Journal of Applied Finance & Banking, vol. 3, no. 1, 2013, 93-107
ISSN: 1792-6580 (print version), 1792-6599 (online)
Scienpress Ltd, 2013

Price Leadership between Spot and Futures Markets

Kiran Kumar[1] and Chakrapani Chaturvedula[2]

Abstract

This paper aims to study the relative information shares of spot and futures market at the individual stock level to measure the price discovery in spot and futures market in the Indian capital markets. We find that the spot and futures prices are co-integrated and mutually adjusting. Building on Information Share approach of Hasbrouck, the price discovery share of futures segment is about 36% compared to that of spot segment is 64%. It is expected that futures market contribute more towards price discovery given huge trading volumes and they carry the natural advantage of cost-effectiveness in terms of leverage benefit. However, the empirical result (or the fact) is spot market leadership in price discovery and this fact is reconciled by probing the clientele of futures market and is consistent with very active participation of retail traders in futures segment.

JEL classification numbers: G130,G140
Keywords: Price Discovery, Information Shares, Stock Futures

1 Introduction

Understanding the influence of one market on the other and role of each market segment in price discovery is the central question in market microstructure design and of utmost importance to regulators and academia. Price discovery is an important function of the exchange and it hints at where do informed traders trade. More precisely, following Schreiber and Schwartz (1986), Price discovery is the process by which markets attempt to find their fair prices. If the markets are efficient and frictionless, then price discovery should be instantaneous and contemporaneous. In practice, between spot and derivatives segments or across different trading venues of the same stock, price discovery takes place in one market and the other markets follow it. The market leader is the one, which

[1] Assistant Professor, NISM Mumbai,
e-mail:Kiran.kumar@nism.ac.in
[2] Associate Professor, Department of Finance and Accounting, IMT, Hyderabad,
e-mail:cchakrpani@imthyderabad.edu.in

Article Info: *Received :* October 11, 2012. *Revised :* November 5, 2012.
Published online : January 15, 2013

provides necessary trading platform or environment to transform the information into prices. All else equal, the price discovery function depends broadly on three factors, viz. trading costs, liquidity and leverage benefits. In essence, the traders assess the direct trade-off of the benefits of leverage in the futures market with the benefits of lower costs of trading and higher liquidity of the spot market. The result of this trade-off is an empirical question that we address here.

Derivative trading started in India in 2000. Since then the average daily derivative trading volume in NSE increased from 20 Million rupees in June 2000 to around 480 billion rupees in August 2007. The trading volume of derivative segment has increased manifold over the years. Though both futures and options were introduced around the same time the size of futures market is at least four times that of the options market. With in the futures market, the Individual Stock Futures (hereafter, ISF) segment is of phenomenal success on Indian bourses and NSE is consistently ranked number one in world ISF segment, even in the absence of strong stock lending mechanism. As of July 2007 NSE ranked number one in the world based on the total number of 18.8 million individual stock futures contracts traded. The next best exchange EUREX has 3.2 million ISF contracts traded3. Though derivatives trading started on Indian bourses in 2000, very few studies looked at the dynamics between spot and derivatives segments. The few existing studies concentrated on providing the direction as to which markets leads or lag the other market.

The major limitation of these studies is that they won't look at the differences in liquidity, leverage and transaction costs in spot and derivative segments and do not look at the over all nature and extent of price discovery provided by each market segment. Spot and derivative markets are strongly linked to each other by complex arbitrage relationships, which ensure long run price tendency towards an equilibrium constraint. The price series cannot diverge and instead follow paths that cannot drift too far apart. Hence, we expect that the time paths of such variables are responsive to the previous period's pricing error, in that the variables adjust to correct for deviations from the long run equilibrium path. Using error correction model and Hasbrouck information shares approach this paper attempts to compute the 'extent' of price discovery in spot and futures market. The paper contributes to the growing literature of linkages between spot and derivatives and to the author's knowledge, is the first paper to examine the relative information shares of spot and futures markets at the individual stock level. The rest of the paper is organized as follows: Section 2 discuses the literature on price discovery in spot and futures market. Third section presents the data used in the study and fourth section lays down the methodology employed in the paper. Last section reports the results and concludes the paper.

2 Literature Review

Empirical papers studying the relationship between cash and derivatives markets mainly looked at three things, firstly, the impact of derivative markets on cash markets by analyzing the underlying characteristics before and after derivative introduction. Secondly, by studying the behavior of the cash market around expiration dates and thirdly by studying the lead lag relationship between cash and derivative markets. Broad evidence seems to suggest that derivative markets do not increase the underlying market but tend to make the underlying market more liquid and more informationally efficient.4

A close look at the empirical literature gives three different approaches that examine dynamics / linkages between the stocks that trade in different segments or the dynamics of spot and derivative segments of same stock. The first one focuses on the lead-lag relationship between the prices of indices of different indices across countries or prices of same stock trading in different venues and here the focus is on spot and derivative (and more so futures) markets.

