are high. This shows that most of the correction in the spot market happens in the first 50 minutes. (Please see Figures 23 for Co-integration graph for ten min, figure 24 for Auto correlations for both spot and futures returns and figure 25 for impulse responses for co-integration results)

Table 7b:
Error Correction Model for change in Nifty Futures Index for Ten minutes

ECM with change in Futures index as the dependent variable

$$\Delta F_t = \alpha_1 + \alpha_f \hat{e}_{t-1} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{ft}$$

Variable	Coefficient	Standard error	T-Stat	Significance
α_2	-0.000022212	0.001634071	-0.01359	0.98915494
α_f (ECM)	0.660269527	0.023437660	28.17131	0.00000000
D_SRT(1)	0.821354790	0.021329845	38.50730	0.00000000
D_SRT(2)	0.781405896	0.018992721	41.14239	0.00000000
D_SRT(3)	0.639195841	0.016269205	39.28870	0.00000000
D_SRT(4)	0.358876220	0.012659745	28.34782	0.00000000
D_SRT(5)	0.136368950	0.007897982	17.26630	0.00000000
D_FRT(1)	-1.477042009	0.009742135	-151.61379	0.00000000
D_FRT(2)	-1.316780661	0.011024525	-119.44103	0.00000000
D_FRT(3)	-1.003155379	0.011048062	-90.79922	0.00000000
D_FRT(4)	-0.611143999	0.009371299	-65.21444	0.00000000
D_FRT(5)	-0.250008343	0.005792860	-43.15801	0.00000000

In table 7b the lagged residual term α_f is (0.660269527) which is also very high at 1% level significant. The futures index also has a very strong correction in the short term, to adjust to the long term equilibrium. Very high value of the correction term reinforces the fact that most of the price discovery happens in the first ten minutes. The positive value of the correction term suggests that there is an upward correction in the futures index. In table 7b all coefficients of spot and futures are significant at 1% level. This shows that the futures index reacts to the immediately preceding spot index value. Only the first 50 minutes spot market information is relevant for the futures index. Any information prior to that period has no relevance for the futures market. Also the futures market is influenced by its own market negatively. It implies whatever information is available in the futures market has no impact on the current value of the futures index. Lagged futures index has an impact on the current value of the futures index. All publicly available information is immediately reflected in the prevailing futures prices. Beyond ten minutes even the lagged spot index has an impact on the futures index.

Table 7c:
Pair-wise Granger Causality Tests on Nifty Spot and futures index for Ten minutes
Sample size: 41625 Lags:2

Null Hypothesis:	Obs	F-Statistic	Probability
FRT does not Granger Cause SRT	41625	339.994	3.E-147
SRT does not Granger Cause FRT		932.574	0.00000

Granger Causality test was done to study the cause and effect relationship between spot index and futures index. Results of the same are given in table 7c. Here the null hypothesis that futures does not cause spot index is rejected and the second hypothesis that spot index do not cause futures index is also rejected. This means that futures index cause spot index and vice versa. Therefore there is a bidirectional relationship and both the variables are influencing each other.

Table 8a:
Error Correction Model for change in Nifty spot Index for One Hour

ECM with change in spot index as the dependent variable

$$\Delta S_t = \alpha_1 + \alpha_s \hat{e}_{t-1} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{st}$$

Variable	Coefficient	Standard error	T-Stat	Significance
α_1	-0.000009976	0.005723089	-0.00174	0.99860922

α_s (ECM)	1.681340472	0.047539789	35.36702	0.00000000
D_SRT(1)	0.409872284	0.043449508	9.43330	0.00000000
D_SRT(2)	0.230114919	0.038481238	5.97993	0.00000000
D_SRT(3)	0.127764925	0.032270901	3.95914	0.00007583
D_SRT(4)	0.091581392	0.024345966	3.76167	0.00016991
D_SRT(5)	0.039816470	0.014664449	2.71517*	0.00663739
D_FRT(1)	-0.701447086	0.027738506	-25.28785	0.00000000
D_FRT(2)	-0.464807218	0.027396269	-16.96608	0.00000000
D_FRT(3)	-0.284777379	0.025361917	-11.22854	0.00000000
D_FRT(4)	-0.169226355	0.020546310	-8.23634	0.00000000
D_FRT(5)	-0.066264385	0.012705130	-5.21556	0.00000019

The estimate of α_s for one hour (1.681340472) is very large and it is at 1% significant level (table 8a). It implies that there is very high correction required in the spot index to adjust to the long term equilibrium values because most of the information gets absorbed in the first one minute. Since the coefficient α_s is positive whatever high correction takes place in the short-run in the spot index, is an upward adjustment. The lagged spot highly significant up to 3 coefficients as well as lagged futures terms are highly significant up to 5 lags. This shows that the spot market reacts to lagged prices in the spot market as well as futures market. Last, fifty minutes information in the spot and futures index is relevant for short term correction in the spot market. (Please see Figures 26 for Co-integration graph for one hr, figure 27 for Auto correlations for both spot and futures returns and figure 28 for impulse responses for co-integration results)

Table 8b:
Error Correction Model for change in Nifty Futures Index for One Hour

ECM with change in Futures index as the dependent variable

$$\Delta F_t = \alpha_1 + \alpha_f \hat{e}_{t-1} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{ft}$$

Variable	Coefficient	Standard error	T-Stat	Significance
α_2	-0.000131281	0.006772665	-0.01938	0.98453523

α_f (ECM)	0.671690058	0.056258264	11.93940	0.00000000
D_SRT(1)	0.759458002	0.051417853	14.77032	0.00000000
D_SRT(2)	0.667772507	0.045538436	14.66393	0.00000000
D_SRT(3)	0.486258782	0.038189165	12.73290	0.00000000
D_SRT(4)	0.326221103	0.028810851	11.32286	0.00000000
D_SRT(5)	0.136649051	0.017353809	7.87430	0.00000000
D_FRT(1)	-1.473713998	0.032825560	-44.89532	0.00000000
D_FRT(2)	-1.266276042	0.032420559	-39.05781	0.00000000
D_FRT(3)	-0.937606870	0.030013120	-31.23990	0.00000000
D_FRT(4)	-0.596181803	0.024314364	-24.51974	0.00000000
D_FRT(5)	-0.242016557	0.015035165	-16.09670	0.00000000

In table 8b the lagged residual term α_f is (0.671690058) which is also very high at 1% level significant. The futures index also has a very strong correction in the short term, to adjust to the long term equilibrium. Very high value of the correction term reinforces the fact that most of the price discovery happens in the first one hour. The positive value of the correction term suggests that there is an upward correction in the futures index. In table 8b all coefficients of spot and futures are significant at 1% level. This shows that the futures index reacts to the immediately preceding spot index value. Any information prior to that period has no relevance for the futures market. Also the futures market is influenced by its own market negatively. It implies whatever information is available in the futures market has no impact on the current value of the futures index. Lagged futures index has an impact on the current value of the futures index. All publicly available information is immediately reflected in the prevailing futures prices. Beyond ten minutes even the lagged spot index has an impact on the futures index.

The entire exercise was repeated by obtaining a reverse representation of Engle and Granger co-integration regression. Simple regression analysis with futures index as a dependent and spot index as independent variable was done. The estimated residuals from this equation were submitted in the two error correction specifications. Almost identical results were obtained in the reverse representation (appendix A-III).

Table 8c:
Pair-wise Granger Causality Tests on Nifty Spot and futures index for Ten minutes
Sample size: 8622 Lags: 2

Null Hypothesis:	Obs	F-Statistic	Probability
FRT does not Granger Cause SRT	8622	131.717	4.5E-57
SRT does not Granger Cause FRT		111.699	1.3E-48

Granger Causality test was done to study the cause and effect relationship between spot index and futures index. Results of the same are given in table 7c. Here the null hypothesis that futures does not cause spot index is rejected and the second hypothesis that spot index do not cause futures index is also rejected. This means that futures index cause spot index and vice versa. Therefore there is a bidirectional relationship and both the variables are influencing each other.

A RESTRICTED VAR (1)- GARCH(1,1) FOR SPOT AND FUTURES RETURNS

Further, we use multivariate GARCH models, which often lead to significant autoregressive effects or significant coefficients for additional explaining variables that cannot be observed without both the GARCH specification and the use of a conditional standard deviation. These models are able:

3. To compute all the time dependent variances and covariance's,
4. To show which covariance's have significant coefficients in the corresponding variance equation.

A VAR (p) augmented with additional variables is written:

$$y_t = c + \sum_{i=1}^{L} \beta_i x_{t-i} + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t$$

Where β_i is a matrix:

$$\beta = \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}, \text{ and}$$

- x variables are returns from 2 markets (spot and futures)
- y has 2 dimensions: spot and futures: $y_t = \begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix}$
- y_{t-i} are lagged endogenous variables (i.e., lags of spot and futures returns)
- ε_t is $N(0,H_t)$, where H_t is in the simple multivariate normal case equal to $\sigma^2 I$. With a symmetric time varying covariance matrix, it becomes:

$$H_t = \begin{pmatrix} h_{11t} & h_{12t} \\ h_{21t} & h_{22t} \end{pmatrix}$$

We examine the case with L (the highest lag of the regressors in x) is equal to 1, and p equal to 1, such that we have 2 equations for spot and futures returns, with residuals ε_{1t} and ε_{2t}.

However, we can use a two dimension VAR(1)-GARCH(1,1) model in the BEKK (Baba *et al.*, 1987; Engle and Kroner, 1995) form to show the volatility transfers between Spot and Futures markets.

VAR (1)-GARCH(1,1) model using BEKK method

As mentioned by Isakov and Perignon (2000), Bollerslev et al (1998) have proposed a diagonal vector (dvec) model where the elements of the lower half H_t matrix are vectorized. The size of the matrices A and B was 3x3 for the 2 dimensional models, due to the coefficient for the covariance. They proposed to make the A and B matrices diagonal. This specification removes the potential interactions in the variances of two markets. On the other hands, the BEKK kind of multivariate GARCH models (Engle and Kroner, 1995) allows to keep these interactions. This is useful to how the volatility transfers from one market to another. Moreover, the BEKK kind of multivariate GARCH can be used association with a VAR specification, allowing a computation of VAR-coefficients that are efficient and consistent even in the residuals of the classical VAR do not present a Gaussian distribution and a constant variance.

We consider a VAR (1)-GARCH (1, 1) model in a BEKK form. The order one is chosen because the influence of on market on the other often lasts not more than one minute.

The mean equation is the following:

$$y_t = k + \beta y_{t-1} + \varepsilon_t \text{, for t=1,2……,T}$$

With $\varepsilon_t \sim N(0, H_t)$, where

$$H_t = C'C + A_1'(\varepsilon_{t-1}\varepsilon'_{t-1})A_1 + B_1'H_{t-1}B_1$$

where the matrices C, A_1, B_1 are of dimension dxd (C is higher triangular), with d equal to the number of equations. Because of paired matrices, symmetry and non negative definiteness of the conditional variance matrix H_t is assured (see Engle and Kroner, 1993, 1995).

In the case with 2 dimensions, we have

3) For the mean equation:

$$y_t = \begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix},\ \mathrm{k} = \begin{pmatrix} \mathrm{k}_1 \\ \mathrm{k}_2 \end{pmatrix},\ \beta = \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix},\ \varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

where β is a 2x2 matrix of coefficients (not symmetric or diagonal), ε_t is a 2x1 vector of estimated residuals in the mean equation (1)

4) For the variance equation (2).

$$A_1 = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix},\ B_1 = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \text{ and } \mathrm{C} = \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix}$$

we note that in this BEKK model, a_{12} and a_{21} are different from each other, as are b_{12} and b_{21}.

The variance system has 11 parameters for two equations. The parameters of the mean and the variance equation are estimated by maximum likelihood.

We estimate a series of bivariate models based on the equations 1 and 2 above in order to show the links existing either between the spot and futures returns. If we develop the equations 1 and 2 above, we find

$$y_{1t} = \mathrm{k}_1 + \beta_{11} y_{1t-1} + \beta_{12} y_{2t-1} + \varepsilon_{1t}$$
$$y_{2t} = \mathrm{k}_2 + \beta_{21} y_{2t-1} + \beta_{22} y_{2t-1} + \varepsilon_{2t}$$

We estimated the model above either for the spot or the futures index and one other market each time. The simultaneous estimation of the parameters in the mean and in the variance equation is reached by maximum likelihood.

THE VOLATILITY TRANSFERS

To explain the volatility transfers between markets in the framework a BEKK-kind of VAR(1)-GARCH(1,1) model for 2 variables, we consider the following variance equitation's:

$$h_{11t} = a_{11}(a_{11}\varepsilon_{1t-1}^2 + a_{21}\varepsilon_{1t-1}\varepsilon_{2t-1}) + a_{21}(a_{11}\varepsilon_{1t-1}\varepsilon_{2t-1} + a_{21}\varepsilon_{2t-1}^2) + b_{11}(b_{11}h_{11t-1} + b_{21}h_{21t-1}) + b_{21}(b_{21}h_{12t-1} + b_{21}h_{22t-1}) + c_{11}^2$$

$$h_{12t} = a_{12}(a_{11}\varepsilon_{1t-1}^2 + a_{21}\varepsilon_{1t-1}\varepsilon_{2t-1}) + a_{22}(a_{11}\varepsilon_{1t-1}\varepsilon_{2t-1} + a_{21}\varepsilon_{2t-1}^2) + b_{12}(b_{11}h_{11t-1} + b_{22}h_{21t-1}) + b_{22}(b_{12}h_{12t-1} + b_{21}h_{22t-1}) + c_{11}c_{12}$$

$$h_{21t} = a_{11}(a_{12}\varepsilon_{1t-1}^2 + a_{22}\varepsilon_{1t-1}\varepsilon_{2t-1}) + a_{21}(a_{12}\varepsilon_{1t-1}\varepsilon_{2t-1} + a_{22}\varepsilon_{2t-1}^2) + b_{11}(b_{12}h_{11t-1} + b_{22}h_{21t-1}) + b_{21}(b_{12}h_{12t-1} + b_{22}h_{22t-1}) + c_{11}c_{12}$$

$$h_{22t} = a_{12}(a_{12}\varepsilon_{1t-1}^2 + a_{22}\varepsilon_{1t-1}\varepsilon_{2t-1}) + a_{22}(a_{12}\varepsilon_{1t-1}\varepsilon_{2t-1} + a_{22}\varepsilon_{2t-1}^2) + b_{12}(b_{12}h_{11t-1} + b_{22}h_{21t-1}) + b_{22}(b_{12}h_{12t-1} + b_{22}h_{22t-1}) + c_{12}^2 + c_{22}^2$$

We are interested first of all in the impact of the squared residuals ε_{1t}^2 and ε_{2t}^2 on the 2 variances h_{11t} and h_{22t}, and the covariance. The volatility transfers are indicated in bold characters. Note that h_{12t} and h_{21t} are equal on the assumption that they were equal for the previous observation at time t-1 and so on until the beginning of the series. Using the BEKK modeling, we can show how far these squared residuals will lead to a strong change in h_{ijt}. We are aware that Isakov and Perignon (2000, p.133) wrote that, in their model, by using the Hadamard product in $B\Theta H_{t-1}$ instead of $B^{'}H_{t-1}B$, they constrain the volatility transmission mechanism. It is true that in this case, the only possible way for a market's volatility to influence another market's volatility is through shocks. However, it is not always sure that B will remain non negative definite or that H_t will have only positive elements on the main diagonal in all possible cases, in any possible situation. Further, the $B' H_t B$ term in the BEKK model involves the presence of h_{11t-1} in the equation for h_{22t} and the presence of h_{22t-1} in the equation for h_{11t}. However, as h_{11t-1} and h_{22t-1} do not increase very fast, the main element of influence remains the squared residuals ε_{1t}^2 and ε_{2t}^2. The volatility spillover, the coefficient a_{21} will be relevant for measuring the effect of the spot markets volatility (h_{22t}) on futures markets volatility (h_{11t}). The coefficient a_{12} will be relevant for measuring the effect of futures market volatility on the spot market volatility. Moreover, the increase in volatility due to h_{t-1} take two steps: a shock happens in t-2, h_{t-1} increases at time t-1 only because of the shock in ε_{1t} or ε_{2t} at time t-2 and the increase in h_{t-1} will further increase h as late as in h_t. As we are interest in the mean impact of a shock after one period (independently from the shock that happened two periods before) and not only in the impact of one precise shock, ε_1 or ε_2 are the only important indicators for the volatility increase the next period.

In the equations 1 and 4 before, we see that the volatility transfers can be described by two figures:

1. Considering that h_{11t} is the variance of the spot market and h_{22t} is the variance of the futures market, we see that the impact of the futures market on the domestic market is given by the coefficients of ε_{2t-1}^{2} in equation 1, that is a $a_{21}{}^{2}$.
2. On the same basis, we see that the impact of the domestic market on the foreign market is given by the coefficients for ε_{1t-1}^{2} in equation 4, that is $a_{12}{}^{2}$.

