Price Discovery and Information Linkages relating to Volatility and Higher Order Moments: An Empirical Analysis for NSE 50 Spot and Derivative Platforms in India

Sanjay Sehgal[a], Piyush Pandey[1b] and Florent Deisting[c]

[a] Professor, Department of Financial Studies, University of Delhi, New Delhi, India, 110 021
[b]Research Scholar, Department of Financial Studies, University of Delhi, New Delhi, India, 110 021
[c] Professor, Groupe ESC Pau – France, rue Saint-John Perse - BP 7512 – 64075, France

***Keywords*: price discovery, information transmission, volatility spillover, higher order moments, Bivariate EGARCH Model**

***JEL Classification*:** G13, G14, G15, C32

[1]Corresponding author, Email: p.pandey_812@yahoo.co.in, Tel: +91-9650955023
Acknowledgements: The authors would like to thank the editor of this journal and an anonymous referee for their helpful comments and suggestions. All errors and omissions are solely ours.
We would also like to thank Ms Priya Obhrai for her research assistance in this project

Price Discovery and Information Linkages relating to Volatility and Higher Order Moments: An Empirical Analysis for NSE 50 Spot and Derivative Platforms in India

Abstract

In this study examines the information transmission process between spot, futures and options segments for the NIFTY 50 index. The data is used from 2003 to 2013. Empirical results show that the spot market leads the price discovery process followed by the futures market and then the options market. The spot market again leads in the volatility spillover process while options dominate the futures contracts. There is a univariate skewness spillover from spot as well as futures to the options platform. Further, long term bidirectional kurtosis spillover is observed between spot and futures with former playing a more dominant role.

Price Discovery and Information Linkages relating to Volatility and Higher Order Moments: An Empirical Analysis for NSE 50 Spot and Derivative Platforms in India

Introduction

Traditional financial research analyzes individual markets without giving much ado about the inter-linkages between similar financial markets. The market players usually trade various products and participate in different markets for speculation, portfolio diversification and risk management. The nature of inter- market linkages could provide better decision making tools for investors, portfolio managers and market regulators. According to the efficient market hypothesis, (Fama and Fench, 1970) any new information is quickly reflected in the underlying spot market and its derivative market (Stole and Whaley, 1990) simultaneously, so that investors cannot make any profits using currently available information in these markets. But in real, there exist market frictions or market imperfections (Chan and Chung, 1990) including various transaction costs and information asymmetry which leads to information dissemination in one market first and subsequent transmission to other markets. This may result in a lead lag relationship and the market that provides higher liquidity, lower costs of trading and fewer restrictions is expected to play a leading role in price discovery which, in turn, determines the extent of arbitrage opportunities available and, thus the level of market efficiency. In market microstructure literature, price discovery has been variously interpreted as, “the search for an equilibrium price” or “the process by which markets attempt to find their fair prices” (Schreiber and Schwartz, 1986) and “the incorporation of the information implicit in investor trading into market prices” (Lehmann, 2002).

As for India, National Stock Exchange (NSE) started trading in the equities segment on November 3, 1994 and within a short span of 1 year became the largest exchange in India in terms of volumes transacted. CNX Nifty or Nifty 50, the benchmark index of NSE comprising of 50 major companies from 23 sectors of Indian economy and provides fully automated screen-based trading system with national reach. It represents about 70.14% of the free float market capitalization of the stocks listed on NSE as on March 31 2014. Impact cost of the CNX Nifty for a portfolio size of Rs 50 lakhs was 0.6% for the month of March 2014. The need for an organized derivatives market was felt, where price risk insurance is furnished to hedgers, gambling to speculators and arbitrageurs undertake the responsibility to restore market equilibrium (Telser, 1981). NSE commenced trading in derivatives with the launch of index futures on June 12, 2000. The futures contracts are based on the popular benchmark CNX Nifty Index. The Exchange introduced trading in Index Options (also based on Nifty) on June 4, 2001. The turnover of the CNX Nifty index was INR 7266.52 crore as on May 19 2015 with a volume of 14.46 crore. On the other hand, the traded value of index futures which was INR 18,806.83 crore with 732118 number of contracts while that of index options was INR 225,182.23 crore on the same day with 1.02 crore number of contracts. Securities Transaction Tax (STT) on equity trading was introduced by Government of India in 2004 wherein transactions in stock, index options and futures would also be subject to transaction tax. The original tax rate was set at 0.125% for a delivery-based equity transaction while it was 0.017% on all futures and options transactions. In the 2013 budget, STT for delivery-based equity trading was revised to 0.1% on the turnover. For Futures, the tax was reduced to 0.01% on the sell-side only. Even after STT parity, the actual transaction costs for options contracts is much lower than spot contracts as they are imposed on option premium in case of former while they are levied on total transaction value in the latter case entailing differential costs for trading in these market platforms.

The manifold increase in trading volumes over the years in derivatives market simultaneously affects the cash market information dissemination efficiency, liquidity and volatility because both markets are inter-linked. The lead-lag relation between price movements of the derivatives market 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. Apart from information content of the prices, volatility is also an important source of information. Ross (1989) argues that stock return volatility is directly related to the flow of information. Volatility is also an important source of another area of interest for regulators and market participants who prefer less volatility to more volatility. Study of volatility linkages can help investment professionals in pricing risk effectively. Empirical literature is heavy on the linkages of financial markets via their volatility to comprehend market assimilation, co-movement and spillover effect. However how the markets interact through their higher moments i.e skewness and kurtosis has not been well understood. This paper tries to contribute to this strand of literature by studying the information linkages between the spot and derivative segments of NSE 50 stock index by examining the price discovery mechanism and subsequently investigating the volatility, skewness and kurtosis spillover process. Skewness linkages explain how markets are linked through the level of asymmetry of their return distribution while studies of kurtosis linkages provide better insights into the spread of fat tail risk across markets since they provide knowledge about markets' relationship through the occurrence of extreme events (Hung, Brooks and Srimon, 2011). The problem of fat tail risks is encountered by hedge fund managers who are into derivative trading and make long short investment strategies.

Understanding the influence of one market on the other and the role of each market segment in price discovery and subsequent information transmission through higher moments is the central question in market microstructure design and is very important to academia as well as regulators. Much of research to date has focused on cash and future segments of the equity market and that too examining the first and second order properties of the price series. We extend the scope of this study by including options segment alongwith spot and futures segment of NSE 50 index and also examine the information transmission process relating to higher order moments besides analyzing price discovery and volatility linkages. The study attempts to examine the following issues for three segments of Indian equity index markets: 1. Price discovery process 2. Volatility spillover 3. Information linkages relating to higher order moments i.e skewness and kurtosis. The remainder of the paper is organized as follows. Section two gives review of literature and the research gap. Section three contains description of data and its sources. Section four deals with the methodological issues. Section five contains the empirical tests along with its interpretation and analysis. Section six provides summary and concluding observations.