Studies which report that index futures lead the cash market in US include Kawaller, Koch and Koch (1987), Stoll and Whaley (1990), Chan (1992), Fleming, Ostdiek and Whaley (1996). Kawaller, Koch and Koch (1987) with an interval of one minute trades and without adjusting for infrequent trading shows that S&P 500 futures lead the cash market by 20 to 45 minutes and the cash market does not lead the futures by more than two minutes. Stoll and Whaley (1990) after adjusting for infrequent trading and with an interval of five minute trades finds that S&P 500 futures market lead the spot on an average by 5 minutes. They also report weak evidence of cash market leading the spot market. Chan (1992) finds similar relationship for MMI index futures. Taking five minute intervals he finds that futures market lead the spot strongly when compared to spot leading the futures. Fleming, Ostdiek and Whaley (1996) also show that futures lead the spot markets and note that investors prefer low cost markets and futures market will react faster to new information. According to them trading costs can explain the results where stock prices lag the futures market. Studies from Non US markets include Iihara, Kato, and Tokunaga (1996) on the Nikkei Stock Average and Abhyankar (1995) on the FTSE 100 and both find that futures lead the spot.

In summary, most studies report that the future market leads cash market by a time ranging from 5 minutes to 45 minutes. However, the cash market leads the future market by not more than one to two minutes. The main reasons attributed for this lead-lag relationship in the literature includes that futures markets have lower transaction costs and ease of trading with ability to short sell and marking to market trading. The next approach looks at the Volatility, following two seminal papers (French and Roll, 1986; and Ross 1989), as it reflects the source of information. French and Roll (1986) found that stock prices are much more volatile during trading hours than non trading hours and this extra volatility in trading hours is caused by differences in flow of information. Ross (1989) found that stock volatility is related to the rate of information flow in perfect markets. The transmission of volatility from one market segment to other segment will lead to price discovery and this approach is well established by applying MGARCH framework. Some important studies in this framework are: Karolyi (1995), Koutmos and Booth (1995), Booth et al (1997) across different markets. Chan, Chan and Karolyi (1991), Kawaller, Koch and Koch (1990), Koutmost and Tucker (1996) looked at volatility spillovers and hence price discovery between spot index and index futures markets.

Third approach, newer techniques developed by Gonzalo and Granger (1995) and Hasbrouck (1995) provide measures to compute price discovery for securities traded in multiple markets. The information share associated with a particular market is defined as the proportional contribution of that market innovation-to-innovation in common efficient price. Capturing the information content revealed in each market explains the price leadership that each market has over other. Papers that have applied similar techniques to futures studies include Booth, So, and Tse (1999) and Tse (1999). Booth, So, and Tse (1999) look at the German DAX index futures, spot and options. They compute Gonzalo-Granger information share and find that futures contribute most to the price discovery process followed by spot and options contribution is negligible. Tse (1999) look at the DJIA futures and spot data for six months from November 1997 to April 1998. Applying the Hasbrouck (1995) information shares approach they find that the futures market dominate the spot market with information shares of 88% and 12 % respectively for both the markets. Chakroborthy Gulen and Mayhew (2004) apply the Hasbrouck information shares approach to investigate the contribution of options market to price discovery. Booth et al. (2002) use the same technique to measure the price discovery by upstairs and downstairs markets in Helsinki Stock Exchange. Huang (2002) apply it to measure the price discovery in NASDAQ stocks by electronic communication networks and NASDAQ market makers. So and Tse (2004) examines the price discovery process between the Hangseng stock index and index futures series, with a common factor approach. Early studies looking at lead lag relationship between Nifty spot index and Nifty index futures market in India using daily data include Thenmozhi (2002) and Anand babu (2003). They find that the futures market in India lead the spot market by at least one to two days. They also find that futures market has more power in disseminating information and therefore has been found to play the leading role in price discovery. Mukherjee and Mishra (2006), by looking at six months intraday data from April 2004 to September 2004, find that neither Nifty index futures nor Nifty spot index lead and there is a strong contemporaneous and bi-directional relationship among the index and index futures market in India. To the best of our knowledge, no paper in India computed information shares for futures and spot markets based on the Hasbrouck (1995) technique and is the first one at the individual stock level.