Table9a:
Parameter estimates for Multivariate GARCH model using NSE, S&P CNX Nifty and Futures returns for One minute data

Coefficients	Estimates	S.E	t-statistic
Mean (1)	-0.0006969	5.853E-05	-11.90687
Mean (2)	-0.0007155	0.0001135	-6.30557
C(1,1)	0.467913	0.0015371	304.40991
C(1,2)	0.3347769	0.0016272	205.7334
C(2,2)	0.0186788	0.0002196	85.07334
A(1,1)	-0.1665226	0.0003736	-445.77576
A(1,2)	0.9207976	0.0004362	2110.9258
A(2,1)	-0.0336564	0.0003474	-96.8779
A(2,2)	0.0026843	4.188E-05	64.09647
B(1,1)	0.9872555	5.017E-05	19680.118
B(1,2)	-0.0037409	6.926E-05	-54.01047
B(2,1)	-0.0066052	5.002E-05	-132.05293
B(2,2)	-0.0001746	0.0005031	-0.34702

Volatility spillovers between spot and futures returns of one minute series discuss in the table 9a. Where both mean equations spot (mean1) and futures (mean2) are different. And in the variance equations deals with 11 parameters, in which a12 and a21 are different indicates volatility spillovers occur in both markets. (see Figure 29 for conditional standard deviations)

Table 9b:
Parameter estimates for Multivariate GARCH model using NSE, S&P CNX Nifty and Futures returns for Five Minutes data

Coefficients	Estimates	S.E	t-statistic
Mean (1)	-0.0013782	0.0004344	-3.17257
Mean (2)	-0.0001486	0.0005331	-0.27866
C(1,1)	-0.5912439	0.0052235	-113.18933
C(1,2)	0.0336299	0.005549	6.06049
C(2,2)	0.1866416	0.0031405	59.43117
A(1,1)	-0.3316888	0.0042022	-78.93186
A(1,2)	0.823237	0.0024585	334.85881
A(2,1)	-0.0081985	0.0019428	-4.21986
A(2,2)	0.0443624	0.0009213	48.15439
B(1,1)	0.9484296	0.0010875	872.12487
B(1,2)	0.0489291	0.0006103	80.17861
B(2,1)	0.0288108	0.0005485	52.52583
B(2,2)	-0.0188815	0.0006514	-28.9882

Volatility spillovers between spot and futures returns of one minute series discuss in the table 9b. Where both mean equations spot (mean1) and futures (mean2) are different. And in the variance equations deals with 11 parameters, in which a12 and a21 are different indicates volatility spillovers occur in both markets. (see Figure 30 for conditional standard deviations).

Table 9c:
Parameter estimates for Multivariate GARCH model using NSE, S&P CNX Nifty and Futures returns for Ten Minutes data

Coefficients	Estimates	S.E	t-statistic
Mean (1)	0.0005509	0.0008901	0.61891
Mean (2)	-0.000548	0.000935	-0.58613
C(1,1)	0.1852097	0.0034995	52.92448
C(1,2)	-0.1963877	0.0051345	-38.24901
C(2,2)	-0.1492863	0.0046086	-32.39308
A(1,1)	0.4928492	0.0052922	93.12753

A(1,2)	0.5228597	0.0158664	32.95381
A(2,1)	1.3380433	0.0084811	157.76789
A(2,2)	0.4837093	0.0129743	37.28204
B(1,1)	-0.3813307	0.0167007	-22.83317
B(1,2)	0.0221125	0.0005478	40.36327
B(2,1)	-0.0204661	0.0006412	-31.91897
B(2,2)	-3.74E-06	0.0106429	-3.51E-04

Volatility spillovers between spot and futures returns of one minute series discuss in the table 9c. Where both mean equations spot (mean1) and futures (mean2) are different. And in the variance equations deals with 11 parameters, in which a12 and a21 are different indicates volatility spillovers occur in both markets. (see Figure 31 for conditional standard deviations).

Table 9d:
Parameter estimates for Multivariate GARCH model using NSE, S&P CNX Nifty and Futures returns for One Hour data

Coefficients	Estimates	S.E	t-statistic
Mean (1)	0.0117203	0.0038022	3.08251
Mean (2)	0.0149042	0.0036067	4.13239
C(1,1)	0.5216691	0.0155649	-37.16745
C(1,2)	0.0050534	0.0115566	0.43727
C(2,2)	-0.6882152	0.0186434	-36.91461
A(1,1)	0.3740795	0.0131959	28.34825
A(1,2)	-0.0188609	0.0004505	-41.86296
A(2,1)	0.4762642	0.0195076	24.41425
A(2,2)	0.7686523	0.0079329	96.89426
B(1,1)	0.6116938	0.0174584	35.03719
B(1,2)	-0.1716824	0.0046192	9.56064
B(2,1)	0.0325396	0.0034035	1.68E-05
B(2,2)	2.82E-07	0.0168201	33.51581

Volatility spillovers between spot and futures returns of one minute series discuss in the table 9a. Where both mean equations spot (mean1) and futures (mean2) are different. And in the variance equations deals with 11 parameters, in which a12 and a21 are different indicates volatility spillovers occur in both markets. (see Figure 32 for conditional standard deviations)

CONCLUSIONS:

This study investigates the lead lag relationship between the spot and the futures market in India, both in terms of return and volatility. With the resemblance of majority of studies of the lead/lag relationship between the spot index and index futures markets in the world, we have found that the index futures market leads up to by 1-5 minutes, and also found that there is a bidirectional relationship between the spot and the index futures. We find a strong contemporaneous relationship between futures and cash prices, along with some significant evidence that futures markets lead spot market during times of high volatility. Consequently, reactions in futures markets are faster and movements in futures prices lead spot price fluctuations.

The results of this study suggest that a bi-directional feedback relationship between spot and futures prices, i.e., when spot prices are affected by their past history, current and past futures prices, and futures prices are affected by their past history, current and past spot prices and other market information. In both cases spot prices lead futures prices. In order to incorporate price co-integration relationship between the spot and index futures markets in the lead lag relationship analysis, we found that, in the long run, both returns are co-integrated.