2. Literature Review

Some researchers believe that both futures markets and options markets may contain more information than the spot market, because traders in these markets are generally large traders and are believed to be better informed. Several papers have found that the futures price leads its underlying index, such as Ghosh (1993), Shyy, Vijayraghavan and

Quinn (1996), So and Tse (2004), and Kang et al. (2006). Other studies have found that the spot index leads its associated futures index, such as Lucian (2008), Bohl, Salm and Wilfling (2009) and Yang, Yang and Zhou (2012). While some studies such as Pizzi et al. (1998), Gee and Karim (2005) and Jackline and Deo (2011) show that there is a bidirectional relationship between spot and futures. In contrast to the abundance of empirical research on the spot futures relationship, there are relatively few studies that examine impact of option trading on price discovery of spot. Bhattacharya (1987), Finucane (1991), Fleming, Ostdiek, and Whaley (1996), Cao, Chen and Griffin (2005), Pan and Poteshman (2006) and Kim and Lee (2010) provide evidence that the options price leads the stock market. However, Stephan and Whaley (1990) document that price changes in the spot market lead price changes in the options market for active CBOE call options about 15 to 20 min on average with a 5-min option price series. Stucki and Wasserfallen (1994), O'Connor (1999), Capelle-Blancard and Vandelanoite (2002), Richard, Yusif, and Liuren (2006) also found that the spot market leads the options market. As for the studies in Indian context is concerned, Thenmozhi (2002), Anandbabu (2003), Gupta and Singh (2006) and Pati and Pradhan (2009) have found that the nifty futures market has more power in disseminating information and therefore has been found to play the leading role in the matter of price discovery. Mukherjee and Mishra (2004) found out a bidirectional relationship between the returns in the spot and futures markets where spot was found to be leading over futures. Reddy and Sebastin (2008) observed information dissemination from spot to futures. There is no study in the Indian context which explores options market role in the price discovery of spot.

As for the volatility spillover, Koutmos and Tucker (1996), J.H. Min and Najand (1999) and Lafuente-Luengo (2009) show that volatility spillovers only run from the futures market to the spot market. Booth, Raymond and Tse (1999), So and Tse (2004), Arianos and Carbone (2009), Cheong and Seong (2013) and Zhou, Huiyan and Shouyang (2014) found out that return volatility in the spot market can influence that in the futures market and vice versa. Kawaller and Koch (1990) and Arshanapalli and Doukas (1994) suggests no volatility spillover between S&P index and its corresponding futures. In the Indian context, Karmakar (2009) confirms that Nifty future is more informationally efficient than the underlying spot market and past innovations originating in future market have the unidirectional significant effect on the present volatility of the spot market. However, Sakthivel and Kamaiah (2010) and Pati and Rajib (2011) shows a bidirectional volatility spillover between nifty spot and futures market. There is no study which explores volatility spillover beyond the spot futures case.

Even in the international context there is limited study focusing on the area of skewness and kurtosis linkages in financial markets. Regarding the skewness transmission, whilst Korkie et al. (2006) provides supports of skewness persistence within equity markets, Hashmi and Tay (2007) find little evidence of a skewness spill-over effect from the global and regional factors. In term of kurtosis linkages, most studies have investigated the issue via the interaction of the occurrence of extreme returns between markets. Examples include Longin and Solnik (2001) and Cumperayot et al. (2006). The common result found is that the occurrence of extreme returns in one market is likely to be positively correlated with that in other markets. Although there is no dearth of literature on price discovery and information transmission in the spot and futures segments of the market, this study extends the work by including the options segment of market and spans a larger and more recent study period. Thus it helps in identifying the dominant and satellite trading platforms of the Indian equity index market. Under the emerging market framework, this is the first attempt to study the information transmission by taking into account higher order moments besides price and volatility spillovers. The literature on skewness and kurtosis spillover effects is at its nascent stage and still evolving.

3 Data Sources and its Description

The sample used in the study is the NSE 50 spot index, NSE 50 index futures and NSE 50 index call options. The period of study is from 27 November 2003 to 13 December 2013. The starting date was chosen so as to coincide with the date from which 91 day Treasury bill yield, which was used as risk free proxy in the Black Scholes Option Pricing Model, was available from Bloomberg. The daily prices data for the NIFTY spot index and all the NIFTY index call option contracts were obtained from National Stock Exchange (NSE) website for the said period. The data of only the call option contracts have been retrieved vis-à-vis the put contracts as the liquidity of former was high in comparison to the latter (monthly Put Call ratio was less than one for 63% of the times during the said period). NIFTY futures daily price series was directly obtained from

Bloomberg (continuous price series of the most liquid near month contracts). For any given day, we selected only those index call option contracts where firstly, some contracts were traded (number of contracts were not zero) and secondly for which the strike price of the next month maturity contract was trading at the underlying price (at the money) or nearest to the underlying price (presently in the money).

4. Methodology

In order to test the relationship between the NSE 50 stock index options and other segments of the equity markets, it is necessary to calculate the implied index level from the NSE 50 stock index options price. Following Manaster and Rendleman (1982) except for dividend paying consideration, the Black-Scholes Option Pricing model is used to recover the implied index level. As an input for the volatility for each day, we compute the conditional volatility estimates of the NSE 50 spot index prices from the GARCH (1, 1) model of the previous day. Thus we now have the times series of spot index (henceforward termed as spot), futures index (henceforward termed as futures) and implied index levels from options price (henceforward termed as options).

4.1 Price Discovery Process

At first stage, stationarity condition using conventional methods of unit root tests viz., Augmented Dickey Fuller (ADF), Phillips and Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests have been used to check for stationarity for all sample series. If two or more series are themselves non-stationary, but a linear combination of them is stationary, then the series is said to be co-integrated. Next, the Johansen and Juselius (1992) test of cointegration was applied to the data to capture the presence of any long run equilibrium relationships between the various sample series. After confirming the long run relationship between the respective pair of variables, Vector Error Correction Model (VECM) test was undertaken to check their short-run dynamics. Accordingly, the VECM for change in the say futures prices and in the spot prices can be represented as under:

$$\Delta F_t = b_1 + \delta_1 ECT_{t-1} \sum_{i=1}^{k} d_{1i} \Delta F_{t-i} + \sum_{i=1}^{k} g_{1i} \Delta S_{t-i} + \varepsilon_{1t} \tag{1}$$

$$\Delta S_t = b_2 + \delta_2 ECT_{t-1} \sum_{i=1}^{k} d_{2i} \Delta F_{t-i} + \sum_{i=1}^{k} g_{2i} \Delta S_{t-i} + \varepsilon_{2t} \tag{2}$$

Where $ECT_{t-1} = F_{t-1} - S_{t-1}$ is the error correction term and its coefficients (δ_1 and δ_2) indicate the speed of adjustment in the futures prices and the spot prices respectively; the smaller the absolute value of the error correction term, faster is the adjustment made by the concerned market towards equilibrium and leads the price discovery process. ΔS_{t-i} and ΔF_{t-i} measure how the current price adjusts to the change in the variables in the previous period. Similarly the VECM analysis is run for other possible pairs (spot/options and futures/options). Results of the VECM tests were confirmed through the Granger Causality Test which indicates direction of the causality.