3 Data Sources and Preliminary Analysis

The data in this study covers 791 trading days from January 2004 to March 2007. Both stock and futures tick-by-tick transactions data give the time price, volume of each transaction. On each day we have stock name, price, traded quantity and time stamped to the last second. We thank NSE Research Initiative for providing both data sets. We explicitly recognize that the high frequency of microstructure data is crucial to testing for pricing dynamics across informationally linked markets for two reasons: First, cointegration models capture “long-run” equilibrium relationships where in time series can diverge temporarily but then readjust to persistent cointegrated patterns. One year data of Reliance trades, at one-minute frequency, is long run in the sense that more than 90,000 such price adjustments can occur. Second, we must guard against observation intervals so long that error correction takes place within rather than between intervals. Just as annual data on household consumption and income cannot detect an error correction process reflecting monthly household budgets, so too, daily stock price data cannot detect the error correction from higher frequency trading strategies. Bearing this in mind, we construct a high frequency comparison of prices of spot and futures segment. We sample at one-minute intervals, recording the last transaction price in each one-minute time partition. If no observation occurs in the interval then the previous period’s price is recorded. Each trading day comprises 330 one-minute time intervals (ie. ignoring the first five minutes of each day) making a total of 2,60,000 (approximately) observations per stock. From one minute price series, we construct continuously compound returns (log returns). The nearby contracts data is used in calculating futures returns, as the nearby contracts are the most actively traded. Further, to remove the effect of rollover of contracts on expiration, we consider middle month contracts data just one day prior to expiration day in place of near futures contracts data. Analysis of the intra-day price discovery process requires the data series be synchronous across the markets. Non-synchronicity of a data series could bias the price discovery abilities of the markets. Nevertheless, it is impossible to have trades in both markets occurring at the same time. To check if the one-minute data interval will introduce bias into the analysis, a careful check of the trading activities of the two markets is necessary.

For both markets, trading is active and the problem of non-synchronicity is not serious. Thus, the problem of infrequent trading is not serious. Results are qualitatively the same for the five-minute interval used. The discussion below is based on the one-minute data interval.

The first step in testing for co integration is to determine the order of integration of each series. The most common approach is the augmented Dickey-Fuller (ADF) test based on Dickey and Fuller. To ensure that sufficient trading activity takes place, only 46 stocks with the most active series are chosen for this study. Table 2 lists the set of stocks considered in the study along with the market capitalization of each stock at the end of the sample period.

3.1 Preliminary Data Analysis

Price discovery will occur in the market for which trading costs are the least, thus providing the highest net profits from information trading. The concern is on indirect trading costs and not the direct costs like brokerage and related fees. The indirect cost is measured through Impact cost, the price concession due to the trade's impact on price. In addition, the market preference of informed traders is a function of the relative depth offered by each market. As futures segment provide extra leverage to the investor, it is expected that the informed investor would like to trade on his information first in futures segment. Stated differently, the informed investor prefers to use his information set in a market, which offers more leverage, lower trading costs and to the extent informed traders trade in a particular market it will lead to higher price discovery in that market. Table 1 reports the average impact cost and trading volume of each stock across spot and futures segment for March 2007 (and similar values appear through out the sample period). As can be seen, the spot market offers lower trading costs and higher liquidity than the futures market, consistently for all the stocks considered in the study. The preference of market place is trade-off of benefits of leverage in futures with the benefits of lower trading costs and higher liquidity in the spot market. The result of this trade-off is an empirical question and will be addressed in next section.

Table 1: Trading Activity of Spot and Futures Market Segment

SYMBOL	**Market Cap** (In Rs.10 million)	**Impact Cost**		**Traded Value** (Rs. 10 million)	
		Spot	Futures	Spot	Futures
ABB	15044	0.07	0.14	16.92	44.02
ACC	13722	0.08	0.1	60.51	223.96
BAJAJAUTO	24563	0.07	0.1	92.95	78.13
BHEL	55349	0.06	0.07	85.19	111.24
BPCL	10946	0.11	0.2	14.21	21.77
CIPLA	18406	0.11	0.14	24.28	18.18

