CHAPTER - IV

PRICE DISCOVERY IN INDIAN SECURITIES MARKET
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This chapter deals with the nature and the implications of relationship between the equities and the derivatives segments of the securities market and narrates the approaches followed by existing studies to analyse such relationship. The aptness of transfer entropy, among the various entropic measures, to quantify directional information is highlighted and the computational aspects of transfer entropy are explained. Then the data used for the analysis are presented and the results obtained are interpreted.

Interactions between different sub-systems of financial market are considered to be an important internal force of the market. Deciphering the role played by highly correlated product lines is an important question faced particularly in stock market. The identification and quantification of causal relationships between the equities and the derivatives segments of the stock market, by analysing the prices over time of an equities market index and a futures contract on the index, furthers the understanding of the market's internal dynamics and has a lot of implications, for all the participants of the market, including the following.

- Detection of causal structure between the equities and the derivatives markets may lead to simplification of the design of control strategies and reduction of the number of measurement channels by exploiting redundant information. Since an impulse in a market is reflected quickly in the other market, policy intervention becomes more effective in the desired direction within reasonable time horizon.
- In case causal relationship exists between the two markets, unexpected changes in equities and futures prices will be more correlated. This will enhance substitutability of futures for position in equities market and will improve risk transfer function of derivatives market.

- Relationship between the markets reduces arbitrage opportunities and the direction of causality serves as a guide to choose the dynamic relationship model between equities and futures prices.

- In case there is no causal relationship between the two markets, hedging results in non-trivial risk exposure to hedgers, however market players may diversify their portfolios across markets thereby reducing their risk exposure.

- Absence of causal relationship also suggests that margins prescribed by market regulators or stock / derivatives exchange authorities, on positions taken by participants in the two markets may be levied separately without netting their positions across the markets i.e. cross-margining may not be possible in such a situation.

**LEAD – LAG RELATIONSHIP BETWEEN MARKET SEGMENTS**

The continuous time relationship between the theoretical value of the futures price and the spot price of an asset at any time \( t \) is given by the cost of carry model

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

where

- \( F_t \) = futures price at time \( t \)
- \( S_t \) = spot price at time \( t \)
\[ r = \text{continuously compounded cost of carrying the asset from the present time } t \text{ to the expiry date } T \]

\[ d = \text{yield on the asset during the remaining period for expiry } (T - t). \]

In perfectly efficient and continuous equities and derivatives markets, risk-less arbitrage opportunities do not appear (in the absence of transaction costs) and hence, if a stock index is taken as an asset, the cost of carry model should be satisfied at every instant \( t \).

So, the instantaneous rate of change in the index value \( (R_S) \) equals the net cost of carry of the stock portfolio \( (r - d) \) plus the instantaneous change in the price of a futures contract on the index \( (R_F) \).

i.e. \[ R_S = (r - d) + R_F, \] where \( R_F = \log \left( \frac{F}{F_{t-1}} \right) \) and \( R_S = \log \left( \frac{S}{S_{t-1}} \right) \).

This implies that

- the contemporaneous rates of return of the futures contract and of the underlying stock index are perfectly positively correlated
- the non-contemporaneous rates of return of the futures contract and of the underlying stock index are not correlated.

However this does not hold exactly, due to several reasons such as

- infrequent trading of the constituent stocks in the index (in some markets) whereas the index futures contract is traded as a single unit
- differential transaction costs and other incidental charges
- greater speed of reflection of investors' views in derivatives market due to high degree of leverage and less capital requirement in the derivatives market.
Hence there may be lead – lag relationship in the price movements of the index futures and the stock index. It is often believed that derivatives market potentially provides an important function of price discovery, implying that futures prices contain useful information about subsequent stock prices, apart from what is contained already in the current stock price. It is also alleged that futures trading influences unduly the underlying stock prices, especially on the expiry days of futures contracts.