4.2 Volatility Spillover

Numerous studies have investigated the process of volatility spillover to evaluate the spread of news from one market that affects the volatility spillover process of another market. The theory of volatility spillovers based on the GARCH models is first introduced and named "meteor showers" by Engle, Ito and Lin (1990). Chan, Chan and Karolyi (1991) provide a detailed discussion on the need to focus on the volatility spillovers between the stock and futures markets. In particular, following Ross (1989), Chan, Chan and Karolyi (1991) contend that "it is the volatility of an asset's price, and not the asset's simple price change, that is related to the rate of flow of information to the market." For each return series, AR (1) process is used as the mean equation. Nelson's (1991) exponential GARCH (EGARCH) model is used for specification of conditional volatility estimates of spot, future and options respectively in order to capture the asymmetric impacts of shocks or innovations on volatilities and to avoid imposing nonnegativity restrictions on the values of GARCH parameters. Using a bivariate EGARCH model (Bollersleve, 1986), we examine the patterns of information flows between the market segments. We use the following model for say spot and future pairs:

$$cvol\_spot_t = \alpha + \beta_1\, resid\_spot^2{}_{t-1} + \beta_2\, cvol\_spot_{t-1}(-1) + \beta_3\, resid\_fut^2{}_{t-1} + \beta_4\, cvol\_fut_{t-1} \quad (3)$$

where, cvol_spot/ cvol_fut= conditional volatility of spot/futures

resid_spot/resid_fut= residuals of mean equation of spot/futures

The coefficient β_1 measures clustering (ARCH effect); β_2 measures persistence (GARCH effect); β_3 measures short term spillover from future to spot and β_4 measures long term spillover from future to spot. Hence this model specification is run on other possible pairs (spot/futures and future/options) using generalized least squares (GLS) regression. The coefficient covariance estimator is a heteroskedasticity and autocorrelation consistent covariance (HAC) or Newey-West estimator which changes the coefficient standard errors of an equation, but not their point estimates.

For modeling relationships between volatilities (variance–covariance matrices of various portfolios) of several markets, Bollerslev, Engle, and Wooldridge (1988) proposed the first multivariate GARCH model for the conditional variance–covariance matrix, namely the VEC model. However, this model is a very general approximation and very difficult to implement in practice. The number of parameters in the model is large with respect to the dimension of the model and it is difficult to impose the positive definiteness of the variance–covariance matrix in the model. Baba, Engle, Kraft and Kroner (BEKK, 1990) suggest a convenient approach for modelling the conditional variances which allows large shocks in one variable to affect the variances of the other variables. This can be viewed as a restricted version of VEC model. BEKK model has a very good property, that is, conditional variance–covariance matrix is positive definite by construction. Keeping in view the above mentioned literature, we now set up a model on the basis of the standardized residuals obtained from the VECM to check the robustness of our volatility spillover results from bivariate EGARCH model.

$$\textit{Mean Equation:} \qquad \gamma_{it} = \mu_{i0} + \sum_{j=1}^{2} \mu_{ij}\gamma_{j,t-1} + \varepsilon_{it} \tag{4}$$

where $\varepsilon_{it} \mid I_{it-1} \sim N(0, h_{it})$, i= 1,2

In equation 4, ν_{it} is the estimated residual of the sample series. ε_{it} is a random error term with conditional variance h_{it}. I_{it-1} denotes the market information at time t-1. Equation (4) specifies the variance equation. i=1,2 denotes the bivariate model. The BEKK parameterization of multivariate GARCH model is written in the following manner:

$$H_{t+1} = C'C + A'\varepsilon_t\varepsilon_t'A + B'H_tB \tag{5}$$

Where the individual elements of C, A and B matrices for equation (5) are mentioned below:

$$A = \begin{bmatrix} a11 & a12 \\ a21 & a22 \end{bmatrix} \qquad B = \begin{bmatrix} b11 & b12 \\ b21 & b22 \end{bmatrix} \qquad C = \begin{bmatrix} c11 & 0 \\ c21 & c22 \end{bmatrix}$$

The off-diagonal elements of matrix A (a_{12} and a_{21}) represent the short-term volatility spillover (ARCH effect) from market 1 to another market 2. The off-diagonal elements of matrix B (b_{12} and b_{21}) represent the long-term volatility spillover (GARCH effect) in the same manner as mentioned above.

4.3 Information transmission using higher moments

We use a 65 day moving average to compute the skewness and kurtosis of the spot, future and option price series. The rationale for taking 65 days is that these are the approximate number of trading days in 3 months. For each return series, AR(1) process is used as the mean equation. Now for each market separately, time varying skewness and kurtosis is specified as an AR (1) process and is dependent on prior return shocks:

$$skew\_spot_t = c + \Upsilon_1\, skew\_spot_{t-1} + \Upsilon_2\, resid\_spot_{t-1} \qquad (6)$$

$$kurt\_spot_t = c + \Upsilon_1\, kurt\_spot_{t-1} + \Upsilon_2\, resid\_spot_{t-1} \qquad (7)$$

where,

skew_spot/ kurt_spot= skewness/ kurtosis of spot

resid_spot= residuals of mean equation of spot

The lagged skewness/ kurtosis terms in eqn 6 and 7 respectively allows for certain persistence or time dependencies in the shape of the return distribution and to capture the impact of a market shock on the degree of asymmetry/ peakedness, we introduce a lagged residual of the mean equation as an explanatory variable. The fitted values for these two equations (6 and 7) help us obtain conditional spot skewness (cskew_spot) and conditional spot kurtosis (ckurt_spot). We obtain these measures for all the three market segments for skewness and kurtosis respectively. We use the following model for say spot and futures to study skewness/ kurtosis spillover effects:

$$cskew\_spot_t = \alpha + \beta_1\, resid\_spot_{t-1} + \beta_2\, cskew\_spot_{t-1} + \beta_3\, resid\_fut_{t-1} + \beta_4\, cskew\_fut_{t-1} \qquad (8)$$

$$ckurt\_spot_t = \alpha + \beta_1\, resid\_spot_{t-1} + \beta_2\, ckurt\_spot_{t-1} + \beta_3\, resid\_fut_{t-1} + \beta_4\, ckurt\_fut_{t-1} \qquad (9)$$

where,

cskew_spot/ cskew_fut= conditional spot/futures skewness

ckurt_spot/ ckurt_fut= conditional spot/futures kurtosis

resid_spot/resid_fut= residuals of mean equation of spot/futures

The coefficient β_1 measures clustering effects; β_2 measures persistence effect; β_3 measures short term skewness/ kurtosis spillover from future to spot and β_4 measures long term skewness/ kurtosis spillover from future to spot. Hence this model specification is run on other possible pairs (spot/options and futures/options) using generalized least squares (GLS) regression.

5. Empirical Results

The time-series graphs of each of the sample series under consideration clearly exhibit the evidence of similar movement in prices (see Figure 1a), implying that there is not much scope of arbitrage in market and the relevant market information is intercepted by each sample market immediately. We have also plotted the continuously compounded daily returns graphs of all sample markets (see Figure 1b). It appears that there is strong case of clustering in the sample market during June 2008 to August 2009 which can be identified with the global economic crisis and its aftermath. The return behaviour of each market appears to be similar as it has been observed in case of actual prices. But it would be interesting to see how the behaviour of these markets changes in terms of their price discovery under first moment condition, volatility spillover in second moments and subsequently higher order moments. The descriptive statistics of sample daily return series is shown in Table 1. The mean returns appear to be same for all the series though being the highest for options (.0501%) and least for spot (.0498%). The standard deviation as a measure of volatility is highest for futures (1.78%) while being equal for spot and options (1.67%). The volatility measures are more than hundred times larger than the mean values. All return series exhibit negative skewness and are also leptokurtic. This automatically leads to the violation of normality assumption as exhibited by Jarque-Bera (JB) statistics. The results imply that all the sample markets are not informationallly efficient. As evident from the ARCH LM test, there is also strong evidence of volatility clustering in sample series, indicating the need for greater analysis of second moment. Ljung-Box (LB) test confirms no autocorrelation in level of sample series up to 12 lags with the exception of spot, while all variables indicate significant autocorrelation in squared terms.

