Relationships between the Spot and Futures Markets in India

Nupur Hetamsaria* and Yildiray Yildirim**

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* ICFAI Business School, Hyderabad, India, nupur@ibsindia.org

** Martin J. Whitman School of Management, Syracuse University, NY, USA, yildiray@syr.edu

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Abstract

The stock index futures and individual stock futures of seven companies traded on the National Stock Exchange of India are analyzed: Reliance Industries, State Bank of India, Tata Steel, Oil and Natural Gas Corporation, Satyam Computer Services, Ranbaxy Laboratories, and ICICI Bank. The question as to whether or not the cost-of-carry model holds in the context of the securities under study, is investigated. A following question, whether or not changes in correlation over time can be attributed to the release of news in the market, is analyzed. The DCC GARCH model developed by Engle is used for the analysis.

Investigations of the lead-lag relationship between the spot and the futures markets, using the Granger causality test, reveal a unidirectional relationship between Nifty futures and the spot index return series. The spot market leads the futures market in the NSE for the period under study, for the index. It is also found that, except for Oil and Natural Gas Corporation, all the individual securities suggest independence of the spot and futures returns.

Keywords: Nifty index futures, stock futures, cost-of-carry model, lead-lag relationship, DCC GARCH model

1. Introduction

Exchange-traded index futures were launched in India in June 2000. Subsequently, other derivative products like index options, stock options, and stock futures, have been established. Derivative products are becoming increasingly popular. S&P CNX Nifty index (the Nifty) futures and stock futures are scaling new heights, breaking volume records daily. This paper analyzes the stock index futures and individual stock futures of seven companies traded on the National Stock Exchange (NSE) of India: Reliance Industries Limited (Reliance), State Bank of India Limited (SBI), Tata Steel (Tisco), Oil and Natural Gas Corporation Limited (ONGC), Satyam Computer Services, Ltd. (Satyam), Ranbaxy Laboratories (Ranbaxy), and ICICI Bank Limited (ICICI). We use daily-closing-price time-series data for the NSE only, since it accounts for about 99.5% of the market in derivatives trading in India in recent years.

We investigate whether or not the cost-of-carry model holds in the context of the securities under study. Can the changes in correlation between returns from the futures market and returns from the spot market over time be attributed to the release of news in the market? The Dynamic Conditional Correlation (DCC) GARCH model developed by Engle (2002) is used for the analysis. To our knowledge, this is the first use of this model in the context of the spot and futures markets.

We also find that, although the correlation between the returns of the futures and the spot markets is very high for the Nifty, ranging from 0.95 to 0.98, it is not constant and vary over time. The cost-of-carry model says that the returns of the spot market and the futures market should be perfectly contemporaneously correlated. However, the results of the DCC GARCH model reject this hypothesis. Also, we see that the dynamic correlation between the spot and the futures markets is sensitive to news releases in the market. Peaks and troughs in correlation are easily attributable to events like market scams or political upheaval in the country. The results of the DCC GARCH model for all seven companies under study indicate that the correlation between the spot and the futures return series is not constant.

Our study further investigates the lead-lag relationship between the spot and the futures markets using the Granger causality test. In the absence of market frictions and transaction costs, the returns on a stock index and its corresponding index futures contract are perfectly positively contemporaneously correlated. However, this does not happen in reality. Empirical research in other countries has shown that there is a lead-lag relationship between the two markets. Trading in the futures market requires little upfront cash compared to trading in the spot market. Consequently, a trader prefers to invest in the futures market rather than the cash market.

We found a unidirectional relationship, at a 5% significance level, between Nifty futures and the spot index return series. The spot market leads the futures market in the NSE of India for the period under study. This result violates the theory that the futures index should lead the spot index because the futures market acts as a price discovery vehicle due to its lower transaction costs and high leverage. Nevertheless, it may confirm that fact that introducing futures increases the information efficiency in the spot market.

In the case of the seven securities under study, other than ONGC all suggest independence since the two null hypotheses—futures does not lead the spot and spot does not lead the futures—are not rejected for all of them (at a 5% significance level). This could result from the fact that we use daily data rather than tick-by-tick data. However, it does indicate a certain degree of maturity in both markets, as far as the individual securities are concerned.

The paper is organized as follows. Section 2 presents a brief background of the Indian derivatives market. Section 3 reviews the relevant literature and explains the cost-of-carry model. In Section 4, we state the objectives and the descriptive statistics of data used for the study. Section 5 outlines the methodology. Section 6 presents the results and analysis, and Section 7 concludes.

2. A Background of the Indian Derivatives Market

Derivatives have had a long presence in India. The commodity derivatives market has been functioning in India since the nineteenth century with organized trading in cotton through the establishment of Cotton Trade Association in 1875. Since then, contracts on various other commodities have been introduced.

To assist market participants to manage risks through hedging, speculation, and arbitrage, the Securities Contracts (Regulation) Act of 1956, (SCRA) was amended in December 1999 to expand the definition of securities to include derivatives so that the whole regulatory framework governing securities trading could apply also to derivative trading.

The passage of this act made derivatives legal as long as they were traded on a recognized stock exchange. A start was made in June 2000 at the NSE and the Bombay Stock Exchange (BSE) with index futures contracts based on the S&P CNX Nifty index and the BSE Sensitive Index (Sensex). This was followed by approval for trading in options based on the Nifty and the Sensex and options on individual securities. Trading in index options commenced in June 2001. Trading in options on individual securities commenced in July 2001. Finally, trading in futures of individual stocks started in November 2001 (See Appendix 1, Evolution of Derivatives Trading in India).

There are currently only two players in the Indian derivatives market, the BSE and the NSE. Developments in the derivatives market during the first half of 2001 show that, in the course of just three months from February to April 2001, the derivatives market was transformed from a competitive duopoly to an effective monopoly. The BSE's market share was effectively wiped out in this short period. While the NSE accounted for about 99.5% of total turnover, the BSE accounted for less than 1% in 2004-05.

Stock futures and index futures are two of the most popular contracts traded on the NSE, with a market share of 59% and 29%, by turnover respectively, of the total derivatives market as of March 31, 2005. The NSE ranks number one in the world in the number of contracts traded for individual stocks futures and fifth for stock index futures, according to the World Federation of Exchanges as of March 31, 2005.

Volumes in the futures segment picked up significantly, as seen in Figure 1, before settling down in recent months. The traded value in the Futures and Options (F&O) segment was Rs.2,988.57 billion in March 2005 compared with a traded value in the cash segment of Rs.1,130.55 billion, a factor of 2.64 over the cash segment. Despite this growth in the derivatives market, questions such as "Does the derivatives market actually facilitate better price discovery?" were inadequately addressed and piqued our interest.

The few previous studies on this topic have found that the introduction of trading in index futures has reduced the volatility in the cash market. These studies concentrated on determining the impact of the introduction of the index futures on the spot index by using a simple F-test (Gupta & Kumar, 2002), a multiple linear regression model (Thenmozhi, 2002), and the GARCH (1,1) model (Shenbagaraman, 2003; Hetamsaria & Deb, 2004). There have been no attempts to test the cost-of-carry model in the Indian context. Mukherjee and Mishra (2006) come closest to our work; using intraday data, they check the lead-lag relationship of the cash and futures markets to find that the cash market leads the futures market.

The cost-of-carry model is a mathematical relationship between the spot and futures market returns. According to this model, the correlation coefficient between the spot market returns and the futures market returns should at all times be one. This implies that one of these markets should not lead the other. Information should get assimilated into the prices of the spot and the futures markets at the same time and the returns should change equally in both. We apply the DCC GARCH model to the spot and futures returns for the first time. With the help of the

DCC GARCH model, we determine whether or not the correlation between the spot and futures market returns is constant. In addition, we apply the Granger causality test to see if a lead-lag relationship exists between the spot and the futures returns in the NSE.

3. Literature Review

Policymakers and regulators are concerned about the impact of futures on the underlying cash market. The theoretical literature provides mixed evidence concerning the price discovery role of futures trading.

Much of the early literature is concerned with futures trading in commodities. Powers (1970) explains that the importance of futures exchanges lies in their facilitation of faster dissemination of information that percolates to the cash market, increasing the overall depth of the market. This is supported by the multi-role theory of the futures market of Danthine (1978).