DRREDDY	12227	0.09	0.12	48.22	57.75
GAIL	22372	0.13	0.18	9.09	19.20
GLAXO	9486	0.11	0.28	6.45	19.10
GRASIM	19186	0.09	0.11	1.14	77.76
HCLTECH	18967	0.09	0.17	21.49	51.38
HDFC	38155	0.1	0.09	47.80	37.22
HDFCBANK	30169	0.09	0.1	102.99	57.40
HEROHONDA	13753	0.11	0.17	36.18	32.40
HINDPETRO	8409	0.12	0.19	18.19	19.88
ICICIBANK	76379	0.09	0.08	353.76	236.20
INFOSYSTCH	114000	0.06	0.05	365.12	286.58
IPCL	8143	0.08	0.14	21.16	28.30
ITC	56866	0.08	0.09	179.30	174.47
JETAIRWAYS	5467	0.1	0.18	34.43	52.23
LANDT	45471	0.07	0.07	117.50	82.55
MANDM	19149	0.08	0.11	69.32	160.83
MARUTI	23696	0.07	0.1	73.17	128.91
MTNL	9245	0.08	0.17	10.39	31.88
NATIONALUM	15054	0.13	0.33	3.88	13.12
NTPC	123888		0.11	54.83	86.98
ONGC	188392	0.1	0.09	113.49	124.73
ORIENTBANK	4701	0.11	0.29	6.07	9.11
PNB	14952	0.1	0.13	35.40	35.88
RANBAXY	13118	0.07	0.12	46.08	63.90
RCOM	86048	0.07	0.08	131.77	262.15
REL	11294	0.09	0.11	15.39	20.28
RELIANCE	190952	0.06	0.05	361.21	565.05
RPL	47210		0.08	41.48	77.34
SAIL	47210	0.08	0.09	126.27	316.45
SATYAM	30969	0.06	0.09	126.33	143.85
SBIN	52338	0.07	0.07	76.38	309.52
SIEMENS	18387	0.09	0.14	19.00	48.83
SUNPHARMA	20341	0.12	0.18	40.64	46.60
SUZLON	28820	0.09	0.11	39.21	49.34
TATAMOTORS	28063	0.07	0.09	95.04	225.70
TATAPOWER	10079	0.11	0.17	9.66	18.25
TATASTEEL	26101	0.06	0.08	143.44	474.40
TCS	120746	0.08	0.08	86.42	123.59
VSNL	11466	0.1	0.18	12.83	26.02
WIPRO	80717	0.1	0.1	40.32	71.54

source:www.nseindia.com

4 Methodology on Price Discovery Measures

Consider the case of a stock whose price can be represented as a random walk and which trades without transaction costs in two venues:

$$p_{1,t} = p_{1,t-1} + \varepsilon_{1,t}$$

$$p_{2,t} = p_{2,t-1} + \varepsilon_{2,t}$$

$$\varepsilon_t \sim WN(0,\Omega) \tag{1}$$

where pjt is the observed price and ε_t is the vector of price innovations at time t. Clearly, there must be a relationship between the innovations in markets 1 and 2; were this not true, the two price series would diverge as each market's price would follow a separate random walk, creating arbitrage opportunities. If we make the additional assumption that traders in market 1 observe market 2 prices with a one-period lag and vice versa, then prices in each market will reflect all information except the current period's innovation in the alternate market. We can express each price as a sum of innovations obtained from two price series and their difference is stationary and hence cointegrated. The non-stationary vector of prices can be represented as a finite order autoregressive process; it can be represented through an error correction model (ECM) of the form:

$$\Delta p_t = \alpha\beta p_{t-1} + \Gamma_1 \Delta p_{t-1} + \Gamma_2 \Delta p_{t-2} + \ldots + \Gamma_k \Delta p_{tk1} + \varepsilon_t \tag{2}$$

where βpt-1 is a stationary combination of lagged price levels and the remaining terms represent a kth-order vector autoregression of first differences. In the case where the vector pt contains two elements, the ECM can be estimated using a two-step procedure in which the cointegration vector β is estimated in the first step through a cointegrating regression; the remaining coefficients can be estimated with OLS (Engle and Granger, 1987). When the vector pt consists of more than two elements, Johansen's reduced rank regression procedure can be used to identify the number of cointegrating relationships (Johansen, 1988); the system can then be estimated in one step using maximum likelihood estimation. Note that the system cannot be modeled as a VAR of differences without the βpt-1 error correction term; such a model is mis-specified because it does not incorporate the long run cointegration relationship, βpt, which prevents the elements of pt from diverging.

However, note that, each market's price change reflects both informational innovation and noise caused by uninformed trading and microstructure effects. Although market i may observe market j's price, participants cannot know with certainty whether market j's price change is due to information or noise. Consequently, market i will react to market j over a number of lags (for example, as traders observe that the innovation persists), or will react to the disequilibrium βpt-1 itself (in equilibrium βpt-1=0) to adjust market i's price for information originating in market j.

In practice, prices may differ due to trading costs; with additional assumption that trading costs are stationary, βpt-1 can be centered (by subtracting its sample mean) and the system can be estimated through OLS (Hasbrouck, 1995).

A number of different approaches to attributing price discovery using the ECM representation have been mentioned in the literature. Harris, McInish, Shoesmith and Wood (1995) describe price discovery occurring on the New York, Midwest and Pacific

Stock Exchanges; they show that when a regional market's price differs from the NYSE's price (an out-of-equilibrium condition where βpt≠0 in Equation 2), the regional exchange's adjustment is greater in magnitude than that of the NYSE: the regional exchange adjusts its price more than the NYSE does to bring prices back to equilibrium. This approach's main advantage is its clear intuition: when market 1 and market 2's prices differ, the magnitude of α term from the ECM suggests which market bears the price discovery burden. However, this methodology ignores the adjustments captured in the VAR terms, potentially discarding the information constrained in significant lagged reactions to innovations in alternate markets.