5.1 Tests of Stationarity and Price Discovery Process

The results of the stationarity tests are shown in Table 2. All unit root tests clearly confirm the existence of unit root at level and exhibit stationarity at first difference for all sample series thus conforming that they are integrated to the first order. The cointegration results (refer table 3, panel A) clearly confirm the strong informational linkages between each of the trading platforms. VECM test (refer table 3, panel B) confirms that error correction coefficient of the spot is smaller than futures and options respectively and similarly coefficient for future is smaller than options. Hence if the co-integrated series is in disequilibrium in the short-run, it is the spot price that makes less adjustment than the futures/ options price in order to restore the equilibrium (and similarly futures price makes less adjustment than options price). Hence spot price leads the price discovery followed by futures price and lastly options price. From investment strategy perspective, the significantly negative EC coefficient for spot series implies that they are over-valued in comparison to a positive EC coefficient for option series (similarly for future and options pair) implying its undervaluation. The information provides market traders an incentive to sell/short-sell spot/future and go long on options and exercise lending opportunities to make arbitrage profits. Such an arbitrage process is probably ensuring a long-run equilibrium relationship between these market pairs as confirmed by cointegration results. The Granger causality test (refer table 3, panel C) reconfirms our VECM findings that there is an observable causality from sample spot to futures, options and from futures to options. In sum, information transmission path is from spot to futures to options. Although the cost of trading is lowest in the options market which has highest volumes of contracts traded daily, it is a surprise that information transmission path as reported in our empirical results is from spot to options which is in contrast to the market efficiency hypothesis. This increased activity in the options segment of the market can be attributed to speculators who are basically small investors/ firms trying to reap leverage benefits and tax arbitrage. Large institutional investors may have limited positions in the options market owing to exposure caps by the market regulators. Thus the spot market still remains the primary segment for investors who do price setting which is followed by derivatives segment participants including speculators (latter seem to play a greater role in options market).

5.2 Volatility Spillover

The estimated results of volatility spillover process estimated from bivariate EGARCH model are shown in table 4; Panel A. Market prices tend to exhibit periods of high and low volatility. This sort of behaviour is called volatility clustering. Volatility clustering

(ARCH effect) was found significant in all the cases, except when spot conditional volatility was the dependent variable and future conditional volatility was the independent variable. This implies that a large shock leads to greater volatility in the next period for a given time series. Volatility persistence (GARCH effect) was found to be significant for all the cases. This further means that the past volatility of all current indices impacts their current volatility significantly. For the spot future pair, there was a bidirectional short term volatility spillover though it was stronger from the spot side to futures (reflected from the absolute value of its coefficient sign). It may be noted that in case of spot, the past innovations in future prices impact the current spot price volatility positively while exactly opposite is the case from futures to spot. However when it comes to long term spillover, there was a weak unidirectional spillover from spot to future (interpreted at 10% level of significance). For the spot options pair, no short term spillover was found but there was a unidirectional long term spillover from spot to options. Finally for the futures options pair, again there was no short term spillover but a weak bidirectional long term spillover was found which was stronger from the options to the future.

The estimated results for volatility spillover from BEKK GARCH model are shown in Table 4; Panel B to check for robustness of results obtained from bivariate EGARCH model. The ARCH effect is confirmed for options and spot series while the volatility persistence (GARCH effect) was found to be significant for all the cases. Turning to cross volatility spillover effects, for the spot futures pair, bidirectional spillover was confirmed which was stronger from the spot side to the futures side. However when it comes to long term spillover, there was a unidirectional spillover observed from spot to futures. For the spot options pair, no short term spillover was observed but there was a weak unidirectional long term spillover confirmed from spot to options. Finally for the futures options pair, no short term as well as long term spillover was observed.

Thus the information in the second moment seems to be again emanating from spot and getting transmitted to options and futures contracts. The two volatility spillover tests present robust findings of the dominance of spot market in the case of NIFTY index trading, as in case of price discovery process. There seems to be a weak longrun bilateral volatility spillover process between options and futures contracts based on EGARCH model results.

5.3 Information Transmission Process through Higher Order Moments

Empirical results from skewness spillover are highlighted in Panel A of table 5 below. The clustering effect was not seen for all the cases of the three market segments except in spot futures pair. Persistence was confirmed for all the cases thus implying that days with high (low) skewness are more likely followed by days with high (low) skewness. For the information transmission via spillovers from one market segment to another, short term skewness spillover was not significant for any of the cases while long term unidirectional skewness spillover was found significant from spot to options and from future to options (the latter is interpreted at 10% level of significance). No long term spillover was however observed between spot and futures contracts.

Empirical results for kurtosis spillover are highlighted in Panel B of table 5 below. The clustering effect was not observed for all the cases except for spot options pair and the case when options was the independent variable and future was one of the dependent variable. Persistence was confirmed for all the cases thus implying that days with high (low) kurtosis are more likely followed by days with high (low) kurtosis. For the information transmission via spillovers from one market segment to another, weak short term unidirectional kurtosis spillover was found from options to spot while long term bidirectional kurtosis spillover was found significant for spot futures pair though stronger from the spot side. The empirical results confirm that the various stock markets segments are linked not only through the prices and return volatility but also through the asymmetries as well as tails of their return distribution.

Summing up, for the spot future pair, no significant clustering effects were exhibited in case of spot market while futures market exhibited significant volatility clustering. The degree of persistence measured by coefficient β_2 was higher in spot than future for all the three moments. As regards to the spillover effects, only bidirectional short term volatility spillover was confirmed which was stronger from the spot side though negative. Thus previous day positive shocks in the spot (futures) market tend to decrease (increase) return volatility in the futures (spot) in the next day. No significant higher moments spillovers were observed in the short run. In the long run, unidirectional volatility spillover was confirmed from spot to futures. As for the higher order moments, significant bidirectional kurtosis spillover was confirmed which was stronger from the spot side. Thus a previous positive shock in the spot market shall lead to increase in return volatility and the probability of extreme events in the next period. On the other hand, a previous shock in the futures market impacts the peakedness of return distribution for the spot market in the opposite direction over the next period.

For the spot options pair, both the clustering and persistence effects were observed for volatility and higher order moments. As regards to spillover effects, only short term unidirectional kurtosis spillover was found from options to spot. Unidirectional long term spillover was confirmed from spot to options for both the second and third moments (volatility and skewness). This implies that previous return shocks in the spot market impact volatility and return asymmetries in the options market for the next period.

For the future options pair of the market, both the clustering and persistence effects were observed for volatility and higher order moments for almost all the cases. As regards to spillover effects, no short term spillover was observed in any of the three moments. A bidirectional long term spillover was confirmed in the second moment which was stronger from the options side than the futures side while a unidirectional long term skewness spillover was confirmed from the futures to the options.

6. Summary and Conclusions

There is no dearth of literature relating to price discovery and information transmission between the various segments of the equity markets more specifically, cash and futures market. This paper takes it a step further by analyzing all three trading platforms for NSE 50 index in India that is spot, futures and options. The study period stretches from November 2003 to December 2013. In order to test the relationship between the NSE 50 stock index options and other segments of the equity markets, it is necessary to calculate the implied index level from the NSE 50 stock index options price. Black-Scholes Option Pricing model was used to recover the implied index level. For the three time series so obtained (spot, futures, implied index value from options), pairwise long run equilibrium was confirmed. The spot platform seems to be the dominant segment in the price discovery process for NSE 50 index followed by futures and then the options segments. This is in contrast to the efficient market hypothesis as one expects the market with lower transaction costs and greater trading volumes to take a lead in the price discovery process. This seems anomalous as derivative markets are expected to be informationally more efficient owing to higher trading volumes and lower trading costs as compared to spot markets. The findings can possibly be explained by the argument that investors take positions in the spot market platform and provide the price signals that are followed by the speculators in the derivative markets.