FIGURES

Figure 1: Spot and futures prices for one minute

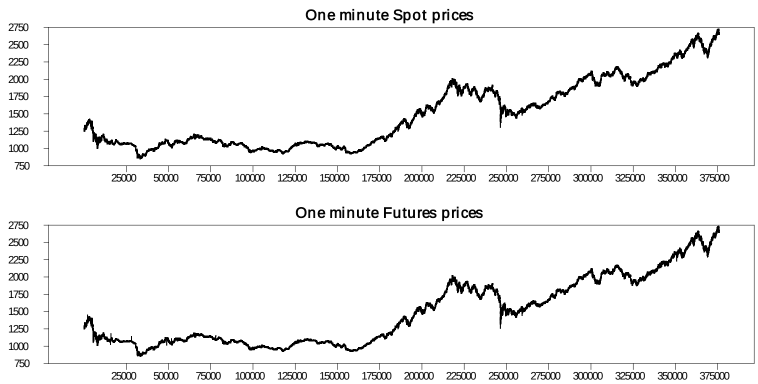


Figure 2: Spot and futures prices for five minutes

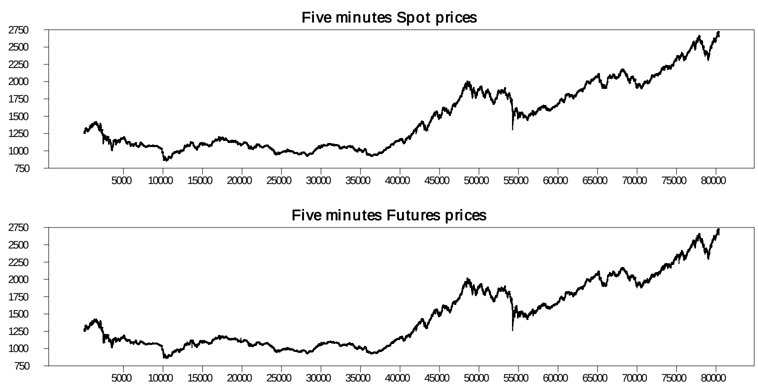


Figure 3: Spot and futures prices for Ten minutes

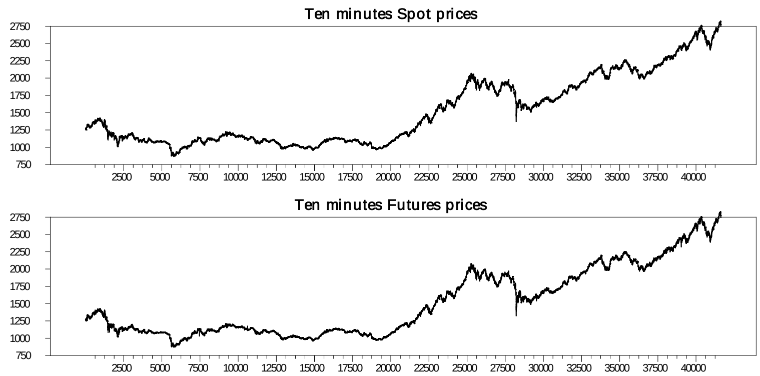


Figure 4: Spot and futures prices for One hour

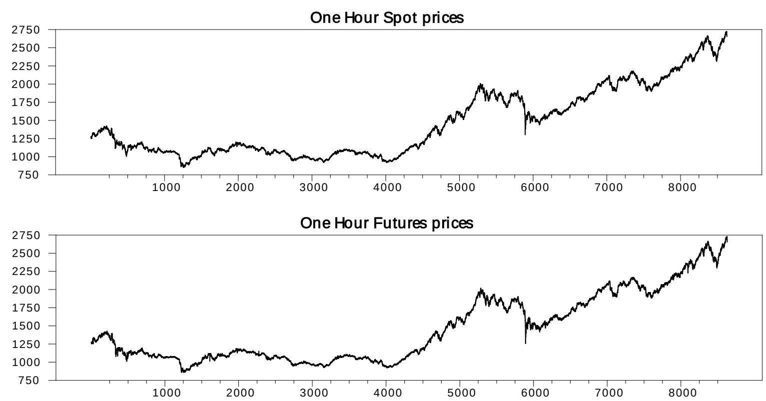


Figure 5: Residuals and squared residuals for one min price series

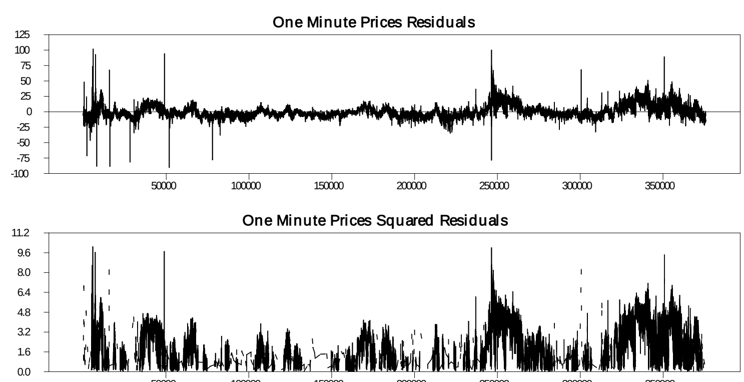


Figure 6: **Residuals and squared residuals for Five min price series**

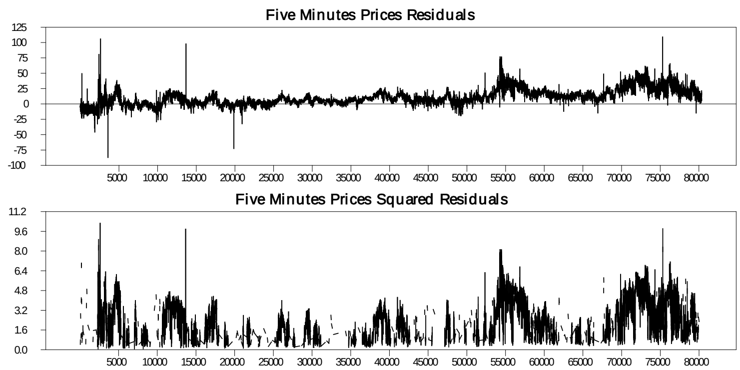


Figure 7: **Residuals and squared residuals for ten min price series**

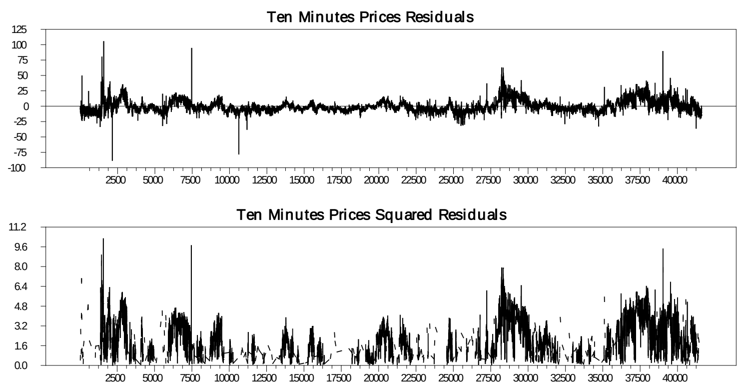


Figure 8: **Residuals and squared residuals for one hour price series**

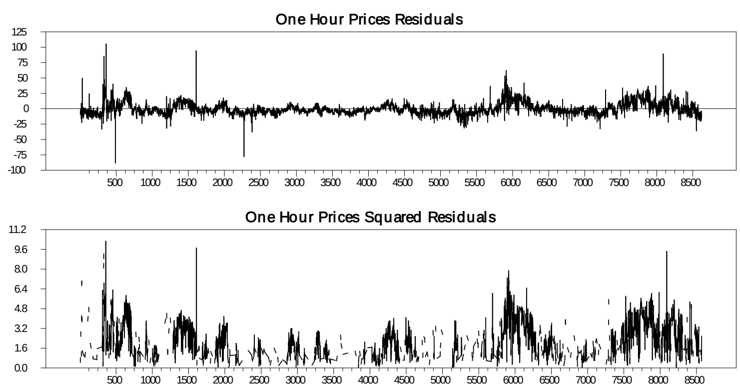


Figure 9: **One Minute Spot and Futures returns series**

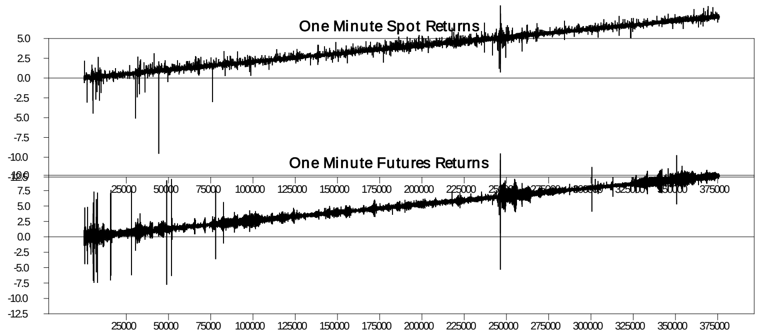


Figure 10: **Five Minutes Spot and Futures returns series**

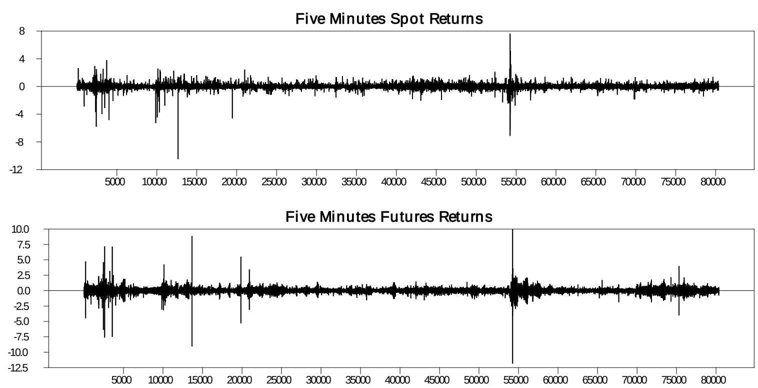


Figure 11: **Ten Minutes Spot and Futures returns series**

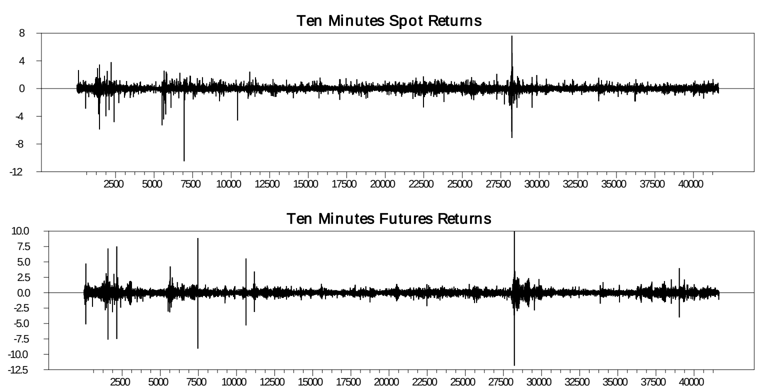


Figure 12: **One Hour Spot and Futures returns series**

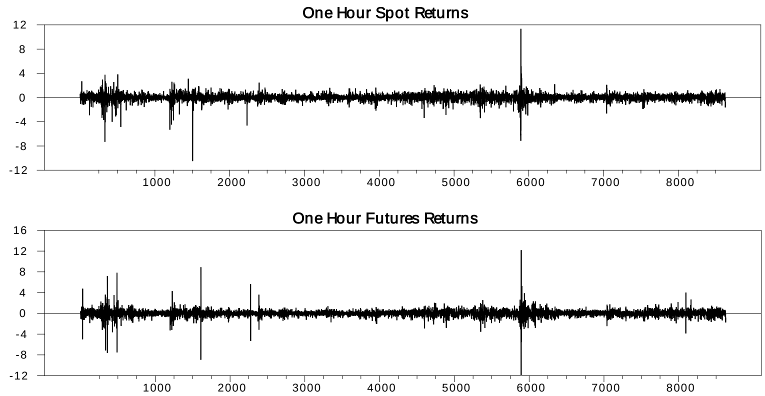


Figure 13: **Residuals and Squared residuals for one minute returns series**

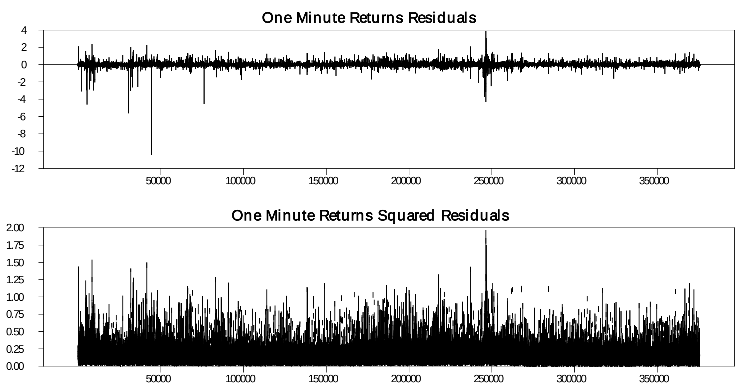


Figure 14: **Residuals and Squared residuals for five minutes returns series**

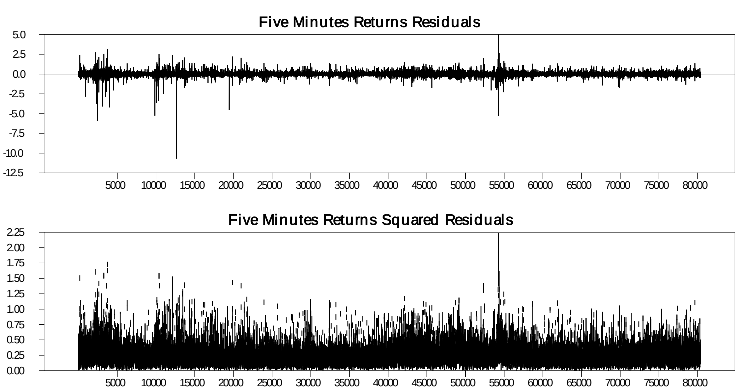


Figure 15: **Residuals and Squared residuals for ten minutes returns series**

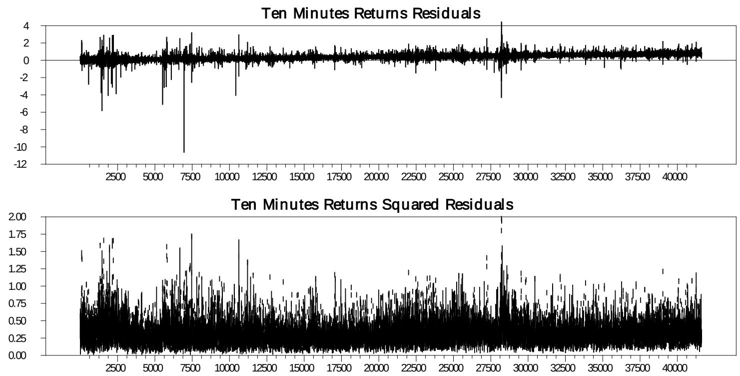


Figure 16: **Residuals and Squared residuals for one hour returns series**

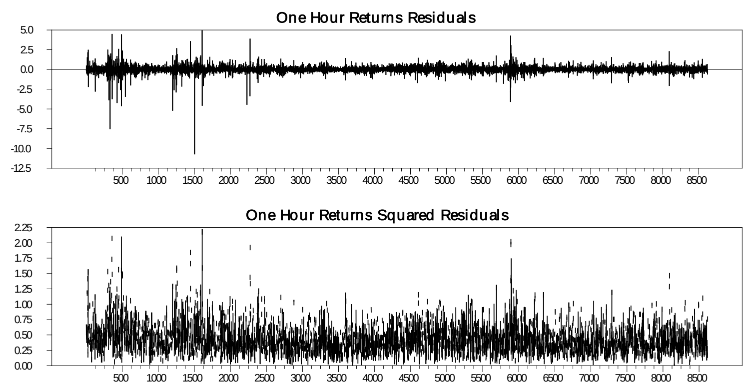


Figure 17: Co-integration Graph for One minute series

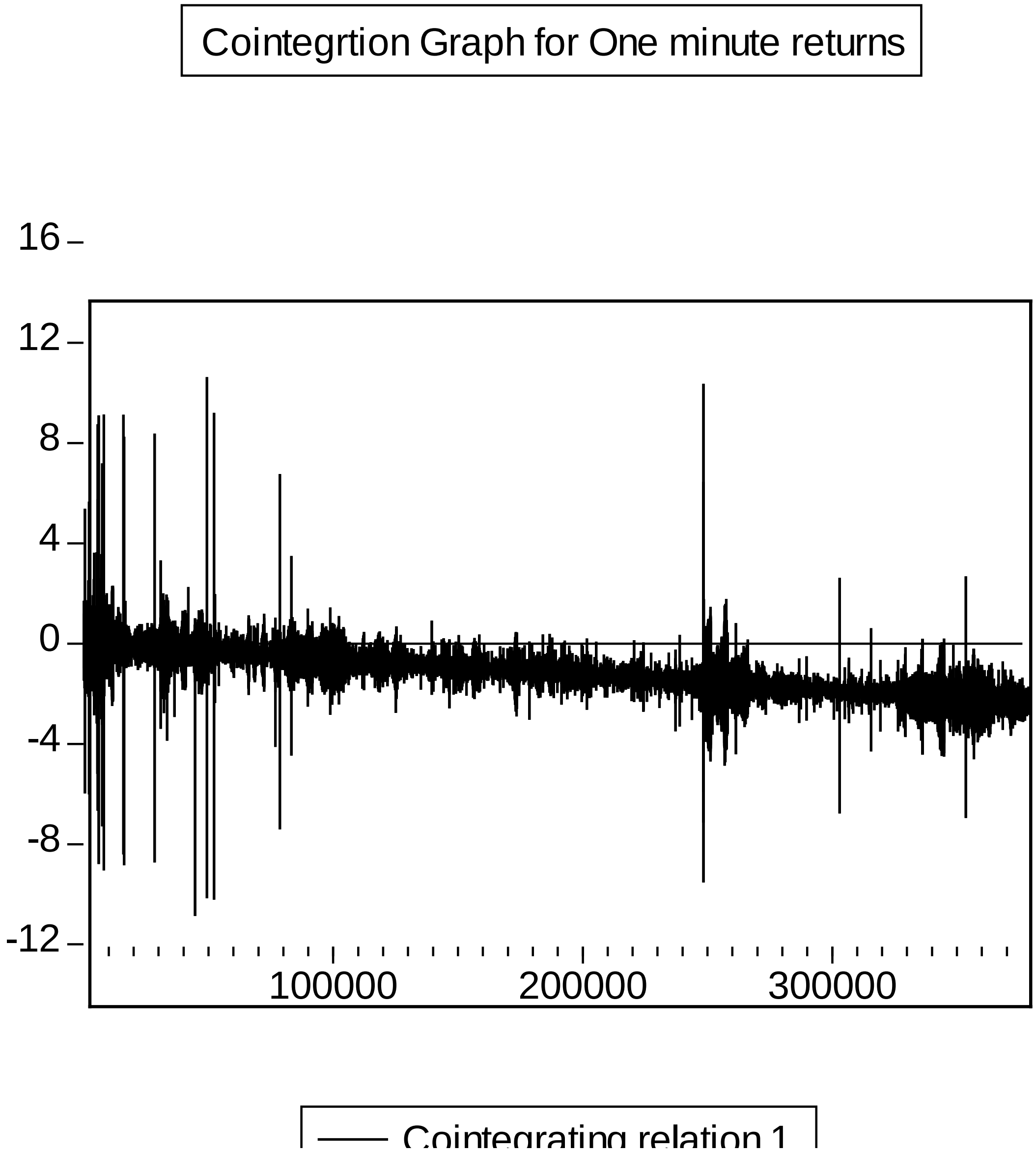


Figure 18: Auto Correlations for both spot and futures returns

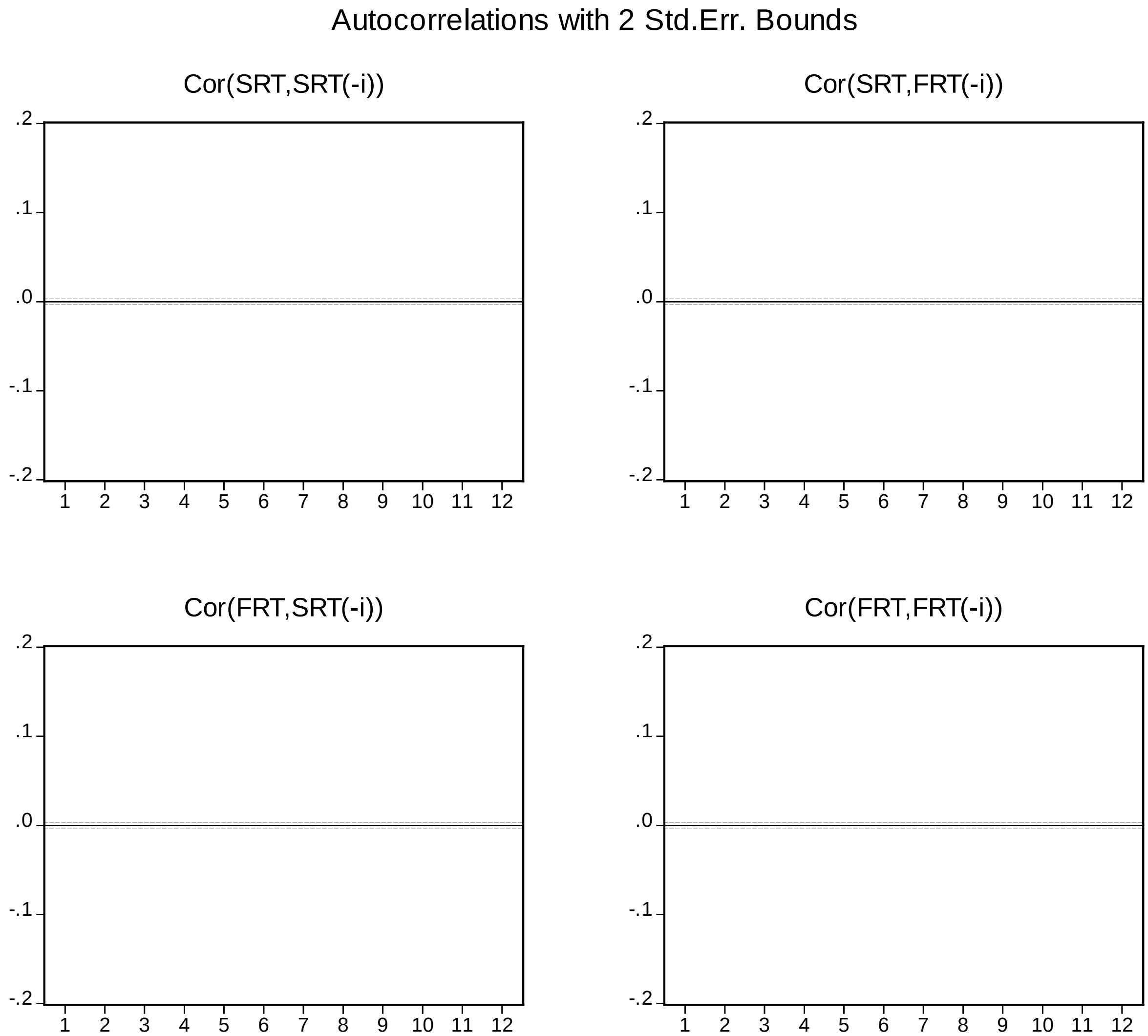


Figure 19: Impulse responses for one minute co-integration results

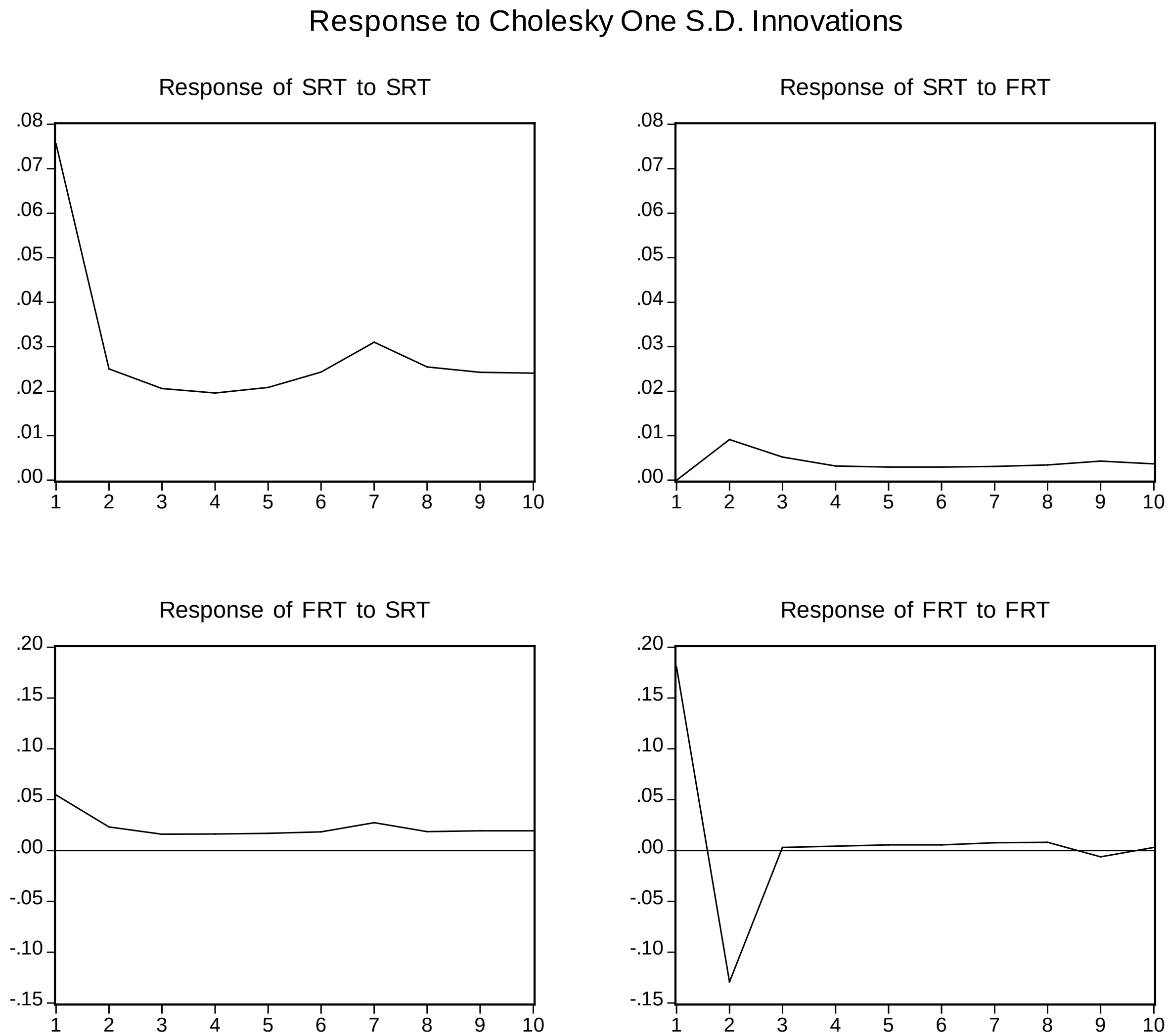


Figure 20: Co-integration Graph for Five minutes returns series

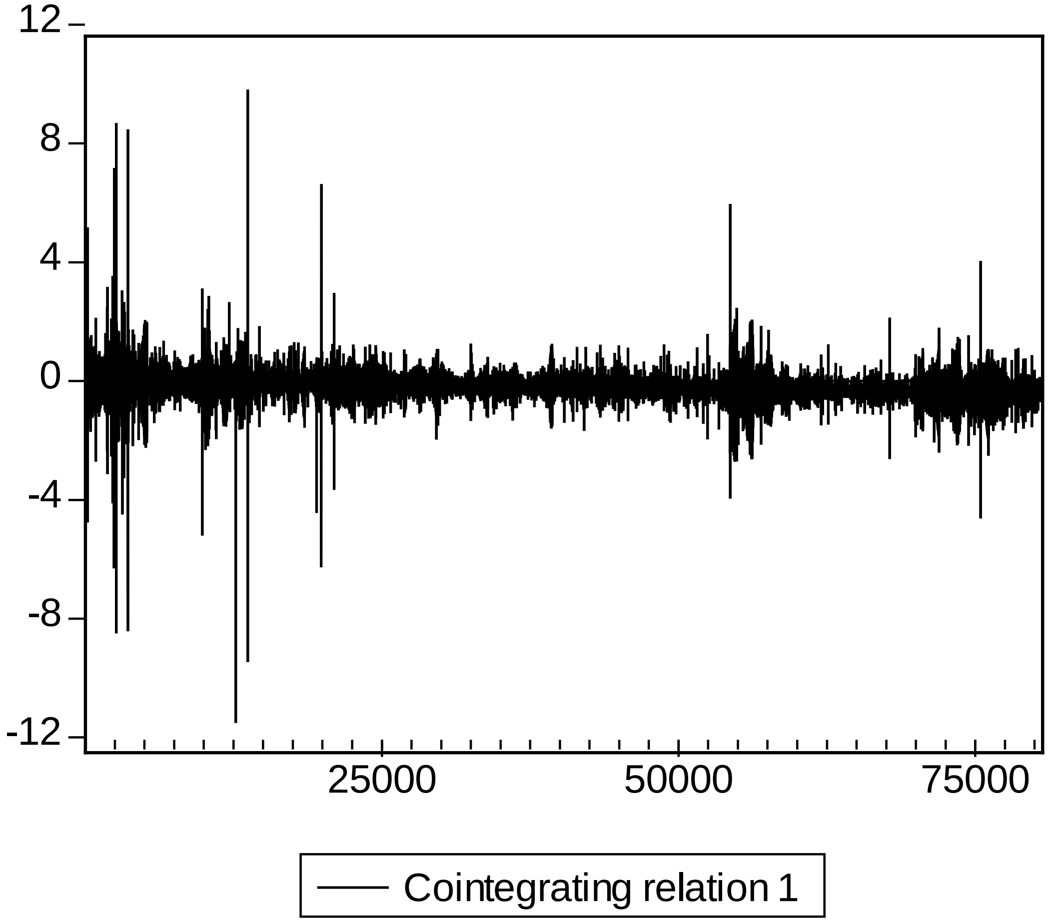


Figure 21: Autocorrelation results for spot and futures returns series for five minutes