Cox (1976) built a theoretical model to show enhanced information flows due to the presence of a centralized futures market. He found that futures trading does not destabilize prices and does not harm the trader in any way. In fact, he finds that the futures market provides more accurate signals for resource allocation, which improves the investment choices of investors.

Grossman (1988) argues that futures have an important informational role, which is not that for synthetic strategies. The use of synthetic strategies may result in more uncertainty about spot and futures prices. On the other hand, real futures contracts should increase market efficiency and make the markets less volatile. Futures increase volatility of the underlying cash market only if the cash market is illiquid.

Bray (1981) provides two theorems and proofs for sufficient conditions under which futures prices reflect all the information about determining the spot price and are informative about the spot price.

Contrary to the above conclusions, much of the theoretical literature claims that derivative is a dirty word (Figlewski (1981) & Stein (1987). It is commonly believed that futures are more volatile than the underlying spot market. The speculators that are attracted to its high leverage are mostly uninformed traders. This lower amount of information in futures traders, compared to cash market traders, likely increases asset volatility. This result in the formation of bubbles and, as a result of speculative trading of futures contracts, the cash market instrument does not reflect its fundamental economic value.

Figlewski (1981) studied the Government National Mortgage Association futures market and finds increased volatility in the cash market after the introduction of futures due to additional noise in futures prices resulting from uninformed trading which is passed on to the cash market.

Stein (1987) built a model that takes into account the imperfections in the information content of speculators, which results in an overall destabilizing of prices and welfare reduction. Kaldor (1939) argues that speculators can cause either price-destabilization or stabilization. In some markets, stabilizing forces may dominate over destabilizing forces; in other markets, it can be just the opposite.

Since the theoretical literature argues both in support of and against futures contracts, it is important to look at empirical investigations. A number of empirical studies have been carried out to examine the impact of the introduction of index and stock futures on the underlying market using methodologies such as simple analysis of variances, linear regression analysis, GARCH models, and causality analysis.

3.1 The Cost-of-carry Model

The cost-of-carry model states that in an efficient market, in the absence of market frictions, the returns in the spot and futures markets should be perfectly contemporaneously correlated. According to this model,

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

where F_t is the stock index futures price quoted at time t, S_t is the value of the underlying stock index, r and d are the risk-free rate and the dividend yield on the underlying index respectively, T is the expiration date of the futures contract, and $(T-t)$ is the time-to-maturity of the futures contract. The risk-free rate of interest and the dividend yield on the underlying stock index are assumed to be known, constant, and continuous.

Stoll and Whaley (1990) expanded equation (1) to express it in the form of returns from the futures and spot markets. Writing (1) in return form,

$$f_t = s_t - (r-d) \qquad (2)$$

where, $f_t = \ln(F_t / F_{t-1})$ and $s_t = \ln(S_t / S_{t-1})$. Clearly, spot and futures returns are perfectly contemporaneously correlated in this model and, as such, one market should not lead the other; that is, returns from one market should not help predict future returns in the other.

However, in reality this does not happen. Empirical research in other countries contradicts the cost-of-carry model. Market frictions such as transaction costs and market microstructure have been held responsible. Stoll and Whaley (1990) give four reasons why the cost-of-carry relation might be violated.

First is the infrequent trading of stocks within the index. Markets for individual stocks 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.

Second is the fact that transaction costs tend to induce noise in the model.

The third reason concerns time delays in the computation and reporting of the stock index value. Time delays can include delays in entering the stock transaction into the computer, delays in computing and transmitting the new index value, and delays in recording the stock index value at the futures exchange.

Fourth, faster dissemination of information in the futures market along with lower transaction costs and higher leverage in the futures market enables traders to act faster on information.

The violations of the cost-of-carry model mean that the returns from these two markets are not perfectly contemporaneously correlated. In our research, we attempt, for the first time to our knowledge, to measure the dynamic correlation between the two markets.

3.2 Lead-lag Relationship Studies

Most studies on the lead-lag relationship have found—generally using the Granger (1969) causality specification—that the futures market leads the underlying stock market. Such results shed some light on the price discovery role of the futures market.

Trading in the futures market requires little upfront cash as compared to the spot market. Consequently, traders prefer the futures market. This preference for cost efficiency can cause the futures market to lead the spot market (Jong & Donders, 1998), serving as a price discovery vehicle.

Kawaller, Koch, and Koch (1987) study the minute-by-minute data of the S&P 500 index and their futures contracts using a three-stage least-squares regression for all trading days during 1984 and 1985. They find that futures prices consistently lead spot prices. However, they also find that there is a much shorter lead from the spot market to the futures market. Harris (1989) studied the five-minute S&P 500 index returns and the returns of its futures contracts over a 10-day period around the crash of October 1987. Even after adjusting for the problem of non-synchronous trading[1], and even though the data period was totally different from that studied by Kawaller et. al., he found that the futures market strongly leads the spot market.

[1] Non-synchronous trading is the situation where securities trade at least once every time interval but not necessarily at the end of the interval (See Brooks, Garrett & Hinich (1999)).

Stoll and Whaley (1990) extended the previous studies by including Major Market Index (MMI) futures, along with S&P 500 futures. Using an ARMA process, they too find that futures lead the spot market by as much as five to 10 minutes. They find that the relationship is not completely unidirectional, similar to the findings of Kawaller et. al. They also 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, the lead-lag relationship between the S&P 500 index and the index futures market persists. They assert that the futures market enhances market efficiency and leads to more complete markets, bringing more private information to the market and allowing for quicker dissemination of information.

Schwarz and Laatsch (1991), study MMI and MMI Maxi futures contracts for the period September 2, 1985 to March 31, 1988. They find that neither market maintains price leadership at all times. However, they say that futures markets are an important means of price discovery in spot markets and oppose restrictions imposed on them after the October 1987 crash.

Chan (1992) reaches the same conclusions as Stoll and Whaley (1990), arguing that the futures market is the main source of market-wide information. He also studies the lead-lag relationship between MMI and MMI futures and S&P 500 futures during significant news releases. He finds that the results are not much different during either good or bad news releases and that the futures market still leads the spot market by approximately the same time.

Jong and Donders (1998) study the index futures on the Amsterdam European Option Exchange (EOE) stock index[2] and argue that lower transaction costs and greater liquidity in the futures market provide more immediacy to traders and hence traders transact in the futures market first, causing it to lead the spot market.

Min and Najand (1999) use the Granger causality test to study the Korean market and find that the futures market leads the cash market returns series by as much as 30 minutes, concluding that the futures market reflects information more rapidly than the spot market. Thenmozhi (2002) examines whether or not movements in futures prices provide predictive information regarding subsequent movements in the index prices, for the NSE. The study shows that information flow is higher in the post futures period, although she does not study the lead-lag relationship in particular.

Sinha and Sharma (2005) find that index futures lead the spot index on the NSE. They also find that for individual stocks, a lead-lag relationship is absent in many cases. However, in a few cases, the stock futures do lead the spot market for the stock. They use linear regression and co-integration techniques for their study. They also conclude that, after the introduction of futures

[2] It is the weighted average of the last transaction prices of 25 stocks

contracts, over the years markets are becoming more efficient, reacting to news simultaneously with faster information flows in both markets.

Many researchers attribute the significant lead-lag relationship between the cash market and the futures market to differences in market microstructure, lower transaction costs and greater liquidity in the futures market being the most common reasons (Grossman & Miller, 1988; Jong & Donders, 1998; Zhong, Darrat, & Otero, 2004). Grunbichler, Longstaff, and Schwartz (1994) say that the significant lead of the futures market over the spot market is unlikely to be due to difference in liquidity in the two markets. They analyzed the lead-lag relationship between the German DAX index[3], which is floor-traded, and DAX index futures contracts, which are screen-traded. Intra-day data was analyzed using a multiple regression framework. The results show a significant lead of futures returns over spot returns. They attribute this lead to the trading mechanism, arguing that screen-based trading enhances price discovery by reducing trading costs, the time taken to execute orders, and the time required to disseminate trade information.