Short term bidirectional volatility spillovers are observed between spot and futures segment which are stronger from the spot side. The spot market again dominates in the long term spillover process. Unilateral volatility spillover are observed from spot to both futures and options market. Further, the options market tends to dominate the futures market in the long term bilateral volatility spillover process. This implies that hedgers prefer options to futures for risk management purposes. Regarding higher order moments, no significant short term skewness spillover effects are observed. In the long run, there is a unidirectional skewness spillover from spot as well as futures to options market. This implies that the return asymmetries in the first two markets impact that in the latter market. There is short term kurtosis spillover from options to spot market. As for the long run, bilateral kurtosis spillover is found between spot and futures, with the former playing a more dominant role. Thus the probability of extreme events in one market impacts similar probability for the other market.

Putting it all together, the spot market seems to be the most dominant platform in the price discovery process as well as information transmission through volatility and higher order moments. Further the futures market dominates the options market in price setting and skewness spillover while the latter plays a lead role in the volatility spillover. Hence all trading segments seem to be playing an important role towards creating a more efficient stock market system in India.

The findings are pertinent for market traders including investment managers, market regulators and the academic community. The fund managers can use the information transmission patterns to frame long/short trading strategies across market segments. The strategies can exploit not only the price linkages but also information transmission through volatility as well as higher moments. From regulators perspective, cross market linkages provides useful information about the level of maturity of the market trading system. This may warrant policy reforms relating to cost of trading, taxation issues and market microstructure aspects. From academic point of view, it is a challenge to explain how observed investor behaviour can defy implications of market efficiency. The study highlights the importance of financial market linkages especially via higher order moments which has implications for several empirical issues relating to asset pricing, value at risk (VaR) estimation and asset allocation. The paper contributes to information transmission literature by studying the various segments of the equity markets in the Indian context and focuses on little explored area of higher order moments.

References

Anandbabu, P (2003). "The Temporal Price Relationship between the Index Futures and the Underlying Cash Index: Evidence from the Indian Stock Market," Paper presented at the *International Conference on Business & Finance*, Hyderabad, India.

B. Arshanapalli, J. Doukas, Common volatility in S&P 500 stock index and S&P 500 stock index futures prices during October 1997, Journal of Futures Markets 14 (1994) 915–925.

Baba, Y., Engle.F.R, Kraft.D, and Kroner.K .(1990). Multivariate simultaneous generalized ARCH, *unpublished manuscript*, University of California, San Diego.

Bhattacharya, M. (1987). Price changes of related securities: The case of call options and stocks. Journal of Financial and Quantitative Analysis, 22, 1−15

Bohl, M. T., Salm, C. A., & Wilfing, B. (2009). Do Individual Index Futures Investors Destabilize the Underlying Spot Market? The Journal of Futures Markets 31(1), 81-101.

Bollerslev, Tim (1986). "Generalized Autoregressive Conditional Heteroskedasticity". Journal of Econometrics 31 (3): 307–327.

Bollerslev, T., Engle R. F. & Wooldridge J. M. (1988). A capital asset pricing model with time–varying covariances, Journal of Political Economy, 96, 116–131

Cao, C., Chen, Z. & M. Griffin. (2005). The informational content of option volume prior to takeovers. Journal of Business, 78, 1073-1109

Capelle-Blancard, G., & Vandelanoite, S. (2002). Relations intrajournalières entre l'indice CAC40 et les options sur indice : quel est le marché préféré des investisseurs informés ?. Annales d'économie et de Statistique, N°66, 2002

Cumperayot, P., Keijer, T., Kouwenberg, R., 2006. Linkages between extreme stock market and currency returns. Journal of International Money and Finance, 25, 528-550.

E.F. Fama (1970), Efficient capital markets: a review of theory and empirical work, Journal of Finance 25 383–417.

Finucane, T. J. (1991). Put–call parity and expected returns. Journal of Financial and Quantitative Analysis, 26, 499−519.

Fleming, J., Ostdiek, B., & Whaley, R. (1996). Trading costs and the relative rates of price discovery in stock, futures and options markets. Journal of Futures Markets, 16, 353–387.

G. Koutmos, M. Tucker, Temporal relationships and dynamic interactions between spot and futures stock markets, Journal of Futures Markets 16 (1996) 55–69

Gee, C. S., & Karim, M. Z. A. (2005). The lead-lag relationship between stock index futures and spot market in Malaysia: A Cointegration and Error Correction Model approach. Chulalongkorn Journal of Economics 17(1), 53-72

Ghosh, A. (1993). Cointegration and Error Correction Models: Intertemporal Causality between Index and Futures Prices. The Journal of Futures Markets 13(2), 193-198.

Gupta, K.. and Singh, B., 2006. Price discovery through Indian equity futures markets, The IUP Journal of Applied Finance

Hashmi, A. R., Tay, A. S., 2007. Global regional sources of risk in equity markets: Evidence from factor models with time-varying conditional skewness. Journal of International Money and Finance, 26, 430-453.

H.R. Stoll, R.E. Whaley (1990), The dynamics of stock index and stock index futures returns, Journal of Financial and Quantitative Analysis 25 441–468.

Hung, D, Brooks, R and Treepongkaruna, S (2011) , Financial Markets Linkages via Higher Moments: A Realized Spill-over Approach

Jackline, S., & Deo, M. (2011). Lead-lag relationship between the futures and spot prices. Journal of Economics and International Finance, 3(7), 424-427.

J.A. Lafuente-Luengo, Intraday realised volatility relationships between the S&P 500 spot and futures market, Journal of Derivatives & Hedge Funds 15 (2009) 116–121.

J.H. Min, M. Najand, A further investigation of the lead-lag relationship between the spot market and stock index futures: early evidence from placecountry-regionKorea, Journal of Futures Markets 19 (1999) 217–232.

K. Chan, P.Y. Chung, (1990) Intraday relationships among index arbitrage, spot and futures price volatility, and spot market volume: a transaction data set, Journal of Banking and Finance 17 663–687.

Kang, J., Lee, C. J., & Lee, S. (2006). An empirical investigation of the lead-lag relations of returns and volatilities among the KOSPI 200 spot, futures and options markets and their explanations. Journal of Emerging Market Finance, 5(3), 235-261.

Kang, S. H., Cheong, C. & Yoon, S. M. (2013). Intraday volatility spillovers between spot and futures indices: Evidence from the Korean stock market. Physical A, 1795–1802.

Kawaller, Ira G., Paul D. Koch and Timothy W. Koch, (1987). The Temporal Price Relationship between S&P 500 Futures Prices and the S&P 500 Index, Journal of Finance 5, 1309-1329.

Karmakar. M . (2009). Price Discoveries and Volatility Spillovers in S&P CNX Nifty Future and its underlying index CNX Nifty", Vikalpa. Vol. 34, No.2

Korkie, B., Sivakumar, R., Turtle, H. J., 2006. Variance spillover and skewness in financial asset returns. The Financial Review, 41, 139-156.

Longin, F., Solnik, B., 2001. Extreme correlation of international equity markets. Journal of Finance, 56, 649-676.

Lucian, S. (2008). Lead – Lag Relationship between the Romanian Cash Market and Futures Market. Working Paper, Bucharest.

Mukherjee, K N and Mishra, R K (2004). “Lead-lag Relationship between Equities and Stock Index Futures Markets and it’s Variation around Information Release: Empirical Evidence from India,” NSE website.