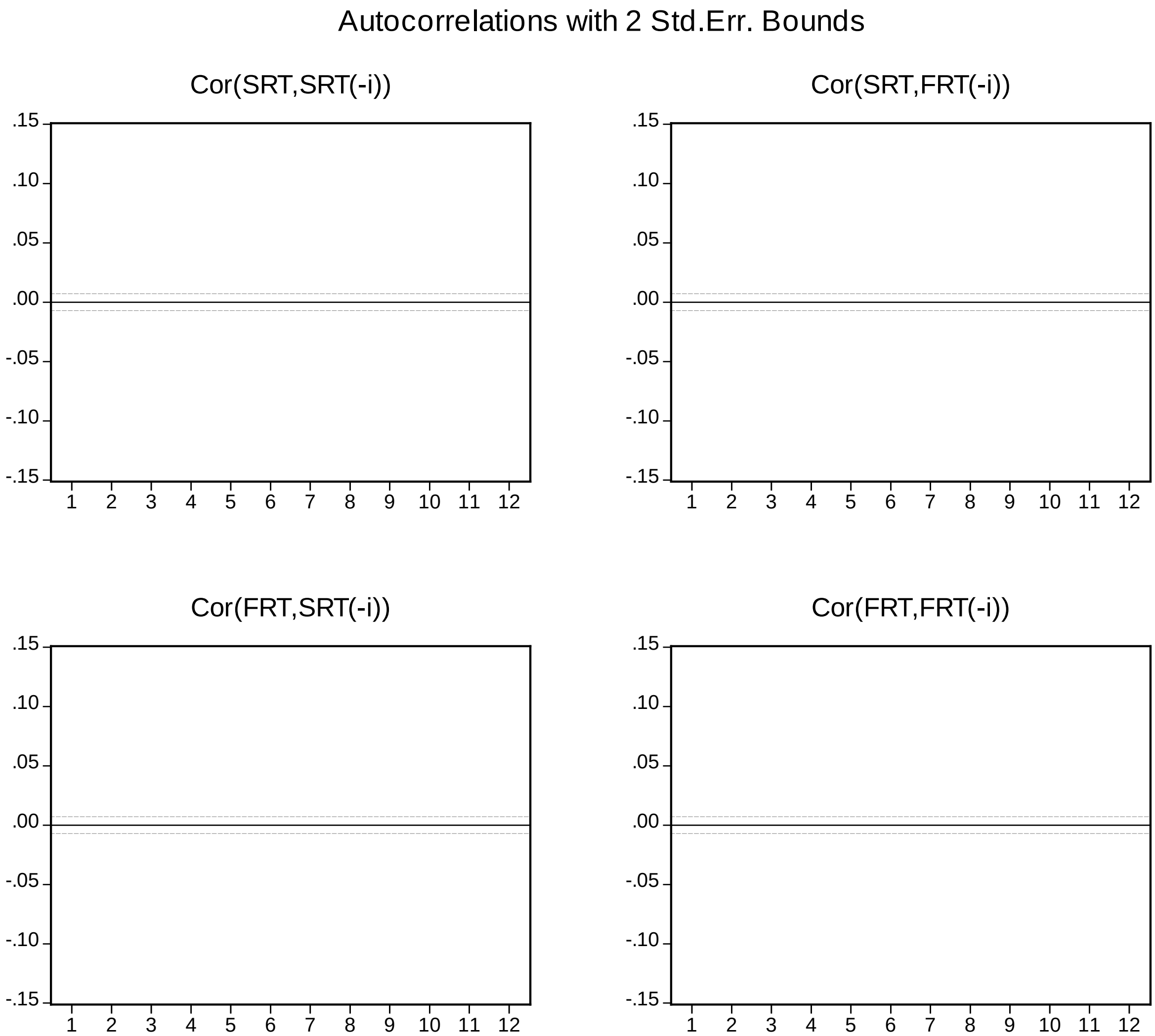


Figure 22: Impulse response for five minute returns series

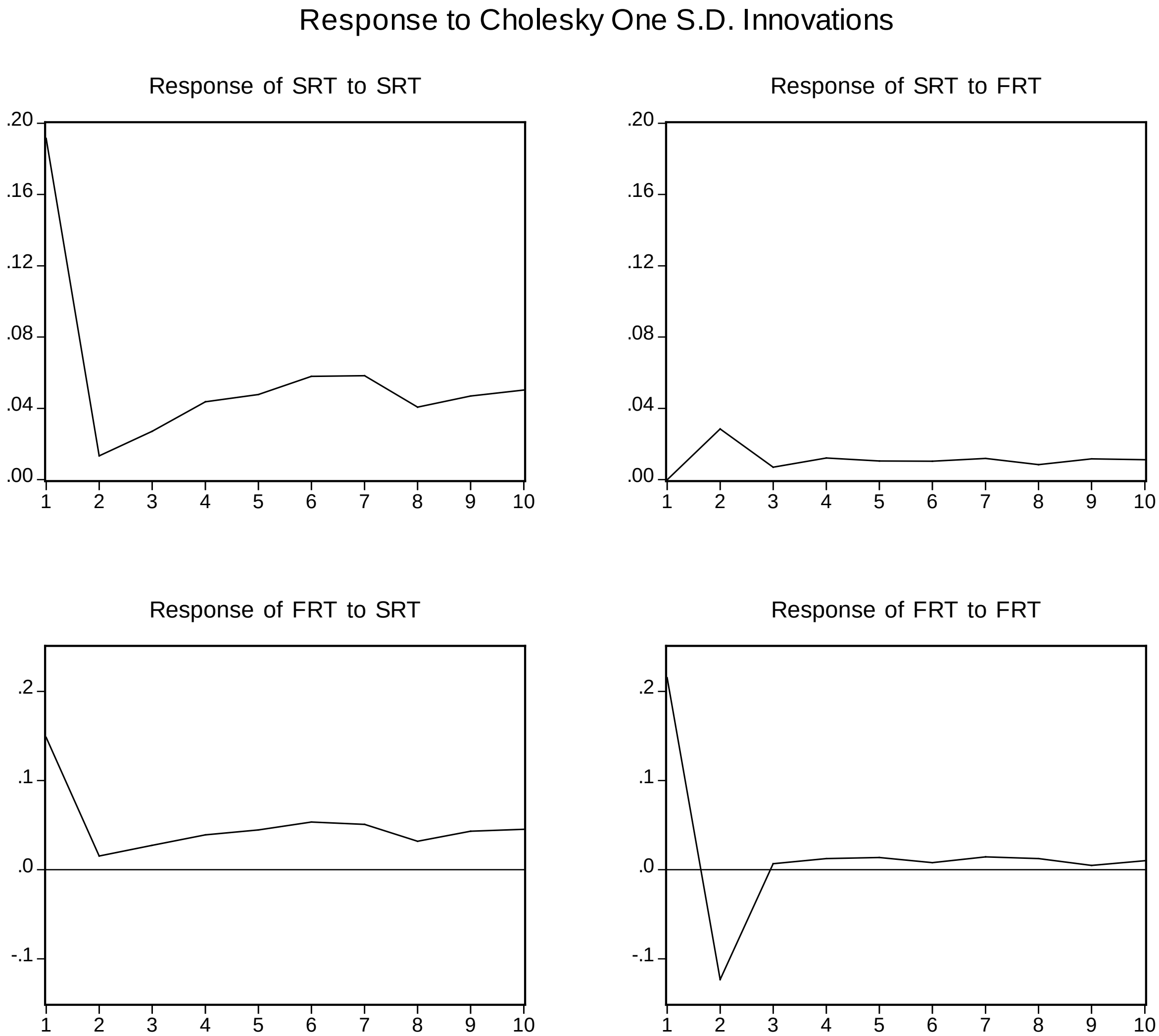


Figure 23: Co-integration Graph for Ten minutes series

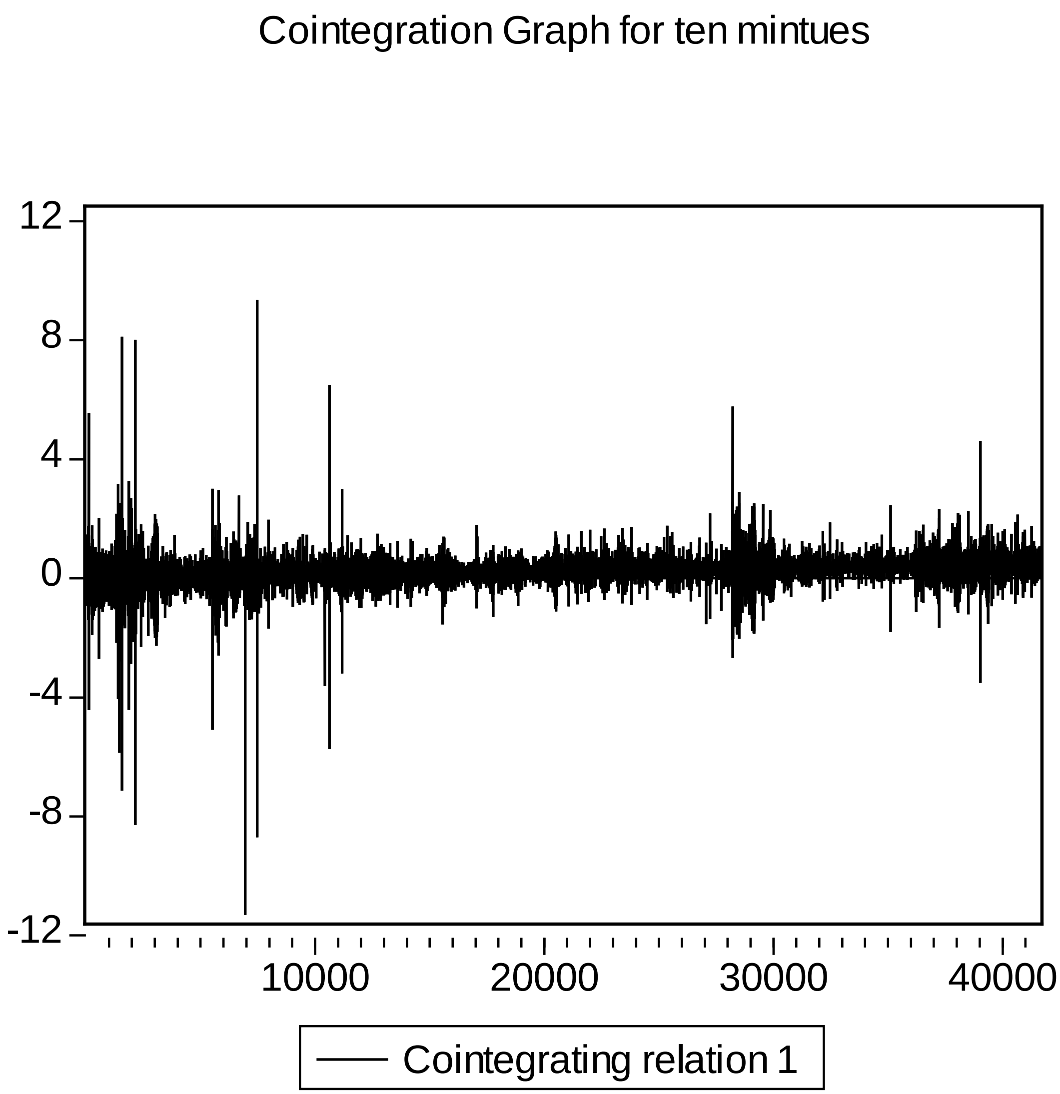


Figure 24: Autocorrelations for spot and futures returns series for ten minutes

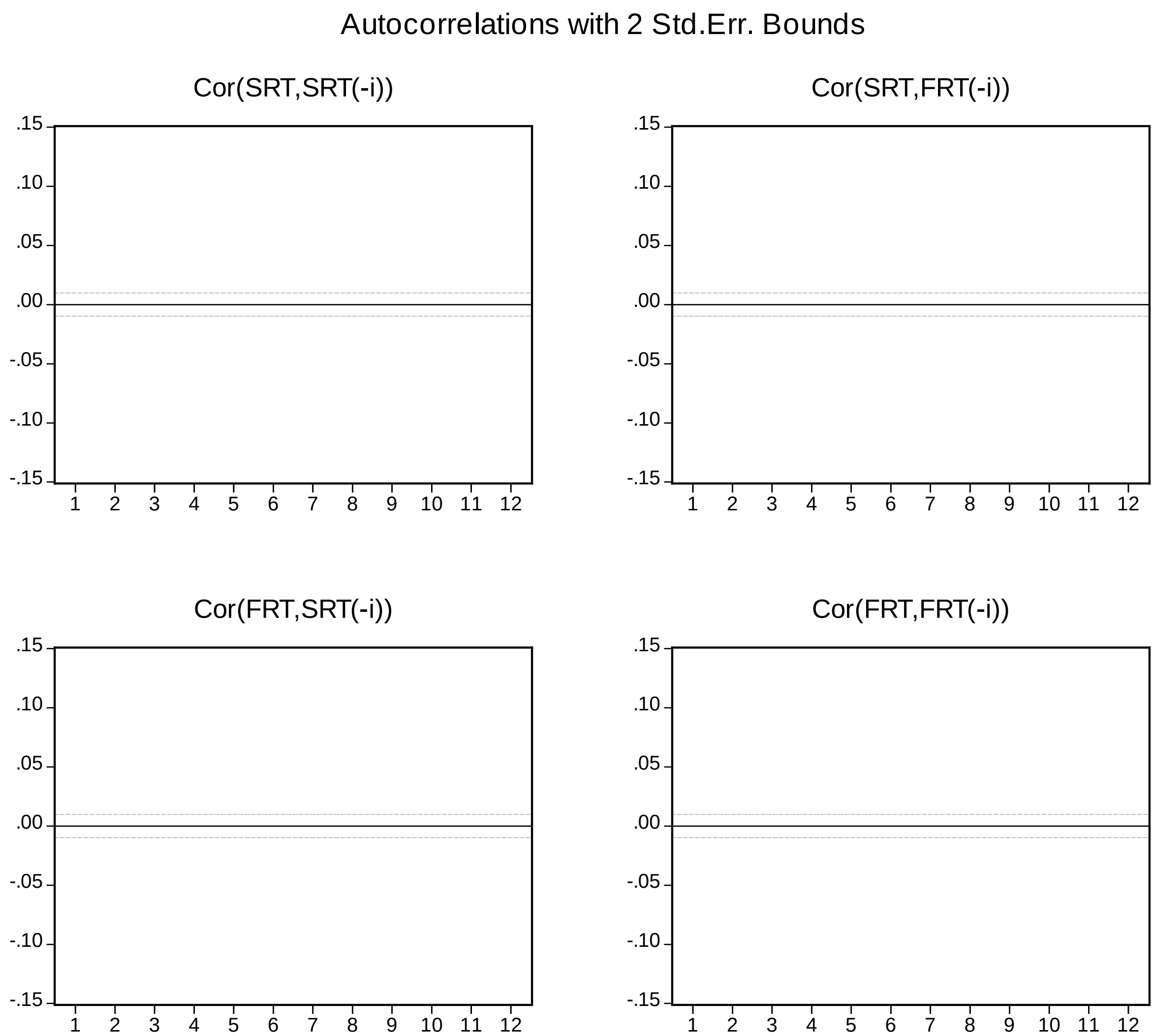


Figure 25: Impulse responses for ten minute returns series

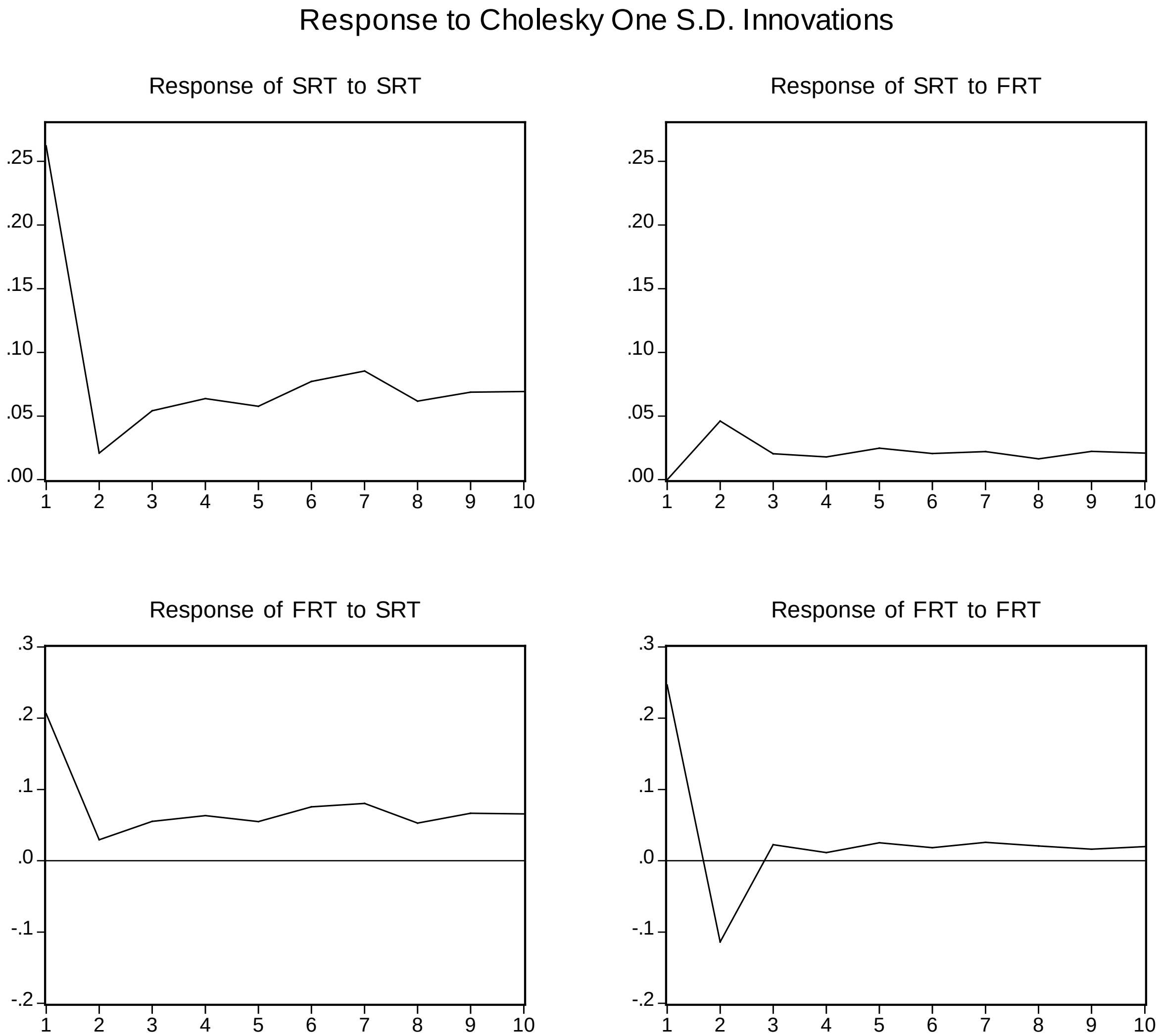


Figure 26: Co-integration graph for One hour

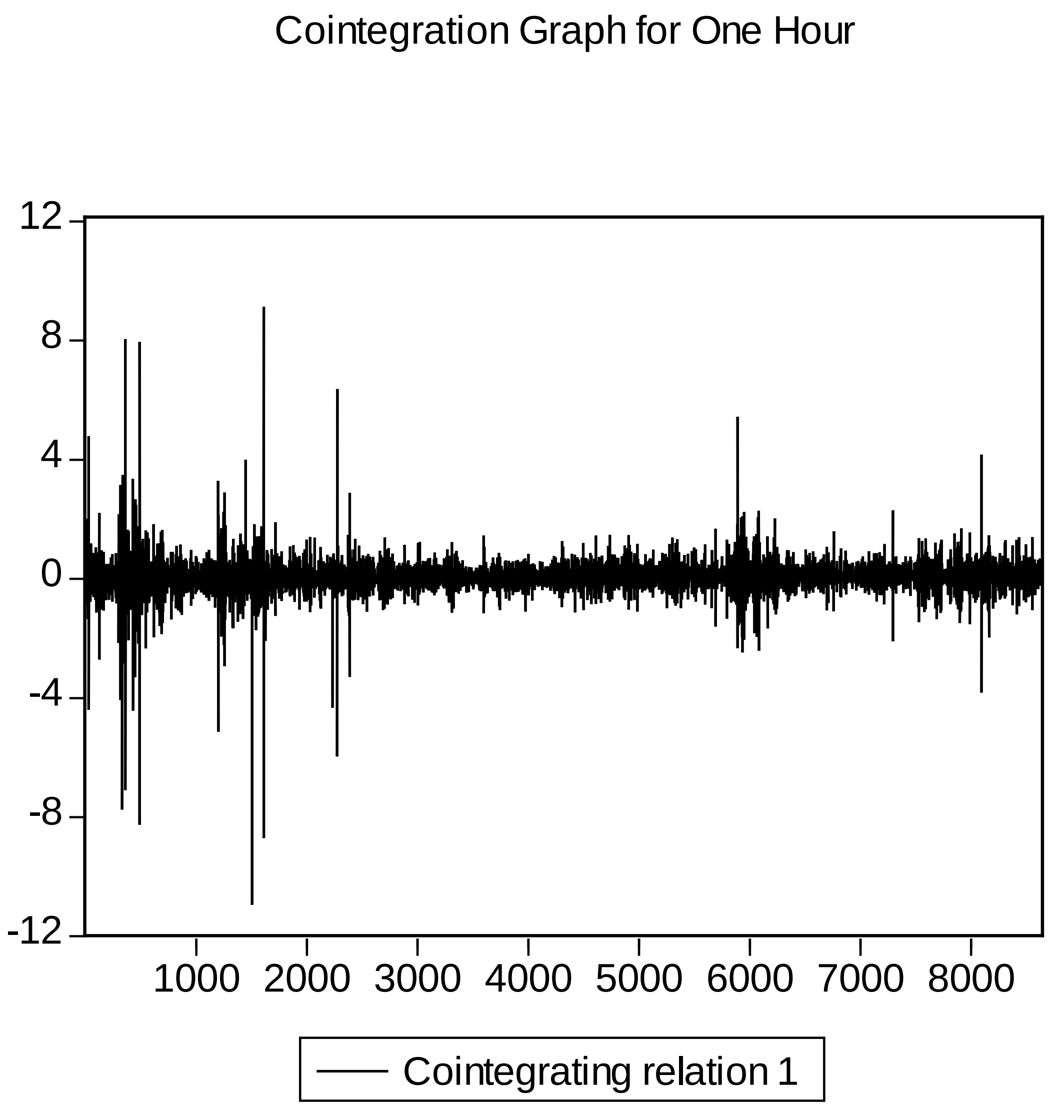


Figure 27: Autocorrelations for spot and futures returns series for one hour

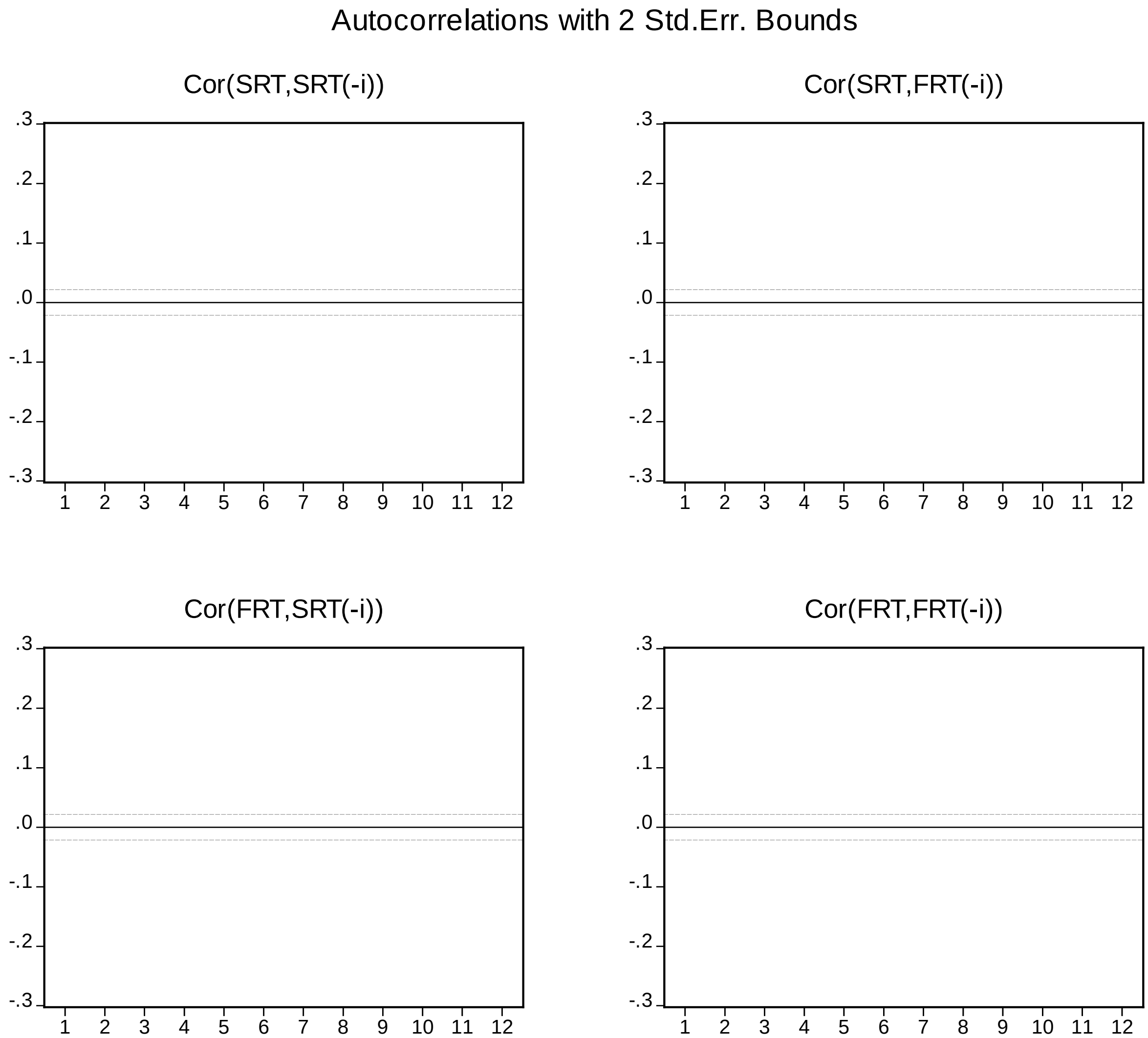


Figure 28: Impulse responses for one hour

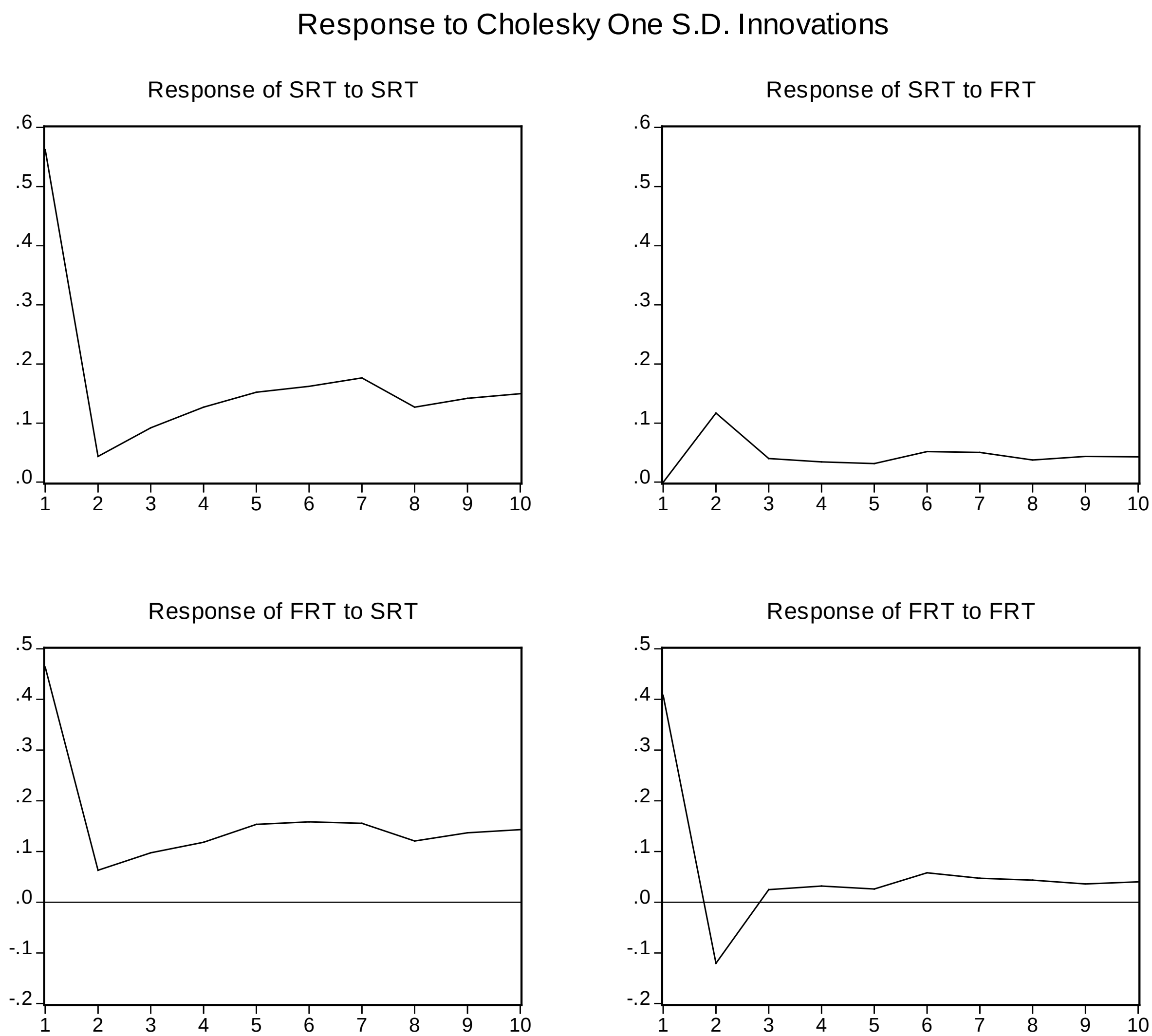


Figure 29: Conditional Standard Deviations Graph for One minute returns series

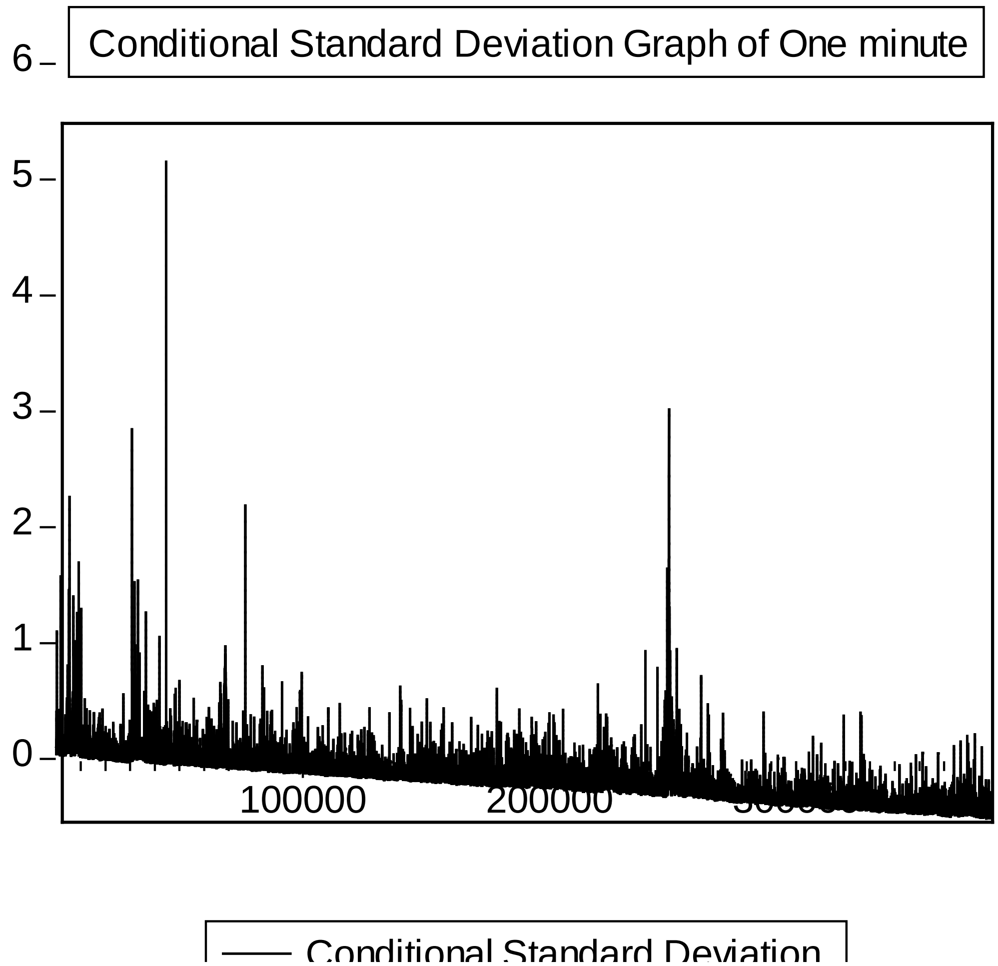


Figure 30: Conditional Standard Deviations of returns series of Five Minutes

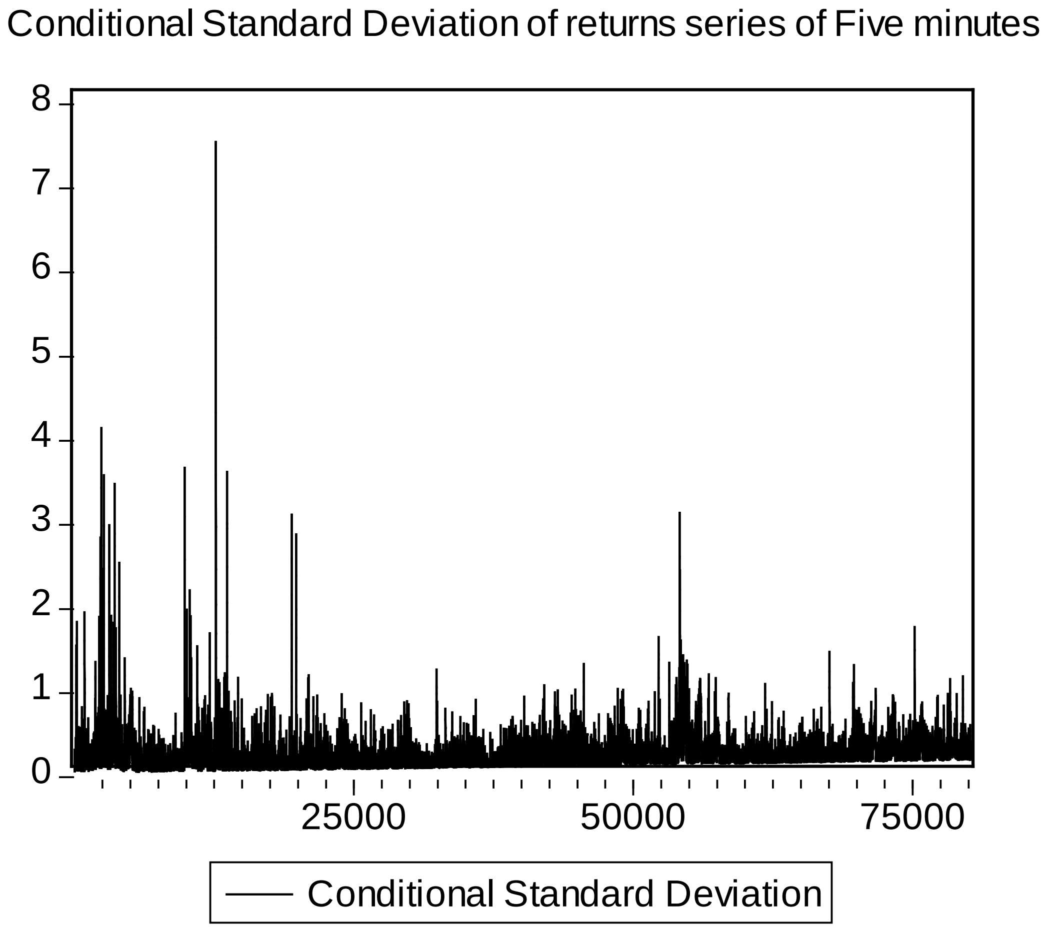


Figure 31: Conditional Standard Deviation of returns series of Ten Minutes

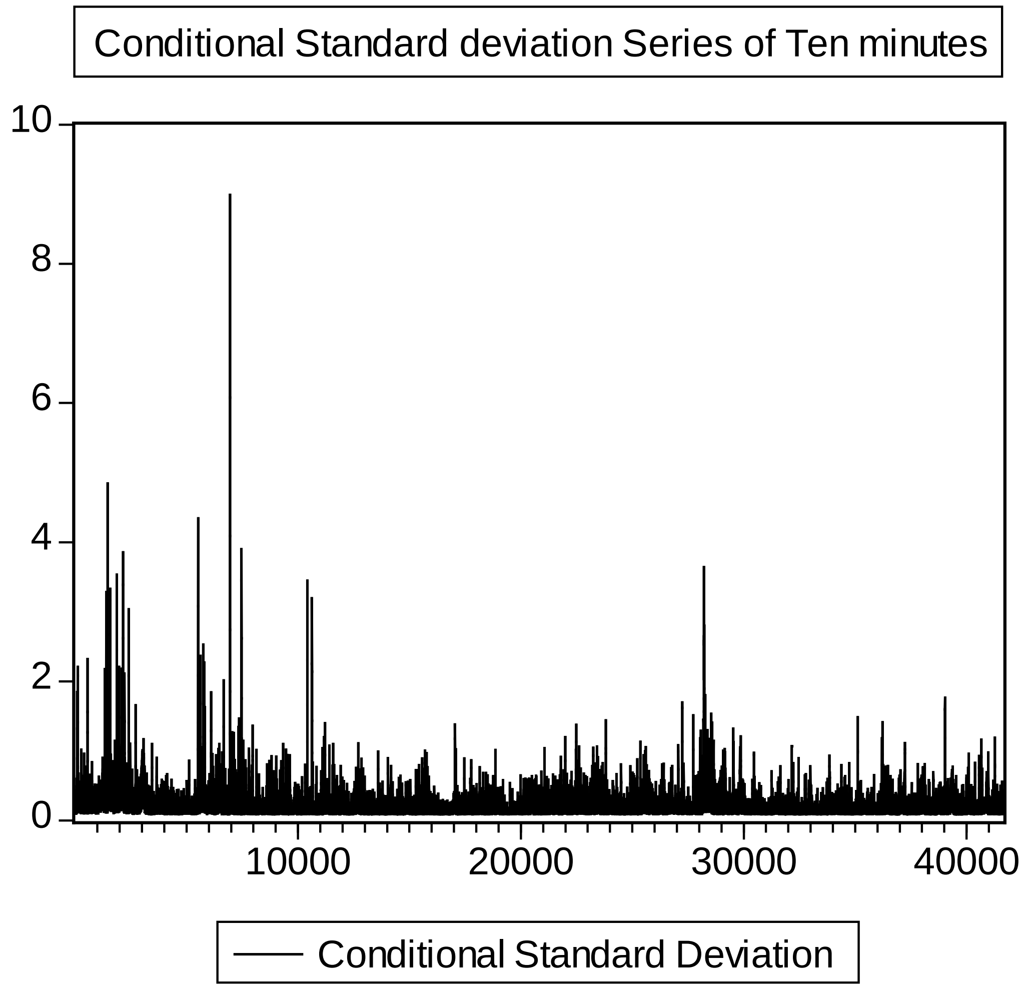
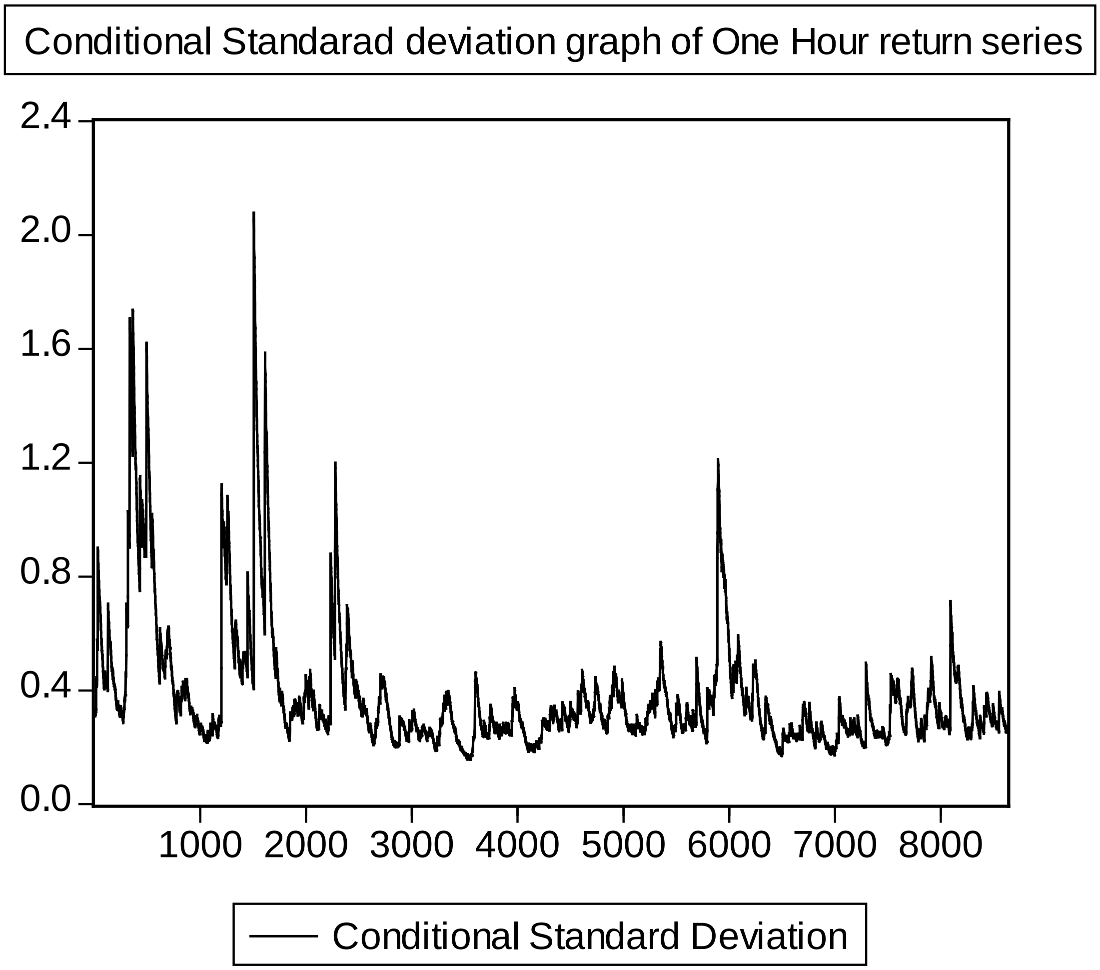


Figure 32: Conditional Standard Deviation of returns series of One hour



THE INTERDEPENDENCE BETWEEN THE SPOT AND INDEX FUTURES MARKETS: AN EMPIRICAL ANALYSIS IN INDIA

CHAPTER - V

SUMMARY AND CONCLUSIONS

CONTENTS:

5.1 SUMMARY AND CONCLUSIONS

5.2 IMPORTANCE OF THE STUDY

5.3 FOR THE FURTHER RESEARCH

5.1. SUMMARY AND CONCLUSIONS:

Even the high frequency data bases are still expensive to collect, maintain, and manipulate, those high frequency observations are also subject to characteristic factors which includes non-synchronous trading, intraday seasonal effects, measurement errors, due to bid-ask spreads or reporting difficulties and even conceptual problems, such as defining a 'return' during an missing text in which no trading occurs. This study is new to its kind in Indian case with high frequency data for the period of January 2001 to November 2005 in order to investigate the lead lag relationship between the spot and the futures market in India, both in terms of return and volatility. With the resemblance of majority of studies of the lead/lag relationship between the spot index and index futures markets in the world, we have found that the index futures market leads up to by 1-5 minutes, and also found that there is a bidirectional relationship between the spot and the index futures. The findings of the study is a strong contemporaneous relationship between futures and cash prices, along with some significant evidence that futures markets lead spot market during times of high volatility. Consequently, reactions in futures markets are faster and movements in futures prices lead spot price fluctuations.

In order to examine the lead-lag relationship between the spot and the futures markets, one of the important roles attributed to the futures markets is that of 'price discovery'; that is, the futures market reflects new information before the spot market. If new market information disseminates in the futures market before the stock market, then the introduction of a futures market increases the amount of information reflected in the spot price.

As Brooks (1999), rightly pointed out that the central tenet of the cost-of-carry model hypothesized that, in a perfect capital market with non-stochastic interest rates and dividend yields, prices of futures contracts and the underlying spot prices are perfectly contemporaneously correlated and no lead lag relationship would exit. But, the efficient market hypothesis states that financial markets efficiently process all relevant information to be reflected simultaneously into both the spot and futures prices and that the price movements in each market are identically and independently distributed.

The explanation is that the futures market is less costly for traders to utilize than the cash market, so the futures market is dominant in revealing economy-wide information. One implication of this explanation is that if traders prefer to trade futures contracts rather than the components stocks, an asymmetric lead-lag relation should hold between the returns of the futures and all individual stocks. And another implication is that the lead-lag relation should change when it becomes more costly or less costly for traders to exploit the information in the cash market.