Frino, Walter, and West (2000) study the lead-lag relationship in Australian markets. They examine the feedback effect around major news releases and find that the lead of the futures market strengthens around any major macroeconomic news release as investors with market-wide information prefer to trade in index futures. On the other hand, the feedback from equities to the futures market strengthens when stock-specific information becomes available. Investors with stock-specific information prefer to trade in the spot market rather than in the futures contract of that stock.

In summary, we see that most researchers agree that futures markets do have certain properties like lower transaction costs, higher leverage, no restriction on short selling, and greater liquidity. This enables them to serve as price discovery vehicles for stock prices and as a significant source of market-wide information. But, we also see that studies are generally restricted to developed countries like US, UK, Japan, and Australia. There is a serious dearth of studies on emerging nations.

4. Objectives and Data

The purpose of this study is to investigate the relationship between the futures and spot markets in India. In particular, we search for answers to the following questions:

[3] DAX Index is a value-weighted index of the 30 largest firms traded on the Frankfurt Stock Exchange (FSE).

1. Does the cost-of-carry model hold in the Indian context? If the correlation between the two markets is dynamic, can the jumps in correlation be related to news releases of some important economic or political events?
2. Is there a unidirectional causality between the stock index futures and the stock index, with one market serving as a price discovery vehicle for the other? Or, are the two markets independent?

The data used in this study were obtained from the NSE of India. Daily closing prices of the S&P CNX[4] Nifty index and the N FUTIDX Nifty[5] were used for the period June 12, 2000 to March 31, 2005, comprising 1209 observations for each series.

The S&P CNX Nifty, is a well diversified 50-stock index accounting for 23 sectors of the economy. It represents about 60% of the total market capitalization as at March 31, 2005. The NSE commenced trading in index futures on June 12, 2000. Index futures contracts are based on the S&P CNX Nifty index. They have a maximum three-month trading cycle: the *near month*? one month to expiry; the *next month*? two months to expiry; and the *far month*? three months to expiry. A new contract is introduced on the trading day following the expiration of the near-month contract. This way, at any time, there are three contracts available for trading in the market, one near month, one next month, and one far month. For a summary of the contract specifications of the index and stock futures on the NSE, see Appendix 2.

The index futures time series analyzed here uses data on the near month contracts, since they are the most heavily traded. Also, it is worth mentioning that the NSE has an approximately 99% market share of the exchange-traded financial derivatives market in India. So, our study concentrates on futures contracts traded on the NSE only.

The closing prices time series are used to generate the rate-of-return time series. The returns for the futures contract and the spot series are calculated as $f_t = \ln(F_t / F_{t-1})$ and $s_t = \ln(S_t / S_{t-1})$ to obtain f_t and s_t, where F_t is the futures price at time t and S_t is the spot price at time t.

Similarly, the last traded prices of seven individual stocks and their near-month futures contracts have been used. The nature and businesses of these companies are summarized in Table 1. They were selected on the basis of the value of contracts traded. The selected stocks represent the public sector (SBI, ONGC), the manufacturing sector (Reliance, Tisco), the service sector (Satyam), the private banking sector (ICICI), and the pharmaceutical sector (Ranbaxy).

[4] S&P prefix belongs to the US based Standard & Poor's Financial Information Services. CNX reflects the identities of the promoters of the index, namely CRISIL and NSE.
[5] N symbolizes the market, i.e. NSE, FUTIDX stands for Futures Index and Nifty is the underlying.

These seven contracts constituted approximately 28% of all futures contracts on individual securities traded on the NSE on March 30, 2005, and approximately 32% of total traded volume on the same day. Reliance was the most active futures contract on individual securities with 16,905 contracts. SBI was the next most active with 16,339 contracts. Tisco was the most heavily traded in terms of value, accounting for 9.08% of the total traded value.

Table 2 summarizes the descriptive statistics of future and spot market returns. The average daily returns in both market is close to zero for the index as well as for the stocks. Using F-Test[6], with 5% significance level, we find that the volatility of the futures market is significantly greater than the volatility of the spot market for the index as well as for all the stocks under consideration, except for Ranbaxy and Satyam. This is consistent with the theory that the futures market attracts less informed traders, increasing volatility. For Ranbaxy and Satyam, the standard deviation of futures returns is less than that of the spot returns, making the spot market significantly more volatile than the futures.

We have 1,209 observations (i.e., prices) after the introduction of index futures. We also take the same number of observations before the introduction of index futures to see if the standard deviation before and after futures is the same. Table 2 shows that there is a significant reduction in standard deviation for the index. The significance of the change in standard deviation has been tested for using the F-Test.[7]

Similarly, we take an equal number of observations for the individual stocks before the introduction of futures and find that the standard deviation has reduced significantly across all stocks. This satisfies our expectation that futures trading results in a more stable spot market due to the transference of speculative activities from the spot market to the futures market.

The correlation between the futures returns and the spot returns is very high in all cases, from 0.96387 for ICICI to 0.9939 for Satyam. This shows that both markets react to information simultaneously and indicates that we may find a strong feedback effect in our analysis. Also, even though the correlation is very high, it is not constant as implied by the cost-of carry model.

Table 3 presents the autocorrelation between the returns of the spot and the futures markets. Although we are studying daily returns, we find significant autocorrelation for the spot index and the index futures and for four of the seven stocks. This shows that the information dissemination process is slow in the Indian market.

[6] F values are calculated as: (variance of the cash market post futures/variance of the futures market). The critical value of F is 1.00 for 5% significance level.
[7] F values are calculated as: (variance of the cash market pre futures/variance of the cash market post futures). The critical value of F is 1.00 for 5% significance level.

Spot index and index futures returns both have significant autocorrelations up to lag 4. This is indicative of the slow dissemination of market-wide information as far as the index is concerned (Chan, 1992). Also, after a certain number of lags (lag 6 in our study), the autocorrelation is insignificant for all the securities under consideration. This is consistent with the findings of Chan for the S&P 500 index, which shows that the correlations decrease as the lag increases.

Furthermore, we find that the behavior of the spot and the futures markets is quite similar. For example, in the case of the Nifty, the auto-correlation coefficient is significant for both the spot and futures markets up to lag 4. Similarly, for SBI, the auto-correlation coefficient is significant for both markets for lag 2 and lag 6.

We also notice that the sign of the coefficient is consistent across the two markets. The sign of the coefficient signifies the direction in which the returns move. If the coefficient is negative, current returns are moving in the opposite direction to that of past returns. Similarly, a positive coefficient indicates that current returns are moving in a direction similar to that of the past.

Even though an index is considered to be representative of its market, it does not necessarily reflect individual stocks. In Table 3, we see that even though the auto-correlation coefficient is significant for lag 6 in the case of SBI, it is not significant in the case of the Nifty. Similar disparities also occur with other stocks. This is because the Nifty is an aggregate of 50 stocks; it reflects the general trend across all 50 stocks, which may not reflect each stock taken individually.

Table 4 shows that, contemporaneously, the daily returns of the spot index and the futures index are very highly correlated, very close to one, as expected from the cost-of-carry model. The lagged returns seem to contain very little forecasting power, as seen from the absolute values of the cross-correlation coefficients.

In this preliminary analysis, for the Nifty, there seems to be a feedback effect between the spot and the futures markets, with both the lead and the lag variables being significant up to the fourth leads and lags. This once again is indicative of the slow information dissemination in the Indian markets as we find significant leads and lags despite using daily data.

ICICI futures lead the spot market as per the results in Table 4. On the other hand, Ranbaxy and Reliance cash markets lead the futures markets. There is no lead-lag relationship for Satyam and Tisco. There seems to be a bi-directional relationship between the spot and futures markets of ONGC and SBI.

As previously emphasized, even in the case of cross-correlation coefficients it must be remembered that the Nifty is an aggregate, whose value may not reflect individual stocks. For example, lag 6 for the Nifty is insignificant, although it is significant for SBI. This is because the value of the Nifty is influenced by the values of the other 49 stocks. The results of the preliminary analysis confirm that there exists a lead-lag relationship between the cash and the futures markets for most of the securities under consideration. Further analysis is required to confirm the results.