Nam, S. O.; S. Y. Oh; H. K. Kim; and B. C. Kim. 2006. “An Empirical Analysis of the Price Discovery and the Pricing Bias in the KOSPI 200 Stock Index Derivatives Markets.” International Review of Financial Analysis 15 no. 4-5: 398–414.

Nelson, D. B. (1991). "Conditional heteroskedasticity in asset returns: A new approach", *Econometrica* 59: 347-370.

Ng, N (1987). “Detecting Spot Forecasts in Futures Prices Using Causality Tests,” Review of Futures Markets, 6(2), 250-267.

O’connor M. (1999). The cross-sectional relationship between trading costs and lead/lag effects in stock and option markets. Financial Review, 34, 95-118

Pan, J., & Poteshman, A. (2006). The information in option volume for stock Prices. Review of Financial Studies, 19(3), 871-908.

Pati, P.C. & Pradhan, P.C. 2009, Information, Price discovery and casuality in the Indian Stock Indes futures market. The IUP Journal of Financial Risk Management , VI(3&4), PP.7-21

Pizzi, M. A., Economopoulos, A. J., & O’Neill, H. M. (1998). An examination of the relationship between stock index cash and futures markets: A cointegration approach. The Journal of Futures Markets 18(3), 297-305.

Powers, M. J. (1970) Does futures trading reduce price fluctuations in the cash markets? *American Economic Review*, 60, 460-4.

R.W. So, Y. Tse, Price discovery in the Hang Seng index markets: index, futures, and the tracker fund, Journal of Futures Markets 24 (2004) 887–907.

Reddy,V.V. & Sebastin, A. , 2008. Interaction between equity and derivatives market in India: Entropy Approach. The ICFAI Journal of Derivatives Market, V(1). Pp, 18-32.

Richard, H., Yusif, S., & Liuren, W. (2006). Price discovery in the U.S. stock options markets: A portfolio approach. Review of Derivatives Research, 9(1), 37-65.

Ross, S A (1989). “Information and Volatility: The No-arbitrage Martingle Approach to Timing and Resolution Irrelevancy,” Journal of Finance, 44(1), 1-17.

S. Arianos, A. Carbone, Cross-correlation of long-range correlated series, Journal of Statistical Mechanics: Theory and Experiment (2009) P03037

S. Kim, G. Lee (2010). Lead-lag relationship between volatility skew and returns: Evidence from KOSPI200 intraday options data Working paper, Hankuk University of Foreign Studies

Sakthivel, P. and Kamaiah, B., (2010),Price Discovery and Volatility Spillover between Spot and Futures Markets: Evidence from India, IUP Journal of Applied Economics, 9, 2, 81 97.

Schwarz, T. V. and Laatsch, F. (1991) Price discovery and risk transfer in stock index cashand futures markets, *Journal of Futures Markets*, 11, 669-83.

Schreiber, P.S.and Schwartz, R.A. (1986). Price discovery in securities markets. Journal of Portfolio Management, Vol. 12 (4), pp. 43-48.

Shyy, G., Vijayraghavan, V., & Quinn, B. S. (1996). A further investigation of the lead-lag relationship between the cash market and stock index futures market with the use of bid/ask quotes: The case of France. The Journal of Futures Markets 16(4), 405-420

So, R.W., & Tse, Y. (2004). Price discovery in the Hang Seng index markets: index, futures, and the tracker fund. The Journal of Futures Markets 24(9), 887-907

Stephan, J. A., & Whaley, R. E. (1990). Intraday price change and trading volume relations in the stock and stock option markets. The Journal of Finance, 45, 191−220.

Stoll, H. R. and Whaley, R. E. (1988) Volatility and futures: message versus messenger, *Journal of Portfolio Management*, 14, 20-2.

Stucki, T. & Wasserfallen, W. (1994). Stock and option markets: the Swiss evidence. Journal of Banking and Finance,18, 881-893.

Telser, G. L. (1981), "Why there Are Organized Futures Markets," Journal of Law and Economics, Vol. 24(1), pp 1-22.

Thenmozhi, M. (2002), "Futures Trading Information and Spot Price Volatility of NSE -50Index Futures Contract", NSE Research Initiative Paper No. 18, http://www.nseindia.com/content/reserch/paper59.pdf

Yang Jian, Yang Zihui & Shou Yinggang. (2012). Intraday price discovery and volatility transmission in stock index and stock index futures markets: Evidence from China. Journal of Futures Markets 32(2), 99–121.