An alternate approach involves identifying the common factors in pt. Stock and Watson (1988) show that if a series is cointegrated, there exists a common factor representation of the form

$$X_t = X_0 + A\tau_i + a_t$$

$$\tau_t = \pi + \tau_{t-1} + \nu_t$$

Where τt is a linear combination of k random walks with drift π and transitory components at. Gonzalo and Granger (1995) present a methodology to identify the permanent and transitory effects in a cointegrated system, expressing the underlying common factor as a weighted average of contemporaneous prices with innovations that are orthogonal to the error correction process (βpt in equation 2). Harris, McInish and Wood (2002) apply the Gonzalo-Granger methodology to trade data for DJIA stocks on the NYSE and regional exchanges, documenting changes in information share and trading volume share over time. This methodology has an attractive basis in permanent- versus transitory- effects decomposition, but requires a simplifying assumption. The Stock and Watson common trend is a true random walk only when the common factor is a combination of prices at all leads and lags. In application, the Gonzalo-Granger common factor is a linear combination of contemporaneous prices. This leaves it with undesirable properties: the innovation in the common factor are generally highly auto correlated and have a significantly larger variance than the innovation in the random walk described by the Stock and Watson common trend model (Hasbrouck, 2002 and DeJong 2002).

A third approach to attribution of price discovery is presented by Hasbrouck (1995). Hasbrouck introduces the information share measure which captures the variation in the underlying random walk introduced by each market. Assuming that each market's price is a random walk and that they share a single common trend, prices at time t can be expressed as

$$p_t = p_0 + \Psi(1)\sum_{i=1}^{t}\varepsilon_t + \Psi(L)\varepsilon_t \tag{3}$$

where ψ(L) is a matrix in the lag operator and $\psi(1)\sum_{i=1}^{t}\varepsilon_t$ captures the random walk common to all prices in pt. The number of common trends is equal to the number of markets, n, less the number of cointegrating relationships. When all markets contribute information, there are n-1 cointegrating vectors leaving a single common trend. When there is a single underlying random walk, the rows of ψ(1) must be identical. The elements of each row quantify the impact of innovations in each market on the underlying shared random walk; if the rows were different, the elements of pt (the prices in each market) would follow separate random walks. After estimating the ECM, ψ(1) (a sum of an infinite series of moving average coefficient) can be approximated from the error correction model's parameters. Since each row of ψ(1) is identical, Equation 3 can be expressed as

$$p_t = p_0 + \Psi(\sum_{i=1}^{t} \varepsilon_t) l + \Psi(L)\varepsilon_t$$

where l is an nx1 column of ones and ψj can be thought of as the proportion of market j's price innovations impou8nded into the underlying random walk shared by all markets.

Hasbrouk's information share measure is similar to a variance decomposition of the s step ahead forecast of a stationary VAR process (Hamilton, 1994). Consider a zero mean covariance stationary vector autoregressive process of order k with no unit roots

$$y_t = \Phi_1 y_{t-1} + ... + \Phi_k y_{t-k} + \varepsilon_t \tag{4}$$

The Wold decomposition theorem states that this process can be represented as an infinite order moving average:

$$y_t = \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + ... + \varepsilon_t$$
$$\varepsilon_t \sim N(0, \Omega) \tag{5}$$

where the VMA coefficients ψ can be calculated by recursive substitution according to the relation

$$\Psi_s = \Phi_1 \Psi_{s-1} + \Phi_2 \Psi_{s-2} + ... + \Phi_p \Psi_{s-p}$$
$$\Psi_0 = I_n$$
$$\Psi_s = 0 \forall s < 0$$
$$Var(y_t) = \Psi \Omega \Psi' \tag{6}$$

where ψ is a vector of ψs.

Hasbrouck's information share measure is given as: $IS_j = \frac{\Psi_j^2 \Omega_{jj}}{\Psi \Omega \Psi'}$ is simply the proportion of variance in the underlying, shared random walk attributable to market j's innovations. Since Ω is generally not diagonal, however, we can only place upper and lower bounds on ISj. This is accomplished by permuting Ψ and Ω, placing the elements corresponding to each particular market in the first and last position in turn, cholesky factorizing each permutation. The iterative cholesky factorizations ascribe the maximum and minimum fraction of total variance in pt to each market, allowing us to bound the information share from above and below. The range spanned by maximum and minimum of these factorizations is a function of what proportion of the variance of εt occurs in the off diagonal elements of Ω. In application, the range of the maximum and minimum information share is smallest when pt is modeled with the finest feasible time resolution so the relationship between innovations in different markets is identified in the greatest possible detail.