We find that the spot index and the index futures, as well as the stock futures and their underlying spot returns, are stationary in levels. The ADF statistics (Dickey & Fuller, 1979, 1981) are large enough, in each case, to reject the null hypothesis of non-stationary at a 5% level of significance. Hence no further differencing is required in the data.

5. Research Methodology

To address the first of our objectives, we apply the DCC GARCH model, tested empirically by Engle and Sheppard (2001), to examine the relationship between the spot index and the index futures markets. This new econometric technique allows us to trace correlation changes over time. An important advantage of this model is its capability to estimate the large time-varying covariance matrices that capture the correlation among markets or different assets. As such, it offers important information on the determinants of correlation between markets in normal times as well as in turbulent periods.

5.1 The DCC GARCH Model

Univariate GARCH models have been widely used in financial studies on volatility dynamics and information transmission. A distinguishing feature of the GARCH model is the fact that it takes care of error variances which may be correlated over time because of the phenomenon of volatility clustering. A potential drawback of these models is that the correlation matrix is assumed to be constant between assets or markets. This restrictive assumption has considerably constrained the applicability of GARCH models. In financial applications, large time-varying covariance matrices are often needed in portfolio management, optimization, and hedging to capture correlations between asset returns that change through time. These needs cannot be met by standard GARCH models.

In view of the difficulties in the standard GARCH models, Engle (2002) develops a dynamic conditional correlation multivariate GARCH model that is capable of estimating large time-varying covariance matrices for different assets.

A particular strength of this estimator is the flexibility it provides in modeling the dynamics of the volatility process. The model can be easily modified to permit asymmetric effects in volatility and to include exogenous factors in the correlation model.

The procedure for estimating this model, which involves two-stage estimation, is relatively straightforward. The first stage involves estimating univariate GARCH models for each asset. The second stage employs transformed residuals from the first-stage estimation to obtain a conditional correlation estimator. This parameterization is shown to preserve the simple interpretation of univariate GARCH models with an easy procedure to compute the correlation estimator. The standard errors for the first-stage parameters are shown to be consistent while the standard errors for the correlation parameters can be modified in order to be consistent.

The DCC multivariate GARCH model assumes that returns (r_t) from k assets are conditionally multivariate normal with zero mean and covariance matrix H_t:

$$r_t \mid F_{t-1} \sim N(0, H_t)$$

and

$$H_t \equiv D_t R_t D_t$$

where D_t is the $k \times k$ diagonal matrix of time-varying standard deviations from the univariate GARCH models with $\sqrt{h_{it}}$ on the ith diagonal and R_t is the time-varying correlation matrix. The return can be either raw returns or a filtered time series. The log-likelihood of the DCC estimator is

$$L = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2p) + 2\log|D_t| + \log|R_t| + e_t^{'}R_t^{-1}e_t) \tag{3}$$

where $e_t \sim N(0, R_t)$ are the residuals normalized by their conditional standard deviation. The elements of D_t are characterized by the GARCH process:

$$h_{it} = w_i + \sum_{p=1}^{P_i} a_{ip} r_{it-p}^2 + \sum_{q=1}^{Q_i} b_{iq} h_{it-p} \tag{4}$$

where i = 1,2,…, k, and $\sum_{p=1}^{P_i} a_{ip} + \sum_{q=1}^{Q_i} b_{iq} < 1$ to ensure stationarity and the usual restrictions for non-negativity apply.

The dynamic correlation structure is

$$Q_t = (1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n)\overline{Q} + \sum_{m=1}^{M} a_m (e_{t-m}e_{t-m}^{'}) + \sum_{n=1}^{N} b_n Q_{t-n} \tag{5}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}$$

where $\overline{Q}$ is the unconditional covariance of the standardized residual from the first-stage univariate GARCH estimation and

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11}} & 0 & 0 & \dots & 0 \\ 0 & \sqrt{q_{22}} & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \dots & \vdots \\ 0 & 0 & 0 & \dots & \sqrt{q_{kk}} \end{bmatrix}$$

where Q_t^* is a diagonal matrix composed of the square root of the diagonal elements of Q_t and the element of R_t is $r_{ijt} = \dfrac{q_{ijt}}{\sqrt{q_{ii} q_{jj}}}$. By the Cauchy-Schwartz inequality, R_t is a correlation matrix.

The estimation involves a two-stage process. At the first stage, the standard univariate GARCH model is estimated. Let $q = (f, y)$ be the parameters of the model, where f represents the parameters of the univariate GARCH model estimated in the first stage and y represents the parameters of the DCC process that is estimated at the second stage. Engle and Sheppard (2001) provide the quasi-likelihood functions for the first and second stages. The first-stage quasi-likelihood function for the ith asset is:

$$QL_1(f \mid r_t) = -\frac{1}{2} \sum_{i=1}^{k} \left(T \log(2p) + \sum_{t=1}^{T} \left(\log(h_{it}) + \frac{r_{it}^2}{h_{it}} \right) \right) \tag{6}$$

which is the sum of the log-likelihoods of the individual GARCH equations for the assets estimated. The second stage is estimated conditional on the parameters estimated at the first stage using the following quasi-likelihood:

$$QL_2(y \mid \hat{f}, r_t) = -\frac{1}{2} \sum_{t=1}^{T} \left(k \log 2p + 2 \log |D_t| + \log(|R_t|) + e_t' R_t^{-1} e_t \right) \tag{7}$$

The asymptotic variance of the estimated parameters $\hat{q}$ is $A^{*-1} B^* A^{*-1}$ where

$$A^* = \begin{bmatrix} \nabla_{ff} \ln f_1(f_0) & 0 \\ \nabla_{fy} \ln f_2(q_0) & \nabla_{yy} \ln f_2(q_0) \end{bmatrix} = \begin{bmatrix} A_{11} & 0 \\ A_{12} & A_{22} \end{bmatrix} \tag{8}$$

$$B^* = \operatorname{var}\left[\sum_{t=1}^{T} \left(T^{-1/2} \nabla_f' \ln f_1(r_t, f_0), T^{-1/2} \nabla_y' \ln f_2(r_t, f_0, j_0) \right) \right] = \begin{bmatrix} B_{11} & B_{12} \\ B_{12} & B_{22} \end{bmatrix} \tag{9}$$

where f_1 and f_2 are the first- and second-stage log-likelihoods. The estimated parameters can therefore be tested using these asymptotic variances.

The model is estimated through the maximum likelihood method using a two-step procedure. At the first step, univariate GARCH parameters are estimated. Then, they are used to estimate the DCC parameters[8].

5.2 The Granger Causality Test

In most empirical studies the lead-lag relationship 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 (Kawaller, Koch, & Koch, 1987; Chan, 1992; Stoll & Whaley, 1990). We also examine the lead-lag relationship between the cash and futures markets by estimating the model suggested by Granger (1969).

The Granger approach to the question of whether X causes Y is to see how much of the current Y can be explained by past values of Y and then to see whether adding lagged values of X can improve the explanation. Y is said to be Granger-caused by X if X helps in the prediction of Y or, equivalently, if the coefficients on the lagged Xs are statistically significant. Granger causality measures precedence and information content but does not by itself indicate causality in the more common use of the term. The application of the standard Granger causality test requires the series of variables to be stationary. If two variables are stationary, the standard form of the Granger causality test can be specified accordingly as follows:

$$\Delta Y_t = a_{11} + \sum_{i=1}^{T_{11}} b_{11i}\Delta Y_{t-i} + n_{11t} \qquad 10(a)$$

$$\Delta Y_t = a_{12} + \sum_{i=1}^{T_{11}} b_{11i}\Delta Y_{t-i} + \sum_{j=1}^{T_{12}} b_{12j}\Delta X_{t-j} + n_{12t} \qquad 10(b)$$

$$\Delta X_t = a_{21} + \sum_{i=1}^{T_{21}} b_{21i}\Delta X_{t-i} + n_{21t} \qquad 10(c)$$

$$\Delta X_t = a_{22} + \sum_{i=1}^{T_{21}} b_{21i}\Delta X_{t-i} + \sum_{j=1}^{T_{22}} b_{22j}\Delta Y_{t-j} + n_{22t} \qquad 10(d)$$

where Δ is the difference operator, Y_t and X_t are the cointegrated variables, T is the number of lags, a and b are parameters to be estimated, and v_t is the error term. If the estimated coefficient on lagged values of X in equation 10(b) is significant, it explains some of the variance of Y that is not explained by lagged values of Y itself. This indicates that X is causally prior to Y and said to Granger-cause Y. Similarly, if the estimated coefficient on lagged values of Y in equation 10(d) is significant, it explains some of the variance of X that is not explained by lagged values of X itself. This indicates that Y is causally prior to X and said to Granger-cause X. F statistics are calculated to examine the goodness of fit.