The lead-lag relation between futures and cash index prices may be attributed to infrequent trading of stocks within the index. Since component stocks may not be traded in the last instant of each time interval, observed index values, which are the averages of the last transaction price of component stocks, cannot update actual developments in the stock market and lag behind "true" index values. If futures price reflect information instantaneously, cash index prices will lag behind futures prices. One of the argument predicts that futures prices lead spot prices when informed traders, hedgers and speculators react to new information by indulging in futures rather than spot transactions due to lower transaction costs, capital requirements and short-selling restrictions in the derivative markets. Since spot transactions require a greater deal of initial outlay and may take a longer time to implement, spot prices are tend to react with a lag. The relative difference between the futures and spot prices will trigger an action with the postponement of current consumption, and then the subsequent change in spot prices arising from the change in demand in spot market.

A theoretical model of cost-of-carry, assert that futures prices are jointly determined by arbitrager's and speculators' demand for futures contracts. Arbitrageur demand depends on the difference between the arbitrage price as determined by the cost-of-carry model and the actual futures prices. Speculator demand depends on the difference between the expected future spot price and actual futures prices.

As Kawaller et al (1998) postulated, the results of the study suggests that a bi-directional feedback relationship between spot and futures prices, i.e., when spot prices are affected by their past history, current and past futures prices, and futures prices are affected by their past history, current and past spot prices and other market information. First, the index arbitrageurs will respond to the violation of the cost-of-carry condition by participating in the spot market. Second, speculators would react following the discrepancy between the current futures prices and the expected futures prices. In both cases spot prices lead futures prices.

In order to incorporate price co-integration relationship between the spot and index futures markets in the lead lag relationship analysis, we found that, in the long run, both returns are co-integrated.

5.2. IMPORTANCE OF THE STUDY:

1. It helps to the investors to take a view on the market for investment for their further analysis.
2. It helps in reducing the risk associated with exposures in both spot and futures markets.
3. Since the cash and futures prices tend to move in the same direction as they both react to the same supply/demand factors, the basis is more stable and predictable than the movement of the prices.
4. It helps to the investors to attain leverage and investors would be to make a larger profit.
5. An investor can trade the 'entire stock market' by buying index futures listed of buying individual securities with the efficiency. As futures leads the spot markets in this study, an investors would be have the advantages of
    a. High liquid, high leverage
    b. Could be able to lower his risk
    c. It might be ease to him for solving his problems related to bad delivery, forged, fake certificates etc.,
6. Empirical evidence suggests, market efficiency and liquidity on the spot market improve once derivative trading leads.

7. It helps to reduce the risks faced by liquidity providers on the markets and it may help to improve liquidity in the markets.
8. It helps to reduce/nullify the counterparty risk in the stock markets.
9. It helps to have a fair price mechanism in the markets.

5.3. FOR THE FURTHER RESEARCH:

1. Any interesting researcher could extend such study for the individual stocks for their betterment of returns and use such information for the better investments.

2. Any serious researcher may extend this study for different informational contents (i.e, impact of news releases, macro economic news, individual company news etc.,) to investigate the lead-lag relationship between the spot (futures) and futures (spot) prices.

3. For the checking check for the connection the volatility transfers, we can also extend use the various Multivariate GARCH models (CC, DCC, Diag-CCC) for capturing true volatile transfers in the markets.

The role of volatility in the price discovery process, volatility spillovers/transformations are important to study of information transmission because volatility is also a source of information. Volatility in one market will spill over to another market, considers information transmission between stock index and index futures markets.