While information share methodology is somewhat more complex and computationally intensive than the common factor analysis suggested by Stock and Watson, it implies an underlying common trend with desirable properties. The innovations in the implied efficient price incorporate the information at all lags in the ECM and tend to have a lower variance than innovations to the Gonzalo-Granger common factor constructed as a linear combination of contemporaneous prices. In the present study, we use Hasbrouck's information share approach to determine the price discovery in spot and futures markets.

5 Results and Discussion

Table 2 reports the results of price discovery attribution in spot and futures segment by using Hasbrouck's Information Share approach. We estimated Information Shares for each day of spot and futures segment across all 46 stocks. As the Hasbrouck methodology identifies a range (lower and upper bound), we average the bounds and take it as Information Share of the market segment for that day5. Further, we take Mean and Median of Information Shares over the sample period for each stock and resulting numbers are reported in Table 3.

As can be read from the Table 3, the Information Share is generally higher in spot segment consistently for all the stocks. The Information Share is highest (lowest) for L&T stock in spot (futures) segment at 90% (10%). On the other hand, the Information Share is lowest (highest) for VSNL stock in spot (futures) segment at 53% (47%). The evidence appears to be quite strong conveying that the spot markets contribution is major

in price discovery. This evidence, prima face, sounds counter intuitive as traditionally we felt that 'informed' investors trade in futures (derivatives) segment as they offer leverage benefits and trades of informed investors cause permanent shifts in prices and hence more price discovery in futures segment. We probe further to see why futures segment is not the leader in price discovery. This probe takes us into look at the trading parties' involvement in futures trading vis-à-vis spot market trading. Table 3 reports the clientele of trading parties share in total derivatives turnover for the period June 2006 to March 2007 (and similar pattern exists through out the sample period). The percentage contribution in total turnover by Institutional trades is about a mere 11% compared to retail share (65%) and proprietary trades (24%). Given the low percentage share of institutional trades in derivatives segment, it is expected that the 'price relevant' information is not getting reflected first in derivatives segment. It is important to note a recent study by, Jones and Lipson (2003), who show that retail order flow, has a minimal impact on price changes compared to nonretail order flow in NYSE and concludes that non-retail order flow carries price-sensitive information. Our finding is in tune with Jones and Lipson (2003), as institutional participation is minimal in derivatives due to the SEBI regulations prevalent in Indian stock market, informed traders prefer spot market and hence spot segment enjoys price leadership over futures segment.

Table 2: Hasbrouck Information Share Measures

SYMBOL	**SPOT**		**FUTURES**	
	Mean	**Median**	**Mean**	**Median**
ABB	59.7%	65.5%	40.3%	34.5%
ACC	60.6%	66.8%	39.4%	33.2%
BAJAJAUTO	58.6%	64.0%	41.4%	36.0%
BHEL	53.7%	56.3%	46.3%	43.7%
BPCL	58.6%	65.0%	41.4%	35.0%

CIPLA	58.2%	64.7%	41.8%	35.3%
DRREDDY	59.2%	66.0%	40.8%	34.0%
GAIL	58.2%	62.7%	41.8%	37.3%
GLAXO	60.3%	66.3%	39.7%	33.7%
GRASIM	57.4%	62.7%	42.6%	37.3%
HCLTECH	54.1%	55.3%	45.9%	44.7%
HDFC	55.1%	55.4%	44.9%	44.6%
HDFCBANK	56.5%	62.8%	43.5%	37.3%
HEROHONDA	57.1%	63.0%	42.9%	37.0%
HINDPETRO	60.9%	68.0%	39.1%	32.0%
ICICIBANK	55.3%	60.3%	44.7%	39.7%
INFOSYSTCH	57.1%	61.3%	42.9%	38.7%
IPCL	60.9%	65.6%	39.1%	34.4%
ITC	59.0%	63.0%	41.0%	37.0%
JETAIRWAYS	57.9%	61.5%	42.1%	38.5%
LANDT	76.0%	90.2%	24.0%	9.8%
MANDM	52.8%	54.2%	47.2%	45.8%
MARUTI	58.0%	63.9%	42.0%	36.1%
MTNL	61.5%	66.6%	38.5%	33.4%
NATIONALUM	57.7%	63.2%	42.3%	36.8%
NTPC	62.3%	71.5%	37.7%	28.5%
ONGC	59.0%	61.8%	41.0%	38.2%
ORIENTBANK	60.6%	66.2%	39.4%	33.8%
PNB	58.5%	64.2%	41.5%	35.8%
RANBAXY	61.2%	68.0%	38.8%	32.0%
RCOM	65.6%	72.7%	34.4%	27.3%
REL	58.0%	63.0%	42.0%	37.0%
RELIANCE	62.9%	68.4%	37.1%	31.6%
RPL	62.3%	72.3%	37.7%	27.7%
SAIL	61.6%	64.5%	38.4%	35.5%
SATYAM	53.1%	55.2%	46.9%	44.8%
SBIN	62.4%	66.7%	37.6%	33.3%
SIEMENS	60.8%	69.1%	39.2%	30.9%
SUNPHARMA	61.8%	70.5%	38.2%	29.5%
SUZLON	57.6%	61.9%	42.4%	38.1%
TATAMOTORS	53.7%	55.7%	46.3%	44.3%
TATAPOWER	56.2%	59.6%	43.8%	40.4%
TATASTEEL	68.4%	71.5%	31.6%	28.5%
TCS	59.6%	65.7%	40.4%	34.3%
VSNL	53.1%	53.1%	46.9%	46.9%
WIPRO	58.5%	66.1%	41.5%	33.9%