[8] Refer Engle (2002) for further discussion on the properties of DCC GARCH model.

A lead-lag relationship between spot market and futures market returns is tested using equations of the form 10(b) and 10(d) above.

$$s_t = a_1 + \sum_{i=1}^{k} b_i s_{t-i} + \sum_{j=1}^{k} c_j f_{t-j} + u_{1t} \tag{11}$$

$$f_t = a_2 + \sum_{i=1}^{k} l_i f_{t-i} + \sum_{j=1}^{k} d_j s_{t-j} + u_{2t} \tag{12}$$

where s_t and f_t are as defined earlier and u_t is a white noise error term. The order of lag k is determined from Table 4, which shows the number of lags up to which the cross-correlation between the spot and the futures markets is significant for all the securities under study. The number of lags used is further supported by the Akaike Information Criterion (AIC). Further, we test the error terms of equations 11 and 12 for autocorrelation using the LB test. We identify four cases here:

1. Unidirectional causality from futures to spot is indicated if the estimated coefficients on the lagged f in (11) are significantly different from zero and the set of estimated coefficients on the lagged s in (12) is not significantly different from zero.
2. Conversely, unidirectional causality from spot to futures is indicated if the set of estimated coefficients on the lagged f in (11) is not statistically different from zero. and the set of the lagged s coefficients in (12) is significantly different from zero.
3. Feedback, or bilateral causality, is suggested when the sets of f and s coefficients are significantly different from zero in both regressions.
4. Finally, independence is suggested when the sets of f and s coefficients are not significant in both regressions.

The results from the above methodology could be unreliable for testing the lead-lag relationship for the spot index and index futures if the stocks within the index trade infrequently. However, the problem of non-synchronous trading does not occur in our data since the stocks in the index are highly liquid and the futures contracts on individual stocks chosen for the study are the most liquid contracts on the NSE. In addition, the two markets open and close at exactly the same time.

6. Empirical Results and Analysis

We applied the DCC GARCH Model to test whether the cost-of-carry model and the null hypothesis of constant correlation holds in the Indian context, between the spot and the futures markets. Next we apply the Granger Causality test to see if there exists a lead lag relationship between the two markets. Some interesting results have been obtained from our analysis which are presented in this section.

6.1 Results of the DCC Study

The null hypothesis of constant correlation is rejected by the Engle (2002) test for the Nifty. The univariate GARCH model is estimated at the first stage by finding the minimum of the AIC to identify the lag length. It is lag one. Table 5 shows the univariate GARCH and DCC parameter estimates for both the futures index and the spot index returns series. w_1^f, a_1^f, b_1^f are GARCH (1,1) parameters for the futures series, and w_1^s, a_1^s, b_1^s are GARCH (1,1) parameters for the spot series. a_1 is the parameter of the lagged value of the independent variable and b_1 is the parameter of the lagged value of the dependent variable.

In the second stage we estimate the DCC parameters, a_1, a_2, a_3, and b_1 and b_2. We test for the DCC (M,N) model where M=1,2,3 and N=1,2. The 'a' lags represent the news term and the 'b' lags represent the decay term. We find that the results for the Nifty support longer lag lengths with the likelihoods improving as the lag lengths increase. However, there is only a marginal improvement in the likelihood ratio. Hence we prefer the DCC(1,1) specification over the others with longer lag lengths; the results presented in Table 5 are only for M=1 and N=1.

We find that the DCC estimates for the Nifty are significant, thereby indicating that the returns from the two markets are not perfectly contemporaneously correlated. We also plot the dynamic correlations obtained from the DCC (1,1) model for the Nifty in Figure 2 and see that, even though the correlation between the returns of the two markets is very high, varying from 0.95 to 0.98, they are not constant and vary over time with small jumps.

Table 5 presents the results of the DCC(1,1) GARCH model for all seven companies and the Nifty. It shows that the correlation between the spot and futures returns is dynamic, not constant. The sum of the coefficients of the DCC parameters is strictly mean-reverting as it never exceeds one. lso, the news impact parameter is always smaller than the decay parameter, suggesting that the contribution of news to dynamic correlation is smaller than the impact of nuisance or random factors which are reflected by the coefficient of the decay term. We find that the DCC parameters are significant, indicating that the correlation between the spot and the futures return series is not constant for all of them.

The estimates of correlation can be used to analyze significant events that occurred during the period under study. Looking at Figure 2, one could try to correlate the fluctuations to any major news releases during the period. For example, the fluctuation in the correlation during the second and third weeks of September 2001 can be attributed to the mayhem in the global markets due to the attacks on the World Trade Centre. Also, the fluctuations in the month of May 2004 are due to the political uncertainty in India after the elections. BJP had lost and the market reacted strongly against the news of Sonia Gandhi being the likely candidate for Prime Minister. A few jumps in correlations could not be explained by the macro level news releases and could be due to news releases which are company specific. We do not analyze such news releases in our study.

6.2 The Granger Causality Test

In this section, we apply the Granger causality test to the post futures data for the securities under study to investigate the lead lag relationship between the spot and the futures markets. The number of lags used is based on the cross-correlation results in Table 4 and the minimum of the AIC criteria.

The results shown in Table 6 suggest that there is a unidirectional relationship between the Nifty futures and the spot index return series (at a 5% significance level), indicating that the spot market leads the futures market in the NSE for the period under study. This could be due to the Indian derivatives market being in the nascent stage. Despite its popularity, the derivatives market is only about five years old. The results also violate the theory that the futures index should lead the spot index since the futures market acts as a price-discovery vehicle due to its lower transaction costs and higher leverage. However, if we increase the significance level to 10%, we find that our interpretation changes. We find a bi-directional causality between the index futures and the spot index market at the 10% significance level.

Except for ONGC, all the other individual securities suggest independence. Both null hypotheses—futures does not lead the spot and spot does not lead the futures—are not rejected for all of them. This could be because we are using daily data instead of tick-by-tick data. However, it does indicate a certain degree of maturity in both markets as far as the individual securities are concerned.

At a 5% significance level, the results for ONGC suggest that ONGC futures lead the ONGC spot market. This is in sharp contrast to the result obtained for the index. However, we had suspected that the results for ONGC and the Nifty would be similar, since ONGC is the largest constituent of the Nifty. At a 10% significance level, we find similar results for both the Nifty and ONGC, i.e., bidirectional causality between the spot and the futures markets.

7. Conclusions

This study sheds light on some of the issues in the Indian futures market. Findings of the DCC GARCH model suggest that the futures market returns and the spot market returns have time-varying correlation rather than constant correlation over time, hence violating the assumption of the cost-of-carry model, even though the contemporaneous correlation between markets is very high. Jumps in correlation over time can be related to various news releases of some important events, mostly of an economic or political nature.

The lead and lag relationship between the daily cash prices and futures prices for the Nifty and seven other securities is investigated over the period June 12, 2000 to March 31, 2005. A Granger causality test was used to arrive at the results. Empirical results at a 5% significance level suggest that the cash index leads the futures index, thus violating the cost-of-carry model and suggesting that the spot market acts as a means of price discovery, resulting in faster dissemination of information, in the Indian financial markets. This indicates the presence of more informed participants in the Indian spot market and the presence of noise traders in the futures market for the Nifty.

However, if we increase the significance level to 10%, we find that our interpretation changes. We find a bi-directional causality between the index futures and the spot index market at the 10% significance level.

Except for ONGC, all the other individual securities suggest independence since both null hypotheses—futures does not lead the spot and spot does not lead the futures—are not rejected for all of them. This could be because we are using daily data instead of tick-by-tick data. However, it does indicate certain degree of maturity in both markets as far as the individual securities are concerned. It would be interested to investigate the same hypotheses using intraday data for prices.