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National Stock Exchange (www.nseindia.com)

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APPENDIX – I
CONSTITUENTS LIST OF S&P CNX NIFTY

Company Name	Industry	Symbol	Series	ISIN Code
ABB Ltd.	ELECTRICAL EQUIPMENT	ABB	EQ	INE117A01022
ACC Ltd.	CEMENT AND CEMENT PRODUCTS	ACC	EQ	INE012A01025
Ambuja Cements Ltd.	CEMENT AND CEMENT PRODUCTS	AMBUJACEM	EQ	INE079A01024
Bharat Heavy Electricals Ltd.	ELECTRICAL EQUIPMENT	BHEL	EQ	INE257A01018
Bharat Petroleum Corporation Ltd.	REFINERIES	BPCL	EQ	INE029A01011
Bharti Airtel Ltd.	TELECOMMUNICATION - SERVICES	BHARTIARTL	EQ	INE397D01016
Cairn India Ltd.	OIL EXPLORATION/PRODUCTION	CAIRN	EQ	INE910H01017
Cipla Ltd.	PHARMACEUTICALS	CIPLA	EQ	INE059A01026
DLF Ltd.	CONSTRUCTION	DLF	EQ	INE271C01023
GAIL (India) Ltd.	GAS	GAIL	EQ	INE129A01019
Grasim Industries Ltd.	CEMENT AND CEMENT PRODUCTS	GRASIM	EQ	INE047A01013
HCL Technologies Ltd.	COMPUTERS - SOFTWARE	HCLTECH	EQ	INE860A01027
HDFC Bank Ltd.	BANKS	HDFCBANK	EQ	INE040A01018
Hero Honda Motors Ltd.	AUTOMOBILES - 2 AND 3 WHEELERS	HEROHONDA	EQ	INE158A01026
Hindalco Industries Ltd.	ALUMINIUM	HINDALCO	EQ	INE038A01020
Hindustan Unilever Ltd.	DIVERSIFIED	HINDUNILVR	EQ	INE030A01027
Housing Development Finance Corporation Ltd.	FINANCE - HOUSING	HDFC	EQ	INE001A01028
I T C Ltd.	CIGARETTES	ITC	EQ	INE154A01025
ICICI Bank Ltd.	BANKS	ICICIBANK	EQ	INE090A01013
Idea Cellular Ltd.	TELECOMMUNICATION - SERVICES	IDEA	EQ	INE669E01016
Infosys Technologies Ltd.	COMPUTERS - SOFTWARE	INFOSYSTCH	EQ	INE009A01021
Larsen & Toubro Ltd.	ENGINEERING	LT	EQ	INE018A01030
Mahindra & Mahindra Ltd.	AUTOMOBILES - 4 WHEELERS	M&M	EQ	INE101A01018
Maruti Suzuki India Ltd.	AUTOMOBILES - 4 WHEELERS	MARUTI	EQ	INE585B01010
NTPC Ltd.	POWER	NTPC	EQ	INE733E01010
National Aluminium Co. Ltd.	ALUMINIUM	NATIONALUM	EQ	INE139A01026
Oil & Natural Gas Corporation Ltd.	OIL EXPLORATION/PRODUCTION	ONGC	EQ	INE213A01011
Power Grid Corporation of India Ltd.	POWER	POWERGRID	EQ	INE752E01010
Punjab National Bank	BANKS	PNB	EQ	INE160A01014
Ranbaxy Laboratories Ltd.	PHARMACEUTICALS	RANBAXY	EQ	INE015A01028

Reliance Capital Ltd.	FINANCE	RELCAPITAL	EQ	INE013A01015
Reliance Communications Ltd.	TELECOMMUNICATION - SERVICES	RCOM	EQ	INE330H01018
Reliance Industries Ltd.	REFINERIES	RELIANCE	EQ	INE002A01018
Reliance Infrastructure Ltd.	POWER	RELINFRA	EQ	INE036A01016
Reliance Petroleum Ltd.	REFINERIES	RPL	EQ	INE475H01011
Reliance Power Ltd.	POWER	RPOWER	EQ	INE614G01033
Siemens Ltd.	ELECTRICAL EQUIPMENT	SIEMENS	EQ	INE003A01024
State Bank of India	BANKS	SBIN	EQ	INE062A01012
Steel Authority of India Ltd.	STEEL AND STEEL PRODUCTS	SAIL	EQ	INE114A01011
Sterlite Industries (India) Ltd.	METALS	STER	EQ	INE268A01031
Sun Pharmaceutical Industries Ltd.	PHARMACEUTICALS	SUNPHARMA	EQ	INE044A01028
Suzlon Energy Ltd.	ELECTRICAL EQUIPMENT	SUZLON	EQ	INE040H01021
Tata Communications Ltd.	TELECOMMUNICATION - SERVICES	TATACOMM	EQ	INE151A01013
Tata Consultancy Services Ltd.	COMPUTERS - SOFTWARE	TCS	EQ	INE467B01029
Tata Motors Ltd.	AUTOMOBILES - 4 WHEELERS	TATAMOTORS	EQ	INE155A01014
Tata Power Co. Ltd.	POWER	TATAPOWER	EQ	INE245A01013
Tata Steel Ltd.	STEEL AND STEEL PRODUCTS	TATASTEEL	EQ	INE081A01012
Unitech Ltd.	CONSTRUCTION	UNITECH	EQ	INE694A01020
Wipro Ltd.	COMPUTERS - SOFTWARE	WIPRO	EQ	INE075A01022
Zee Entertainment Enterprises Ltd.	MEDIA & ENTERTAINMENT	ZEEL	EQ	INE256A01028

APPENDIX II
CONTRACT SPECIFICATIONS

The security descriptor for the S&P CNX Nifty futures contracts is:

Market type : N
Instrument Type : FUTIDX
Underlying : NIFTY
Expiry date : Date of contract expiry

Instrument type represents the instrument i.e. Futures on Index, Underlying symbol denotes the underlying index which is S&P CNX Nifty and its Expiry date identifies the date of expiry of the contract. Normally, the trading cycle in S&P CNX Nifty futures contracts have a maximum of 3-month trading cycle - the near month (one), the next month (two) and the far month (three). A new contract is introduced on the trading day following the expiry of the near month contract. The new contract will be introduced for three month duration. This way, at any point in time, there will be 3 contracts available for trading in the market i.e., one near month, one mid month and one far month duration respectively. Normally, the expiry day S&P CNX Nifty futures contracts expire on the last Thursday of the expiry month. If the last Thursday is a trading holiday, the contracts expire on the previous trading day.