**APPROACHES TO STUDY THE RELATIONSHIP**

We have a set of simultaneously recorded variables - index futures price and stock index value - over a period of time and it is required to measure to what extent the time series corresponding to such variables contribute to the generation of information and at what rate they exchange information. Various methods have been proposed for the simultaneous analysis of two series and generally cross-correlation and cross-spectrum are used for measuring relationships between such time series, however these methods suffer from the drawbacks that

- they measure only linear relations i.e. the non-linear characteristics of the interactions between capital market segments which have been evidenced by different studies are not considered

- they lack directional information i.e. they simply say how far the two market segments move together and do not identify the market segment where price discovery happens.
Introducing time delay in the observations pertaining to one market segment may facilitate identifying asymmetric relationship and hence direction of information flow, however non-linear relationships will still remain unexplored.

Garbade and Silber (1983)\(^1\) has presented an analytical model of simultaneous price dynamics which suggests that over short intervals, the correlation of price changes is a function of the elasticity of arbitrage between an asset in spot market and its counterpart futures contract. Granger (1988)\(^2\) has introduced an error correction model which takes into account non-stationarity of co-integrated variables and distinguishes between short run deviations from equilibrium indicative of price discovery and long run deviations which account for efficiency and stability. These approaches involve estimation of simultaneous linear equations in a pair of variables with time lags and have been used in a number of studies examining the source of price discovery.

A statistically rigorous approach to the detection of interdependence, including non-linear dynamic relationships, between time series is provided by tools defined using the information theoretic concept of entropy which is model independent (providing qualitative inferences across diverse model configurations).

**ENTROPIC MEASURES TO STUDY CAUSAL RELATIONSHIP**

Harry Joe (1989)\(^3\) has proposed relative entropy based measures of multi-variate dependence for continuous and categorical variables, however these measures require the
estimation of probability density or mass functions. C.W. Granger et al (2004) have proposed a transformed metric entropy measure of dependence for both continuous and discrete variables. Metric entropy is a measure of distance unlike relative entropy which is a measure of only divergence, however the utility of metric entropy in studying statistical dependence based on causality is to be tested.

Since mutual information measures the deviation from independence of the variables, it has been proposed as a tool to measure the relationship between financial market segments. Further, mutual information is non-parametric and depends on higher moments of the probability distributions of the variables, unlike correlation which depends on the first two moments only. However mutual information is a symmetric measure and does not contain dynamical information nor directional sense. The conditional entropies $H(Y / X) = H(X,Y) - H(X)$ and $H(X / Y) = H(X,Y) - H(Y)$ are non-symmetric, however the absence of symmetry is not due to information flow but on account of the different individual entropies. Some authors, for example Vastano and Swinney (1988), have proposed the introduction of time delay in one of the variables while computing mutual information and the use of such time delayed mutual information to define velocity of information transport in spatio-temporal systems. However this does not distinguish information actually exchanged from shared information due to a common input signal or history. Therefore mutual information does not quantify the actual overlap of the information content of two variables. Further, there may be causal relationship without detectable time delays and conversely there may be time delays which do not reflect the naively expected causal structure between the two time series. Another issue is that the
estimation of time delayed mutual information calls for a large quantity of noise free stationary data – a condition rarely met in real world situations.

Another information theoretic measure called transfer entropy has been introduced by Thomas Schreiber (2000)\(^6\) to study relationship between dynamical systems. Robert Marschinski and H.Kantz (2002)\(^7\) have used an improved estimator called effective transfer entropy and concluded that the US stock index Dow Jones has higher relative impact on the German stock index DAX. Seung Ki Back et al (2005)\(^8\) have applied transfer entropy on daily closing prices of 135 stocks in New York Stock Exchange for studying information flow among groups of companies and discriminated the market-leading companies from the market-sensitive ones.

TRANSFER ENTROPY

Transfer entropy is an information theoretic concept that quantifies the degree to which a dynamical process affects the transition probabilities i.e. the dynamics of another. Transfer entropy has the properties of mutual information and also takes the dynamics of information transport into account. Transfer entropy quantifies the exchange of information between two systems, separately for both the directions and conditional to common input signal.