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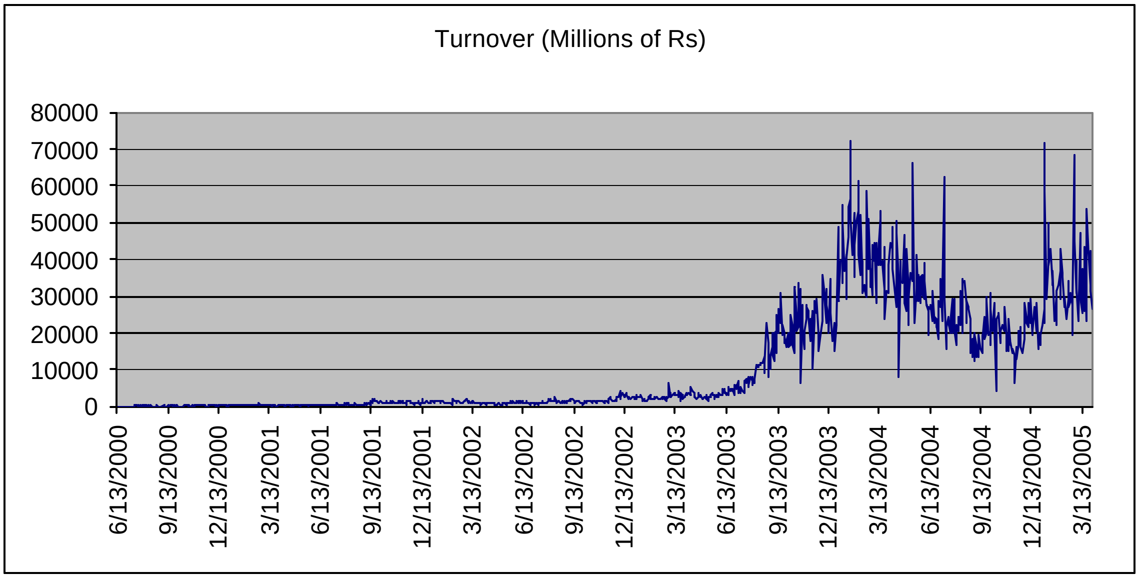
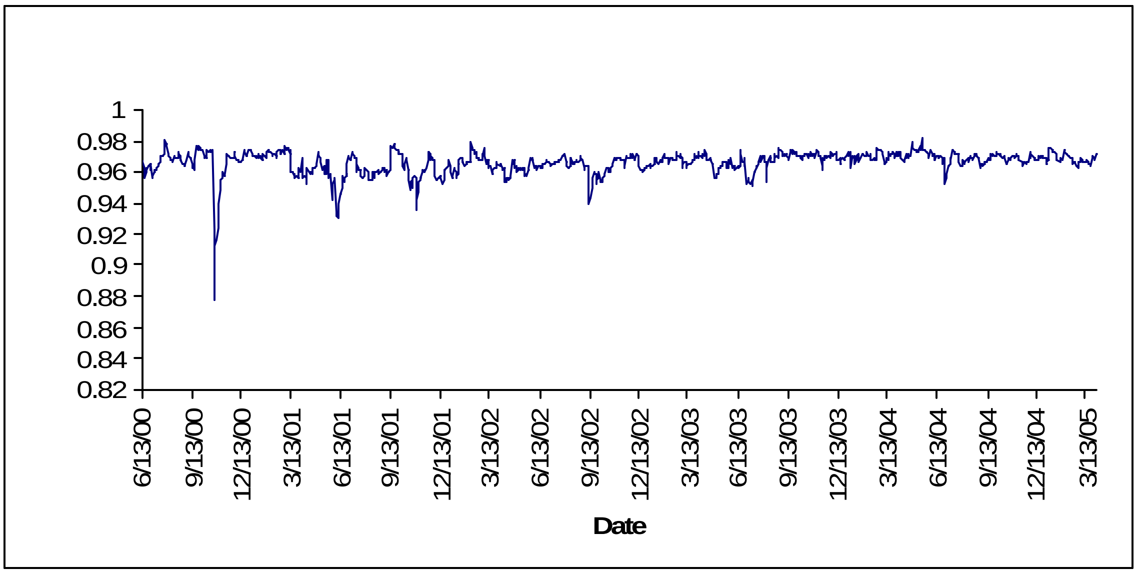
Figure 1: Growth of Derivatives Turnover on the NSE



Data Source: www.nseindia.com

Notes: Futures were introduced on NSE in June 2000. Volumes in the futures segment picked up significantly after June 2003 as seen in the figure above. The traded value in the Futures and Options (F&O) segment was Rs.2,988.57 billion in March 2005 compared with a traded value in the cash segment of Rs.1,130.55 billion, a factor of 2.64 over the cash segment.

Figure 2: Nifty DCC (1,1)-Plot of Dynamic Correlation between Spot and Futures Market Returns (Estimated using the DCC GARCH Model)



Notes: The plot in figure 2 shows that the correlation between the returns of the two markets is very high, varying from 0.95 to 0.98. However, they are not constant and vary over time with small jumps. The fluctuations can be correlated to any major news releases during the period. For example, the fluctuation in the correlation during the second and third weeks of September 2001 can be attributed to the mayhem in the global markets due to the attacks on the World Trade Centre. Also, the fluctuations in the month of May 2004 are due to the political uncertainty in India after the elections. BJP had lost and the market reacted strongly against the news of Sonia Gandhi being the likely candidate for Prime Minister.

Table 1: As at March 30, 2005

Serial No.	Symbol	Exp. Date	No. of Contracts	% of Contracts to Total Contracts*	Traded Value (in Rs million)	% of Traded Value to Total Traded Value**
1	Reliance	3/31/2005	16905	6.30	5576.5	5.90
2	SBI	3/31/2005	16339	6.10	5315.0	5.63
3	Tisco	3/31/2005	15883	5.92	8579.9	9.08
4	ONGC	3/31/2005	8789	3.28	2251.2	2.38
5	Satyam	3/31/2005	6314	2.35	3014.7	3.19
6	Ranbaxy	3/31/2005	5987	2.23	2487.0	2.63
7	ICICIBANK	3/31/2005	4826	1.80	2588.4	2.74
	TOTAL			27.98		31.55

Source: www.nseindia.com

**The total number of contracts traded in futures on individual securities was 268,258 on March 30, 2005.*

***The total traded value of futures on individual securities was Rs 94,466.1 million on March 30, 2005.*

- Reliance is India's largest private sector enterprise, a Fortune Global 500 company. Its revenues add up to US$23 billion. The activities of the company span exploration and production of oil and gas, petroleum refining and marketing, petrochemicals, and textiles.

- SBI is the largest bank in India. It is also, measured by the number of branch offices and employees, the largest bank in the world. It has an asset base of US$126 billion and revenues of about US$12.1 billion. The bank is largely owned by the Government, through the Reserve Bank of India, having a 60% stake. The bank is listed on the London Stock Exchange.

- Tisco is Asia's first and India's largest integrated private sector steel company. The company is world's lowest cost producer of steel and in 2005 was recognized as the world's best steel producer. It has revenues of over US$3 billion. It produces 4 million tons of saleable steel, annually.

- ONGC is a public sector petroleum company, contributing about 77% of India's crude oil production and 81% of India's natural gas production. It is the highest profit making company in India, with revenues of about US$10 billion. It is the most valuable company in India, by market capitalization.

- Satyam is a consulting and information technology services company. Its network spans 55 countries, across six continents, and serves over 469 global companies, 156 of which are Fortune 500 corporations. Its revenues are just over a billion US dollars. It is also listed on the New York Stock Exchange.

- Ranbaxy is India's largest pharmaceutical company and is ranked among the top 10 generic companies worldwide. It is an integrated, research-based company, producing a wide range of quality, affordable generic medicines. Its revenues currently stand at US$1.2 billion, out of which 28% is from sales to the US.