Trading Parameters of the Index futures includes; Contract size, the contract size of the futures contracts on Nifty may not be less than Rs. 2 lakhs at the time of introduction. The permitted lot size for futures contracts & options contracts shall be the same for a given underlying or such lot size as may be stipulated by the Exchange from time to time. And the price step in respect of S&P CNX Nifty futures contracts is Re.0.05. The Base price of S&P CNX Nifty futures contracts on the first day of trading would be theoretical futures price. The base price of the contracts on subsequent trading days would be the daily settlement price of the futures contracts. And its prices bands are no day minimum/maximum price ranges applicable for S&P CNX Nifty futures contracts. However, in order to prevent erroneous order entry by trading members, operating ranges are kept at +/- 10 %. In respect of orders which have come under price freeze, members would be required to confirm to the Exchange that there is no inadvertent error in the order entry and that the order is genuine. On such confirmation the Exchange may approve such order. The quantity freeze Order which may come to the exchange as a quantity freeze shall be based on the notional value of the contract of around Rs. 5 crores. In respect of orders which have come under quantity freeze, members would be required to confirm to the Exchange that there is no inadvertent error in the order entry and that the order is genuine. On such confirmation, the Exchange may approve such order. However, in exceptional cases, the Exchange may, at its discretion, not allow the orders that have come under quantity freeze for execution for any reason whatsoever including non-availability of turnover / exposure limits. The order type/Order Book/Order attribute includes a) Regulator lot order, b) Stop loss order, c) Immediate or cancel and d) Spread Order.

APPENDIX – III
REVERSE REPRESENTATION OF ENGLE GRANGER'S CO-INTEGRATION REGRESSION

Step 1: The first step is to present the variables for their order of integration. This has been done in the main section and the results 2b.
Step 2: To test the long run equilibrium relation, a co-integration equation was run, with futures index as the dependent variable

$$F_t = \beta_0^{'} + \beta_1^{'} S_t + e_t^{'}$$

Where F_t is the futures returns at time t, S_t is the spot return series and $e_t^{'}$ is the residual term.

Table A1: **Test for co-integration and the fitted ECM for F_t**

	Coefficient estimated	Coefficient value	t-ratio
One Min	$\beta_0^{'}$	0.0001624348	0.44096
	$\beta_1^{'}$	0.4755755574	91.77303
Five Min	$\beta_0^{'}$	0.0005753899	0.63011
	$\beta_1^{'}$	0.6401425388	126.89406
Ten Min	$\beta_0^{'}$	0.0012140215	0.86265
	$\beta_1^{'}$	0.6613111778	116.35854
One Hour	$\beta_0^{'}$	0.0040331148	0.81475
	$\beta_1^{'}$	0.7263879861	79.47694

Table A2: Engle-Granger Co-integration test statistics

	Engle-Granger Co-integration t-statistics
One Min	-345.98006**
Five min	-141.80332**
Ten Min	-96.07065**
One Hour	-41.72303**

The above tables give the Engle-Granger test results on the residuals of co-integration equation. This test is done to determine if the residuals of the co-integration equation are stationary.

Step 3: Estimating the Error correction Model by regressing changes in spot index on last period's futures index equilibrium error and lagged futures and spot index. Regressing changes in futures index on last periods of futures index equilibrium error and lagged futures and spot index.

$$\Delta S_t = \alpha_1^{'} + \alpha_s^{'} \hat{e}_{t-1}^{'} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{st}^{'}$$
$$\Delta F_t = \alpha_2^{'} + \alpha_f^{'} \hat{e}_{t-1}^{'} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{ft}^{'}$$

In the above equations, ΔS_t and ΔF_t denote, respectively, the first differences in the log of spot and futures prices for one time period, $\hat{e}_{t-1}^{'}$ is the lagged error correction term from the co-integrating equation and $\varepsilon_{st}^{'}$ and $\varepsilon_{ft}^{'}$ are the white noise disturbance terms

Table A3: Error Correction Model for change in Nifty spot Index for one minute

ECM with change in spot index as the dependent variable

$$\Delta S_t = \alpha_1^{'} + \alpha_s^{'} \hat{e}_{t-1}^{'} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{st}^{'}$$

Variable	**Coefficient**	**Standard error**	**T-Stat**
$\alpha_1^{'}$	-0.000000498	0.000123776	-0.00402
$\alpha_s^{'}$ (ECM)	0.066635749	0.003504070	19.01667
D_SRT(1)	-0.711482747	0.002209921	-321.94945
D_SRT(2)	-0.550918371	0.002265216	-243.20792
D_SRT(3)	-0.424554294	0.002168034	-195.82457
D_SRT(4)	-0.300812661	0.001971892	-152.55026
D_SRT(5)	-0.166481612	0.001625532	-102.41670
D_FRT(1)	0.088383423	0.003165041	27.92489
D_FRT(2)	0.091518673	0.002646392	34.58244
D_FRT(3)	0.073640765	0.002024287	36.37862
D_FRT(4)	0.046172557	0.001351412	34.16615
D_FRT(5)	0.018613233	0.000679417	27.39590

Table A4: Error Correction Model for change in Nifty Futures Index for one minute

ECM with change in Futures index as the dependent variable

$$\Delta F_t = \alpha_2^{'} + \alpha_f^{'} \hat{e}_{t-1}^{'} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{ft}^{'}$$

Variable	Coefficient	Standard error	T-Stat
$\alpha_2^{'}$	-0.000002572	0.000303790	-0.00846
$\alpha_f^{'}$ (ECM)	3.221198853	0.008600190	374.54972
D_SRT(1)	-0.906568586	0.005423905	-167.14317
D_SRT(2)	-0.519829157	0.005559617	-93.50089
D_SRT(3)	-0.258425491	0.005321100	-48.56618
D_SRT(4)	-0.097521469	0.004839701	-20.15031
D_SRT(5)	-0.029457218	0.003989614	-7.38348
D_FRT(1)	1.496755072	0.007768099	192.67971
D_FRT(2)	0.953320081	0.006495154	146.77405
D_FRT(3)	0.550106441	0.004968295	110.72339
D_FRT(4)	0.267515519	0.003316830	80.65397
D_FRT(5)	0.086092180	0.001667522	51.62882

Table A5: Error Correction Model for change in Nifty spot Index for Five minutes

ECM with change in spot index as the dependent variable

$$\Delta S_t = \alpha_1^{'} + \alpha_s^{'} \hat{e}_{t-1}^{'} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{st}^{'}$$

Variable	Coefficient	Standard error	T-Stat
$\alpha_1^{'}$	-0.000007494	0.000680429	-0.01101
$\alpha_s^{'}$ (ECM)	0.078827291	0.015011141	5.25125
D_SRT(1)	-1.017243212	0.009357673	-108.70686
D_SRT(2)	-0.873855414	0.008652770	-100.99141
D_SRT(3)	-0.647594174	0.007544365	-85.83813
D_SRT(4)	-0.416397237	0.005991413	-69.49900
D_SRT(5)	-0.172109688	0.003950338	-43.56835
D_FRT(1)	0.143423612	0.013601685	10.54455
D_FRT(2)	0.146575825	0.011493710	12.75270
D_FRT(3)	0.128098811	0.008934004	14.33834
D_FRT(4)	0.084407399	0.006098045	13.84171
D_FRT(5)	0.032730985	0.003156071	10.37080

Table A6: Error Correction Model for change in Nifty Futures Index for Five minute

ECM with change in Futures index as the dependent variable

$$\Delta F_t = \alpha_2^{'} + \alpha_f^{'} \hat{e}_{t-1}^{'} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{ft}^{'}$$

Variable	Coefficient	Standard error	T-Stat
$\alpha_2^{'}$	0.000000885	0.000893277	9.90803e-04
$\alpha_f^{'}$ (ECM)	2.693986708	0.019706839	136.70314
D_SRT(1)	-1.259337410	0.012284886	-102.51112
D_SRT(2)	-0.878553992	0.011359479	-77.34105
D_SRT(3)	-0.558021460	0.009904349	-56.34105
D_SRT(4)	-0.319295332	0.007865612	-40.59383
D_SRT(5)	-0.109361822	0.005186059	-21.08765
D_FRT(1)	1.077098041	0.017856485	60.31971
D_FRT(2)	0.646510549	0.015089106	42.84618
D_FRT(3)	0.362816450	0.011728688	30.93410
D_FRT(4)	0.184097198	0.008005601	22.99605
D_FRT(5)	0.061263583	0.004143335	14.78606

Table A7: Error Correction Model for change in Nifty spot Index for Ten minutes

ECM with change in spot index as the dependent variable

$$\Delta S_t = \alpha_1^{'} + \alpha_s^{'} \hat{e}_{t-1}^{'} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{st}^{'}$$

Variable	Coefficient	Standard error	T-Stat
$\alpha_1^{'}$	-0.000021960	0.001300518	-0.01689
$\alpha_s^{'}$ (ECM)	0.158497442	0.023136490	6.85054
D_SRT(1)	-1.067009415	0.014718089	-72.49646
D_SRT(2)	-0.866206268	0.013487804	-64.22145
D_SRT(3)	-0.609209964	0.011640930	-52.33345
D_SRT(4)	-0.414537753	0.009089528	-45.60608
D_SRT(5)	-0.188328656	0.005849339	-32.19657
D_FRT(1)	0.238939930	0.020932969	11.41453
D_FRT(2)	0.253620960	0.017797826	14.25011
D_FRT(3)	0.196595291	0.014087686	13.95512
D_FRT(4)	0.126383947	0.009902855	12.76237
D_FRT(5)	0.049661806	0.005279408	9.40670

Table A8: Error Correction Model for change in Nifty Futures Index for Ten minutes

ECM with change in Futures index as the dependent variable

$$\Delta F_t = \alpha_2^{'} + \alpha_f^{'} \hat{e}_{t-1}^{'} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{ft}^{'}$$

Variable	Coefficient	Standard error	T-Stat
$\alpha_2^{'}$	0.000003652	0.001507336	0.00242
$\alpha_f^{'}$ (ECM)	2.431781709	0.026815842	90.68452
D_SRT(1)	-1.166707101	0.017058679	-68.39375
D_SRT(2)	-0.792593403	0.015632744	-50.70085
D_SRT(3)	-0.468535957	0.013492164	-34.72652
D_SRT(4)	-0.282629589	0.010535018	-26.82763
D_SRT(5)	-0.109549425	0.006779548	-16.15881
D_FRT(1)	0.894272802	0.024261899	36.85914
D_FRT(2)	0.576892261	0.020628180	27.96622
D_FRT(3)	0.339640128	0.016328024	20.80106
D_FRT(4)	0.180857306	0.011477687	15.75729
D_FRT(5)	0.061101154	0.006118982	9.98551

Table A9: Error Correction Model for change in Nifty spot Index for One Hour

ECM with change in spot index as the dependent variable

$$\Delta S_t = \alpha_1^{'} + \alpha_s^{'} \hat{e}_{t-1}^{'} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{st}^{'}$$

Variable	Coefficient	Standard error	T-Stat
$\alpha_1^{'}$	-0.000107804	0.006121999	-0.01761
$\alpha_s^{'}$ (ECM)	0.173294272	0.060753620	2.85241
D_SRT(1)	-1.160852189	0.041416268	-28.02889
D_SRT(2)	-1.024127950	0.037230108	-27.50806
D_SRT(3)	-0.772473920	0.031563505	-24.47364
D_SRT(4)	-0.456075359	0.024145514	-18.88862
D_SRT(5)	-0.194663865	0.014838519	-13.11882
D_FRT(1)	0.333266775	0.054995486	6.05989
D_FRT(2)	0.368155228	0.047049266	7.82489
D_FRT(3)	0.310088355	0.037739992	8.21644
D_FRT(4)	0.181596680	0.027036489	6.71673
D_FRT(5)	0.072815864	0.015010148	4.85111

Table A10: Error Correction Model for change in Nifty Futures Index for One Hour

ECM with change in Futures index as the dependent variable

$$\Delta F_t = \alpha_2^{'} + \alpha_f^{'} \hat{e}_{t-1}^{'} + lagged(\Delta S_t, \Delta F_t) + \varepsilon_{ft}^{'}$$

Variable	**Coefficient**	**Standard error**	**T-Stat**
$\alpha_2^{'}$	0.000009218	0.006407628	0.00144
$\alpha_f^{'}$ (ECM)	2.172948438	0.063588148	34.17222
D_SRT(1)	-1.211487571	0.043348591	-27.94757
D_SRT(2)	-0.893429909	0.038967120	-22.92779
D_SRT(3)	-0.607697188	0.033036136	-18.39492
D_SRT(4)	-0.310578577	0.025272050	-12.28941
D_SRT(5)	-0.108720051	0.015530827	-7.00027
D_FRT(1)	0.790228159	0.057561362	13.72845
D_FRT(2)	0.542800566	0.049244402	11.02258
D_FRT(3)	0.352891453	0.039500793	8.93378
D_FRT(4)	0.172735968	0.028297906	6.10420
D_FRT(5)	0.066552365	0.015710463	4.23618

SYNOPSIS OF THESIS

TITLED

THE INTERDEPENDENCE BETWEEN THE SPOT AND INDEX FUTURES MARKETS IN INDIA: AN EMPIRICAL ANALYSIS

BY
VARADI. VIJAY KUMAR
(04SEPH05)

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DR. B. NAGARJUNA

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UNIVERSITY OF HYDERABAD

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THE INTERDEPENDENCE BETWEEN THE SPOT AND INDEX FUTURES MARKETS IN INDIA: AN EMPIRICAL ANALYSIS

INTRODUCTION:

The Indian capital market has witnessed a major transformation and structural change over the last decade. As a result of the initiated financial sector reforms by the government, Indian capital market mounted to an international touchstone. As a part of such reforming process, one of the important steps taken in the secondary market is the introduction of derivative product viz., Index Futures in two major Indian stock exchanges viz., National Stock Exchange of India Ltd (NSE) and Bombay Stock Exchange (BSE) in June 2000. Index Futures were introduced to enhance information flow of the cash market, to provide tools for risk management and wider investment choices to investors in order to make the markets more complete and compete. Though, the inception of the said derivative product along with other equity-based derivatives (viz., Index Option, Stock Options and Stock Futures) trading has significantly altered the movement of stock prices in Indian spot market, it is yet to be proved whether these derivative products has served the purpose claimed by the regulators. In order words, in an efficient capital market where all available information is fully and instantaneously utilized to determine the market price of securities, prices in the futures and spot market should move simultaneously without any delay. In addition, if markets are complete and perfect, derivative and underlying spot prices must reflect information simultaneously; otherwise, difference in prices would induce arbitrage opportunity. However, in the presence of market imperfections such as transaction cost, asymmetric information and other market microstructure effects, prices for the same underlying may differ in these two markets at any given point of time. Therefore, a thorough understanding of inter-linkages between spot and futures markets, in returns and volatility, is of concern for practitioners, regulators apart from researchers. So, before moving to understand the inter-linkages between spot and futures markets study makes a serious attempt to review the existing literature and presents the observations including gaps particularly to Indian studies.

REVIEW OF LITERATURE:

To understand the long-run and short-run behaviors of individual cash and futures market movements and their interactions is crucial to studies that address the aforementioned issues. In recent literature, issues of a wide range about the S&P 500 cash and futures market relationship have been addressed, including the price and volatility lead-lag relationship (for example, see Herbst et.al., 1987; Kawaller et.al., 1987, 1990; Stoll &Whaley, 1990; Cheung & Ng, 1991; Chan et.al., 1991; Chan, 1992; Koutmos, & Tucker, 1996), the price conintegration (for example, see Wahab & Leshangri ,1993; Wang & Yau, 1994), and the futures hedging issues related to the price integration and conditional covariance heteroskedasticity (for example, Myers, 1991;; Ghosh, 1993; Lien & Luo, 1994). The co-integration test originated by Engle and Granger (1987) is now used widely in studying the price co-movement between the S&P cash and futures markets with growing understandings that their close relationship is of a long-run nature, and that this long-run relationship can be frequently disturbed by short-run deviations between the two markets. Thus error correction model (ECM), the key concept address the long and short-run interactions, need to be applied.