Table 3: Trading Activity in Derivatives by Category of Investors Institutional, Retail and Proprietary Investors Turnover Analysis

	Institutional Investors			**Retail**		**Proprietary**
Month	*Gross Traded Value*	*Percentage Contribution*	*Gross Traded Value*	*Percentage Contribution*	*Gross Traded Value*	*Percentage Contribution*
June-06	111779	10.04%	652052	58.55%	349777	31.41%
July-06	94851	9.94%	557292	58.39%	302366	31.68%
August-06	88388	9.41%	558022	59.41%	292921	31.18%
September-06	104801	10.02%	645166	61.69%	295926	28.29%
October-06	111794	11.05%	627887	62.09%	271635	26.86%
November-06	117279	9.02%	830812	63.93%	351566	27.05%
December-06	141779	10.59%	833279	62.26%	363266	27.14%
January-07	144,267	11.50%	798,496	63.63%	312,150	24.87%
February-07	154,352	10.97%	913,964	64.96%	338,668	24.07%
March-07	158,847	11.45%	906,178	65.31%	322,501	23.24%

References

[1] Abhyankar, Abhay H., Return and Volatility Dynamics in the FT-SE 100 Stock Index and Stock Index Futures Markets, *Journal of Futures Markets*, **15**, (1995), 457-488.

[2] Anand Babu P. et al., The Temporal Price Relationship between the IndexFutures and the Underlying Cash Index: Evidence from the Indian Stock Market,Paper Presented at the *International Conference on Business & Finance* (2003),Hyderabad, India.

[3] Baillie, R. T., Booth, G., Tse, Y., and Zabotina, T.V, Price Discovery and Common Factor Models, *Journal of Financial Markets,* **5**, (2002), 309-321.

[4] Booth, G. G., So, R. W., & Tse, Y, Price discovery in the German equity index derivatives markets. *The Journal of Futures Markets*, **19**(6), (2002), 619-643.

[5] Booth, G.Geoffrey, Ji-Chai Lin, Teppo Martikainen, and Yiuman Tse, Trading and pricing in upstairs and downstairs stock markets, *Review of Financial Studies* **15**, (2002), 1111–1135.

[6] Chakravarty, Sugato, Huseyin Gulen, & Stewart Mayhew, Informed trading in stock and option markets. *Journal of finance*, **54**(3), (2002), 1235-1257.

[7] Chan, K., K.C. Chan and G.A. Karolyi, Intraday volatility in the stock index and stock index futures markets, *Review of Financial Studies* **4**, (1991), 657-684.

[8] Chan, Kalok, A Further Analysis of the Lead-Lag Relationship between the Cash Market and Stock Index Futures Market, *Review of Financial Studies* **5**, (1991), 123-152.

[9] De Jong, F., Measures of Contribution to Price Discovery: A Comparison, *Journal of Financial Markets*, **5**, (2002), 323-327.

[10] Engle R F and Granger G W, Cointegration and Error Correction: Representation, Estimation and Testing, *Econometrica*, **55**, (1987), 251-276.

[11] Fleming, J., Ostdiek, B., & Whaley, R. E, Trading costs and the relative rates of price discovery in stock, futures, and option markets. *The Journal of Futures Markets*, **16**, (1996), 353-387.

[12] French, K R and Roll, R, Stock Return Variances: The Arrival of Information and the Reaction of Traders, *Journal of Financial Economics*, **17**, (1986), 5-26.

[13] Gonzalo, J. and Granger, C W J, Estimation of Common Long-Memory Components in Cointegrated Systems, *Journal of Business and Economic Statistics*, **13**, (1995), 27-35.

[14] Hamilton, J.D., *Time Series Analysis*, Princeton University Press, 1994.