- ICICI is India's largest private bank with total assets of about US$56.3 billion. It offers a wide range of banking products and financial services to corporate and retail customers in the areas of investment banking, life and non-life insurance, venture capital, and asset management. Its revenues add up to approximately US$3.2 billion.

Table 2: Summary of Descriptive Statistics of Returns

	N	MIN	MAX	MEAN	STD	CORR
The Nifty Index						
Futures Contracts	1208	-0.16258	0.09593	0.00028	0.01503	0.96707
Cash Market (after)	1208	-0.13054	0.07969	0.00029	0.01453	
Cash Market (before)	1208	-0.08840	0.09934	0.00028	0.01772	
Cash Market (all)	2417	-0.13054	0.09934	0.00028	0.01620	
STOCKS						
ICICI						
Futures Contracts	546	-0.13066	0.12104	0.00176	0.02360	0.96387
Cash Market (after)	546	-0.11159	0.12973	0.00176	0.02348	
Cash Market (before)	546	-0.17587	0.14825	0.00010	0.03393	
Cash Market (all)	1093	-0.17587	0.14825	0.00093	0.02916	
ONGC						
Futures Contracts	546	-0.16759	0.11019	0.00157	0.02445	0.98173
Cash Market (after)	546	-0.13961	0.11181	0.00159	0.02411	
Cash Market (before)	546	-0.08321	0.18238	0.00230	0.02743	
Cash Market (all)	1093	-0.13961	0.18238	0.00194	0.02581	
Ranbaxy						
Futures Contracts	852	-0.48162	0.10138	0.00043	0.02387	0.98787
Cash Market (after)	852	-0.48861	0.09536	0.00043	0.02394	
Cash Market (before)	852	-0.64893	0.11448	0.00041	0.03948	
Cash Market (all)	1705	-0.64893	0.11448	0.00042	0.03263	
Reliance						
Futures Contracts	852	-0.17499	0.11982	0.00085	0.01978	0.98773
Cash Market (after)	852	-0.16557	0.12459	0.00085	0.01968	
Cash Market (before)	852	-0.10525	0.12226	0.00074	0.02917	
Cash Market (all)	1705	-0.16557	0.12459	0.00080	0.02487	
Satyam						
Futures Contracts	852	-0.16369	0.11338	0.00118	0.03001	0.99319
Cash Market (after)	852	-0.16823	0.09637	0.00118	0.03021	
Cash Market (before)	852	-1.54251	0.14843	-0.00089	0.07446	
Cash Market (all)	1705	-1.54251	0.14843	0.00016	0.05680	
SBI						
Futures Contracts	852	-0.17112	0.11347	0.00139	0.02276	0.99015
Cash Market (after)	852	-0.15376	0.09535	0.00139	0.02213	
Cash Market (before)	852	-0.10501	0.09478	-0.00003	0.02961	
Cash Market (all)	1705	-0.15376	0.09535	0.00068	0.02613	
Tisco						
Futures Contracts	852	-0.45372	0.11523	0.00185	0.02883	0.98730
Cash Market (after)	852	-0.45206	0.11010	0.00186	0.02852	
Cash Market (before)	852	-0.17244	0.11392	-0.00051	0.03216	
Cash Market (all)	1705	-0.45206	0.11392	0.00071	0.03042	

Table 3: Autocorrelation of Spot and Futures Returns

	Spot	Futures
The Nifty Index		
Lag 1	**0.11416***	**0.05900***
Lag 2	**-0.10405***	**-0.08205***
Lag 3	0.03533	**0.06734***
Lag 4	**0.10976***	**0.08340***
Lag 5	0.03214	0.01195
Lag 6	-0.05404	-0.03728
ICICI		
Lag 1	0.04300	0.03621
Lag 2	**-0.8549***	**-0.09258***
Lag 3	-0.04863	-0.00077
Lag 4	-0.03443	0.01354
Lag 5	-0.04995	**0.08906***
Lag 6	-0.01244	-0.01898
ONGC		
Lag 1	**0.14916***	**0.14294***
Lag 2	**-0.08980***	**-0.09989***
Lag 3	0.00677	0.01801
Lag 4	0.05264	0.04338
Lag 5	**-0.09316***	-0.07222
Lag 6	0.00792	-0.03137
Ranbaxy		
Lag 1	0.06713	0.05596
Lag 2	-0.01170	-0.01889
Lag 3	0.01170	0.02724
Lag 4	0.01184	0.02496
Lag 5	-0.04466	-0.03403
Lag 6	-0.00354	0.00245
Reliance		
Lag 1	0.01373	0.00185
Lag 2	**-0.07414***	-0.06503
Lag 3	-0.00805	0.00608
Lag 4	0.03460	0.04431
Lag 5	0.01021	0.01366
Lag 6	-0.06586	-0.06031
Satyam		
Lag 1	0.0032	-0.00587
Lag 2	-0.05127	-0.04044
Lag 3	0.03007	0.04837
Lag 4	-0.01223	-0.01954
Lag 5	-0.03663	-0.03019
Lag 6	-0.04094	-0.03714
SBI		
Lag 1	0.03003	0.02513
Lag 2	**-0.08952***	**-0.09780***
Lag 3	0.03841	0.04280
Lag 4	0.02701	0.02792
Lag 5	-0.02609	-0.01693
Lag 6	**-0.08189***	**-0.08307***
Tisco		
Lag 1	0.03384	0.02905
Lag 2	-0.04530	-0.04210
Lag 3	-0.01952	-0.01650
Lag 4	0.01884	0.01696
Lag 5	0.05798	0.05520
Lag 6	-0.04600	-0.04904

* *Significant at a 5% level.*

Table 4: Cross-correlation

Lag k	$(r(s_t, f_{t+k}))$	Lag k	$(r(s_t, f_{t+k}))$	Lag k	$(r(s_t, f_{t+k}))$
The Nifty Index		**Ranbaxy**		**SBI**	
-6	-0.04230	-6	0.00178	-6	**-0.08212***
-5	0.02589	-5	-0.04128	-5	-0.02217
-4	**0.09319***	-4	0.01672	-4	0.02559
-3	**0.05909***	-3	0.02091	-3	0.04099
-2	**-0.06673***	-2	-0.01200	-2	**-0.08586***
-1	**0.08789***	-1	0.0617	-1	0.02706
0	**0.96724***	0	**0.98783***	0	**0.9905***
1	**0.10419***	1	**0.06908***	1	0.03593
2	**-0.10880***	2	-0.01744	2	**-0.09956***
3	0.04043	3	0.01517	3	0.03449
4	**0.10324***	4	0.02150	4	0.03348
5	0.02185	5	-0.03538	5	-0.01996
6	-0.04951	6	-0.00201	6	**-0.08282***
ICICI		**Reliance**		**Tisco**	
-6	-0.02265	-6	-0.05981	-6	-0.04944
-5	-0.07652	-5	0.01049	-5	0.05558
-4	-0.01423	-4	0.02985	-4	0.01401
-3	0.00463	-3	0.01332	-3	-0.01543
-2	**-0.08712***	-2	-0.05587	-2	-0.03394
-1	0.05022	-1	-0.00976	-1	0.02695
0	**0.96358***	0	**0.98734***	0	**0.98733***
1	0.04944	1	0.02177	1	0.03919
2	-0.08210	2	**-0.07467***	2	-0.05180
3	-0.05335	3	-0.01438	3	-0.02218
4	-0.02619	4	0.05008	4	0.02195
5	-0.05676	5	0.01279	5	0.05868
6	-0.01254	6	-0.06504	6	-0.04191
ONGC		**Satyam**			
-6	-0.02509	-6	-0.03644		
-5	-0.07851	-5	-0.03348		
-4	0.06308	-4	-0.00855		
-3	0.01024	-3	0.048		
-2	**-0.08656***	-2	-0.02644		
-1	**0.13895***	-1	0.00976		
0	**0.98174***	0	**0.99373***		
1	**0.16767***	1	0.00906		
2	**-0.10315***	2	-0.05733		
3	0.01258	3	0.03608		
4	0.04065	4	-0.01860		
5	**-0.08503***	5	-0.03428		
6	-0.01824	6	-0.04047		