Several studies have examined the lead-lag relationship between futures and spot markets (e.g., Kwaaller et.al., 1987; Chan, Chan and Karolyi, 1991; chan, 1992; Quan, 1992; Crain and Lee, 1995; Cheung and Ng, 1996, 1996; Shyv et al., 1996; Jong et.al., 1996; Scalia, 1998; Mind and Nijand, 1999 Silvapulle and Moosa, 1999; and Frino et.al., 2000). Lead-lag relationships are examined on returns and volatilities. The results of these studies generally suggest that futures prices lead spot prices, and that there is a bidirectional causality between the volatilities of futures and spot markets. For example, Kwaller et.al. (1987) investigate the intraday price relationship between S&P 500 futures and spot markets, and find that near by futures prices lead index by twenty to forty-five minutes. Cahn et.al (1991) examine intraday relationship between returns and volatility of the returns in the S&P 500 futures and spot markets. They find that futures lead spot returns and the there is strong bidirectional causality in volatility. Min and Najand (1999) study the lead-lag relationship in returns and volatility of the returns between Korea Composite Stock Price Index (KOSPI) 200 spot and futures markets. They find that futures prices lead spot prices by as long as 30 minutes while there is a bidirectional causality in volatility. The main argument for the observed lead-lag relationship between the spot and futures markets in that futures prices lead spot prices because futures have lower transaction costs and fewer restrictions on short selling. When new information arrives, less cash and time are required to trade in the futures markets than to trade in the spot market. Therefore, informed traders trade in the futures markets. The general finding that there is a bi-directional causality between the volatilities of the futures and spot prices indicates that each market takes advantages of the other market's information processing ability while adjusting to the information.

These studies use high frequency data (one minute / five minute returns) and employ range of techniques from simple granger causality to complex VAR-GARCH, co-integration type of models. The common thread of learning from the literature is that the futures market leads the spot market and the lead varies from, as per the market under consideration, five to forty minutes. However, spot market rarely leads the futures market. The common explanations for observing such inter-linkage between the two markets are the infrequent trading of component stocks of the index in spot market and the higher leverage offered by futures markets to the investors. Apart from this, while examining the volatility spillover, Abhyankar (1995), Tse (1999) and Min (1999) have documented that unlike a uni-directional effect from futures to spot in returns, there is a bi-directional or contemporaneous relationship among the spot and the derivative markets, with bad news having a greater impact on volatility.

NEED FOR THE PRESENT STUDY:

As observed after a detailed investigation in earlier literature that most of these studies are on developed markets, one should take care in extending these results to emerging markets. Since India being an emerging market in derivative products and being transformed as one of the largest with respect to trading volumes in these segments, significant lack of a comprehensive study with respect to emerging markets is needed. . Though there exist few studies as of now, Thenmozhi 2002; Anand Babu 2004; Kedarninath Mukharjee et.al 2007; Bhaskar Sinha 2007, all these studies looked at lead-lag relation between spot and index futures markets by employing daily and monthly data except for one study by Kedanath Mukharjee et.al. Hence most of the studies are not able to capture intra-day dynamics that die out on a daily basis. Further, these studies employ granger causality type of techniques and hence not able to address volatility spillover between the markets. The present study attempts to fill these gaps along with others and tries to be a comprehensive one for the lead-lag relationship study for the India.

OBJECTIVES OF THE STUDY:

Therefore, to answer the above said research questions, the present study are being contemplated with the following specific objectives:

I. To investigate the lead lag relationship between the spot and futures market in India, both in terms of return and volatility
   a. To discover market co-movements
   b. To explain price leadership effects
   c. Volatility spillovers across markets

II. To incorporate price co-integration relationship between spot and futures markets in the lead lag relationship analysis.

The present study seeks to contribute to the existing knowledge base and literature by not only examining the actual lead-lag relationship among the Indian spot and futures market in terms of return and volatility, and also in terms co-integration effect.

DATA SOURCES:

The basic data proposed to be used in this study consist of intraday price histories from January 2001 to November 2005 for the nearby contract of nifty index futures, nifty spot index. The required intra-day data will be obtained from NSE Research Initiative and then we construct five minute, one minute, ten minute and one hour (logarithmic) return series for both Nifty spot and futures indices.

METHODOLOGY:

In this section we investigate the lead-lag relationship between the S&P CNX Nifty Index and Index Futures contracts for India. Most tests of the lead-lag relationship make use of intra-daily data on stock index and stock index futures returns. One of the problems associated with tests of lead-lag relationships based on intra-daily data is the possible effect non-synchronous trading can have on the results. Indeed, the evidence suggests that it can have a substantive impact on observed return behaviour (Stoll and Whaley. 1990; Miller *et al.,* 1994). To minimize the possible effects of non-synchronous trading and hence reduce the possibility of identifying a spurious lead-lag relationship while at the same time allowing for lead-lag relationships to genuinely exist we use five minutes or one minute data returns on both the S&P CNX Nifty and Futures contracts over the period over the period 1st January 2001 to 30th November 2005 respectively. The S&P CNX Nifty Index should not exhibit any non-synchronous trading effects since it is calculated from mid-quotes that are binding, that is, market makers will trade at the quoted prices. Therefore, assuming that market makers update their quotes, non-trading effects should not be present. The S&P 500 Index is constructed on the basis of transaction prices and therefore non-synchronous trading effects may be present and thus may contaminate the results. Fortunately, a check to determine whether non-trading effects are present can be undertaken since if they are, from the models in Lo and MacKiniay (1990) and Miller *et al.* (1994), observed returns will follow a first-order auto-regressive process with a positive coefficient on lagged observed returns.

The importance of this is that if factors such as non-trading are present then they may induce a spurious lead-lag relationship because in the case of non-trading the index will contain stale prices and thus the futures will appear to lead the spot for no other reason than the effect of stale prices on the index. Note also that technically, we can distinguish between non-trading and non-synchronous trading. Non-synchronous trading is the situation where securities trade at least once every time interval but not necessarily at the end of the interval, whereas non-trading is the situation where securities do not trade for several time intervals. However, since the effect of both of these is to induce autocorrelation in stock returns, we will use the two interchangeably here.

This section elaborates on the statistical methods of analyzing the temporal relationship between index futures and nifty index. The time series variables tending to behave like random walks are addressed in this empirical analysis to avoid spurious results. Basing on the existing econometric literature the data considered for present study are verified with time series properties of stationarity. The unit root test of Augmented Dickey-fuller (ADF) was first tested for the presence of stationarity at level term for both Index futures and Nifty Index. If unit root exists, the series are non-stationary. So the ADF test has been performed at the first difference to find the stationarity.

$$\Delta X_t = \alpha + \gamma U_{kt-1} + \delta \Delta U_{kt} + \varepsilon_t$$

Where ΔX is the difference in X at time 't' [$X_t - X_{t-1}$], U_{kt-1} is lag one observation of series U. ε_t is the random error variable with (0, σ^2).

To examine the theoretical relationship between the price of an index futures contract and the price level of the underlying index is

$$F_t = S_t e^{[(r-d)(T-t)]} \qquad (1)$$

The market force driving the cost-of-carry relation (1) is never ending search for a 'free-lunch'. When the futures price is above the level implied by the RHS of (1), a riskless arbitrage profit equal to the difference between the futures price and the index price plus the cost of carry, a long arbitrage profit of $F_t - S_t e^{[(r-d)(T-t)]}$ can be earned by selling the futures contract and buying the stock index portfolio, financing the stock purchase with riskless barrowings.

On the other hand, when the futures price falls below the RHS of (1), a short arbitrage profit of $S_t e^{[(r-d)(T-t)]} - F_t$ it can be earned by buying the futures and selling the portfolio stocks, investing the proceeds of the sale of stock at the riskless rate of interest.

In perfectly efficient and continuous future and stock markets in the absence of transaction cost, riskless arbitrage profit opportunities should not appear so the cost-of-carry relation (1) should be satisfied at every instant 't' during the futures contract life.

If this is not the case, the instantaneous rate of price appreciation in the stock index equal that cost of carry of the stock portfolio plus the instantaneous relative price change of the futures contract i.e.,

$$R_{s,t} = (r-d) + R_{f,t}$$

Where $R_{s,t} = Ln(S_t / S_{t-1})$, and $R_{f,t} = Ln(F_t / F_{t-1})$ (2)

Several implications follow from equation (2) under the assumptions that the short term interest rate and the dividend yield rate of the stock index are constant and that the index futures and stock markets are different and continuous.

1. The expected rate of price appreciation on the stock index portfolio $E(R_{s,t})$ equals to net cost of carry $(r-d)$ plus the expected rate of return on the futures contract $E(R_{f,t})$.
2. The standard deviation of the rate of return on the futures contract equals the standard deviation of the rate of return of the underlying stock index.
3. The contemporaneous rates of return on the futures contract and the underlying stock portfolio are perfectly positively correlated.
4. The rates of return of the futures contract and of the underlying stock index portfolio are serially uncorrelated.
5. The non-contemporaneous rates of return of the futures contract and the underlying stock portfolio are uncorrelated.

By nature, all the above implications are based on the assumption that the cost-of-carry relation (1) holds at all points in time. However, it has been shown, that (1) does not hold exactly; indeed one of the puzzles in stock index futures-is the frequency with which deviations from (1) are observed.

Violations of the cost-of-carry relation may appear for a variety of reasons, some are purely technological. An **important one among them is the** infrequent trading of stock with in the index. Since Markets for individual stocks are not perfectly continuous. Stock index prices which are averages of the last transaction prices of component stocks-lag actual developments in the stock market (Fisher,1966 described it). Cohen, et.al (1986) gives a more general discussion of serial correlation of stock index returns in terms of delays in the price adjustment of securities. Lo and Mackinlay (1988) model the effects of infrequent trading on index returns under restrictive assumptions. Assuming that the index futures prices instantaneously reflect new information, observed futures returns should be expected to lead observed stock index returns because of infrequent trading, even though there is no economic significance to this behaviour, whatsoever.

A **second reason** for violation of relation (1) is that transaction costs tend to induce noise in the relation (2). The prices used in the computations of returns are transaction prices, and these transaction prices tend to fluctuate randomly between the bids & ask levels. The random price movement between bid and ask prices in successive transactions induces negative serial correlation in observed returns even though the true returns are serially independent.

Similarly, at the individual security level, the negative serial correlation due to the bid/ask price effect is understandable, but the effect seems less likely when one considers a stock index portfolio for which movements between the bid and ask for some stocks could be offset by opposite movements from the ask to bid for other stocks; however, to the extent that the rates of return of the stocks in the index are positively correlated and/or that the index is narrowly based, negative serial correlation in individual stock return attributable to the bid/ask price effect also might appear in the stock index returns.

A **third reason** in violation of the cost of carry relation has to do with time delays in the computation and reporting of the stock index value. Once the transaction in the stock market takes place, the transaction information is entered into a computer and transmitted to the particular service that updates and transmits the index level. Three time delays therefore possible.

1. The delay in entering the stock transaction into the computer
2. The delay in computing and transmitting the new index value, and
3. The delay in recording stock index value at the futures exchange

Assuming that the new information arrives in the stock and futures markets simultaneously, such delays would tend to show the futures market returns leading stock index returns.

In order to examine all the adverted things above, study reports first descriptive statistics that includes stationary results and identifies their order of integration (hire Engle-Granger tests), then proceeds for co-integration analysis by employing VECM (Vector Error Correction Model) to verify the existence of lead-lag relationship.

$$\Delta \mathrm{S}_{\mathrm{t}} = \alpha_1 + \alpha_s \hat{e}_{t-1} + lagged\left(\Delta S_t, \Delta F_t\right) + \varepsilon_{s,t}$$
$$\Delta \mathrm{F}_{\mathrm{t}} = \alpha_1 + \alpha_f \hat{e}_{t-1} + lagged\left(\Delta S_t, \Delta F_t\right) + \varepsilon_{f,t}$$

In the above equations, ΔS_t and ΔF_t denote, respectively, the first differences in the log of spot and futures prices for one time period. $\hat{e}_{t-1}$ is the lagged error correction term from the co-integrating equation and $\varepsilon_{s,t}$ and $\varepsilon_{f,t}$ are the white noise disturbance terms. The above equations describe the short-run as well as long-run dynamics of the equilibrium relationship between spot index and futures index. They provide information about the feedback interaction between the two variables.

As pointed out earlier, the important gap identified and not attempted so far in Indian studies i.e., (for) verification of volatility spillover effects - the present study employs VAR – MGARCH family of techniques(VAR(1)-GARCH(1,1) using BEKK technique) as against ineffectual univariate analysis that provides more deeper insights.

To explain the volatility transfers between markets in the framework a BEKK-kind of VAR(1)-GARCH(1,1) model for 2 variables, we consider the following variance equitation’s:

$$h_{11t} = a_{11}(a_{11}\varepsilon_{1t-1}^2 + a_{21}\varepsilon_{1t-1}\varepsilon_{2t-1}) + a_{21}(a_{11}\varepsilon_{1t-1}\varepsilon_{2t-1} + a_{21}\varepsilon_{2t-1}^2) + b_{11}(b_{11}h_{11t-1} + b_{21}h_{21t-1}) + b_{21}(b_{21}h_{12t-1} + b_{21}h_{22t-1}) + c_{11}^2$$

$$h_{12t} = a_{12}(a_{11}\varepsilon_{1t-1}^2 + a_{21}\varepsilon_{1t-1}\varepsilon_{2t-1}) + a_{22}(a_{11}\varepsilon_{1t-1}\varepsilon_{2t-1} + a_{21}\varepsilon_{2t-1}^2) + b_{12}(b_{11}h_{11t-1} + b_{22}h_{21t-1}) + b_{22}(b_{12}h_{12t-1} + b_{21}h_{22t-1}) + c_{11}c_{12}$$

$$h_{21t} = a_{11}(a_{12}\varepsilon_{1t-1}^2 + a_{22}\varepsilon_{1t-1}\varepsilon_{2t-1}) + a_{21}(a_{12}\varepsilon_{1t-1}\varepsilon_{2t-1} + a_{22}\varepsilon_{2t-1}^2) + b_{11}(b_{12}h_{11t-1} + b_{22}h_{21t-1}) + b_{21}(b_{12}h_{12t-1} + b_{22}h_{22t-1}) + c_{11}c_{12}$$

$$h_{22t} = a_{12}(a_{12}\varepsilon_{1t-1}^2 + a_{22}\varepsilon_{1t-1}\varepsilon_{2t-1}) + a_{22}(a_{12}\varepsilon_{1t-1}\varepsilon_{2t-1} + a_{22}\varepsilon_{2t-1}^2) + b_{12}(b_{12}h_{11t-1} + b_{22}h_{21t-1}) + b_{22}(b_{12}h_{12t-1} + b_{22}h_{22t-1}) + c_{12}^2 + c_{22}^2$$

We are interested first of all in the impact of the squared residuals ε_{1t}^2 and ε_{2t}^2 on the 2 variances h_{11t} and h_{22t}, and the covariance. The volatility transfers are indicated in bold characters. Note that h_{12t} and h_{21t} are equal on the assumption that they were equal for the previous observation at time t-1 and so on until the beginning of the series. Using the BEKK modeling, we can show how far these squared residuals will lead to a strong change in h_{ijt}. We are aware that Isakov and Perignon (2000, p.133) wrote that, in their model, by using the Hadamard product in $B \Theta H_{t-1}$ instead of $B^{'} H_{t-1} B$, they constrain the volatility transmission mechanism. It is true that in this case, the only possible way for a market's volatility to influence another market's volatility is through shocks. However, it is not always sure that B will remain non negative definite or that H_t will have only positive elements on the main diagonal in all possible cases, in any possible situation. Further, the $B^{'} H_t B$ term in the BEKK model involves the presence of h_{11t-1} in the equation for h_{22t} and the presence of h_{22t-1} in the equation for h_{11t}. However, as h_{11t-1} and h_{22t-1} do not increase very fast, the main element of influence remains the squared residuals ε_{1t}^2 and ε_{2t}^2. The volatility spillover, the coefficient a_{21} will be relevant for measuring the effect of the spot markets volatility (h_{22t}) on futures markets volatility (h_{11t}). The coefficient a_{12} will be relevant for measuring the effect of futures market volatility on the spot market volatility. Moreover, the increase in volatility due to h_{t-1} take two steps: a shock happens in t-2, h_{t-1} increases at time t-1 only because of the shock in ε_{1t} or ε_{2t} at time t-2 and the increase in h_{t-1} will further increase h as late as in h_t. As we are interest in the mean impact of a shock after one period (independently from the shock that happened two periods before) and not only in the impact of one precise shock, ε_1 or ε_2 are the only important indicators for the volatility increase the next period.

ORGANIZATION OF THE THESIS:

The study has been organized into five chapters along with annexure and tables. The first chapter discusses the importance of the study with detailed objectives and data sources and its limitations and scope of the study. Chapter two takes up the review of literature includes; Theoretical and Empirical perspective along with focus on developed and emerging markets context with special due to Indian market scenario; key concepts of understanding of the problem; implications & gaps from the review; and problem solving methods. Chapter three is concerned with the methodological aspects and techniques used to attain the objectives of the study. In chapter four discussed the results follows findings and final chapter provide conclusions and recommendations for the further research.

SUMMARY AND CONCLUSIONS:

The present study is new to its kind in Indian case where the high frequency data for the period of January 2001 to November 2005 have been employed to investigate the lead lag relationship between the spot and futures market in India, both in terms of return and volatility by filling the gaps in the existing studies. Major finding are as follows; with the resemblance of majority of studies of the lead/lag relationship between the spot index and index futures markets in the world, we have found that the index NSE Nifty Index futures leads by up to 1-5 minutes on NSE Nifty Spot Index; also found that there is a bi-directional relationship between the spot and index futures; and also we found a strong contemporaneous relationship between futures and cash prices, along with some significant evidence that futures markets leads spot market during times of high volatility. Consequently, it has been observed that reactions in futures markets are faster, and movements in futures prices lead spot price fluctuations. Coming to other investigation viz., examining the lead-lag relationship between the spot and futures markets for different informational contents, One of the important roles attributed by the index futures markets is that of 'price discovery'; that is, the futures market reflects new information before the spot market. To elaborate, if new market information disseminates in the futures market before the stock market, then the introduction of a futures market increases the amount of information reflected in the spot price Hence to conclude, Booth, So, and Tse (1999) studied information sharing among index derivatives and found that futures prices lead spot prices. Here, the fact that futures markets contribute significantly to the discovery of the spot asset price justifies price discovery as an important aspect of market efficiency. Additionally, the study ascertained from price co-integration relationship between the spot and index futures markets in the lead - lag relationship analysis, that in the long run both returns are co-integrated.

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