The rate at which the entropy of a stochastic process \(X_n\), \(n = 1,2,\ldots\) grows with \(n\) is given by
\[ h_n(X) = - \sum p(x_{n+1}) \log p(x_{n+1} / x_n, x_{n-1}, \ldots, x_1) \]

\[ = - \sum p(x_{n+1}) \log \left( \frac{p(x_{n+1}, x_n, x_{n-1}, \ldots, x_1)}{p(x_n, x_{n-1}, \ldots, x_1)} \right) \]

\[ = - \sum p(x_{n+1}) \log p(x_{n+1}, x_n, x_{n-1}, \ldots, x_1) + \sum p(x_{n+1}) \log p(x_n, x_{n-1}, \ldots, x_1) \]

\[ = H_{n+1}(X) - H_n(X) \]

where \( H_n(X) \) is the entropy of the process given by \( n \) dimensional delay vectors constructed from \( X_n \). Thus \( h_n(X) \) denotes the information still transmitted by \( x_{n+1} \) when \( x_1, x_2, \ldots, x_n \) are known or the missing information required to forecast \( x_{n+1} \) using \( x_1, x_2, \ldots, x_n \). Alternatively, \(- h_n(X)\) denotes the information known about \( x_{n+1} \) from \( x_1, x_2, \ldots, x_n \).

The generalization of the entropy rate to construct mutual information rate between two variables \( (X, Y) \) is done using the generalised Markov property

\[ p(x_{n+1} / x_n, x_{n-1}, \ldots, x_{n-k+1}) = p(x_{n+1} / x_n, x_{n-1}, \ldots, x_{n-k+1}, y_n, y_{n-1}, \ldots, y_{n-l+1}) \]

where \( k \) and \( l \) denote the number of past observations included in the variables \( X \) and \( Y \) respectively. In the absence of information flow from \( Y \) to \( X \), the state of \( Y \) has no influence on the transition probabilities of \( X \). Just as mutual information is quantified as the deviation from the independence of the variables \( X \) and \( Y \) and is defined as the relative entropy between the joint distribution \( p(x,y) \) and the product distribution \( p(x)p(y) \), the mutual information rate is quantified as the deviation from the independence of the entropy rates and is defined as the relative entropy between the transition probabilities \( p(x_{n+1} / x_n, x_{n-1}, \ldots, x_{n-k+1}, y_n, y_{n-1}, \ldots, y_{n-l+1}) \) and \( p(x_{n+1} / x_n, x_{n-1}, \ldots, x_{n-k+1}) \). This is
termed as transfer entropy and denoted as $T_{Y \rightarrow X}$. If $k$ and $l$ denote block lengths taken in the variables $X$ and $Y$ respectively, then

$$T_{Y \rightarrow X}(k,l) = \sum p(x_{n+1}, x_n, x_{n-1}, \ldots, x_{n-k+1}, y_n, y_{n-1}, \ldots, y_{n-l+1}) \log \left\{ \frac{p(x_{n+1}/x_n, x_{n-1}, \ldots, x_{n-k+1}, y_n, y_{n-1}, \ldots, y_{n-l+1})}{p(x_{n+1}/x_n, x_{n-1}, \ldots, x_{n-k+1})} \right\}$$

$$= -H_{k+1}(X,Y) + H_k(X,Y) + H_k(X) - H_k(X,Y)$$

$$= h_k(X) - h_k(X,Y)$$

Obviously, $0 \leq T_{Y \rightarrow X}(k,l) \leq H(X)$. Also, $T_{Y \rightarrow X}$ is asymmetric and takes into account only statistical dependencies originating in the variable $Y$ and not those deriving from a common input signal. Further, transfer entropy is closely related to conditional entropy extended to two variables $X$ and $Y$ and may be explained as follows.

Transfer entropy = (Information about future observation $x_{n+1}$ gained from past observations of $X_n$ and $Y_n$) - (Information about future observation $x_{n+1}$ gained from past observations of $X_n$ only) = Information flow from $Y_n$ to $X_n$.

**COMPUTATIONAL ASPECTS**

The computation of transfer entropy from a time series to another may be done in two ways—

(i) The symbolic encoding method divides the range of the data set into $S$ disjoint intervals such that the number of data points in every interval is constant and assigns one symbol to each interval. Then $p(x_n) = 1/S$ so that $H(X) = \log_2 S$. 

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However, determining the partition is a contentious issue, called the generating partition problem and even for a two dimensional deterministic system, the partition lines may exhibit considerably complicated geometry.