* *Significant at a 5% level.*

Table 5: Univariate GARCH (1,1) and DCC (1,1) Estimation

Parameters	NIFTY	ICICI	ONGC	Ranbaxy	Reliance	Satyam	SBI	Tisco
w_1^f	0.000017* (1.5844E-09)	0.000110* (5.1918E-09)	0.000015* (1.0061E-08)	0.000537* (8.4747E-08)	0.000136* (2.5573E-04)	0.000035* (3.2389E-09)	0.000009* (1.2242E-08)	0.000771* (7.8239E-08)
a_1^f	0.195860* (1.1776E-02)	0.119600* (6.9928E-03)	0.182330* (1.2238E-02)	0.000000 (7.7493E-05)	0.230660* (1.5585E-02)	0.111320* (9.8267E-04)	0.088948* (2.1113E-03)	0.092901 (5.3833E-02)
b_1^f	0.724140* (1.0268E-02)	0.678980* (1.2438E-02)	0.817670* (1.0785E-02)	0.055515 (6.8445E-01)	0.420080* (1.0032E-02)	0.850480* (1.6270E-03)	0.898580* (2.3551E-03)	0.000000 (1.2309E-01)
w_1^s	0.000019* (9.4742E-10)	0.000276* (6.3234E-09)	0.000015* (1.3315E-08)	0.000542* (9.1349E-08)	0.000139* (1.3792E-09)	0.000037* (3.0178E-09)	0.000009* (1.0401E-08)	0.000765* (2.2119E-08)
a_1^s	0.200590* (8.1044E-03)	0.204130* (6.4924E-03)	0.154640* (1.1025E-02)	0.000000 (2.3656E-05)	0.255790* (3.7340E-03)	0.102510* (7.2247E-04)	0.086279* (1.4473E-03)	0.077785 (4.7065E-02)
b_1^s	0.706330* (8.2816E-03)	0.294490* (3.9453E-02)	0.838980* (1.0938E-02)	0.053491 (7.1417E-01)	0.391380* (1.0689E-02)	0.857240* (1.3030E-03)	0.900100* (1.8743E-03)	0.000000 (1.8130E-01)
a_1	0.038752* (6.0233E-04)	0.123680* (6.1290E-03)	0.070399* (6.3822E-04)	0.009819* (3.1380E-05)	0.180830* (8.9951E-03)	0.023013* (1.2783E-04)	0.017465* (2.1927E-04)	0.038012* (8.9321E-04)
b_1	0.807900* (5.9981E-04)	0.427640* (1.6514E-02)	0.906400* (1.1439E-03)	0.948830* (6.0532E-04)	0.342970* (2.2499E-02)	0.934750* (6.5171E-04)	0.954500* (8.9577E-04)	0.832950* (1.1062E-02)
Log-Likelihood	8715.2	3342.7	3553.1	5556.7	5889.8	5513.8	5815.5	5249.300000
Likelihood-Mean	7.214609	6.122094	6.50755	6.521993	6.912904	6.471543	6.825694	6.161206362
Likelihood-Median	7.630650	6.72865	6.9628	7.17465	7.4428	6.9248	7.37395	6.86935

Note: Standard errors are reported in parenthesis. w_1^f, a_1^f, b_1^f *are GARCH (1,1) parameters for futures series, and* w_1^s, a_1^s, b_1^s *are GARCH (1,1) parameters for spot series.* a_1 *and* b_1 *are DCC(1,1) parameters.*

**Significant at a 5% level*

Table 6: Granger-Causality Results

Null Hypothesis	No. of Lags	F-Statistic	Probability
S&P CNX NIFTY: Data Period 12/6/2000-31/03/2005 Degrees of Freedom: 1204			
Nifty Futures does not Granger-Cause Spot Nifty	4	1.92112**	0.10460
Spot Nifty does not Granger-Cause Nifty Futures	4	8.90034*	4.4E-07
ICICI Bank: Data Period 31/01/2003-31/03/2005 Degrees of Freedom:544			
ICICI Bank Futures does not Granger-Cause Spot ICICI Bank	2	0.31040	0.73329
Spot ICICI Bank does not Granger-Cause ICICI Bank Futures	2	1.37048	0.25487
ONGC: Data Period 31/01/2003-31/03/2005 Degrees of Freedom: 541			
ONGC Futures does not Granger-Cause Spot ONGC	5	2.83080*	0.01556
Spot ONGC does not Granger-Cause ONGC Futures	5	2.11839**	0.06184
RANBAXY: Data Period 9/11/2001-31/03/2005 Degrees of Freedom: 851			
Ranbaxy Futures does not Granger-Cause Spot Ranbaxy	1	0.25999	0.61026
Spot Ranbaxy does not Granger-Cause Ranbaxy Futures	1	1.05891	0.30376
RELIANCE: Data Period 9/11/2001-31/03/2005 Degrees of Freedom: 850			
Reliance Futures does not Granger-Cause Spot Reliance	2	0.82360	0.43920
Spot Reliance does not Granger-Cause Reliance Futures	2	0.25019	0.77871
SBI: Data Period 9/11/2001-31/03/2005 Degrees of Freedom: 846			
SBI Futures does not Granger-Cause Spot SBI	6	1.55556	0.15720
Spot SBI does not Granger-Cause SBI Futures	6	1.34050	0.23638
SATYAM: Data Period 9/11/2001-31/03/2005 Degrees of Freedom: 851			
Satyam Futures does not Granger-Cause Spot Satyam	1	2.26367	0.13281
Spot Satyam does not Granger-Cause Satyam Futures	1	0.07406	0.78559
TISCO: Data Period 9/11/2001-31/03/2005 Degrees of Freedom: 851			
Tisco Futures does not Granger-Cause Spot Tisco	1	1.06265	0.30291
Spot Tisco does not Granger-Cause Tisco Futures	1	0.05259	0.81867

**Significant at a 5% level*

***Significant at a 10% level*

Appendix 1: Evolution of Derivatives Trading in India

1956	Enactment of the Securities Contracts (Regulation) Act which prohibited all options in securities.
1969	Issue of Notification which prohibited forward trading in securities.
1995	Promulgation of the Securities Laws (Amendment) Ordinance, which withdrew prohibition on options.
1996	Setting up of L.C.Gupta Committee to develop regulatory framework for derivatives trading in India.
1998	Constitution of J.R.Varma Group to develop measures for risk containment for derivatives.
1999	Enactment of the Securities Law (Amendment) Act, which defined derivatives as securities.
2000	Withdrawal of 1969 Notification.
May 2000	SEBI granted approval to NSE and BSE to commence trading of derivatives.
Jun 2000	Trading in index futures commenced.
Jun 2001	Trading in index options commenced. Ban on all deferral products imposed.
Jul 2001	Trading in stock options commenced. Rolling settlement introduced for active securities.
Nov 2001	Trading in stock futures commenced.
June 2003	Trading in interest rate futures commenced.

Source: Ravi Narain, "Derivatives Markets in India:2003", ed. by Susan Thomas, Invest India- Tata McGraw Hill, 2003, Chapter 2, Table 2.1, p. .30.
Note: The table has been updated to include the interest rate futures.

Appendix 2: Contract Specifications

	Index Futures	**Stock Futures**
Date of start	June 12, 2000	November 12, 2001
Security Description	N FUTIDX NIFTY	N FUTSTK
Underlying	S & P CNX Nifty Index	Individual Securities
Contract Size	100 or multiples thereof (Minimum Value of Rs. 2 Hundred Thousands)	Multiples of 100, as may be specified by NSE
Tick Size/Price Steps	Rs. 0.05	
Expiration Months	Three near months	
Trading Cycle	A maximum of three-month trading cycle? the near month (one), the next month (two) and the far month (three); a new contract is introduced on the next trading day following the expiry of near-month contract.	
Last Trading/Expiration Day	Last Thursday of the expiry month or the preceding trading day, if last Thursday is a trading holiday	
Settlement	In cash on T+1 basis	
Daily Settlement Price	Closing price of futures contract on the trading day	
Final Settlement Price	Closing value of underlying index/security on the last trading day of the futures contract	
Settlement Day	Last trading day	
Trading Hours	9.55 AM to 3.30 PM	
Margins	Upfront initial margin on daily basis	

Source: www.nseindia.com