[15] Harris, F.H., McInish, T.H., and Wood, R.A., Security Price Adjustment Across Exchanges: An Investigation of Common Factor Components for Dow Stocks. *Journal of Financial Markets*, **5**(3), (2002), 277-308.

[16] Harris, F.H., McInish, T.H., Shoesmith, G.L., and Wood, R.A., Cointegration, Error Correction, and Price Discovery on Informationally Linked Security Markets, *Journal of Financial and Quantitative Analysis*, **30**(4), (1995), 563--579.

[17] Hasbrouck, J, One Security, Many Markets: Determining the Contributions to Price Discovery, *The Journal of Finance*, **50**(4), (1995), 1175-1199.

[18] Hasbrouck, J. Stalking the Efficient Price in Market Microstructure Specifications: An Overview, *Journal of Financial Markets*, **5**, (2002), 329-339.

[19] Hasbrouck, Joel, Intraday price formation in U.S. equity index markets, *Journal of Finance*, **58**(6), (2003), 2375-2400.

[20] Huang, Roger D., The quality of ECN and Nasdaq market maker quotes, *Journal of Finance*, **57**, (2002),1285–1319.

[21] Iihara, Yoshia, Kiyoshi Kato and Toshifumi Tokunaga, Intraday Return Dynamics between the Cash and the Futures Markets in Japan, *Journal of Futures Markets*, **16**, (1996),147-162.

[22] Johansen, S., Statistical Analysis of Co-integration Vectors, *Journal of Economic Dynamics and Control*, **12**, (1988), 231-254.

[23] Jones, Charles, M and Lipson M L, Why NYSE Retail Orders Get Better (Yes, Better) Executions, University of Columbia Working Paper, 2003.

[24] Karolyi, G.A., A multivariate GARCH model of international transmissions of stock returns and volatility: The case of the United States and Canada, *Journal of Business and Economic Statistics*, **13**, (1995), 11-25.

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

[26] Kawaller, Ira G., Paul D. Koch and Timothy W. Koch, Intraday relationships between volatility in S&P 500 futures prices and volatility in the S&P 500 index, *Journal of Banking and Finance*, **14**, (1990), 373-397.

[27] Kedarnath Mukherjee and Mishra R.K. (2006), Lead-Lag Relationship between Equities and Stock Index Futures Market and it's Variation around Information Release: Empirical Evidence from India, *NSE Research Paper*, NSE India.

[28] Koutmos, G. and G.G. Booth, Asymmetric volatility transmission in international stock markets, *Journal of International Money and Finance*, **14**, (1995), 747- 762.

[29] Koutmos, G. and M. Tucker, Temporal relationships and dynamic interactions between spot and futures stock markets, *Journal of Futures Markets*, **16**, (1996), 55-69.
[30] Mayhew S, The impact of derivatives on cash markets: What have we learned? *University of Georgia working paper*, 2000.
[31] Ross, S, Information and Volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy, *Journal of Finance*, **44**, (1989), 1-17.
[32] Schreiber, P.S. and R. A. Schwartz , Price Discovery in Securities Markets, *Journal of Portfolio Management*, **12**, (1986), 43-48.
[33] So, R. and Y. Tse, Price Discovery in Hang Seng Index Markets: Index, Futures and Tracking Fund, *Journal of Futures Markets*, **24**, (2004), 887-907.
[34] Stock, J H, Watson, M W, Testing for Common Trends, *Journal of American Statistical Association*, **83**, (1988), 1097-1107.
[35] Stoll, Hans R. and Robert E. Whaley, The Dynamics of Stock Index and Stock Index Futures Returns, *Journal of Quantitative and Financial Analysis*, **25**, (1990), 441-468.
[36] Thenmozhi M. Futures Trading, Information and Spot Price Volatility of NSE-50 Index Futures Contract, NSE Research Paper, NSE India, (2003).
[37] Tse, Y, Price discovery and volatility spillovers in the DJIA index and futures markets. *Journal of Futures Markets*, **19**(8), (1999), 911—930.

Appendix

Individual stock futures and contract specification:
As of September 2007 NSE is trading futures and options on six indices and individual stock futures and options on 207 securities. Futures at any point of time are offered for three maturities, namely, near month, next month and far month. The last Thursday of each month is the expiry date. If the last Thursday happens to be a holiday then expiration date would be the next trading day. The minimum price increment in futures is 5 paisa.

Parameter	**Futures on Individual Stocks**
Underlying Instrument	207 Securities FUTSTK
Trading Cycle Expiry Day Permitted Lot size	3 month trading cycle - the near month (one), the next month (two) and the far month (three) Last Thursday of the expiry month. If the last Thursday is a trading holiday, then the expiry day is the previous trading day. Underlying Specific
Price Steps	Rs.0.05
Price Bands	Operating range of 20% of the base price