(ii) The correlation integral method computes the fraction of data points lying within boxes of constant size $\varepsilon$, after embedding the data set into an appropriate phase space and uses the formula $H_n(X, 2\varepsilon) \sim - \log_2 \{C_n(X, \varepsilon)\}$ where $C_n$ is the generalised correlation integral of order $n$. However, determining the box size $\varepsilon$ remains as a contentious issue. The parameter $\varepsilon$ plays the role of defining the resolution or the scale of concerns, just as the number of symbols $S$ does in the symbolic encoding method.

The symbolic encoding method has the advantage of neutralising undesirable effects due to very inhomogeneous histograms and it also ignores the trivial information gained by just observing marginal distributions. Further, for data with an approximately symmetric distribution, the concrete meaning of partitions is intuitive with $S = 2$ corresponding to the two possible signs of the increments and $S = 3$ corresponding to the three possible moves viz. larger gain, roughly neutral and larger loss.

For a given partition, $T_{Y \rightarrow X}(k,l)$ is a non-increasing function of the block length $k$ of the series $X$, since inclusion of more number of past observations in the variable $X$ is likely to result in reduction of flow of information from $Y$ in the estimation of the next value of $X$. The parameter $k$ is to be chosen as large as possible in order to find an invariant value for $T_{Y \rightarrow X}$, however due to the finite size of real time series, it is required to find a
reasonable compromise between unwanted finite sample effects and a high value for $k$. Further, a very small value of $k$ may lead to misinterpretation of information contained in past observations of actually both series as an information flow from $Y$ to $X$ and hence $k$ may be chosen as large as possible.

Further, in order to consider appropriate value of $k$, it is proposed that the concept of mutual information with delay $k$ i.e. $I(k)$, of a time series, as illustrated in the previous chapter, be used and that the value of $k$ in respect of which the first minimum of $I(k)$ occurs may be chosen. Also, the choices for $l$ are $l = k$ or $l = 1$ and, for computational reasons, $l = 1$ is preferred usually.

**PRESENTATION OF DATA**

In this study, the symbolic encoding method is used to compute transfer entropy between the equities segment and the derivatives segment of the Indian stock market. National Stock Exchange of India (NSEIL) being the leading stock exchange of India, the 50 stock index of the equities segment of the exchange viz. Nifty and the near month index futures contract traded in the derivatives segment of the exchange are considered as representatives of the two market segments, for identifying price discovery in the Indian stock market. Due to high liquidity in both the segments of the Exchange, there are a large number of trades every minute in the component stocks of the Nifty index and in the near month Nifty futures. Hence there is a need to look at high frequency data instead of daily closing values of the index and daily closing prices of the futures contract.
Further, electronic trading facility and digital communication network enable incredibly fast information transport, especially between these market segments which have a large number of common or closely connected participants. Hence a trading day appears to be too long a period for the purpose of measuring the time taken for information dissemination from one market segment to the other. So, analysis of minute-to-minute data may be more meaningful in the study of such price discovery.

In light of the above, the average of the values realised by the Nifty index and the average of the prices at which the near month Nifty futures was traded, during a minute were computed for every minute during the trading hours over the period October 2005 – September 2006. Thus two time series, each with 82777 data points were obtained for the variables Nifty index (X) and near month Nifty futures (Y). These price series were transformed to log returns series since such transformation satisfies additive property of the returns and makes the results invariant in spite of arbitrary scaling of the price data. Further, on account of such transformation, stationary character of the two series may be assumed so that meaningful analysis may be made. The summary statistics of the resultant time series are given below.

<table>
<thead>
<tr>
<th></th>
<th>Nifty index</th>
<th>Near month Nifty futures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>-0.02974</td>
<td>-0.05115</td>
</tr>
<tr>
<td>1st Quartile</td>
<td>-0.00024</td>
<td>-0.00030</td>
</tr>
<tr>
<td>Mean</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>Median</td>
<td>0.00002</td>
<td>0.00002</td>
</tr>
<tr>
<td>3rd Quartile</td>
<td>0.00026</td>
<td>0.00033</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.02792</td>
<td>0.02999</td>
</tr>
<tr>
<td>Number of data points</td>
<td>82776</td>
<td>82776</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.00075</td>
<td>0.00088</td>
</tr>
</tbody>
</table>
EMPIRICAL RESULTS