Fig 1a: Time series graph of daily price series

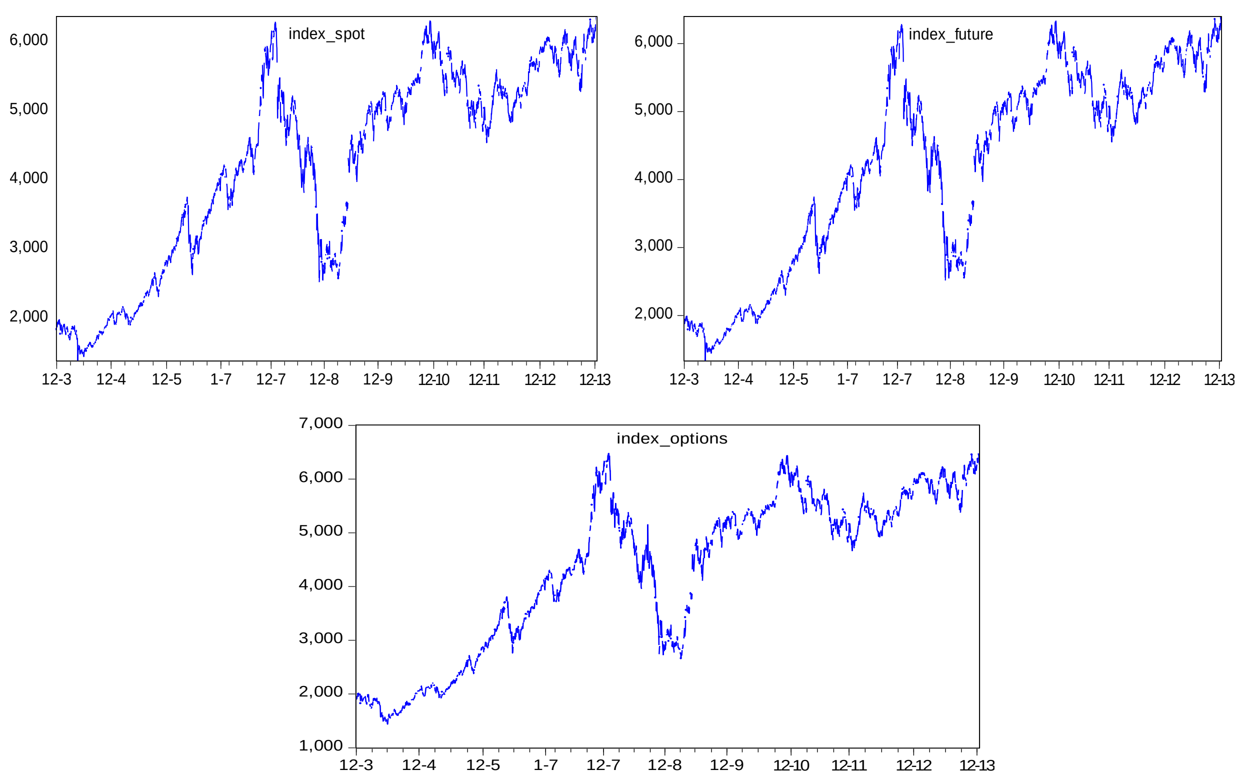

Fig 1b: Times series graph of daily return series

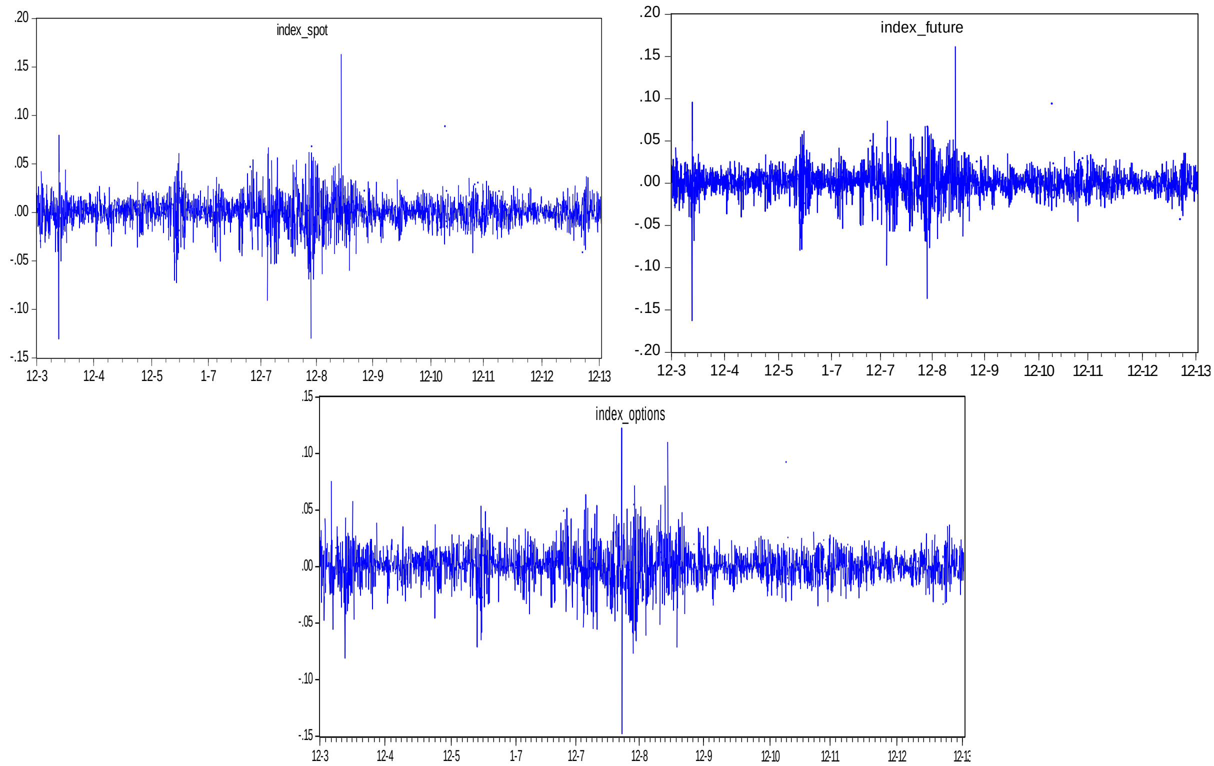

Table 1: Descriptive Statistics of sample return series

	Spot	Future	Options
Mean	0.000498	0.000500	0.000501
Median	0.000990	0.000895	0.000344
Maximum	0.163343	0.161947	0.122554
Minimum	-0.130539	-0.162581	-0.147765
Std. Dev.	0.0167	0.0178	0.0167
Skewness	-0.1896	-0.3655	-0.1272
Kurtosis	12.0814	12.4823	9.5872
Jarque-Bera	8371.794 [0.000]*	9165.355 [0.000]*	4403.508 [0.000]*
Arch	111.689 [0.000]*	142.153 [0.000]*	267.040 [0.000]*
LB	32.421 [0.001]*	20.757 [0.054]	17.375 [0.136]
LB^2	1010.700 [0.000]*	1087.600 [0.000]*	1147.2 [0.000]*
Observations	2432	2432	2432

Notes: * denotes level of significance at 5% . Values in parentheses [ ] indicate the p-values.
JB=Jarque Bera and LB= Ljung Box. LB statistics is reported up to 12 lags.
Spot here denotes spot index, future here denotes futures index and options here denotes implied index from options

Table 2: Tests of Stationarity

Variables	ADF Level	ADF First Difference	PP Level	PP First Difference	KPSS Level	KPSS First Difference
Spot	-2.545	-46.336*	-2.455	-46.333*	0.448	0.036*
Future	-2.521	-48.256*	-2.542	-48.252*	0.441	0.034*
Options	-2.432	-50.169*	-2.345	-50.211*	0.494	0.0394*
Critical Values						
1%	-3.963				0.216	
5%	-3.412				0.146	
10%	-3.128				0.119	

Note: * indicates the level of significance at 5%.

Table 3: Price Discovery Process

Panel A: Test for Cointegration

	Trace Test Null	Trace Test Statistics	Trace Test 95% Critical Value	Maximum Eigenvalue Test Null	Maximum Eigenvalue Test Statistics	Maximum Eigenvalue Test 95% Critical Value
spot and future	r=0	139.217*	15.495	r=0	137.275*	14.265
	r=1	1.942	3.4841	r=1	1.942	3.841
spot and options	r=0	128.949*	15.494	r=0	126.938*	14.264
	r=1	2.011	3.841	r=1	2.011	3.841
future and options	r=0	125.055*	15.495	r=0	123.182*	14.265
	r=1	1.873	3.841	r=1	1.873	3.841

Panel B: VECM Test

Cointegrating Pair	Variable	Error Correction Coefficient	Variable	Error Correction Coefficient	Lead	Lag
spot and future	spot	-0.122 [-1.111]	future	-0.297 [-2.553]*	spot	future
spot and options	spot	-0.002 [-0.087]	options	0.139 [5.189]*	spot	options
future and options	future	-0.012 [-0.456]	options	0.121 [4.777]*	future	options

Panel C: Granger Causality Test

Null Hypothesis	F Statistic	Prob.
spot does not granger cause future	4.175*	0.016
future does not granger cause spot	1.384	0.251
spot does not granger cause options	72.103*	0.000
options does not granger cause spot	0.075	0.784
future does not granger cause options	63.509*	0.000
options does not granger cause future	0.546	0.460

Notes: a) * indicates level of significance at 5%, values in parentheses, [ ] show t-values.
b) The lag structure is decided based on the minimum values of the Schwartz information Criterion which was 1 for all cases.