The symbolic encoding method partitions the range of the data set into disjoint bins and assigns a symbol to each bin, with marginal equal probability for every symbol. The transfer entropy value depends on the number of bins (S) into which the data set is partitioned and also on the block length k chosen for the variable X and the block length l for Y (however, l is chosen to be 1 generally). Hence transfer entropy $T_{y\rightarrow x}$ (derivatives market to equities market) was computed for the number of bins S ranging from 2 to 8, the block length k for X ranging from 1 to 10 and the block length l for Y equal to 1. Similarly, transfer entropy $T_{x\rightarrow y}$ (equities market to derivatives market) was computed for the number of bins ranging from 2 to 8, the block length for Y ranging from 1 to 10 and the block length for X equal to 1. The computed values are presented in table 4.1 and charts 4.1 and 4.2.

For a given partition, the transfer entropy $T_{y\rightarrow x}$ is expected to decrease with increase in the block length of the series X. The transfer entropy in both the directions behaves reasonably for partitions $S = 5, 6, 7, 8$ of the data analysed and for block length of the transferee series $k = 5, 6$ or more. Further transfer entropy approaches zero for $k = 10$ or more. Hence, meaningful results may be obtained from transfer entropy values computed for partitions $S = 5, 6, 7, 8$ and block length of the transferee series $k = 5, 6, \ldots, 10$.

Further, in order to consider appropriate values of k, the mutual information of the two time series containing the values of the Nifty index (X) and near month Nifty futures (Y), for delays ranging from a day to 20 days are computed and given in table 4.2. It may be observed that the first minimum has occurred for $k = 8$ and 3 for the two series. Hence,
meaningful results may be obtained from transfer entropy values computed for partitions 
S = 6, 7, 8 and block length of the transferee series k ≥ 3.

From the transfer entropy values given in the table 4.1, a flow of information from 
minute t of one series to minute t+1 of the other series is observed in both the directions,
which suggests interactions between equities and derivatives markets at a time scale of a 
minute or less. The flow from the derivatives market to the equities market is more 
pronounced than the flow in the reverse direction. For the interpretation of the transfer 
entropy values, the following measures have been defined.

NET INFORMATION FLOW (NIF)

The net information flow is defined to measure the disparity in influences of the two 
variables on each other. If the net information flow defined as NIF_{Y→X} = T_{Y→X} - T_{X→Y}
is positive, then the variable Y may be said to influence the variable X.

NORMALISED DIRECTIONALITY INDEX (NDI)

The normalised directionality index is defined in order that relevant but small-scale 
causal structure is not neglected and quantified as NDI(X,Y) = \frac{T_{Y→X} - T_{X→Y}}{T_{Y→X} + T_{X→Y}}. The index 
varies from -1 (in case of uni-directional causality from X to Y) through 0 (in case of 
equal feedback between the two variables) to +1 (in case of uni-directional causality 
from Y to X), with intermediate values corresponding to bidirectional causality between
the two variables X and Y. The index thus has the property of coefficient of correlation between two variables and also has the additional feature of directionality.

RELATIVE EXPLANATION ADDED (REA)

The measured amount of information flow from Y to X is compared with the total flow of information in X. This ratio measures how much of \( x_{n+i} \) is additionally explained when the past values of X are already known and then the last value \( y_n \) of Y is taken into account. This is called relative explanation added and is defined as

\[
REA_{y \rightarrow x} (k, l) = \frac{T_{y \rightarrow x} (k, l)}{h_k (X)}
\]

Similarly, \( REA_{x \rightarrow y} (k, l) = \frac{T_{x \rightarrow y} (k, l)}{h_k (Y)} \). The ratio varies from 0 (in case of no information flow at all from a variable to the other) to 1 (in case of all the information in the current value of one variable being transferred from past values of the other variable) with intermediate values corresponding to the amount of information in one variable caused by the other variable.

The NIF values from the derivatives segment (Y) to the equities segment (X) and the REA for both the directions, in respect of the two market segments, are presented in the table 4.1 and charts 4.3 to 4.5 Also, the normalised directionality index values are presented in the table 4.1

(a) It is observed that NIF from the derivatives segment to the equities segment is generally positive except for one or two values of the block length of the transferee
series, for each partition. Hence the information flow from the derivatives segment to the equities segment is dominant over that in the reverse direction.