Table 4: Tests of Volatility Spillover

Panel A: Bivariate EGARCH Model

Dependent Variable	**α**	**β_1**	**β_2**	**β_3**	**β_4**
cvol_spot		resid_spot(-1)^2	cvol_spot (-1)	resid_fut(-1)^2	cvol_fut(-1)
	.001	-0.043	1.024	0.112	-0.1445
	[5.547]*	[-0.587]	[9.246]*	[2.278]*	[-1.531]
cvol_fut		resid_fut(-1)^2	cvol_fut (-1)	resid_spot(-1)^2	cvol_spot (-1)
	.001	0.234	0.621	-0.165	0.255
	[6.036]*	[4.721]*	[5.230]*	[-2.221]*	[1.882]**
cvol_spot		resid_spot(-1)^2	cvol_spot (-1)	resid_opt(-1)^2	cvol_opt(-1)
	.001	0.084	0.845	0.003	0.024
	[5.099]*	[2.882]*	[21.561]*	[0.706]	[1.221]
cvol_opt		resid_opt(-1)^2	cvol_opt (-1)	resid_spot(-1)^2	cvol_spot (-1)
	.000	0.057	0.902	0.002	0.024
	[4.448]*	[10.328]*	[99.642]*	[0.303]	[2.279]*
cvol_fut		resid_fut(-1)^2	cvol_fut(-1)	resid_opt(-1)^2	cvol_opt (-1)
	.000	0.099	0.816	-0.004	0.044
	[5.853]*	[4.206]*	[21.062]*	[-0.710]	[1.730]**
cvol_opt		resid_opt(-1)^2	cvol_opt (-1)	resid_fut(-1)^2	cvol_fut (-1)
	.000	0.056	0.907	0.002	0.017
	[4.190]*	[10.988]*	[101.369]*	[0.567]	[1.935]**

Notes: * denotes significance at 5% level; ** denotes significance at 10% level
b) Independent variable; coefficient; T Statistic [ ]
b) cvol_spot here refers to conditional spot volatility and resid_spot refers to residual of mean spot equation and likewise
c) Coefficient β_1 measures clustering (ARCH effect); Coefficient β_2 measures persistence (GARCH effect); Coefficient β_3 measures short term spillover and coefficient β_4 measures long term spillover

Panel B: BEKK GARCH Model

Variable	**Coeff**	**Std error**	**T-Stat**
Mean(1)	1.5712	0.8720	[1.802]**
Mean(2)	-0.1854	1.3777	[-0.135]
Mean(3)	1.4619	0.8119	[1.801]**
A(1,1)	-0.2365	0.1669	[-1.417]
A(1,2)	-0.4108	0.2586	[-1.589]
A(1,3)	-0.3763	0.1567	[-2.401]*
A(2,1)	-0.1991	0.2206	[-0.903]
A(2,2)	0.9199	0.1571	[5.854]*
A(2,3)	-0.2049	0.1992	[-1.029]
A(3,1)	0.7244	0.2714	[2.669]*
A(3,2)	-0.1342	0.3012	[-0.445]
A(3,3)	0.8558	0.2419	[3.537]*
B(1,1)	1.0033	0.0658	[15.238]*
B(1,2)	0.1741	0.1978	[0.880]
B(1,3)	0.0150	0.0625	[0.239]

B(2,1)	0.1683	0.1587	[1.060]
B(2,2)	0.4282	0.1274	[3.361]*
B(2,3)	0.1714	0.1440	[1.191]
B(3,1)	-0.2036	0.1014	[-2.008]*
B(3,2)	0.3174	0.1815	[1.749]**
B(3,3)	0.7847	0.0906	[8.663]*
Log Likelihood	-32949.98		

Notes: * denotes significance at 5% level; ** denotes significance at 10% level
b) Independent variable; coefficient; T Statistic [ ]
c) Models estimated using QMLE with robust (heteroskedasticity/misspecification) standard errors.
d) Mean (i) denotes the mean equation coefficients. In the variance equations, A denotes the ARCH terms and β denotes the GARCH terms. 1, 2 and 3 refers to futures, options, spot in that order
e) The coefficient A (1,2) for example can be interpreted as the short-term volatility spillover moving from futures to its options
f) The coefficient B (1,2) represents the long-term volatility spillover from futures to options. Others interpreted in same manner

Table 5: Information Transmission through higher moments

Panel A: Skewness Spillover

Dependent Variable	**Constant** α	**Independent Variables** β1	β2	β3	β4
cskew_spot		resid_spot(-1)	cskew_spot (-1)	resid_fut(-1)	cskew_fut(-1)
	-0.002	0.216	1.038	1.384	-0.049
	[-0.705]	[0.119]	[14.777]*	[0.721]	[-0.722]
cskew_fut		resid_fut(-1)	cskew_fut (-1)	resid_spot(-1)	cskew_spot (-1)
	-0.002	3.283	0.929	-1.756	0.060
	[-0.754]	[1.400]	[13.718]*	[-0.795]	[0.868]
cskew_spot		resid_spot(-1)	cskew_spot (-1)	resid_opt(-1)	cskew_opt(-1)
	-0.000	2.004	1.026	-0.395	-0.039
	[-0.156]	[4.729]*	[39.527]*	[-1.632]	[-1.485]
cskew_opt		resid_opt(-1)	cskew_opt (-1)	resid_spot(-1)	cskew_spot (-1)
	0.000	1.163	0.941	0.080	0.050
	[0.321]	[6.944]*	[37.710]*	[0.599]	[2.101]*
cskew_fut		resid_fut(-1)	cskew_fut (-1)	resid_opt(-1)	cskew_opt (-1)
	-0.000	2.069	1.011	-0.534	-0.025
	[-0.291]	[3.432]*	[38.415]*	[-1.358]	[-0.930]
cskew_opt		resid_opt(-1)	cskew_opt (-1)	resid_fut(-1)	cskew_fut (-1)
	0.000	1.150	0.951	0.093	0.039
	[0.301]	[6.509]*	[38.326]*	[0.536]	[1.656]**

Panel B: Kurtosis Spillover

Dependent Variable	**Constant** α	**Independent Variables** β$_1$	β$_2$	β$_3$	β$_4$
ckurt_spot		resid_spot(-1)	ckurt_spot (-1)	resid_fut(-1)	ckurt_fut (-1)
	-0.021	10.051	1.189	-11.659	-0.225
	[-2.038]*	[0.909]	[12.736]*	[-0.993]	[-2.332]*
ckurt_fut		resid_fut(-1)	ckurt_fut (-1)	resid_spot(-1)	ckurt_spot (-1)
	-0.021	-15.780	0.699	14.063	0.266
	[-2.006]*	[-1.084]	[6.331]*	[1.024]	[2.485]*
ckurt_spot		resid_spot(-1)	ckurt_spot (-1)	resid_opt(-1)	ckurt_opt (-1)
	-0.019	-4.559	0.935	2.645	0.032
	[-1.904]**	[-1.732}**	[25.654]*	[1.847]**	[0.922]
ckurt_opt		resid_opt(-1)	ckurt_opt (-1)	resid_spot(-1)	ckurt_spot (-1)
	-0.014	0.988	0.951	-0.681	0.028
	[-1.402]	[2.174]*	[33.837]*	[-1.211]	[1.157]
ckurt_fut		resid_fut(-1)	ckurt_fut (-1)	resid_opt(-1)	ckurt_opt (-1)
	-0.019	-5.659	0.916	3.670	0.049
	[-1.884]**	[-1.501]	[27.822]*	[1.493]	[1.567]
ckurt_opt		resid_opt(-1)	ckurt_opt (-1)	resid_fut(-1)	ckurt_fut (-1)
	-0.014	1.059	0.962	-0.726	0.017
	[-1.407]	[1.941]**	[40.612]*	[-1.029]	[0.810]

Notes: * denotes significance at 5% level; ** denotes significance at 10% level
b) independent variable; coefficient; T Statistic [ ]
b) cskew_spot/ ckurt_spot here refers to spot conditional skewness/ kurtosis and resid_spot refers to residual of mean spot equation and likewise for others
c) Coefficient β$_1$ measures clustering effect; Coefficient β$_2$ measures persistence effect; Coefficient β$_3$ measures short term spillover and coefficient β$_4$ measures long term spillover
d) Newey West estimation of least squares to have heteroskadasticity and autocorrelation corrected standard errors