(b) From the values of NDI(X,Y), it is observed that the information flow from the derivatives segment to the equities segment is dominant over that in the reverse direction.

(c) For partitions $S = 5, 6, 7, 8$, the REA by the derivatives segment to the equities segment increases with the block length taken for the equities segment initially and then stabilises for block length exceeding 6. This implies that the information flown from the derivatives segment in the prediction of the next price for the Nifty index in the equities segment cannot be compensated by the inclusion of more number of past values realised by the index.

For partitions $S = 5, 6, 7, 8$, the REA by the equities segment to the derivatives segment increases with the block length taken for the derivatives segment initially, however the REA falls for block length exceeding 7. This implies that the contribution of information from the equities segment to the prediction of the next price for the index futures contract in the derivatives segment, diminishes if we take into account a longer memory of the derivatives segment.

It is also observed that the REA by the last value of index futures contract in the derivatives segment to the current value of Nifty index in the equities segment is generally larger than the REA by the last value of Nifty index in the equities segment to the current value of index futures contract in the derivatives segment, thus reinforcing the observation made from the values of NIF.
CONCLUSION

Transfer entropy values between the Nifty index and the near month Nifty futures contract for the period October 2005 – September 2006 have been computed and found to be in consonance with the results of previous studies using other methods, however it may be noted that transfer entropy quantifies information transmission, including non-linear dynamic relationship also. Thus transfer entropy proves to be a promising measure to identify directional information. Specifically, in the Indian stock market, apart from information flow from index futures to Nifty index, information dissemination in the reverse direction also is observed during the period considered, however the flow from index futures to Nifty index is generally more pronounced. It is to be noted that, in the computation of transfer entropy, determination of the appropriate partition which is referred to as generating partition problem and the block length of the transferee time series, has to be done with utmost care.
Table 4.1 – Transfer entropy (T), Relative explanation added (REA) and Net information flow (NIF) and Normalised directionalitity index (NDI) (between equities and derivatives segments of the Indian capital market)

<table>
<thead>
<tr>
<th>Block</th>
<th>Derivatives segment (Y)</th>
<th>Equities segment (X)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>h(X,Y)</td>
<td>h(X)</td>
</tr>
<tr>
<td>2</td>
<td>0.830353</td>
<td>0.854484</td>
</tr>
<tr>
<td>3</td>
<td>0.828952</td>
<td>0.839139</td>
</tr>
<tr>
<td>4</td>
<td>0.827527</td>
<td>0.818660</td>
</tr>
<tr>
<td>5</td>
<td>0.825037</td>
<td>0.809551</td>
</tr>
<tr>
<td>6</td>
<td>0.824413</td>
<td>0.807170</td>
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<tr>
<td>7</td>
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<td>0.807474</td>
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<td>8</td>
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<td>0.807672</td>
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<tr>
<td>9</td>
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<td>0.817350</td>
</tr>
<tr>
<td>10</td>
<td>0.815076</td>
<td>0.817573</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Block</th>
<th>Derivatives segment (Y)</th>
<th>Equities segment (X)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>h(X,Y)</td>
<td>h(X)</td>
</tr>
<tr>
<td>3</td>
<td>0.855735</td>
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<td>4</td>
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<tr>
<td>10</td>
<td>0.813486</td>
<td>0.865468</td>
</tr>
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</table>

Note: (between equities and derivatives segments of the Indian capital market)
<table>
<thead>
<tr>
<th>Delay</th>
<th>Nifty index</th>
<th>Nifty futures</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>1.841461</td>
<td>1.607819</td>
</tr>
<tr>
<td>2</td>
<td>1.597199</td>
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Chart 4.3

NET INFORMATION FLOW (DERIVATIVES TO EQUITIES)

Chart 4.4

RELATIVE EXPLANATION ADDED (DERIVATIVES TO EQUITIES)
Chart 4.5

RELATIVE EXPLANATION ADDED (EQUITIES TO DERIVATIVES)
REFERENCES


